Machine Learning for Public Policy: Applications in Infrastructure and Air Pollution

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Abstract

While machine learning has become ubiquitous in certain fields, its public policy applications in the infrastructure and air pollution domains are relatively understudied. This work develops two frameworks to analyze (1) the impacts of infrastructure and social equity and (2) the impact of area source pollution on resultant concentrations to better inform public policy along these two domains. This work employs a range of machine learning techniques to perform variable search and selection and analyzes causal connections between infrastructure (i.e., bridges) and social equity factors. Further, a novel neural network design that combines vector autoregression techniques with pollution data capably predicts pollution concentrations for two species of $PM_{2.5}$. Throughout this work, the techniques and frameworks are specifically designed to be accessible by engineers and policymakers in the infrastructure and air quality managements domains.

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Chapter 1 Introduction

Infrastructure and environmental problems present issues that current techniques cannot always adequately address. For example, it is difficult to isolate social and equity impacts of infrastructure; it is also difficult and costly to determine air pollution exposure concentrations. This thesis assesses the possibility of using machine learning techniques to make inroads into these issues. These algorithms can reveal and quantify previously undiscovered links between data and do so at faster computational speeds than more conventional empirical or simulation methods. This ability is particularly useful in situations where large quantities of disparate data are available and whose linkages are not always ascertainable for first principles in engineering and social science. This is especially the case when the signal of interest can be relatively small or obscured by irrelevant information.

Thus far, machine learning (ML) has been used on many other applications but less so on issues related to infrastructure and air pollution. In infrastructure, the studies that do use ML typically focus on technical aspects of these topics and less on understanding their social impacts (Abuodeh et al. 2019; Alipour et al. 2017; Rumelhart et al. 1986). In air pollution, machine learning has been used for three main areas of interest: source apportionment, forecasting or prediction of air pollution and quality or exposure and generating hypotheses (Bellinger et al. 2017). When it has been used in these instances, other researchers have used it as a module in a chemical transport model (CTM), a city-scale $PM_{2.5}$ predictor using only wind and precipitation, and to generate sensor-level data using satellite imagery. Therefore, this thesis will apply Least Absolute Shrinkage and Selection Operator (LASSO), causal machine learning algorithms, vector autoregression (VAR), and convolutional neural networks (CNN), to address social equity influences in infrastructure and air pollution exposure concentrations in these domains.

That ML literature which specifically focuses on bridges primarily focus on highly technical aspects of bridges and their maintenance (Alipour et al. 2017; Kushida et al. 1997; Lu et al. 2017).

The literature on maintaining bridges describes how government institutions can maximize resources to optimize maintenance of the greatest number of bridges (Chengalur-Smith et al. 1997; Mohammadi Jamshid et al. 1995). These studies primarily use cost as the outcome and have technical measures as the explanatory factors such as: condition ratings, structural safety requirements, and age of bridge. Their primary concern is to rank-order bridges for maintenance priority. When researchers do take user cost factors into consideration, they tend to focus on factors affected only during construction or rehabilitation such as detour lengths, traffic delays, and congestion (Liu and Frangopol 2005; Liu Min and Frangopol Dan M. 2006; Liu Ming and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017). This literature is primarily concerned with technical engineering factors before and during construction or maintenance (Amini, Nikraz, and Fathizadeh, 2016), and the main consideration given to social factors is the impact on the bridge users during those same periods. Understanding wider social impacts of infrastructure, such as bridges, on populous that do not necessarily use but proximate such infrastructure is still generally understudied and the motivation of this work.

ML methods can be used to examine disparate data to discover new insights about the social impacts of infrastructure. ML techniques are capable of identifying trends and relationships that are difficult or impossible to learn through other methods. By focusing ML methods on the social impacts of infrastructure, we can add quantitative evidence to existing qualitative evidence and theoretical foci about society and the built environment. The literature around society and the built environment has the following foci.

The predominant focus here reconceptualizes the built environment as a conduit for both intended and unintended social connections (Audretsch et al. 2015; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). As Howe and colleagues (2016) write, “Infrastructural deficiencies can both index preexisting inequalities, just as they may, simultaneously, deepen those inequalities” (Howe et al. 2016 p. 551).

On the one hand, infrastructure improves the flow of goods and services such that it can help recognize market opportunities. In an infrastructure study from 2001-2005, the researchers found the impact of infrastructure on new startup activity varies by type and industry (Audretsch et al. 2015). On the other hand, while those using the focal infrastructure may see benefits, the populations living near the infrastructure may experience harm. These deleterious effects may have disproportionately negative effects on the poor and marginalized (Epting 2016; Faoziyah 2016; Grabowski et al. 2017; Star 1999). A marginalized population is one which is "excluded from mainstream social, economic, cultural, or political life (Cook 2008)."

Another focus argues that in the perception of the built environment as technical engineering objects, social values are often taken for granted (Grabowski et al. 2017; Leonardi and Barley 2010; Star 1999; Star and Bowker 2006). Generally speaking, this literature is comprised of a rich set of detailed qualitative studies, with few large-scale quantitative analyses (Desai and Armanios 2018, as a rare exception). It is not yet clear how widespread are the social impacts from the built environment, particularly the degree to which the built environment affects proximate marginalized populations. In fact, prior studies have noted this is largely ignored and not subject to the same breadth and depth of public and governmental review (Schindler 2015).

With regard to air pollution, the literature is clear that there are adverse health effects due to air pollution, particularly from fine particulate matter ($PM_{2.5}$) (Krewski et al. 2009; Lepeule et al. 2012; Stieb et al. 2002). These health effects are a motivating factor for this research. Second, due to the complexities of the interactions between different chemical species, some of the true relationships of these chemical species are not fully understood nor are they accurately predicted by linear modelling techniques (Fiore et al. 2003; Karydis et al. 2007; Stieb et al. 2002). This is the primary motivation for employing machine learning techniques, generally, and neural networks, in particular, which have been successful at modelling many relationships (linear and non-linear) not readily identified by other methods (Hornik 1991; Hornik et al. 1989; Huang et al. 2016). Third, ML techniques are only beginning to be used in studies on air pollution (Bellinger et al. 2017; Kelp et al. 2020; Kleine Deters et al. 2017; Xue et al. 2019).

Within the ML in atmospheric pollution space, the majority of work is attempting to use available sensor networks to predict future air pollution (Bellinger et al. 2017; Feng et al. 2015; Kleine Deters et al. 2017; Xue et al. 2019). Researchers are also using ML to make more computationally efficient modules for use in Chemical Transport Models (CTM), the gold standard in air pollution modelling (Kelp et al. 2020, 2019). This work is using ML to develop a computationally efficient model that learns how chemical species interact based on a CTM in order to predict air pollution concentrations with known adverse health consequences.

Problem Statement

The author focuses on two domains for which machine learning may make inroads – infrastructure and air pollution. The first domain of interest comes from the social and environmental justice and civil engineering domains. The author asks *what is the relationship between infrastructure (specifically, bridges) and socioeconomic equity?* The ultimate goal would be to establish a causal link between the two. Awareness of and desire to promote sustainability in the civil engineering domain has gained traction in the most recent decades. While desire to incorporate sustainability is present, there are not a lot of examples of it in the civil engineering literature. One of the possible reasons for this is that it is a very difficult problem that requires disparate data sources. The publicly available data sources are not easily combined into actionable data. Additionally, due to all the other factors that influence people's socioeconomic wellbeing, attributing specific wellbeing effects to infrastructure is difficult. In the 50th anniversary edition of the Journal of Construction and Engineering Management, Professor Levitt opined, "Bringing the third dimension of sustainability—social equity—into an overall cost–benefit sustainability calculus is much more challenging […] and is extremely difficult to reduce to one-dimensional quantitative metrics (Levitt Raymond E. 2007 p. 627)". Doloi (2018) observed "theories for quantitative evaluation of social performance and underlying social value creation in public infrastructure projects from a community perspective remain unexplored" (p. 1). Thus, the information policymakers need to make better decisions concerning infrastructure and social equity is not easily combined to gain insights to make better policies.

The second domain is to apply machine learning to air pollution. The state of the science chemical transport models are computationally and temporally expensive (Kelp et al. 2019). In spite of all the research that has gone into developing these models, there are still some phenomena that are not completely understood. Even for the chemical reactions that are well understood, the temporal scales at which reactions and other processes occur vary widely. This is an added measure of complexity for which chemical transport models must account. These models are also not readily accessible to policymakers. Simplified models exist to aid policymakers, but they too have shortcomings and often have difficulty modeling non-linear and/or nonstationary behavior of some chemical species. The author's motivation of studying air pollution is to better assess its impact on human health, by data-driven machine learning. Here too, the desire is to discover causal links and estimate properties of causal influences. First, the author seeks to test whether ML techniques can effectively link emissions to concentrations of fine particulate matter chemical species. Second, the author focuses on volatile organic compounds (VOC) to test whether ML can outperform existing models in one or more dimensions.

Common to both of these domains is the fact that performing scientific experiments are nearly impossible due to cost and ethical concerns. To perform the gold standard of a randomized controlled trial with infrastructure could cost hundreds of thousands to millions of dollars and would take many years to decades to properly assess long-term socio-economic effects. It would also be unethical to install a pollution creating device in close proximity to population centers in order to test air pollution effects on health and well-being. Therefore, this type of work is typically restricted to natural experiments.

Machine learning is particularly adept at disambiguating signals from big data. Many algorithms have also been developed to analyze data with the intent of discovering causal links between the variables. Many of these methods are well developed and accessible. The author plans to use these methods to make inroads to the following objectives.

Aims and Objectives

The aim for the first domain is to create an empirical framework and research design for linking bridge data to socioeconomic data and present a case study using these methods. The overall research design seeks to compare “treated” tracts (i.e., those that receive a restrictive bridge) to “control” tracts that mirror, as much as possible, those treated tracts. This work provides a protocol for how to combine the most granular, publicly available infrastructure and socioeconomic data to assess equity impacts of infrastructure using accessible machine learning methods. One of the more challenging parts for social equity domain non-experts is the selection of available variables and therefore the author provides quantitative analysis of available variables and methods to assess the causal link between these variables. The authors feel advancing this method may also help policymakers more sharply assess and prioritize which bridges to replace or rehabilitate that may promise the greatest social benefits. The authors specifically focus on bridges here to assess the feasibility of this approach but feel this protocol can be applied to other forms of physical infrastructure.

The aim of the second domain is to first build a machine-learned model based on a state of the science chemical transport model, focusing the model on nonlinear and/or nonstationary causal influences in a data-driven manner. That model could then be made available to a wider audience concerned with air pollution and health policy.

Chapter 2 Methodological Framework and Feasibility Study to Assess Social Equity Impacts of the Built Environment

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Abstract

Civil engineers recognize the need to better address the potential consequences of infrastructure systems on social equity. However, the challenge has been translating social equity concerns into metrics that are usable in engineering analyses. In this case study, the authors aim to identify such metrics that can be subsequently used by engineers who seek to make equity-informed infrastructure construction, replacement and rehabilitation decisions. Combining geospatial and statistical techniques on publicly available data sources, this research proposes a quantitative framework for how to incorporate social equity metrics into infrastructure analyses. The feasibility of this framework is analyzed in the case of Pennsylvania's bridge system. This feasibility study finds that selection effects (i.e., factors that drive bridge siting) are stronger than treatment effects (i.e., changes that occur after bridge construction) of bridges on social equity. Consistent variables are also identified as correlated with such effects (e.g., demographic and, to a lesser degree, family variables). Overall, this research proposes measures and an approach that helps local government transportation agencies better incorporate social equity into infrastructure construction, replacement and rehabilitation.

Introduction

Civil engineers increasingly recognize the need to better consider the potential consequences of infrastructure systems on social equity. In the 50th anniversary edition of the Journal of Construction and Engineering Management, Levitt (2007) opined, "Bringing the third dimension of sustainability—social equity—into an overall cost-benefit sustainability calculus is much more challenging […] and is extremely difficult to reduce to one-dimensional quantitative metrics (p. 627)”. In a recent analysis of transportation plans, Manaugh, et al (2015) found that even with an increased emphasis on sustainability, social equity is still poorly understood and poorly operationalized if used at all. Doloi (2018) observed “theories for quantitative evaluation of social performance and underlying social value creation in public infrastructure projects from a community perspective remain unexplored” (p. 1). A pressing concern then for engineers and policymakers alike is how to consider social equity in prioritization of infrastructure funding and maintenance.

Grounded in philosophical discussions around equity (Rawls 1971; Walzer 1983), the working definition of social equity used here is the process by which assets are “distributed evenly over people, irrespective of the differences between those people – unless convincing arguments can be provided for another way of distribution” (Martens et al. 2012 p. 687). The first part (even distribution irrespective of differences) refers to “horizontal” equity which argues the “equal distribution of effects (benefits and costs) among individuals” (El-Geneidy et al. 2016 p. 542). The second part (unless convincing arguments otherwise) refers to “vertical” equity, which requires “special considerations for socially and economically disadvantaged groups in the sense that benefits should be intentionally provided to them” (El-Geneidy et al. 2016 p. 542). As applied here, social equity is therefore viewed as even distribution of the benefits and costs of infrastructure assets (horizontal equity), unless factors, for which the authors seek to identify here, undermine this distribution in ways that especially impact more marginalized groups (vertical equity).

Prior work in environmental and social justice makes a compelling case for considering socioeconomic factors in particular when building and maintaining physical infrastructure to ensure equity to those marginalized (Bullard 1990; Grabowski et al. 2017). Studies have observed deleterious segregation effects of transportation infrastructure (Grannis 1998; Reardon et al. 2008). In two cities, the size and speed of road networks were better predictors of racial contiguity than geographic closeness and larger streets with higher speeds acted as boundaries to neighborhoods (Grannis 1998). In a study emphasizing the importance of scale on segregation patterns, the researchers posit that "It seems plausible that the built environment (including highways, street networks, railroads, and public transportation systems) may influence residential segregation patterns (and vice versa)" (Reardon et al. 2008 p. 509). In a legal review, Schindler (2015) noted that infrastructure accessibility "can shape the demographics of a city and isolate a neighborhood from those surrounding it, often intentionally" (p. 1939). In so doing, the built environment controls human behavior by constraining physical movement. Overall, infrastructure can have asymmetric influences on a populous that is especially harmful to the most vulnerable.

To initiate this undertaking, the authors scope this case study to bridges, a form of infrastructure argued to impact physical connectivity in potentially asymmetric ways. Restrictive bridge heights are argued to constrict the passage of certain vehicles, which may disproportionately affect those groups who rely more on public transportation, and may thus segregate across different socioeconomic and demographic groups (Winner 1980). A study that simulated the effect of a bridge linking two populations centers in Indonesia concluded that while the bridge was expected to equalize benefits between the districts, the model demonstrated that the majority of benefits accrued to the already more developed population (Faoziyah 2016).

To assess the feasibility of incorporating social equity in bridge systems, the authors more specifically ask: *how do restrictive bridges impact social equity?* By "restrictive," the authors mean those bridges that are below 4.27 meters (14 feet) and "non-restrictive" bridges are those bridges that are 4.27 meters (14 feet) or above. This is both a prominent regulatory clearance standard for bridges and also a key cutoff that can inhibit the passage of certain vehicles such as commercial trucks (Desai and Armanios 2018). Such restrictions may have social equity implications if certain groups rely on vehicles that are now blocked by such bridges (Winner 1980). This is also especially applicable since restrictive bridge clearances further serve as an important component of sufficiency ratings, which helps ascertain to what degree a structurally deficient bridge is eligible for federal funding (Small et al. 1999). The authors also consider whether a tract is more likely to receive any bridge at all as a lack of bridges is also another possible source of restrictions (Table 1).

Table 1. New bridges built by underclearance category during a census period (e.g., 1961-1970)

Year	Restrictive	Non-restrictive	All bridges
1970	56	1,773	5,816
1980	15	995	3,360
1990	12	536	2,987
2000	7	588	2,697
2010	4	658	2,872
Total	94	4,550	17,732

A necessary first step is to empirically identify those social equity factors that are associated with infrastructure placement, planning, and subsequent usage. Historically, this has proven to be a challenging enterprise (Doloi 2018; Levitt Raymond E. 2007). Infrastructure and socioeconomic data are not just managed across dispersed sources; they are also at different levels of analysis and availability (Manaugh et al. 2015). Infrastructure data is located at specific point locations and usually updated annually or at more granular temporal scales. However, historical (e.g., as early as the 1970s) socioeconomic data is most easily accessible every ten years through the U.S. Census, and adequately detailed social equity measures tend to appear in more recent decades and less so in earlier decades. Moreover, the most granular geophysical level for which this is publicly available is usually a census tract (average area size – 36 km^2 or 13.9 mi^2), and tracts change in size and shape with changes in population (GeoLytics 2018). This study's aim then is to assess the feasibility of integrating these existing methods and data sources to address this pressing yet empirically challenging need to gauge the social equity impacts of infrastructure.

To arrive at a comprehensive list of socioeconomic measures of equity, the authors conducted an extensive literature review and identified four research areas whereby infrastructure is argued to impact social equity: neighborhood effects (Crowder and South 2008; Sampson et al. 1999, 2002; Sharkey 2014), social justice (Brady et al. 2017; Schindler 2015), environmental justice

Table 2. Most influential variables from the study's selection models with description and effect direction.

Variable	Variable Category (in bold) / Description	Directional Effect on Selection: Restrictive	Non-restrictive	All New
	Income			
***IHS-transformed Real Average income**	Inverse Hyperbolic Sine Transformation of average household income in past 12 months (2010 Constant $ US)	NS	+	+
***IHS-transformed Real Aggregate income**	Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US)	+	+	+
***% Welfare rate**	Percentage of households with public assistance inc. (incl. SSI) last year of total households	NS	–	+
	Demographic			
***% Minority**	Non-White percentage of total population	NS	–	–
***% African American**	Black/African American percentage of total population	NS	–	–
***% Hispanic**	Percentage Hispanic/Latino of total population	NS	–	–
	Family			
***% single-parent families w/kids**	Percentage of single-parent families with own children under 18 years old of total families and subfamilies	NS	NS	–
***% female-headed families**	Percentage female-headed families with or without own children of total families and subfamilies	NS	NS	–
	Transportation			
***IHS-transformed Travel on public transportation**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included)	–	+	NS
***IHS-transformed Commute over 45 minutes**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes	NS	–	NS
	Education			
***% Associate Degree Graduate**	Percentage of persons 25+ years old who have an associate degree but no bachelor's degree	–	–	NS
***% bachelor's or higher Degree Graduate**	Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	+	NS	NS

* Lagged variable when used as an independent variable

Note: NS = not significant, + = positive relationship, - = negative relationship.

(Bullard 1990; Carless 2018; Pathak et al. 2011), and segregation (Crowder et al. 2012; Farley and H. Frey 1994; Lee et al. 2008). The neighborhood effects literature argues infrastructure, such as roads, create boundaries that isolate neighborhoods. When such boundaries isolate, for example, more affluent from less affluent neighborhoods, this can create social equity disparity in these neighborhoods. The social justice literature argues minorities suffer systemic structural disadvantages creating social inequity. The environmental justice literature argues undesirable, often high-polluting infrastructure, is sited in minority neighborhoods. This leads to more adverse environmental and health outcomes for these neighborhoods, an example of social inequity. The segregation literature argues infrastructure has effectively, whether intended or not, isolated minorities from majority populations, which creates social equity imbalances for these minorities. Based on this review, the authors classified the equity measures used in these perspectives into the following themes across these research areas: wealth status, race, family composition, education, and housing. Since the object of this study is transportation infrastructure, the authors also added available transportation-related variables.

The authors then looked for quantitative sources to collect such measures in a way that could adequately be mapped onto the 50-70 year design life of a bridge (Hu Xiaofei and Madanat Samer 2015; Neves et al. 2006). As per the challenges discussed in the previous paragraph, a dataset that normalized tracts to a reference year that accounts for population change would greatly facilitate a comparative analysis over time as such a reference point. The Neighborhood Change Database (NCdB) is a dataset with such normalized tracts and the longest duration available to the authors was from 1970 to 2010 (GeoLytics 2018). The authors then searched the census data as provided by the NCdB (GeoLytics 2018), and identified forty-one variables that most closely matched or proxied for these aforementioned social equity and transportation categories. This study's main variables are listed in Table 2 and more fully in the Appendix I, Section C, Table 22 - Table 30.

What the authors subsequently present then is a novel empirical approach and research design for linking bridge data to this socioeconomic data. To gauge the feasibility of such an approach, the authors use bridge data from the Pennsylvania Department of Transportation's (PennDOT) Bridge Management System v. 2.0 (BMS2) (Pennsylvania Department of Transportation 2018a) and census tract data from the Neighborhood Change Database (GeoLytics 2018). As of 2017, Pennsylvania has the second-highest number of structurally deficient bridges in the country (FHWA 2017). Thus, Pennsylvania serves as a good candidate case to ascertain whether social equity measures could help further plan funding around those bridges in need of repair and maintenance.

The overall research design seeks to compare "treated" tracts (i.e., those that receive a restrictive bridge) to a "control" tract that mirror, as much as possible, those treated tracts. To do that, the authors begin with the full sample of tracts as a baseline using a simple circular buffer around the bridges to approximate interactions between the bridge and nearby tracts (see Appendix I, Section E). The authors then sharpen the treated tracts using a network analysis that identifies the bridge service area to isolate better the treated tracts that are connected by the bridge (Liu Min and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017). The authors finally sharpen the control tracts using a coarsened exact matching (CEM) technique to isolate better those tracts that do not receive a restrictive bridge but as closely as possible approximate the treatment tracts (Desai 2018; Iacus et al. 2008, 2009, 2012). The authors hope through this novel empirical approach and research design, this study can provide a protocol for how to combine the most granular, publicly available infrastructure and socioeconomic data to assess equity impacts of infrastructure. The authors feel advancing this method may also help policymakers more sharply assess and prioritize which bridges to replace or rehabilitate that may promise the greatest social benefits. The authors specifically focus on bridges here to assess the feasibility of this approach but feel this protocol can be applied to other forms of physical infrastructure.

Physical Infrastructure (Bridge Systems) on Social Equity – Selection vs. Treatment

To guide the research design and analysis, the authors first assessed the existing literature and ways in which social impacts of infrastructure are considered. The authors only briefly summarize those efforts here, in the Introduction and Table 3. Appendix I, Section H provides a more extensive literature review for the interested reader. More specifically, the authors needed to integrate sociological thinking into the civil engineering dialogue. While civil engineering depicts bridges as facilitating flows, sociology posits that bridges may actually serve as barriers. Infrastructure, when built well, is taken for granted, and only when infrastructure malfunctions do people recognize its obstructive power (Star 1999). For example, while most people see bridges as a conduit for access, Winner (1980) shows in his depiction of Robert Moses' parkway bridges in New York that for those who rely on public transportation, bridges can also act as a conduit for exclusion. While prior research has debated about the issues of equity that arise from specific cases of physical infrastructure, namely whether designers intended or not to create these obstacles (Joerges 1999; Winner 1980; Woolgar and Cooper 1999), few have empirically analyzed the magnitude and scope of these equity problems through a large-N quantitative analysis.

Generally, civil engineers accept that infrastructure improves the lives of people who live and work near it. However, this belief is restricted in scope. Namely, when discussing social issues from an infrastructure perspective, the focus is predominantly on user costs or economic impact to surrounding businesses of an infrastructure system, and predominantly during the construction or maintenance period of said systems (Liu Min and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017; Yavuz et al. 2017). Meanwhile, local communities which may not use but neighbor these systems may also be affected, and this is less considered. Further, few studies have attempted to quantify the social effects of infrastructure, and more specifically, bridges, which are the authors' focus here. Since Winner (1980) brought up his concerns about infrastructure's impact on social equity, there have been few attempts to quantify that impact on a wider, more systematic scale. In short, infrastructure may be conduits for more direct and intended positive connections but also more indirect and hidden negative connections.

Table 3. Main papers that inform the theoretical framework for this study

Author(s)	Year	Main Findings	How impacts study
Levitt	2007	Social equity is a key neglected dimension of sustainability in construction management	Impetus for performing study
Winner	1980	Bridge clearances can be used to obstruct the mobility of certain populations over others	Drives focus on bridges as a case study for assessing social equity impacts of infrastructure
Howe, et al	2016	Infrastructural deficiencies can both index preexisting inequalities, just as they may, simultaneously, deepen those inequalities	Drives our distinction between the "selection" and "treatment" associations of infrastructure on equity
Grannis	1998	Tertiary street connections are better predictors of same race than spatial adjacency	Inform our view that bridges can obstruct besides enable connectivity, both prior to and after their construction
Star	1999	One person's benign infrastructure is another's major hurdle (steps and wheelchairs)	Informs the view used here that infrastructure can benefit and harm different groups simultaneously
Desai & Armanios	2018	Bridges are institutional "relics" in that standards from the existing social system are explicitly built into the physical attributes of the bridge, and these attributes persist even when these social systems and resulting standards may later change	Helps informs how equity may be associated with infrastructure through social factors that predate the building of the system
Bullard	1990	Hazardous waste facility siting associated with more minority communities	Informs how communities that predate infrastructure construction can be associated where such systems are sited

Therefore, in this study, the authors consider how bridges might inhibit movement or create disproportionate effects on populations surrounding the bridge. In summary, this study seeks to join sociological thinking, namely Winner's (1980) theoretical conjecture around the social impacts of bridges, into the civil engineering discourse, per Levitt's (2007) call. To put it more plainly, the authors see bridges as an interesting subject of research not just for what they facilitate but also for what they may obstruct. The aims of this study are to quantify the possible social benefits and costs of bridges to better understand the associations between infrastructure and social equity.

To guide the inclusion of social factors into engineering research, the authors consider two potential relationships between bridges and the surrounding population: “selection” (i.e., how the social factors affect where bridges are placed) and “treatment” (i.e., what changes once a bridge is built). Reaffirming Howe and colleagues (2016), the authors define selection as how “Infrastructural deficiencies can… index preexisting inequalities,” and treatment as how infrastructure “may, simultaneously, deepen those inequalities (p. 551).” The authors’ aim here in assessing the impacts of physical infrastructure on social equity is to disentangle these two effects more clearly.

Prior research suggests that social factors do influence where new infrastructure is placed as a means to regulate access (Joerges 1999; Winner 1980; Woolgar and Cooper 1999). Examples of such selection effects abound, especially in the social justice, environmental justice and segregation literature that argues polluting industries, power plants, and major thoroughfares are more likely to be placed in poor and minority neighborhoods (Bullard 1990; Carless 2018; Grannis 1998). These studies argue that a lack of power or awareness amongst these neighborhoods allows these polluting industries to be concentrated in these areas. The purpose of focusing on selection effects is to test which, if any, social factors predict or are associated with where a certain type of bridge will be built, or if a bridge will be built at all. Also, if the authors do not examine selection effects, they may overlook prevailing conditions prior to placement of a bridge that may be more deterministic of future social equity factors than what happens after the bridge is constructed (Howe et al. 2016). From this literature, the authors posit that *tracts with more marginalized populations (e.g., lower-income, higher poverty and/or a higher percentage of minorities) are associated with more restrictive bridges.*

The purpose of focusing on treatment effects is to ascertain whether restrictive bridges subsequently predict or are associated with social factors that may or may not deepen inequalities. Prior literature has shown that infrastructure institutionalizes political systems extant during construction, and those norms can persist for many years or decades after that (Desai and Armanios 2018). While there are certainly many mechanisms that could help to explain this deepening, one of the mechanisms could be as simple as moving. As people choose to move and self-organize, Grannis (1998) explains that people like to live down the street from people similar to themselves and that infrastructure acts as a de facto barrier. Therefore, people choose to move to neighborhoods separated by barriers that group them with similar others. Whether this mechanism or others, the authors would posit that *tracts with a higher percentage of restrictive bridges will be associated with more negative levels of social equity.*

Data

As noted at the onset of this study, historical empirical challenges in assessing equity impacts due to infrastructure necessitated significant effort to develop the dataset for this analysis. In particular, such an analysis requires integrating and cleaning disparate sources that vary in both spatial and temporal resolution. Therefore, a lack of available data and methods to merge disparate infrastructure and social equity data across levels of analysis are arguably a key reason that analyses on equity impacts of infrastructure have not been undertaken despite calls to do so (Doloi 2018; Levitt Raymond E. 2007).

To initiate this process, the authors used GIS software buffering and intersection functions to link physical infrastructure data (often a point source) to its appropriate census tract (a polygon area). The authors will expound upon these processes in greater detail in subsequent sections. Given the reporting errors that occur in such data (Tierney et al. 2012; Turnbull et al. 2013), the authors went through an extensive cleaning process to check the bounds of each variable and, if extensively prone to error, checked for alternative sources. For more details on the data acquisition and cleaning process used in this study, please consult Appendix I, Section A.

In particular, the authors integrate two types of data - physical infrastructure and social demographic data. The physical infrastructure data came from PennDOT's BMS2 (Pennsylvania Department of Transportation 2018a) and OpenStreetMaps street network data hosted by Geofabrik GmbH ("Geofabrik Download Server" 2018). Other analysts use National Bridge Inventory data for such an analysis (Desai and Armanios 2018). However, the authors chose BMS2 as PennDOT gave us access to this data, and this access afforded the authors data closer to the source of reporting for NBI (e.g., NBI relies on reporting from state DOTs). However, the tradeoff is that only the latest measures are preserved and PennDOT only provided access to highway bridges. The authors compiled total counts of bridges by underclearance height and counts of new bridges built in the current census period (10 years) by these aforementioned types (see Table 1). To gauge if there was any significant bias, the authors compared BMS2 data with NBI data for PA bridges. BMS2 serves as a conservative estimate of restrictive bridges in that BMS2 reports fewer restrictive bridges than NBI data, given it is based on current data. Another important boundary condition to these results is that these are exclusively highway bridges and underclearances that are only reported if there is a road or railway beneath the bridge (under record) (Pennsylvania Department of Transportation 2018b pp. 3-36-3–42). However, for the purpose of a feasibility study, this is useful as this will also likely provide conservative estimates of the results given that the authors do not have all bridges in each locale based on the assumption that more bridges will produce more or stronger effects. Moreover, for conducting widescale equity evaluations of infrastructure, most infrastructure managers would rely on these or similar datasets. In the Limitations section, the authors discuss this further as well as possible future approaches to alleviate this.

The social demographic data comes from the Neighborhood Change Database (NCdB) from 1970-2010 (GeoLytics 2018). These two data sources compile a total of 36,986 bridges in 3,217 census tracts. Two data subsets were used to overcome a lack of sampling in the census data for primarily rural tracts in 1970 and 1980 (see Appendix I, Section D, Fig. 33 for a map of the rural tracts not sampled in 1970 and 1980). The first subset removed 1970 and 1980 time periods from the data. The total number of tracts and bridges did not change, but the number of time periods changed from five to three. The other subset used to compensate for the missing data was to create a list of tracts with missing samples and then remove those tracts from the subset. Using the data cleaning and merging process noted previously, the authors only removed those tracts with missing data and were left with 20,005 bridges in 2,529 census tracts that were usable for analysis. In conducting statistical tests between included and excluded tracts, due to data availability, those tracts that were excluded from the analysis through this process indeed tended to be in rural, less populous counties (see Appendix I, Section D, Fig. 33 and Table 31). Given the authors' focus to analyze variation in socio-economic impacts due to infrastructure, urban tracts are likely where much of the social equity dynamics of interest occur, so excluding rural tracts is less of a concern. For more detail on the data acquisition and cleaning process, see Appendix I, Section A.

Research Design and Empirical Approach

The ideal research design for assessing the social equity impacts of a restrictive bridge would be to randomize the placement of a new restrictive bridge and assess its effects in relation to the same tract without such a bridge. Given that this design is not feasible, the authors use the following research design to approximate as much as possible this ideal empirical strategy. This design aims to compare as closely as possible "treated" tracts (e.g., receive a new restricted bridge) with "control" tracts that most closely approximate these tracts and never receive such a bridge. Fig. 1 summarizes the authors' process.

After analyzing the full sample to create a baseline, the authors first sharpen the treated tracts through a network analysis that helps more accurately identify a focal bridge's service area. The network analyst extension in ArcGIS uses Dijkstra's algorithm (see Appendix I, Section J) to trace the OpenStreetMaps street network out from a bridge (point source) to build a service area (polygon area) to determine which census tracts interact with the bridge (El-Geneidy et al. 2014; Liang et al. 2016; Tanguy et al. 2017). This analysis is used to exclude nearby tracts that do not share a road network with the bridge. To illustrate the importance of this analysis, the authors compare this service area analysis to a circular buffer for one bridge (see Fig 2). When using a circular buffer, the number of tracts counted as "treated" would be five. However, the service area network analysis would more conservatively only count two tracts as treated.

The authors then sharpen the control tracts through coarsened exact matching (CEM). CEM aims to match treated (e.g., tracts with a restrictive bridge) and control tracts along observable factors to ensure improved covariate balance between the two groups (see Appendix I, Section K). In this way, one can more safely assume that unobservables are more likely randomly distributed across these groups (Iacus et al. 2008, 2009, 2012). In short, this approach is used to ensure the control tracts are as equivalent as possible to the treated tracts. To ensure CEM did achieve greater balance, the authors conduct t-tests of the means, Kolmogorov-Smirnov tests (ks-test) of the distribution and a Bayesian alternative to the t-test (Kruschke and Meredith 2018). As shown in Appendix I, Section I, Table 63 - Table 70, overall and univariate imbalance (L1) greatly improved in comparison to the full sample baseline. The t-tests and ks-tests were no longer significant across the matching controls, and the Bayesian tests also showed a move toward a more unified distribution. All of which indicates CEM achieved greater treatment-control group balance.

Overall, the authors' approach seeks to find the sharpest set of treatment tracts that receive a new restrictive bridge to the most equivalent control tracts that do not receive such a bridge. The authors use a variety of methods (e.g., service area network analysis – sharpens treatment and CEM – sharpens control) to ensure achievement as close as possible to the ideal. The authors also ran analyses on tracts with any new bridge, regardless of underclearance or presence of under-record route. These analyses were to ascertain whether restrictions were due more to the height of an existing (or new) bridge construction or due to lack of connectivity in the form of having (or not) any new bridge construction.

Variables

To inform variable selection, the authors used the procedure discussed in the introduction and depicted in Fig. 3. Given that bridges are the authors' key interest, the authors used the following commonly accepted physical infrastructure variables: PennDOT structure ID, NBI structure number, underclearance height, latitude, longitude, year built, and year of construction or year of last major reconstruction (Desai and Armanios 2018; Youssef et al. 1991). Given the sheer volume of proposed socioeconomic variables in prior studies and with the additional need to assess which of these variables are most salient to the feasibility case study of interest (Pennsylvania), the authors used the following variable selection process.

First, and as discussed in the Introduction, the authors conducted a literature review and collected variables that prior social equity studies argued link infrastructure to equity outcomes. Second, since many of the variables measure closely related phenomena, the authors then tested for correlation, found that several variables were highly correlated (r=0.7 or greater) and were, therefore, not selected for use in the models (See Appendix I, Section B, Table 18 - Table 21). After this reduction, twenty-four variables remained (see Appendix I, Section C, Table 22 - Table 30). Since many of the variables of interest measured different aspects of the same or highly similar phenomena, they were analyzed in separate models with the intent of minimizing remaining correlations and isolating variables that measure the same phenomena. For example, real average income and real aggregate income are two variables that essentially measure the same phenomena and are therefore not used at the same time in any model.

Dependent Variables

See Appendix I, Section C, Table 30 for an exhaustive list, and the relevant citations informing the inclusion of analyzed variables. For the selection effect models, the authors regress on restrictive bridge measures – the underclearance height. The primary measure is whether a bridge is restrictive (under 4.27 meters or 14 feet) or non-restrictive (over 4.27 m or 14 ft), in line with prior studies (Desai and Armanios 2018). To assess whether effects pertain to any new bridge construction more generally, the authors also have a separate measure for all bridges including those that do not have a road or railroad (under-record) beneath them. The authors also consider more granular measures for underclearance height, and the authors report the results from these more refined height distinctions in Appendix I, Section G.

The authors specify the dependent variables in two ways. The first is as a dichotomous variable (0/1), signifying that a new bridge of that underclearance height was built in that tract during the focal census period (10 years). Since the census is a decennial survey, the authors chose to match the ten-year window to the census timing (e.g., changes during 1961-1970 are recorded in the 1970 census). The other dependent variable is a total count of new bridges built during the census period. For the treatment effect models, the authors use the socioeconomic factors as the dependent variables with these new bridge group variables as independent variables.

Independent Variables

In the selection models, the independent variables are the aforementioned socioeconomic factors. In the treatment models, the independent variables are the bridge treatment term, the bridge treatment group term, and their interaction term. Each independent variable was lagged by one time period (e.g., one 10-year census period). The complete set of independent variables from the literature review is in Appendix I, Section C, Table 22 - Table 30). Later in the Results section, the authors summarize those variables that proved most significant and, thus, have the greatest likelihood to guide future decision-making in Table 2.

The treatment model independent variables are dichotomous variables (i.e. binary, 1 or 0). The treatment term is the time period on or after the treatment group receives treatment (treatment = receiving a new restrictive bridge; in additional analyses, treatment = receiving any new bridge). The census period when a new bridge appears in a tract begins the treatment time. The treatment group is those tracts that will at any point, receive a bridge. Thus, the event study interaction term is one for those periods in which a treatment tract receives a bridge and zero for all other instances. Fig. 4 provides a graphical representation of all tracts receiving a restrictive bridge treatment.

Tracts without any new bridges comprise the control group, so these bridges were linked to the treatment group through random assignment of a treatment year (Borusyak and Jaravel 2016). This step of assigning a treatment year to non-treated tracts is necessary for an event study. Event study models are designed to analyze the effects of events on different units at different times. The authors use event study in the same sense as Borusyak and Jaravel (2016), de Faria, et al. (2017), and Clay, et al. (2016). A difference-in-difference analysis studies an event that affects all individuals in the study in the same time period and thus, the treatment time is universal for all individuals in the study. To briefly illustrate this, those control tracts before random treatment year assignment would have a treatment term and treatment group term equaling zero in all time periods. However, those control tracts after random treatment year assignment would have a treatment group term remaining as zero, but now a treatment term equal to one after the period of assignment. For treatment groups, the group variables would consistently equate to one. Prior to the tract receiving a treatment bridge, the treatment term equals zero, but after the treatment year, the treatment term equals one.

Control Variables

The authors then control for engineering factors around bridge placement. The first is the need to span a geophysical impediment such as a chasm or a river (ASCE 2016). Since Pennsylvania has many rivers, the authors selected tract water area (as a percentage of total tract area) as a proxy variable for geophysical impediments. The second is population density to account for potential demand for bridges. After examining the sizes of tracts and their proximity to cities, the authors created two dichotomous variables to act as rural definitions based on natural cutoffs in the data around population centers. The reason for this is that tract areas are a function of population and so rural tracts have sparser populations which leads to larger tract size. To ensure the size of the tract was not consequential to the model, the authors used two size specifications. The first used the mean of tract area (4million square meters) and the other was a more extreme size that more than doubled the mean (10 million square meters). Graphical representations showing tracts coded as urban are available in Appendix I, Section D, Fig. 31 - Fig. 32. Related to rural definitions is the overall area of each tract. Because census tracts attempt to create geographic regions with a similar number of residents, the relation between tract area and population is part of the definition of a census tract. The authors decided, therefore, to also use tract area size as a control variable to better account for comparably sized tracts in conjunction with population density. See Appendix I, Section C, Table 30 for the complete set of variables used in the main analysis.

Statistical Methods and Models

Selection Effect Models

The selection effect model is designed to analyze the probability of a tract receiving a new restrictive bridge. This selection effect is of interest because the authors want to know if there are associations between the decision to build a new restrictive bridge in a tract based on the population that lives there prior to its construction. A logistic model is designed to predict probabilities based on provided factors. The treatment effect model is designed to determine the difference in consequences between tracts that received a new restrictive bridge and those that did not.

Logistic regression was used and found to have the best goodness of fit of the selection effect models used. The goodness of fit measures used for this model are AIC and BIC. Linear probability, OLS, and Poisson regression models were also used to analyze selection effects and details can be found in Appendix I, Section G. These produced largely consistent results for most variables (Fig. 5 - Fig. 7). The equation for this model was as follows:

Equation 1. *Logistic Regression Model Specification*

$$logit(p(x)) = \ log \frac{p(x)}{1 - p(x)} = \beta_0 + \boldsymbol{\gamma_k X_{k,i,t-1}} + \delta_t + e_{i,t}$$

where *logit(p(x))* is the probability that a variable designating a new restrictive bridge was built in the census period, in tract i, in census year t, $\boldsymbol{\gamma_k}$ is a vector of control variable coefficients, **X** is a vector of variables of social interest, and δ is a fixed effect for each census year.

Treatment Effect Model

The authors employed an event study model to analyze treatment effects (Borusyak and Jaravel 2016; Clay et al. 2016; de Faria et al. 2017). Fixed effects and difference-in-difference models were also used to analyze treatment effects and details can be found in Appendix I, Section G. These produced generally consistent results for most variables. The equation for this model was as follows:

Equation 2. Event Study treatment effect model specification

$$z_{i,t} = \beta_0 + \beta_1 (x_{i,t} \times g_{i,t}) + \beta_2 x_{i,t} + \beta_3 g_{i,t} + \boldsymbol{\gamma_k C_{k,i,t-1}} + \delta_t + f_i + e_{i,t}$$

where z is a social equity variable of interest, in tract i, in year t, β_1 is the event study coefficient for the treatment and group interaction term, x is a dummy variable designating the tract received a new restrictive bridge treatment, g is a dummy variable designating the tract as receiving a restrictive bridge at any time, $\boldsymbol{\gamma_k}$ is a vector of control variable coefficients, **C** is a vector of lagged control variables, δ is a fixed effect for each census year, and f is a time-invariant tract fixed effect (Borusyak and Jaravel 2016; Clay et al. 2016; de Faria et al. 2017).

Regardless of the model, due to the nature of census data, errors were found to be heteroskedastic in nature. Therefore, robust standard errors were calculated using a variance-covariance matrix and Wald test (Zeileis 2004, 2006). All standard errors and p-values reported are the results of these calculations.

Results

Results presented here focus on three bridge categories: restrictive bridges (under 4.27 m or 14 ft), non-restrictive bridges (over 4.27 m or 14 ft), and all bridges (including those without an under-record route). Results are considered from the perspective of new restrictive bridges. Variables were considered to have an association if the point estimate and standard error did not encapsulate zero. Figs. Fig**. 5**-Fig. **7**report the coefficient estimates for various selection models from the analysis. As will become evident, the treatment effect models were generally inconsistent and not robust, so those models are only reported in Appendix I, Section F.

Before going into greater detail, these analyses lead to several overall insights. First, social factors seem more significantly associated with bridge selection as opposed to treatment, especially the demographic variables and, to a lesser degree, family variables. Percentage of Hispanic, African American, and non-White populations all are negatively associated with the placement of non-restrictive bridges, or any bridge construction, and these associations are consistent and robust. Regarding family variables, those households with more single parents with children and female-led households were associated with less bridge construction of any kind, and these associations were consistent and robust. Education variables, finance, housing, and transportation variables generally did not yield consistent nor robust associations (see Appendix, Section G, Fig. 40 - Fig. 46 for all model comparison plots). Overall, this suggests that tracts with more non-White demographics and single or female-led households are associated with less infrastructure, which suggests less physical connectivity and mobility. A summary of these variables that proved significant is available in Table 2.

Second, physical factors that arguably capture more technical rationales for bridge construction have less association on selection or treatment, even before CEM is applied to handle potential selection along these variables. Rural tracts and water area all hover around zero in both sets of models. This result suggests social as opposed to technical factors are perhaps more associated with bridge construction, particularly where it is sited. That said, the measures used as proxies for technical causes or reasons for building a bridge are limited to water and land area. The reason is social context often informs the appropriate variables that can hypothetically influence whether a locale needs a bridge and whether it receives it. Since the context was Pennsylvania and many bridges are used to traverse bodies of water and geophysical features such as ravines, land and water area were selected as proxies. These proxies may not be applicable across social contexts as these measures may not adequately capture other possible contextual sources of geophysical variation such as elevation change. Thus, while this suggests social factors may matter more than technical factors in bridge siting and that the overall framework may be replicable, the authors cautiously note that the realities of the local context should guide the variables included.

Selection Effect Model Results

The authors graphically represent the coefficient estimates across models in Fig. 5, Fig. 6 & Fig. 7, with remaining comparisons shown in Appendix I, Section G, Fig. 40 - Fig. 46. For baseline cases and full panel results, see Appendix I, Section E. Results shown in this section are those after CEM is applied, and the authors will discuss this further in the Robustness Checks section.

In terms of selection effects, most demographic variables were robustly and consistently negatively associated with non-restrictive bridges and all new bridge placement. Percent Hispanic, African American, and non-White had robust and consistently negative associations. Based on the literature, this association is not surprising as these at-risk groups are typically located in less affluent neighborhoods that often do not receive the benefit of new infrastructure (Brady et al. 2017). The literature also reports that these variables can be indicators associated with spatial segmentation (i.e., segregation) and migration patterns due to social and economic characteristics (Crowder et al. 2012; Lee et al. 2008). However, foreign-born were neither consistent nor robust in their associations (Fig. 7) which seems consistent with prior literature that found the influence of foreign-born populace to mitigate segregation (Lee et al. 2008).

Regarding family variables (percent single parents with children, percent female head of household, percent under 18-years-old, and adult to child ratio), the most prominent effects were those on any new bridge placement. Tracts with more female-led households and single parents with children were robustly and consistently associated with less new bridge construction (Fig. 6) which confirms prior literature findings that used these factors to measure concentrated disadvantage (Sharkey 2014). That literature would find that these are groups are at higher risk of poverty and spatial segmentation (Crowder et al. 2012; Sharkey 2014).

Regarding the education variables (percent of population with: eight years of education, a high school education, an Associate's degree, or a bachelor's degree), only percent of population with an Associate's degree and with a bachelor's degree had estimates associated with new restrictive bridges, but these estimates had a small magnitude and were similar to the estimates for non-restrictive bridges. Tracts with more individuals with associate degrees were consistently associated with decreases in restrictive bridge clearances, and individuals with bachelor's degrees are consistently associated with increases in non-restrictive bridge clearances. Yet, neither are robust associations. Prior literature finds that higher education levels are associated with more affluent neighborhoods for which new infrastructure can be an indicator (Crowder et al. 2012; Lee et al. 2008; Sampson et al. 1999). Therefore, perhaps, these associations are not robust due to education being closely tied to affluence, and affluence has a stronger association with new infrastructure.

However, generally speaking, affluence also seems to be a less consequential association. Of the financial variables (average household income, aggregate household income, percent below the poverty line, and percent receiving welfare), there were no consistent nor robust results for restrictive bridges. All the variables were robust for non-restricted bridges, but the coefficients for average income and aggregate income were small in magnitude. Only the percentage of population below the poverty line was robust for all new bridges. Aggregate household income was consistently negative for all bridge types. These findings are somewhat surprising as the literature typically postulates that these measures are all associated with more affluent neighborhoods (Crowder et al. 2012; Sampson et al. 1999). Conversely, the percent population receiving welfare was consistently positive for all bridge types. However, these were not robust associations.

Across models, the housing variables (percent vacant housing, percent renter-occupied housing, owner to renter ratio, and percent change in housing supply) also did not yield robust nor consistent associations. The literature typically shows that homeownership increases resident involvement in advocating for improvements to their neighborhood including new infrastructure (Sampson et al. 2002; Tach and Emory 2017a). Moreover, this literature also finds a positive association with housing supply changes as new infrastructure often accompanies new housing and improving socio-economic conditions (Farley and H. Frey 1994). However, our study did not find evidence to support those findings.

Across models, the transportation variables (travel on public transportation, commute time over 45 minutes, commute time between 25 and 45 minutes, and commute time less than 25 minutes) only yielded consistent associations with commute times between 25 and 45 minutes, but none were robust. The only robust results were for commute times over 45 minutes for non-restricted bridges and travel on public transportation for both non-restrictive and all new bridges.

Interestingly, the physical variables (4 million meters^2 rural indicator, 10 million meters^2 rural indicator, total bridges, and water area percent) usually hovered around zero. None of the variables were robust for restricted bridges. Non-restricted bridges had robust measures for percent water area, rural tract dummy indicator for over 4 million m^2, and total bridges. All bridges had robust measures for rural tract indicator for over 4 million m^2 and total bridges. This result suggests the prevailing technical reasons, namely the need to traverse waterbodies, or economic reasons, namely greater population demand, for bridges were less associated with the type of new bridge infrastructure deployed in a locale.

The authors posited a selection effect - social factors would influence where restrictive bridges are placed. The authors find associations that partially support this assertion. Demographic variables are associated with where less-restrictive bridges are placed as well as where any new bridge construction is sited. Family variables are associated with where any new bridge construction is sited.

Treatment Effect Model Results

The full results of all the models are available in the Appendix I, Section F, Table 36 - Table 51 with visual representations in Fig. 34 - Fig. 39. The treatment effect associations of receiving a new bridge on social factors generally appear to be very small and not very significant. Of the twenty-four variables, only four have robust associations across all bridge types. The first is that percent Hispanic is negatively associated with any type of bridge after construction (restrictive, non-restrictive, or any). The second is that population traveling on public transportation is negatively associated with both new restrictive and non-restrictive bridges. Given that these results are consistent across restrictive and non-restrictive bridges, the authors cannot draw insights from these associations as they pertain to treatment effects from bridge restrictions. The third is that the owner to renter ratio is positively associated with only non-restrictive bridge construction. This result may suggest that locales with more non-restrictive bridges are perhaps associated with greater wealth and thus more homeownership. Individuals receiving Associate degrees are negatively associated with restrictive bridges. This result may suggest that locales with more restrictive bridges perhaps are associated with greater difficulty in placing educational opportunities with these locales or for individuals to travel to other locales with these opportunities. That said, the authors' assertions of a treatment effect due to restrictive bridges are largely unsupported with these associations. Few variables have a robust treatment association and if they do, it is usually not clear whether they are uniquely associated with restrictive or non-restrictive bridges.

Robustness Checks

Even though the authors recognized, based on the data, that a logistic model would likely be the most appropriate model to analyze selection effects, the authors began by using simpler methods to test if there is a measurable effect that warranted more sophisticated methods. The linear probability model was not good as the predictions were out of range (i.e., below 0 or above 1) for over 65% of the predictions. That said, the results were consistent with those from the main logistic regression model. Due to the nature of census data primarily consisting of counts, a Poisson regression model was also developed. The results varied slightly, but the results were consistent with the logistic models.

During the data exploration phase of this work, the authors compared variable transformations and their effects on the goodness of fit for the various models. Transformations included percentage of total populations, log+1, and inverse hyperbolic sine (Burbidge et al. 1988; MacKinnon and Magee 1990). In almost every case, inverse hyperbolic sine outperformed the log transformation. Since the interpretability of log and inverse hyperbolic sine are similar and in order to provide a consistent basis for analysis, the authors chose only to use the inverse hyperbolic sine. In cases where the percentage transformation performed as well or better than the inverse hyperbolic sine, the percentage transformation was selected.

Supplementary Analysis

Undoubtedly, bridges do not operate in isolation. The prior literature contends that the built environment acts as a conduit for both intended and unintended social connections (Audretsch et al. 2015; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). If so, then our findings may work in concert with other infrastructure systems and local policies. To gauge this possibility, the authors ran three supplementary analyses by splitting the data on the median value of three variables that could capture the effects of exogenous factors. The three factors attempt to capture the effects of roads, public transportation availability, and local community salience. The variables used for each are the lane road length in a tract, the number of people who use public transportation, and the number of National Historic Registration of Places locations within a tract. In particular, we find that when negative associations between new and non-restrictive bridges and non-white, African-American, and Hispanic population percentages were significant, they were more so for tracts with less road mileage, with more public transportation usage, and with fewer National Registered Historic Places. This suggests these negative associations are worsened when a tract has fewer alternative travel routes, greater reliance on public transportation, and has less awareness of their local infrastructure (as communities need to apply to nationally register local infrastructure as a historic place). For a more detailed discussion of these analyses can be found in Appendix I, Section G, Table 52 - Table 60 and Fig. 47 - Fig. 67.

Limitations

There were two overriding limitations to the data used. The first is that the authors only had access to highway system bridges. As previously discussed, this likely provides conservative estimates. The other major limitation was a lack of high-fidelity social variables that were consistently available in the NCdB. As the census has evolved, there is an increasing number of variables that more finely account for demographics and finances. Very few of these variables existed in 1970, but due to the enduring nature of bridges, the authors chose variables that could help disentangle the long-term effects of bridges. It is possible that restricting the time scale to more recent decades may yield clearer results especially concerning financial and demographic social factors. That said and as noted in the study's motivation, the authors chose to use such data because this is the most accurate publicly available data for engineers to assess equity impacts. Moreover, the authors wanted to develop a methodology that reflects the 50-70 year design life of a bridge (Hu Xiaofei and Madanat Samer 2015; Neves et al. 2006).

Second, the data is strictly from the state of Pennsylvania. While Pennsylvania is a great candidate for a study on bridges since it contains a disproportionately large number of bridges, the results here are likely to differ when applied to another context. Expanding this study to cover all states could provide more statistical power for the study's results and potentially find associations not present in Pennsylvania. This expansion would also help assess the study's generalizability in terms of findings and approaches.

Discussion and Conclusion

In seeking to make inroads to more general calls for civil engineers to better understand the social equity impact on the built environment (Levitt Raymond E. 2007; Reardon et al. 2008), this study specifically asks *how do restrictive bridges impact social equity?* To make progress into this challenge, this study develops a methodological framework and applies it to the case of Pennsylvania's bridge system as a proof-of-concept. As applied to this case, the authors find that selection effects (i.e., factors influencing placement) are more consequential than treatment effects (i.e., factors that change after placement) on social equity. In particular, demographic variables seem to play the strongest associative role and then family-based variables. Interestingly, technical factors that drive bridge siting have fewer implications on equity than do these aforementioned social factors. Table 2 summarizes the key factors found that associate bridge infrastructure with social equity. The authors hope that this table helps engineers more clearly identify those key factors for which they can focus when considering the impacts infrastructure on equity. In particular, the most salient variables seem to be those that measure demographic and family factors, and this case study recommends that these factors are a good starting point for infrastructure managers and engineers to assess equity impacts from infrastructure.

Besides identifying a targeted set of key measures in Table 2 for which engineers can ascertain equity impacts from infrastructure (in this case bridge infrastructure), this study also makes several additional contributions that may, perhaps, generalize beyond the Pennsylvania bridge case used here. First, this study presents what the author's see as a replicable methodology for assessing the equity impacts of infrastructure in other contexts. Prior literature is unable to assess relationships between infrastructure and equity because these assessments require dispersed data sources that differ in both temporal and spatial resolution (Grannis 1998; Knaap and Oosterhaven 2002; Lee et al. 2008; Liu Min and Frangopol Dan M. 2006; Sampson et al. 2002; Star and Bowker 2006). The authors demonstrate a method to bring these disparate available data sources together to provide insights into the social impacts of infrastructure. This study contributes a research design that incorporates network service area analysis and CEM to make inroads into harmonizing and isolating, as much as possible, treatment locales, comparable control locales, and the most salient equity variables for analysis. Such a design can aid infrastructure managers and engineers in assessing equity impacts of infrastructure while reducing the need for extensive data integration or extensive social science expertise to inform equity variable selection. The authors hope other engineers will test the replicability of this method in other locales to assess further the robustness of this approach to other local conditions, which will help further develop boundary conditions for this methodology.

Second, and particular to this case study, this study finds social factors may matter more than technical factors in understanding the equity impacts of infrastructure, and the identified associations seem more consequential at selection than treatment. Prior literature seems to argue that there are both selection and treatment effects on infrastructure-equity relationships (Audretsch et al. 2015; Grabowski et al. 2017; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). However, in terms of this case study, the authors find that selection is a more prominent factor. This finding intuitively makes sense given the longevity of these systems and that social context at the time often drives bridge construction and siting decisions (Desai and Armanios 2018).

A third contribution is to demonstrate that it is possible to use quantitative methods with publicly available data to discover associations between infrastructure and social factors. In contrast to the current civil engineering literature that focuses on impacts to infrastructure users primarily during construction or maintenance (Liu and Frangopol 2005; Liu Min and Frangopol Dan M. 2006; Liu Ming and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017), this paper has shown that it is possible to look at longer-term equity impacts to those communities who may not use but rather border such infrastructure. This possibility provides a challenge for the civil engineering community to look beyond focusing on the time period during construction or maintenance to understand broader, longer-lasting social impacts of bridges and other physical infrastructure to nearby communities.

Additionally, the authors see pragmatic managerial implications in planning and maintenance. The first practical implication is that this study helps address prior research that has shown engineers have trouble operationalizing social equity factors in transportation plans (Manaugh et al. 2015). Therefore, this case study suggests that engineers and managers, particularly those working on Pennsylvania bridge systems, may want to consider including demographic and family measures in their maintenance planning and siting processes. Moreover, they may also want to weigh such factors in ways that recognize the higher barriers infrastructure presents in more disadvantaged neighborhoods. The variables demonstrated here can be operationalized, are available from the American Community Survey, and prior literature has shown they are useful in identifying such concentrated disadvantage (Sharkey 2014). As with this study's methodology, the authors hope not just the robustness of the methods are assessed through additional case studies, but also compare and contrast equity findings from those case studies to the one conducted here. In this way, the scholarly and managerial community can collectively advance a more generalized set of findings and conditions for which social factors drive infrastructure-equity relationships, whether they are associative or causal, and whether they occur at infrastructure selection, subsequent treatment, or both.

The second practical implication is that infrastructure managers are increasingly asked to repair an ever-growing set of outdated bridges with budgets that are increasing but insufficient to address infrastructure demands completely. As the most recent ASCE report stated, "In 2018, the Commonwealth of PA estimated that $7.7 billion is needed for bridge repairs. Under current funding practices, it would take 13 years to reach the national average of poor condition bridges (ASCE 2019)." This estimate suggests infrastructure managers could benefit from having other metrics for which to prioritize further and identify the most critical bridges in need of repair during their planning processes. Including equity dimensions through this methodology may present an additional set of factors that can allow infrastructure managers to prioritize bridge needs under budgetary constraints more effectively.

As a final concluding thought, the authors should strongly note that the intent of this study is not to blame any individual party for the equity-based social ills that these infrastructure systems present. Increasingly, all parties recognize these important yet difficult social challenges. As a clear example, the state of Pennsylvania's Department of Transportation and Department of Community and Economic Development actively sponsored and shared their expertise with the authors to conduct this work because they recognize these challenges and want to address them. Thus, the authors also see this equity-based approach to infrastructure as a novel and exciting frontier to bring various government and academic stakeholders together not just to acknowledge these social ills but try to present possible approaches that can advance effective solutions.

Data Availability Statement

Data analyzed during the study were provided by a third party. Requests for data should be directed to the provider indicated in the Acknowledgements.

Disclaimer

The views expressed in this article are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, the U.S. Government.

Notation

The following symbols are used in this paper:

$\mathbf{C}$ = a vector of lagged control variables;

d = a dichotomous variable designating the interaction of the group and treatment variables;

e = the error term;

f = a time-invariant tract fixed effect;

g = a dummy variable designating the tract as receiving a new bridge at any time (group term);

i = the tract index;

k = the index for a particular variable;

logit(p(x)) = the probability that a variable designating a new bridge was built in the preceding 10 years;

t = the year index;

$\mathbf{X}$ = a vector of variables of social interest;

x = a dummy variable designating the tract received a new bridge treatment (treatment term);

y = either a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years or the count of such bridges;

z = a social equity variable of interest;

β_0 = the intercept;

β_1 = the event study coefficient for the treatment and group interaction term;

β_2 = the coefficient for the treatment term;

β_3 = the coefficient for the group term;

$\boldsymbol{\gamma_k}$ = a vector of control variable coefficients;

δ = a fixed effect for each census year;

λ = he Lagrange multiplier that balances the tradeoff between the squared error loss and the L_1 penalty

Figures

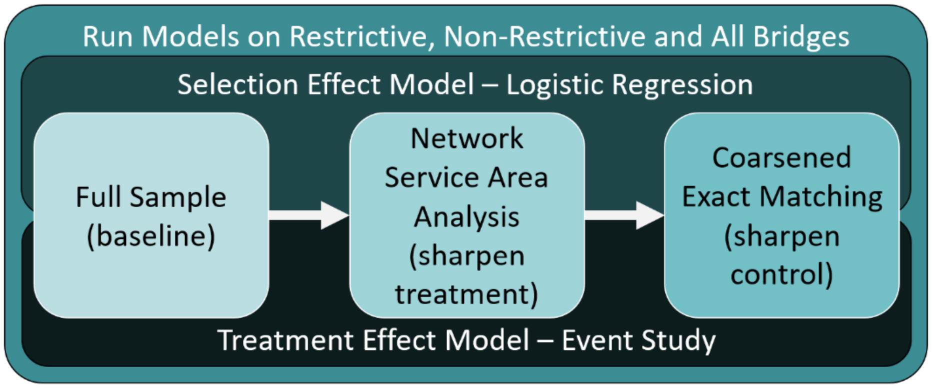

Fig. 1. Flow diagram of research design

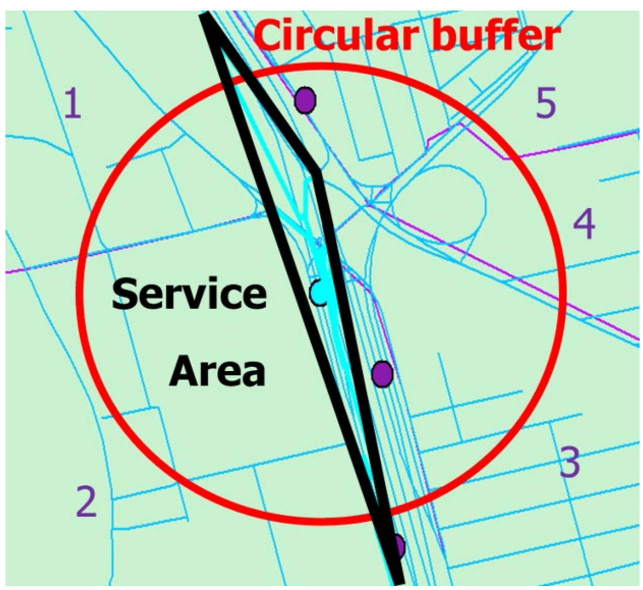

Fig. 2. Comparing circular buffer to service area analysis. Circular buffer (large circle) intersects five tracts while service area (triangle) intersects two tracts (numbered 1-5). The small dot inside the triangle indicates bridge location.

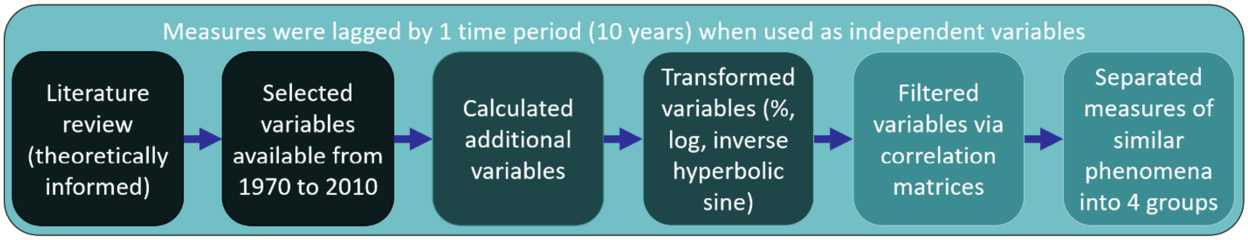

Fig. 3. Flow diagram of variable selection process.

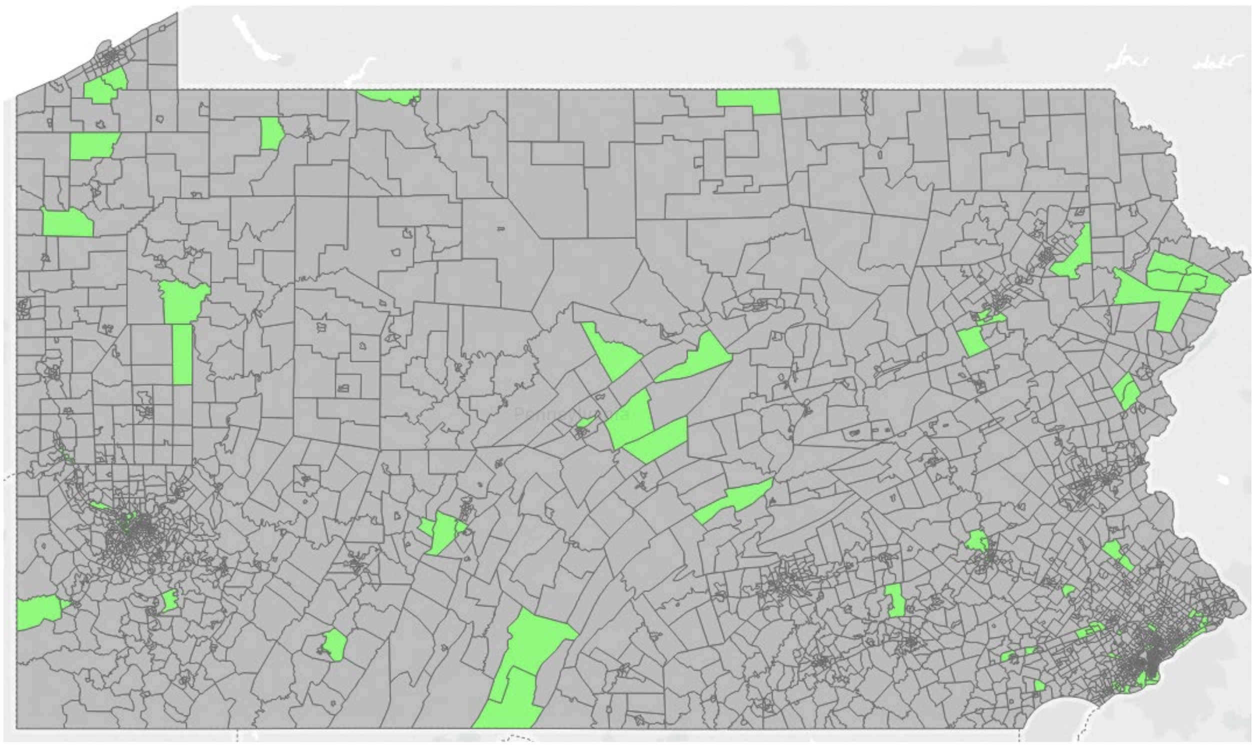

Fig. 4. Graphic depicting tracts that received a new restrictive bridge throughout the time period of study

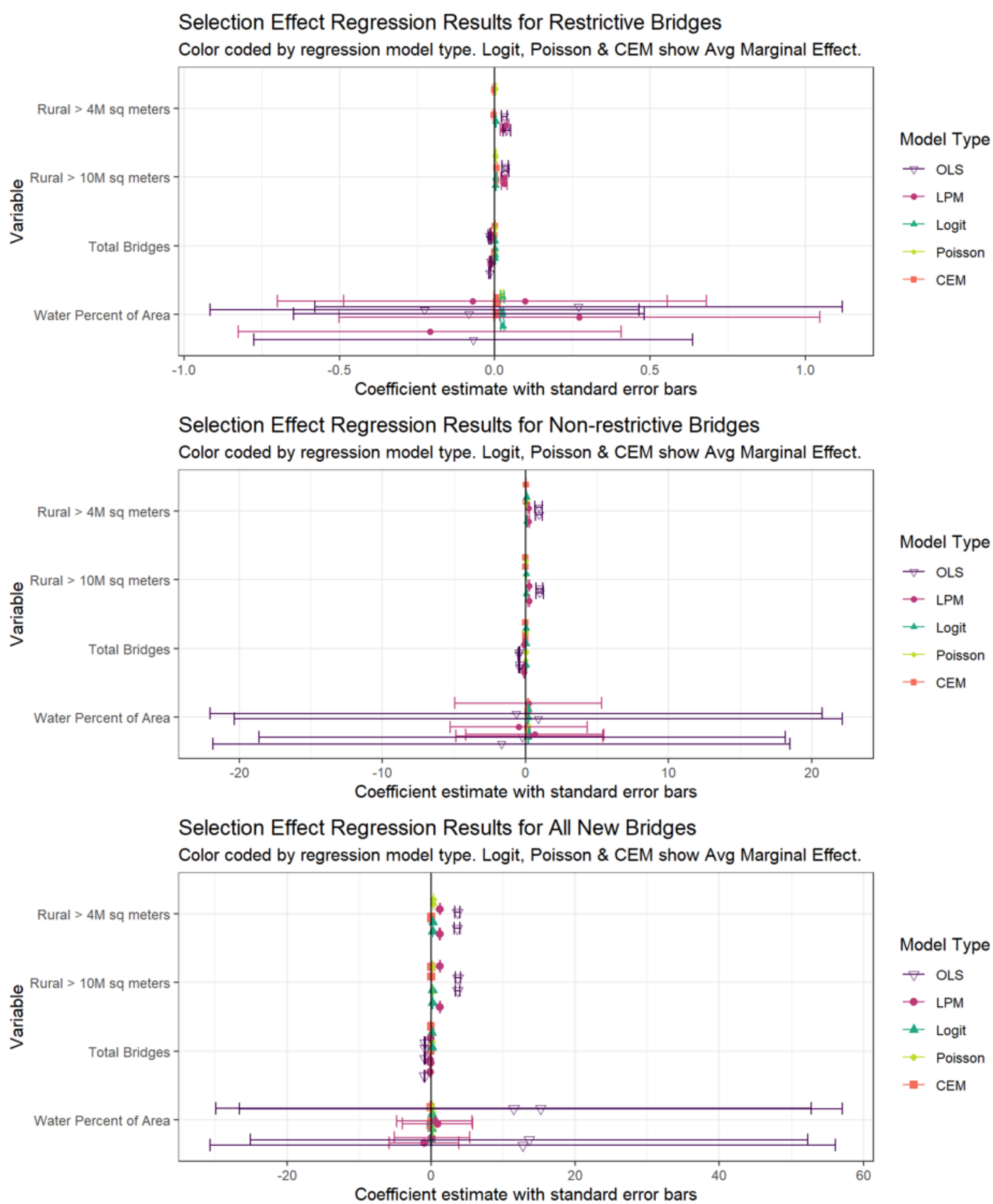

Fig. 5. Graphical representation of physical variables for various models for restricted, non-restricted, and all bridges.

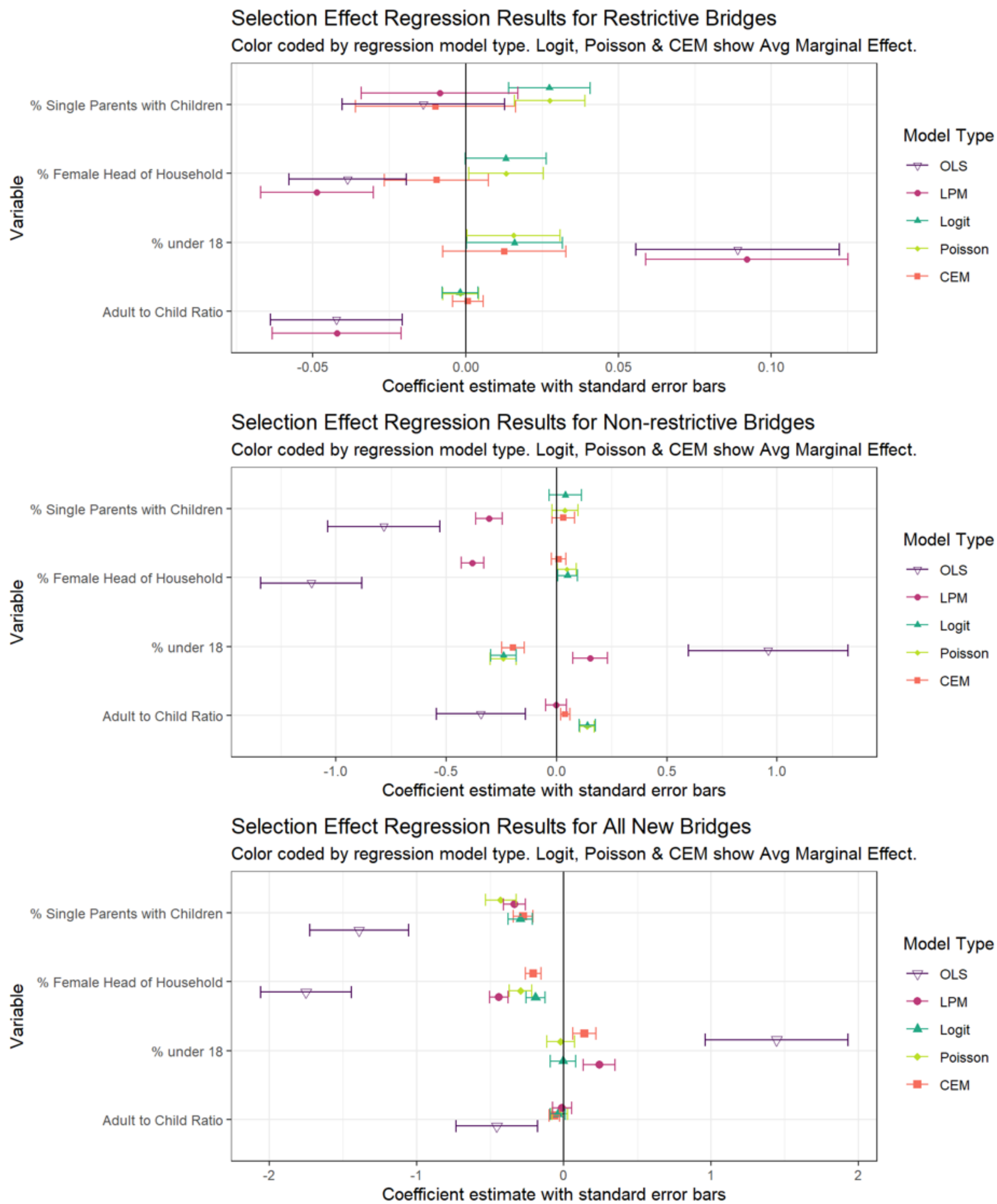

Fig. 6. Graphical representation of family variables for various model for restricted, non-restricted, and all bridges.

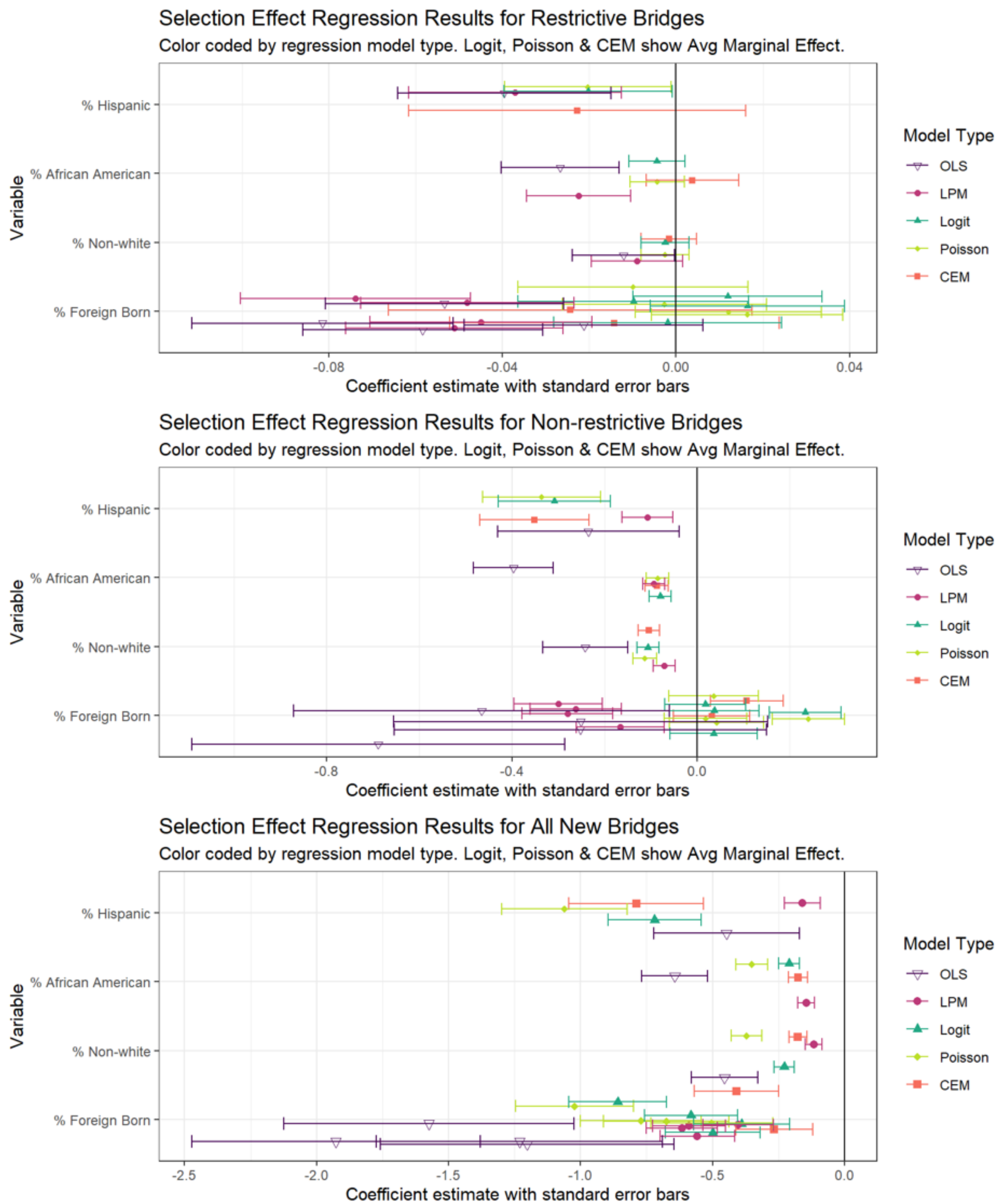

Fig. 7. Graphical representation of demographic variables for various models for restricted, non-restricted, and all bridges.

Chapter 3 Machine Learning to Assess Variable Importance and Causality of Social Equity Impacts of the Built Environment

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Abstract

When assessing the impact and consequences of infrastructure systems on social equity, it is very difficult to include quantitative metrics that capture social equity factors for inclusion into cost-benefit analyses. Civil engineers increasingly recognize the need to include these social factors as a means of addressing social sustainability. Previous studies have shown that the general benefits of infrastructure are not enjoyed universally by neighboring locales. In this study, the authors expand their previous framework to ease the burden on civil engineers, non-experts of the

social equity domain, by adding accessible machine learning methods to provide quantitative analysis and selection of available variables and to discover the causal links between these variables. This research demonstrates further quantitative methods to incorporate social equity and sustainability into the engineering calculus. These machine learning methods help to obviate the need for domain expertise to guide variable selection thus allowing engineers to competently select meaningful variables. Through triangulating several algorithms and techniques, the authors identify consistent variables that are of causal or associational importance to infrastructure and social equity (e.g., demographic, family, transportation and financial variables). The authors also propose a workflow that should prove useful to engineers and decisionmakers.

Introduction

Civil engineers are increasingly concerned about the impacts of infrastructure on social equity. As with prior work (El-Geneidy et al. 2016 p. 542; Jones and Armanios n.d.; Martens et al. 2012 p. 687), this study's working definition of social equity is the uniform cost-benefit distribution of infrastructure assets (what some call "horizontal equity"), unless factors are identified for which such a uniform distribution especially impacts more marginalized groups (what some call "vertical equity"). Our aim here is to ascertain what are those equity factors that would help us capture and remediate such deleterious and asymmetric impacts of infrastructure on marginalized groups.

While civil engineers increasingly recognize equity as a key concern, numerous recent studies note that there is a dearth of approaches to help assist civil engineers make more equity-informed infrastructure decisions. Grabowski et al (2017) note a clear need for interdisciplinary frameworks that ensure equity concerns factor into all physical infrastructure lifecycle phases. While there is newfound emphasis on incorporating equity into all phases of the infrastructure lifecycle, there is recognition that doing so has been historically difficult. As noted by Levitt (2007 p. 627), "Bringing the third dimension of sustainability—social equity—into an overall cost–benefit sustainability calculus is much more challenging […] and is extremely difficult to reduce to one-dimensional quantitative metrics". Presumably, the difficulty of incorporating these metrics may explain why "theories for quantitative evaluation of social performance and underlying social value creation in public infrastructure projects from a community perspective remain unexplored" (Doloi 2018 p. 1). This work seeks to address this gap to aid policymakers and engineers in making social equity factors more accessible.

This work builds upon a previous empirical framework only very recently set forth to aid civil engineers, policymakers, and other infrastructure stakeholders in making equity-informed infrastructure decisions (Jones and Armanios n.d.). While this work is an important and significant contribution, this study has two key limitations for which we seek to address in this work. First, this study requires engineers to have a strong grasp of the social equity literature. These studies are spread across different literatures including but not limited to neighborhood effects (Crowder and South 2008; Sampson et al. 1999, 2002; Sharkey 2014), social justice (Brady et al. 2017; Schindler 2015), environmental justice (Carless 2018; Pathak et al. 2011), and segregation (Crowder et al. 2012; Farley and H. Frey 1994; Lee et al. 2008; Lichter et al. 2015). This knowledge strongly informed the selection of 24 variables that prior literature would surmise as having equity implications (Jones and Armanios n.d.). This study seeks to relax these assumptions by using methods that can help engineers isolate only the most important of these variables for their respective context and needs without having such an extensive working knowledge of these social equity literatures. Second, the study is correlational; it shows important associations between specific demographic and family-based factors and equity impacts of infrastructure (e.g., where new and non-restrictive bridge constructions are sited). This study hopes to ascertain how causal are these factors on infrastructure decision-making.

Overall then, this study seeks to develop a methodological framework that can underpin and extend the empirical framework provided by Jones & Armanios (n.d.). This study particularly seeks to help civil engineers more quickly identify the most important social equity factors and ascertain the extent to which these are causal on infrastructure equity impacts. At the same time, this study's choice of computational methods attempts to account for the fact that infrastructure stakeholders may not necessarily have extensive working knowledge of the social equity literature as was needed in the Jones & Armanios (2020) approach.

The authors chose to examine the relationship of socioeconomic measures with bridges. This was chosen to ensure direct compatibility with the Jones & Armanios (2020) study, which was also their infrastructure of choice. Moreover, prior researchers have argued bridges especially impact physical connectivity, and thus access to goods and services, in potentially asymmetric ways. Winner (1980) first argued that restrictive bridge heights were designed to constrict passage of certain vehicles and those restrictions disproportionately affect certain demographics more than others. In order to assess the feasibility of incorporating social equity in infrastructure systems, Jones & Armanios (n.d.) asked: "*how do restrictive bridges impact social equity?*" As per prior studies (Desai and Armanios 2018), the Jones & Armanios (n.d.) study, and as adopted here, restrictive bridges are defined as those below 4.27 meters (14 feet) as this height is a commonly used regulatory clearance standard for bridges as it inhibits the passage of certain vehicles such as commercial trucks. The authors refine the original Jones & Armanios (2020) question to the following: *what are the most important of these social factors and to what degree do they casually explain the equity impacts of restrictive bridges?*

To answer this more refined question, this work uses Least Absolute Shrinkage and Selection Operator (LASSO) and Markov Blanket-based causal search algorithms to analyze the feasibility of allowing variable selection to be driven from a purely computational viewpoint (Chang 2016; Desai 2018; Jain et al. 2014; Kamarianakis et al. 2012; Tibshirani 1996). These two methods were chosen for several reasons. First, they provide a bridge between empirically-grounded statistical machine learning (ML) methods (e.g., OLS and logistic regression) and more causal-focused ML search methods, and so they share some commonalities and yield similar, if not identical, results. Therefore, these two methods were chosen based on their similarities and their already demonstrated accessibility for engineering applications such as the ones studied here (Aliferis et al. 2010; Ma and Statnikov 2017; Ramsey et al. 2017). Moreover, this choice of bridging between statistical and causal ML methods also allow for greater ease of comparability to the purely empirically-informed methods used in the Jones & Armanios (n.d.) study (e.g., service area network analysis, coarsened exact matching, and event study methods).

Finally, recall that the hope of this study is to reduce the time and social equity working knowledge that infrastructure stakeholders must have to implement these equity-informed frameworks. Jones & Armanios (n.d.) hand-selected and verified variables from the available socio-economic data. As noted previously, this is a time and knowledge intensive process that may not be available or feasible for infrastructure stakeholders. Here, the authors use LASSO and Markov Blanket-based (MB) methods to directly search more than 200 variables of potential relevance. Then, the authors use causal search algorithms to discover any associations or causal linkages previously undiscovered by all previous steps. By adding these two steps, the authors hope to aid in variable selection, thus providing a means for infrastructure stakeholders who are not domain experts in social sciences, to incorporate social equity factors into these civil engineering domains. By incorporating these social equity factors, the authors hope to better enable policymakers to maximize social benefits as they prioritize infrastructure placement, replacement, rehabilitation and maintenance, even if they have less working knowledge of the state of the art in social equity research. We will now go into greater detail as to the methods of our study and then present the results and how they compare to the Jones & Armanios (n.d.) study upon which this study builds.

Methods

Data

For this study, the authors utilized the two data types previously integrated in prior studies - physical infrastructure and social demographic data (Jones and Armanios n.d.). The physical infrastructure data came from the Pennsylvania Department of Transportation's (PennDOT) Bridge Management System v2.0 (BMS2) (Pennsylvania Department of Transportation 2018b) and OpenStreetMaps street network data hosted by Geofabrik GmbH ("Geofabrik Download Server" 2018). The social demographic data came from the Neighborhood Change Database (NCdB) from 1970-2010 (GeoLytics 2018). The final dataset contains 20,005 bridges in 2,529 census tracts. For more detail surrounding the data acquisition and cleaning process, the authors refer the reader to the Jones & Armanios study (n.d.) for more details on the data acquisition and cleaning processes used. These processes were replicated here to ensure identical data was used so as to ensure direct comparability across these studies.

Research Design

An experimental research design would assess social equity impacts of a restrictive bridge by randomly placing a new restrictive bridge in a tract and assess the effects in relation to the exact same tract (or an almost identical tract) without such a bridge. Given the cost and time prohibitions of such a method, Jones & Armanios (n.d.) follow a natural experiment design to approximate this ideal empirical strategy. The overall aim of this design is to compare as closely as possible those tracts that are "treated" (e.g., receive a new restricted bridge) to those "control" tracts that most closely approximate these tracts prior to bridge placement but never receive such a bridge. Fig. 8 summarizes the authors' process from their prior work with the extensions included in this work. For the sake of clarity, the authors note the entire research design process here. However, in this section, the authors will briefly describe the first three steps and Causal Search part of the flow diagram in Fig. 8, and discuss LASSO and MB-based variable selection methods in the <u>Variables section</u>.

After first running analysis on the entire sample, Jones & Armanios (n.d.) sharpened the treated tracts by conducting a network analysis using GIS software to help target a more accurate and conservative service area. This analysis was used to exclude nearby tracts that do not share a road network with the bridge. The authors thirdly sharpened the control tracts through the use of coarsened exact matching (CEM) (Iacus et al. 2008, 2009). The aim of using CEM was to match treatment (in this case tracts with a new restrictive bridge) and control tracts along observable factors (water area, land area, population, total bridges and time period) to ensure improved covariate balance between the two groups. This approach was used to ensure the control tracts are as similar as possible to the treated tracts. For a more detailed explanation of the first three steps please refer to this previous study (Jones and Armanios n.d.).

Overall, the Jones & Armanios (n.d.) approach sought to find the sharpest set of treatment tracts that receive a new restrictive bridge to the most equivalent control tracts that do not receive a new restrictive bridge. The authors did this through a variety of methods (e.g., service area network analysis – sharpens treatment and coarsened exact matching – sharpens control) to ensure that they achieve as closely as possible to this ideal. The authors also ran analysis on tracts with any new bridge, regardless of underclearance or presence of under-record route. This was to ascertain whether influences were due more to the height of existing or new bridge constructions or due to lack of connectivity in the form of having (or not having) any type of new bridge construction.

Here, the authors add important methodological steps that help select variables using the LASSO algorithm (to be discussed shortly) and Markov blanket-based algorithms to predetermine variable selection (Tibshirani 1996). Then, the authors used causal search algorithms on both sets of variables, the original literature-review-based variables and the new computational-based variables, to attempt to identify any significant causal relationships. Finally, the authors used the same models as the previous work to quantitatively measure the effects of the variables. This approach enhances our understanding of which variables are the most important and most causality linked to equity impacts than what is possible in the Jones & Armanios (2020) study. Moreover, this approach also relaxes the need for domain expertise that was important for the Jones & Armanios (2020) study.

Variables

As previously noted, there were two types of variables used: physical infrastructure and socioeconomic. For physical infrastructure variables, the authors used the following variables: PennDOT structure ID, NBI structure number, underclearance height, latitude, longitude, year built, and year of construction or year of last major reconstruction (Desai 2018; Youssef et al. 1991). For socioeconomic variables, the authors conducted a variable selection process as depicted in Fig. 9.

As detailed in Jones & Armanios (n.d.), the authors conducted an extensive literature review in the research areas of neighborhood-effects (Crowder and South 2008; Sampson et al. 1999, 2002; Sharkey 2014), social justice (Brady et al. 2017; Schindler 2015), environmental justice (Carless 2018; Pathak et al. 2011), and segregation (Crowder et al. 2012; Farley and H. Frey 1994; Lee et al. 2008; Lichter et al. 2015). Based on this review, the authors found the following themes: wealth status, race, family composition, education, and housing. Since the object of this study is transportation infrastructure, the authors also added available transportation-related variables. Census data (GeoLytics 2018) captured 41 variables that most closely matched or proxied for these categories. After taking correlation of variables that measured approximately the same phenomena into account (r=0.7 or greater), 24 variables remained (Jones and Armanios n.d.).

The authors here developed a parsimonious methodologically informed approach that relaxes the need for social equity domain expertise. Given social context can inform which variables are likely to be more relevant or salient in a given case study (Abend et al. 2013; Sampson et al. 2002), the authors used the LASSO and MB-based algorithms as an alternative to expert knowledge in order to quantitatively narrow variable selection. LASSO fits a generalized linear model using a penalized maximum likelihood function to guide selection of appropriate variables (Friedman et al. 2010). The initial set of variables included census data variables and a few transformations (e.g., percentages, log +1, inverse hyperbolic sine) for a total of 216 variables (Burbidge et al. 1988; MacKinnon and Magee 1990). This process included not just those variables identified in the literature review but also any additional variables which may be reasonably suspected of importance for an engineer managing bridge infrastructure from all those available in the original PennDOT and Geolytics census datasets.

As discussed before, to further attest to whether any of the variables selected, by either LASSO or MB-based algorithms, could guide infrastructure decision-making in the event equity is deemed a key concern, the authors then applied ML causal search algorithms (e.g., FGES without MB restrictions). These algorithms quantify probabilities for which those variables could causally affect an outcome. For comparison and to investigate the usefulness of each procedure, the authors present the results for each step of the process in the Causal Search section of the Results. Due to the similarities in results between LASSO and the Markov blanket-based algorithms one can think of using these algorithms to triangulate and facilitate the variable search. Hereafter, for ease of reference, the authors refer to the LASSO and Markov blanket-based results as ML search results.

Alternatively, the authors also chose a causal search algorithm that does not restrict itself to the Markov Blanket to ensure that relevant variables were not being neglected by the previous algorithms. Due to the relative computational efficiency, the authors selected the fast greedy equivalence search (FGES) algorithm but now with an expanded search process that includes but is not limited to the Markov blanket. Unlike before, FGES here is not restricted to the Markov blanket as opposed to previously with FGES-MB, which allows it to engage in wider causal search (Ramsey et al. 2017). The purpose of opening the aperture of the search space is to ensure that all important or causal variables are discovered. FGES is also a relatively easy algorithm to implement increasing its utility for engineers and decisionmakers. Finally, the authors employ the Fast Causal Inference (FCI) algorithm to test for latent (e.g., unobservable) variables (Spirtes et al. 1993). FCI was designed to discover DAG from conditional independence information from observed variables. In spite of its name, it is rather expensive computationally and is only applied after variable selection is completed through other ML search algorithms. FCI was also used to analyze the causal relations of the variables identified through the previous study's literature review for comparative purposes (Jones and Armanios n.d.).

To engage in the causal search aspects of this study, the authors used the software package, Tetrad (http://www.phil.cmu.edu/tetrad/), to run ML-based causal search analyses (Glymour et al. 2017) (see appendices K and L for information about these algorithms). Tetrad is a software package that is a collection of machine learning algorithms for causal analysis. These algorithms perform causal search that can be used to identify causal relationships between variables by analyzing their observed data. Tetrad contains many of the most well-known algorithms such as PC, FGES, FCI, etc. (Glymour et al. 2014). Since the authors are interested in discovering how specific variables are related to others, in this case restrictive new bridges, the authors began exploration with algorithms that utilized a MB. As previously noted, this choice was due to the ease at which an engineer could use these algorithms. These are quite flexible and share similarities with LASSO, as well as have been used in other engineering applications such as traffic event detection and variable selection for concrete strength prediction (Abuodeh et al. 2019; Yan et al. 2016)

Dependent Variables

Table 4 details the variables found to be causally related to the three bridge categories along with relevant literature references (see Appendix II, Section B, Table 72 for the exhaustive list of analyzed variables). To ensure the greatest compatibility with the Jones & Armanios (2020) study, we run the same two sets of regression models. The first set of regressions models are on restrictive bridge measures – the underclearance height. The primary measure is whether a bridge is restrictive (under 4.27 meters or 14 feet) or non-restrictive (over 4.27 m or 14 ft). To assess whether effects pertain to any new bridge construction more generally, the authors also have a separate measure for all bridges including those that do not have a road or railroad (under-record) beneath them. The authors specify these dependent variables in two ways. The first is as a dichotomous variable (i.e., binary 0 or 1) signifying that a new bridge of that underclearance height was built in that tract during the census period (10 years). Since the census is a decennial survey, the authors chose to use this ten-year window to match the census timing. The other dependent variable is a total count of the number of new bridges of each group built during the census period. The second set of regressions models are on socioeconomic factors delineated in greater detail in the Independent Variables section, and the three new and restrictive bridge measures previously discussed are now the independent variables.

Independent Variables

For the first set of regression models on the previously aforementioned new and restrictive bridge measures, the independent variables are the entirety of socioeconomic factors identifiable in PennDOT and Geolytics census data. For this set of models, each independent variable was lagged by one time period (i.e., one census period or ten years). The complete set of independent variables from the literature review is in Jones and Armanios (n.d.) Appendix I, Section C. For convenience here, the authors have placed those variables that proved to be most relevant and have the highest likelihood to guide future decision-making in Table 4.

For the second set of regression models on socioeconomic factors, the independent variables are the event study interaction term, the bridge treatment term (e.g., when a new restrictive bridge of interest is constructed), and the bridge treatment group term (e.g., the census tract that receives such a bridge). These independent variables are also dichotomous (i.e., binary 0 or 1). The event study interaction term is one in all periods where both the treatment and control variables are one, the treatment term changes to one and remains one in each time period after the treatment time period and the treatment group term is one in all time periods if that tract ever receives the treatment bridge. provides a graphical representation of all tracts receiving a restrictive bridge treatment. For tracts that received a new bridge, the census period when a new bridge was built is the treatment time period. Tracts without any new bridges comprised the control group.

Control Variables

The authors control for the same engineering factors around bridge placement as did the Jones & Armanios (n.d.) study. These controls were used for matching during coarsened exact matching (CEM). The first two controls are the tract's land and water areas as proxies for geophysical impediments. The third is the number of people living within the tract. The fourth is the total number of bridges in the tract as a measure for how much infrastructure was already present. The final control is the treatment time. These are the five aspects used to match treatment tracts with control tracts. For the event study model, the lagged socio-economic variables serve as control variables.

LASSO and Markov blanket-based ML variable search

While there are several social equity literatures to guide selection of relevant socioeconomic variables, the authors wanted to ensure that the results were not biased due to background knowledge based variable selection. Moreover, the authors wanted to develop a replicable approach that an engineer not necessarily familiar with these insights could employ without having to conduct a similarly exhaustive search as was performed in the Jones & Armanios (n.d.) study. Additionally, in considering that causal discovery algorithms can be temporally and computationally expensive with large numbers of variables, it would be useful to eliminate those variables with limited causal likelihoods. For these reasons, the authors sought a means to computationally assess variable appropriateness without the need for predetermined selection by the researcher or an expert with domain expertise. The LASSO and Markov blanket-based algorithms were selected as means to determine which variables are most relevant for different types of new bridges (Friedman et al. 2010; Ramsey et al. 2017; Ramsey 2006; Tibshirani 1996). Both LASSO and the MB-based algorithms can be configured with a penalty coefficient that controls how parsimonious the results are. Both have options that make them compatible with linear and non-linear relationships. The algorithms are also computationally efficient and therefore accessible to a large audience. Therefore, it is relatively easy and not very time consuming to experiment with several values. The authors compared the results of LASSO and the two Markov-blanket based algorithms (i.e., Markov Blanket Fan Search (MBFS) and Fast Greedy Equivalence Search-Markov Blanket (FGES-MB)) and found that the results were very similar and identical in some cases. LASSO helps assess which variables are most important (e.g., variables with the largest coefficients), while MB-based approaches help detect causality (e.g., determine causal linkages).

In this paper, we assume that the causal relations are acyclic (without feedback); as a consequence, the causal structure can be represented by a Directed Acyclic Graph (DAG). The reason is that the target variables (T in Fig. 10) in this study are the physical infrastructure of interest (e.g., bridges), while the parents (P in Fig. 10) and children (C in Fig. 10) are social factors. Social factors may influence where they are cited (social factors as "parents"), or what impacts come from them (social factors as "children"). However, feedback is less possible, at least immediately, given extended design life of physical infrastructure like bridges. In other words, once a bridge is built, we assume it cannot necessarily be rebuilt purely due to social factors, at least not immediately. Discussions with bridge managers suggest the decision to replace a bridge is due more immediately to the condition of the bridge and economic factors than social factors, which suggests this is a reasonable assumption. In graphical models represented by a DAG, Markov blankets are the set of variables (e.g., other bridge infrastructure and socioeconomic variables of interest) that make a given node (e.g., the focal bridge infrastructure variable of interest) independent of all variables outside of the Markov blanket conditional on the variables included in the Markov blanket. This means that the Markov blanket of a particular node includes its parents, its children and the other parents of its children (Fig. 10) (Koller and Friedman 2012; Pearl 1988). Markov blankets are useful as these methods find a parsimonious number of variables causally linked to the target node (i.e., bridge variables interactions with socioeconomic and other bridge variables). It is important to note here that not all variables found in a Markov Blanket will be causally linked to the target node (e.g., parents of the node's children). In deploying methods utilizing a Markov Blanket, the authors specifically started with the fast greedy equivalence search-Markov blanket (FGES-MB) (Ramsey et al. 2017) and Markov blanket fan search (MBFS) (Ramsey 2006) algorithms. Both of these methods are based on Meek's (1997) greedy equivalence search (GES) algorithm (Glymour et al. 2017). FGES-MB restricts the FGES algorithm to the union of edges over the target variable's Markov Blanket. MBFS is similar to FGES-MB, but it is based on the Peter and Clark (PC) algorithm instead of GES (Spirtes and Glymour 1991). Therefore, MBFS is a PC search that is restricted to just the Markov blanket of the target variable (see Appendix II, Section E). Again, since the authors are primarily interested in how the bridge variables interact with the rest of the variables, setting the bridge variable as the primary node of interest in a Markov Blanket is ideal. These algorithms make a good introduction to the world of causal search and should also act as a metaphorical "bridge" from statistical methods to causal methods.

As discussed earlier, the authors were able to use these ML search algorithms to evaluate all the available variables suggested by the literature review, as well as several transformations of these aforementioned variables, and other variables that might be reasonably selected by an engineer interested in a similar infrastructure problem (Fig. 9). By using both the count of the number of bridges by underclearance height and a dichotomous dummy variable that is one insofar as at least one bridge of that type is built in that census period (10 years), the authors ran OLS and logit regressions to determine the influence of these socioeconomic variables which is part of the LASSO process and serve as a baseline upon which the algorithm can optimize.

Once the authors formulated all the variables for inclusion, they used ML search algorithms to guide variable inclusion into the main models (see Appendix II, Sections D - E). LASSO uses a lambda parameter to guide inclusion of only the most important variables in the final parsimonious model. Lambda is a penalty coefficient used to drive the beta coefficients to zero (James et al. 2013; Tibshirani 1996). The authors searched three values of lambda in order to create a more parsimonious list of relevant variables: the minimum mean cross-validated error value of lambda, the largest value of lambda one standard error away from that minimum and a value half-way between the first two values on a log scale. The reason for these three values of lambda is that the minimum value was not parsimonious enough (e.g., LASSO found 94 variables for all new bridges), the value of lambda that was one standard error away was too parsimonious (e.g., LASSO found 2 variables for restricted bridges), but the one in the middle found a reasonably parsimonious number of variables including demographic variables (e.g., LASSO found 12 variables for all new bridges). Similarly, the Markov blanket algorithms have a penalty discount. By varying the value, the search results will be more or less parsimonious (the authors used 2, the default, and 0.001 with SEM BIC scoring and Fisher Z scoring). By including any variables found by these three algorithms and FGES, the authors were able to narrow the list of relevant variables (including transformations) from 216 variables down to 34 (29 were found by LASSO and MB-based searches and 5 additional variables by FGES—see Fig. 13 and Appendix II, Section E for results from the ML search algorithms). Therefore, ML search can be a useful preprocessing step. These algorithms safely eliminate unimportant variables from the dataset allowing the causal discovery algorithms and engineers to only focus on the most relevant variables.

Equation 1. *LASSO linear model specification*

$$\min_{\gamma_0, \gamma} \frac{1}{N} \sum_{i=1}^{N} l(y_{i,t}, \gamma_0 + \gamma^T x_{i,t-1} + \delta_t) + \lambda(\|\gamma\|_1)$$

where *l(y, η)* is negative log-likelihood contribution for observation *i*, *y* is the count of new restrictive bridges built in the preceding 10 years, in census year *t*, γ represents the variable coefficients, *x* represents 216 variables of social interest, δ is a fixed effect for each census year and λ is the tuning parameter controlling the strength of the LASSO penalty (Hastie and Qian 2016).

Equation 2. LASSO logistic model specification

$$\min_{(\gamma_0,\gamma)\in\mathbb{R}^{p+1}} -\left[\frac{1}{N}\sum_{i=1}^{N} y_{i,t}\ (\gamma_0 + x_{i,t-1}^{T}\gamma + \delta_t)\ -\ log(1 + e^{(\gamma_0 + x_{i,t-1}^{T}\gamma + \delta_t)})\right] +\ \lambda(\|\gamma\|_1)$$

where the objective function uses the negative binomial log-likelihood, y is a dummy variable designating a new restrictive bridge was built during the census period, in census year t, γ represents the variable coefficients, x represents 216 variables of social interest, δ is a fixed effect for each census year and λ is the tuning parameter controlling the strength of the LASSO penalty (Hastie and Qian 2016).

Of the 34 ML search-selected variables, eighteen were directly included by the literature review in the Jones & Armanios (n.d.) study with an additional seven being variants of variables included by the variable review. Only nine variables were not suggested by the literature review (see Appendix I, Section C for more information). Even though 25 of these were suggested by the literature review, only nineteen of these variables were previously included in the models (Jones and Armanios n.d.) as the ML search algorithms (MB and LASSO) chose variants to these variables. More specifically, share of white population was not used previously in order to use share of different types of minority groups and some minority groups were rare in Pennsylvania; only four of five education variables were used; various occupational measures were suggested by the literature review but were highly correlated with income; and only one type of vacant housing was used.

There are a few variables that were identified by ML search that are not included in Table 4. These variables are: land area, water area, tract population density, and transformations of variables included in the table. These variables were used as controls for CEM or were redundant and not included in the table or the models themselves.

The ML search algorithms found two rural tract indicator variables, seven demographic variables, five family variables, four transportation or commute-related variables, two related to education, ten variables related to finances or income and four housing variables (Table 4). The nine variables found by ML search that were not suggested by the literature review are: rural tract indicator (10 M and 4 M square meters), commute less than 25 minutes, commute between 25 and 45 minutes, commute over 45 minutes, travel on public transportation, population working at home, population working in county, and vacant housing for occasional use. The seven variables related to the literature review that were not used in the prior study are: IHS transformation of population born outside US; IHS transform of foreign born population; precision crafter workers; IHS transform of farm, fishery and forestry workers; military females and military males. The ability of these algorithms to select so many variables consistent with the literature review provides a great deal of confidence in both the algorithms and the sociological literature.

Table 4. ML search discovered variable descriptions by category with relevant citations. The prior column annotates if the exact variable was used in the Jones & Armanios (n.d.) study. The lit column denotes if the variable was suggested by the literature review directly (D), is a variant (V) or was not included (N).

Cat	Variable description	Citation	Prior?	Lit?
	Rural tract indicator > 10M sq. meters	Jones & Armanios, 2020	Y	N
	Rural tract indicator > 4M sq. meters	Jones & Armanios, 2020	Y	N
Demographic	% African Americans	Brady, et al, 2017; Crowder, et al, 2012, Lee, et al, 2008;	N	D
	% Hispanic	Brady, et al, 2017; Crowder, et al, 2012; Lee, et al, 2008	N	V
	% Native American	Brady, et al, 2017; Crowder, et al, 2012	N	D
	% Asian	Brady, et al, 2017; Crowder, et al, 2012	N	D
	% White	Brady, et al, 2017; Crowder, et al, 2012	Y	D
	IHS-transformed Born outside U.S	Lee, et al, 2008; Lichter, et al, 2015	N	V
	IHS-transformed foreign-born	Lee, et al, 2008; Lichter, et al, 2015	Y	V
Family	Lagged % female-headed families	Sharkey, 2014; Crowder, et al, 2012	Y	D
	% married families w/kids	Sampson, et al, 1999; Crowder, et al, 2012	N	D
	Lagged Male-headed families with children	Sharkey, 2014; Crowder, et al, 2012	N	D
	IHS-transformed Male-headed families without children	Sampson, et al, 1999; Crowder, et al, 2012	N	V
	% children	Sampson, et al, 1999; Sharkey, 2014; Crowder, et al, 2012; Tach & Emory, 2017	Y	D
Commute	Commute less than 25 minutes	Jones & Armanios, 2020	Y	N
	Lagged Commute 25-45 minutes	Jones & Armanios, 2020	Y	N
	Commute over 45 minutes	Jones & Armanios, 2020	Y	N
	IHS-transformed Travel on public transportation	Jones & Armanios, 2020	Y	N
Ed	Completed 8 years of school	Sampson, et al, 1999; Crowder, et al, 2012; Lee, et al, 2008; de Faria, et al, 2017	Y	D
	% Some College	Sampson, et al, 1999; Crowder, et al, 2012; Lee, et al, 2008; de Faria, et al, 2017	N	D
Financial	IHS-transformed Work at home	this study	N	N
	Work in county	this study	N	N
	Precision crafters	Lee, et al, 2008; Lichter, et al, 2015	N	V
	IHS-transformed Farm, fishery and forestry workers	Lee, et al, 2008; Lichter, et al, 2015	N	V
	Military males	Lee, et al, 2008; Lichter, et al, 2015	N	V
	Military females	Lee, et al, 2008; Lichter, et al, 2015	N	V
	Lagged IHS-transformed Real Aggregate income	Sampson, et al, 1999; Lee, et al, 2008	Y	D
	Lagged IHS-transformed Real Average income	Sampson, et al, 1999; Lee, et al, 2008	Y	D
	% Poverty rate	Sharkey, 2014; Crowder, et al, 2012	Y	D
	% Welfare rate	Sharkey, 2014	Y	D
Housing	% Vacant housing	Farley & Frey, 1994; Lee, et al, 2008	Y	D
	Vacant housing for occasional use	this study	N	N
	% New housing	Farley & Frey, 1994; Lee, et al, 2008	Y	D
	Owner to Renter rate	McCabe, 2016; Sampson, et al, 1999; Crowder, et al, 2012	Y	D

Statistical Models

The LASSO and MB-selected variables were then fed into the statistical models used in the Jones & Armanios (n.d.)study to compare the results achieved across these two studies. In order to maintain the same setup as the first study, similar variables were separated into four groups (see Appendix I, Section C for groupings and Section F for model results). The first set of regression models are designed to analyze the probability of a tract receiving a new restrictive bridge. This model should determine if there are pre-existing conditions that determine where a new bridge is built. The second set of regression models is designed to determine the difference in consequences between tracts that received a new restrictive bridge and those that did not. Event study models are designed to analyze the effects of events on different units at different times. There are several different models called event study models, but the authors use event study in the same sense as Borusyak and Jaravel (2016), de Faria, et al (2017), and Clay, et al (2016). The models are provided here for convenience, but the reader should refer to the Jones & Armanios (n.d.) study for more information as these models are similarly deployed here as they were in this study. Again, this was a conscious choice to enhance comparability between the two studies.

For the first set of models, a logistic regression model was used and found to have the best goodness of fit of the selection effect models used and details can be found in Appendix I, Section G.

Equation 3. *Logistic Regression Model Specification*

$$logit(p(x)) = \; log\frac{p(x)}{1-p(x)} = \beta_0 + \boldsymbol{\gamma}_k \boldsymbol{X}_{k,i,t-1} + \delta_t + e_{i,t}$$

where logit(p(x)) is the probability that a variable designating a new restrictive bridge was built in the census period, in tract i, in census year t, $\boldsymbol{\gamma}_k$ is a vector of control variable coefficients, $\boldsymbol{X}$ is a vector of variables of social interest, and δ is a fixed effect for each census year.

For the second set of models, the authors employed an event study model to analyze treatment effects (Borusyak and Jaravel 2016; Clay et al. 2016; de Faria et al. 2017). Details about other models considered can be found in Jones & Armanios (n.d.).

Equation 4. *Event Study treatment effect model specification*

$$z_{i,t} = \beta_0 + \beta_1(x_{i,t} \times g_{i,t}) + \beta_2 x_{i,t} + \beta_3 g_{i,t} + \boldsymbol{\gamma}_k \boldsymbol{C}_{k,i,t-1} + \delta_t + \boldsymbol{f}_i + e_{i,t}$$

where z is a social equity variable of interest, in tract i, in year t, β_1 is the event study coefficient for the treatment and group interaction term, x is a dummy variable designating the tract received a new restrictive bridge treatment, g is a dummy variable designating the tract as receiving a restrictive bridge at any time, $\boldsymbol{\gamma}_k$ is a vector of control variable coefficients, $\boldsymbol{C}$ is a vector of lagged control variables, δ is a fixed effect for each census year, and $\boldsymbol{f}$ is a time-invariant tract fixed effect (Borusyak and Jaravel 2016; Clay et al. 2016; de Faria et al. 2017).

Due to the nature of census data, errors were found to be heteroskedastic in nature. Therefore, robust standard errors were calculated using a variance covariance matrix and Wald test (Zeileis 2004, 2006). All standard errors and p-values reported are the results of these calculations.

Results

Results presented here focus on three bridge categories: restrictive bridges (under 4.27 m or 14 ft), non-restrictive bridges (over 4.27 m or 14 ft), and all bridges (including those without an under-record route). Results are considered from the perspective of new restrictive bridges. To make interpretations, the authors use average marginal effect sizes. While there is debate on the overall appropriateness of comparing different types of models, average marginal effects are the most comparable measures when looking across different types of model specifications (Bogard 2016; Davis 2018; Fernihough 2019; Williams 2018). Table 5 and Fig. 13 report the coefficient estimates for the bridge siting models based on ML search selected variables. Variables were considered to have a robust effect if the point estimate and standard error did not encapsulate zero. 24 of the 34 variables have at least one significant effect with one of the bridge categories. We summarize the key points here before delving into greater detail in subsequent sections.

First, the authors find consistent results with previous models but along different variables than the Jones & Armanios (n.d.) study. While the Jones & Armanios (n.d.) statistical models find restrictions evident in non-white populations around bridge placement, ML search also finds another opposite yet similar effect - less restrictions in white populations around bridge placement (Fig. 13 and Table 5). There are four variables for which there was a significant result in the previous study and none in this study: travel on public transportation, 8 years if education, HIS-transformed real average income and HIS-transformed real aggregate income. Four variables have significant findings where there was not one in the previous study: rural indicator 10M m^2, rural indicator 4M m^2, % children, and % welfare rate. Even though LASSO found the IHS-transformed African American variable, the authors chose to use % African American for the sake of consistency, both for the other race based demographic variables and with the previous study. The ML search techniques also discovered four new industry-based associations. The number of precision crafter and farm, fishery, and forestry workers were negatively associated with non-restrictive bridge construction. The IHS-transformed count of military males and females were also found but not with any significance.

Second, causal machine learning algorithms found some sources of causality. These algorithms discovered the structural relationship between variables (i.e., the count of a particular type of bridge and the dummy indicator signifying that a particular type of bridge had been built in a tract) demonstrating their efficacy at finding causal links (Spirtes and Scheines 2004; Spirtes and Zhang 2016). These searches also discovered causal relationships between bridges and several variables of sociological interest. These results will be explained in more detail in the following section discussing causal search. Overall, these results indicate that incorporating causal-search early in the variable discovery process both has resonance with the prior purely empirical approaches of the Jones & Armanios (n.d.) study and sheds novel light. In particular, a different set of parsimonious variables were selected when using computationally-informed variable selection (instead of literature based as previously done), and some new factors were identified, namely industry-based factors (e.g., farm, fishery, and forestry, precision crafters and military).

Bridge Placement Model with ML search-selected variables

ML search helped the authors identify not just key variables but also combinations of transformations to best model the data (see Variable Search section and Appendix II, Section E). Table 5 and Fig. 13 summarize the results from the model.

The ML search-selected variables show similar trends after CEM to Jones & Armanios (n.d.) study (Fig. 13 and Appendix II, Section C). While the previous results show associations with non-white populations, ML search shows similar relationships for white populations as well as non-white populations. In particular, while previous results show non-white populations are associated with fewer constructed bridges, the ML search model shows that white populations are more influential with more constructed bridges. In other words, tracts with more white populations are at least associated with more bridges, which mirrors previous results that non-white populations are associated with fewer bridges. This is an opposite yet symmetric result to what was found previously. There were no robust associations found for restrictive bridges for tracts based on their white population size. Also, the effects on the Hispanic population are consistent to what was found previously and robust.

The LASSO approach also uncovered previously unconsidered industry-based influences on bridge construction. The literatures primarily divide workers between white-collar and blue-collar jobs, and only the variable for white collar workers (professional occupations) was included in the previous models after following the variable selection method (Jones and Armanios n.d.). For example, ML search methods find a robust but small positive association between the number of farm, fishery, and forestry workers and any bridge construction and a minute negative association for non-restrictive bridges. Perhaps, these industries heavily rely on trucking and other large vehicles to ensure sufficient flows of its products that necessitate an extensive bridge network that does not cross over other routes (under records).

Overall, this model using ML search -selected variables finds results that are similar to those previously reported (Jones and Armanios n.d.) but through different variables. The ML search algorithms also helped uncover some new industry-based associations with bridge construction.

Post-Placement Bridge Effect Models

This interaction captures the difference between those tracts that received a new bridge and those that did not. To assess effects of bridge variables, models were compared to the same model without the bridge variables. In all models the differences in R^2 were very small suggesting that bridge variables do not have much, if any, explanatory power for the treatment effect. Therefore, as with the Jones & Armanios (n.d.) study, the authors see bridge siting as playing more of an equity impact than effects that are identified after bridge placement.

Causal Search

The machine learning results demonstrate relationships identifiable by using causal search algorithms. Detailed results for each of the algorithms used follow.

FGES-MB and MBFS

Using all 216 of the potential variables available, the same set of data used by the LASSO algorithm, the algorithms targeted one bridge category variable at a time. Since the MBFS algorithm does not assume linearity, the authors ran the algorithm on both the count of the number of new bridge types built as well as on the dummy variable indicating that at least one of a type of bridge was built (see Fig. 11 and Appendix II, Section A for scatterplots demonstrating relationships between variables) . Unlike MBFS, FGES-MB does make a linearity assumption and therefore only the count of the number of new bridge types was used. This means the authors ran sixteen searches using MBFS and eight with FGES-MB for a total of 24 searches. Many of the possibly causal links discovered using these methods were of a structural nature, e.g. the links between military males and females and their respective IHS-transformations seen in Fig. 12. These two search algorithms found eight of the 28 variables deemed relevant by LASSO (see Appendix II, Section D for results).

Table 5. Bridge placement models with LASSO & MB-based variables after CEM. Variables not encapsulating the null are in **bold**.

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years	Restrictive	Non-restrictive	All New
Rural tract indicator > 10M sq. meters	-0.124	-0.066	**0.960*** **
	(0.426)	(0.103)	**(0.185)**
Rural tract indicator > 4M sq. meters	-1.289*	0.265*	**0.948*** **
	(0.601)	(0.112)	**(0.105)**
Lagged African American Percentage	-0.040	**-0.990** **	**-2.417*** **
	(0.853)	**(0.313)**	**(0.473)**
Lagged Hispanic Population Percentage	-2.490	**-3.996** **	**-8.351** **
	(4.375)	**(1.457)**	**(2.600)**
Lagged Native Americans percentage	-116.283	-32.675	-6.097
	(137.095)	(23.672)	(19.715)
Lagged Asian, Native Hawaiian and other percentage	-9.433	2.177	0.438
	(18.601)	(1.558)	(1.918)
Lagged Percentage of White Population	-0.640	**0.764* **	**0.760** **
	(1.316)	**(0.330)**	**(0.282)**
Lagged IHS-transformed Population Born Outside U.S.	-0.084	**-0.065* **	**-0.133*** **
	(0.143)	**(0.033)**	**(0.032)**
Lagged IHS-transformed Population Foreign Born	-0.406	0.025	**-0.162*** **
	(0.243)	(0.055)	**(0.048)**
Lagged % female-headed families	-1.664	-0.571	**-3.111*** **
	(3.880)	(0.835)	**(0.783)**
Lagged Percentage Married Couples with Children	1.840	-0.526	**1.131* **
	(2.136)	(0.519)	**(0.509)**
Lagged IHS-transformed male-headed families w/kids	0.067	**-0.085* **	0.014
	(0.214)	**(0.037)**	(0.041)
Lagged IHS-transformed Male Single Parent with Children	-0.248	0.064	**-0.162*** **
	(0.320)	(0.051)	**(0.044)**
Lagged Population Percentage under 18	0.434	**-2.190** **	**1.627* **
	(2.496)	**(0.728)**	**(0.695)**
Lagged Population with Commute < 25 minutes	0.001	**0.001*** **	0.000
	(0.000)	**(0.000)**	(0.000)
Lagged Commute 25-45 minutes	0.001	**-0.001*** **	0.000
	(0.001)	**(0.000)**	(0.000)
Lagged Population with Commute > 45 minutes	0.001	**-0.002*** **	0.000
	(0.001)	**(0.000)**	(0.000)
Lagged IHS-transformed Population Travel on Public Transportation	-0.068	0.042	-0.010
	(0.115)	(0.031)	(0.033)

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years	**Restrictive**	**Non-restrictive**	**All New**
Lagged over 25-yr-olds with at Least 8 Years Education	0.001	**0.001****	0.000
	(0.001)	**0.000**	0.000
Lagged percentage of over 25-yr-olds with Some College	**-26.024****	-2.597	-2.941
	(8.515)	(2.032)	(2.057)
Lagged IHS-transformed Population Work at home	-0.300	**-0.129****	**0.097***
	(0.159)	**(0.041)**	**(0.043)**
Lagged Population Work in county	0.001	**0.000****	0.000
	(0.001)	**(0.000)**	(0.000)
Lagged Precision crafters	0.005	**-0.002****	0.000
	(0.003)	**(0.000)**	(0.000)
Lagged IHS-transformed Farm, fishery and forestry workers	0.144	**-0.084****	0.004
	(0.137)	**(0.032)**	(0.040)
Lagged IHS-transformed Military females	0.412	0.094	-0.252
	(0.216)	(0.077)	(0.153)
Lagged IHS-transformed Military males	0.004	0.054	0.065
	(0.154)	(0.036)	(0.037)
Lagged IHS-transformed Real Average income	0.062	0.012	-0.014
	(0.092)	(0.027)	(0.027)
Lagged IHS-transformed Real aggregate income	0.079	**-0.046****	0.027
	(0.074)	**(0.017)**	(0.018)
Lagged Population Percentage Below the Poverty Line	5.639	**1.859****	**1.838****
	(3.124)	**(0.591)**	**(0.630)**
Lagged Population Percentage Receiving Welfare	0.402	**2.111****	**-2.384****
	(3.653)	**(0.699)**	**(0.797)**
Lagged Percentage Housing Units Vacant	-0.202	0.878	-0.708
	(3.587)	(0.851)	(1.439)
Lagged Vacant housing for occasional use	0.003	-0.001	-0.003
	(0.003)	(0.001)	(0.003)
Lagged Percent Change in Housing Unit Supply	-0.491	-0.051	0.002
	(1.784)	(0.386)	(0.090)
Lagged Owner to Renter Ratio	-0.008	-0.001	0.000
	(0.007)	(0.001)	(0.000)

***p < 0.001, **p < 0.01, *p < 0.05

FGES

Finally, the authors thought it valuable to run FGES with all variables. The algorithms found 13,246 edges or links between variables. The authors first narrowed down this list by eliminating all links that linked nodes with two bridge variables or two non-bridge variables. By sorting and eliminating linkages not targeted, there were only 23 remaining connections. Of these 23, all but five had already been discovered by the LASSO and MB-based search algorithms (see Appendix II, Section F). These five variables or a variant thereof had previously been included in the literature review-based models in Jones & Armanios (n.d.). All five variables were used in the bridge placement and post-placement models.

With regard to the main concern of this research, the bridge variables, the algorithm found 23 potential causal links. The following probabilities are estimates of the probability of the existence of an edge and should be considered as a measure of the confidence in the edge, but not necessarily the correctness of the output. It is also important to note that direct edges can be found even when none exist and the true relationship is actually multiple indirect paths (e.g., A→E could be found when the true relationship is multiple paths of intermediate nodes between A and E such as A→B→D→E or A→C→D→E or A→D→E). Regardless of the actual path, finding the causal links between variables is the object of this research. See Table 6 for the probabilities of each of the found 23 edges or links. From the table, most edges are low probability. The one exception being the IHS-transformed count of total bridges is causally connected to the rural 4M m^2 variable.

FCI

FCI is an extension of the PC algorithm (Spirtes and Glymour 1991). It is computationally expensive and benefits from a variable selection pre-process. Spirtes, et al. (1993) have proven that FCI is robust at estimating acyclic graphs eve in the presence of latent variables and selection variables. Latent variables are those that are not recorded or included in our data, but affect the data nonetheless. Using conditional independence information from observed variables and operating under the faithfulness assumption, FCI is able to learn a Markov equivalence class of DAGs (Colombo et al. 2012)

The authors used FCI on both the literature review-based variable and the ML search-based variables. See Table 7 and Table 8 for results. The results have been filtered to only show results describing a relationship between a bridge and a non-bridge variable.

The relationship signified by "<->" in Table 7 and Table 8 means that there is an unmeasured confounder of the two nodes. There may exist other variables along the causal pathway between the unmeasured confounder and the node. This means that neither node is a cause of the other. The "o->" indicates that either node1 is the cause of node2 or there is an unmeasured confounder or both. This expanded knowledge means that some of the relationships identified through the ML search methods are not causal relationships after all. However, these findings do mean that there is some other unknown variable that is causally related to both nodes and can be pursued to gain better understanding of the casual relationships of these variables.

The relationship signified by "<-- (dd, nl)" in Table 8 means that there is a causal relationship from node 2 to node 1, "dd" signifies definitely direct and "nl" signifies no latent confounder. When examining the literature review-based variables, FCI found that the rural 10M m^2 indicator definitely directly influences the total number of IHS-transformed total bridges with no latent confounder.

FCI then was a valuable check to confirm or refute causality findings from other algorithms. Overall, what the results from these causal search algorithms suggest is that some of the variables identified by the literature review and ML search algorithms are causal in their relationship to bridge infrastructure even though the measured effects are small. These algorithms show some of the causal links between infrastructure and sociological variables of interest. They can also be used to identify selection trends that may or may not have been intentional.

The authors contend that the causal links and non-causal associations discovered by using this framework extension are worthy of consideration and may lead to further understanding of how to employ infrastructure in a more socially responsible manner to promote greater social equity. The discovered causal links may serve as a starting point for greater causal understanding of the system.

Incorporating these or similarly appropriate algorithms into the workflow would be of use to engineers and policymakers concerned with if and how their infrastructure projects impact local residents' well-being. To maximize the contribution of theses algorithms they should be employed early in the process. The optimal point is shortly after data collection is complete in order to aid with variable selection. See Fig. 14 for a flow diagram illustrating this recommendation. These techniques allow engineers and policymakers to cast a wide net over potential variables and provide an efficient and computationally tractable method to discover the most relevant variables. By using multiple methods, variable value can be triangulated and justified more fully.

Robustness Checks

During the data exploration phase of this work, the authors compared variable transformations and their effects on goodness of fit for the various models. Transformations included percentages of total populations, log +1, and inverse hyperbolic sine (Burbidge et al. 1988; MacKinnon and Magee 1990). In almost every case, inverse hyperbolic sine outperformed the log transformation. Since the interpretability of log and inverse hyperbolic sine are similar and in order to provide a consistent basis for analysis the authors chose to only use the inverse hyperbolic sine if the percentage transformation was inappropriate.

Table 6. Causal links found by FGES algorithm with all data.

Node1	Int	Node2	Ensemble	No Edge	-->	<--
IHS new total bridges	<--	Rural tract ind (10M)	0.167	0.833		0.167
Total bridges	-->	Rural tract ind (10M)	0.667	0.333	0.667	
IHS total bridges	-->	Rural tract ind (10M)	0.833	0	0.833	0.167
newbridge.under14	<--	Rural tract ind (10M)	0.333	0.667		0.333
IHS total bridges	-->	Rural tract ind (4M)	1	0	1	
Owner occupied housing	-->	New total bridges	0.167	0.833	0.167	
Log foreign born	-->	New restrictive bridges	0.167	0.833	0.167	
Log Male head of house w/kids	-->	New restrictive bridges	0.167	0.833	0.167	
IHS real average income	-->	IHS total bridges	0.167	0.833	0.167	
IHS real aggregate income	-->	IHS total bridges	0.333	0.667	0.333	
Log real average income	-->	IHS total bridges	0.167	0.833	0.167	
% Male head of house w/kids	-->	IHS total bridges	0.333	0.667	0.333	
Population density	-->	IHS total bridges	0.5	0.333	0.5	0.167
Some college	-->	Total non-restrictive bridges	0.167	0.833	0.167	
Commute < 25 min	<--	Restrictive bridges	0.167	0.833		0.167
Commute 25-45 min	<--	Restrictive bridges	0.167	0.833		0.167
% Some college	<--	Restrictive bridges	0.167	0.833		0.167
Female head of house	<--	Restrictive bridges	0.167	0.833		0.167
% Female head of house	<--	Restrictive bridges	0.167	0.833		0.167
IHS new houses	<--	Restrictive bridges	0.167	0.833		0.167
IHS Native American	<--	Restrictive bridges	0.167	0.833		0.167
Log vacant housing	<--	Restrictive bridges	0.167	0.833		0.167
Welfare	<--	Restrictive bridges	0.167	0.833		0.167

Table 7. Filtered FCI results for the ML search-based variables

Node1	int	node2	ens	no edge	->	<-	->	<-	o->	<-o	<->
IHS foreign born	<->	Total new bridges	1								1
Occasional use vacant housing	<->	Total new bridges	1								1
Farm, fish, forest workers	<->	New bridge ind	0.8					0.2			1
IHS public trans	<->	New bridge ind	0.8					0.2			1
% female head of house	<->	New bridge ind	0.6					0.2		0	1
Total new bridges	<->	Rural tract ind (10M)	1								1
New bridge ind	<->	Rural tract ind (10M)	0.6		0			0.2			1
% new housing	<->	Restrictive bridge ind	0.4	0.4						0	0
Non-restrictive indicator	o->	Rural tract ind (10M)	0.8	0.2					1		
Non-restrictive indicator	o->	Rural tract ind (10M)	0.8	0.2					1		

Table 8. Filtered FCI results for the literature review-based variables

Node1	Int	Node2	Ens	No edge	-->	<--	<->
IHS total bridges	<->	Rural indicator (4M)	1				1
New bridge ind	<->	Rural indicator (10M)	1				1
IHS total bridges	<-- (dd,nl)	Rural indicator (10M)	0.8		0	1	
Land Area	<->	Total bridges	1				1
Land Area	<->	IHS total bridges	1				1
Water Area	<->	IHS total bridges	0.8	0.2			1

Limitations

The limitations that Jones & Armanios (n.d.) identify also apply here, hence these are discussed only briefly here. There were two overriding limitations to the data used: first, the authors only had access to highway system bridges and second, a lack of high fidelity social variables that were consistently available in the NCdB, and third, the data is strictly from the state of Pennsylvania. As previously noted, even when a causal link is identified, it is still possible that the link is not direct or that a latent confounder exists.

Discussion and Conclusion

The authors developed a framework to make inroads to a general call for civil engineers to better understand the social equity impact on the built environment (Levitt Raymond E. 2007; Reardon et al. 2008), this study extended that framework to specifically address variable selection and causality discovery. As applied to the case study of Pennsylvania, the authors found that equity impacts are greater from those factors influencing bridge placement rather than that change after bridge placement as does the Jones & Armanios (n.d.) study. However, this ML-based approach reveals some interesting differences that further refine this prior study. While demographic variables seem to play the strongest role as in the prior study, the ML-based variable and causal search approaches used here also identify some new factors, namely industry-based factors (e.g., fishery, farming, and forestry, precision crafters and military) (see Table 9 for a summary of findings and Appendix II, Section C for detailed results). These algorithms had similar results showing that triangulating these algorithms can be gainfully employed for variable selection purposes and discovered relevant, consistent variables and some variables not emphasized or suggested by the literature review (see Appendix II, Section B for more details). Moreover, the causal ML-based search mechanisms also found several causal links (e.g., rural indicators, area land, area water and population density) not suggested by the literature review nor discovered by the LASSO and Markov blanket algorithms. Overall, then, the ML-based approaches advanced here to ascertain equity impacts from infrastructure help confirm but also refine the purely empirical-based approaches in prior studies. These refinements further isolate and reveal new infrastructure variables that may be important and associated with, if not causally linked, to equity considerations. This is done in a way that relaxes the need for engineers to have social equity domain expertise.

As summarized in Fig. 8, this study extends the previous research design by incorporating ML-based variable and causal search algorithms to make inroads into discovering the most salient equity variables for analysis and the causality of identified associations. The motivation behind this extension is to provide confidence in these tools in order to relax the need for domain expertise. The authors hope that with these extensions the previous methodology will become even more attractive to engineers by alleviating the need for deep knowledge of the social equity domain. A potential workflow diagram is included here in Fig. 14 to illustrate how these techniques could be used efficiently.

The main contribution of this extension is to demonstrate that it is possible to use quantitative methods with data very similar to publicly available data to discover valuable associations and causal relationships between infrastructure and social factors. Moreover, these methods can be employed by engineers with little familiarity in underlying theory around social equity. These extensions should provide additional metrics for which to further prioritize and identify the most critical bridges in need of repair. Therefore, including equity dimensions through this methodology presents an additional set of factors that can advance such needs and allow infrastructure managers to prioritize bridge needs more effectively in ways that more closely match budgetary constraints.

Policy Recommendations

Given the efficacy of the machine learning methods explored in this study, the authors feel it is even more feasible to modify DOT practices to encourage including social equity concerns in their policies and procedures. Since this paper also provides additional evidence for the general efficacy offered by infrastructure investments, the authors recommend that state and local transportation departments adopt policies to identify neighborhoods within their jurisdiction that would most benefit from infrastructure investment and identify what kind of infrastructure would be of most benefit to those neighborhoods and then prioritize those investments especially for historically underserved populations. This may be especially useful because even when funding is often too limited to cover all infrastructure projects identified as critical with technical factors alone. Thus, having a computationally efficient and parsimonious equity-informed approaches such as the one here could help uncover additional factors that can further help states prioritize critical infrastructure for funding in ways technical factors alone cannot accomplish.

Table 9. Most relevant variables from the study's selection models with description and effect direction. (*An "†" denotes a lagged variable when used as an independent variable. NS stands for not significant and denotes that the null effect was encompassed by the point estimate and standard error. "–" denotes a negative direction and "+" denotes a positive direction).*

Cat	Variable description	Restrictive	Non-restrictive	All Bridges
	Rural tract indicator > 10M sq. meters	NS	NS	NS
Demographic	†Rural tract indicator > 4M sq. meters	-	+	+
	†% White	NS	+	+
	†% African Americans	NS	-	-
	†% Native American	-	-	NS
	†% Asian	NS	NS	+
	†% Hispanic	NS	-	-
	†IHS-transformed Born outside U.S.	NS	-	NS
Family	†IHS-transformed foreign-born	NS	-	-
	†Lagged % female-headed families	-	-	-
	†% married families w/kids	NS	+	NS
	†Lagged Male-headed families with children	NS	NS	NS
	†IHS-transformed Male-headed families without children	-	NS	-
Commute	†% children	NS	-	NS
	†Commute less than 25 minutes	NS	+	NS
	†Lagged Commute 25-45 minutes	NS	-	NS
	†Commute over 45 minutes	NS	-	NS
Ed	†IHS-transformed Travel on public transportation	NS	+	+
	†Completed 8 years of school	NS	NS	NS
Financial	†% Some College	-	NS	NS
	†IHS-transformed Work at home	-	-	+
	†Work in county	NS	NS	NS
	†Precision crafters	NS	NS	NS
	†IHS-transformed Farm, fishery and forestry workers	NS	-	+
	†Military males	-	NS	NS
	†Military females	NS	+	NS
	†Lagged IHS-transformed Real Aggregate income	NS	-	NS
	†Lagged IHS-transformed Real Average income	+	NS	NS
Housing	†% Poverty rate	NS	NS	+
	†% Welfare rate	+	+	+
	†% Vacant housing	NS	NS	NS
	†Vacant housing for occasional use	NS	NS	NS

Future Work

Some further work is desirable to better understand the differences in results between the MB-based search algorithms and the LASSO algorithm. It is possible that linearity (or the lack thereof) is partially responsible for the difference. Further work is necessary to confirm if the linearity assumptions are warranted and/or to perform ML-based methods that account for nonlinearity such as kernel-based methods (Mohri et al. 2018; Zhang et al. 2012).

Environmental impacts of construction and changes to traffic could also be incorporated in order to measure health impacts of infrastructure. This could help this framework address more sustainability factors. Including pollution and its impact on environment and resident health could provide additional prioritization factors. These additional factors may provide additional data-based justification for changes to funding priorities or provide additional awareness and justification useful for engaging with civic leaders and citizens in the process of securing appropriate funding levels to address these concerns. The most obvious extension would be to apply this framework to other locales to test its efficacy and apply to the nation as a whole.

Data Availability Statement

Data analyzed during the study were provided by a third party. Requests for data should be directed to the provider indicated in the Acknowledgements.

Disclaimer

The research and views presented are those of the authors and do not necessarily represent the views of the Department of Defense or any of its components.

Notation

The following symbols are used in this paper:

$\boldsymbol{C}$ = a vector of lagged control variables;

d = a dichotomous variable designating the interaction of the group and treatment variables;

e = the error term;

f = a time-invariant tract fixed effect;

g = a dummy variable designating the tract as receiving a new bridge at any time (group term);

i = the tract index;

k = the index for a particular variable;

logit(p(x)) = the probability that a variable designating a new bridge was built in the preceding 10 years;

t = the year index;

$\boldsymbol{X}$ = a vector of variables of social interest;

x = a dummy variable designating the tract received a new bridge treatment (treatment term);

y = either a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years or the count of such bridges;

z = a social equity variable of interest;

β_0 = the intercept;

β_1 = the event study coefficient for the treatment and group interaction term;

β_2 = the coefficient for the treatment term;

β_3 = the coefficient for the group term;

$\boldsymbol{\gamma_k}$ = a vector of control variable coefficients;

δ = a fixed effect for each census year;

λ = the Lagrange multiplier that balances the tradeoff between the squared error loss and the L_1 penalty

Figures

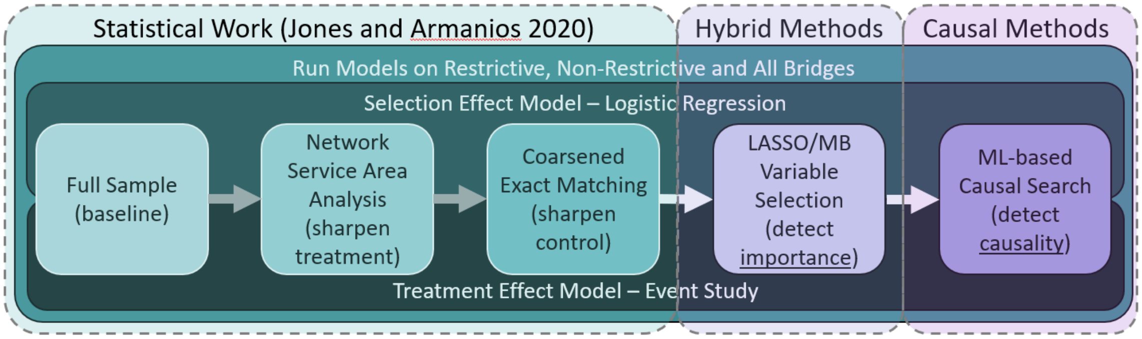

Fig. 8. Flow diagram of research design.

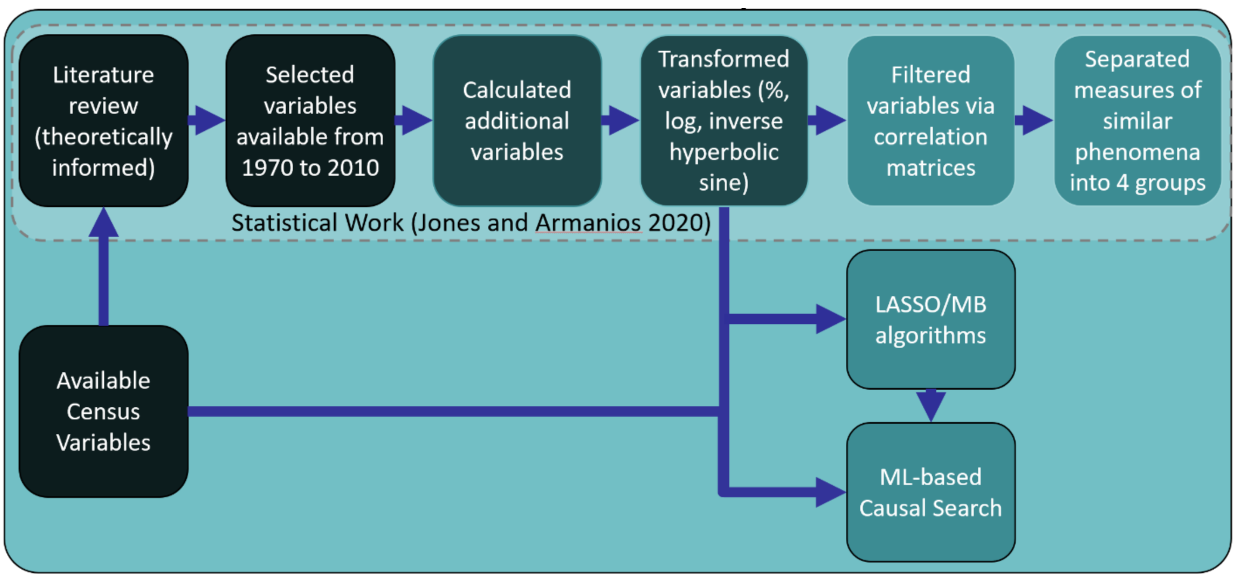

Fig. 9. Variable selection process flow diagram

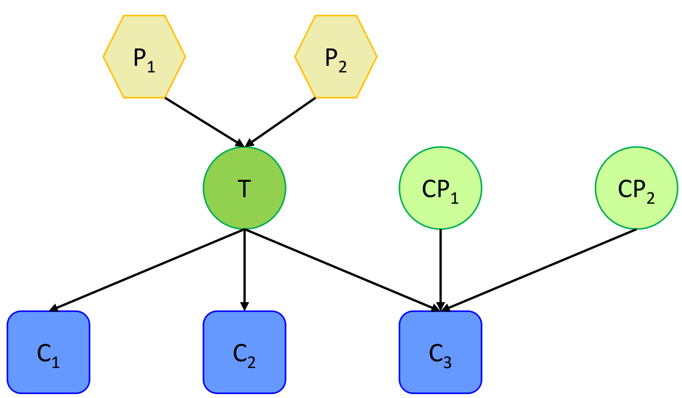

Fig. 10. Sample Markov Blanket showing a target variable's (T) parents (P), children (C) and parents of children (CP)

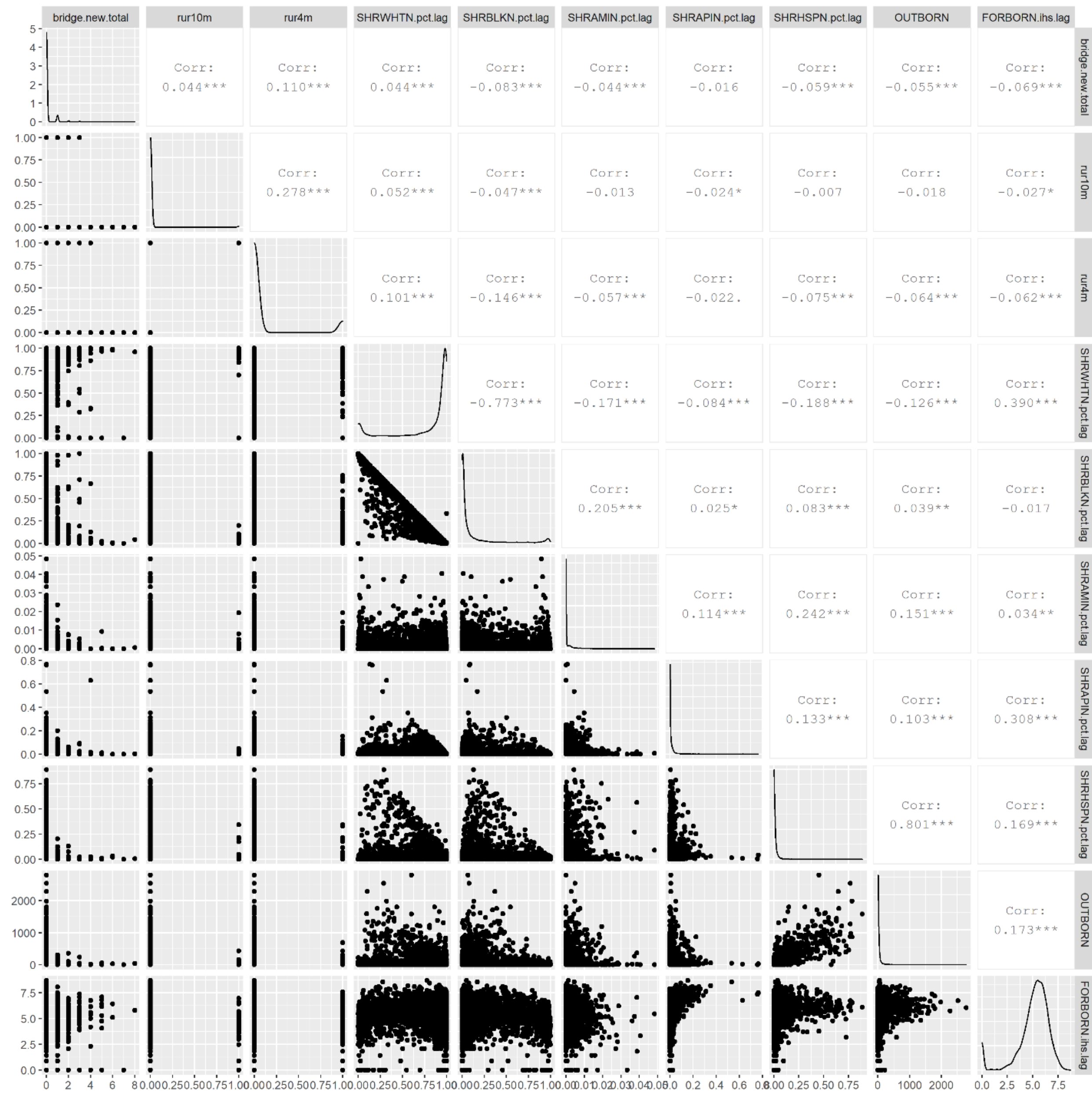

Fig. 11. Example plot showing all new bridge demographic variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables. Additional plots for other variables and bridge types are available in the appendix.

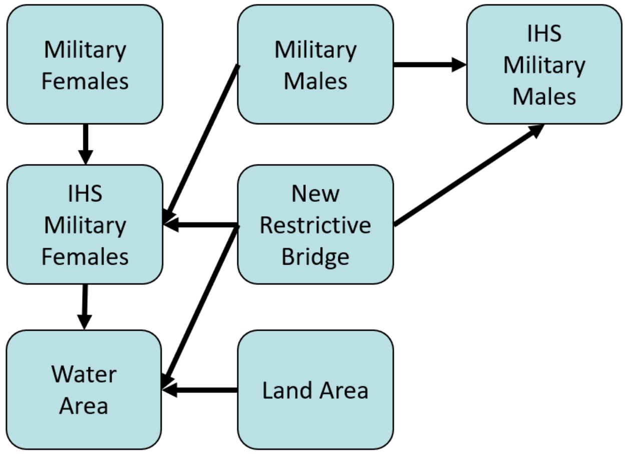

Fig. 12. Graph of FGES-MB discovered relationships for the category consisting of all new restrictive bridges

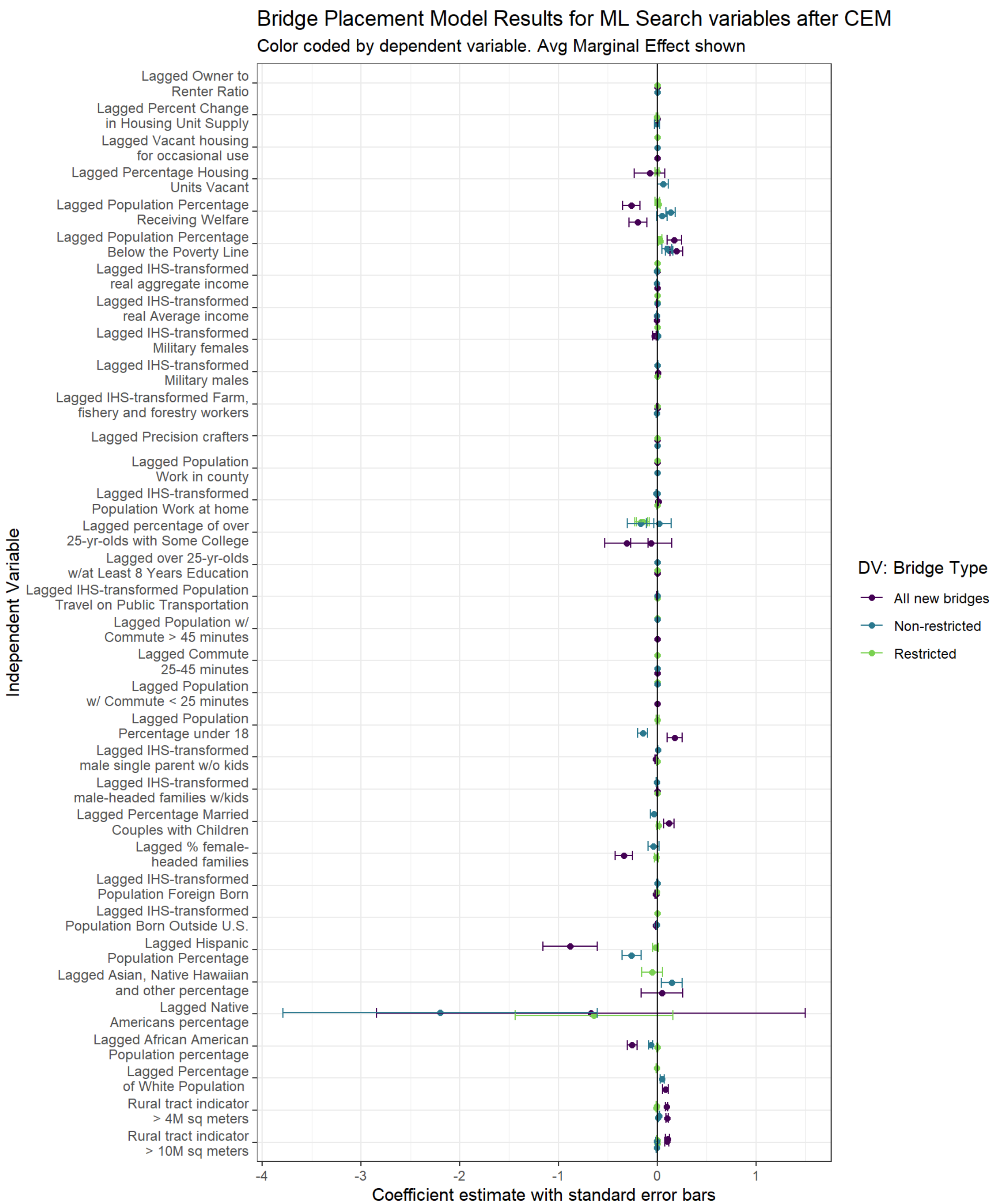

Fig. 13. Bridge placement models average marginal effect results for all ML search variables

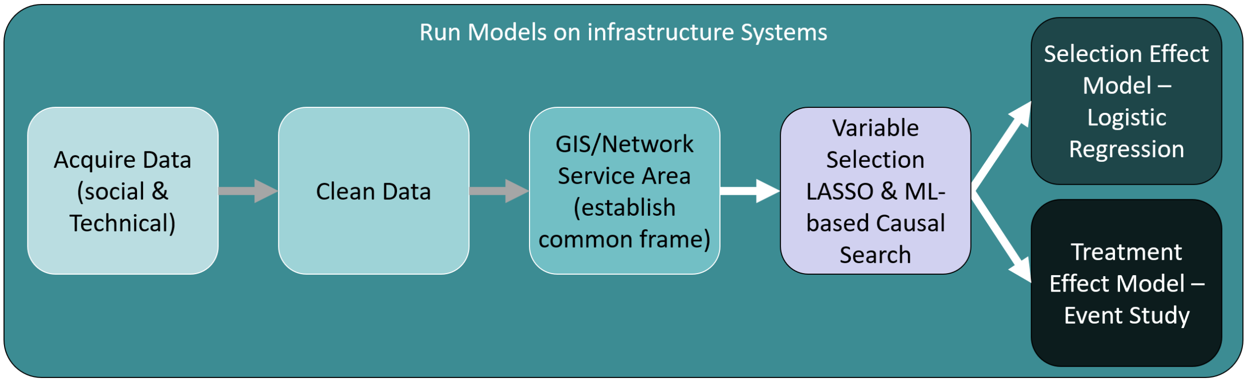

Fig. 14. Workflow diagram to use these techniques in an efficient manner

Chapter 4 Machine Learning Methods to Predict Air Pollution Concentration for Policymakers

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Abstract

Machine learning techniques have been employed to discover insights, solve and accurately predict many highly complex problems in the past two decades. This work applied these advancements to atmospheric pollution modeling. This paper represents a step toward applying machine learning to mimic chemical transport models (CTM). The ultimate goal is to develop a machine learning-based atmospheric chemistry model that is both accurate and computationally efficient. This paper took one small step toward that goal by developing a machine learning algorithm that: learns causes and effects of three chemical species from the area emission inputs and concentration outputs of a CTM, lays a groundwork for learning other atmospheric chemical interactions, and reduces computational costs for simulating atmospheric pollution to make these simulations more accessible to policymakers on a standard personal computer with a modest GPU. This work does not provide an adequate substitute for a CTM for our target audience but represents a step in that direction.

Introduction

State of the art air chemistry and chemical transport models (CTM) simulate interactions of chemicals and meteorological conditions in the atmosphere at heavy computational cost. These models are computationally intensive and require a fairly extensive background in the sciences, as well as additional training particularly focused on these models. Therefore, the model results and their interpretations are often intractable to laypersons or policymakers. Reduced complexity models (RCM) are much less computationally intensive and are far more accessible. However, the reduced accuracy, while adequate to conduct comparative analysis across different potential policies, is not necessarily adequate to base actual policy upon (Gilmore et al. 2019). A policy is generally required to be evaluated using a CTM in order to qualify for consideration by a governmental entity like the Environmental Protection Agency (EPA). Sub-federal government entities have varying and different requirements for simulations to inform policy. So, there exists a tradeoff between desiring the most accurate simulation possible while also desiring expanded access and reduced computational costs.

Similar friction in other domains (e.g., agent modelling, the geosciences, natural language processing) has been solved in recent decades through the use of machine learning models (Karpatne et al. 2017; Tenney et al. 2019; Vinyals et al. 2019). Machine learning models have been very successful at simulating or predicting highly complex systems at fractions of the computational cost of systems which explicitly simulate the system. Recent work in the atmospheric pollution domain has shown the promise of reducing computational times in the range of ~250 times with the same hardware and up to ~3,700 times with a graphics processing unit (GPU) (Kelp et al. 2020, 2019).

Besides computational savings, machine learning has also shown in other domains (e.g., image recognition) to be capable of finding mechanisms that elude other quantitative methods (Hornik 1991; Hornik et al. 1989; Huang et al. 2016). There exist some non-linear interactions within air quality engineering that are still not well understood in situ (Fiore et al. 2003; Karydis et al. 2007; Stieb et al. 2002). Machine learning may be able to discover these mechanisms, provide additional understanding of, or at least predict, these non-linear interactions.

The ultimate goal is to develop a machine learning model with a much lower computation cost, but similar accuracy compared to a state of the art CTM. This work does not reach that goal but represents a step toward that goal. In order to evaluate the promise of machine learning techniques to find causal relationships with reduced computation costs, the authors develop a machine learning model based on the input and output of a CTM. The authors begin by learning and predicting a very well understood species with known adverse health effects: elemental carbon (EC) (Krewski et al. 2009; Lepeule et al. 2012; Stieb et al. 2002). The authors selected this species because it is inert and does not interact with other species in order to evaluate how well the ML model was able to accurately learn and predict EC. If the model is unable to learn EC, it would be reasonable to suspect that it would not be capable of learning other species with complex interactions. It was also chosen due to its contribution to PM2.5 with related health effects.

Literature Review

There are several themes that the authors identified. First, the literature is clear that there are adverse health effects due to air pollution, particularly from fine particulate matter ($PM_{2.5}$) (Krewski et al. 2009; Lepeule et al. 2012; Stieb et al. 2002). The authors note that these health effects are a motivating factor for this research. Second, due to the complexities of the interactions between different chemical species, some of the true relationships of these chemical species are not fully understood nor are they accurately predicted by linear modelling techniques (Fiore et al. 2003; Karydis et al. 2007; Stieb et al. 2002). This is the primary motivation for employing machine learning techniques, generally, and neural networks, in particular, which have been successful at modelling many relationships (linear and non-linear) not readily identified by other methods (Hornik 1991; Hornik et al. 1989; Huang et al. 2016). Third, machine learning techniques are beginning to be used in studies on air pollution. At least two studies have shown the reduction in computation cost when using ML algorithms to model one chemical process compared to that chemical process module in a CTM (Kelp et al. 2020, 2019) on the order of ~250 to ~3,700 times reduction. Kelp et al (2020, 2019) did not model an entire CTM, but focused on a single module that modelled one chemical process. Structurally, the module was made to only model the interactions within a single grid cell (accounting for inputs and outputs of surrounding cells). Fourth, reduced complexity models (RCM) with differing mechanisms used to reduce the complexity are sufficiently accurate to base policy recommendations upon (Gilmore et al. 2019; Heo et al. 2016; Muller et al. 2011). For this reason, the authors believe a sufficiently accurate machine learning model can be developed to provide expanded access to policymakers. See Appendix III, Section A for additional information about these themes.

Muller et al (2011) use the Air Pollution Emission Experiments and Policy (APEEP) RCM model to estimate damages from six major pollutants by industry. This is a good example of an RCM for use by policymakers. Using this model, Muller et al (2011) calculate damages by industry and delineate which provide a greater ratio of gross external damages to value added. The Estimating Air pollution Social Impact Using Regression (EASIUR) model was developed to specifically estimate public health costs of fine particulate matter ($PM_{2.5}$). Using their EASIUR RCM, Heo et al (2016) were able to demonstrate results with fractional errors which are similar to or less than CTM's performance. Gilmore et al (2019) compared several chemical transport models (CTM) with reduced complexity models (RCM) and found that the reduced complexity models predicted $PM_{2.5}$ with only a modest reduction in accuracy when compared to CTMs. The RCMs predictions were within a factor of two to three which is usually less sensitive than the value of a statistical life (VSL) and other uncertainties. Therefore, these findings support using RCMs as valid tools for policy formulation and analysis.

Within the machine learning in atmospheric pollution space and to our knowledge, none of the articles the authors reviewed had the same objective or methods as those in this study (i.e., develop a model based on a CTM with a feedforward network to estimate the transport of emissions to concentrations). There are several that share similarities with the goals and methods and the authors share details about these articles below in order to better delineate commonalities and differences. Only the Kelp et al (2020, 2019) papers are trying to emulate part of a CTM, the rest of the papers are using real-world measurements of one kind or another to make predictions about the same real-world measurements. Feng et al (2015) created a hybrid model using wavelet transformations with a neural network to predict coarse $PM_{2.5}$ levels up to two days in advance in China based on temperature, wind, humidity, general conditions, day of year and day of week. Kleine Deters et al (2017) developed a neural network to predict $PM_{2.5}$ concentrations solely based on wind and precipitation levels in Quito, Ecuador. This method is computationally less expensive than CTMs. They argue that weather sensors are both more accurate and less expensive than $PM_{2.5}$ sensors. Their technique also demonstrated limitations of using only weather data with a neural net to predict air pollution. Kelp et al (2019) developed a neural network to emulate the carbon bond mechanism Z (CBM-Z) gas-phase chemical mechanism. This model predicted the hourly concentrations of 77 chemical species with an average root mean square error (RMSE) of 1.97 ppb (median is 0.02 ppb) (Kelp et al. 2019). Using GPUs, this model was able to achieve speedup of 4,250 times compared to a CTM. The model requires more work in order to constrain propagation errors that compound over time. In their later work (Kelp et al. 2020), they were able to improve the stability of their model and forecast further into the future. They were also able to show that it is possible to reasonably compress the number of species modeled without appreciable degradation of accuracy, thus reducing memory requirements. They also explored the variable space extensively to test the limitations of their model. Xue et al (Xue et al. 2019) combined inputs from satellites, CTMs, and in-situ readings to develop a machine learning model to predict $PM_{2.5}$. The model was trained using data from 2013-2016. The model was then applied to the time period from 2000-2012, a period known for having missing measurements. Their model produced predictions for daily, monthly and annual averages. They then added a generalized additive model to interpolate missing predictions due to missing satellite data. This two-stage estimation technique sacrificed daily prediction accuracy but significantly improved monthly and annual prediction accuracy. Their predictions found increasing pollution during the period from 2000-2007 and decreased pollution thereafter. They offer these data in the hope that others will use them to perform large-scale epidemiological studies. Bellinger et al. (2017) identified potential areas for future work including deep learning and geo-spatial pattern mining.

In the machine learning literature, Hornik et al. (1991; 1989) show how feedforward neural networks are universal approximators. Since that time, many applications have established this principle and a plethora of feedforward network architectures have been developed. Huang et al

(2016) build upon that architecture and demonstrated deep neural network advantages including: less prone to overfitting, ease of training and regularizing effects. A fairly recent focus of deep learning has been the utility of autoregressive feedforward nets. The simplest and most readily able to replace statistical autoregressive models is AR-net (Triebe et al. 2019). AR-net is a simple feedforward autoregressive network that is as equally interpretable as a non-neural network autoregressive statistical model. The two major advantage this neural net-based method has over the traditional statistical method is that it is more computationally efficient and can therefore handle larger datasets and larger orders (number of lags). Google's Wavenet and PixelCNN are more complicated examples of this class of learning architecture (Oord et al. 2016b; a). Several models in this class have been shown to outperform more complex and computationally expensive recurrent neural nets (RNN) and long short-term memory (LSTM) models (Dauphin et al. 2017; Kalchbrenner et al. 2016; Vaswani et al. 2017). Bai et al. (2018) performed an empirical evaluation of convolutional nets versus RNN and developed a "generic" auto-regressive network they call a temporal convolution network. Their work showed not only an improvement in task performance but also a reduction in computational costs. This literature informed the authors' choices in ML architecture for the task at hand.

Methodology

Data

The data for this project covers three calendar years in 1990, 2001 and 2010. These three years were chosen due to data availability. Carnegie Mellon University's Center for Atmospheric Particle Studies (CAPS) has already simulated three full years (excepting 4 days) (Xing et al. 2013). CAPS researchers modeled these three years due to availability of the U.S. EPA's National Emission Inventory (NEI). The NEI data was formatted to be used as the input for the Particulate Matter Comprehensive Air Quality Model with Extensions (PMCAMx). The data consist of three general categories: pollution sources, meteorological conditions, and resultant concentrations (Appendix

III, Table 1). The model developed in this work only uses the area pollution sources and the resultant concentrations (Table 10). Area pollution sources are the input and resultant concentrations are the output. The data are hourly measurements covering the continental United States (CONUS) divided into 36 km x 36 km cells (Fig. 15). For this work, as previously noted, the authors concentrate on the well-understood EC species. The authors chose to divide EC (and other species) particulate matter into two regulated size categories with the smaller size shown to have health effects: fine ($PM_{2.5}$) EC and coarse (PM_C) EC. Hereafter, the authors refer to fine EC as $EC_{2.5}$ and coarse EC as EC_C. The authors use the EPA's definition for fine and coarse (US EPA 2014). Fine particulate matter is $\leq$ 2.5μm. Course particulate matter is $\leq$ 10μm and $>$ 2.5μm.

Due to the limited number of air pollution species, the authors found that a major portion of time to train the models was actually being used to gather data from the disparate files. Therefore, a function was developed that would pre-load the subset of data desired for each training run. After gathering the hourly data from the daily files into input and output dataset containing all hourly data for three years, the data was lagged (number of lags dependent on geographic scale—lags decreased as geographic scale increased, see Vector Autoregression section) and stored in a third dataset. The authors then identically randomized the order of the data in all three datasets. This means that the random order of hourly measurements is in the same order and position in each of the three datasets. The order must be synchronized to allow the model to properly parse the data during training. Finally, the datasets were split using current best practices into train (80%), validation (5%) and test (15%) datasets. These data were used to train, validate and test this model. See Table 10 for additional details about the data.

Table 10. Data characteristics of file types representing one day of measurements

Data Type	Layers	Rows	Columns	Variables	Time Steps
Output Files					
Daily Hourly Concentration Output	1	82	132	509	24
Emission Source Input Files					
Area - On Road Pollution	1	116	152	114	24
Area - Non-road Pollution	1	116	152	114	24

Preliminary Analysis

Before implementing a neural network, the authors analyzed the data to determine if other methods were more appropriate. Therefore, the authors employed vector auto regression (VAR), Least Absolute Shrinkage and Selection Operator (LASSO), and Constraint-based Causal Discovery from Nonstationary/HeterOgeneous Data (CD-NOD) methods. The results from that analysis guided the parameters of the neural network and a synopsis of those results are included here. For this preliminary analysis, the full dataset was not used and could not be used due to the computational costs of these preliminary methods. Instead, the authors used small sample grids consisting of a group of 3 x 3 or 11 x 11 cells (Fig. 15). The 3 x 3 grids were randomly selected and centered in the Pacific Ocean and Mexico. The 11 x 11 grid was centered around New York City. The authors started with the smallest sized grid that would have at least one cell with bordering cells on each side in order to test for interactions between the cells. The 11 x 11 grid was then used to test if interactions persist over a larger geographic area and to observe computational requirements for larger samples.

Vector Auto Regression (VAR)

VAR is a multivariate algorithm used to analyze how multiple time series interact. This method is used to determine how much information is contained in the past. It is considered autoregressive because it is concerned with how past measurements influence the present measurement. The authors only used the CTM output data for the VAR analysis. To ensure VAR is a suitable method for the data, some preliminary tests were run including: stationarity, Granger causality (Granger 1969), Johansen's co-integration (Johansen 1991), augmented Dickey-Fuller test, and order selection. (See appendix for more information on these tests.) Granger's causality tests showed that past values contain information about the present value meaning that there is an autoregressive component to the concentrations. Johansen's co-integration test showed that the autoregressive nature of the concentrations has a long run, statistical relationship. The augmented Dickey-Fuller test showed that the data was stationary. The temporal order selection process determined that as the regions increased in size, the order decreased. The smallest regions determined a temporal order of four lags was optimal while the largest region (CONUS) had an optimal order of one lag. These orders were used in all future models. Each variable is modeled as a function of past variables. The coefficients measure the spatial relationship. The preliminary analysis showed that including an autoregressive aspect to our model would provide non-trivial information. See appendix for the more information and preliminary results.

Least Absolute Shrinkage and Selection Operator (LASSO)

VAR analysis determined the optimal order (number of lags) of the output data. To test for variable importance and geographic adjacency dependencies, the authors used the LASSO algorithm (Tibshirani 1996). It was originally developed for ordinary least square (OLS) as an alternative to subset selection and ridge regression techniques. LASSO effectively performs both functions at the same time. LASSO shrinks some variable coefficients and sets others to 0, which effectively subsets the data. See appendix for more information and preliminary results which show that LASSO found similar but more parsimonious results than VAR (typically only 7~8 coefficients were found to be important by LASSO, whereas VAR provided an estimate for all 121 grid cells for each temporal lag). LASSO showed that there is a geographic component to the autoregressive data emphasizing proximity (up to 200 km) as an important component.

Causal Discovery from Nonstationary/HeterOgeneous Data (CD-NOD)

A common assumption made to use many causal discovery algorithms is that the data provided are stationary, i.e. the joint probability distribution (and by extension the mean and variance) does not change over time. Despite the stationarity results from the augmented Dickey-Fuller tests, the CD-NOD results showed there is sufficient non-trivial non-stationarity present in the concentration data that can be used to make causal inferences. (See appendix, Table 8.) Therefore, in addition to a VAR component, the desired model should also include a time-varying component (Table 11) capable of recognizing recurring or seasonal shift in the underlying distributions. The CD-NOD algorithm's purpose is to detect non-stationarity and use that information to build a causal structure in the form of a directed acyclic graph (DAG) (Zhang et al. 2017). CD-NOD explicitly identifies which nodes (variables) in the graph have non-stationarity and uses that information to better detect the causal structural skeleton of the graph. Further assumptions and the algorithm can be found in the appendix. Due to the computational costs of the algorithm, the authors used LASSO to find a more parsimonious set of lagged variables in order to eliminate any lagged variables that were not influential on the non-lagged variables. Of the 72 lagged variables (four (4) temporal lags each for $EC_{2.5}$ and EC_{C} (2) for each grid (9), see appendix, Table 8), LASSO determined 22 were salient. Finally, the authors then selected a two-month period of transition between seasons (February and March of 1990) to use as a test case. The resulting recovered graph structure showed that there are causal links between different grid cells as expected likely due to prevailing weather patterns.

With this preliminary analysis complete, the authors felt there was sufficient justification to proceed with further analysis. The next section will provide details about the approach used to develop an explainable neural network capable of simulating air pollution at a regional or national scale.

Approach

The authors built upon this foundation by employing neural networks. The first foray into the space employed the temporal convolution network (TCN) (Bai et al. 2018). While Bai et al. (2018) showed the superior predictive ability of convolution neural networks (CNN), CNNs are not as interpretable as feedforward networks due to the regularization that maps the feature space to a new objective function and acts as a layer of abstraction and is typically accompanied by a reduction in dimensionality. Feedforward networks are capable of approximating any continuous function without feedback loops or regularization. As the model is applied to other species, interpretability will become important. After some preliminary results from TCN, the authors determined to develop their own non-CNN model. For the sake of interpretability, the authors also chose not to pursue a long short-term memory (LSTM) model or a recurrent neural network (RNN) model. Both of these models include feedback loops that make interpretability and feature extraction more difficult.

The authors iteratively developed a model that began with using a simple neural network configured as a vector autoregression model. After searching for a ready-made model and only finding autoregressive neural networks (Triebe et al. 2019) and far more complicated LSTM-inspired networks like WaveNet (Oord et al. 2016a), the authors developed their own (Jones and Zhang n.d.). The VAR neural network (VARNN) itself was trivial, but the data preparation was not. See appendix for a model diagram and preliminary results. Both a linear (LinVARNN) and non-linear model (VARNN) was created along with utility scripts to make operating the model as trivial as possible to employ. The most encouraging result from this iteration was the computational savings over traditional VAR models in terms of memory and time. Using the traditional VAR models, the 11x11 grid subset was infeasible to model on the author's personal computer (PC) requiring over 100 GB of memory and thus requiring a server. The same data was handled by the

NN version on the author's PC, only used 3% of the GPU's processing capabilities and completed in a fraction of the time.

The next iteration added area emissions to the VAR component of the model creating a hybrid vector autoregressive model (HyVARNN). The model takes as input both the autoregressive component up to k past lags and couples those with emission data. These inputs pass through several hidden layers and finally emerge as concentrations. The authors experimented with many hyperparameters and found that optimal results were attainable with a relatively shallow network. The model scaled well and the entire continental United States (CONUS) was modeled on a Nvidia Tesla T4 GPU with 15 GB of memory. See appendix for sample results. Since one of the goals of this work is to make these models as accessible as possible, smaller scale models were also developed and tested using a PC with a Nvidia GeForce MX150 with 2 GB of memory.

Table 11. Time and seasonality variables

Variable	Possible Values
Year	1990, 2001, 2010
Month	1-12
Day of Year	1-366
Day of month	1-31
Weekday	1-7
Hour	1-24

Finally, the authors added a time component (Table 11) to both the inputs and the previous outputs of the model (HyVARNN-T). Each iteration required more work on the data preparation and loading than on the neural network itself. See Fig. 16 for a graphical representation of the model and Equation 5 for a functional representation.

Equation 5. Vector autoregressive hybrid model functional representation

$$C_t = G\left(\sum_{i=1}^{k} A_i^{(t)} C_{t-i}\,, E^{(t)}\right)$$

where:

C_t are concentrations at time t

A is a coefficient for concentration with different influence from time $^{(t)}$ periods, causal relation between locations, represented by a vector autoregressive feedforward neural network,

E are emissions,

G is the function representing the feedforward network that takes A and E as inputs and outputs concentrations.

Each model was trained on a subset of data as previously explained in the data section. The authors first performed some trial runs on the smallest 3x3 grid located in Mexico in order to determine the optimal combination of optimizer and loss function. Based on the functions available for the type of data, there were three candidate optimizers and two loss functions. The Adam optimizer outperformed RMSProp and stochastic gradient descent (SGD) (see appendix Table 9 for more details). Huber or the smooth L1 function outperformed mean square error (MSE).

Fig. 17 depicts the modelling process. The process begins by gathering data from the daily data files and subsetting the desired region. Next, the prior output concentrations are lagged temporally (according to the order determined by the VAR analysis) to be used as inputs into the VAR component of the network. Then, the three datasets are identically randomized, as previously discussed, before being split into a training set (80%), validation set (5%), and test set (15%). There are no rules for how much each split should contain, but best practices general use similar divisions. This split is important for the training of the network. In order to ensure that the test set does not influence the training of the network, the validation set is used as a means for testing the model while it is being trained. After each epoch of training, the validation set is treated as a test set to check the progress of training. When training the authors tasked the optimizer with following a regime that reduced the learning rate by a factor of 10 whenever it determines loss during the previous seven consecutive optimizations to be equal or less than the current value. The learning rate is then fixed for the next 100 epochs before it is allowed to be further reduced. Additionally, the authors also allowed for early stopping while training. Early stopping was based upon the validation mean squared error (MSE). In order to allow the learning rate reduction to have a chance, the early stopping conditions required eleven consecutive validation test cycles to be equal or less than the current validation loss. Early stopping did not occur frequently, but when it did it was typically because the network had learned the average of the data and not a function that reproduced the CTM output to any acceptable degree.

Research scope and Constraints

The scope of this current work is to develop an interpretable machine learning model capable of faithfully reproducing the results of a state of the art CTM at a lower computational cost. By interpretability, the authors mean the ability to analyze the network to determine what it is doing and how. To aid in this pursuit, the authors kept the number of hidden layers low and utilized a feed-forward network. Additionally, a major focus is to ensure that the developed model is more accessible to engineers and policymakers both in terms of hardware requirements as well as specialized knowledge. This initial foray is scoped to only model two size categories of EC with a goal to add other species. Ideally, the model will be capable of representing the entire CONUS. Even if hardware constraints do allow that, regional models will be developed and trained on six US regions. Since one of the objectives of this work is to make the model accessible to policymakers, the model has been designed to allow for regional and smaller geographic areas to allow it to be run on different hardware configurations.

Results

The model was intentionally run on different hardware configurations. The final model was too large to run on a single GPU with 15 GB of memory, so two different sized regional models were developed (see Fig. 15 for a graphical depiction of the regions). The larger regional model covers 810,000 km^2 (503,311 mi^2) and trained at six locations (see Fig. 15). A smaller regional model covering 291,600 km^2 (181,192 mi^2) was also developed that could be run on a personal computer. See

Table 12 and Table 13 for training and test statistics. Times do not include data loading (typically between 19 and 30 seconds) from two files that had already gathered all the PMCAMx files into two separate files: one for input and one for output. Preloading the data took considerably longer and could take up to two hours. Depending on the number of species and the hardware used, it took between 20 and 60 minutes to train the models for 100 epochs using 80% of the three years of hourly data. Once a model was trained it never took more than 3 seconds to generate 3 years of data regardless of the size of the region including CONUS.

See Fig. 18 and Fig. 19 for representative results of average hourly actuals from PMCAMx (top row), average hourly predictions for the test set (middle row), data the model has never experienced, from HyVARNN-T, and average hourly error (prediction – actual on bottom row). The pink regions were underpredicted by the model and green regions represent overprediction. These results show that the model is very good at predicting $EC_{2.5}$, but ineffective at predicting EC_C. This is a very understandable result considering that this run only included area pollutants which do not include any EC_C data. By examining the scale ranges, EC_C data are also very small and the model appears to not be capable of making predictions that close to zero. Figs. Fig. 18 and Fig. 19 show that both regional models stay within an error range of +0.02/-0.01 μg/m^3 for $EC_{2.5}$, and +0.006/-0.006 μg/m^3 for EC_C. The average error is almost two orders of magnitude less than the values for $EC_{2.5}$ and an order of magnitude more than the values of EC_C for the smaller region and the same order of magnitude for the larger region. The pattern for $EC_{2.5}$ shows that the errors are not random like for EC_C. The predictions fall within the same range as the actuals and seem to mirror them quite well. However, when examining the time series plots in Figs. Fig. 20 and Fig. 21, it is clear that the average errors don't tell the entire story. For $EC_{2.5}$, the errors generally at least an order of magnitude less than the values. For EC_C, the errors are much worse—2~3 orders of magnitude greater than the values of EC_C. Another way to look at the data is via a the scatterplots in Fig. 22. If the model was able to perfectly predict the emissions, all of the data points would fall on a 45° line from the origin (prediction would equal actual). While $EC_{2.5}$ predictions are not perfect, they do cluster near this 45° line. EC_C, however, does not match at all. The predictions vary from -0.006 to 0.01 μg/m^3 while the actual data only varies from 0 to 0.001 μg/m^3. It also appears to overpredict the major metropolitan areas. The model accuracy would increase greatly for EC_C if it could be taught to not predict negative values. Two methods were used to actualize this limitation, but the end results were less accurate than the current model. Training the model on all six regions produced better results than clamping (restricting values to 0 or above) or adding a rectified linear unit (ReLU-which only produces positive values) to the output. One other item worthy of mention is that the edges of the model do not appear to suffer more than other grid cells. Edges are often difficult for CTMs to accurately predict.

Time series plots for 3 sample grid cells from 1990 are shown in Figs. Fig. 20 and Fig. 21 and other years are available in the appendix. 1990 has the most volatile data and the model struggles to match the peaks more in 1990 than in any other year. This is at least partly due to 1990 having higher pollutant levels than later years. These plots generally show that the model does not fluctuate as much as the actual measurements, but closely approximates the values on average. While the predictions for EC_C are gross overpredictions, the predictions do appear to mimic the fluctuations but in a more exaggerated manner.

The authors also calculated several statistics for the test set and the entire dataset. See

Table 14 and Table 15 for the test set statistics and appendix for statistics for the entire dataset. The authors chose to include the following statistics according to the specifications set forth by Boylan and Russell (2006), and Chang and Hanna (2004): mean fractional error (MFE), mean fractional bias (MFB), Pearson's correlation coefficient, and fraction of predictions within a factor of two observations (FAC2). A perfect model would have MFE of 0, MFB of 0, Pearson's of 1 and FAC2 of 1. Further, Boylan and Russell (2006) proposed criteria against which to compare air quality models. For EC, they proposed an MFE criteria threshold of ~110% at 1 μg/m^3 average concentration and a goal of ~80% at 1 μg/m[3] average concentration. Boylan and Russell (2006) note that MFE cannot be negative, but that is only true if the model does not predict negative values like this one does for EC_C. All of the models far exceed the performance goals for $EC_{2.5}$ (see

Table 14 and Table 15). Even though the larger model shows that it also exceeds the performance goals for EC_C, it is likely that it is due to large amounts of negative predictions and not truly due to a good fit. The overall statistics are better than those shown in

Table 14 and Table 15 since they only reflect the test set that the model had not experienced. The overall statistics are available in the appendix.

The authors were able to include additional species and model SO_2 and sulfate (PSO_4). The results are also very promising. Based on the average hourly predictions and errors (Fig. 24 and Fig. 25), it appears that SO2 also hovers around zero and the model ends up predicting negative values that overall average out much better than for EC. So, at first glance it appears that the errors for SO2 are miniscule (Fig. 24 and Fig. 25). See

Table 16 and Table 17 for test set statistics. The model does great predicting fine PSO_4, but not so well for SO_2 or coarse PSO_4.

Discussion

Considering that this level of accuracy was achieved by only using two of the twelve CTM input types (see Appendix III, Table 1 for list of all available inputs) is quite encouraging as it is likely that the accuracy will increase as more input types are added. The other encouraging results are the speeds at which the model was built, trained and can generate predictions. Even if the smaller model were used to generate data for the entire country it would take less than 50 seconds to generate three years of data for the entire continental US. The larger regional model would take less than 20 seconds to generate the three years of data for the entire continental US. Even if hardware limitations required that models had to be built for each species or a small number of related species, the speed at which the models can generate data is orders of magnitude faster than

CTMs. These results bode well for continuing to pursue and refine these and similar models. By incorporating these models into an RCM, the performance could be increased.

Additionally, there are a couple of other areas not yet mentioned that improve accessibility for policymakers. The data formats used by the model are generic and therefore more accessible than those used by a CTM. A sample dataset that could be easily modified could be included with an RCM to allow policymakers to design and test scenarios. The smaller model can easily be run on a personal computer with an inexpensive GPU. A GPU is not strictly necessary, but the authors have not yet tested speeds without a GPU.

Table 12. HyVARNN-T model training and test statistics for a 15 x 15 grid region for 2 sizes of EC on a PC with a Nvidia MX150 GPU wit 2GB of memory. Best value in **bold.** * Trained on all six regions, statistics come from predicting WA data.

Region	Hidden Layers	Neurons/ Hid Layer	Test Loss	Test MSE	All MSE	Time to train 1k epochs	Time to predict 3 yrs
CA	5	462	0.0065	0.0133	0.0132	**00:35:38**	**00:00:01**
GL	5	462	0.0075	0.0157	0.0154	Unavailable	00:00:02
NY	5	462	0.0099	0.0209	0.0210	00:36:47	**00:00:01**
SE	5	462	0.0066	0.0136	0.0134	00:37:55	**00:00:01**
TX	5	462	0.0037	0.00743	0.00730	00:35:57	**00:00:01**
WA	5	462	**0.0025**	**0.00502**	**0.00499**	Unavailable	00:00:02
All 6*	5	462	0.0132	0.0137	0.0136	Unavailable	00:00:01

Table 13. HyVARNN-T model training and test statistics for a 25 x 25 grid region for 2 sizes of EC on a server with a single Nvidia Tesla T4 GPU with 15 GB of memory. Best value in **bold**.

Region	Hidden Layers	Neurons/ Hid Layer	Test Loss	Test MSE	All MSE	Time to train 1k epochs	Time to predict 3 yrs
CA	5	1262	0.0038	0.00774	0.0076	00:25:24	**00:00:02**
GL	5	1262	0.0053	0.011	0.0108	**00:23:24**	**00:00:02**
NY	5	1262	0.0084	0.0174	0.0174	00:26:09	**00:00:02**
SE	5	1262	0.0065	0.0132	0.0131	n/a	**00:00:02**
TX	5	1262	0.0050	**0.0102**	0.00997	00:26:50	**00:00:02**
WA	5	1262	**0.0014**	0.00276	**0.00276**	00:25:47	**00:00:02**
All 6	5	1262	0.0202	0.0435	0.0439	00:42:02	**00:00:13**

Table 14. Test set statistics for 15 x 15 grid size regions. Mean Fractional Error (MFE), Mean Fractional Bias (MFB), Pearson's Correlation Coefficient and Fraction of data within a factor of 2 (FAC2). Values in *italics* meet accuracy goals as set forth by Boylan and Russell (2006). (**Bolded** value is best in that column.) Measures are the mean of hourly measurements for each hour in each grid cell.

	$EC_{2.5}$				**EC_C**			
Region	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**
CA	*0.293*	*0.055*	0.678	0.925	**-0.605**	2.000	0.003	**0.087**
GL	*0.264*	*0.051*	0.785	0.947	-0.049	1.770	-0.014	0.037
NY	*0.253*	*0.052*	**0.867**	0.946	-0.141	1.890	-0.005	0.024
SE	*0.230*	*0.045*	0.818	0.960	0.109	**1.533**	0.000	0.038
TX	***0.202***	***0.039***	0.823	**0.970**	-0.434	2.098	-0.008	0.045
WA	*0.295*	*0.057*	0.658	0.923	-0.187	1.898	**0.010**	0.029

Table 15. Test set statistics for 25 x 25 grid size regions. Mean Fractional Error (MFE), Mean Fractional Bias (MFB), Pearson's Correlation Coefficient and Fraction of data within a factor of 2 (FAC2). Values in *italics* meet accuracy goals as set forth by Boylan and Russell (2006). (**Bolded** value is best in that column.) Measures are the mean of hourly measurements for each hour in each grid cell.

	$EC_{2.5}$				**EC_C**			
Region	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**
CA	*0.268*	*0.043*	0.739	0.943	-0.399	2.059	0.013	0.031
GL	*0.249*	***0.030***	0.784	**0.955**	-0.309	1.964	-0.002	0.038
NY	*0.281*	*0.059*	**0.818**	0.928	0.175	1.392	0.008	0.060
SE	*0.268*	*0.065*	0.759	0.930	**-3.248**	4.840	0.002	0.052
TX	***0.241***	*0.053*	0.781	0.950	-1.468	3.063	0.010	0.050
WA	*0.248*	*0.047*	0.757	0.944	7.366	**-5.837**	**0.052**	**0.080**

Table 16. Test set statistics for 15 x 15 grid size regions. Mean Fractional Error (MFE), Mean Fractional Bias (MFB), Pearson's Correlation Coefficient and Fraction of data within a factor of 2 (FAC2). Values in italics meet accuracy goals as set forth by Boylan and Russell (2006). (Bolded value is best in that column.) Measures are the mean of hourly measurements for each hour in each grid cell.

	SO_2				Fine PSO_4				Coarse PSO_4			
Region	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**
CA	0.149	1.407	0.018	0.051	*0.089*	*0.012*	0.904	0.991	0.823	0.292	0.683	0.489
GL	0.055	1.377	0.037	0.087	**0.084**	*0.009*	0.914	**0.992**	2.020	**-1.178**	0.746	**0.544**
NY	12.696	-11.566	**0.122**	**0.219**	*0.116*	**0.008**	**0.981**	0.982	**0.460**	0.611	**0.793**	0.380
SE	0.264	**0.825**	0.079	0.193	*0.143*	*0.018*	0.953	0.977	0.492	0.482	0.756	0.479
TX	-0.247	1.439	0.051	0.139	*0.126*	*0.011*	0.969	0.984	0.519	0.420	0.740	0.512
WA	**-1.337**	2.886	0.047	0.062	*0.137*	*0.019*	0.878	0.970	0.678	0.356	0.643	0.470

Table 17. Test set statistics for 25 x 25 grid size regions. Mean Fractional Error (MFE), Mean Fractional Bias (MFB), Pearson's Correlation Coefficient and Fraction of data within a factor of 2 (FAC2). Values in italics meet accuracy goals as set forth by Boylan and Russell (2006). (Bolded value is best in that column.) Measures are the mean of hourly measurements for each hour in each grid cell.

	SO_2				Fine PSO_4				Coarse PSO_4			
Region	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**	**MFE ↓**	**MFB ↓**	**Pearson ↑**	**FAC2 ↑**
CA	-0.315	1.885	0.017	0.062	**0.121**	*0.016*	0.794	**0.988**	0.898	0.550	0.358	0.359
GL	**-2.893**	4.115	0.088	0.167	*0.147*	**0.014**	**0.952**	0.979	**0.628**	0.772	0.588	0.288
NY	-0.670	1.816	**0.107**	0.198	*0.169*	*0.016*	0.952	0.970	1.042	0.874	0.556	0.270
SE	0.862	**0.207**	0.087	**0.218**	*0.194*	*0.032*	0.928	0.954	0.803	0.535	**0.639**	0.377
TX	0.618	0.610	0.053	0.139	*0.173*	*0.023*	0.946	0.968	0.883	0.504	0.571	0.386
WA	-0.635	2.187	0.034	0.067	*0.161*	*0.031*	0.726	0.963	0.884	**0.473**	0.289	**0.391**

Limitations and Applicability

The intrinsic limitation of using CTM inputs and outputs is that the algorithms will be limited to learning the methods employed by the CTM. In other words, the underlying assumptions and limitations of the CTM will end up being emulated by the ML model. This means that it is only able to discover real-world causal relationships between species that are correctly modeled by the CTM. Transitioning to real-world measurements would greatly improve the probability of discovering true causal relationships. Another aspect of using the CTM inputs and outputs is that the ML model will not be capable of exceeding the accuracy of the CTM. Best case scenario is that it will be able to match the accuracy of the CTM. After transitioning to the real-world measured outputs, the possibility to achieve accuracy higher than the CTM exists.

Another possible limitation is related to major shifts in pollution regimes. As entire sectors move away from certain forms of fuels, the distribution of pollutants produced also changes drastically. Since the data is separated by decades, these changes may or may not be gradual enough for the ML algorithm to learn. The current results seem to be able to handle changes during the period of this work, but future changes may drastically alter pollution patterns and break the model (this depends on the level of abstraction the model is able to actuate).

Since this work has not yet incorporated meteorological data (see Appendix III, Table 1 for available data), a major source of variation, the time and season variables (Table 11) provide valuable information that is likely better represented by actual weather conditions. The lack of meteorological data may explain the diminished variability in the model's predictions of EC. Once these weather conditions are included, the time and season variables' contributions will likely diminish and may even become unnecessary. Ideally, the model will learn the chemical and physical interactions and then modify those interactions according to the meteorological conditions—in essence learning the chemistry and physics of the system. The two-time variables that may retain some value are hour of day and day of week. Hour of day can be considered as a proxy for the angle and presence of the sun since sunlight affects chemical reactions in the atmosphere. Day of week can capture human activity as people's activities vary based on the day of week (e.g., weekends).

Not yet including point sources (see Appendix III, Table 1), especially electricity generating units (EGU), is a limitation for being able to accurately predict concentrations, generally, and SO_2, particularly, since they major sources of pollution. The current model is capable of incorporating this information in its present form. The issue to this point is being able to only include the point sources within the regions being analyzed. A computationally efficient method has not yet been attempted and including all 111,255 point sources would likely exceed memory capacity of available hardware.

Another important limitation that will need to be addressed in future work is to use the predictions as the past values given to the VAR portion of the model. Currently, the model always uses temporally lagged CTM outputs as the past values of concentrations. To better test for compounding errors, the prediction routing will need to be modified to only predict one hour at a time to allow the model to feed the concentrations predictions back into the inputs as past concentration values. Kelp et al's (2020) paper specifically worked towards making their module more stable and were able to increase stability to longer than a week without runaway error compounding.

Validation

Before any model was allowed to process data, a test set and a validation set were separated from the training data. The validation data was used for hyperparameter tuning and to test predictions during training. Only after training was completed and the model was taken out of learning mode was it allowed to process the test data. Future work should include comparing this model's predictions with the same validation methods used by the team who generated the CTM data (Xing et al. 2013). The authors could also include in the future work using the atmospheric model evaluation tool (AMET) (Appel et al. 2011) as it has recently added the ability to evaluate CAMx models.

Lee et al (2011) developed an emulator for an aerosol microphysics module used in a CTM in order to quantify uncertainty. Due to the size of the search space for the chosen variables, running the CTM for the required number of runs would be computationally and temporally prohibitive, therefore a Gaussian process emulator was used to reduce time and computation costs. Their method of validating their emulator may prove to be a useful method for the authors to use as an additional validation in future work.

Disclaimer

The research and views presented are those of the authors and do not necessarily represent the views of the Department of Defense or any of its components.

Notation

The following symbols are used in this paper:

$\boldsymbol{C}$ = a vector of lagged control variables;

d = a dichotomous variable designating the interaction of the group and treatment variables;

$\boldsymbol{C}$ = a vector of air pollution concentrations

A = a coefficient for concentration with different influences from different time periods, causal relation between locations, represented by a vector autoregressive feedforward neural network

$\boldsymbol{E}$ = vector of emissions

G = the function representing the feedforward network that takes A and **E** as inputs and calculates or predicts air pollution concentrations.

Figures

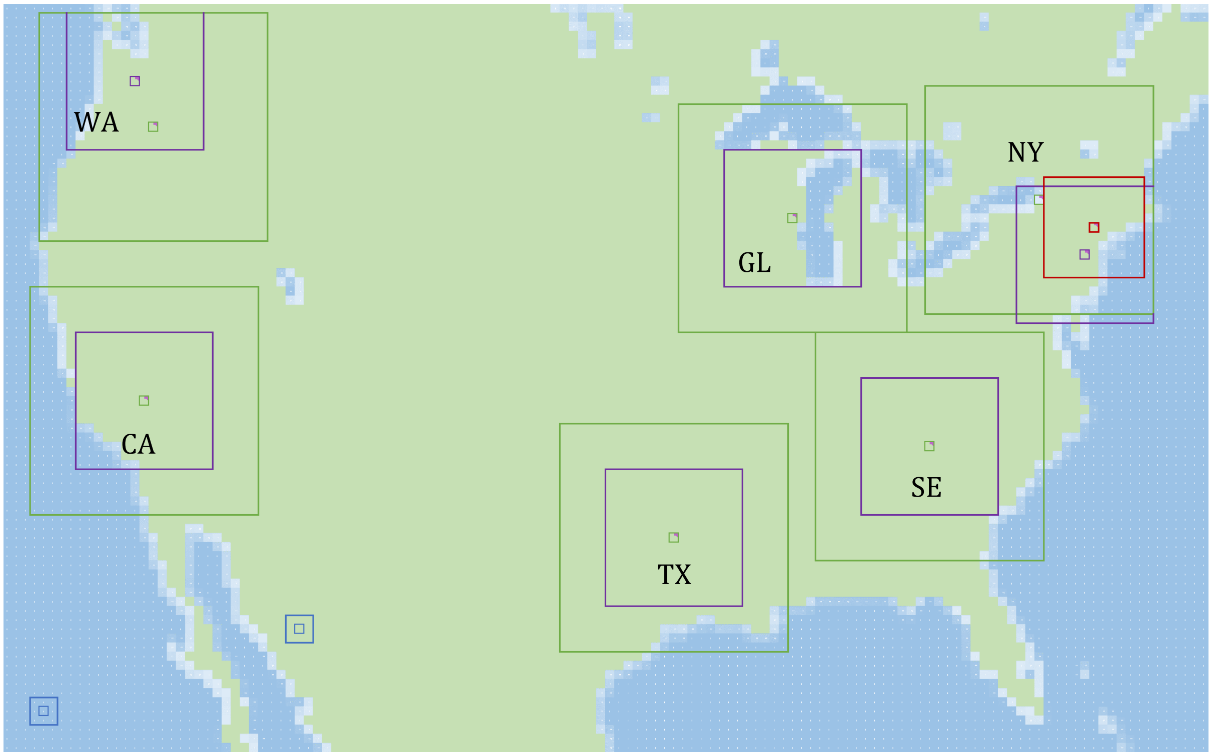

Fig. 15. Lambert Conformal Projection with 36 km^2 grid cells showing fraction of grid cell covered by water. The small 3x3 blue squares were used for preliminary analysis. The red 11x11 square was also used for preliminary analysis and hyperparameter tuning. The 15x15 purple regions were modeled using a personal computer with a GPU with 2 GB memory. The green 25x25 regions were modeled using a server with a GPU with 15 GB memory.

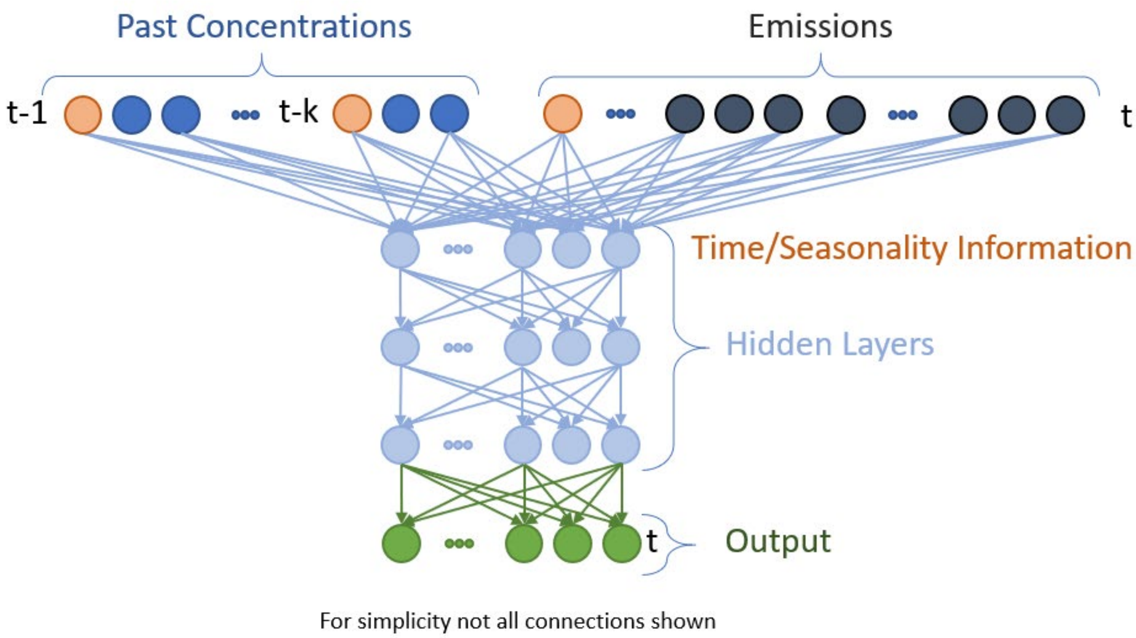

Fig. 16. Graph representation of the vector autoregressive hybrid model. Inputs include past measures of concentrations (blue), current measures of emissions (grey) and both are coupled with six time variables (orange).

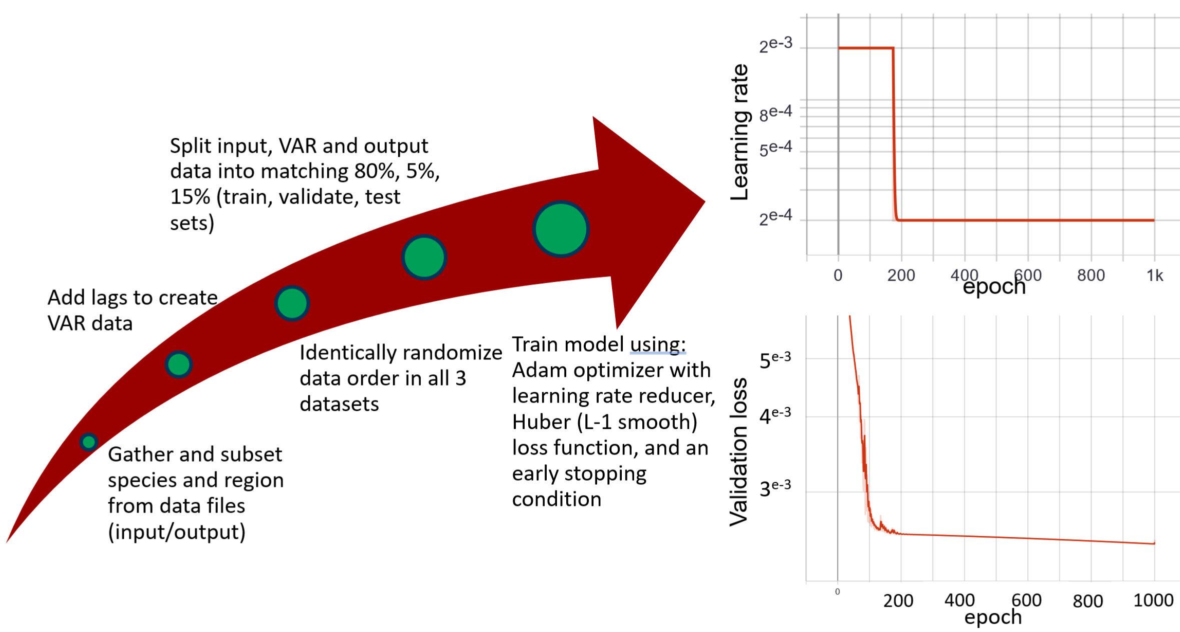

Fig. 17. Flow diagram of modelling process. The top right graph shows a sample of the learning rate reducer. The bottom right graph shows the validation set loss after each epoch.

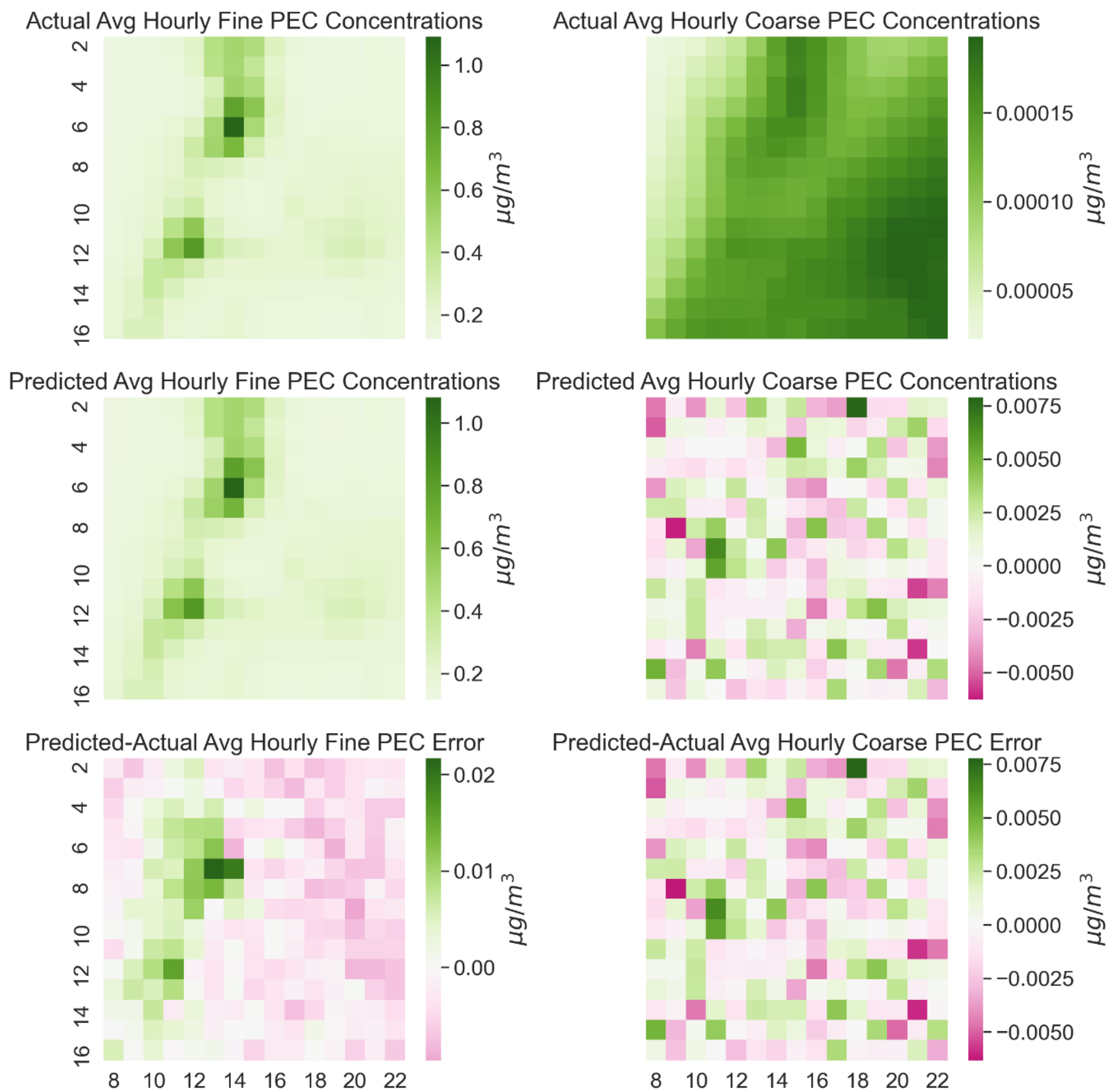

Fig. 18. Test set average hourly measurements for the 15x15 grid region in Washington state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

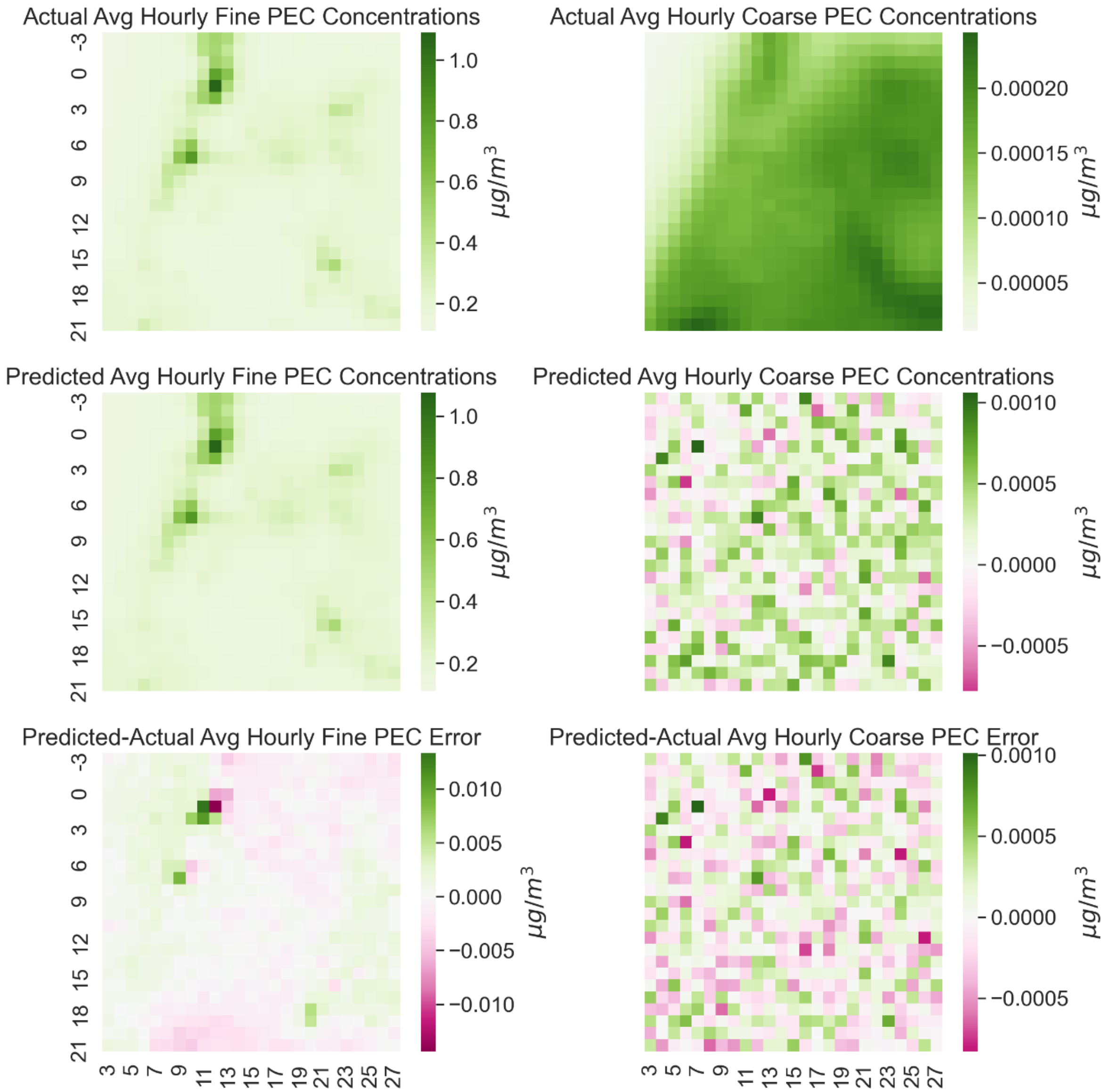

Fig. 19. Test set average hourly measurements for the 25x25 grid region in Washington state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

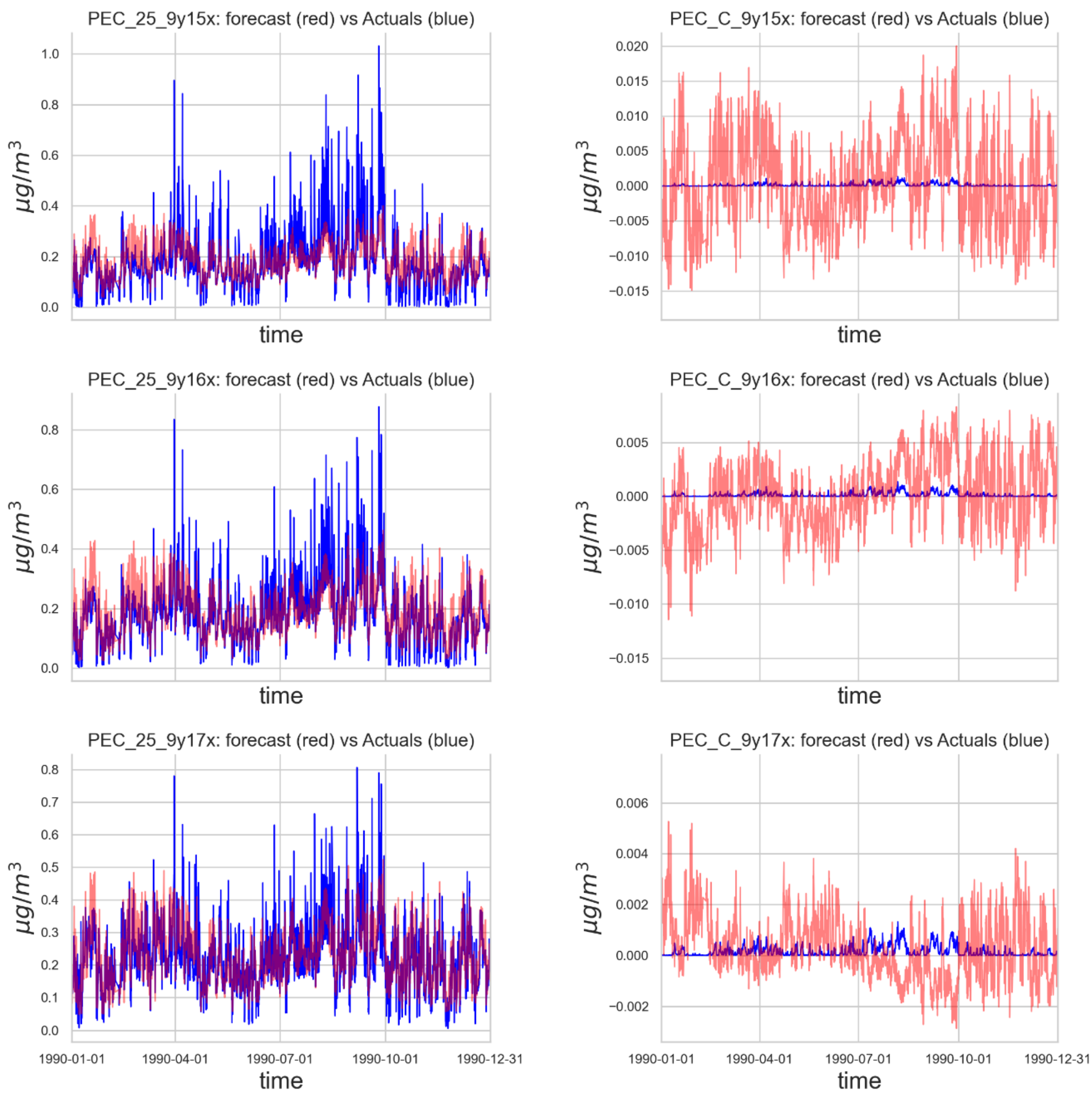

Fig. 20. Small Washington region prediction (red) vs actual (blue) in 1990 for $EC_{2.5}$ (left) and EC_C (right) in three grid cells in the middle of the region. The red is transparent, so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

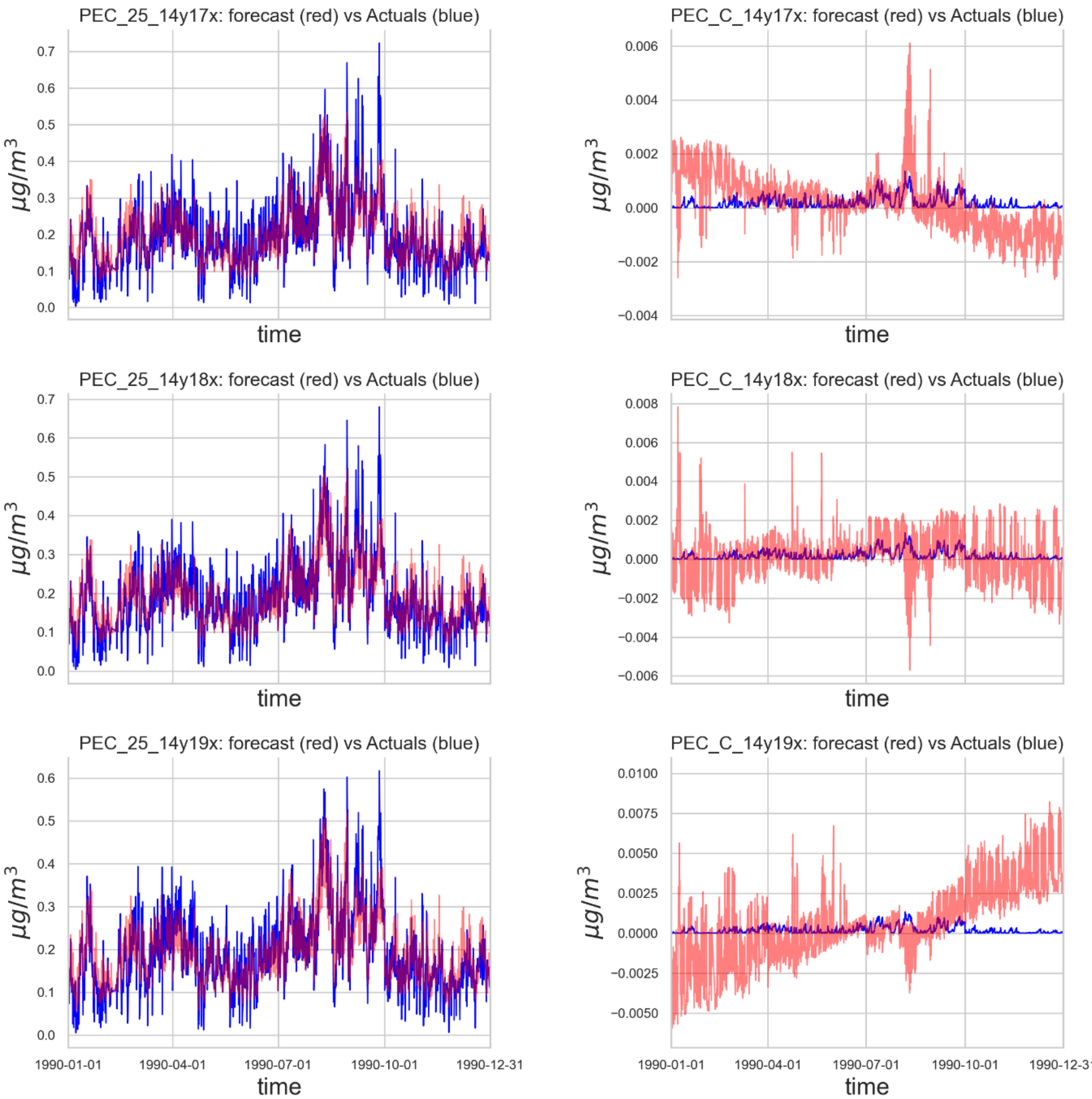

Fig. 21. Large Washington region prediction (red) vs actual (blue) in 1990 for $EC_{2.5}$ (left) and EC_C (right) in three grid cells in the middle of the region. The red is transparent, so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

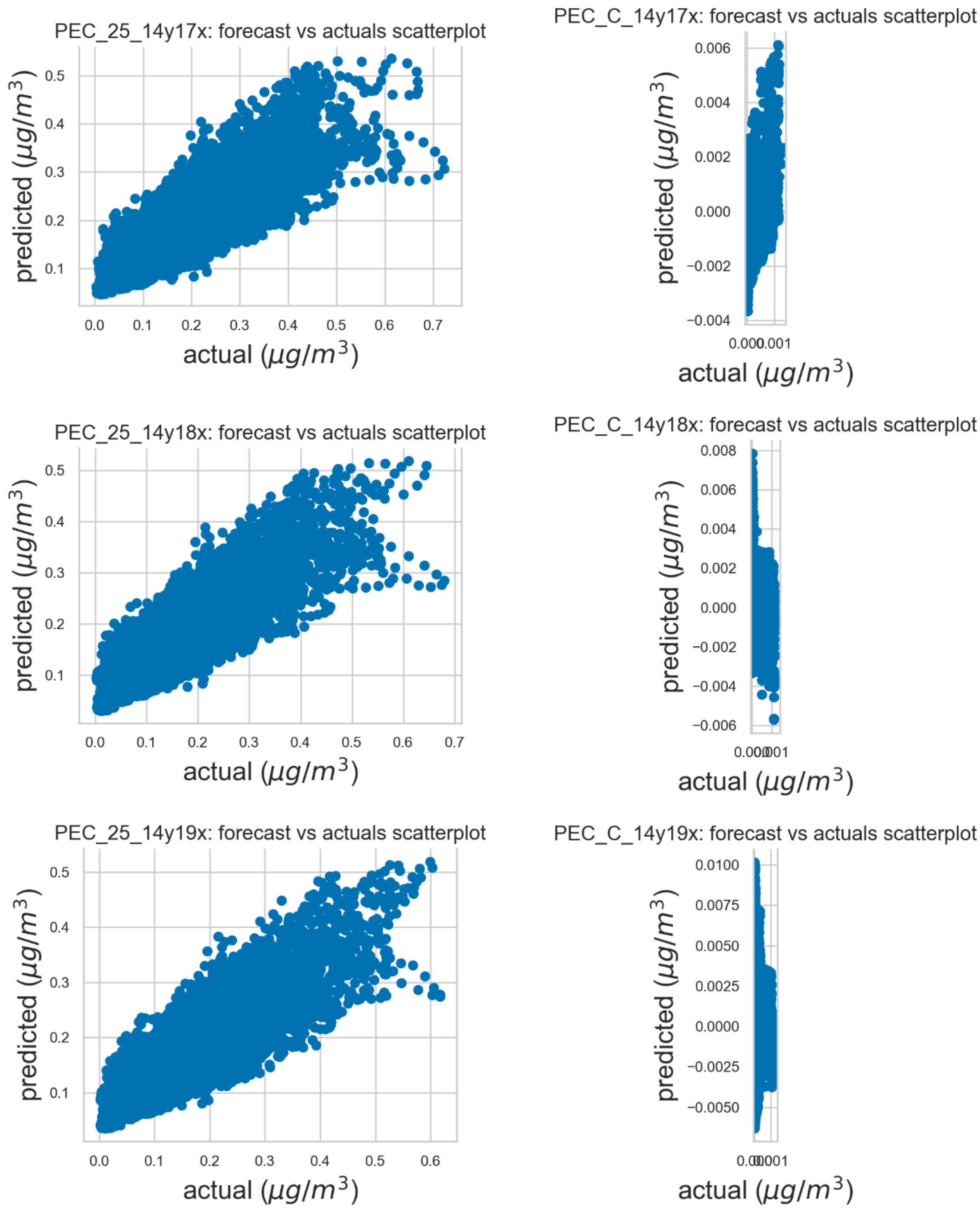

Fig. 22. Scatterplots of predicted to actual values of $EC_{2.5}$ (left) and EC_C (right) for three grid cells in the middle of the region. The plot area has a consistent aspect ratio for x and y axes. A perfect plot would find all points on a 45° diagonal. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

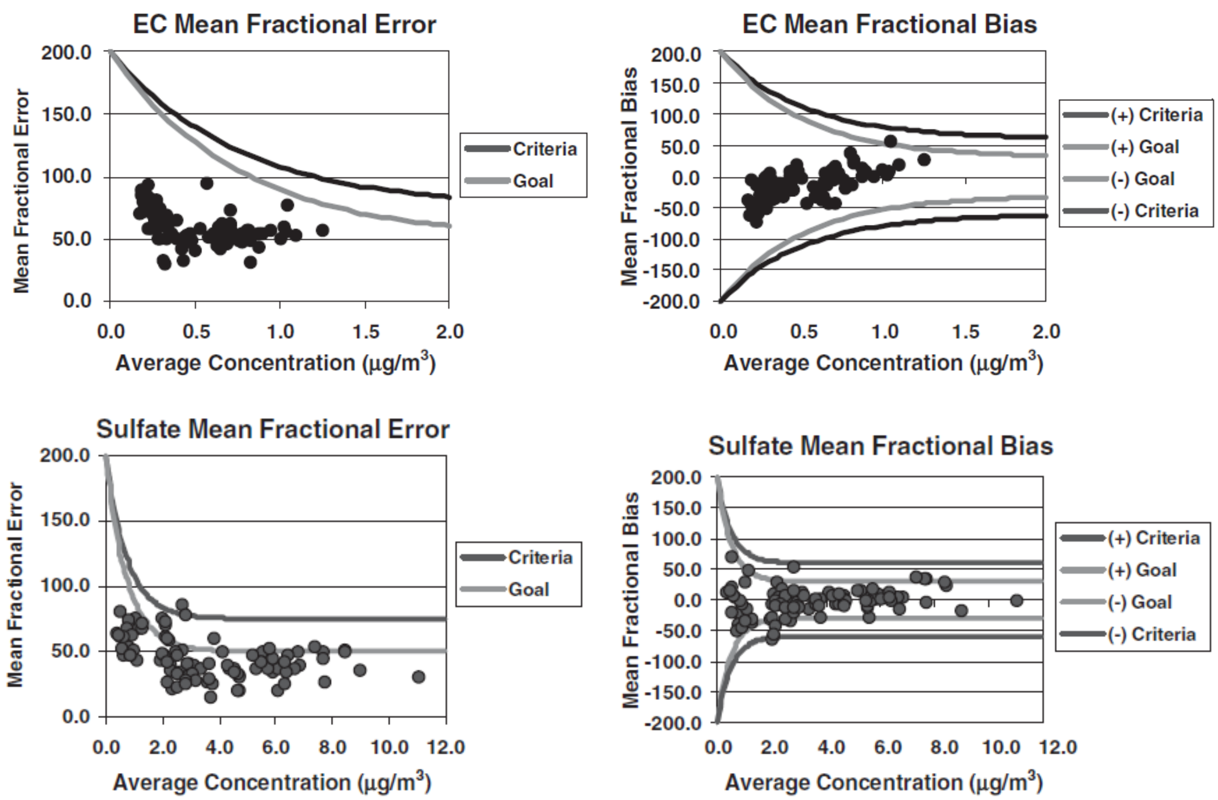

Fig. 23. Elemental carbon (μg/m³) and Sulfate(μg/m³) MFE (left) and MFB (right) for all benchmark runs compared to proposed performance goals and criteria from Boylan and Russel (2006) shown here as reference for criteria and goal performance measures.

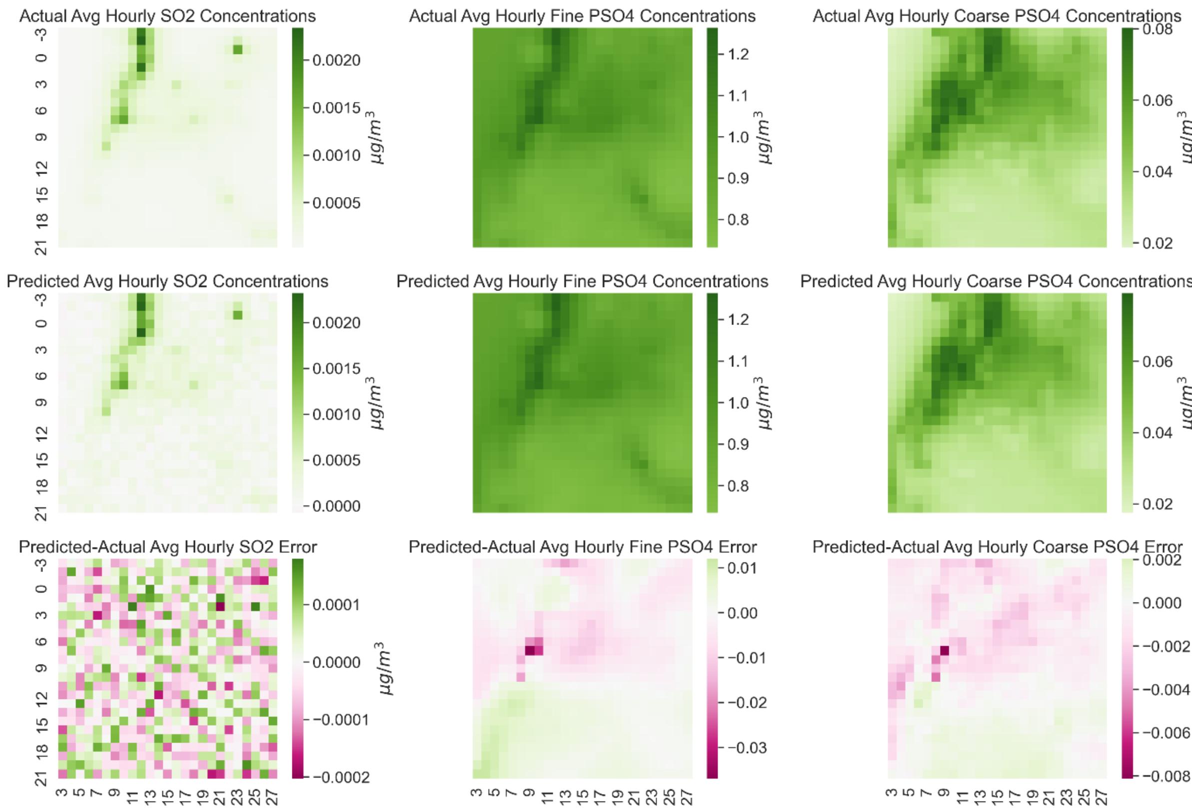

Fig. 24. Test set average hourly measurements for the 25x25 grid region in Washington state. SO_2 is on the left, Fine PSO_4 is in the middle and coarse PSO_4 is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

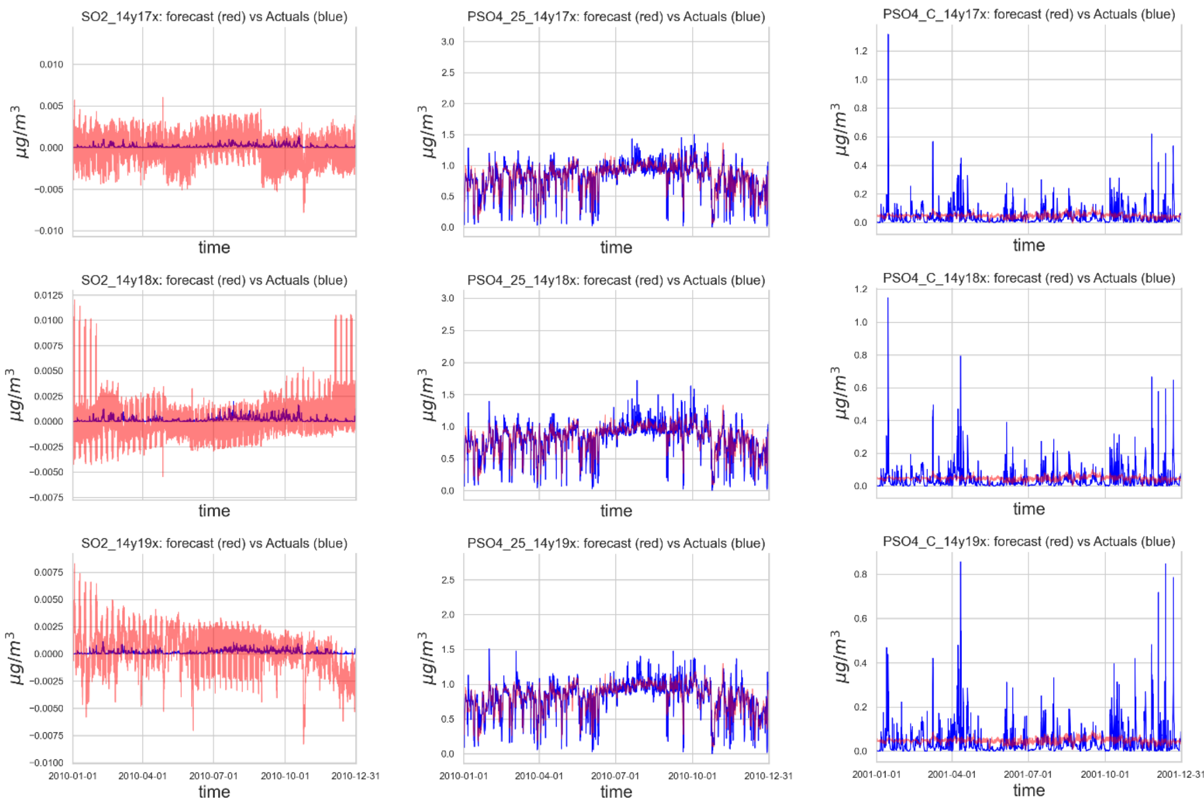

Fig. 25. Large Washington region prediction (red) vs actual (blue) in 2010 for fine PSO_4 (middle) and coarse PSO_4 (right) in three grid cells in the middle of the region. The red is transparent, so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

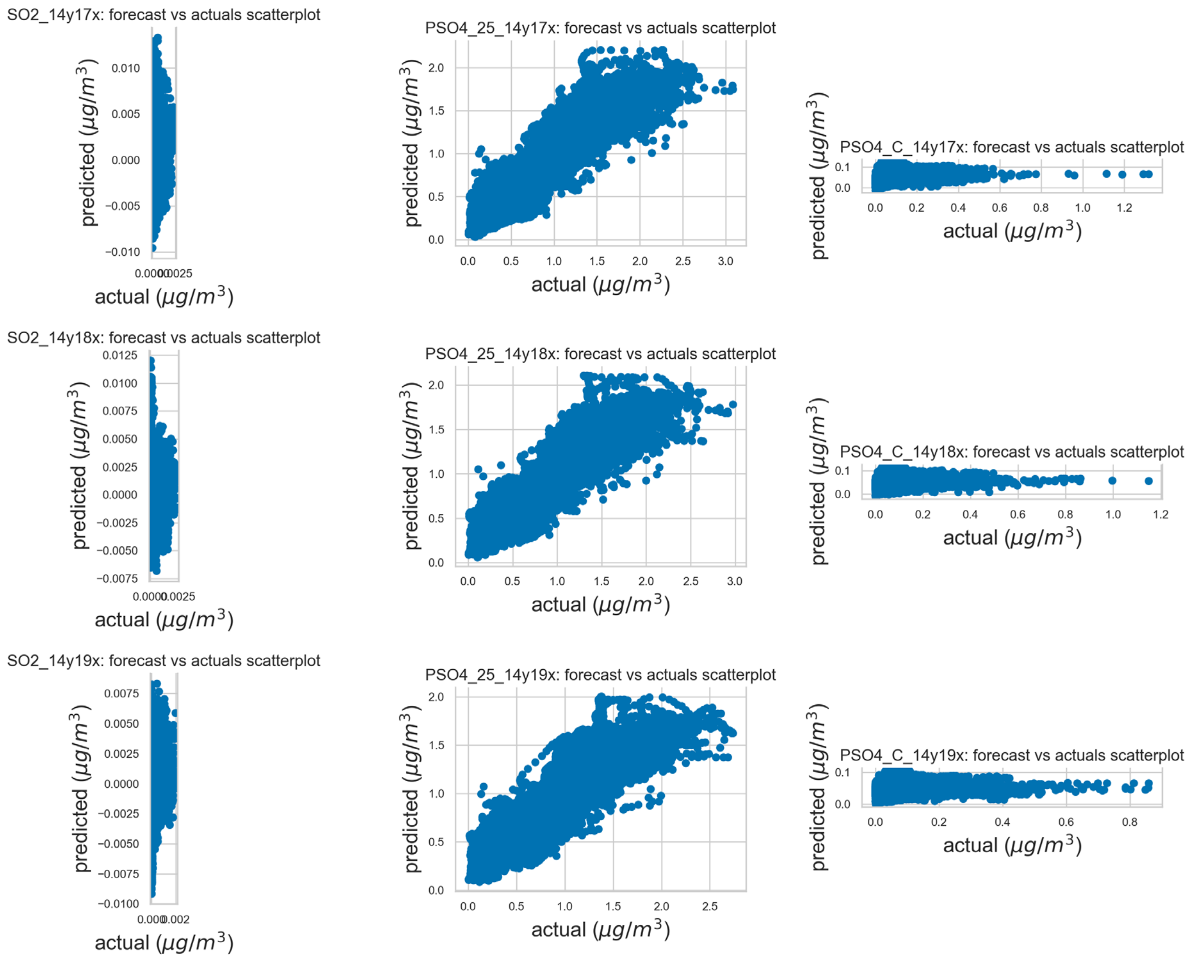

Fig. 26. Scatterplots of predicted to actual values of SO_2 (left), $PSO_{4,2.5}$ (left) and $PSO_{4,C}$ (right) for three grid cells in the middle of the region. The plot area has a consistent aspect ratio for x and y axes. A perfect plot would find all points on a 45° diagonal. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

Chapter 5 Summary and conclusions

I here summarize key findings and contributions from this dissertation. From the first domain of infrastructure and equity, the analyses lead to several overall insights. First, social factors seem more significantly associated with bridge selection as opposed to treatment, especially the demographic variables and, to a lesser degree, family variables. Percentage of Hispanic, African American, and non-White populations all are negatively associated with the placement of non-restrictive bridges or any bridge construction and these associations are consistent and robust. Regarding family variables, those households with more single parents with children and female-led households were associated with less bridge construction of any kind, and these associations were consistent and robust. Education variables, finance, housing, and transportation variables generally did not yield consistent nor robust associations. Overall, this suggests that tracts with more non-White demographics and single or female-led households are associated with less infrastructure, which suggests less physical connectivity and mobility. LASSO notes similar results but with less associative strength, while also uncovering potential industry-based influences on bridge infrastructure. ML causal-based search mechanisms note some of these factors are associative rather than causal, but they do find some causal connections. In particular, the Fast Casual Inference algorithm finds that some connections are due to latent confounders and more research is needed to better identify these confounders.

Second, physical factors that arguably capture more technical rationales for bridge construction have less association on selection or treatment, even before CEM is applied to handle potential selection along these variables. Rural tracts and water area all hover around zero in both sets of models. This suggests social as opposed to technical factors are perhaps more associated with bridge construction, particularly where it is sited. That said, the measures used as proxies for technical causes or reasons for building a bridge are limited to water and land area. The reason this may be is that social context often informs the appropriate variables that can hypothetically influence whether a locale is in need of a bridge and whether it receives it. Since the context was Pennsylvania and many bridges are used to traverse bodies of water and geophysical features such as ravines, land and water area were selected as proxies. These proxies may not be applicable across social contexts as these measures may not adequately capture other possible contextual sources of geophysical variation such as elevation change. Thus, while this suggests social factors may matter more than technical factors in bridge siting and that the overall framework may be replicable, the authors cautiously note that the variables included should be guided by the realities of the local context.

In terms of the models using the ML search-selected variables, the authors found consistent results with previous models along different variables. ML search finds another parallel effect to the literature-review based demographic variables - less restrictions in white populations around bridge placement. In other words, tracts with more white populations are associated with more bridges, which mirrors previous results that non-white populations are associated with less bridges. The ML-based search technique also discovered new industry-based associations of bridge construction. The number of precision crafters, farm, fishery, and forestry workers were negatively associated with non-restrictive bridge construction.

Second, causal machine learning algorithms found some sources of causality, but most variables are merely associational. These algorithms discovered structural relationships between variables (e.g., the count of a particular type of bridge and the dummy indicator signifying that a particular type of bridge had been built in a tract). These searches also discovered associations between bridge types and rural tract dummy indicator variables. Ultimately, eighteen of the 32 variables identified by LASSO and MB machine learning algorithms were found to have a possible causal connection. When employing the fast greedy equivalence search (FGES) algorithm, which is not restricted to a Markov Blanket, the algorithm found 16 low probability causal connection and only one high probability connection (IHS-transformed count of total bridges -> rural 4M m^2

indicator). FCI found that nonrestrictive bridges were either causally influence the rural 10M m^2 indicator or there is an unmeasured confounder or both. When examining the literature review-based variables, FCI found that the rural 10M m2 indicator definitely directly influences with no latent confounder the total number of IHS-transformed total bridges. FCI then was a valuable check to confirm or refute causality findings from other algorithms. Overall, what the results from these causal search algorithms suggest is that some of the variables identified by the literature review and ML search algorithms are causal in their relationship to bridge infrastructure. Overall, these results indicate that most of the findings are associational and not necessarily causal.

With regard to the second domain, the authors were able to develop a rather effective algorithm for predicting chemical species which contribute to health issues with $PM_{2.5}$. Along the way the authors also discovered a method to apply neural networks to a popular form of econometric analysis (VAR). The machine learning based algorithm was much more efficient in terms of memory, power, and time. As the authors tested for time variability, the vector autoregression model, with nonlinearity and/or nonstationary causal influences, found that the optimal lag decreased as the geophysical size of the problem set increased. This was counterintuitive and not what the authors expected. The authors ended up developing a hybrid neural network that took as input emission and past periods of output to accurately predict $PM_{2.5}$ chemical species. The model the authors developed shows great potential to become even more accurate as more environmental variables are added into the model. Even with the limited area emissions and a limited number of pollution concentration lags, the model was able to learn to predict future pollution concentrations to a reasonable degree of accuracy. With the added computational efficiencies brought to the table by the neural network, the author believes the model is worth further development to add it to a reduced complexity model in order to make air pollution modeling more accessible to local and state policymakers. After the model has successfully integrated other meteorological factors, it would be a valuable exercise to attempt to transfer it to real-world data.

Contributions

The first study provides several contributions. First, this study presents a replicable methodology for assessing equity impacts of infrastructure. Prior literature is unable to assess relationships between infrastructure and equity because these assessments require dispersed data sources that differ in both temporal and spatial resolution (Grannis 1998; Knaap and Oosterhaven 2002; Lee et al. 2008; Liu Min and Frangopol Dan M. 2006; Sampson et al. 2002; Star and Bowker 2006). The authors demonstrate a method to bring disparate available data sources together to provide insights into the social impacts of infrastructure. This study contributes a research design that incorporates network service area analysis and CEM to make inroads into harmonizing and isolating as much as possible treatment locales, comparable control locales, and the most salient equity variables for analysis according to our extensive literature review thus minimizing the need for expert variable selection. The authors hope other engineers will test the replicability of this method in other locales to further assess the robustness of this approach to other local conditions, which will help further develop boundary conditions for this methodology.

Second, and particular to the Pennsylvania case study, the authors found social factors matter more than the limited technical factors at our disposal in understanding the equity impacts of infrastructure and identified associations seem more consequential at selection than treatment. Prior literature seems to argue that there are both selection and treatment effects on infrastructure-equity relationships (Audretsch et al. 2015; Grabowski et al. 2017; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). However, in terms of this case study, the authors find selection is a more prominent factor. This intuitively makes sense given the longevity of these systems and the social context at the time that drives bridge construction and siting (Desai and Armanios 2018). As with this study's methodology, the authors hope not just the robustness of the methods are assessed through additional case studies, but also compare and contrast equity findings from those case studies to the one conducted here. In this way, the scholarly community can collectively advance a more generalized set of findings and conditions for which social factors drive infrastructure-equity relationships, whether they are associative or causal, and whether they occur at infrastructure selection, subsequent treatment, or both.

A third contribution is to demonstrate that it is possible to use quantitative methods with publicly available data to discover associations between infrastructure and socioeconomic factors. In contrast to the current civil engineering literature that focuses on construction or maintenance impacts only during construction (Liu and Frangopol 2005; Liu Min and Frangopol Dan M. 2006; Liu Ming and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017), this paper has shown that it is possible to look at longer term equity impacts of infrastructure. This provides a challenge for the civil engineering community to look beyond strictly focusing on the time period during construction or maintenance to understand more long-lasting social impacts of bridges and other physical infrastructure.

Additionally, the authors see pragmatic managerial implications. Infrastructure managers are increasingly asked to repair an ever-growing set of outdated bridges with budgets that are increasing but not adequate to completely address infrastructure demands. As the most recent ASCE report stated, "In 2018, the Commonwealth of PA estimated that $7.7 billion is needed for bridge repairs. Under current funding practices, it would take 13 years to reach the national average of poor condition bridges (ASCE 2019)." This suggests infrastructure managers could benefit from having other metrics for which to further prioritize and identify the most critical bridges in need of repair. Therefore, including equity dimensions through this methodology presents an additional set of factors that can advance such needs and allow infrastructure managers to prioritize bridge needs more effectively under budgetary constraints.

The main contribution of the first study's extension (Study 2) is to demonstrate that it is possible to use quantitative methods with publicly available data to distinguish causal relationship from associative relationship. Even in those cases where causality could not be confirmed, valuable associations were discovered with the ability to impact the socioeconomic conditions of some of society's at-risk and underserved communities. Moreover, these methods can be employed by engineers with little familiarity in underlying sociological theory, statistics, and machine learning algorithms. These extensions should provide additional metrics with which to further prioritize and identify the most critical bridges in need of repair. Therefore, including equity dimensions through this methodology presents an additional set of factors that can advance such needs and allow infrastructure managers to more effectively prioritize infrastructure maintenance and manpower in ways that more closely match budgetary constraints.

The first contribution of the second domain was not expected. Vector autoregressive algorithms are a well-known and well-used tool in the economist's toolbox which is why the authors were surprised that the method has not been modeled using a neural network. The advantages in terms of memory, time and computation power were unexpectedly large. With virtually no resource on the GPU, the VAR neural net was able to duplicate jobs that require servers to complete. By integrating emissions with time-varying autoregressive pollution concentrations the authors were able to quickly learn the underlying functions of a couple of chemical species with impact on human health. Further development is warranted to ascertain just how accurate such a model can become. The computational efficiencies and human capital savings are significant. During the development of the model the authors kept their eye on accessibility and ensured that there is sufficient utility in a regional model. The authors found that adding the temporal aspect improved the model and provided useful information to the neural network.

The second contribution was an ML algorithm capable of learning chemical interactions based on a CTM. The first two iterations of this algorithm took past concentrations and area pollution sources as inputs in order to predict future concentrations. The algorithm models $PM_{2.5}$ for EC and PSO_4 very well with these limited inputs. Based on the predictive power of the model based on these two inputs, further development is warranted.

Future Work

As previously noted, there are opportunities to replicate the case study framework in other locales outside Pennsylvania or at a larger national scale. Applying this methodology to other types of infrastructure may also yield new insights into the interactions of infrastructure with equity. The results of the causal methods discovered that some associations are the result of currently unknown or unmeasured factors and work is needed to find these factors, especially in ways that account for potential nonlinearity. As for the air pollution models, there are a plethora of future research directions. One of the first steps could be to integrate the available meteorological factors one at a time to delineate and quantify the differential contributions of each discrete factor. The same model or a similar construct may be useful in econometric domains which employ VAR models. One of the challenges the authors faced was limited computing resources, and so regional models were developed. Incorporating the hybrid VAR neural network with time dependencies into a reduced complexity model as its prediction engine could open the doors to policymakers and concerned citizens by making complex air pollution models accessible to them at their desk.

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Appendix I: Methodological Framework and Feasibility Study to Assess Social Equity Impacts of the Built Environment Supplemental information

Code and some data are available at: https://github.com/ZhongSiming/SocialBridges

Section A Data Processes

Figures S1 and S2 summarized the data acquisition and cleaning process.

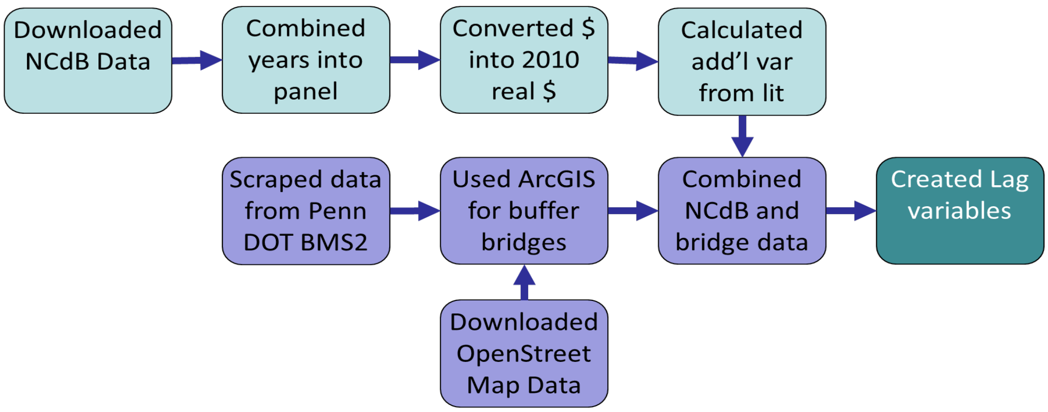

Fig. 27. Flow diagram of data acquisition process. NCdB = Neighborhood Change Database, BMS=Bridge Management System, converted to 2010 real dollars using CPI

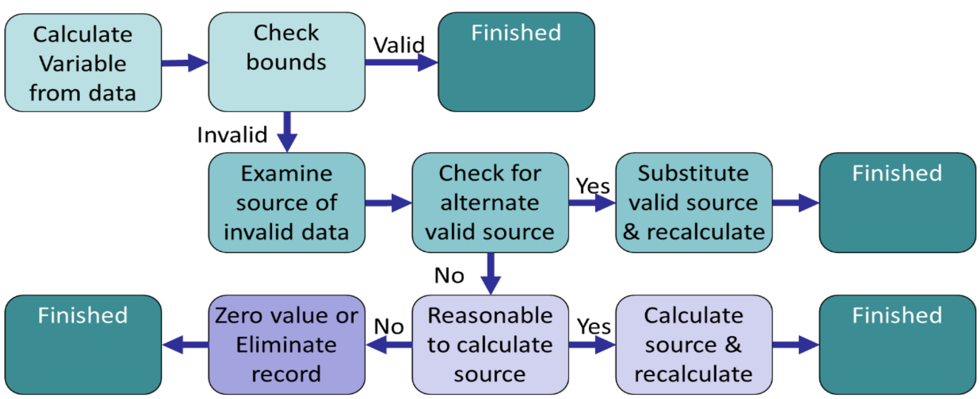

Fig. 28. Flow diagram of data cleaning process.

This data is at the resolution of a census tract, which serves as the level of analysis. Since census tracts change over time, the data used was standardized by Geolytics using the 2010 census tract boundaries in their Neighborhood Change Database (NCdB) (GeoLytics 2018). There are approximately six hundred tracts that do not have data for the 1970 and 1980 census years because the census was not conducted in these rural tracts (see Robustness Checks section and Fig. 7 for additional details). Other researchers have used data standardized by Geolytics to help determine socioeconomic factors surrounding power generation infrastructure and spatial segmentation of classes (Carless 2018; Sharkey 2014). For example, combining Geolytics standardized data with administrative data from a federal housing renewal program was used by other researchers to track urban inequality over time (Tach and Emory 2017b). Despite the standardization performed by GeoLytics, steps were still required to identify and mitigate data inconsistencies. Thus, the NCdB serves as a widely accepted high-resolution dataset for social demographic data.

For this analysis, the data used focuses on bridges with a route (road or highway) that will allow motorized vehicles to pass under the bridge. This paper focuses on two types of bridges: restrictive and non-restrictive. Using the convention developed by Desai and Armanios (2018) to analyze the National Bridge Inventory data, the minimum underclearance considered is 3 meters (9.8 feet). Of these bridges, restrictive bridges are defined as those with an underclearance of fewer than 4.27 meters (14 feet) which allow cars, buses and light trucks to pass. Non-restrictive bridges are defined as those with an underclearance of 4.27 meters (14 feet) or higher which would enable commercial trucks to pass. As bridge underclearance drops lower to less than 3.66 meters (12 feet) or 3.05 meters (10 feet), buses and smaller trucks also become restricted. These restrictions can have a disproportionate effect on small businesses and marginalized populations which rely on small trucks and buses for movement of goods and people. While the federal government does not regulate commercial vehicle height (Federal Highway Administration 2004), the states restrict vehicle height from 4.11 meters (13 feet 6 inches) to 4.27 meters (14 feet) (for example, Pennsylvania "Title 75" 2018, 7). Thus, an underclearance of 4.27 meters (14 feet) was chosen because ("Size and Weight Limitations" 2018) it is the highest bound that begins to restrict non-military vehicles.

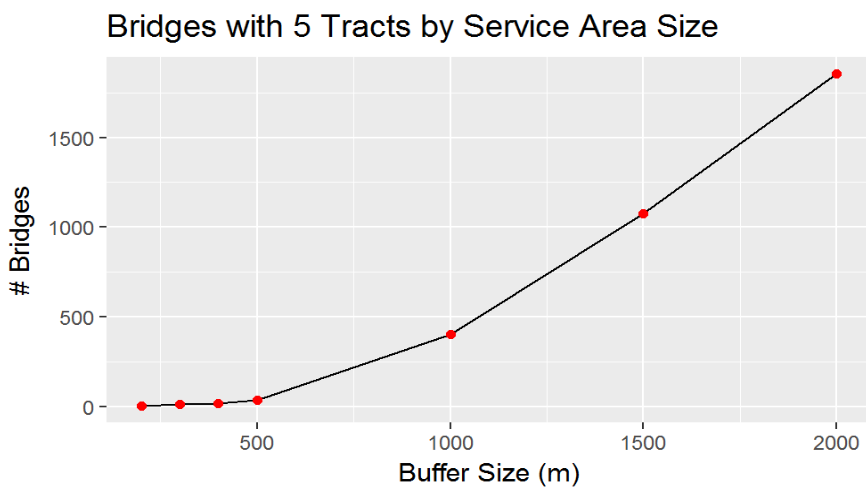

Fig. 29. Number of bridges by service area length

Since bridges may act as boundaries, the authors needed to find a quantitative method to define a boundary bridge (i.e., a bridge that straddles between tracts or could serve as a barrier between tracts). Fig. 3 and Fig. 4 summarize the result of this process. To ascertain the size range the authors should consider for the service area analysis, the authors ran a sensitivity analysis where the service area size varied from 200 to 2,000 meters from the bridge of interest. This identified bridges with service areas that overlapped with 1, 2, 3, 4, and 5 tracts. The authors used these service areas to ascertain at what size they see a pronounced shift in the number of bridges comprising each group (see Appendix I, Section A, Fig. 29 - Fig. 30). Using this approach, the most appropriate natural cutoff was found to be 400 meters from the bridge. This range incidentally is almost identical to the buffer values used in a prior analysis of income and race on busy roadways (Turnbull et al. 2013 p. 32). The lines represent the number of tracts intersected by a bridge's service area. The y-axis represents the number of bridges with a service area that intersects the specified number of tracts as specified by the line. The x-axis represents how far the street network was traced away from the bridge while building the service area. As the number of tracts increases the number of bridges with a service area intersecting that number of tracts decreases.

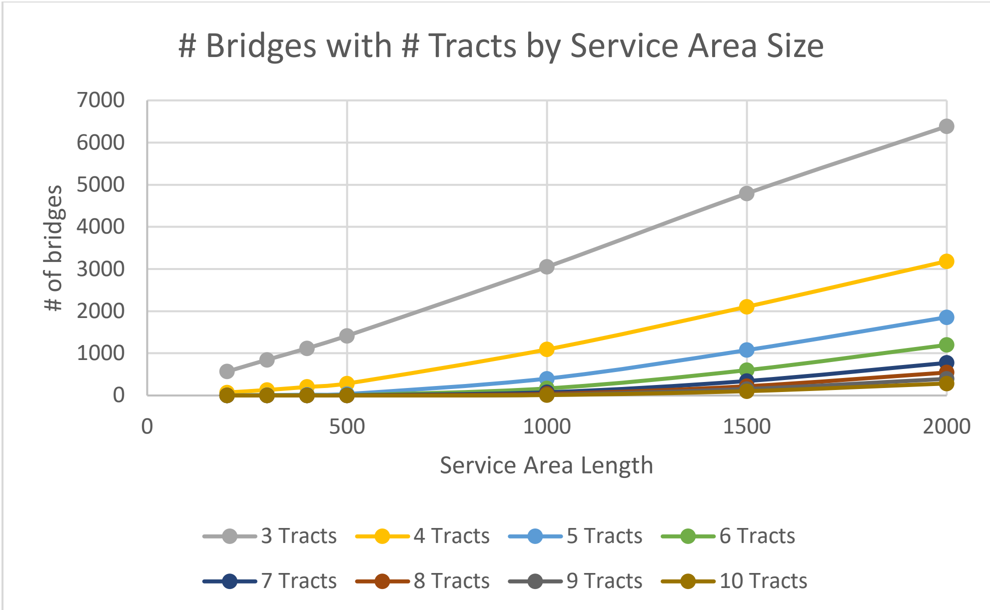

Fig. 30. Number of bridges with the number of tracts by service area length

Section B Correlation Matrices

Table 18. Correlation matrix for set 1 variables

	newbridg	AREAWA	rur10m	bridge.to	AVHHIN.2	MINORIT	FORBORN	TRVLPBN.	EDUC8.la	EDUC16.l	POVRATN	OWNRNT	VACHU.la	NEWHOU
newbridge.under14.mod	**1.00**	0.06	0.02	-0.03	-0.06	-0.01	-0.03	-0.04	-0.03	-0.03	-0.02	-0.01	-0.03	-0.02
AREAWATR.pct	0.06	**1.00**	-0.08	0.02	0.00	0.00	0.00	0.01	0.01	-0.03	0.06	-0.01	0.08	-0.02
rur10m	0.02	-0.08	**1.00**	0.58	-0.10	-0.26	-0.29	-0.39	0.03	-0.05	-0.21	0.01	0.04	0.13
bridge.total.ihs.lag	-0.03	0.02	0.58	**1.00**	0.35	-0.21	-0.09	-0.07	0.19	0.16	-0.04	0.03	0.21	0.19
AVHHIN.2010real.ihs.lag	-0.06	0.00	-0.10	0.35	**1.00**	0.22	0.44	0.70	0.35	0.38	0.44	0.05	0.39	0.12
MINORITY.lag.pct	-0.01	0.00	-0.26	-0.21	0.22	**1.00**	0.22	0.46	0.24	0.06	0.67	-0.03	0.33	-0.10
FORBORN.lag.pct	-0.03	0.00	-0.29	-0.09	0.44	0.22	**1.00**	0.57	0.12	0.32	0.28	-0.03	0.14	-0.01
TRVLPBN.ihs.lag	-0.04	0.01	-0.39	-0.07	0.70	0.46	0.57	**1.00**	0.15	0.24	0.48	-0.06	0.25	-0.04
EDUC8.lag.pct	-0.03	0.01	0.03	0.19	0.35	0.24	0.12	0.15	**1.00**	0.27	0.44	-0.04	0.37	0.09
EDUC16.lag.pct	-0.03	-0.03	-0.05	0.16	0.38	0.06	0.32	0.24	0.27	**1.00**	0.07	-0.03	0.14	0.06
POVRATN.lag.pct	-0.02	0.06	-0.21	-0.04	0.44	0.67	0.28	0.48	0.44	0.07	**1.00**	-0.05	0.50	-0.02
OWNRNT.pct.lag	-0.01	-0.01	0.01	0.03	0.05	-0.03	-0.03	-0.06	-0.04	-0.03	-0.05	**1.00**	-0.04	-0.01
VACHU.lag.pct	-0.03	0.08	0.04	0.21	0.39	0.33	0.14	0.25	0.37	0.14	0.50	-0.04	**1.00**	0.13
NEWHOUS.lag.pct	-0.02	-0.02	0.13	0.19	0.12	-0.10	-0.01	-0.04	0.09	0.06	-0.02	-0.01	0.13	**1.00**

Table 19. Correlation matrix for set 2 variables

	newbridge	AREAWAT	rur4m	bridge.tot	AVHHINN.	FORBORN.	SPWKID.la	COMMUT.	EDUCA.lag	VACHU.lag	NEWHOUS
newbridge.under14.mod	**1.00**	0.06	0.02	-0.03	-0.06	-0.03	-0.03	-0.05	-0.04	-0.03	-0.02
AREAWATR.pct	0.06	**1.00**	-0.07	0.02	0.00	0.00	0.05	-0.01	-0.01	0.08	-0.02
rur4m	0.02	-0.07	**1.00**	0.57	-0.08	-0.27	-0.32	-0.01	0.04	-0.03	0.14
bridge.total.ihs.lag	-0.03	0.02	0.57	**1.00**	0.34	-0.09	-0.07	0.31	0.27	0.21	0.19
AVHHINN.2010real.ihs.lag	-0.06	0.00	-0.08	0.34	**1.00**	0.44	0.47	0.70	0.46	0.39	0.12
FORBORN.lag.pct	-0.03	0.00	-0.27	-0.09	0.44	**1.00**	0.24	0.28	0.15	0.14	-0.01
SPWKID.lag.pct	-0.03	0.05	-0.32	-0.07	0.47	0.24	**1.00**	0.45	0.31	0.47	-0.03
COMMUT2.ihs.lag	-0.05	-0.01	-0.01	0.31	0.70	0.28	0.45	**1.00**	0.66	0.40	0.18
EDUCA.lag.pct	-0.04	-0.01	0.04	0.27	0.46	0.15	0.31	0.66	**1.00**	0.30	0.07
VACHU.lag.pct	-0.03	0.08	-0.03	0.21	0.39	0.14	0.47	0.40	0.30	**1.00**	0.13
NEWHOUS.lag.pct	-0.02	-0.02	0.14	0.19	0.12	-0.01	-0.03	0.18	0.07	0.13	**1.00**

Table 20. Correlation matrix for set 3 variables

	newbridge	AREAWAT	rur10m	bridge.tot	SHRBLKN.l	AD2CHILD	FORBORN.	WELFARN.	COMMUT	EDUC12.la	RNTOCC.la	VACHU.lag	NEWHOUS
newbridge.under14.mod	**1.00**	0.06	0.02	-0.03	-0.01	-0.06	-0.03	-0.02	-0.05	-0.04	-0.04	-0.03	-0.02
AREAWATR.pct	0.06	**1.00**	-0.08	0.02	0.01	0.03	0.00	0.05	-0.02	0.01	0.07	0.08	-0.02
rur10m	0.02	-0.08	**1.00**	0.58	-0.24	-0.13	-0.29	-0.22	-0.02	0.07	-0.36	0.04	0.13
bridge.total.ihs.lag	-0.03	0.02	0.58	**1.00**	-0.20	0.31	-0.09	-0.07	0.31	0.31	-0.06	0.21	0.19
SHRBLKN.lag.pct	-0.01	0.01	-0.24	-0.20	**1.00**	0.18	0.12	0.68	0.17	0.10	0.39	0.31	-0.10
AD2CHILD.ihs.lag	-0.06	0.03	-0.13	0.31	0.18	**1.00**	0.45	0.37	0.70	0.49	0.65	0.39	0.09
FORBORN.lag.pct	-0.03	0.00	-0.29	-0.09	0.12	0.45	**1.00**	0.20	0.29	0.07	0.48	0.14	-0.01
WELFARN.lag.pct	-0.02	0.05	-0.22	-0.07	0.68	0.37	0.20	**1.00**	0.39	0.28	0.57	0.48	-0.06
COMMUT4.ihs.lag	-0.05	-0.02	-0.02	0.31	0.17	0.70	0.29	0.39	**1.00**	0.63	0.41	0.39	0.17
EDUC12.lag.pct	-0.04	0.01	0.07	0.31	0.10	0.49	0.07	0.28	0.63	**1.00**	0.24	0.41	0.10
RNTOCC.lag.pct	-0.04	0.07	-0.36	-0.06	0.39	0.65	0.48	0.57	0.41	0.24	**1.00**	0.32	-0.02
VACHU.lag.pct	-0.03	0.08	0.04	0.21	0.31	0.39	0.14	0.48	0.39	0.41	0.32	**1.00**	0.13
NEWHOUS.lag.pct	-0.02	-0.02	0.13	0.19	-0.10	0.09	-0.01	-0.06	0.17	0.10	-0.02	0.13	**1.00**

Table 21. Correlation matrix for set 4 variables

	newbridge	AREAWAT	rur4m	bridge.tot	SHRHSPN.l	FORBORN.	CHILD.lag.	FHHTOT.la	TRVLPBN.i	COMMUT	EDUC8.lag	OWNRNT.	VACHU.lag	NEWHOUS
newbridge.under14.mod	**1.00**	0.06	0.02	-0.03	-0.02	-0.03	-0.05	-0.03	-0.04	-0.05	-0.03	-0.01	-0.03	-0.02
AREAWATR.pct	0.06	**1.00**	-0.07	0.02	0.01	0.00	-0.03	0.06	0.01	-0.04	0.01	-0.01	0.08	-0.02
rur4m	0.02	-0.07	**1.00**	0.57	-0.15	-0.27	0.00	-0.39	-0.37	0.00	-0.03	0.02	-0.03	0.14
bridge.total.ihs.lag	-0.03	0.02	0.57	**1.00**	-0.09	-0.09	0.32	-0.11	-0.07	0.30	0.19	0.03	0.21	0.19
SHRHSPN.lag.pct	-0.02	0.01	-0.15	-0.09	**1.00**	0.28	0.20	0.36	0.22	0.17	0.35	-0.02	0.19	-0.04
FORBORN.lag.pct	-0.03	0.00	-0.27	-0.09	0.28	**1.00**	0.31	0.31	0.57	0.30	0.12	-0.03	0.14	-0.01
CHILD.lag.pct	-0.05	-0.03	0.00	0.32	0.20	0.31	**1.00**	0.48	0.63	0.46	0.24	-0.07	0.33	0.12
FHHTOT.lag.pct	-0.03	0.06	-0.39	-0.11	0.36	0.31	0.48	**1.00**	0.63	0.48	0.44	-0.06	0.46	-0.10
TRVLPBN.ihs.lag	-0.04	0.01	-0.37	-0.07	0.22	0.57	0.63	0.63	**1.00**	0.46	0.15	-0.06	0.25	-0.04
COMMUTX.log.lag	-0.05	-0.04	0.00	0.30	0.17	0.30	0.46	0.48	0.46	**1.00**	0.50	-0.06	0.41	0.16
EDUC8.lag.pct	-0.03	0.01	-0.03	0.19	0.35	0.12	0.24	0.44	0.15	0.50	**1.00**	-0.04	0.37	0.09
OWNRNT.pct.lag	-0.01	-0.01	0.02	0.03	-0.02	-0.03	-0.07	-0.06	-0.06	-0.06	-0.04	**1.00**	-0.04	-0.01
VACHU.lag.pct	-0.03	0.08	-0.03	0.21	0.19	0.14	0.33	0.46	0.25	0.41	0.37	-0.04	**1.00**	0.13
NEWHOUS.lag.pct	-0.02	-0.02	0.14	0.19	-0.04	-0.01	0.12	-0.10	-0.04	0.16	0.09	-0.01	0.13	**1.00**

Section C Variables

Census data utilizes multiple categories for certain phenomena such as education or provides subsets of certain phenomena such as single parents. Since these phenomena have multiple variables and are often linear combinations and therefore not linearly independent, each of these variables were placed in separate sets of variables for use in the models in order to avoid issues of multicollinearity (see Tables S5 - S12). For example, there are six different measures of educational achievement, one measures those who completed more than elementary but did not complete high school. The authors chose to only use the four educational variables that correspond to the completion of some level of school: elementary, high, associate degree, and bachelor's degree or higher. Population density is an example of a variable that is highly correlated with many other variables such as income, poverty rate, welfare, renter-occupied housing, three kinds of single parents, and three commute measures.

The neighborhood-effects literature helps select key socio-economic factors for this research because this literature attempts to illuminate the social and institutional processes and mechanisms responsible for neighborhood-level outcomes. This literature has identified key mechanisms such as: concentrated disadvantage, "life-cycle status, residential stability, homeownership, density and ethnic heterogeneity (Sampson et al. 2002 p. 446)." A study focused on determining the spatial separation of the black middle class created an index of neighborhood concentrated disadvantage based on five census tract characteristics: "welfare receipt, poverty, unemployment, female-headed households, and density of children (percentage of residents under 18) (Sharkey 2014 p. 910)." A study focused on spatial dynamics affecting collective efficacy for children used: concentrated immigration, percentage of owner-occupied homes, percentage of population in professional or managerial occupations, ratio of adults to children, population density (persons per square kilometer), education, income, occupational prestige, sex, current marital status, homeownership, mobility (number of moves in the past five years), years in the neighborhood, and age (Sampson et al. 1999 pp. 640–1). They found the most consistent predictors of collective efficacy were characteristics of stable neighborhoods: concentrated affluence, low population density, and residential stability (Sampson et al. 1999). A study concerned with white flight used socio-economic status indicators including sex, marital status, number of children, homeownership level, poverty level, and concentration of single-mother families, among others to conclude that whites take the racial composition of nearby neighborhoods into account when they choose where to move (Crowder and South 2008).

Table 22. List of independent variables in set 1 in Selection Effect Model with references to other works

Variable	Description	Citation
Area (Water)	Area (Water)	This study
Rural tract indicator > 10M sq. meters	Rural indicator for tracts greater than 10M sq. meters	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged IHS-transformed Real Average income	Lagged Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
Lagged % Minority	Lagged Non-White percentage of total population	Brady et al, 2017; Crowder et al, 2012
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged IHS-transformed Travel on public transportation	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included)	This study
Lagged % bachelor's or higher Degree Graduate	Lagged Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Poverty rate	Lagged Percentage of total persons below the poverty level in past 12 months	Sharkey 2014; Crowder et al, 2012
Lagged Owner to Renter rate	Lagged Ratio of Owner-Occupied housing units to Renter Occupied Housing units	McCabe 2016; Sampson et al, 1999; Crowder et al, 2012
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 23. List of independent variables in set 2 in Selection Effect Model with references to other works

Variable	Description	Citation
Area (Water)	Area (Water)	This study
Rural tract indicator > 4M sq. meters	Rural indicator for tracts greater than 4M sq. meters (median area)	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged IHS-transformed Real Aggregate income	Lagged Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % single-parent families w/kids	Lagged Percentage of single-parent families with own children under 18 years old of total families and subfamilies	Sampson et al, 1999; Crowder et al, 2012
Lagged IHS-transformed Commute less than 25 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes or work at home	This study
Lagged % Associate Degree Graduate	Lagged Percentage of Persons 25+ years old who have an associate degree but no bachelor’s degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 24. List of independent variables in set 3 in Selection Effect Model with references to other works

Variable	Description	Citation
Area (Water)	Area (Water)	This study
Rural tract indicator > 10M sq. meters	Rural indicator for tracts greater than 10M sq. meters	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged % African American	Lagged Black/African American percentage of total population	Brady et al, 2017; Crowder et al, 2012; Lee et al, 2008
Lagged Adult to child ratio	Lagged Ratio of adults 18+ years old to children under 18 years old (adults/children)	Sampson et al, 1999; Sharkey, 2014
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % Welfare rate	Lagged Percentage of households with public assistance inc. (incl. SSI) last year of total households	Sharkey, 2014
Lagged IHS-transformed Commute 25-45 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes	This study
Lagged % High School Graduate	Lagged Percentage of Persons 25+ years old who have completed high school but no college	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Renter-occupied	Lagged Percentage of renter-occupied housing units of total housing units	Crowder, Tanner et al, 2012; Albright, 2018; Pathak, Reader, and Casper, 2011;
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 25. List of independent variables in set 4 in Selection Effect Model with references to other works

Variable	Description	Citation
Area (Water)	Area (Water)	This study
Rural tract indicator > 4M sq. meters	Rural indicator for tracts greater than 4M sq. meters (median area)	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged % Hispanic	Lagged Percentage of Hispanic/Latino of total population	Brady et al, 2017; Crowder et al, 2012; Lee et al, 2008;
Lagged % children	Lagged Percentage of Children under 18 years old of total population	Sampson et al, 1999; Sharkey, 2014; Crowder et al, 2012
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % female-headed families	Percentage of female-headed families with or without own children of total families and subfamilies	Sharkey, 2014; Crowder et al, 2012
Lagged IHS-transformed Commute over 45 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes	This study
Lagged % Completed 8 years of school	Lagged Percentage of Persons 25+ years old who have completed 0-8 years of school	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged Owner to Renter rate	Lagged Ratio of Owner-Occupied housing units to Renter Occupied Housing units	McCabe, 2016; Sampson et al, 1999; Crowder et al, 2012
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 26. List of independent variables in set 1 in Treatment Effect Model with references to other works

Variable	Description	Citation
New restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in this or a previous time period	This study
New restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in any time period	This study
Area (Water)	Area (Water)	This study
Rural tract indicator > 10M m^2	Rural indicator for tracts greater than 10M sq. meters	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged IHS-transformed Real Average income	Lagged Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
Lagged % Minority	Lagged Non-White percentage of total population	Brady et al, 2017; Crowder et al, 2012
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged IHS-transformed Travel on public transportation	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included)	This study
Lagged % bachelor's or higher Degree Graduate	Lagged Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Poverty rate	Lagged Percentage of total persons below the poverty level in past 12 months	Sharkey, 2014; Crowder et al, 2012
Lagged Owner to Renter rate	Lagged Ratio of Owner-Occupied housing units to Renter Occupied Housing units	McCabe, 2016; Sampson et al, 1999; Crowder et al, 2012
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 27. List of independent variables in set 2 in Treatment Effect Model with references to other works

Variable	Description	Citation
New restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in this or a previous time period	This study
New restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in any time period	This study
Area (Water)	Area (Water)	This study
Rural tract indicator > 4M sq. meters	Rural indicator for tracts greater than 4M sq. meters (median area)	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged IHS-transformed Real Aggregate income	Lagged Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % single-parent families w/kids	Lagged Percentage of single-parent families with own children under 18 years old of total families and subfamilies	Sampson et al, 1999; Crowder et al, 2012
Lagged IHS-transformed Commute less than 25 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes or work at home	This study
Lagged % Associate Degree Graduate	Lagged Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 28. List of independent variables in set 3 in Treatment Effect Model with references to other works

Variable	Description	Citation
New restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in this or a previous time period	This study
New restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in any time period	This study
Area (Water)	Area (Water)	This study
Rural tract indicator > 10M m^2	Rural indicator for tracts greater than 10M sq. meters	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged % African American	Lagged Black/African American percentage of total population	Brady et al, 2017; Crowder et al, 2012; Lee et al, 2008
Lagged Adult to child ratio	Lagged Ratio of adults 18+ years old to children under 18 years old (adults/children)	Sampson et al, 1999; Sharkey, 2014
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % Welfare rate	Lagged Percentage of households with public assistance inc. (incl. SSI) last year of total households	Sharkey, 2014
Lagged IHS-transformed Commute 25-45 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes	This study
Lagged % High School Graduate	Lagged Percentage of Persons 25+ years old who have completed high school but no college	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged % Renter-occupied	Lagged Percentage of renter-occupied housing units of total housing units	Crowder, Tanner t al, 2012; Albright, 2018; Pathak, Reader, and Casper, 2011;
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 29. List of independent variables in set 4 in Treatment Effect Model with references to other works

Variable	Description	Citation
New restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in this or a previous time period	This study
New restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance under 4.27 m (14 ft) and over 3 m (9.8 ft) was built in this tract in any time period	This study
Area (Water)	Area (Water)	This study
Rural tract indicator > 4M sq. meters	Rural indicator for tracts greater than 4M sq. meters (median area)	This study
Lagged IHS-transformed Total bridges	Lagged Inverse Hyperbolic Sine Transformation of Total number of bridges in and near the tract	This study
Lagged % Hispanic	Lagged Percentage of Hispanic/Latino of total population	Brady et al, 2017; Crowder et al, 2012; Lee et al, 2008;
Lagged % children	Lagged Percentage of Children under 18 years old of total population	Sampson et al, 1999; Sharkey, 2014; Crowder et al, 2012
Lagged % foreign-born	Lagged Percentage of Foreign-born of total population	Lee et al, 2008;
Lagged % female-headed families	Percentage of female-headed families with or without own children of total families and subfamilies	Sharkey, 2014; Crowder et al, 2012
Lagged IHS-transformed Commute over 45 minutes	Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes	This study
Lagged % Completed 8 years of school	Lagged Percentage of Persons 25+ years old who have completed 0-8 years of school	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
Lagged Owner to Renter rate	Lagged Ratio of Owner-Occupied housing units to Renter Occupied Housing units	McCabe, 2016; Sampson et al, 1999; Crowder et al, 2012
Lagged % Vacant housing	Lagged Percentage of vacant housing units	Tach and Emory, 2017
Lagged % New housing	Lagged Percentage of change in number of housing units since last census of total housing units	Farley and Frey, 1994; Lee et al, 2008
Year	Year	This study
Tract	Census Tract Identifier	This study

Table 30. List of all used variables with references to other works

	Variable	Description	Citation
Physical Infrastructure Data	**New restrictive bridge dummy**	Dummy variable denoting that a new bridge with an underclearance under 14 ft & over 9.8 ft was built in this tract in the last 10 years	This study
	New restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance under 14 ft & over 9.8 ft was built in this tract in this or a previous time period	This study
	New restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance under 14 ft & over 9.8 ft was built in this tract in any time period	This study
	New restrictive bridge count	Total number of bridges in and near the tract with underclearance under 14 ft & over 9.8 ft built in the last 10 years	This study
	New non-restrictive bridge dummy	Dummy variable denoting that a new bridge with an underclearance over 14 ft was built in this tract in the last 10 years	This study
	New non-restrictive bridge treatment dummy	Dummy variable denoting that a new bridge with an underclearance over 14 ft was built in this tract in this or a previous time period	This study
	New non-restrictive bridge treatment group dummy	Dummy variable denoting that a new bridge with an underclearance over 14 ft was built in this tract in any time period	This study
	New non-restrictive bridge count	Total number of bridges in and near the tract with underclearance over 14 ft built in the last 10 years	This study
	All new bridge dummy	Dummy variable denoting that a new bridge was built in this tract in the last 10 years	This study
	All new bridge treatment dummy	Dummy variable denoting that a new bridge was built in this tract in this or a previous time period	This study
	All new bridge treatment group dummy	Dummy variable denoting that a new bridge was built in this tract in any time period	This study
	All new bridge count	Total number of bridges in and near the tract built in the last 10 years	This study
	***IHS-transformed total bridges**	Inverse hyperbolic sine transformation of total number of bridges in and near the tract	This study
	Tract	Census Tract Identifier	This study
	Area (Land)	Area (Land)	This study
	% water area	Percentage of area composed of water	This study
	Rural tract indicator > 10M sq. meters	Rural indicator for tracts greater than 10M sq. meters	This study
	Rural tract indicator > 4M sq. meters	Rural indicator for tracts greater than 4M sq. meters (median area)	This study
	Year	Year	This study
	Treatment Normalized Year	Treatment normalized year (0 is year of treatment)	This study

Table 30. List of all used variables with references to other works *(cont'd)*

Social Demographic Data	***IHS-transformed Real Average income**	Inverse Hyperbolic Sine Transformation of average household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
	***IHS-transformed Real Aggregate income**	Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US)	Sampson et al, 1999; Lee et al, 2008
	Population	Total population	
	***% Poverty rate**	Percentage of total persons below the poverty level in past 12 months	Sharkey, 2014; Crowder et al, 2012, Carless, 2018
	***% Welfare rate**	Percentage of households with public assistance inc. (incl. SSI) last year of total households	Sharkey, 2014
	***% Minority**	Non-White percentage of total population	Brady et al, 2017; Crowder et al, 2012
	***% African American**	Black/African American percentage of total population	Brady et al, 2017; Carless, 2018; Crowder et al, 2012; Lee et al, 2008
	***% Hispanic**	Percentage of Hispanic/Latino of total population	Brady et al, 2017; Crowder et al, 2012; Lee et al, 2008;
	***% foreign-born**	Percentage of Foreign-born of total population	Lee et al, 2008;
	***% children**	Percentage of Children under 18 years old of total population	Sampson et al, 1999; Sharkey, 2014; Crowder et al, 2012
	***IHS-transformed adult to child ratio**	Inverse Hyperbolic Sine Transformation of ratio of adults 18+ years old to children under 18 years old (adults/children)	Sampson et al, 1999; Sharkey, 2014
	***% single-parent families w/kids**	Percentage of single-parent families with own children under 18 years old of total families and subfamilies	Sampson et al, 1999; Crowder et al, 2012
	***% female-headed families**	Percentage of female-headed families with or without own children of total families and subfamilies	Sharkey, 2014; Crowder et al, 2012
	***IHS-transformed Travel on public transportation**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included)	This study
	***IHS-transformed Commute less than 25 minutes**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes	This study
	***IHS-transformed Commute 25-45 minutes**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes	This study
	***IHS-transformed Commute over 45 minutes**	Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes	This study
	***% Completed 8 years of school**	Percentage of persons 25+ years old who have completed 0-8 years of school	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
	***% High School Graduate**	Percentage of persons 25+ years old who have completed high school but no college	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
	***% Some College**	Percentage of Persons 25+ years old who have completed some college but no degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008
	***% Associate Degree Graduate**	Percentage of persons 25+ years old who have an associate degree but no bachelor's degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008

Table 30. List of all used variables with references to other works *(cont'd)*

Social Demographic Data	***% bachelor's or higher Degree Graduate**	Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	Sampson et al, 1999; Crowder et al, 2012; Lee et al, 2008; Carless, 2018
	***Owner to Renter rate**	Ratio of Owner-Occupied housing units to Renter Occupied Housing units	McCabe, 2016; Sampson et al, 1999; Crowder et al, 2012
	***% Renter-occupied**	Percentage of renter-occupied housing units of total housing units	Crowder et al, 2012; Pathak, Reader, Tanner & Casper, 2011;
	***% Vacant housing**	Percentage of vacant housing units	Tach & Emory, 2017
	***% New housing**	Percentage of change in number of housing units since last census of total housing units	Farley & Frey, 1994; Lee et al, 2008

Section D Rural Tracts

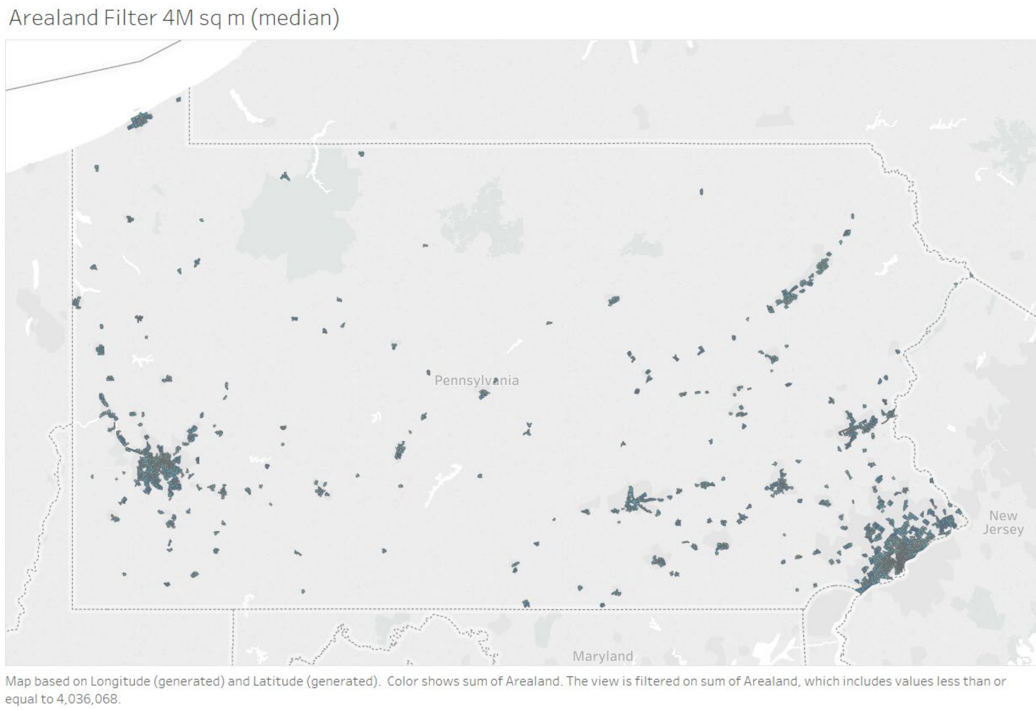

Fig. 31. The blue areas depict tracts coded as zero for the Rural 4 million m² variable

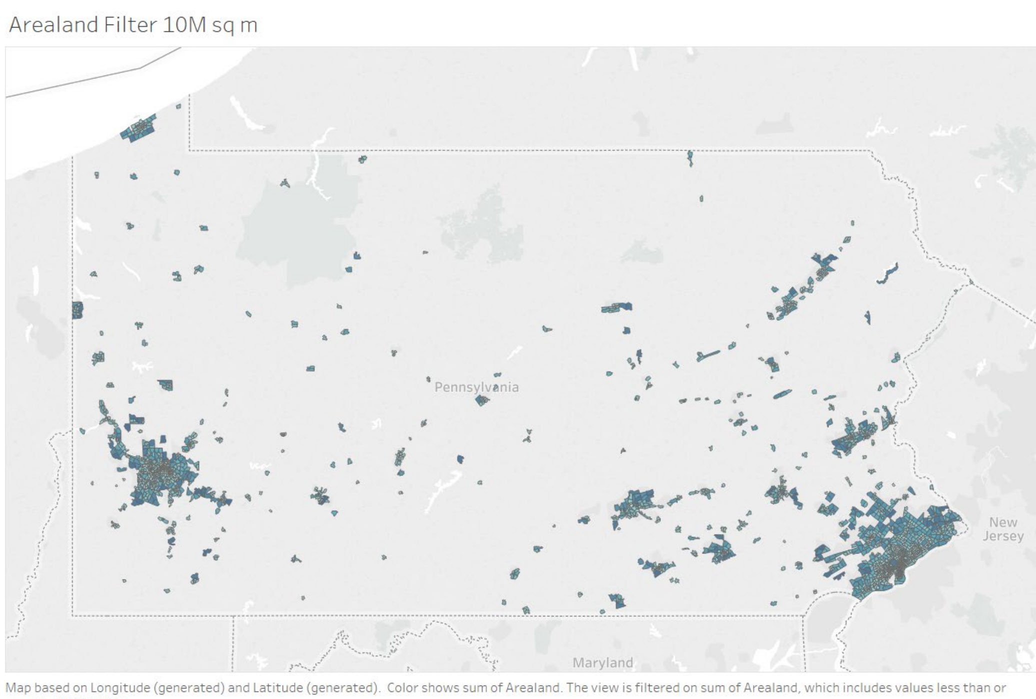

Fig. 32. The blue areas depict tracts coded as zero for the Rural 10 million m² variable

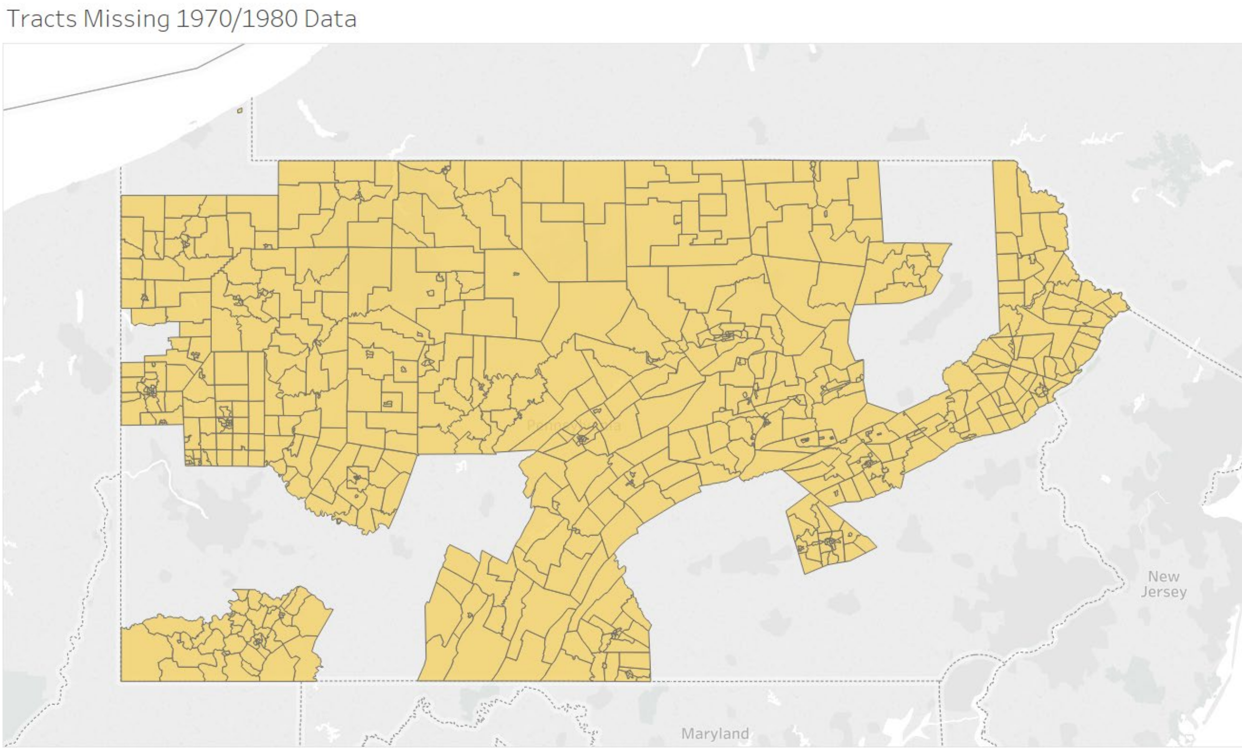

Fig. 33. The yellow areas depict tracts missing census data for 1970 and 1980 data

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts

	Area (Land)	Area (Water)	Rural tract indicator > 10M sq. m	Rural tract indicator > 4M sq. m
Mean Difference (Data tracts – missing tracts)				
All years	-90926591.552	-934094.421	-0.411	-0.349
T-Test				
All years	-37.938	-20.684	-46.478	-41.718
All years p-values	5.93E-265	3.50E-90	0.00E+00	0.00E+00
Kolmogorov-Smirnov Test				
All years	0.483	0.343	0.411	0.349
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00

*Note: Tracts normalized across years to 2010 census boundaries to ensure accurate comparisons

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Population	Population Density	Real Aggregate income	Real Average income	Poverty level	Welfare
			Mean Difference			
1970	3694.414	2840.743	59928426.306	52749.310	360.972	44.602
1980	2527.604	2269.499	38234156.131	29008.216	263.626	87.220
1990	-81.983	1837.990	19594643.847	14350.610	-80.060	-0.010
2000	-178.047	1775.125	17763525.653	13693.529	-51.119	3.965
2010	-157.954	1808.055	18519507.905	14071.550	-41.622	4.630
All years	1160.807	2106.283	30808051.968	24774.643	90.359	28.081
			T-Test			
1970	97.382	34.317	88.383	91.039	40.413	29.069
1970 p-values	0.00E+00	3.57E-214	0.00E+00	0.00E+00	8.96E-278	7.11E-161
1980	32.525	30.599	22.680	30.160	21.019	24.447
1980 p-values	3.95E-157	2.19E-180	1.55E-91	3.69E-140	5.38E-90	2.06E-120
1990	-1.327	24.523	13.153	20.245	-5.217	-0.003
1990 p-values	1.85E-01	1.67E-121	6.61E-38	2.13E-85	2.08E-07	9.98E-01
2000	-2.790	24.516	9.326	16.886	-3.376	1.070
2000 p-values	5.35E-03	2.18E-121	3.10E-20	7.10E-61	7.56E-04	2.85E-01
2010	-2.238	24.926	8.149	15.243	-2.338	2.445
2010 p-values	2.54E-02	2.41E-125	7.00E-16	3.81E-50	1.95E-02	1.46E-02
All years	28.713	62.015	31.748	48.063	12.381	17.939
All years p-values	1.18E-166	0.00E+00	6.42E-205	0.00E+00	7.88E-35	9.94E-71
			Kolmogorov-Smirnov Test			
1970	0.987	0.987	0.986	0.986	0.985	0.939
1970 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1980	0.671	0.717	0.561	0.475	0.665	0.664
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1990	0.064	0.490	0.213	0.333	0.264	0.174
1990 p-values	2.36E-02	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.11E-14
2000	0.079	0.494	0.170	0.284	0.247	0.174
2000 p-values	2.32E-03	0.00E+00	4.98E-14	0.00E+00	0.00E+00	1.18E-14
2010	0.074	0.489	0.154	0.271	0.190	0.150
2010 p-values	5.34E-03	0.00E+00	1.40E-11	0.00E+00	0.00E+00	5.24E-11
All years	0.335	0.592	0.311	0.294	0.332	0.306
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Whites	Minorities	African Americans	American Indians	Asians	Hispanics	Foreign-born
			Mean Difference				
1970	3291.229	403.189	391.329	0.000	0.000	38.465	157.642
1980	2095.705	431.892	387.607	2.683	17.247	45.845	115.335
1990	-512.120	430.137	367.348	-0.663	28.818	51.725	77.824
2000	-672.730	494.683	388.792	1.031	58.530	80.349	110.881
2010	-728.035	570.081	404.131	2.324	97.194	130.930	150.616
All years	694.810	465.997	387.841	1.075	40.358	69.463	122.459
			T-Test				
1970	92.698	16.151	15.769	NA	NA	13.641	44.389
1970 p-values	0.00E+00	6.31E-56	1.65E-53	NA	NA	5.60E-41	9.88E-324
1980	27.199	18.444	17.229	13.584	12.808	9.161	31.453
1980 p-values	2.36E-122	1.30E-71	4.25E-63	8.68E-41	1.84E-36	9.05E-20	1.74E-186
1990	-8.220	18.433	17.079	-1.764	10.528	7.760	18.713
1990 p-values	5.16E-16	5.88E-72	2.60E-62	7.80E-02	2.67E-25	1.14E-14	2.71E-73
2000	-10.568	20.804	18.442	2.601	14.271	8.891	18.687
2000 p-values	4.43E-25	2.79E-90	3.54E-72	9.39E-03	1.58E-44	1.03E-18	4.19E-73
2010	-10.730	20.884	18.205	5.135	15.798	9.422	16.919
2010 p-values	8.68E-26	2.86E-90	1.75E-70	3.03E-07	8.92E-54	9.96E-21	2.22E-60
All years	17.715	41.662	38.403	6.831	23.884	17.877	46.973
All years p-values	5.00E-68	0.00E+00	8.25E-308	8.97E-12	1.91E-123	1.15E-70	0.00E+00
			Kolmogorov-Smirnov Test				
1970	0.987	0.860	0.743	0.000	0.000	0.727	0.972
1970 p-values	0.00E+00	0.00E+00	0.00E+00	1.00E+00	1.00E+00	0.00E+00	0.00E+00
1980	0.669	0.639	0.572	0.254	0.421	0.596	0.667
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1990	0.168	0.351	0.317	0.199	0.244	0.197	0.366
1990 p-values	1.00E-13	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2000	0.209	0.378	0.324	0.115	0.294	0.251	0.365
2000 p-values	0.00E+00	0.00E+00	0.00E+00	1.26E-06	0.00E+00	0.00E+00	0.00E+00
2010	0.225	0.408	0.369	0.062	0.360	0.294	0.345
2010 p-values	0.00E+00	0.00E+00	0.00E+00	3.00E-02	0.00E+00	0.00E+00	0.00E+00
All years	0.333	0.345	0.344	0.031	0.202	0.272	0.469
All years p-values	0.00E+00	0.00E+00	0.00E+00	1.05E-02	0.00E+00	0.00E+00	0.00E+00

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Married families with children	Single-parent families w/kids	Male-headed families with children	Female-headed families	Female-headed families with children	Children	Adult to child ratio
				Mean Difference			
1970	437.542	59.663	8.909	110.165	50.754	1207.400	0.959
1980	247.588	65.340	7.927	113.685	57.412	653.345	0.271
1990	-47.944	13.885	-2.566	40.446	16.451	-48.268	0.031
2000	-29.616	15.497	-5.565	42.909	21.061	-9.095	-0.003
2010	-8.937	12.842	-6.988	43.367	19.830	12.231	-0.007
All years	119.727	33.445	0.344	70.114	33.102	363.123	0.250
				T-Test			
1970	92.981	38.003	48.356	47.330	34.645	86.468	148.362
1970 p-values	0.00E+00	1.56E-251	0.00E+00	0.00E+00	3.02E-216	0.00E+00	0.00E+00
1980	26.558	28.196	24.936	32.909	27.079	29.908	7.329
1980 p-values	2.98E-118	8.00E-155	7.07E-120	2.93E-199	1.04E-144	3.53E-143	6.41E-13
1990	-6.526	5.357	-4.530	10.492	7.179	-2.874	4.709
1990 p-values	1.00E-10	9.41E-08	6.45E-06	3.59E-25	9.57E-13	4.13E-03	2.78E-06
2000	-4.033	5.224	-6.480	11.172	8.554	-0.528	-0.461
2000 p-values	5.84E-05	1.94E-07	1.36E-10	2.94E-28	2.19E-17	5.98E-01	6.45E-01
2010	-1.242	4.062	-8.584	10.613	7.786	0.667	-0.807
2010 p-values	2.14E-01	5.08E-05	2.97E-17	1.12E-25	1.10E-14	5.05E-01	4.20E-01
All years	28.968	23.204	0.886	36.373	28.725	35.349	22.406
All years p-values	1.95E-171	3.11E-115	3.76E-01	9.36E-270	5.20E-174	1.14E-246	3.15E-104
				Kolmogorov-Smirnov Test			
1970	0.986	0.980	0.833	0.985	0.974	0.988	0.987
1970 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1980	0.671	0.667	0.567	0.674	0.667	0.671	0.470
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1990	0.161	0.091	0.157	0.129	0.090	0.108	0.183
1990 p-values	1.24E-12	2.49E-04	6.04E-12	2.93E-08	2.85E-04	6.37E-06	4.44E-16
2000	0.143	0.106	0.173	0.157	0.115	0.074	0.133
2000 p-values	5.20E-10	1.03E-05	1.70E-14	5.26E-12	1.16E-06	5.06E-03	8.87E-09
2010	0.138	0.105	0.206	0.150	0.114	0.063	0.140
2010 p-values	2.34E-09	1.39E-05	0.00E+00	5.10E-11	1.58E-06	2.65E-02	1.10E-09
All years	0.335	0.332	0.260	0.335	0.330	0.337	0.293
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Travel on public transportation	Travel in private vehicle	Travel by other means	Commute less than 25 minutes	Commute 25-45 minutes	Commute over 45 minutes
			Mean Difference			
1970	206.656	1023.670	143.645	0.000	0.000	0.000
1980	146.371	826.214	31.795	449.302	446.601	150.561
1990	121.862	11.073	-11.559	-66.999	117.434	52.849
2000	95.711	-83.223	-6.138	-95.246	74.681	18.619
2010	101.792	-66.328	-2.662	-2.198	0.000	0.000
All years	134.478	342.281	31.016	56.972	127.743	44.406
			T-Test			
1970	33.096	99.255	44.012	NA	NA	NA
1970 p-values	5.55E-201	0.00E+00	0.00E+00	NA	NA	NA
1980	33.994	29.478	4.317	22.783	38.803	34.076
1980 p-values	5.91E-213	5.41E-139	1.76E-05	3.87E-92	1.93E-222	3.55E-212
1990	28.202	0.415	-1.843	-2.926	14.418	11.084
1990 p-values	8.85E-155	6.78E-01	6.56E-02	3.51E-03	2.66E-44	1.09E-27
2000	27.339	-2.860	-1.091	-4.224	8.004	2.523
2000 p-values	6.89E-148	4.30E-03	2.76E-01	2.59E-05	2.65E-15	1.18E-02
2010	25.339	-2.047	-0.496	-0.853	NA	NA
2010 p-values	2.62E-129	4.08E-02	6.20E-01	3.94E-01	NA	NA
All years	64.947	20.833	11.660	4.638	27.228	16.372
All years p-values	0.00E+00	2.44E-92	4.93E-31	3.60E-06	4.04E-156	3.87E-59
			Kolmogorov-Smirnov Test			
1970	0.932	0.986	0.982	0.000	0.000	0.000
1970 p-values	0.00E+00	0.00E+00	0.00E+00	1.00E+00	1.00E+00	1.00E+00
1980	0.687	0.670	0.525	0.670	0.680	0.668
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1990	0.544	0.067	0.080	0.079	0.211	0.156
1990 p-values	0.00E+00	1.54E-02	1.97E-03	2.22E-03	0.00E+00	6.44E-12
2000	0.468	0.126	0.083	0.120	0.156	0.090
2000 p-values	0.00E+00	7.00E-08	1.11E-03	3.51E-07	8.24E-12	2.97E-04
2010	0.469	0.106	0.098	0.084	0.000	0.000
2010 p-values	0.00E+00	9.67E-06	6.61E-05	9.12E-04	1.00E+00	1.00E+00
All years	0.567	0.333	0.296	0.141	0.187	0.137
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Completed 8 years of school	Completed 9-12 years of school	High School Graduate	Some College	Associate Degree Graduate	bachelor's or higher Degree Graduate
			Mean Difference			
1970	604.240	438.502	713.514	151.479	0.000	196.350
1980	286.405	269.568	608.338	181.801	0.000	243.837
1990	-47.492	-10.627	-193.634	70.342	18.487	177.821
2000	-27.957	-40.771	-301.168	39.791	8.717	209.485
2010	-9.435	-43.550	-322.319	15.508	-17.841	244.241
All years	161.152	122.624	100.946	91.784	1.873	214.347
			T-Test			
1970	68.608	70.782	90.782	67.045	NA	46.490
1970 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	NA	0.00E+00
1980	29.430	30.007	29.449	33.398	NA	27.969
1980 p-values	3.24E-148	2.26E-151	4.03E-138	1.36E-174	NA	1.12E-144
1990	-6.680	-1.186	-9.667	12.394	6.698	15.211
1990 p-values	3.83E-11	2.36E-01	3.12E-21	1.37E-33	3.12E-11	1.61E-49
2000	-5.760	-4.413	-13.861	5.399	2.668	13.707
2000 p-values	1.08E-08	1.12E-05	3.56E-40	8.03E-08	7.72E-03	7.51E-41
2010	-2.235	-6.414	-13.693	1.736	-3.643	12.661
2010 p-values	2.56E-02	2.04E-10	2.53E-39	8.29E-02	2.82E-04	3.44E-35
All years	40.948	27.338	8.068	22.632	0.919	31.179
All years p-values	0.00E+00	3.40E-155	9.16E-16	3.30E-108	3.58E-01	1.22E-201
			Kolmogorov-Smirnov Test			
1970	0.987	0.987	0.987	0.988	0.000	0.986
1970 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00	0.00E+00
1980	0.673	0.674	0.674	0.670	0.000	0.669
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00	0.00E+00
1990	0.186	0.116	0.211	0.195	0.134	0.228
1990 p-values	1.11E-16	1.05E-06	0.00E+00	0.00E+00	6.67E-09	0.00E+00
2000	0.187	0.170	0.278	0.101	0.072	0.231
2000 p-values	1.11E-16	5.10E-14	0.00E+00	3.18E-05	7.59E-03	0.00E+00
2010	0.164	0.195	0.298	0.052	0.107	0.232
2010 p-values	4.30E-13	0.00E+00	0.00E+00	1.08E-01	8.09E-06	0.00E+00
All years	0.332	0.336	0.337	0.334	0.018	0.333
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	3.68E-01	0.00E+00

Table 31. Results of statistical tests for all variables comparing tracts missing census data vs. all other tracts (cont'd)

	Professionals	New housing	Owner-occupied	Renter-occupied	Vacant housing
			Mean Difference		
1970	576.935	0.000	792.541	372.230	44.218
1980	503.089	-238.787	434.435	303.980	50.425
1990	238.065	-1140.348	-66.299	63.743	-167.595
2000	190.374	-52.641	-112.652	57.553	-167.687
2010	187.655	-11.628	-122.604	64.956	-176.736
All years	339.224	-288.681	185.084	172.492	-83.475
			T-Test		
1970	77.525	NA	90.420	52.182	38.542
1970 p-values	0.00E+00	NA	0.00E+00	0.00E+00	5.33E-258
1980	37.436	-8.716	15.461	28.148	15.502
1980 p-values	5.08E-212	1.82E-17	1.12E-47	8.64E-142	5.19E-50
1990	16.743	-34.124	-3.465	5.397	-11.287
1990 p-values	4.08E-58	5.08E-152	5.49E-04	8.09E-08	2.66E-27
2000	11.714	-5.819	-5.357	4.591	-11.906
2000 p-values	2.12E-30	7.74E-09	1.02E-07	4.88E-06	5.88E-30
2010	9.680	-0.769	-5.152	4.640	-12.266
2010 p-values	1.63E-21	4.42E-01	3.02E-07	3.88E-06	1.59E-31
All years	40.043	-23.832	15.014	29.283	-15.059
All years p-values	2.62E-310	7.94E-117	9.19E-50	2.35E-176	9.47E-50
			Kolmogorov-Smirnov Test		
1970	0.988	0.000	0.986	0.980	0.971
1970 p-values	0.00E+00	1.00E+00	0.00E+00	0.00E+00	0.00E+00
1980	0.678	0.445	0.537	0.667	0.665
1980 p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1990	0.267	0.667	0.103	0.136	0.310
1990 p-values	0.00E+00	0.00E+00	2.05E-05	4.32E-09	0.00E+00
2000	0.205	0.242	0.133	0.143	0.318
2000 p-values	0.00E+00	0.00E+00	1.09E-08	4.27E-10	0.00E+00
2010	0.199	0.078	0.143	0.152	0.328
2010 p-values	0.00E+00	2.63E-03	4.90E-10	2.43E-11	0.00E+00
All years	0.334	0.180	0.308	0.332	0.327
All years p-values	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00

Section E Logistic selection effect (SE) results (full panel and circular buffers)

Table 32. Bridges built by underclearance category during census period (e.g., 1961-1970)

Year	Mini	Low	Medium	High	Super	Restrictive	Non-restrictive	All bridges
1970	6	50	944	436	393	56	1,773	5,816
1980	11	4	510	153	332	15	995	3,360
1990	3	9	194	95	247	12	536	2,987
2000	3	4	134	171	283	7	588	2,697
2010	0	4	115	256	287	4	658	2,872
Total	23	71	1,897	1,111	1,542	94	4,550	17,732

Table 33. Restrictive bridge SE logistic model results (full panel and circular buffers)

DV: Dichotomous variable denotes a new restrictive bridge was built in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	5.268***	5.423***	4.988***	4.849***
	(1.168)	(1.112)	(1.131)	(1.132)
Rural tract indicator > 10M sq. meters	0.970***		0.927***	
	(0.273)		(0.272)	
Rural tract indicator > 4M sq. meters		1.235***		1.277***
		(0.299)		(0.307)
Lagged IHS-transformed Total bridges	0.099	0.061	0.192*	0.082
	(0.096)	(0.102)	(0.086)	(0.100)
Lagged IHS-transformed Real Average Income	-0.011			
	(0.053)			
Lagged IHS-transformed Real Aggregate Household Income		0.089**		
		(0.030)		
Lagged non-White Population	-1.062			
	(1.034)			
Lagged African American Population Percentage of			-1.134	
			(1.152)	
Lagged Hispanic Population Percentage of				-18.001
				(14.234)
Lagged Population Percentage of Foreign-born	-0.026	4.21	3.173	-0.43
	(4.873)	(3.420)	(3.573)	(5.850)
Lagged Population Percentage of under 18				14.346***
				(3.134)
Lagged IHS-transformed Adult to Child Ratio			0.184	
			(0.259)	
Lagged Percentage of single parents with Children		3.014		
		(1.667)		
Lagged Percentage of female Head of Household				-3.341
				(1.915)
AIC	747.527	715.729	730.279	683.437
BIC	916.611	861.756	891.677	852.522
Log Likelihood	-351.764	-338.864	-344.139	-319.719
Deviance	703.527	677.729	688.279	639.437
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Table 33. Restrictive bridge SE logistic model results (full panel and circular buffers) cont'd

DV: Dichotomous variable denotes a new restrictive bridge was built in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged IHS-transformed Population Travel on Public Transportation	0.065 (0.110)			0.199 (0.115)
Lagged IHS-transformed Population with Commute < 25 minutes		-0.365*** (0.098)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.280** (0.104)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.784*** (0.151)
Lagged Over 25-yr-old with at Least 8 Years Education	-14.965 (7.978)			-4.188 (5.445)
Lagged Over 25-yr-old with at Least High School Education			-3.402* (1.423)	
Lagged Over 25-yr-old with Associate Degree		-20.402* (8.687)		
Lagged Over 25-yr-old with bachelor's degree	-2.13 (2.495)			
Lagged Population Percentage of Below the Poverty Line	2.413 (1.662)			
Lagged Population Percentage of Receiving Welfare			3.628 (2.008)	
Lagged Owner to Renter Ratio	-0.051 (0.042)			-0.101 (0.068)
Lagged Percentage of Housing Units Renter-occupied			1.807 (1.035)	
Lagged Percentage of Housing Units Vacant	-3.205 (3.335)	-0.974 (2.177)	0.004 (2.316)	0.261 (1.955)
Lagged Percent Change in Housing Unit Supply	-1.134* (0.569)	-0.897 (0.531)	-1.028 (1.027)	-1.682* (0.738)
AIC	747.527	715.729	730.279	683.437
BIC	916.611	861.756	891.677	852.522
Log Likelihood	-351.764	-338.864	-344.139	-319.719
Deviance	703.527	677.729	688.279	639.437
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Table 34. Non-restrictive bridge SE logistic model results (full panel and circular buffers)

DV: Dummy variable denoting that a new non-restrictive bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	2.513***	2.814***	2.435***	2.550***
	(0.413)	(0.421)	(0.412)	(0.408)
Rural tract indicator > 10M sq. meters	0.648***		0.623***	
	(0.078)		(0.079)	
Rural tract indicator > 4M sq. meters		0.982***		1.108***
		(0.081)		(0.080)
Lagged IHS-transformed total bridges	0.330***	0.245***	0.328***	0.293***
	(0.037)	(0.038)	(0.039)	(0.037)
Lagged IHS-transformed real average income	-0.022			
	(0.016)			
Lagged IHS-transformed real aggregate household income		-0.005		
		(0.007)		
Lagged non-White population percentage of	-1.238***			
	(0.288)			
Lagged African American population percentage of			-0.920**	
			(0.344)	
Lagged Hispanic/Latino population percentage of				-5.249**
				(1.596)
Lagged foreign-born population percentage of	-0.136	2.347*	0.339	1.33
	(1.233)	(0.990)	(1.064)	(1.093)
Lagged population percentage of under 18				-1.538***
				(0.417)
Lagged IHS-transformed adult to child ratio			0.201	
			(0.139)	
Lagged percentage of single parents with children		1.099		
		(0.731)		
Lagged percentage of female-headed families				1.207**
				(0.458)
AIC	9621.492	9547.857	9638.509	9488.454
BIC	9759.834	9663.142	9769.165	9626.796
Log Likelihood	-4792.746	-4758.929	-4802.255	-4726.227
Deviance	9585.492	9517.857	9604.509	9452.454
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Table 34. Non-restrictive bridge SE logistic model results (full panel and circular buffers) cont'd

DV: Dummy variable denoting that a new non-restrictive underclearance bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged IHS-transformed population travel on public transportation	0.114***			0.137***
	(0.027)			(0.027)
Lagged IHS-transformed population with commute < 25 minutes		0.069		
		(0.045)		
Lagged IHS-transformed population with commute > 25 < 45 minutes			-0.016	
			(0.034)	
Lagged IHS-transformed population with commute > 45 minutes				-0.078*
				(0.036)
Lagged percentage of persons 25+ years old who have completed 0-8 years of school	-0.168			1.793
	(1.438)			(1.102)
Lagged percentage of persons 25+ years old who have completed high school but no college			-0.782	
			(0.492)	
Lagged percentage of persons 25+ years old who have an associate degree but no bachelor's degree		-3.075		
		(3.145)		
Percentage of persons 25+ years old who have a bachelor's or graduate/professional degree	0.545			
	(0.425)			
Lagged population percentage of below the poverty line	2.302***			
	(0.525)			
Lagged population percentage of Receiving welfare			1.975**	
			(0.719)	
Lagged owner to renter ratio	-0.001			-0.001
	(0.001)			(0.001)
Lagged percentage of housing units renter-occupied			0.910**	
			(0.285)	
Lagged percentage of housing units vacant	-2.280***	-1.653*	-2.309***	-1.467**
	(0.692)	(0.701)	(0.689)	(0.536)
Lagged percent change in housing unit supply	-0.097	-0.114	-0.064	-0.056
	(0.603)	(0.757)	(0.659)	(0.494)
AIC	9621.492	9547.857	9638.509	9488.454
BIC	9759.834	9663.142	9769.165	9626.796
Log Likelihood	-4792.746	-4758.929	-4802.255	-4726.227
Deviance	9585.492	9517.857	9604.509	9452.454
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Table 35. All new bridges SE logistic model results (full panel and circular buffers)

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	-0.209 (0.434)	-0.016 (0.478)	-0.292 (0.428)	0.005 (0.490)
Rural tract indicator > 10M sq. meters	1.485*** (0.062)		1.490*** (0.063)	
Rural tract indicator > 4M sq. meters		1.912*** (0.075)		1.858*** (0.076)
Lagged IHS-transformed Total bridges	0.753*** (0.027)	0.778*** (0.028)	0.773*** (0.027)	0.770*** (0.028)
Lagged IHS-transformed Real Average Income	-0.022* (0.009)			
Lagged IHS-transformed Real Aggregate Household Income		0.007 (0.006)		
Lagged non-White Population Percentage of	-2.117*** (0.265)			
Lagged African American Population Percentage of			-1.869*** (0.279)	
Lagged Hispanic Population Percentage of				-7.093*** (1.586)
Lagged Population Percentage of Foreign-born	-2.941* (1.257)	-7.803*** (1.278)	-6.073*** (1.222)	-4.359** (1.418)
Lagged Population Percentage of under 18				1.118*** (0.305)
Lagged IHS-transformed Adult to Child Ratio			-0.098 (0.118)	
Lagged Percentage of single parents with Children		-1.705*** (0.479)		
Lagged Percentage of female Head of Household				-1.340*** (0.403)
AIC	11034.913	10775.511	11008.14	10758.508
BIC	11203.997	10921.538	11169.538	10927.593
Log Likelihood	-5495.456	-5368.755	-5483.07	-5357.254
Deviance	10990.913	10737.511	10966.14	10714.508
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Table 35. All new bridges SE logistic model results (full panel and circular buffers) cont'd

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged IHS-transformed Population Travel on Public Transportation	-0.032			-0.037*
	(0.018)			(0.019)
Lagged IHS-transformed Population with Commute < 25 minutes		-0.071***		
		(0.016)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.083***	
			(0.016)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.126***
				(0.017)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education	-3.374***			0.938
	(0.672)			(0.725)
Lagged percentage of over 25-yr-olds with at Least High School Education			-0.955***	
			(0.213)	
Lagged percentage of over 25-yr-olds with Associate Degree		-6.724***		
		(1.346)		
Lagged percentage of over 25-yr-olds with bachelor's degree	-0.986***			
	(0.232)			
Lagged Population Percentage of Below the Poverty Line	1.470**			
	(0.458)			
Lagged Population Percentage of Receiving Welfare			0.662	
			(0.644)	
Lagged Owner to Renter Ratio	0			0
	0.000			0.000
Lagged Percentage of Housing Units Renter-occupied			0.328	
			(0.239)	
Lagged Percentage of Housing Units Vacant	-1.298***	-0.205	-0.655	0.018
	(0.327)	(0.335)	(0.342)	(0.342)
Lagged Percent Change in Housing Unit Supply	0.044	0.057	0.11	0.016
	(0.058)	(0.061)	(0.104)	(0.059)
AIC	11034.913	10775.511	11008.14	10758.508
BIC	11203.997	10921.538	11169.538	10927.593
Log Likelihood	-5495.456	-5368.755	-5483.07	-5357.254
Deviance	10990.913	10737.511	10966.14	10714.508
Num. obs.	16085	16085	16085	16085

***p < 0.001, **p < 0.01, *p < 0.05

Section F Full Model Results

To make interpretations, the authors use the average marginal effect sizes. While there is debate on the overall appropriateness of comparing different types of models, average marginal effects are the most comparable measures when looking across different types of model specifications (Bogard 2016; Davis 2018; Fernihough 2019; Williams 2018). For example, using the average marginal effect size, a small increase in the percentage of the non-White population, is associated with a reduced probability of having a non-restrictive bridge and any new bridge construction, by 10.4% and 17.7%, respectively. While these variables were also negatively associated with fewer restrictive bridges, these associations were not robust. Per Table 1 in the main article, these effects could be more prominent to non-restrictive as opposed to restrictive bridges due to sample size (there are far fewer restrictive bridges).

Table 36. Mini bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new mini bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	3.493 (4.461)	7.54 (5.727)	9.046 (7.012)	5.562 (5.668)
Rural tract indicator > 10M sq. meters	1.916 (3.642)		2.965 (3.135)	
Rural tract indicator > 4M sq. meters		2.514 (1.634)		1.948 (1.419)
Lagged IHS-transformed Total bridges	-1.609* (0.692)	-1.35 (0.755)	-1.153 (0.760)	-1.592* (0.652)
Lagged IHS-transformed Real Average Income	0.163 (0.280)		0.567 (0.828)	
Lagged IHS-transformed Real Aggregate Household Income		-0.258 (0.233)		0.075 (0.163)
Lagged Population Percentage of Below the Poverty Line	0.126 (10.365)			
Lagged Population Percentage of Receiving Welfare			0.546 (8.823)	
Lagged non-White Population Percentage of	2.352 (2.440)			
Lagged African American Population Percentage of			-0.561 (1.824)	
Lagged Hispanic Population Percentage of				-3.991 (6.601)
Lagged Population Percentage of Foreign-born		5.417 (16.132)		3.937 (16.647)
Lagged Population Percentage of under 18		7.566 (11.235)		
Lagged IHS-transformed Adult to Child Ratio			-12.438 (13.690)	
AIC	89.488	77.026	80.512	84.606
BIC	152.358	139.896	143.382	147.476
Log Likelihood	-30.744	-24.513	-26.256	-28.303
Deviance	67.907	58.219	61.103	63.667
Num. obs.	659	659	659	659

***p < 0.001, **p < 0.01, *p < 0.05

Table 36. Mini bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new mini bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		12.566 (9.279)		
Lagged Percentage of female Head of Household				4.876 (8.822)
Lagged IHS-transformed Population Travel on Public Transportation	-0.628 (0.483)			-0.647 (0.475)
Lagged IHS-transformed Population with Commute < 25 minutes		4.771** (1.746)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			3.84 (2.443)	
Lagged IHS-transformed Population with Commute > 45 minutes				1.049 (1.082)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				27.468 (15.453)
Lagged percentage of over 25-yr-olds with at Least High School Education			33.497* (15.964)	
Lagged percentage of over 25-yr-olds with Associate Degree		18.917 (23.891)		
Lagged percentage of over 25-yr-olds with bachelor's degree	1.085 (6.994)			
Lagged Owner to Renter Ratio	-0.058 (0.325)			
Lagged Percentage of Housing Units Renter-occupied			7.73 (8.902)	
Lagged Percentage of Housing Units Vacant	-1.771 (13.748)			
Lagged Percent Change in Housing Unit Supply		-1.229 (1.446)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	89.488	77.026	80.512	84.606
BIC	152.358	139.896	143.382	147.476
Log Likelihood	-30.744	-24.513	-26.256	-28.303
Deviance	67.907	58.219	61.103	63.667
Num. obs.	659	659	659	659

***p < 0.001, **p < 0.01, *p < 0.05

Table 37. Low bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new low bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	-0.48	-1.132	-0.462	-0.44
	(4.472)	(3.598)	(3.453)	(3.410)
Rural tract indicator > 10M sq. meters	1.121		0.755	
	(0.960)		(0.833)	
Rural tract indicator > 4M sq. meters		-0.407		-0.713
		(1.012)		(0.937)
Lagged IHS-transformed Total bridges	-0.254	-0.066	-0.289	-0.103
	(0.267)	(0.323)	(0.256)	(0.311)
Lagged IHS-transformed Real Average Income	0.018		0	
	(0.091)		(0.186)	
Lagged IHS-transformed Real Aggregate Household Income		0.012		0.036
		(0.084)		(0.053)
Lagged Population Percentage of Below the Poverty Line	7.605**			
	(2.454)			
Lagged Population Percentage of Receiving Welfare			2.962	
			(7.600)	
Lagged non-White Population Percentage of	-2.529			
	(2.221)			
Lagged African American Population Percentage of			0.561	
			(3.622)	
Lagged Hispanic Population Percentage of				-8.616
				(22.214)
Lagged Population Percentage of Foreign-born		-19.525		-16.426
		(14.315)		(11.392)
Lagged Population Percentage of under 18		-0.651		
		(4.537)		
Lagged IHS-transformed Adult to Child Ratio			0.364	
			(1.224)	
AIC	213.801	219.897	222.37	221.386
BIC	308.094	314.19	316.663	315.679
Log Likelihood	-92.9	-95.949	-97.185	-96.693
Deviance	190.603	197.558	199.653	199.181
Num. obs.	6218	6218	6218	6218

***p < 0.001, **p < 0.01, *p < 0.05

Table 37. Low bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new low bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		-1.382 (4.540)		
Lagged Percentage of female Head of Household				-2.056 (2.732)
Lagged IHS-transformed Population Travel on Public Transportation	-0.107 (0.174)			-0.088 (0.145)
Lagged IHS-transformed Population with Commute < 25 minutes		0.115 (0.302)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.023 (0.196)	
Lagged IHS-transformed Population with Commute > 45 minutes				0.033 (0.192)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				-0.833 (8.803)
Lagged percentage of over 25-yr-olds with at Least High School Education			2.858 (7.508)	
Lagged percentage of over 25-yr-olds with Associate Degree		-27.687 (16.409)		
Lagged percentage of over 25-yr-olds with bachelor's degree	2.275 (3.457)			
Lagged Owner to Renter Ratio	-0.015 (0.034)			
Lagged Percentage of Housing Units Renter-occupied			-2.064 (1.904)	
Lagged Percentage of Housing Units Vacant	-1.841 (6.825)			
Lagged Percent Change in Housing Unit Supply		-0.09 (4.375)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	213.801	219.897	222.37	221.386
BIC	308.094	314.19	316.663	315.679
Log Likelihood	-92.9	-95.949	-97.185	-96.693
Deviance	190.603	197.558	199.653	199.181
Num. obs.	6218	6218	6218	6218

***p < 0.001, **p < 0.01, *p < 0.05

Table 38. Medium bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new medium bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	3.003***	3.641***	3.094***	3.540***
	(0.800)	(0.815)	(0.789)	(0.795)
Rural tract indicator > 10M sq. meters	-0.037		-0.034	
	(0.172)		(0.170)	
Rural tract indicator > 4M sq. meters		0.271		0.315
		(0.191)		(0.180)
Lagged IHS-transformed Total bridges	-0.179**	-0.259***	-0.171**	-0.248***
	(0.060)	(0.066)	(0.060)	(0.068)
Lagged IHS-transformed Real Average Income	-0.045		-0.04	
	(0.023)		(0.039)	
Lagged IHS-transformed Real Aggregate Household Income		0.021		-0.028
		(0.023)		(0.015)
Lagged Population Percentage of Below the Poverty Line	2.618**			
	(0.801)			
Lagged Population Percentage of Receiving Welfare			2.587*	
			(1.169)	
Lagged non-White Population Percentage of	-1.081*			
	(0.436)			
Lagged African American Population Percentage of			-1.023	
			(0.528)	
Lagged Hispanic Population Percentage of				-1.933
				(1.657)
Lagged Population Percentage of Foreign-born		1.528		1.517
		(1.999)		(1.877)
Lagged Population Percentage of under 18		-2.224*		
		(1.118)		
Lagged IHS-transformed Adult to Child Ratio			0.048	
			(0.480)	
AIC	2478.188	2479.23	2480.922	2492.258
BIC	2578.972	2580.014	2581.706	2593.042
Log Likelihood	-1225.094	-1225.615	-1226.461	-1232.129
Deviance	2620.194	2622.058	2623.637	2634.709
Num. obs.	9886	9886	9886	9886

***p < 0.001, **p < 0.01, *p < 0.05

Table 38. Medium bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new medium bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		1.626 (1.113)		
Lagged Percentage of female Head of Household				0.513 (0.698)
Lagged IHS-transformed Population Travel on Public Transportation	0.073 (0.040)			0.103* (0.044)
Lagged IHS-transformed Population with Commute < 25 minutes		0.307* (0.139)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			0.052 (0.055)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.043 (0.050)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				1.711 (2.496)
Lagged percentage of over 25-yr-olds with at Least High School Education			-2.108* (1.057)	
Lagged percentage of over 25-yr-olds with Associate Degree		-1.71 (5.579)		
Lagged percentage of over 25-yr-olds with bachelor's degree	1.412* (0.605)			
Lagged Owner to Renter Ratio	-0.003 (0.004)			
Lagged Percentage of Housing Units Renter-occupied			1.177** (0.444)	
Lagged Percentage of Housing Units Vacant	1.437 (1.129)			
Lagged Percent Change in Housing Unit Supply		-0.06 (1.105)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	2478.188	2479.23	2480.922	2492.258
BIC	2578.972	2580.014	2581.706	2593.042
Log Likelihood	-1225.094	-1225.615	-1226.461	-1232.129
Deviance	2620.194	2622.058	2623.637	2634.709
Num. obs.	9886	9886	9886	9886

***p < 0.001, **p < 0.01, *p < 0.05

Table 39. High bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new high bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	1.384 (1.067)	1.722 (1.093)	0.663 (1.149)	1.267 (1.127)
Rural tract indicator > 10M sq. meters	0.005 (0.188)		0.112 (0.183)	
Rural tract indicator > 4M sq. meters		0.601* (0.237)		0.585* (0.229)
Lagged IHS-transformed Total bridges	-0.277*** (0.068)	-0.338*** (0.080)	-0.241*** (0.070)	-0.345*** (0.081)
Lagged IHS-transformed Real Average Income	-0.001 (0.028)		-0.052 (0.052)	
Lagged IHS-transformed Real Aggregate Household Income		0.049 (0.026)		0.006 (0.019)
Lagged Population Percentage of Below the Poverty Line	0.953 (0.913)			
Lagged Population Percentage of Receiving Welfare			1.526 (1.358)	
Lagged non-White Population Percentage of	-0.423 (0.482)			
Lagged African American Population Percentage of			-0.943 (0.516)	
Lagged Hispanic Population Percentage of				-0.573 (1.548)
Lagged Population Percentage of Foreign-born		1.944 (1.811)		3.192 (1.687)
Lagged Population Percentage of under 18		-3.987** (1.239)		
Lagged IHS-transformed Adult to Child Ratio			0.634 (0.512)	
AIC	2504.713	2492.682	2500.031	2495.957
BIC	2606.156	2594.124	2601.473	2597.4
Log Likelihood	-1238.357	-1232.341	-1236.015	-1233.979
Deviance	2570.307	2557.223	2567.554	2561.345
Num. obs.	10362	10362	10362	10362

***p < 0.001, **p < 0.01, *p < 0.05

Table 39. High bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new high bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		1.767 (1.189)		
Lagged Percentage of female Head of Household				0.948 (0.771)
Lagged IHS-transformed Population Travel on Public Transportation	-0.022 (0.038)			0.014 (0.042)
Lagged IHS-transformed Population with Commute < 25 minutes		0.142 (0.085)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.033 (0.058)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.190*** (0.054)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				-4.081 (2.709)
Lagged percentage of over 25-yr-olds with at Least High School Education			-1.974** (0.745)	
Lagged percentage of over 25-yr-olds with Associate Degree		4.969 (6.093)		
Lagged percentage of over 25-yr-olds with bachelor's degree	1.759*** (0.447)			
Lagged Owner to Renter Ratio	0 (0.001)			
Lagged Percentage of Housing Units Renter-occupied			0.637 (0.457)	
Lagged Percentage of Housing Units Vacant	0.017 (0.900)			
Lagged Percent Change in Housing Unit Supply		-0.048 (0.530)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	2504.713	2492.682	2500.031	2495.957
BIC	2606.156	2594.124	2601.473	2597.4
Log Likelihood	-1238.357	-1232.341	-1236.015	-1233.979
Deviance	2570.307	2557.223	2567.554	2561.345
Num. obs.	10362	10362	10362	10362

***p < 0.001, **p < 0.01, *p < 0.05

Table 40. Super bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new super bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	2.060*	3.024**	2.380*	2.894**
	(1.012)	(0.961)	(0.999)	(0.954)
Rural tract indicator > 10M sq. meters	0.229		0.162	
	(0.169)		(0.165)	
Rural tract indicator > 4M sq. meters		0.376*		0.415*
		(0.186)		(0.184)
Lagged IHS-transformed Total bridges	-0.145*	-0.201**	-0.161**	-0.215***
	(0.058)	(0.063)	(0.058)	(0.064)
Lagged IHS-transformed Real Average Income	-0.077**		-0.118**	
	(0.024)		(0.041)	
Lagged IHS-transformed Real Aggregate Household Income		0.011		-0.035*
		(0.020)		(0.014)
Lagged Population Percentage of Below the Poverty Line	2.013*			
	(0.831)			
Lagged Population Percentage of Receiving Welfare			2.571*	
			(1.039)	
Lagged non-White Population Percentage of	-2.087***			
	(0.503)			
Lagged African American Population Percentage of			-1.387**	
			(0.486)	
Lagged Hispanic Population Percentage of				-3.947*
				(1.748)
Lagged Population Percentage of Foreign-born		-1.216		-0.484
		(2.137)		(1.865)
Lagged Population Percentage of under 18		-2.378*		
		(1.015)		
Lagged IHS-transformed Adult to Child Ratio			1.028*	
			(0.423)	
AIC	3015.648	3040.826	3026.976	3020.527
BIC	3116.618	3141.796	3127.945	3121.497
Log Likelihood	-1493.824	-1506.413	-1499.488	-1496.264
Deviance	3138.718	3161.805	3150.077	3141.968
Num. obs.	10018	10018	10018	10018

***p < 0.001, **p < 0.01, *p < 0.05

Table 40. Super bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new super bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		-0.579 (1.104)		
Lagged Percentage of female Head of Household				-1.03 (0.670)
Lagged IHS-transformed Population Travel on Public Transportation	0.086* (0.037)			0.107** (0.041)
Lagged IHS-transformed Population with Commute < 25 minutes		0.054 (0.057)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.001 (0.050)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.103* (0.050)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				7.003*** (1.341)
Lagged percentage of over 25-yr-olds with at Least High School Education			2.371** (0.804)	
Lagged percentage of over 25-yr-olds with Associate Degree		-8.972* (4.387)		
Lagged percentage of over 25-yr-olds with bachelor's degree	-2.115** (0.644)			
Lagged Owner to Renter Ratio	0 (0.001)			
Lagged Percentage of Housing Units Renter-occupied			-0.217 (0.438)	
Lagged Percentage of Housing Units Vacant	1.009 (1.235)			
Lagged Percent Change in Housing Unit Supply		-0.073 (0.712)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	3015.648	3040.826	3026.976	3020.527
BIC	3116.618	3141.796	3127.945	3121.497
Log Likelihood	-1493.824	-1506.413	-1499.488	-1496.264
Deviance	3138.718	3161.805	3150.077	3141.968
Num. obs.	10018	10018	10018	10018

***p < 0.001, **p < 0.01, *p < 0.05

Table 41. Restrictive bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	1.078 (2.057)	0.86 (1.694)	1.142 (1.728)	1.179 (1.720)
Rural tract indicator > 10M sq. meters	0.891 (0.558)		0.806 (0.557)	
Rural tract indicator > 4M sq. meters		-0.424 (0.643)		-0.529 (0.582)
Lagged IHS-transformed Total bridges	-0.318 (0.179)	-0.066 (0.193)	-0.317 (0.183)	-0.141 (0.187)
Lagged IHS-transformed Real Average Income	0.054 (0.075)		0.039 (0.106)	
Lagged IHS-transformed Real Aggregate Household Income		-0.02 (0.070)		0.051 (0.047)
Lagged Population Percentage of Below the Poverty Line	4.097 (2.353)			
Lagged Population Percentage of Receiving Welfare			1.68 (4.143)	
Lagged non-White Population Percentage of	-0.288 (1.130)			
Lagged African American Population Percentage of			0.66 (1.841)	
Lagged Hispanic Population Percentage of				-3.597 (6.079)
Lagged Population Percentage of Foreign-born		-4 (6.733)		-2.247 (5.903)
Lagged Population Percentage of under 18		2.066 (3.270)		
Lagged IHS-transformed Adult to Child Ratio			0.123 (0.865)	
AIC	354.579	355.932	360.186	359.615
BIC	450.44	451.793	456.047	455.476
Log Likelihood	-163.289	-163.966	-166.093	-165.807
Deviance	339.259	345.278	345.023	346.241
Num. obs.	6955	6955	6955	6955

***p < 0.001, **p < 0.01, *p < 0.05

Table 41. Restrictive bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		-1.611 (4.200)		
Lagged Percentage of female Head of Household				-1.511 (2.644)
Lagged IHS-transformed Population Travel on Public Transportation	-0.12 (0.121)			-0.128 (0.123)
Lagged IHS-transformed Population with Commute < 25 minutes		0.183 (0.317)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.032 (0.203)	
Lagged IHS-transformed Population with Commute > 45 minutes				0.077 (0.209)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				0.552 (8.205)
Lagged percentage of over 25-yr-olds with at Least High School Education			-0.058 (5.921)	
Lagged percentage of over 25-yr-olds with Associate Degree		-18.271 (14.222)		
Lagged percentage of over 25-yr-olds with bachelor's degree	2.89 (2.482)			
Lagged Owner to Renter Ratio	-0.012 (0.023)			
Lagged Percentage of Housing Units Renter-occupied			-1.614 (1.411)	
Lagged Percentage of Housing Units Vacant	-3.432 (5.563)			
Lagged Percent Change in Housing Unit Supply		-0.57 (3.969)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	354.579	355.932	360.186	359.615
BIC	450.44	451.793	456.047	455.476
Log Likelihood	-163.289	-163.966	-166.093	-165.807
Deviance	339.259	345.278	345.023	346.241
Num. obs.	6955	6955	6955	6955

***p < 0.001, **p < 0.01, *p < 0.05

Table 42. Non-restrictive bridge selection effect logistic model CEM results

DV: Dummy variable denoting that a new over 14-ft bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	1.925*	2.555***	1.817*	2.496***
	(0.768)	(0.743)	(0.764)	(0.748)
Rural tract indicator > 10M sq. meters	-0.004		-0.008	
	(0.126)		(0.123)	
Rural tract indicator > 4M sq. meters		0.449**		0.472***
		(0.141)		(0.136)
Lagged IHS-transformed Total bridges	-0.067	-0.154**	-0.056	-0.154**
	(0.045)	(0.050)	(0.046)	(0.052)
Lagged IHS-transformed Real Average Income	-0.063***		-0.082**	
	(0.018)		(0.029)	
Lagged IHS-transformed Real Aggregate Household Income		0.021		-0.032**
		(0.015)		(0.011)
Lagged Population Percentage of Below the Poverty Line	2.171***			
	(0.595)			
Lagged Population Percentage of Receiving Welfare			1.934*	
			(0.845)	
Lagged non-White Population Percentage of	-1.551***			
	(0.340)			
Lagged African American Population Percentage of			-1.286***	
			(0.369)	
Lagged Hispanic Population Percentage of				-5.224**
				(1.752)
Lagged Population Percentage of Foreign-born		0.463		1.59
		(1.227)		(1.168)
Lagged Population Percentage of under 18		-2.942***		
		(0.747)		
Lagged IHS-transformed Adult to Child Ratio			0.576	
			(0.311)	
AIC	4713.531	4708.67	4711.262	4700.148
BIC	4814.968	4810.107	4812.699	4801.586
Log Likelihood	-2342.765	-2340.335	-2341.631	-2336.074
Deviance	4924.773	4917.775	4925.182	4909.864
Num. obs.	10358	10358	10358	10358

***p < 0.001, **p < 0.01, *p < 0.05

Table 42. Non-restrictive bridge selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new over 14-ft bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		0.45 (0.754)		
Lagged Percentage of female Head of Household				0.136 (0.479)
Lagged IHS-transformed Population Travel on Public Transportation	0.054 (0.028)			0.091** (0.031)
Lagged IHS-transformed Population with Commute < 25 minutes		0.057 (0.049)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.054 (0.038)	
Lagged IHS-transformed Population with Commute > 45 minutes				-0.154*** (0.038)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				2.511 (1.507)
Lagged percentage of over 25-yr-olds with at Least High School Education			-0.216 (0.604)	
Lagged percentage of over 25-yr-olds with Associate Degree		-5.994 (3.104)		
Lagged percentage of over 25-yr-olds with bachelor's degree	0.271 (0.389)			
Lagged Owner to Renter Ratio	-0.001 (0.001)			
Lagged Percentage of Housing Units Renter-occupied			0.501 (0.311)	
Lagged Percentage of Housing Units Vacant	0.222 (0.848)			
Lagged Percent Change in Housing Unit Supply		-0.073 (0.544)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	4713.531	4708.67	4711.262	4700.148
BIC	4814.968	4810.107	4812.699	4801.586
Log Likelihood	-2342.765	-2340.335	-2341.631	-2336.074
Deviance	4924.773	4917.775	4925.182	4909.864
Num. obs.	10358	10358	10358	10358

***p < 0.001, **p < 0.01, *p < 0.05

Table 43. All new bridges selection effect logistic model CEM results

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
% Water Area	-1.044	-0.413	-1.005	-0.479
	(1.092)	(1.079)	(1.091)	(1.094)
Rural tract indicator > 10M sq. meters	0.401		0.421	
	(0.348)		(0.344)	
Rural tract indicator > 4M sq. meters		0.327*		0.315*
		(0.132)		(0.132)
Lagged IHS-transformed Total bridges	-0.322***	-0.364***	-0.304***	-0.390***
	(0.060)	(0.060)	(0.058)	(0.061)
Lagged IHS-transformed Real Average Income	0.028		0.073*	
	(0.023)		(0.037)	
Lagged IHS-transformed Real Aggregate Household Income		-0.007		0.03
		(0.020)		(0.016)
Lagged Population Percentage of Below the Poverty Line	1.443*			
	(0.682)			
Lagged Population Percentage of Receiving Welfare			1.089	
			(0.949)	
Lagged non-White Population Percentage of	-2.000***			
	(0.389)			
Lagged African American Population Percentage of			-1.977***	
			(0.407)	
Lagged Hispanic Population Percentage of				-9.095**
				(2.924)
Lagged Population Percentage of Foreign-born		-4.647**		-3.074
		(1.803)		(1.678)
Lagged Population Percentage of under 18		1.584		
		(0.899)		
Lagged IHS-transformed Adult to Child Ratio			-0.73	
			(0.400)	
AIC	3587.598	3599.245	3588.673	3580.556
BIC	3682.779	3694.426	3683.853	3675.736
Log Likelihood	-1779.799	-1785.623	-1780.336	-1776.278
Deviance	3806.165	3816.145	3810.28	3789.159
Num. obs.	6625	6625	6625	6625

***p < 0.001, **p < 0.01, *p < 0.05

Table 43. All new bridges selection effect logistic model CEM results (cont'd)

DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years				
	Set 1	**Set 2**	**Set 3**	**Set 4**
Lagged Percentage of single parents with Children		-3.134*** (0.774)		
Lagged Percentage of female Head of Household				-2.398*** (0.612)
Lagged IHS-transformed Population Travel on Public Transportation	-0.060* (0.028)			-0.021 (0.035)
Lagged IHS-transformed Population with Commute < 25 minutes		0.008 (0.049)		
Lagged IHS-transformed Population with Commute > 25 < 45 minutes			-0.079 (0.047)	
Lagged IHS-transformed Population with Commute > 45 minutes				0.012 (0.052)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education				4.709* (2.121)
Lagged percentage of over 25-yr-olds with at Least High School Education			1.147 (0.888)	
Lagged percentage of over 25-yr-olds with Associate Degree		2.428 (4.089)		
Lagged percentage of over 25-yr-olds with bachelor's degree	-0.232 (0.509)			
Lagged Owner to Renter Ratio	0 0.000			
Lagged Percentage of Housing Units Renter-occupied			-0.219 (0.341)	
Lagged Percentage of Housing Units Vacant	-1.103 (1.438)			
Lagged Percent Change in Housing Unit Supply		0.009 (0.112)		
Year Fixed Effect Included?	Yes	Yes	Yes	Yes
AIC	3587.598	3599.245	3588.673	3580.556
BIC	3682.779	3694.426	3683.853	3675.736
Log Likelihood	-1779.799	-1785.623	-1780.336	-1776.278
Deviance	3806.165	3816.145	3810.28	3789.159
Num. obs.	6625	6625	6625	6625

***p < 0.001, **p < 0.01, *p < 0.05

Table 44. Mini bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new mini bridge (SE)	t value (p value)	new mini bridge Treatment Variable (SE)	t value (p value)	new mini bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-1.1 (0.755)	-1.45 (0.147)	0.664 (0.646)	1.03 (0.305)	-4.59 (3.42)	-1.34 (0.179)	12	1	7.63e-05 (0.000114)	0.995 (0.992)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.3)	-1.36 (1.11)	-1.22 (0.222)	0.83 (0.866)	0.959 (0.338)	-6.61 (5.53)	-1.2 (0.232)	12	1	4.66e-05 (6.84e-05)	0.997 (0.994)
Non-White percentage of total population	0.0217 (0.0478)	0.455 (0.649)	0.0361 (0.0237)	1.52 (0.128)	0.0297 (0.116)	0.256 (0.798)	12	1	0.000414 (0.000603)	0.969 (0.947)
Black/African American percentage of total population	0.0437 (0.0498)	0.877 (0.381)	0.0244 (0.0186)	1.32 (0.188)	0.0602 (0.123)	0.489 (0.625)	12	1	0.000291 (0.000369)	0.963 (0.937)
Percentage of Hispanic/Latino of total population	-0.0174 (0.0131)	-1.33 (0.183)	0.0147 (0.00892)	1.65 (0.1)	-0.00136 (0.0241)	-0.0565 (0.955)	12	1	0.0027 (0.0043)	0.907 (0.84)
Percentage of Foreign-born of total population	-0.04 (0.022)	-1.82 (0.0693)	0.0162 (0.0112)	1.45 (0.148)	0.0205 (0.0392)	0.523 (0.601)	12	1	0.00168 (0.00263)	0.93 (0.88)
Percentage of Children under 18 years old of total population	-0.0382 (0.0348)	-1.1 (0.273)	0.0283 (0.0193)	1.47 (0.142)	-0.0491 (0.102)	-0.48 (0.631)	12	1	0.00036 (0.000559)	0.983 (0.972)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.02)	-0.0844 (0.0804)	-1.05 (0.295)	0.0533 (0.0643)	0.83 (0.407)	-0.467 (0.297)	-1.57 (0.116)	12	1	6.22e-05 (8.04e-05)	0.993 (0.987)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.0156 (0.0392)	-0.396 (0.692)	0.0245 (0.016)	1.53 (0.127)	0.003 (0.107)	0.0281 (0.978)	12	1	0.000325 (0.000383)	0.95 (0.915)
Percentage of female-headed families with or without own children of total families and subfamilies	0.0819 (0.0717)	1.14 (0.253)	0.0234 (0.0196)	1.19 (0.234)	0.0188 (0.163)	0.116 (0.908)	12	1	0.000303 (0.000388)	0.962 (0.935)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.37)	0.0468 (0.698)	0.0671 (0.947)	-0.01 (0.36)	-0.0278 (0.978)	5.14 (1.57)	3.27 (0.0011)	12	1	2.78e-07 (-8.93e-05)	0.975 (0.956)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.2)	-0.681 (0.61)	-1.12 (0.265)	-0.0124 (0.456)	-0.0273 (0.978)	-1.87 (2.14)	-0.872 (0.384)	12	1	2.7e-05 (-3.89e-07)	0.987 (0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.45)	-0.81 (0.593)	-1.37 (0.173)	0.0812 (0.42)	0.193 (0.847)	-1.37 (2.11)	-0.651 (0.515)	12	1	4.73e-05 (2.79e-05)	0.985 (0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.83)	-0.812 (0.55)	-1.48 (0.141)	-0.174 (0.397)	-0.437 (0.662)	-3.65 (1.97)	-1.85 (0.0647)	12	1	0.000125 (0.000152)	0.982 (0.97)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.0319 (0.018)	1.77 (0.0767)	0.00504 (0.00616)	0.819 (0.413)	-0.00153 (0.0371)	-0.0413 (0.967)	12	1	0.000584 (0.000852)	0.958 (0.927)
Percentage of Persons 25+ years old who have completed high school but no college	0.0239 (0.0419)	0.57 (0.569)	0.0182 (0.011)	1.65 (0.0997)	0.0759 (0.0757)	1 (0.316)	12	1	7.21e-05 (9.23e-05)	0.991 (0.985)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00701 (0.009)	-0.779 (0.436)	-0.00276 (0.00479)	-0.576 (0.564)	0.0103 (0.0198)	0.52 (0.603)	12	1	7.87e-05 (4.86e-05)	0.976 (0.958)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0549 (0.0602)	-0.911 (0.362)	-0.00996 (0.0107)	-0.928 (0.354)	-0.088 (0.0946)	-0.93 (0.352)	12	1	0.000112 (0.000122)	0.98 (0.966)
Percentage of total persons below the poverty level in past 12 months	0.000993 (0.0302)	0.0329 (0.974)	0.0272 (0.0118)	2.31 (0.0212)	-0.134 (0.0615)	-2.18 (0.0298)	12	1	0.00064 (0.000953)	0.959 (0.93)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.0207 (0.0321)	0.644 (0.52)	0.0243 (0.00691)	3.51 (0.00046 6)	-0.021 (0.054)	-0.39 (0.697)	12	1	0.00171 (0.00275)	0.947 (0.909)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	1.66 (22.3)	0.0744 (0.941)	14.8 (20)	0.74 (0.459)	-50.6 (104)	-0.484 (0.628)	12	1	0.000741 (-0.000116)	0.607 (0.325)
Percentage of renter-occupied housing units of total housing units	-0.00953 (0.0295)	-0.323 (0.747)	-0.018 (0.0176)	-1.02 (0.307)	-0.204 (0.0724)	-2.81 (0.005)	12	1	5.98e-05 (6.03e-05)	0.988 (0.979)
Percentage of vacant housing units	-0.0238 (0.0169)	-1.41 (0.159)	0.00281 (0.00716)	0.392 (0.695)	0.158 (0.156)	1.01 (0.312)	12	1	6.73e-05 (-7.4e-06)	0.965 (0.94)
Percentage of change in number of housing units since last census of total housing units	-0.239 (0.165)	-1.45 (0.148)	-0.106 (0.125)	-0.847 (0.397)	-0.429 (0.418)	-1.03 (0.306)	12	1	6.34e-06 (1.7e-06)	0.997 (0.996)

Table 44. Mini bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new mini bridge (SE)	t value (p value)	new mini bridge Treatment Variable (SE)	t value (p value)	new mini bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.254	-0.537	0.698	1.4	-5.3	-2.02			0.00113	0.996
	(0.474)	(0.592)	(0.5)	(0.163)	(2.62)	(0.0432)	10	2	(0.00195)	(0.994)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.3)	-0.143	-0.24	0.83	1.34	-7.87	-1.69			0.000691	0.997
	(0.595)	(0.81)	(0.619)	(0.181)	(4.64)	(0.0904)	10	2	(0.00119)	(0.995)
Non-White percentage of total population	-0.0315	-0.795	0.00795	0.308	0.0254	0.388			0.0121	0.981
	(0.0396)	(0.427)	(0.0258)	(0.758)	(0.0654)	(0.698)	10	2	(0.0208)	(0.968)
Black/African American percentage of total population	-0.0242	-0.689	-0.00526	-0.32	0.0892	1.35			0.0177	0.981
	(0.0351)	(0.491)	(0.0164)	(0.749)	(0.066)	(0.177)	10	2	(0.0303)	(0.967)
Percentage of Hispanic/Latino of total population	-0.0249	-1.59	0.0101	0.941	0.0113	0.425			-0.00502	0.899
	(0.0156)	(0.111)	(0.0107)	(0.347)	(0.0266)	(0.671)	10	2	(-0.00861)	(0.827)
Percentage of Foreign-born of total population	-0.013	-0.971	0.0223	2.11	-0.00482	-0.224			0.0234	0.952
	(0.0134)	(0.332)	(0.0106)	(0.0353)	(0.0215)	(0.823)	10	2	(0.0402)	(0.918)
Percentage of Children under 18 years old of total population	-0.0398	-2.2	0.0205	1.45	-0.0546	-0.725			0.005	0.988
	(0.0181)	(0.0282)	(0.0142)	(0.148)	(0.0753)	(0.469)	10	2	(0.00858)	(0.98)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.02)	0.0253	0.401	0.0608	1	-0.607	-2.38			0.000537	0.993
	(0.0631)	(0.689)	(0.0608)	(0.317)	(0.256)	(0.0177)	10	2	(0.000921)	(0.988)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.076	-1.63	-0.00651	-0.488	0.0908	1.07			0.0127	0.963
	(0.0467)	(0.104)	(0.0133)	(0.626)	(0.085)	(0.286)	10	2	(0.0218)	(0.936)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.0163	-0.411	-0.00618	-0.441	0.0496	0.649			0.0214	0.984
	(0.0396)	(0.681)	(0.014)	(0.659)	(0.0765)	(0.517)	10	2	(0.0367)	(0.972)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.37)	-0.26	-0.415	0.3	0.76	4.65	3.68			-0.00111	0.973
	(0.625)	(0.678)	(0.395)	(0.448)	(1.26)	(0.000245)	10	2	(-0.00191)	(0.954)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.2)	0.198	0.608	0.191	0.619	-2.58	-2.12			0.00591	0.993
	(0.327)	(0.544)	(0.309)	(0.536)	(1.22)	(0.0345)	10	2	(0.0101)	(0.987)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.45)	-0.0772	-0.26	0.317	1.22	-2.16	-1.73			0.00626	0.991
	(0.297)	(0.795)	(0.259)	(0.221)	(1.25)	(0.0844)	10	2	(0.0107)	(0.985)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.83)	-0.0585	-0.202	0.0786	0.288	-4.59	-4.04			0.00706	0.989
	(0.29)	(0.84)	(0.273)	(0.773)	(1.14)	(5.68e-05)	10	2	(0.0121)	(0.982)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.0323	2.07	0.0061	1.04	-0.0287	-0.935			0.00442	0.962
	(0.0156)	(0.0388)	(0.00585)	(0.297)	(0.0306)	(0.35)	10	2	(0.00758)	(0.934)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0313	-0.798	0.0107	0.867	0.14	2.25			-0.000609	0.99
	(0.0393)	(0.425)	(0.0124)	(0.386)	(0.0622)	(0.0249)	10	2	(-0.00105)	(0.984)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0114	-1.05	-0.00774	-1.53	0.0413	1.93			-0.00222	0.973
	(0.0109)	(0.296)	(0.00505)	(0.125)	(0.0214)	(0.0539)	10	2	(-0.00381)	(0.954)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0313	0.671	-0.00404	-0.255	-0.166	-2.81			0.00113	0.981
	(0.0467)	(0.502)	(0.0159)	(0.799)	(0.0591)	(0.00507)	10	2	(0.00194)	(0.968)
Percentage of total persons below the poverty level in past 12 months	-0.0224	-0.635	0.00265	0.242	-0.0854	-1.43			-0.00153	0.957
	(0.0353)	(0.525)	(0.0109)	(0.808)	(0.0598)	(0.154)	10	2	(-0.00262)	(0.926)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00168	-0.0807	0.0213	2.71	-0.0356	-1.26			0.0245	0.97
	(0.0208)	(0.936)	(0.00788)	(0.00693)	(0.0281)	(0.206)	10	2	(0.042)	(0.948)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	5.55	0.261	8.74	0.464	-132	-1.21			-0.0565	0.55
	(21.3)	(0.794)	(18.8)	(0.643)	(110)	(0.227)	10	2	(-0.0969)	(0.228)
Percentage of renter-occupied housing units of total housing units	0.0438	1.16	0.00843	0.623	-0.285	-4.7			0.00294	0.991
	(0.0378)	(0.247)	(0.0135)	(0.533)	(0.0606)	(2.93e-06)	10	2	(0.00504)	(0.984)
Percentage of vacant housing units	-0.0257	-2.04	-0.00186	-0.359	0.159	1.17			0.00156	0.967
	(0.0126)	(0.0413)	(0.00517)	(0.72)	(0.136)	(0.242)	10	2	(0.00268)	(0.943)
Percentage of change in number of housing units since last census of total housing units	-0.0578	-0.598	-0.0262	-0.358	-0.503	-2.55			7.45e-05	0.997
	(0.0965)	(0.55)	(0.0732)	(0.72)	(0.197)	(0.0109)	10	2	(0.000128)	(0.996)

Table 44. Mini bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new mini bridge (SE)	t value (p value)	new mini bridge Treatment Variable (SE)	t value (p value)	new mini bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.327 (0.599)	0.547 (0.585)	0.575 (0.53)	1.09 (0.278)	-7.04 (2.53)	-2.78 (0.00546)	12	3	0.00113 (0.00193)	0.996 (0.994)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.3)	0.527 (0.702)	0.751 (0.453)	0.688 (0.643)	1.07 (0.285)	-9.69 (4.32)	-2.24 (0.0252)	12	3	0.000735 (0.00125)	0.997 (0.996)
Non-White percentage of total population	0.0302 (0.0552)	0.547 (0.584)	0.00948 (0.0214)	0.443 (0.658)	0.266 (0.114)	2.34 (0.0197)	12	3	0.0122 (0.0209)	0.981 (0.968)
Black/African American percentage of total population	0.0517 (0.0568)	0.911 (0.363)	-0.00511 (0.0134)	-0.382 (0.703)	0.317 (0.12)	2.64 (0.00837)	12	3	0.0159 (0.0272)	0.979 (0.964)
Percentage of Hispanic/Latino of total population	-0.011 (0.0122)	-0.903 (0.367)	0.00841 (0.00967)	0.87 (0.385)	0.0384 (0.027)	1.42 (0.155)	12	3	0.00307 (0.00494)	0.907 (0.84)
Percentage of Foreign-born of total population	-0.0325 (0.0194)	-1.68 (0.093)	0.0218 (0.0111)	1.97 (0.0496)	-0.0456 (0.034)	-1.34 (0.18)	12	3	0.0109 (0.0185)	0.939 (0.896)
Percentage of Children under 18 years old of total population	0.00773 (0.021)	0.369 (0.713)	0.0132 (0.0141)	0.935 (0.35)	-0.0351 (0.0725)	-0.485 (0.628)	12	3	0.00519 (0.00887)	0.988 (0.98)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.02)	-0.00582 (0.0611)	-0.0953 (0.924)	0.0662 (0.0618)	1.07 (0.284)	-0.713 (0.245)	-2.91 (0.00371)	12	3	0.00085 (0.00144)	0.993 (0.989)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.0201 (0.0374)	0.537 (0.591)	-0.0156 (0.00923)	-1.69 (0.0913)	0.257 (0.111)	2.32 (0.0206)	12	3	0.0172 (0.0294)	0.967 (0.944)
Percentage of female-headed families with or without own children of total families and subfamilies	0.0508 (0.063)	0.806 (0.42)	0.00529 (0.0136)	0.388 (0.698)	0.319 (0.152)	2.1 (0.0362)	12	3	0.0118 (0.0202)	0.974 (0.955)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.37)	-0.186 (0.694)	-0.268 (0.789)	0.279 (0.403)	0.692 (0.489)	3.71 (1.16)	3.21 (0.00137)	12	3	-0.00182 (-0.00321)	0.973 (0.953)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.2)	0.129 (0.473)	0.272 (0.786)	0.0773 (0.333)	0.232 (0.817)	-4.59 (1.32)	-3.49 (0.000502)	12	3	0.00378 (0.00645)	0.991 (0.984)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.45)	0.141 (0.449)	0.314 (0.754)	0.164 (0.277)	0.592 (0.554)	-4.2 (1.25)	-3.35 (0.000848)	12	3	0.00407 (0.00694)	0.989 (0.981)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.83)	0.0206 (0.407)	0.0505 (0.96)	-0.0484 (0.291)	-0.166 (0.868)	-6.34 (1.15)	-5.53 (4.05e-08)	12	3	0.0047 (0.00801)	0.987 (0.978)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.0318 (0.0178)	1.78 (0.0755)	0.00854 (0.00627)	1.36 (0.174)	-0.0252 (0.032)	-0.79 (0.43)	12	3	-0.000162 (-0.000429)	0.957 (0.926)
Percentage of Persons 25+ years old who have completed high school but no college	0.0145 (0.0339)	0.427 (0.67)	0.00578 (0.012)	0.48 (0.632)	0.179 (0.0715)	2.5 (0.0127)	12	3	-0.000887 (-0.00156)	0.99 (0.983)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	0.000496 (0.0103)	0.0483 (0.961)	-0.0105 (0.00499)	-2.1 (0.0364)	0.0425 (0.0205)	2.07 (0.0384)	12	3	-0.000263 (-0.000539)	0.975 (0.957)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0269 (0.0495)	-0.544 (0.587)	-0.00383 (0.0152)	-0.251 (0.802)	-0.203 (0.0867)	-2.34 (0.0197)	12	3	-0.00162 (-0.00286)	0.979 (0.963)
Percentage of total persons below the poverty level in past 12 months	0.00939 (0.0299)	0.314 (0.754)	0.00155 (0.0097)	0.16 (0.873)	0.0455 (0.0818)	0.556 (0.578)	12	3	-0.0079 (-0.0137)	0.95 (0.915)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000194 (0.0284)	0.00683 (0.995)	0.0289 (0.00836)	3.46 (0.000556)	0.0174 (0.0441)	0.395 (0.693)	12	3	0.0109 (0.0185)	0.956 (0.925)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-5.9 (24.5)	-0.241 (0.81)	16.3 (19.6)	0.831 (0.406)	-63.1 (95.7)	-0.659 (0.51)	12	3	-0.0573 (-0.0998)	0.549 (0.225)
Percentage of renter-occupied housing units of total housing units	-0.00222 (0.0279)	-0.0795 (0.937)	0.0122 (0.0133)	0.915 (0.36)	-0.424 (0.082)	-5.18 (2.74e-07)	12	3	0.00121 (0.00203)	0.989 (0.981)
Percentage of vacant housing units	0.00568 (0.0106)	0.538 (0.591)	-0.00697 (0.00487)	-1.43 (0.153)	0.176 (0.127)	1.39 (0.166)	12	3	0.00539 (0.00915)	0.971 (0.949)
Percentage of change in number of housing units since last census of total housing units	0.0319 (0.115)	0.278 (0.781)	-0.0693 (0.0817)	-0.849 (0.396)	-1 (0.34)	-2.95 (0.00321)	12	3	0.000134 (0.000222)	0.998 (0.996)

Table 44. Mini bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new mini bridge (SE)	t value (p value)	new mini bridge Treatment Variable (SE)	t value (p value)	new mini bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.0367	0.0744	0.67	1.4	-4.5	-1.82			0.00115	0.996
	(0.493)	(0.941)	(0.478)	(0.161)	(2.48)	(0.0694)	12	4	(0.00196)	(0.994)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.3)	0.124	0.219	0.992	1.53	-6.57	-1.49			0.000728	0.997
	(0.567)	(0.827)	(0.646)	(0.125)	(4.4)	(0.135)	12	4	(0.00123)	(0.996)
Non-White percentage of total population	0.00799	0.233	-0.00982	-0.718	-0.0743	-0.793			0.00812	0.977
	(0.0344)	(0.816)	(0.0137)	(0.473)	(0.0937)	(0.428)	12	4	(0.0138)	(0.961)
Black/African American percentage of total population	0.0191	0.52	-0.0246	-1.71	-0.0441	-0.456			0.0131	0.976
	(0.0367)	(0.603)	(0.0144)	(0.0885)	(0.0967)	(0.648)	12	4	(0.0224)	(0.959)
Percentage of Hispanic/Latino of total population	-0.0132	-1.45	0.00849	1.23	0.0226	0.821			-0.00211	0.902
	(0.00909)	(0.147)	(0.00689)	(0.218)	(0.0275)	(0.412)	12	4	(-0.00414)	(0.831)
Percentage of Foreign-born of total population	-0.0201	-1.17	0.0267	1.95	0.0312	1.06			0.0147	0.943
	(0.0171)	(0.241)	(0.0136)	(0.0509)	(0.0294)	(0.289)	12	4	(0.0249)	(0.902)
Percentage of Children under 18 years old of total population	-0.0125	-0.606	0.0112	0.772	-0.0977	-1.21			0.00475	0.988
	(0.0207)	(0.545)	(0.0145)	(0.44)	(0.0806)	(0.226)	12	4	(0.00808)	(0.979)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.02)	0.0021	0.0374	0.086	1.57	-0.44	-1.82			0.000783	0.993
	(0.0562)	(0.97)	(0.0547)	(0.117)	(0.241)	(0.0686)	12	4	(0.00131)	(0.988)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.0152	-0.455	-0.0225	-0.973	-0.0124	-0.121			0.0145	0.965
	(0.0334)	(0.649)	(0.0231)	(0.331)	(0.103)	(0.904)	12	4	(0.0248)	(0.939)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00208	0.0456	-0.0337	-1.75	-0.112	-0.948			0.0145	0.977
	(0.0455)	(0.964)	(0.0192)	(0.0798)	(0.118)	(0.344)	12	4	(0.0247)	(0.96)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.37)	-0.0759	-0.129	-0.0667	-0.216	4.81	3.33			0.00015	0.975
	(0.587)	(0.897)	(0.309)	(0.829)	(1.45)	(0.000905)	12	4	(0.000124)	(0.956)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.2)	0.229	0.671	0.224	0.708	-2.21	-1.93			0.00486	0.992
	(0.341)	(0.503)	(0.317)	(0.479)	(1.14)	(0.0534)	12	4	(0.00829)	(0.986)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.45)	0.151	0.442	0.24	0.857	-1.76	-1.5			0.00498	0.99
	(0.341)	(0.659)	(0.28)	(0.392)	(1.17)	(0.135)	12	4	(0.00848)	(0.983)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.83)	0.111	0.373	0.0397	0.14	-3.93	-3.77			0.00634	0.989
	(0.298)	(0.709)	(0.285)	(0.889)	(1.04)	(0.000175)	12	4	(0.0108)	(0.98)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.0261	2	0.00452	0.817	-0.0392	-1.21			0.00618	0.963
	(0.0131)	(0.0462)	(0.00554)	(0.414)	(0.0323)	(0.226)	12	4	(0.0104)	(0.937)
Percentage of Persons 25+ years old who have completed high school but no college	0.0107	0.325	-0.00604	-0.468	0.0623	1.01			0.000361	0.991
	(0.033)	(0.745)	(0.0129)	(0.64)	(0.0617)	(0.313)	12	4	(0.000573)	(0.985)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00565	-0.512	-0.00433	-0.813	0.0298	1.44			0.00132	0.977
	(0.011)	(0.608)	(0.00532)	(0.416)	(0.0207)	(0.151)	12	4	(0.00214)	(0.96)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00889	0.206	0.0139	1.12	-0.0737	-0.969			0.00135	0.982
	(0.0431)	(0.837)	(0.0125)	(0.265)	(0.0761)	(0.333)	12	4	(0.00221)	(0.968)
Percentage of total persons below the poverty level in past 12 months	0.0149	0.465	-0.00664	-0.496	-0.171	-2.32			-0.00462	0.954
	(0.0321)	(0.642)	(0.0134)	(0.62)	(0.0738)	(0.0205)	12	4	(-0.00817)	(0.92)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.0149	-0.765	0.016	2.03	-0.0792	-2.46			0.0188	0.964
	(0.0194)	(0.444)	(0.00788)	(0.0422)	(0.0322)	(0.014)	12	4	(0.0321)	(0.938)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-5.99	-0.232	19.7	0.913	-18	-0.186			0.00762	0.614
	(25.9)	(0.817)	(21.6)	(0.362)	(96.9)	(0.852)	12	4	(0.011)	(0.336)
Percentage of renter-occupied housing units of total housing units	0.0177	0.742	0.017	1.57	-0.222	-3.35			0.00201	0.99
	(0.0239)	(0.459)	(0.0108)	(0.116)	(0.0664)	(0.000842)	12	4	(0.0034)	(0.983)
Percentage of vacant housing units	-0.000627	-0.0524	-0.00694	-0.788	0.153	1.15			0.00527	0.97
	(0.012)	(0.958)	(0.00882)	(0.431)	(0.133)	(0.251)	12	4	(0.00889)	(0.949)
Percentage of change in number of housing units since last census of total housing units	-0.102	-0.85	0.00326	0.0425	-0.2	-0.876			4.03e-05	0.997
	(0.12)	(0.396)	(0.0766)	(0.966)	(0.228)	(0.381)	12	4	(5.55e-05)	(0.996)

Table 45. Low bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new low bridge (SE)	t value (p value)	new low bridge Treatment Variable (SE)	t value (p value)	new low bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.6)	-0.829	-1.23	-0.318	-0.858	-1.21	-0.504			3.3e-05	0.992
	(0.676)	(0.22)	(0.37)	(0.391)	(2.4)	(0.615)	12	1	(4.21e-05)	(0.988)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.939	-0.962	-0.637	-1.12	-2	-0.522			3.99e-05	0.992
	(0.977)	(0.336)	(0.566)	(0.261)	(3.84)	(0.602)	12	1	(5.24e-05)	(0.989)
Non-White percentage of total population	-0.0698	-1.07	-0.00222	-0.541	0.0495	0.729			0.00035	0.964
	(0.065)	(0.283)	(0.0041)	(0.589)	(0.0679)	(0.466)	12	1	(0.00048)	(0.949)
Black/African American percentage of total population	-0.0568	-0.899	-0.00421	-1.29	0.0441	0.665			0.000366	0.967
	(0.0632)	(0.369)	(0.00326)	(0.197)	(0.0663)	(0.506)	12	1	(0.000506)	(0.953)
Percentage of Hispanic/Latino of total population	-0.0171	-2.62	0.00119	0.496	0.00149	0.201			0.000187	0.877
	(0.00653)	(0.0089)	(0.0024)	(0.62)	(0.00742)	(0.841)	12	1	(0.00019)	(0.824)
Percentage of Foreign-born of total population	-0.0106	-1.86	8.83e-05	0.0339	0.00425	0.595			6.29e-05	0.877
	(0.0057)	(0.0629)	(0.0026)	(0.973)	(0.00714)	(0.552)	12	1	(1.12e-05)	(0.822)
Percentage of Children under 18 years old of total population	-0.0233	-1.61	0.00425	0.522	-0.0218	-0.403			2.07e-05	0.98
	(0.0144)	(0.106)	(0.00813)	(0.602)	(0.054)	(0.687)	12	1	(1.69e-05)	(0.971)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0973	-1.09	-0.0179	-0.627	-0.0348	-0.156			2.66e-05	0.99
	(0.089)	(0.274)	(0.0285)	(0.531)	(0.223)	(0.876)	12	1	(3.19e-05)	(0.986)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00897	-0.589	-0.00146	-0.273	0.0432	1.84			1.6e-05	0.963
	(0.0152)	(0.556)	(0.00535)	(0.785)	(0.0235)	(0.0655)	12	1	(-7.16e-07)	(0.947)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.0128	-0.643	-0.00428	-0.569	0.0365	1.17			3.18e-05	0.966
	(0.0199)	(0.52)	(0.00752)	(0.569)	(0.0312)	(0.242)	12	1	(2.41e-05)	(0.951)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.55)	-0.687	-1.7	-0.177	-1.02	1.36	1.51			0.000136	0.948
	(0.403)	(0.0887)	(0.174)	(0.31)	(0.9)	(0.131)	12	1	(0.000162)	(0.925)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.16)	-0.164	-0.435	0.0857	0.489	-0.0377	-0.0257			6.67e-06	0.985
	(0.376)	(0.663)	(0.175)	(0.625)	(1.46)	(0.979)	12	1	(-4.5e-08)	(0.978)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.5)	-0.302	-0.791	0.11	0.648	-0.767	-0.551			1.61e-05	0.981
	(0.382)	(0.429)	(0.169)	(0.517)	(1.39)	(0.582)	12	1	(1.09e-05)	(0.973)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.9)	-0.238	-0.73	0.134	0.934	-1.18	-1.13			2.69e-05	0.98
	(0.327)	(0.466)	(0.143)	(0.35)	(1.05)	(0.26)	12	1	(2.62e-05)	(0.972)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00253	0.309	-0.00352	-1.24	0.0147	1			7.37e-05	0.928
	(0.00816)	(0.757)	(0.00283)	(0.214)	(0.0146)	(0.317)	12	1	(5.99e-05)	(0.897)
Percentage of Persons 25+ years old who have completed high school but no college	0.0135	0.486	-0.00269	-0.426	0.0965	2.45			2.69e-06	0.991
	(0.0279)	(0.627)	(0.00632)	(0.67)	(0.0393)	(0.0141)	12	1	(-1.74e-06)	(0.987)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0187	-2.52	0.00368	1.95	0.00323	0.38			0.000168	0.961
	(0.00741)	(0.0117)	(0.00188)	(0.0507)	(0.0085)	(0.704)	12	1	(0.000217)	(0.944)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0563	-2.41	0.00599	0.845	-0.0373	-1.14			7.03e-05	0.971
	(0.0234)	(0.016)	(0.00709)	(0.398)	(0.0328)	(0.256)	12	1	(8.28e-05)	(0.959)
Percentage of total persons below the poverty level in past 12 months	-0.0784	-1.19	-0.00162	-0.244	0.144	1.99			0.000698	0.923
	(0.066)	(0.234)	(0.00664)	(0.807)	(0.072)	(0.0463)	12	1	(0.000955)	(0.889)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00693	-0.663	-0.00169	-0.55	0.0236	1.69			4.73e-05	0.878
	(0.0105)	(0.507)	(0.00308)	(0.582)	(0.0139)	(0.0904)	12	1	(-1.01e-05)	(0.825)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	14	2.69	-7.8	-1.77	-35.4	-2.64			0.000867	0.257
	(5.2)	(0.00726)	(4.41)	(0.0773)	(13.4)	(0.00823)	12	1	(0.00077)	(-0.0688)
Percentage of renter-occupied housing units of total housing units	-0.021	-1.3	-0.00846	-0.846	0.037	0.956			3.98e-05	0.979
	(0.0161)	(0.192)	(0.01)	(0.398)	(0.0387)	(0.339)	12	1	(4.39e-05)	(0.97)
Percentage of vacant housing units	-0.0188	-2.04	0.00201	0.32	0.103	3.4			5.14e-05	0.926
	(0.00923)	(0.0418)	(0.00628)	(0.749)	(0.0303)	(0.000675)	12	1	(2.66e-05)	(0.894)
Percentage of change in number of housing units since last census of total housing units	0.521	1.39	-0.311	-0.779	-0.712	-1.34			7.77e-05	0.24
	(0.375)	(0.166)	(0.399)	(0.436)	(0.532)	(0.181)	12	1	(-0.000376)	(-0.0932)

Table 45. Low bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new low bridge (SE)	t value (p value)	new low bridge Treatment Variable (SE)	t value (p value)	new low bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.6)	-0.418	-0.586	-0.308	-0.881	-1.33	-0.69			0.000978	0.992
	(0.714)	(0.558)	(0.35)	(0.378)	(1.93)	(0.49)	10	2	(0.00141)	(0.989)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.357	-0.348	-0.638	-1.21	-2.4	-0.794			0.00129	0.993
	(1.03)	(0.728)	(0.53)	(0.228)	(3.02)	(0.427)	10	2	(0.00185)	(0.991)
Non-White percentage of total population	-0.0658	-1.13	0.00275	0.678	0.0395	0.627			-0.00778	0.956
	(0.0584)	(0.26)	(0.00405)	(0.497)	(0.063)	(0.531)	10	2	(-0.0112)	(0.937)
Black/African American percentage of total population	-0.0525	-0.903	-0.000991	-0.343	0.0368	0.589			-0.00529	0.962
	(0.0582)	(0.367)	(0.00289)	(0.732)	(0.0624)	(0.556)	10	2	(-0.0076)	(0.945)
Percentage of Hispanic/Latino of total population	-0.0137	-3.1	0.00187	0.824	-0.00443	-0.641			-0.00876	0.868
	(0.00443)	(0.00193)	(0.00227)	(0.41)	(0.00691)	(0.521)	10	2	(-0.0126)	(0.811)
Percentage of Foreign-born of total population	-0.00897	-1.94	0.000714	0.249	0.00298	0.43			-0.00218	0.874
	(0.00463)	(0.053)	(0.00287)	(0.803)	(0.00692)	(0.667)	10	2	(-0.00314)	(0.819)
Percentage of Children under 18 years old of total population	-0.0161	-1.34	0.00433	0.705	-0.0441	-1.41			0.00601	0.986
	(0.012)	(0.181)	(0.00614)	(0.481)	(0.0312)	(0.158)	10	2	(0.00863)	(0.98)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0616	-0.703	-0.0132	-0.487	-0.0278	-0.141			0.000182	0.99
	(0.0877)	(0.482)	(0.0271)	(0.626)	(0.197)	(0.888)	10	2	(0.000261)	(0.986)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00214	-0.154	-0.000886	-0.165	0.0373	1.9			-0.00094	0.962
	(0.0139)	(0.878)	(0.00537)	(0.869)	(0.0196)	(0.0572)	10	2	(-0.00135)	(0.946)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00138	-0.0906	-0.00125	-0.164	0.0326	1.33			-0.0026	0.964
	(0.0152)	(0.928)	(0.00758)	(0.87)	(0.0245)	(0.184)	10	2	(-0.00374)	(0.948)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.55)	-0.589	-1.52	-0.113	-0.673	1.26	1.58			0.000562	0.948
	(0.388)	(0.129)	(0.169)	(0.501)	(0.796)	(0.115)	10	2	(0.000809)	(0.925)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.16)	-0.0775	-0.287	0.0247	0.203	-0.646	-0.704			0.00552	0.99
	(0.27)	(0.774)	(0.122)	(0.839)	(0.918)	(0.481)	10	2	(0.00794)	(0.986)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.5)	-0.206	-0.802	0.0495	0.422	-1.38	-1.57			0.00632	0.987
	(0.257)	(0.423)	(0.117)	(0.673)	(0.878)	(0.116)	10	2	(0.00909)	(0.982)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.9)	-0.152	-0.668	0.0896	0.89	-1.73	-2.55			0.00567	0.986
	(0.228)	(0.504)	(0.101)	(0.373)	(0.679)	(0.0109)	10	2	(0.00815)	(0.98)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00298	0.416	-0.00131	-0.454	0.0172	1.27			-0.00138	0.927
	(0.00718)	(0.678)	(0.00288)	(0.65)	(0.0135)	(0.203)	10	2	(-0.00198)	(0.895)
Percentage of Persons 25+ years old who have completed high school but no college	0.0289	0.909	-0.00537	-0.809	0.0945	2.25			-0.00126	0.99
	(0.0318)	(0.363)	(0.00664)	(0.419)	(0.0421)	(0.0247)	10	2	(-0.00181)	(0.986)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0185	-2.54	0.00354	1.74	0.00594	0.72			5.83e-06	0.961
	(0.00729)	(0.0112)	(0.00203)	(0.0817)	(0.00824)	(0.471)	10	2	(8.39e-06)	(0.944)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0642	-2.59	0.0126	1.49	-0.0178	-0.597			-0.00303	0.968
	(0.0248)	(0.0097)	(0.00847)	(0.136)	(0.0298)	(0.551)	10	2	(-0.00435)	(0.954)
Percentage of total persons below the poverty level in past 12 months	-0.0715	-1.11	0.00119	0.179	0.14	2			0.00085	0.923
	(0.0646)	(0.268)	(0.00662)	(0.858)	(0.07)	(0.0461)	10	2	(0.00122)	(0.89)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.0058	-0.635	0.00137	0.396	0.0288	2.33			-0.0051	0.873
	(0.00913)	(0.525)	(0.00346)	(0.692)	(0.0124)	(0.0201)	10	2	(-0.00733)	(0.818)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	12	2.39	-7.46	-1.68	-31.8	-2			0.00839	0.265
	(5.03)	(0.0168)	(4.43)	(0.0923)	(15.9)	(0.0453)	10	2	(0.0121)	(-0.0575)
Percentage of renter-occupied housing units of total housing units	-0.00132	-0.0595	-0.00381	-0.398	0.0382	1.21			-0.00141	0.978
	(0.0222)	(0.953)	(0.00957)	(0.691)	(0.0315)	(0.225)	10	2	(-0.00202)	(0.968)
Percentage of vacant housing units	-0.00792	-0.87	2.69e-05	0.00464	0.0884	4.13			0.00514	0.931
	(0.0091)	(0.385)	(0.00581)	(0.996)	(0.0214)	(3.62e-05)	10	2	(0.00739)	(0.901)
Percentage of change in number of housing units since last census of total housing units	0.76	1.7	-0.387	-0.89	-0.811	-1.63			-0.000395	0.24
	(0.447)	(0.089)	(0.434)	(0.373)	(0.498)	(0.103)	10	2	(-0.000568)	(-0.0934)

Table 45. Low bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new low bridge (SE)	t value (p value)	new low bridge Treatment Variable (SE)	t value (p value)	new low bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.6)	-0.401	-0.619	-0.376	-1.04	-3.13	-1.48			0.000712	0.992
	(0.649)	(0.536)	(0.36)	(0.296)	(2.11)	(0.138)	12	3	(0.00102)	(0.989)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.33	-0.343	-0.74	-1.35	-5.36	-1.6			0.000844	0.993
	(0.96)	(0.731)	(0.549)	(0.178)	(3.35)	(0.11)	12	3	(0.00121)	(0.99)
Non-White percentage of total population	-0.0676	-1.09	-0.00283	-0.659	0.0564	0.857			-0.00148	0.963
	(0.0618)	(0.274)	(0.0043)	(0.51)	(0.0658)	(0.392)	12	3	(-0.00216)	(0.946)
Black/African American percentage of total population	-0.0578	-0.943	-0.00475	-1.42	0.048	0.733			0.000451	0.968
	(0.0613)	(0.346)	(0.00335)	(0.156)	(0.0655)	(0.464)	12	3	(0.000627)	(0.953)
Percentage of Hispanic/Latino of total population	-0.0139	-3.05	0.00149	0.604	-0.00123	-0.179			-0.0121	0.865
	(0.00456)	(0.00227)	(0.00246)	(0.546)	(0.00687)	(0.858)	12	3	(-0.0175)	(0.806)
Percentage of Foreign-born of total population	-0.0044	-0.78	-0.00176	-0.572	1.58e-05	0.00203			0.00501	0.881
	(0.00564)	(0.436)	(0.00307)	(0.567)	(0.00778)	(0.998)	12	3	(0.00713)	(0.83)
Percentage of Children under 18 years old of total population	-0.0154	-0.847	0.00276	0.37	-0.101	-2.46			0.00384	0.984
	(0.0181)	(0.397)	(0.00746)	(0.712)	(0.0412)	(0.0141)	12	3	(0.00551)	(0.977)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0621	-0.833	-0.0224	-0.816	-0.15	-0.734			0.000328	0.99
	(0.0745)	(0.405)	(0.0275)	(0.415)	(0.204)	(0.463)	12	3	(0.000465)	(0.986)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00384	-0.26	-0.00101	-0.2	0.0231	1.16			0.001	0.964
	(0.0148)	(0.795)	(0.00507)	(0.841)	(0.02)	(0.247)	12	3	(0.00142)	(0.948)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00645	-0.392	-0.00285	-0.383	0.0193	0.745			-0.00052	0.966
	(0.0165)	(0.695)	(0.00745)	(0.702)	(0.0259)	(0.456)	12	3	(-0.00077)	(0.951)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.55)	-0.627	-1.47	-0.14	-0.864	0.843	1.01			-5.41e-05	0.947
	(0.426)	(0.141)	(0.162)	(0.388)	(0.837)	(0.314)	12	3	(-0.000112)	(0.924)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.16)	-0.0529	-0.12	0.039	0.256	-1.92	-1.69			0.0031	0.988
	(0.44)	(0.904)	(0.152)	(0.798)	(1.13)	(0.0908)	12	3	(0.00444)	(0.983)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.5)	-0.18	-0.434	0.0691	0.481	-2.67	-2.54			0.00419	0.985
	(0.413)	(0.664)	(0.144)	(0.631)	(1.05)	(0.011)	12	3	(0.00601)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.9)	-0.174	-0.494	0.133	1.12	-2.72	-3.45			0.00448	0.985
	(0.353)	(0.621)	(0.118)	(0.263)	(0.788)	(0.000556)	12	3	(0.00643)	(0.978)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00503	0.847	-0.00311	-1.06	0.00972	0.792			0.000729	0.929
	(0.00594)	(0.397)	(0.00293)	(0.289)	(0.0123)	(0.428)	12	3	(0.001)	(0.898)
Percentage of Persons 25+ years old who have completed high school but no college	0.0186	0.661	-0.00341	-0.523	0.0635	1.55			-0.000845	0.99
	(0.0281)	(0.509)	(0.00653)	(0.601)	(0.0409)	(0.121)	12	3	(-0.00122)	(0.986)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0199	-2.69	0.00398	2.07	0.00776	0.934			0.00089	0.962
	(0.0074)	(0.00722)	(0.00193)	(0.0388)	(0.00831)	(0.35)	12	3	(0.00126)	(0.945)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.046	-1.79	0.00442	0.578	0.0123	0.405			-0.000129	0.971
	(0.0257)	(0.0741)	(0.00764)	(0.563)	(0.0303)	(0.685)	12	3	(-0.000204)	(0.959)
Percentage of total persons below the poverty level in past 12 months	-0.0691	-1.15	-0.00128	-0.204	0.116	1.73			0.0042	0.927
	(0.0602)	(0.251)	(0.0063)	(0.839)	(0.067)	(0.0842)	12	3	(0.00599)	(0.894)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00368	-0.387	0.000166	0.0508	0.0169	1.36			-0.00758	0.871
	(0.0095)	(0.698)	(0.00326)	(0.959)	(0.0125)	(0.175)	12	3	(-0.011)	(0.814)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	7.66	1.45	-7.34	-1.65	-16.9	-1.19			0.0119	0.268
	(5.27)	(0.146)	(4.46)	(0.0996)	(14.2)	(0.235)	12	3	(0.0166)	(-0.0529)
Percentage of renter-occupied housing units of total housing units	0.00158	0.0575	-0.0086	-0.866	-0.00552	-0.139			0.00034	0.98
	(0.0274)	(0.954)	(0.00993)	(0.387)	(0.0397)	(0.889)	12	3	(0.000476)	(0.971)
Percentage of vacant housing units	-0.00787	-0.84	-0.000414	-0.0707	0.0565	2.51			0.00593	0.932
	(0.00936)	(0.401)	(0.00585)	(0.944)	(0.0225)	(0.0121)	12	3	(0.00848)	(0.902)
Percentage of change in number of housing units since last census of total housing units	0.499	1.42	-0.349	-0.861	-0.98	-2.04			-0.000101	0.24
	(0.353)	(0.157)	(0.406)	(0.389)	(0.481)	(0.0416)	12	3	(-0.000632)	(-0.0934)

Table 45. Low bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new low bridge (SE)	t value (p value)	new low bridge Treatment Variable (SE)	t value (p value)	new low bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.6)	-0.737	-0.867	-0.341	-0.92	-1.62	-0.809			0.00052	0.992
	(0.85)	(0.386)	(0.371)	(0.358)	(2.01)	(0.419)	12	4	(0.000743)	(0.989)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.923	-0.73	-0.621	-1.13	-3.2	-1.03			0.000828	0.993
	(1.27)	(0.466)	(0.552)	(0.26)	(3.12)	(0.305)	12	4	(0.00118)	(0.99)
Non-White percentage of total population	-0.0498	-0.974	0.00383	0.956	0.0358	0.688			-0.0049	0.959
	(0.0512)	(0.33)	(0.00401)	(0.339)	(0.052)	(0.491)	12	4	(-0.00709)	(0.941)
Black/African American percentage of total population	-0.0412	-0.788	-0.000363	-0.121	0.0319	0.607			-0.00467	0.962
	(0.0522)	(0.431)	(0.003)	(0.904)	(0.0526)	(0.544)	12	4	(-0.00676)	(0.946)
Percentage of Hispanic/Latino of total population	-0.0064	-1.88	0.00279	1.37	0.00419	0.577			0.0389	0.916
	(0.0034)	(0.0602)	(0.00204)	(0.171)	(0.00727)	(0.564)	12	4	(0.0559)	(0.879)
Percentage of Foreign-born of total population	-0.00288	-0.416	0.000687	0.233	-0.00965	-1.05			0.0126	0.889
	(0.00692)	(0.677)	(0.00295)	(0.816)	(0.00921)	(0.295)	12	4	(0.0181)	(0.84)
Percentage of Children under 18 years old of total population	-0.0228	-1.52	0.00429	0.635	-0.0568	-1.89			0.00575	0.986
	(0.015)	(0.128)	(0.00675)	(0.525)	(0.03)	(0.0587)	12	4	(0.00825)	(0.979)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0805	-0.881	-0.0128	-0.465	-0.082	-0.406			-5.21e-05	0.99
	(0.0913)	(0.378)	(0.0274)	(0.642)	(0.202)	(0.684)	12	4	(-8.46e-05)	(0.986)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00173	0.114	-0.000271	-0.0488	0.0424	2.04			-0.000861	0.962
	(0.0152)	(0.909)	(0.00555)	(0.961)	(0.0208)	(0.0414)	12	4	(-0.00127)	(0.946)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00683	-0.332	0.00163	0.195	0.0547	1.59			-0.00297	0.963
	(0.0206)	(0.74)	(0.00837)	(0.846)	(0.0344)	(0.113)	12	4	(-0.0043)	(0.947)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.55)	-0.825	-2.15	-0.136	-0.792	1.65	1.89			0.000658	0.948
	(0.384)	(0.0318)	(0.171)	(0.428)	(0.874)	(0.0594)	12	4	(0.000896)	(0.925)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.16)	-0.314	-0.953	0.0236	0.165	-1.16	-1.32			0.00467	0.99
	(0.33)	(0.341)	(0.144)	(0.869)	(0.877)	(0.186)	12	4	(0.0067)	(0.985)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.5)	-0.424	-1.32	0.0511	0.374	-1.67	-2.03			0.00535	0.986
	(0.32)	(0.185)	(0.137)	(0.709)	(0.824)	(0.0426)	12	4	(0.00768)	(0.98)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.9)	-0.385	-1.34	0.0889	0.811	-1.94	-3.02			0.00639	0.987
	(0.287)	(0.179)	(0.11)	(0.417)	(0.643)	(0.00256)	12	4	(0.00917)	(0.981)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.000602	0.0712	-0.00122	-0.401	0.0211	1.49			0.0018	0.93
	(0.00846)	(0.943)	(0.00305)	(0.688)	(0.0142)	(0.137)	12	4	(0.00252)	(0.899)
Percentage of Persons 25+ years old who have completed high school but no college	0.0338	1.14	-0.00638	-1.09	0.0812	2.12			-0.000471	0.991
	(0.0296)	(0.253)	(0.00586)	(0.276)	(0.0384)	(0.0343)	12	4	(-0.000686)	(0.987)
Percentage of Persons 25+ years old who have an associate degree but no bachelor’s degree	-0.0174	-2.5	0.00422	2.03	0.00998	1.17			9.49e-05	0.961
	(0.00696)	(0.0125)	(0.00208)	(0.0422)	(0.00853)	(0.242)	12	4	(9.9e-05)	(0.944)
Percentage of Persons 25+ years old who have a bachelor’s or graduate/professional degree	-0.0701	-2.87	0.0137	1.72	-0.0325	-1.14			-0.00254	0.969
	(0.0244)	(0.00409)	(0.00794)	(0.0857)	(0.0285)	(0.254)	12	4	(-0.00368)	(0.955)
Percentage of total persons below the poverty level in past 12 months	-0.0739	-1.14	0.00268	0.367	0.134	1.98			-0.00134	0.921
	(0.0649)	(0.255)	(0.0073)	(0.713)	(0.068)	(0.0483)	12	4	(-0.002)	(0.886)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.0146	-1.28	0.00279	0.702	0.039	2.17			-0.0037	0.875
	(0.0114)	(0.199)	(0.00398)	(0.483)	(0.018)	(0.0303)	12	4	(-0.00544)	(0.819)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	11.4	2.35	-7.74	-1.77	-16.5	-1.12			0.00467	0.261
	(4.85)	(0.0188)	(4.37)	(0.0768)	(14.8)	(0.265)	12	4	(0.006)	(-0.0635)
Percentage of renter-occupied housing units of total housing units	-0.0056	-0.241	-0.00184	-0.17	0.0239	0.598			-0.00311	0.976
	(0.0233)	(0.81)	(0.0108)	(0.865)	(0.0399)	(0.55)	12	4	(-0.00449)	(0.966)
Percentage of vacant housing units	-0.00337	-0.332	-0.00108	-0.183	0.061	2.89			0.0111	0.937
	(0.0102)	(0.74)	(0.00591)	(0.855)	(0.0211)	(0.00388)	12	4	(0.016)	(0.91)
Percentage of change in number of housing units since last census of total housing units	0.67	1.45	-0.395	-0.906	-1.03	-1.88			-0.000581	0.239
	(0.461)	(0.146)	(0.436)	(0.365)	(0.546)	(0.0596)	12	4	(-0.00157)	(-0.0944)

Table 46. Medium bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new medium bridge (SE)	t value (p value)	new medium bridge Treatment Variable (SE)	t value (p value)	new medium bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.306	-1.64	0.0771	0.621	-0.392	-0.231			4.85e-06	0.99
	(0.187)	(0.102)	(0.124)	(0.534)	(1.7)	(0.818)	12	1	(3.16e-06)	(0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.624	-2.14	0.0925	0.479	6.5	2.72			7.67e-06	0.991
	(0.292)	(0.0326)	(0.193)	(0.632)	(2.39)	(0.00656)	12	1	(7.32e-06)	(0.987)
Non-White percentage of total population	-0.00258	-0.324	0.000885	0.452	0.122	3.1			2e-06	0.958
	(0.00795)	(0.746)	(0.00196)	(0.651)	(0.0393)	(0.00195)	12	1	(-1.28e-05)	(0.941)
Black/African American percentage of total population	-0.00921	-1.28	0.000981	0.611	0.0969	3.53			3.27e-05	0.959
	(0.00719)	(0.2)	(0.0016)	(0.541)	(0.0275)	(0.000425)	12	1	(3.05e-05)	(0.943)
Percentage of Hispanic/Latino of total population	-0.004	-1.74	0.00215	1.86	-0.083	-1.73			7.03e-05	0.87
	(0.0023)	(0.0821)	(0.00116)	(0.0629)	(0.0481)	(0.0844)	12	1	(4.99e-05)	(0.819)
Percentage of Foreign-born of total population	0.00421	1.39	-0.00103	-0.869	0.0779	2.12			4.69e-05	0.887
	(0.00303)	(0.165)	(0.00119)	(0.385)	(0.0366)	(0.0336)	12	1	(2.33e-05)	(0.842)
Percentage of Children under 18 years old of total population	-0.0119	-2.16	0.00584	1.8	0.152	3.91			2.64e-05	0.979
	(0.00552)	(0.0308)	(0.00325)	(0.0725)	(0.0389)	(9.22e-05)	12	1	(2.89e-05)	(0.97)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.988)	-0.0214	-1	-0.000798	-0.0621	-0.0654	-0.266			3.99e-06	0.987
	(0.0213)	(0.315)	(0.0128)	(0.95)	(0.245)	(0.79)	12	1	(5.83e-07)	(0.981)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00711	-2.06	0.00307	1.88	0.436	15.5			3.63e-05	0.954
	(0.00346)	(0.0397)	(0.00163)	(0.0597)	(0.0281)	(1.61e-53)	12	1	(3.38e-05)	(0.937)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.0068	-1.7	0.00178	0.874	0.431	7.47			1.25e-05	0.969
	(0.004)	(0.089)	(0.00203)	(0.382)	(0.0577)	(9.01e-14)	12	1	(5.82e-06)	(0.956)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.7)	-0.506	-3.51	0.0798	1.1	11.6	2.68			0.000128	0.936
	(0.144)	(0.000447)	(0.0724)	(0.271)	(4.35)	(0.0074)	12	1	(0.000155)	(0.911)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.27)	-0.345	-2.68	0.107	1.36	-0.833	-0.582			2.53e-05	0.982
	(0.129)	(0.00739)	(0.0785)	(0.173)	(1.43)	(0.56)	12	1	(2.85e-05)	(0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.67)	-0.256	-2.03	0.107	1.44	1.32	1.15			2.1e-05	0.979
	(0.126)	(0.042)	(0.0741)	(0.149)	(1.14)	(0.249)	12	1	(2.14e-05)	(0.97)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.05)	-0.285	-2.56	0.107	1.63	8.57	2.16			3.11e-05	0.978
	(0.111)	(0.0105)	(0.0655)	(0.103)	(3.98)	(0.0311)	12	1	(3.5e-05)	(0.969)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00403	-1.15	-0.000411	-0.291	0.0557	0.566			4.01e-05	0.906
	(0.0035)	(0.25)	(0.00141)	(0.771)	(0.0983)	(0.571)	12	1	(2.09e-05)	(0.868)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0164	-2.24	0.00129	0.449	-0.623	-7.54			1.51e-05	0.988
	(0.00732)	(0.0248)	(0.00286)	(0.653)	(0.0826)	(5.13e-14)	12	1	(1.67e-05)	(0.984)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	9.13e-05	0.0447	0.000595	0.598	-0.412	-6.47			3.25e-06	0.957
	(0.00204)	(0.964)	(0.000993)	(0.55)	(0.0636)	(1.01e-10)	12	1	(-1.15e-05)	(0.94)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.029	3.1	0.00227	0.612	-0.341	-0.946			0.000113	0.968
	(0.00937)	(0.00198)	(0.00371)	(0.54)	(0.36)	(0.344)	12	1	(0.000145)	(0.955)
Percentage of total persons below the poverty level in past 12 months	-0.0116	-1.5	0.000129	0.0495	0.506	4.36			7.47e-05	0.917
	(0.00771)	(0.134)	(0.0026)	(0.96)	(0.116)	(1.34e-05)	12	1	(7.33e-05)	(0.884)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00281	-0.698	-2.96e-05	-0.0213	0.107	2.5			1.62e-05	0.88
	(0.00403)	(0.485)	(0.00139)	(0.983)	(0.0431)	(0.0126)	12	1	(-2.18e-05)	(0.833)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-26.3	-1.03	-3.73	-0.749	-132	-3.1			0.000655	0.357
	(25.5)	(0.301)	(4.98)	(0.454)	(42.4)	(0.00192)	12	1	(0.000676)	(0.104)
Percentage of renter-occupied housing units of total housing units	-0.00209	-0.273	0.00152	0.406	0.787	5.26			1.09e-06	0.971
	(0.00765)	(0.785)	(0.00374)	(0.685)	(0.15)	(1.49e-07)	12	1	(-9.17e-06)	(0.96)
Percentage of vacant housing units	0.0015	0.372	-3e-04	-0.134	0.42	4.63			1.55e-06	0.899
	(0.00402)	(0.71)	(0.00224)	(0.893)	(0.0908)	(3.67e-06)	12	1	(-3.52e-05)	(0.859)
Percentage of change in number of housing units since last census of total housing units	0.251	0.532	-0.405	-1.27	1.4	1.13			8.86e-05	0.419
	(0.471)	(0.595)	(0.319)	(0.204)	(1.25)	(0.26)	12	1	(-9.19e-05)	(0.189)

Table 46. Medium bridge treatment effect event study model w/ CEM results (cont'd)

Dependent Variable	Interaction Estimator for new medium bridge (SE)	t value (p value)	new medium bridge Treatment Variable (SE)	t value (p value)	new medium bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.0245	-0.137	0.038	0.324	-2.91	-1.4			0.00124	0.992
	(0.179)	(0.891)	(0.117)	(0.746)	(2.07)	(0.161)	10	2	(0.00173)	(0.988)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.154	-0.564	0.0237	0.134	3.86	1.55			0.00143	0.992
	(0.273)	(0.573)	(0.177)	(0.894)	(2.48)	(0.12)	10	2	(0.002)	(0.989)
Non-White percentage of total population	0.00277	0.342	0.00263	1.14	0.101	0.571			-0.01	0.948
	(0.00811)	(0.732)	(0.0023)	(0.253)	(0.177)	(0.568)	10	2	(-0.014)	(0.927)
Black/African American percentage of total population	-0.00522	-0.737	0.00188	1.05	0.0702	0.641			-0.00663	0.953
	(0.00708)	(0.461)	(0.0018)	(0.296)	(0.11)	(0.522)	10	2	(-0.00924)	(0.934)
Percentage of Hispanic/Latino of total population	-0.00281	-1.2	0.00189	1.6	-0.171	-2.32			-0.00364	0.866
	(0.00234)	(0.231)	(0.00118)	(0.11)	(0.0734)	(0.0202)	10	2	(-0.00508)	(0.814)
Percentage of Foreign-born of total population	0.00498	1.6	-0.000555	-0.46	0.108	5.77			-0.00309	0.883
	(0.00312)	(0.11)	(0.00121)	(0.646)	(0.0187)	(8.15e-09)	10	2	(-0.00431)	(0.837)
Percentage of Children under 18 years old of total population	-0.000313	-0.0639	0.00461	1.69	0.0296	0.529			0.00543	0.984
	(0.00489)	(0.949)	(0.00273)	(0.0915)	(0.0559)	(0.596)	10	2	(0.00757)	(0.978)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.988)	-0.00613	-0.284	-0.00334	-0.26	-0.218	-0.881			0.000274	0.987
	(0.0215)	(0.776)	(0.0128)	(0.795)	(0.248)	(0.378)	10	2	(0.000382)	(0.982)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00306	-0.875	0.00228	1.41	0.305	14.8			-0.000871	0.954
	(0.0035)	(0.382)	(0.00162)	(0.16)	(0.0206)	(4.62e-49)	10	2	(-0.00121)	(0.935)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.000547	-0.135	0.000875	0.443	0.297	2.99			0.000552	0.969
	(0.00404)	(0.892)	(0.00198)	(0.658)	(0.0992)	(0.00276)	10	2	(0.000769)	(0.957)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.7)	-0.378	-2.71	0.074	1.06	9.53	1.97			0.00119	0.938
	(0.139)	(0.00668)	(0.0697)	(0.288)	(4.84)	(0.049)	10	2	(0.00166)	(0.913)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.27)	-0.0679	-0.643	0.0593	0.956	-2.05	-1.72			0.0061	0.988
	(0.106)	(0.521)	(0.062)	(0.339)	(1.19)	(0.0858)	10	2	(0.00851)	(0.983)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.67)	0.000931	0.0088	0.0644	1.07	-1.22	-1.08			0.00618	0.985
	(0.106)	(0.993)	(0.06)	(0.283)	(1.13)	(0.281)	10	2	(0.00862)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.05)	-0.0784	-0.819	0.0687	1.22	5.75	1.27			0.0051	0.983
	(0.0957)	(0.413)	(0.0561)	(0.221)	(4.54)	(0.205)	10	2	(0.00711)	(0.976)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00226	-0.665	-0.000205	-0.149	0.0327	0.401			-0.000162	0.905
	(0.0034)	(0.506)	(0.00138)	(0.882)	(0.0816)	(0.688)	10	2	(-0.000226)	(0.868)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0143	-1.56	-0.00227	-0.657	-1.04	-9.82			-0.0025	0.986
	(0.00913)	(0.118)	(0.00346)	(0.511)	(0.106)	(1.3e-22)	10	2	(-0.00348)	(0.98)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0013	-0.612	0.000103	0.1	-0.416	-10.6			-0.0018	0.955
	(0.00212)	(0.54)	(0.00103)	(0.92)	(0.0393)	(4.63e-26)	10	2	(-0.00251)	(0.937)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0265	2.15	0.00727	1.58	0.226	0.554			-0.00889	0.959
	(0.0123)	(0.0318)	(0.00461)	(0.115)	(0.407)	(0.58)	10	2	(-0.0124)	(0.942)
Percentage of total persons below the poverty level in past 12 months	-0.00492	-0.639	-0.000234	-0.096	0.442	3.06			0.00145	0.918
	(0.0077)	(0.523)	(0.00244)	(0.924)	(0.144)	(0.0022)	10	2	(0.00202)	(0.886)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	2.73e-05	0.00676	-4.22e-06	-0.00325	0.123	2.07			0.00373	0.884
	(0.00404)	(0.995)	(0.0013)	(0.997)	(0.0592)	(0.0382)	10	2	(0.00519)	(0.838)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-28.9	-1.18	-2.13	-0.409	-61.9	-1.32			-0.0245	0.332
	(24.5)	(0.237)	(5.22)	(0.683)	(47.1)	(0.188)	10	2	(-0.0341)	(0.0689)
Percentage of renter-occupied housing units of total housing units	0.0084	1.09	0.000615	0.169	0.607	2.91			0.0023	0.973
	(0.00768)	(0.274)	(0.00363)	(0.866)	(0.208)	(0.00359)	10	2	(0.00321)	(0.963)
Percentage of vacant housing units	0.0078	2.1	-0.00148	-0.686	0.287	3.28			0.007	0.906
	(0.00372)	(0.0359)	(0.00215)	(0.493)	(0.0874)	(0.00103)	10	2	(0.00975)	(0.869)
Percentage of change in number of housing units since last census of total housing units	0.262	0.56	-0.445	-1.34	2.77	1.57			-6.21e-05	0.418
	(0.468)	(0.576)	(0.333)	(0.181)	(1.76)	(0.115)	10	2	(-8.66e-05)	(0.189)

Table 46. Medium bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new medium bridge (SE)	t value (p value)	new medium bridge Treatment Variable (SE)	t value (p value)	new medium bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.222	-1.2	0.0498	0.397	-4.62	-2.82			0.000618	0.991
	(0.186)	(0.232)	(0.126)	(0.692)	(1.64)	(0.00483)	12	3	(0.000858)	(0.987)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.486	-1.69	0.044	0.227	0.276	0.105			0.000675	0.992
	(0.288)	(0.0919)	(0.194)	(0.821)	(2.62)	(0.916)	12	3	(0.000937)	(0.988)
Non-White percentage of total population	0.000128	0.0158	0.00127	0.626	0.075	1.32			-0.00344	0.954
	(0.00812)	(0.987)	(0.00203)	(0.532)	(0.0567)	(0.186)	12	3	(-0.00482)	(0.936)
Black/African American percentage of total population	-0.00741	-1.04	0.00121	0.756	0.0599	2.18			-0.00114	0.958
	(0.00714)	(0.299)	(0.0016)	(0.45)	(0.0275)	(0.0293)	12	3	(-0.0016)	(0.941)
Percentage of Hispanic/Latino of total population	-0.00297	-1.27	0.00171	1.43	-0.0925	-1.98			-0.00765	0.862
	(0.00233)	(0.203)	(0.0012)	(0.154)	(0.0466)	(0.0472)	12	3	(-0.0107)	(0.808)
Percentage of Foreign-born of total population	0.00419	1.38	-0.000998	-0.843	0.0821	2.65			-0.000434	0.886
	(0.00304)	(0.168)	(0.00119)	(0.4)	(0.0309)	(0.008)	12	3	(-0.000647)	(0.841)
Percentage of Children under 18 years old of total population	-0.00809	-1.53	0.00453	1.48	-0.0644	-1.37			0.00371	0.982
	(0.00528)	(0.125)	(0.00306)	(0.139)	(0.0469)	(0.17)	12	3	(0.00517)	(0.975)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.988)	-0.0168	-0.788	-0.00184	-0.14	-0.243	-0.977			0.000129	0.987
	(0.0213)	(0.431)	(0.0131)	(0.888)	(0.249)	(0.328)	12	3	(0.000175)	(0.981)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00572	-1.72	0.00244	1.57	0.31	5.39			0.00207	0.957
	(0.00333)	(0.0859)	(0.00155)	(0.117)	(0.0575)	(7.23e-08)	12	3	(0.00287)	(0.939)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00458	-1.19	0.000966	0.503	0.286	7.59			0.00173	0.97
	(0.00386)	(0.236)	(0.00192)	(0.615)	(0.0377)	(3.67e-14)	12	3	(0.0024)	(0.959)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.7)	-0.447	-3.13	0.0751	1.04	8.82	1.94			-0.000453	0.936
	(0.143)	(0.00175)	(0.072)	(0.297)	(4.54)	(0.0519)	12	3	(-0.000656)	(0.911)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.27)	-0.272	-2.2	0.0688	0.929	-4.34	-1.99			0.00328	0.985
	(0.123)	(0.0277)	(0.0741)	(0.353)	(2.18)	(0.0464)	12	3	(0.00457)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.67)	-0.182	-1.54	0.0721	1.03	-2.82	-1.83			0.00378	0.983
	(0.118)	(0.123)	(0.0701)	(0.303)	(1.54)	(0.0678)	12	3	(0.00526)	(0.976)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.05)	-0.219	-2.12	0.0756	1.23	4.68	1.49			0.0037	0.981
	(0.103)	(0.0341)	(0.0613)	(0.217)	(3.14)	(0.135)	12	3	(0.00516)	(0.974)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00299	-0.888	-0.000692	-0.509	-0.00543	-0.0588			0.00267	0.908
	(0.00337)	(0.374)	(0.00136)	(0.611)	(0.0923)	(0.953)	12	3	(0.00369)	(0.872)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0142	-1.84	-0.000659	-0.223	-0.711	-6.2			-0.000835	0.987
	(0.0077)	(0.0652)	(0.00296)	(0.824)	(0.115)	(5.99e-10)	12	3	(-0.00117)	(0.982)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00048	-0.228	0.000635	0.648	-0.355	-6.49			0.00099	0.958
	(0.0021)	(0.82)	(0.000979)	(0.517)	(0.0546)	(8.87e-11)	12	3	(0.00136)	(0.941)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0257	2.6	0.00511	1.35	-0.235	-0.519			-0.00135	0.966
	(0.00991)	(0.0094)	(0.0038)	(0.179)	(0.454)	(0.604)	12	3	(-0.0019)	(0.953)
Percentage of total persons below the poverty level in past 12 months	-0.00942	-1.26	-0.000524	-0.215	0.365	2.91			0.00487	0.922
	(0.00746)	(0.207)	(0.00243)	(0.829)	(0.126)	(0.00362)	12	3	(0.00676)	(0.891)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00191	-0.463	-5.06e-06	-0.00375	0.0466	0.929			0.0031	0.883
	(0.00412)	(0.643)	(0.00135)	(0.997)	(0.0501)	(0.353)	12	3	(0.00428)	(0.837)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-23	-0.945	-2.32	-0.447	34.3	0.364			-0.0206	0.336
	(24.3)	(0.345)	(5.18)	(0.655)	(94.1)	(0.716)	12	3	(-0.0289)	(0.0741)
Percentage of renter-occupied housing units of total housing units	0.000129	0.0172	0.000678	0.192	0.464	4.79			0.00348	0.975
	(0.0075)	(0.986)	(0.00353)	(0.848)	(0.0968)	(1.7e-06)	12	3	(0.00485)	(0.965)
Percentage of vacant housing units	0.00434	1.15	-0.00117	-0.551	0.284	2.7			0.00747	0.907
	(0.00376)	(0.248)	(0.00213)	(0.581)	(0.105)	(0.0069)	12	3	(0.0104)	(0.87)
Percentage of change in number of housing units since last census of total housing units	0.259	0.547	-0.428	-1.32	2.92	2.21			3.49e-05	0.419
	(0.473)	(0.584)	(0.325)	(0.188)	(1.32)	(0.0273)	12	3	(-0.000167)	(0.189)

Table 46. Medium bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new medium bridge (SE)	t value (p value)	new medium bridge Treatment Variable (SE)	t value (p value)	new medium bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.285	-1.56	0.0637	0.569	1.28	0.928			0.00157	0.992
	(0.183)	(0.119)	(0.112)	(0.569)	(1.38)	(0.354)	12	4	(0.00219)	(0.989)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.576	-2.02	0.0624	0.362	8.23	4.53			0.00161	0.992
	(0.285)	(0.0434)	(0.172)	(0.717)	(1.82)	(6.12e-06)	12	4	(0.00223)	(0.99)
Non-White percentage of total population	0.00568	0.737	0.00124	0.542	0.283	3.84			-0.00827	0.95
	(0.00771)	(0.461)	(0.00228)	(0.588)	(0.0737)	(0.000126)	12	4	(-0.0116)	(0.93)
Black/African American percentage of total population	-0.00392	-0.592	0.00123	0.688	0.165	3.37			-0.00652	0.953
	(0.00662)	(0.554)	(0.00178)	(0.492)	(0.0488)	(0.000743)	12	4	(-0.00912)	(0.934)
Percentage of Hispanic/Latino of total population	-0.0012	-0.572	0.000227	0.229	0.00983	0.448			0.036	0.906
	(0.0021)	(0.567)	(0.000988)	(0.819)	(0.0219)	(0.654)	12	4	(0.0502)	(0.869)
Percentage of Foreign-born of total population	0.00579	1.84	-0.00116	-0.992	0.147	4.16			0.00119	0.888
	(0.00315)	(0.0658)	(0.00117)	(0.321)	(0.0353)	(3.18e-05)	12	4	(0.0016)	(0.843)
Percentage of Children under 18 years old of total population	-0.00872	-1.78	0.00494	1.79	0.22	3.43			0.00501	0.984
	(0.0049)	(0.0749)	(0.00276)	(0.0735)	(0.0642)	(0.000615)	12	4	(0.00697)	(0.977)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.988)	-0.0209	-0.967	-0.00173	-0.139	-0.022	-0.109			0.000892	0.987
	(0.0216)	(0.333)	(0.0124)	(0.889)	(0.202)	(0.913)	12	4	(0.00124)	(0.982)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.0048	-1.43	0.00213	1.35	0.425	9.01			0.00134	0.956
	(0.00336)	(0.153)	(0.00158)	(0.178)	(0.0471)	(2.5e-19)	12	4	(0.00185)	(0.938)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00382	-0.958	0.000556	0.278	0.44	7.61			0.000362	0.969
	(0.00398)	(0.338)	(0.002)	(0.781)	(0.0578)	(3e-14)	12	4	(0.000487)	(0.957)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.7)	-0.49	-3.46	0.0778	1.08	12.7	2.68			0.000586	0.937
	(0.142)	(0.000537)	(0.072)	(0.28)	(4.73)	(0.00734)	12	4	(0.000781)	(0.912)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.27)	-0.309	-2.63	0.0792	1.14	-0.205	-0.225			0.00418	0.986
	(0.118)	(0.00861)	(0.0694)	(0.254)	(0.914)	(0.822)	12	4	(0.00582)	(0.98)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.67)	-0.223	-1.94	0.0751	1.13	1.84	1.02			0.00411	0.983
	(0.115)	(0.0522)	(0.0662)	(0.257)	(1.81)	(0.309)	12	4	(0.00572)	(0.976)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.05)	-0.253	-2.62	0.0733	1.28	9.16	2.23			0.00482	0.982
	(0.0966)	(0.00874)	(0.0571)	(0.199)	(4.1)	(0.0255)	12	4	(0.00671)	(0.975)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00227	-0.656	-0.000794	-0.578	0.131	1.24			0.00441	0.91
	(0.00347)	(0.512)	(0.00137)	(0.563)	(0.106)	(0.215)	12	4	(0.0061)	(0.874)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0198	-2.32	-0.00129	-0.401	-0.89	-8.29			-0.00136	0.987
	(0.00857)	(0.0206)	(0.00321)	(0.688)	(0.107)	(1.34e-16)	12	4	(-0.0019)	(0.982)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.000837	-0.397	3.54e-05	0.0347	-0.435	-9.33			-0.00146	0.955
	(0.00211)	(0.691)	(0.00102)	(0.972)	(0.0466)	(1.35e-20)	12	4	(-0.00206)	(0.937)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0317	2.8	0.0068	1.61	-0.0581	-0.121			-0.00518	0.962
	(0.0113)	(0.00519)	(0.00423)	(0.108)	(0.48)	(0.904)	12	4	(-0.00724)	(0.948)
Percentage of total persons below the poverty level in past 12 months	-0.00811	-1.1	-0.000415	-0.166	0.541	4.85			0.00265	0.919
	(0.00736)	(0.271)	(0.00249)	(0.868)	(0.112)	(1.27e-06)	12	4	(0.00365)	(0.888)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.00236	-0.58	3.07e-05	0.0226	0.147	2.27			0.000848	0.881
	(0.00406)	(0.562)	(0.00136)	(0.982)	(0.0644)	(0.023)	12	4	(0.00112)	(0.834)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-27.3	-1.08	-3.65	-0.738	-32.1	-0.698			0.000798	0.357
	(25.4)	(0.282)	(4.95)	(0.461)	(45.9)	(0.485)	12	4	(0.000756)	(0.104)
Percentage of renter-occupied housing units of total housing units	0.00129	0.169	0.001	0.274	0.718	4.54			0.00168	0.973
	(0.0076)	(0.865)	(0.00367)	(0.784)	(0.158)	(5.6e-06)	12	4	(0.00233)	(0.962)
Percentage of vacant housing units	0.00303	0.819	-0.00106	-0.495	0.404	3.26			0.00873	0.908
	(0.0037)	(0.413)	(0.00214)	(0.62)	(0.124)	(0.00111)	12	4	(0.0121)	(0.872)
Percentage of change in number of housing units since last census of total housing units	0.214	0.461	-0.434	-1.32	0.593	0.4			-0.00021	0.418
	(0.464)	(0.644)	(0.33)	(0.188)	(1.48)	(0.689)	12	4	(-0.000615)	(0.189)

Table 47. High bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new high bridge (SE)	t value (p value)	new high bridge Treatment Variable (SE)	t value (p value)	new high bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.0814	0.51	-0.0305	-0.249	0.196	0.621	12	1	7.42e-07	0.986
	(0.16)	(0.61)	(0.123)	(0.803)	(0.316)	(0.535)			(-4.76e-06)	(0.98)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.0914	0.364	-0.0797	-0.415	0.51	1.05	12	1	9.61e-07	0.986
	(0.251)	(0.716)	(0.192)	(0.678)	(0.486)	(0.294)			(-4.17e-06)	(0.981)
Non-White percentage of total population	0.00315	0.814	0.000453	0.259	0.0072	1.04	12	1	1.24e-05	0.954
	(0.00387)	(0.415)	(0.00175)	(0.795)	(0.00689)	(0.296)			(-9.41e-07)	(0.935)
Black/African American percentage of total population	-0.00539	-1.63	0.000669	0.482	0.00404	1.17	12	1	3.49e-05	0.957
	(0.00331)	(0.104)	(0.00139)	(0.63)	(0.00345)	(0.241)			(3.21e-05)	(0.939)
Percentage of Hispanic/Latino of total population	0.00153	0.96	-0.000917	-0.954	0.0104	1.25	12	1	3.63e-05	0.852
	(0.00159)	(0.337)	(0.000961)	(0.34)	(0.00839)	(0.213)			(-8.29e-06)	(0.791)
Percentage of Foreign-born of total population	0.00497	2.07	-0.00186	-1.62	-0.0101	-1.83	12	1	0.00019	0.88
	(0.0024)	(0.0381)	(0.00115)	(0.106)	(0.00551)	(0.0675)			(0.000221)	(0.829)
Percentage of Children under 18 years old of total population	0.00459	0.966	-0.00101	-0.3	-0.021	-1.65	12	1	4.82e-06	0.971
	(0.00475)	(0.334)	(0.00336)	(0.764)	(0.0127)	(0.0998)			(-4.88e-06)	(0.959)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.983)	0.00227	0.142	-0.00221	-0.194	0.0558	1.96	12	1	2.58e-07	0.981
	(0.0159)	(0.887)	(0.0114)	(0.846)	(0.0284)	(0.0496)			(-7.34e-06)	(0.973)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00024	-0.0758	0.000513	0.316	0.0201	1.49	12	1	1.35e-06	0.947
	(0.00317)	(0.94)	(0.00162)	(0.752)	(0.0135)	(0.135)			(-1.95e-05)	(0.925)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.000366	-0.097	0.00284	1.38	0.012	1.02	12	1	2.2e-05	0.962
	(0.00378)	(0.923)	(0.00205)	(0.167)	(0.0117)	(0.305)			(1.59e-05)	(0.947)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.51)	-0.401	-3.52	0.0303	0.39	-1.31	-2.65	12	1	0.000179	0.925
	(0.114)	(0.000427)	(0.0777)	(0.696)	(0.494)	(0.00814)			(0.000223)	(0.893)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.103	-0.979	0.0103	0.14	0.551	1.76	12	1	3.81e-06	0.977
	(0.105)	(0.327)	(0.0738)	(0.889)	(0.313)	(0.0788)			(-4.09e-06)	(0.967)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.72)	-0.0081	-0.0802	0.0124	0.171	0.319	1.16	12	1	2.61e-07	0.973
	(0.101)	(0.936)	(0.0726)	(0.864)	(0.276)	(0.248)			(-1.05e-05)	(0.962)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.08)	0.0629	0.701	-0.0124	-0.2	-0.288	-0.676	12	1	2.28e-06	0.974
	(0.0897)	(0.483)	(0.0617)	(0.841)	(0.426)	(0.499)			(-7.21e-06)	(0.963)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.000689	-0.265	0.00113	0.705	0.00355	0.224	12	1	1.54e-05	0.901
	(0.0026)	(0.791)	(0.00161)	(0.481)	(0.0158)	(0.822)			(-1.85e-05)	(0.859)
Percentage of Persons 25+ years old who have completed high school but no college	-0.00428	-0.874	0.00253	0.805	-0.014	-1.29	12	1	3.21e-06	0.987
	(0.0049)	(0.382)	(0.00314)	(0.421)	(0.0109)	(0.197)			(-5.56e-07)	(0.982)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.000911	-0.567	-0.000765	-0.644	0.0106	1.4	12	1	1.6e-05	0.952
	(0.00161)	(0.571)	(0.00119)	(0.52)	(0.00752)	(0.16)			(3.24e-06)	(0.932)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00613	0.956	-0.000716	-0.192	0.0508	2.21	12	1	8.22e-06	0.957
	(0.00641)	(0.339)	(0.00373)	(0.848)	(0.023)	(0.0272)			(-5.89e-06)	(0.938)
Percentage of total persons below the poverty level in past 12 months	0.000644	0.149	0.0041	1.55	0.00567	0.41	12	1	8.61e-05	0.911
	(0.00433)	(0.882)	(0.00265)	(0.122)	(0.0138)	(0.682)			(8.61e-05)	(0.874)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000379	-0.131	-0.000474	-0.339	-0.0123	-1.56	12	1	5.34e-06	0.886
	(0.00289)	(0.896)	(0.0014)	(0.734)	(0.00789)	(0.119)			(-3.87e-05)	(0.838)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	6.88	0.675	-7.11	-1.13	-3.36	-0.379	12	1	0.000113	0.514
	(10.2)	(0.499)	(6.28)	(0.258)	(8.86)	(0.705)			(-3.71e-05)	(0.31)
Percentage of renter-occupied housing units of total housing units	-0.00174	-0.296	0.00359	1.07	0.0883	7.34	12	1	1.12e-05	0.964
	(0.00589)	(0.767)	(0.00335)	(0.283)	(0.012)	(2.33e-13)			(1.2e-06)	(0.949)
Percentage of vacant housing units	0.00642	1.86	0.000311	0.125	-0.0632	-1.87	12	1	6.3e-05	0.885
	(0.00345)	(0.0631)	(0.00249)	(0.901)	(0.0339)	(0.0621)			(4.28e-05)	(0.837)
Percentage of change in number of housing units since last census of total housing units	0.449	1.71	-0.184	-0.678	-0.185	-0.69	12	1	7.53e-05	0.24
	(0.262)	(0.0873)	(0.271)	(0.498)	(0.268)	(0.49)			(-0.000201)	(-0.0782)

Table 47. High bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new high bridge (SE)	t value (p value)	new high bridge Treatment Variable (SE)	t value (p value)	new high bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.107	0.76	-0.0468	-0.445	0.654	2.47	10	2	0.00255	0.988
	(0.141)	(0.447)	(0.105)	(0.656)	(0.265)	(0.0137)			(0.00361)	(0.983)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.133	0.606	-0.108	-0.665	1.29	3.08	10	2	0.00274	0.989
	(0.22)	(0.545)	(0.163)	(0.506)	(0.418)	(0.00206)			(0.00389)	(0.984)
Non-White percentage of total population	0.00778	1.73	5.63e-05	0.028	0.00483	0.274	10	2	-0.0137	0.94
	(0.0045)	(0.0842)	(0.00201)	(0.978)	(0.0176)	(0.784)			(-0.0195)	(0.915)
Black/African American percentage of total population	-0.00232	-0.631	0.000217	0.139	8.47e-05	0.00927	10	2	-0.0108	0.946
	(0.00367)	(0.528)	(0.00157)	(0.89)	(0.00914)	(0.993)			(-0.0153)	(0.924)
Percentage of Hispanic/Latino of total population	0.0016	1	-0.00144	-1.44	0.00916	0.908	10	2	-0.00547	0.847
	(0.00159)	(0.316)	(0.000998)	(0.15)	(0.0101)	(0.364)			(-0.00775)	(0.783)
Percentage of Foreign-born of total population	0.00577	2.38	-0.00188	-1.61	-0.00919	-1.29	10	2	-0.00274	0.877
	(0.00243)	(0.0175)	(0.00117)	(0.108)	(0.00712)	(0.197)			(-0.00389)	(0.825)
Percentage of Children under 18 years old of total population	0.00777	1.92	-0.00205	-0.785	-0.00346	-0.292	10	2	0.0101	0.981
	(0.00406)	(0.0555)	(0.0026)	(0.432)	(0.0119)	(0.771)			(0.0143)	(0.973)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.983)	8.44e-05	0.00538	-0.00299	-0.277	0.0814	2.97	10	2	0.000416	0.981
	(0.0157)	(0.996)	(0.0108)	(0.782)	(0.0274)	(0.003)			(0.00059)	(0.974)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.000277	0.085	-0.000359	-0.226	0.0216	1.34	10	2	0.0011	0.948
	(0.00325)	(0.932)	(0.00159)	(0.821)	(0.0162)	(0.182)			(0.00156)	(0.927)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00105	0.272	0.00178	0.921	0.0139	0.811	10	2	0.00221	0.965
	(0.00385)	(0.786)	(0.00193)	(0.357)	(0.0171)	(0.417)			(0.00313)	(0.95)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.51)	-0.325	-2.93	0.0324	0.422	-1.06	-1.88	10	2	0.00244	0.927
	(0.111)	(0.00344)	(0.0768)	(0.673)	(0.563)	(0.0595)			(0.00346)	(0.896)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.0691	-0.852	-0.0157	-0.285	0.921	4.84	10	2	0.00917	0.986
	(0.0811)	(0.394)	(0.0552)	(0.776)	(0.19)	(1.33e-06)			(0.013)	(0.98)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.72)	0.0207	0.253	-0.0154	-0.273	0.666	2.4	10	2	0.00977	0.983
	(0.0816)	(0.8)	(0.0562)	(0.785)	(0.278)	(0.0166)			(0.0139)	(0.976)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.08)	0.0895	1.18	-0.0384	-0.772	-0.0305	-0.0572	10	2	0.00791	0.982
	(0.0759)	(0.238)	(0.0497)	(0.44)	(0.534)	(0.954)			(0.0112)	(0.975)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.000277	0.109	0.000986	0.63	0.00614	0.333	10	2	0.00175	0.902
	(0.00254)	(0.913)	(0.00156)	(0.529)	(0.0184)	(0.739)			(0.00248)	(0.861)
Percentage of Persons 25+ years old who have completed high school but no college	-0.0104	-1.73	0.000337	0.0914	-0.0199	-1.22	10	2	-0.00309	0.984
	(0.00601)	(0.0835)	(0.00369)	(0.927)	(0.0163)	(0.222)			(-0.00438)	(0.978)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00222	-1.38	-0.000809	-0.701	0.00755	0.914	10	2	-0.000518	0.951
	(0.00161)	(0.168)	(0.00115)	(0.483)	(0.00827)	(0.361)			(-0.000734)	(0.931)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0157	1.97	0.00278	0.599	0.0632	2.63	10	2	-0.0127	0.944
	(0.00796)	(0.0494)	(0.00463)	(0.549)	(0.024)	(0.00862)			(-0.018)	(0.921)
Percentage of total persons below the poverty level in past 12 months	0.00279	0.654	0.00322	1.34	0.0112	0.599	10	2	0.00951	0.92
	(0.00427)	(0.513)	(0.0024)	(0.18)	(0.0188)	(0.549)			(0.0135)	(0.887)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000973	0.347	-0.000357	-0.283	-0.0048	-0.53	10	2	0.0129	0.899
	(0.00281)	(0.729)	(0.00126)	(0.777)	(0.00905)	(0.596)			(0.0183)	(0.856)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	3.12	0.296	-5.86	-0.997	-0.276	-0.0381	10	2	-0.0814	0.432
	(10.6)	(0.767)	(5.87)	(0.319)	(7.24)	(0.97)			(-0.115)	(0.194)
Percentage of renter-occupied housing units of total housing units	0.00108	0.187	0.00247	0.778	0.0977	5.05	10	2	0.00427	0.968
	(0.00575)	(0.852)	(0.00317)	(0.436)	(0.0193)	(4.52e-07)			(0.00605)	(0.955)
Percentage of vacant housing units	0.00705	2.14	-0.000791	-0.335	-0.0565	-1.56	10	2	0.0121	0.897
	(0.00329)	(0.0323)	(0.00237)	(0.738)	(0.0361)	(0.118)			(0.0172)	(0.854)
Percentage of change in number of housing units since last census of total housing units	0.406	1.71	-0.183	-0.643	-0.244	-0.919	10	2	0.000231	0.24
	(0.238)	(0.0875)	(0.285)	(0.52)	(0.265)	(0.358)			(0.000328)	(-0.0777)

Table 47. High bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new high bridge (SE)	t value (p value)	new high bridge Treatment Variable (SE)	t value (p value)	new high bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.0487	0.316	-0.0734	-0.642	0.624	2.31	12	3	0.00178	0.987
	(0.154)	(0.752)	(0.114)	(0.521)	(0.271)	(0.0211)			(0.00252)	(0.982)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.0255	0.105	-0.154	-0.865	1.23	3.36	12	3	0.0018	0.988
	(0.243)	(0.917)	(0.179)	(0.387)	(0.366)	(0.000778)			(0.00255)	(0.983)
Non-White percentage of total population	0.00615	1.54	0.000548	0.314	0.00983	1.24	12	3	-0.00187	0.952
	(0.00398)	(0.123)	(0.00175)	(0.754)	(0.00795)	(0.216)			(-0.00267)	(0.932)
Black/African American percentage of total population	-0.00342	-1.08	0.000915	0.677	0.00626	1.83	12	3	0.000741	0.958
	(0.00316)	(0.279)	(0.00135)	(0.498)	(0.00342)	(0.0671)			(0.00103)	(0.94)
Percentage of Hispanic/Latino of total population	0.00205	1.28	-0.000966	-0.979	0.0103	1.34	12	3	-0.00728	0.845
	(0.0016)	(0.201)	(0.000987)	(0.328)	(0.0077)	(0.181)			(-0.0104)	(0.78)
Percentage of Foreign-born of total population	0.0052	2.15	-0.00208	-1.83	-0.00966	-1.72	12	3	-0.000308	0.879
	(0.00242)	(0.0317)	(0.00114)	(0.0678)	(0.00561)	(0.0853)			(-0.000486)	(0.829)
Percentage of Children under 18 years old of total population	0.00401	0.885	-0.00249	-0.85	-0.00407	-0.448	12	3	0.00769	0.979
	(0.00453)	(0.376)	(0.00293)	(0.396)	(0.00909)	(0.654)			(0.0109)	(0.97)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.983)	0.00118	0.0737	-0.00549	-0.493	0.078	2.7	12	3	0.00052	0.981
	(0.016)	(0.941)	(0.0111)	(0.622)	(0.0289)	(0.00693)			(0.00073)	(0.974)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.000395	-0.129	0.000461	0.3	0.0221	1.55	12	3	0.00493	0.952
	(0.00307)	(0.898)	(0.00154)	(0.764)	(0.0142)	(0.121)			(0.00698)	(0.932)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.000359	-0.0963	0.00282	1.48	0.0164	1.37	12	3	0.004	0.966
	(0.00372)	(0.923)	(0.00191)	(0.139)	(0.0119)	(0.17)			(0.00566)	(0.952)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.51)	-0.345	-3.03	0.0156	0.202	-1.11	-2.02	12	3	0.000115	0.925
	(0.114)	(0.00244)	(0.0772)	(0.84)	(0.549)	(0.0429)			(0.000133)	(0.893)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.156	-1.59	-0.0237	-0.362	0.924	2.91	12	3	0.00579	0.982
	(0.0981)	(0.113)	(0.0654)	(0.717)	(0.318)	(0.00365)			(0.00821)	(0.975)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.72)	-0.0512	-0.55	-0.019	-0.303	0.669	3.14	12	3	0.00691	0.98
	(0.0932)	(0.583)	(0.0627)	(0.762)	(0.213)	(0.00172)			(0.0098)	(0.972)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.08)	0.0365	0.45	-0.0388	-0.721	-0.0189	-0.0456	12	3	0.00614	0.98
	(0.081)	(0.652)	(0.0538)	(0.471)	(0.414)	(0.964)			(0.00871)	(0.972)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.000776	-0.303	0.000936	0.598	0.00816	0.498	12	3	0.00396	0.905
	(0.00256)	(0.762)	(0.00156)	(0.55)	(0.0164)	(0.618)			(0.00558)	(0.864)
Percentage of Persons 25+ years old who have completed high school but no college	-0.00662	-1.33	0.00312	0.994	-0.0107	-0.562	12	3	-0.000452	0.987
	(0.00496)	(0.182)	(0.00314)	(0.32)	(0.019)	(0.574)			(-0.000647)	(0.981)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00113	-0.708	-0.000552	-0.496	0.00786	1.15	12	3	0.00186	0.954
	(0.00159)	(0.479)	(0.00111)	(0.62)	(0.00682)	(0.249)			(0.00262)	(0.934)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0101	1.55	-0.00175	-0.465	0.0477	1.83	12	3	-0.000502	0.956
	(0.00652)	(0.12)	(0.00376)	(0.642)	(0.0261)	(0.0673)			(-0.00073)	(0.938)
Percentage of total persons below the poverty level in past 12 months	0.000437	0.111	0.00361	1.57	0.00916	0.576	12	3	0.0133	0.924
	(0.00393)	(0.911)	(0.00229)	(0.116)	(0.0159)	(0.565)			(0.0188)	(0.892)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000335	-0.116	-0.000951	-0.742	-0.00774	-0.956	12	3	0.00972	0.895
	(0.00289)	(0.908)	(0.00128)	(0.458)	(0.00809)	(0.339)			(0.0137)	(0.852)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	9.16	0.878	-6.85	-1.16	-0.478	-0.0349	12	3	-0.0748	0.439
	(10.4)	(0.38)	(5.89)	(0.245)	(13.7)	(0.972)			(-0.106)	(0.203)
Percentage of renter-occupied housing units of total housing units	-0.00233	-0.411	0.00287	0.938	0.091	11.3	12	3	0.00559	0.969
	(0.00567)	(0.681)	(0.00306)	(0.349)	(0.00808)	(3.29e-29)			(0.00792)	(0.957)
Percentage of vacant housing units	0.00636	1.9	-0.000206	-0.0896	-0.0561	-1.81	12	3	0.0138	0.899
	(0.00335)	(0.0581)	(0.0023)	(0.929)	(0.0311)	(0.0709)			(0.0196)	(0.857)
Percentage of change in number of housing units since last census of total housing units	0.388	1.53	-0.185	-0.696	-0.179	-0.867	12	3	-2.25e-05	0.24
	(0.253)	(0.125)	(0.266)	(0.486)	(0.207)	(0.386)			(-0.00034)	(-0.0783)

Table 47. High bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new high bridge (SE)	t value (p value)	new high bridge Treatment Variable (SE)	t value (p value)	new high bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.00481	0.0344	-0.00628	-0.0632	0.0486	0.179	12	4	0.00365	0.989
	(0.14)	(0.973)	(0.0994)	(0.95)	(0.271)	(0.858)			(0.00517)	(0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.00482	-0.0219	-0.0492	-0.318	0.321	0.676	12	4	0.0037	0.99
	(0.22)	(0.983)	(0.155)	(0.75)	(0.475)	(0.499)			(0.00525)	(0.986)
Non-White percentage of total population	0.0064	1.44	0.00124	0.634	-0.000973	-0.0897	12	4	-0.0111	0.943
	(0.00444)	(0.15)	(0.00195)	(0.526)	(0.0108)	(0.929)			(-0.0157)	(0.919)
Black/African American percentage of total population	-0.00324	-0.905	0.000738	0.471	-0.00196	-0.332	12	4	-0.0094	0.948
	(0.00358)	(0.366)	(0.00156)	(0.637)	(0.0059)	(0.74)			(-0.0134)	(0.926)
Percentage of Hispanic/Latino of total population	0.00024	0.17	-0.000149	-0.186	0.00476	0.727	12	4	0.0333	0.886
	(0.00142)	(0.865)	(0.000801)	(0.853)	(0.00654)	(0.467)			(0.0471)	(0.838)
Percentage of Foreign-born of total population	0.0055	2.26	-0.00149	-1.33	-0.0114	-1.96	12	4	0.000841	0.88
	(0.00243)	(0.0238)	(0.00112)	(0.185)	(0.00582)	(0.0503)			(0.00112)	(0.83)
Percentage of Children under 18 years old of total population	0.00331	0.803	-0.000635	-0.251	-0.0261	-2.01	12	4	0.01	0.981
	(0.00413)	(0.422)	(0.00253)	(0.802)	(0.013)	(0.0444)			(0.0142)	(0.973)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.983)	-0.00388	-0.255	0.000143	0.0139	0.0426	1.67	12	4	0.00211	0.983
	(0.0152)	(0.799)	(0.0103)	(0.989)	(0.0255)	(0.0951)			(0.00299)	(0.976)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00174	-0.563	0.000266	0.173	0.0146	0.906	12	4	0.00367	0.951
	(0.0031)	(0.574)	(0.00154)	(0.863)	(0.0162)	(0.365)			(0.00518)	(0.93)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00121	-0.323	0.00242	1.25	0.00676	0.405	12	4	0.00174	0.964
	(0.00376)	(0.746)	(0.00194)	(0.211)	(0.0167)	(0.686)			(0.00244)	(0.949)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.51)	-0.38	-3.36	0.036	0.476	-1.26	-2.57	12	4	0.00201	0.927
	(0.113)	(0.000786)	(0.0756)	(0.634)	(0.492)	(0.0103)			(0.0028)	(0.896)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.147	-1.57	-0.00345	-0.0597	0.491	2.42	12	4	0.00753	0.984
	(0.0935)	(0.116)	(0.0578)	(0.952)	(0.202)	(0.0154)			(0.0107)	(0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.72)	-0.0588	-0.65	0.00236	0.0408	0.254	0.985	12	4	0.00822	0.981
	(0.0904)	(0.516)	(0.0578)	(0.967)	(0.258)	(0.325)			(0.0117)	(0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.08)	0.00933	0.118	-0.0228	-0.468	-0.369	-0.677	12	4	0.00832	0.983
	(0.0789)	(0.906)	(0.0487)	(0.64)	(0.545)	(0.499)			(0.0118)	(0.975)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00095	-0.381	0.00172	1.12	0.00102	0.0592	12	4	0.00535	0.906
	(0.0025)	(0.703)	(0.00154)	(0.262)	(0.0172)	(0.953)			(0.00753)	(0.866)
Percentage of Persons 25+ years old who have completed high school but no college	-0.013	-2.31	0.000758	0.222	-0.0225	-1.32	12	4	-0.00151	0.986
	(0.00562)	(0.0209)	(0.00341)	(0.824)	(0.0171)	(0.187)			(-0.00215)	(0.98)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00164	-1.02	-0.00114	-0.954	0.0104	1.38	12	4	-0.000213	0.952
	(0.00161)	(0.309)	(0.0012)	(0.34)	(0.00758)	(0.169)			(-0.000332)	(0.931)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0193	2.6	0.00138	0.322	0.0682	2.77	12	4	-0.00674	0.95
	(0.00744)	(0.00936)	(0.00428)	(0.747)	(0.0246)	(0.00557)			(-0.0096)	(0.929)
Percentage of total persons below the poverty level in past 12 months	0.000123	0.0291	0.00345	1.41	0.000838	0.0479	12	4	0.0104	0.921
	(0.00421)	(0.977)	(0.00245)	(0.16)	(0.0175)	(0.962)			(0.0147)	(0.888)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000101	0.0355	-0.000363	-0.282	-0.0113	-1.23	12	4	0.00931	0.895
	(0.00284)	(0.972)	(0.00129)	(0.778)	(0.00921)	(0.219)			(0.0131)	(0.851)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	7.98	0.776	-5.41	-0.868	-6.09	-0.721	12	4	0.00246	0.516
	(10.3)	(0.438)	(6.23)	(0.385)	(8.45)	(0.471)			(0.00319)	(0.313)
Percentage of renter-occupied housing units of total housing units	-0.00218	-0.376	0.00233	0.75	0.0866	5.1	12	4	0.00397	0.968
	(0.00579)	(0.707)	(0.00311)	(0.453)	(0.017)	(3.48e-07)			(0.00562)	(0.954)
Percentage of vacant housing units	0.00403	1.21	9.09e-06	0.00394	-0.0698	-1.99	12	4	0.0145	0.9
	(0.00333)	(0.226)	(0.0023)	(0.997)	(0.0351)	(0.0471)			(0.0205)	(0.858)
Percentage of change in number of housing units since last census of total housing units	0.407	1.75	-0.199	-0.716	-0.231	-0.929	12	4	-0.000134	0.24
	(0.233)	(0.0809)	(0.278)	(0.474)	(0.248)	(0.353)			(-0.000651)	(-0.0787)

Table 48. Super bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new super bridge (SE)	t value (p value)	new super bridge Treatment Variable (SE)	t value (p value)	new super bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.127	0.791	-0.0434	-0.459	-0.235	-0.624	12	1	1.85e-06	0.988
	(0.161)	(0.429)	(0.0945)	(0.647)	(0.377)	(0.533)			(-1.8e-06)	(0.983)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.143	0.563	-0.0156	-0.104	-0.125	-0.215	12	1	8.9e-07	0.988
	(0.254)	(0.574)	(0.15)	(0.917)	(0.583)	(0.83)			(-2.91e-06)	(0.984)
Non-White percentage of total population	0.00162	0.487	0.000745	0.413	0.00699	1.02	12	1	5.83e-06	0.956
	(0.00333)	(0.627)	(0.00181)	(0.68)	(0.00686)	(0.308)			(-7.81e-06)	(0.939)
Black/African American percentage of total population	-0.00268	-0.933	0.000775	0.53	0.00249	0.589	12	1	7.93e-06	0.958
	(0.00287)	(0.351)	(0.00146)	(0.596)	(0.00424)	(0.556)			(-3.98e-06)	(0.942)
Percentage of Hispanic/Latino of total population	-0.00139	-0.852	-0.000628	-0.619	0.00459	0.557	12	1	3.64e-05	0.859
	(0.00163)	(0.394)	(0.00101)	(0.536)	(0.00824)	(0.578)			(-2.88e-07)	(0.805)
Percentage of Foreign-born of total population	0.00224	1.25	0.000125	0.124	0.00417	1.25	12	1	3.68e-05	0.89
	(0.00178)	(0.21)	(0.001)	(0.901)	(0.00334)	(0.211)			(1.14e-05)	(0.847)
Percentage of Children under 18 years old of total population	0.00497	1.1	-0.00166	-0.607	0.0125	1.35	12	1	6.65e-06	0.975
	(0.00453)	(0.273)	(0.00274)	(0.544)	(0.00926)	(0.178)			(1.36e-07)	(0.965)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.985)	0.00212	0.128	-0.00181	-0.195	-0.0327	-0.909	12	1	1.75e-07	0.983
	(0.0166)	(0.898)	(0.00927)	(0.845)	(0.036)	(0.363)			(-5.82e-06)	(0.977)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.0011	0.439	0.000589	0.439	0.0114	0.993	12	1	5.48e-06	0.948
	(0.00249)	(0.66)	(0.00134)	(0.661)	(0.0115)	(0.321)			(-1.13e-05)	(0.927)
Percentage of female-headed families with or without own children of total families and subfamilies	-7.08e-05	-0.0228	0.00233	1.42	-0.00985	-0.981	12	1	1.43e-05	0.964
	(0.0031)	(0.982)	(0.00164)	(0.156)	(0.01)	(0.326)			(7.1e-06)	(0.951)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.64)	-0.525	-5.06	0.171	2.37	1.14	1.33	12	1	0.000321	0.933
	(0.104)	(4.31e-07)	(0.0722)	(0.018)	(0.861)	(0.184)			(0.000421)	(0.907)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.31)	-0.0179	-0.172	0.0427	0.716	-0.0422	-0.193	12	1	2.5e-06	0.98
	(0.104)	(0.864)	(0.0597)	(0.474)	(0.218)	(0.847)			(-3.81e-06)	(0.972)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.71)	0.024	0.24	0.0523	0.893	0.49	3.09	12	1	6.85e-06	0.977
	(0.1)	(0.81)	(0.0586)	(0.372)	(0.158)	(0.00202)			(1.22e-06)	(0.968)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.07)	-0.00889	-0.101	0.0249	0.484	0.15	0.393	12	1	1.41e-06	0.977
	(0.088)	(0.919)	(0.0514)	(0.629)	(0.381)	(0.694)			(-6.39e-06)	(0.968)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00182	0.702	-0.00374	-2.46	0.0279	1.41	12	1	0.000161	0.896
	(0.0026)	(0.483)	(0.00152)	(0.0141)	(0.0198)	(0.16)			(0.000186)	(0.856)
Percentage of Persons 25+ years old who have completed high school but no college	0.00483	1.06	-0.00236	-0.806	0.0109	0.387	12	1	3.54e-06	0.987
	(0.00455)	(0.288)	(0.00293)	(0.42)	(0.0281)	(0.699)			(9.26e-08)	(0.981)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00185	-1.25	0.00126	1.35	-0.0139	-1.43	12	1	2.47e-05	0.954
	(0.00147)	(0.21)	(0.000936)	(0.177)	(0.00974)	(0.153)			(1.75e-05)	(0.936)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00232	0.404	0.00352	0.976	-0.0167	-0.364	12	1	1.51e-05	0.96
	(0.00576)	(0.687)	(0.00361)	(0.329)	(0.0458)	(0.716)			(6.6e-06)	(0.945)
Percentage of total persons below the poverty level in past 12 months	0.0046	1.07	0.00138	0.65	-0.000819	-0.0483	12	1	5.35e-05	0.915
	(0.00429)	(0.284)	(0.00213)	(0.515)	(0.017)	(0.962)			(4.35e-05)	(0.882)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-5.12e-05	-0.0226	0.000235	0.19	0.0165	1.48	12	1	7.78e-07	0.889
	(0.00227)	(0.982)	(0.00123)	(0.849)	(0.0112)	(0.14)			(-3.87e-05)	(0.847)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-2.45	-0.199	-1.44	-0.219	6.01	0.448	12	1	1.68e-05	0.39
	(12.3)	(0.843)	(6.6)	(0.827)	(13.4)	(0.654)			(-0.000196)	(0.155)
Percentage of renter-occupied housing units of total housing units	0.00541	0.999	0.00425	1.37	-0.0104	-0.542	12	1	3.56e-05	0.967
	(0.00542)	(0.318)	(0.00311)	(0.171)	(0.0193)	(0.588)			(3.73e-05)	(0.954)
Percentage of vacant housing units	0.00731	1.49	-0.000444	-0.2	-0.0155	-0.843	12	1	8.13e-05	0.898
	(0.00492)	(0.137)	(0.00222)	(0.842)	(0.0184)	(0.4)			(7.6e-05)	(0.859)
Percentage of change in number of housing units since last census of total housing units	-0.00556	-0.0689	0.345	1.92	-0.0625	-0.241	12	1	0.000101	0.366
	(0.0806)	(0.945)	(0.18)	(0.0551)	(0.259)	(0.809)			(-8.74e-05)	(0.122)

Table 48. Super bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new super bridge (SE)	t value (p value)	new super bridge Treatment Variable (SE)	t value (p value)	new super bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.223	1.55	-0.0683	-0.79	-0.141	-0.387	10	2	0.00198	0.99
	(0.144)	(0.122)	(0.0865)	(0.43)	(0.365)	(0.699)			(0.00274)	(0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.28	1.26	-0.0596	-0.44	0.0744	0.133	10	2	0.00205	0.991
	(0.222)	(0.207)	(0.135)	(0.66)	(0.559)	(0.894)			(0.00285)	(0.987)
Non-White percentage of total population	0.000119	0.0316	0.00252	1.24	0.00608	0.315	10	2	-0.0144	0.941
	(0.00378)	(0.975)	(0.00203)	(0.215)	(0.0193)	(0.753)			(-0.02)	(0.919)
Black/African American percentage of total population	-0.00296	-0.965	0.00197	1.23	0.000688	0.0593	10	2	-0.0114	0.947
	(0.00307)	(0.335)	(0.00161)	(0.219)	(0.0116)	(0.953)			(-0.0158)	(0.927)
Percentage of Hispanic/Latino of total population	-0.00179	-1.08	-7.63e-05	-0.0745	0.000993	0.09	10	2	-0.00473	0.854
	(0.00166)	(0.28)	(0.00102)	(0.941)	(0.011)	(0.928)			(-0.00655)	(0.798)
Percentage of Foreign-born of total population	0.00137	0.751	0.000285	0.279	0.0057	1.45	10	2	-0.00245	0.887
	(0.00183)	(0.453)	(0.00102)	(0.781)	(0.00392)	(0.146)			(-0.0034)	(0.844)
Percentage of Children under 18 years old of total population	0.00811	2.21	-0.00264	-1.13	0.0123	0.954	10	2	0.00766	0.982
	(0.00367)	(0.0269)	(0.00233)	(0.257)	(0.0129)	(0.34)			(0.0106)	(0.976)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.985)	0.00802	0.497	-0.00262	-0.285	-0.0249	-0.725	10	2	0.000293	0.983
	(0.0162)	(0.62)	(0.00919)	(0.776)	(0.0344)	(0.469)			(0.000406)	(0.977)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00297	1.21	0.000951	0.71	0.0061	0.403	10	2	-0.000203	0.947
	(0.00244)	(0.224)	(0.00134)	(0.478)	(0.0151)	(0.687)			(-0.000282)	(0.927)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00241	0.798	0.00263	1.64	-0.0148	-0.915	10	2	0.000657	0.965
	(0.00302)	(0.425)	(0.0016)	(0.101)	(0.0162)	(0.36)			(0.00091)	(0.952)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.64)	-0.472	-4.7	0.149	2.08	1.05	1.15	10	2	0.00154	0.934
	(0.101)	(2.64e-06)	(0.0717)	(0.038)	(0.909)	(0.249)			(0.00214)	(0.908)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.31)	0.0511	0.639	0.0135	0.281	-0.0044	-0.0232	10	2	0.0072	0.987
	(0.08)	(0.523)	(0.0481)	(0.779)	(0.19)	(0.981)			(0.00998)	(0.982)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.71)	0.0984	1.26	0.0266	0.56	0.481	3.27	10	2	0.00753	0.985
	(0.0784)	(0.209)	(0.0474)	(0.576)	(0.147)	(0.00106)			(0.0104)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.07)	0.0691	0.96	-0.00439	-0.0991	0.0833	0.2	10	2	0.00618	0.983
	(0.0719)	(0.337)	(0.0443)	(0.921)	(0.417)	(0.841)			(0.00856)	(0.976)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00179	0.71	-0.00377	-2.5	0.0275	1.4	10	2	0.000663	0.897
	(0.00252)	(0.478)	(0.0015)	(0.0123)	(0.0197)	(0.161)			(0.000919)	(0.857)
Percentage of Persons 25+ years old who have completed high school but no college	0.00957	1.76	-0.00226	-0.663	-0.00917	-0.27	10	2	-0.00342	0.983
	(0.00543)	(0.0779)	(0.0034)	(0.507)	(0.0339)	(0.787)			(-0.00474)	(0.977)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00173	-1.18	0.00129	1.34	-0.0152	-1.61	10	2	-0.00176	0.952
	(0.00147)	(0.239)	(0.00096)	(0.18)	(0.00942)	(0.107)			(-0.00244)	(0.933)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.00338	-0.465	0.00295	0.669	0.0136	0.271	10	2	-0.0126	0.948
	(0.00727)	(0.642)	(0.0044)	(0.503)	(0.0502)	(0.786)			(-0.0174)	(0.927)
Percentage of total persons below the poverty level in past 12 months	0.00616	1.47	0.0013	0.618	-0.00288	-0.134	10	2	0.00539	0.92
	(0.00419)	(0.142)	(0.0021)	(0.537)	(0.0214)	(0.893)			(0.00746)	(0.889)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000272	0.128	-0.000103	-0.0893	0.019	1.36	10	2	0.00836	0.898
	(0.00212)	(0.898)	(0.00115)	(0.929)	(0.014)	(0.174)			(0.0116)	(0.858)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-3.66	-0.302	-0.437	-0.0627	6.96	0.565	10	2	-0.0294	0.361
	(12.1)	(0.763)	(6.96)	(0.95)	(12.3)	(0.572)			(-0.0408)	(0.115)
Percentage of renter-occupied housing units of total housing units	0.00987	1.94	0.00402	1.33	-0.0136	-0.554	10	2	0.0027	0.969
	(0.00509)	(0.0528)	(0.00304)	(0.185)	(0.0247)	(0.58)			(0.00375)	(0.957)
Percentage of vacant housing units	0.00998	2.23	-0.00114	-0.534	-0.0202	-0.929	10	2	0.00987	0.908
	(0.00447)	(0.0257)	(0.00214)	(0.593)	(0.0217)	(0.353)			(0.0137)	(0.873)
Percentage of change in number of housing units since last census of total housing units	0.00932	0.154	0.319	1.83	-0.00778	-0.0442	10	2	-6.55e-05	0.366
	(0.0605)	(0.878)	(0.175)	(0.0679)	(0.176)	(0.965)			(-9.08e-05)	(0.122)

Table 48. Super bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new super bridge (SE)	t value (p value)	new super bridge Treatment Variable (SE)	t value (p value)	new super bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.122 (0.151)	0.809 (0.419)	-0.0615 (0.0905)	-0.68 (0.497)	-0.0204 (0.282)	-0.0726 (0.942)	12	3	0.00138 (0.0019)	0.989 (0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.117 (0.235)	0.496 (0.62)	-0.0416 (0.143)	-0.291 (0.771)	0.282 (0.424)	0.665 (0.506)	12	3	0.00134 (0.00185)	0.99 (0.986)
Non-White percentage of total population	0.00286 (0.00347)	0.825 (0.41)	0.00103 (0.00183)	0.56 (0.575)	0.01 (0.00763)	1.32 (0.188)	12	3	-0.00286 (-0.00398)	0.953 (0.935)
Black/African American percentage of total population	-0.00137 (0.00281)	-0.489 (0.625)	0.00092 (0.00144)	0.638 (0.523)	0.00423 (0.00478)	0.885 (0.376)	12	3	0.000178 (0.000232)	0.959 (0.943)
Percentage of Hispanic/Latino of total population	-0.00108 (0.00168)	-0.64 (0.522)	-0.000558 (0.00103)	-0.544 (0.586)	0.00256 (0.00757)	0.339 (0.735)	12	3	-0.00873 (-0.0121)	0.85 (0.793)
Percentage of Foreign-born of total population	0.00173 (0.00181)	0.956 (0.339)	0.00025 (0.00101)	0.248 (0.804)	0.00637 (0.00342)	1.86 (0.0624)	12	3	-0.000259 (-0.000399)	0.89 (0.847)
Percentage of Children under 18 years old of total population	0.00528 (0.00394)	1.34 (0.181)	-0.00237 (0.00252)	-0.937 (0.349)	0.0165 (0.00546)	3.02 (0.00256)	12	3	0.00582 (0.00806)	0.981 (0.973)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.985)	0.00184 (0.0162)	0.114 (0.91)	-0.00346 (0.00922)	-0.375 (0.707)	-0.0145 (0.0358)	-0.405 (0.685)	12	3	0.000375 (0.000514)	0.984 (0.977)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00222 (0.00241)	0.921 (0.357)	0.000168 (0.00127)	0.132 (0.895)	0.00809 (0.0123)	0.66 (0.509)	12	3	0.00337 (0.00465)	0.951 (0.932)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00138 (0.003)	0.458 (0.647)	0.00201 (0.00153)	1.31 (0.189)	-0.0123 (0.00829)	-1.48 (0.139)	12	3	0.00275 (0.0038)	0.967 (0.955)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.64)	-0.487 (0.103)	-4.74 (2.23e-06)	0.155 (0.0729)	2.12 (0.0337)	1.1 (0.892)	1.23 (0.217)	12	3	2.34e-05 (8.05e-06)	0.932 (0.906)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.31)	-0.0339 (0.091)	-0.373 (0.709)	0.0348 (0.0545)	0.639 (0.523)	0.142 (0.232)	0.611 (0.541)	12	3	0.00426 (0.00589)	0.984 (0.978)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.71)	0.019 (0.0866)	0.219 (0.826)	0.0397 (0.0525)	0.756 (0.45)	0.627 (0.172)	3.65 (0.000267)	12	3	0.00497 (0.00688)	0.982 (0.975)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.07)	-0.000741 (0.077)	-0.00961 (0.992)	0.00853 (0.0472)	0.181 (0.857)	0.232 (0.29)	0.802 (0.423)	12	3	0.00465 (0.00644)	0.981 (0.974)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00185 (0.00253)	0.729 (0.466)	-0.00374 (0.0015)	-2.49 (0.0128)	0.024 (0.0204)	1.17 (0.24)	12	3	0.00315 (0.00433)	0.899 (0.86)
Percentage of Persons 25+ years old who have completed high school but no college	0.00782 (0.00468)	1.67 (0.095)	-0.0028 (0.00296)	-0.945 (0.345)	-0.00789 (0.0327)	-0.241 (0.809)	12	3	-0.000762 (-0.00106)	0.986 (0.98)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00197 (0.00146)	-1.35 (0.177)	0.00132 (0.000932)	1.41 (0.157)	-0.0134 (0.00974)	-1.38 (0.168)	12	3	0.000908 (0.00124)	0.954 (0.937)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.00139 (0.0061)	-0.228 (0.82)	0.004 (0.00375)	1.07 (0.286)	0.0136 (0.0517)	0.263 (0.793)	12	3	-0.00209 (-0.00292)	0.958 (0.942)
Percentage of total persons below the poverty level in past 12 months	0.00476 (0.00412)	1.16 (0.247)	0.000971 (0.00199)	0.489 (0.625)	-0.00101 (0.014)	-0.0721 (0.942)	12	3	0.00826 (0.0114)	0.923 (0.893)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000202 (0.00217)	-0.0931 (0.926)	1.6e-06 (0.00115)	0.00139 (0.999)	0.0223 (0.0121)	1.84 (0.0664)	12	3	0.00641 (0.00885)	0.896 (0.856)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	0.165 (12)	0.0138 (0.989)	-2.36 (6.81)	-0.347 (0.729)	0.445 (15.4)	0.0289 (0.977)	12	3	-0.0247 (-0.0344)	0.366 (0.121)
Percentage of renter-occupied housing units of total housing units	0.00657 (0.00487)	1.35 (0.177)	0.00347 (0.00285)	1.22 (0.224)	-0.00659 (0.0128)	-0.514 (0.607)	12	3	0.00418 (0.00579)	0.971 (0.959)
Percentage of vacant housing units	0.00842 (0.00456)	1.85 (0.0648)	-0.00123 (0.00212)	-0.582 (0.56)	-0.0174 (0.0176)	-0.992 (0.321)	12	3	0.0112 (0.0154)	0.909 (0.874)
Percentage of change in number of housing units since last census of total housing units	-0.0471 (0.0739)	-0.638 (0.524)	0.359 (0.187)	1.91 (0.0557)	-0.0893 (0.119)	-0.752 (0.452)	12	3	-6.57e-05 (-0.000319)	0.366 (0.121)

Table 48. Super bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new super bridge (SE)	t value (p value)	new super bridge Treatment Variable (SE)	t value (p value)	new super bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.0571	0.4	-0.0332	-0.397	-0.426	-2.32	12	4	0.00257	0.99
	(0.143)	(0.689)	(0.0836)	(0.692)	(0.183)	(0.0203)			(0.00356)	(0.987)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.0591	0.265	-0.0191	-0.146	-0.555	-1.73	12	4	0.00257	0.991
	(0.223)	(0.791)	(0.131)	(0.884)	(0.322)	(0.0842)			(0.00356)	(0.988)
Non-White percentage of total population	0.000928	0.249	0.00313	1.62	0.0127	1.29	12	4	-0.0124	0.943
	(0.00372)	(0.803)	(0.00193)	(0.105)	(0.00984)	(0.197)			(-0.0172)	(0.922)
Black/African American percentage of total population	-0.00315	-1.04	0.00243	1.58	0.00512	0.803	12	4	-0.0109	0.947
	(0.00303)	(0.298)	(0.00154)	(0.115)	(0.00638)	(0.422)			(-0.0152)	(0.927)
Percentage of Hispanic/Latino of total population	-0.0013	-0.904	0.000512	0.607	0.00591	0.933	12	4	0.0401	0.899
	(0.00144)	(0.366)	(0.000844)	(0.544)	(0.00634)	(0.351)			(0.0555)	(0.86)
Percentage of Foreign-born of total population	0.00211	1.15	0.000434	0.45	0.0057	1.58	12	4	0.00216	0.892
	(0.00183)	(0.249)	(0.000965)	(0.653)	(0.00361)	(0.115)			(0.00294)	(0.85)
Percentage of Children under 18 years old of total population	0.00313	0.84	-0.00134	-0.592	0.00526	0.557	12	4	0.00736	0.982
	(0.00373)	(0.401)	(0.00227)	(0.554)	(0.00945)	(0.578)			(0.0102)	(0.975)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.985)	-0.00118	-0.0738	-0.00137	-0.156	-0.0508	-2.07	12	4	0.00133	0.984
	(0.016)	(0.941)	(0.00882)	(0.876)	(0.0246)	(0.0385)			(0.00184)	(0.978)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00109	0.455	0.00152	1.18	0.00957	0.777	12	4	0.00255	0.95
	(0.0024)	(0.649)	(0.00129)	(0.239)	(0.0123)	(0.437)			(0.00351)	(0.931)
Percentage of female-headed families with or without own children of total families and subfamilies	0.000262	0.0862	0.00331	2.06	-0.0122	-1.19	12	4	0.00041	0.965
	(0.00304)	(0.931)	(0.00161)	(0.0392)	(0.0103)	(0.235)			(0.000548)	(0.951)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.64)	-0.527	-5.15	0.165	2.28	1.07	1.21	12	4	0.000969	0.933
	(0.102)	(2.7e-07)	(0.0721)	(0.0224)	(0.89)	(0.228)			(0.00131)	(0.908)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.31)	-0.0557	-0.615	0.0323	0.637	-0.283	-1.51	12	4	0.00554	0.985
	(0.0905)	(0.538)	(0.0507)	(0.524)	(0.187)	(0.13)			(0.00767)	(0.98)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.71)	-0.00875	-0.101	0.0456	0.918	0.264	1.14	12	4	0.0059	0.983
	(0.0869)	(0.92)	(0.0497)	(0.359)	(0.232)	(0.255)			(0.00817)	(0.976)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.07)	-0.0431	-0.589	0.0217	0.502	-0.0502	-0.162	12	4	0.00643	0.983
	(0.0732)	(0.556)	(0.0432)	(0.615)	(0.309)	(0.871)			(0.0089)	(0.977)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00115	0.462	-0.00331	-2.23	0.028	1.33	12	4	0.00472	0.901
	(0.00249)	(0.644)	(0.00148)	(0.0257)	(0.0211)	(0.185)			(0.00648)	(0.862)
Percentage of Persons 25+ years old who have completed high school but no college	0.00293	0.548	-0.00131	-0.408	-0.0045	-0.128	12	4	-0.00188	0.985
	(0.00534)	(0.584)	(0.0032)	(0.683)	(0.0352)	(0.898)			(-0.00261)	(0.979)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.0013	-0.885	0.00106	1.1	-0.0152	-1.5	12	4	-0.00152	0.952
	(0.00147)	(0.376)	(0.000957)	(0.27)	(0.0101)	(0.134)			(-0.00214)	(0.934)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.0051	0.744	0.00134	0.329	0.00328	0.059	12	4	-0.00681	0.953
	(0.00686)	(0.457)	(0.00409)	(0.742)	(0.0556)	(0.953)			(-0.00946)	(0.935)
Percentage of total persons below the poverty level in past 12 months	0.00419	1.01	0.00196	0.945	-0.00203	-0.14	12	4	0.00646	0.921
	(0.00415)	(0.313)	(0.00207)	(0.345)	(0.0145)	(0.889)			(0.0089)	(0.891)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000501	-0.229	1.94e-05	0.0161	0.0152	1.06	12	4	0.00475	0.894
	(0.00219)	(0.819)	(0.0012)	(0.987)	(0.0143)	(0.287)			(0.00653)	(0.853)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-3.18	-0.256	-0.769	-0.115	11.5	0.853	12	4	-0.000675	0.39
	(12.4)	(0.798)	(6.66)	(0.908)	(13.5)	(0.394)			(-0.00126)	(0.154)
Percentage of renter-occupied housing units of total housing units	0.00564	1.07	0.00478	1.55	-0.015	-0.848	12	4	0.00207	0.969
	(0.00525)	(0.282)	(0.00308)	(0.121)	(0.0177)	(0.396)			(0.00285)	(0.957)
Percentage of vacant housing units	0.00592	1.29	-7.6e-06	-0.00363	-0.0205	-1.03	12	4	0.0114	0.91
	(0.00458)	(0.196)	(0.00209)	(0.997)	(0.02)	(0.305)			(0.0158)	(0.875)
Percentage of change in number of housing units since last census of total housing units	-0.0182	-0.241	0.332	1.9	-0.164	-1.03	12	4	-0.000287	0.366
	(0.0753)	(0.809)	(0.175)	(0.0581)	(0.159)	(0.302)			(-0.00074)	(0.121)

Table 49. Restrictive bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for new under 14 ft bridge (SE)	t value (p value)	new under 14 ft bridge Treatment Variable (SE)	t value (p value)	new under 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.5)	-1.01	-1.88	0.441	1.4	-1.4	-0.601	12	1	4.98e-05	0.989
	(0.541)	(0.0607)	(0.315)	(0.162)	(2.33)	(0.548)			(6.58e-05)	(0.984)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-1.25	-1.59	0.636	1.29	-2.07	-0.548	12	1	3.78e-05	0.99
	(0.786)	(0.112)	(0.494)	(0.198)	(3.77)	(0.584)			(4.9e-05)	(0.985)
Non-White percentage of total population	-0.0476	-0.954	0.00189	0.259	0.0272	0.557	12	1	0.000138	0.966
	(0.0499)	(0.34)	(0.00727)	(0.795)	(0.0489)	(0.577)			(0.000181)	(0.951)
Black/African American percentage of total population	-0.0422	-0.86	9.5e-05	0.0131	0.0316	0.659	12	1	0.000146	0.966
	(0.049)	(0.39)	(0.00725)	(0.99)	(0.048)	(0.51)			(0.000192)	(0.95)
Percentage of Hispanic/Latino of total population	**-0.0119**	**-2.92**	0.00329	1.29	-0.00382	-0.915	12	1	0.000228	0.874
	(0.00409)	**(0.00353)**	(0.00255)	(0.196)	(0.00417)	(0.36)			(0.000256)	(0.816)
Percentage of Foreign-born of total population	-0.0037	-0.752	0.000112	0.0324	0.00639	1.06	12	1	8.32e-06	0.862
	(0.00492)	(0.452)	(0.00346)	(0.974)	(0.00601)	(0.288)			(-7.09e-05)	(0.799)
Percentage of Children under 18 years old of total population	-0.019	-1.41	0.00452	0.557	-0.0323	-0.621	12	1	2e-05	0.978
	(0.0135)	(0.158)	(0.00812)	(0.578)	(0.052)	(0.535)			(1.58e-05)	(0.968)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.104	-1.5	0.0574	1.91	-0.101	-0.464	12	1	0.000105	0.986
	(0.0696)	(0.134)	(0.0301)	(0.0568)	(0.217)	(0.643)			(0.000144)	(0.979)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.0146	-1.05	0.00584	0.773	**0.0441**	**2.13**	12	1	6.85e-05	0.96
	(0.014)	(0.296)	(0.00756)	(0.44)	**(0.0207)**	**(0.0334)**			(7.54e-05)	(0.941)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00617	-0.311	0.00101	0.0964	0.0341	1.16	12	1	2.29e-06	0.961
	(0.0198)	(0.756)	(0.0105)	(0.923)	(0.0293)	(0.245)			(-2.04e-05)	(0.943)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.61)	**-0.751**	**-2.29**	0.342	1.91	**1.92**	**3.54**	12	1	0.000277	0.955
	(0.328)	**(0.0219)**	(0.179)	(0.0559)	**(0.541)**	**(0.000397)**			(0.000377)	(0.934)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.19)	-0.0636	-0.189	0.0404	0.228	-0.179	-0.126	12	1	1.6e-06	0.984
	(0.337)	(0.85)	(0.178)	(0.82)	(1.42)	(0.9)			(-7.49e-06)	(0.976)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.55)	-0.178	-0.519	0.148	0.88	-0.403	-0.304	12	1	2.72e-05	0.979
	(0.342)	(0.604)	(0.168)	(0.379)	(1.33)	(0.761)			(2.7e-05)	(0.97)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.94)	-0.178	-0.608	0.136	0.925	-1.83	-1.95	12	1	2.98e-05	0.977
	(0.292)	(0.543)	(0.147)	(0.355)	(0.94)	(0.0515)			(2.98e-05)	(0.967)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00403	0.511	-0.00164	-0.461	0.0152	1.08	12	1	2.04e-05	0.921
	(0.0079)	(0.61)	(0.00355)	(0.645)	(0.014)	(0.28)			(-1.76e-05)	(0.885)
Percentage of Persons 25+ years old who have completed high school but no college	-0.000719	-0.0295	0.00902	1.24	**0.1**	**3.02**	12	1	1.78e-05	0.988
	(0.0244)	(0.976)	(0.00725)	(0.213)	**(0.0332)**	**(0.00256)**			(1.9e-05)	(0.983)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	**-0.017**	**-2.96**	0.0035	1.49	-0.00255	-0.377	12	1	0.000176	0.956
	(0.00576)	**(0.00308)**	(0.00235)	(0.137)	(0.00677)	(0.706)			(0.000231)	(0.936)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0337	-1.29	0.0123	1.28	-0.0524	-1.52	12	1	8.45e-05	0.964
	(0.0262)	(0.198)	(0.00958)	(0.199)	(0.0345)	(0.129)			(0.000101)	(0.947)
Percentage of total persons below the poverty level in past 12 months	-0.0652	-1.26	0.00152	0.207	0.0914	1.69	12	1	0.000396	0.933
	(0.0518)	(0.208)	(0.00735)	(0.836)	(0.054)	(0.0906)			(0.000536)	(0.902)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000506	-0.0487	-0.000639	-0.112	-0.00633	-0.532	12	1	2.73e-06	0.872
	(0.0104)	(0.961)	(0.0057)	(0.911)	(0.0119)	(0.595)			(-7.32e-05)	(0.813)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-1.04	-0.0596	19.2	0.751	-69.9	-1.16	12	1	0.000567	0.296
	(17.5)	(0.952)	(25.5)	(0.452)	(60.4)	(0.247)			(0.000401)	(-0.0265)
Percentage of renter-occupied housing units of total housing units	-0.0213	-1.61	0.0139	1.75	0.0245	0.647	12	1	7.02e-05	0.978
	(0.0132)	(0.108)	(0.00797)	(0.0806)	(0.038)	(0.518)			(8.9e-05)	(0.968)
Percentage of vacant housing units	**-0.019**	**-2.24**	0.00131	0.211	0.0456	1.65	12	1	4.89e-05	0.922
	(0.00847)	**(0.0253)**	(0.00619)	(0.833)	(0.0277)	(0.0995)			(2.42e-05)	(0.886)
Percentage of change in number of housing units since last census of total housing units	0.749	1.65	-0.469	-1.17	-0.524	-1.4	12	1	0.000142	0.334
	(0.455)	(0.1)	(0.401)	(0.242)	(0.375)	(0.163)			(-0.000195)	(0.0286)

Table 49. Restrictive bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new under 14 ft bridge (SE)	t value (p value)	new under 14 ft bridge Treatment Variable (SE)	t value (p value)	new under 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.5)	-0.992	-1.35	0.453	1.61	-1.31	-0.679	12	4	0.000826	0.99
	(0.734)	(0.177)	(0.282)	(0.108)	(1.94)	(0.497)			(0.0012)	(0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-1.19	-1.12	0.747	1.7	-2.48	-0.807	12	4	0.000997	0.991
	(1.06)	(0.262)	(0.438)	(0.0884)	(3.08)	(0.42)			(0.00144)	(0.987)
Non-White percentage of total population	-0.0351	-0.842	0.00157	0.207	-0.00458	-0.115	12	4	-0.00587	0.96
	(0.0418)	(0.4)	(0.00761)	(0.836)	(0.04)	(0.909)			(-0.00859)	(0.942)
Black/African American percentage of total population	-0.0329	-0.781	-0.000931	-0.13	0.00333	0.0832	12	4	-0.00477	0.961
	(0.0422)	(0.435)	(0.00719)	(0.897)	(0.04)	(0.934)			(-0.00699)	(0.943)
Percentage of Hispanic/Latino of total population	**-0.00635**	**-2.08**	0.00344	1.3	0.000513	0.126	12	4	0.0259	0.899
	(0.00306)	**(0.038)**	(0.00265)	(0.195)	(0.00406)	(0.9)			(0.0377)	(0.853)
Percentage of Foreign-born of total population	0.00515	0.817	-0.000282	-0.0965	-0.00487	-0.635	12	4	0.0194	0.882
	(0.0063)	(0.414)	(0.00293)	(0.923)	(0.00768)	(0.526)			(0.0282)	(0.828)
Percentage of Children under 18 years old of total population	-0.0202	-1.46	0.0082	1.26	-0.051	-1.68	12	4	0.00477	0.983
	(0.0139)	(0.145)	(0.00653)	(0.209)	(0.0305)	(0.0939)			(0.00694)	(0.975)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0876	-1.16	0.0571	2.01	-0.0973	-0.49	12	4	8.92e-05	0.986
	(0.0756)	(0.247)	(0.0284)	(0.0447)	(0.199)	(0.624)			(0.000117)	(0.979)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00788	-0.625	0.00473	0.678	**0.0353**	**2.1**	12	4	-0.00109	0.958
	(0.0126)	(0.532)	(0.00698)	(0.498)	**(0.0168)**	**(0.036)**			(-0.00163)	(0.939)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.0122	-0.589	0.00205	0.2	0.0402	1.33	12	4	-0.0036	0.957
	(0.0207)	(0.556)	(0.0102)	(0.841)	(0.0304)	(0.185)			(-0.00529)	(0.937)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.61)	**-0.851**	**-2.65**	**0.377**	**2.17**	**1.73**	**3.31**	12	4	-0.000366	0.954
	(0.321)	**(0.00799)**	**(0.174)**	**(0.0299)**	**(0.523)**	**(0.000933)**			(-0.000575)	(0.933)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.19)	-0.134	-0.478	0.119	0.887	-0.675	-0.824	12	4	0.00431	0.988
	(0.281)	(0.633)	(0.135)	(0.375)	(0.819)	(0.41)			(0.00628)	(0.983)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.55)	-0.249	-0.899	0.216	1.76	-0.727	-0.957	12	4	0.0051	0.984
	(0.277)	(0.368)	(0.123)	(0.0792)	(0.76)	(0.339)			(0.00742)	(0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.94)	-0.26	-1.14	0.205	1.88	**-2.07**	**-4.08**	12	4	0.00648	0.984
	(0.229)	(0.256)	(0.109)	(0.0603)	**(0.506)**	**(4.56e-05)**			(0.00943)	(0.976)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00179	0.208	-0.000774	-0.217	0.0174	1.37	12	4	-0.00121	0.92
	(0.00861)	(0.835)	(0.00356)	(0.828)	(0.0128)	(0.172)			(-0.00183)	(0.883)
Percentage of Persons 25+ years old who have completed high school but no college	0.00365	0.14	0.00707	0.892	**0.1**	**3.15**	12	4	-6e-04	0.988
	(0.026)	(0.889)	(0.00792)	(0.372)	**(0.0318)**	**(0.00165)**			(-0.000886)	(0.982)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	**-0.0182**	**-3.1**	0.00299	1.22	0.00294	0.453	12	4	0.000109	0.956
	(0.00589)	**(0.00198)**	(0.00246)	(0.223)	(0.00647)	(0.65)			(0.000119)	(0.936)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0282	-1.01	0.0139	1.49	**-0.0793**	**-2.72**	12	4	-0.00288	0.961
	(0.0278)	(0.31)	(0.00936)	(0.137)	**(0.0292)**	**(0.00662)**			(-0.00423)	(0.943)
Percentage of total persons below the poverty level in past 12 months	-0.0598	-1.16	0.00144	0.184	0.0683	1.33	12	4	-0.00413	0.928
	(0.0516)	(0.247)	(0.00785)	(0.854)	(0.0513)	(0.183)			(-0.00608)	(0.895)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.0102	-0.942	0.00203	0.335	-0.00225	-0.157	12	4	-0.00154	0.87
	(0.0108)	(0.346)	(0.00607)	(0.737)	(0.0144)	(0.875)			(-0.00237)	(0.811)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	5.79	0.427	18.7	0.735	-63.8	-0.982	12	4	0.00125	0.297
	(13.5)	(0.669)	(25.4)	(0.462)	(65)	(0.326)			(0.00119)	(-0.0257)
Percentage of renter-occupied housing units of total housing units	-0.0108	-0.619	0.0134	1.46	0.00301	0.0902	12	4	-0.00378	0.974
	(0.0175)	(0.536)	(0.00917)	(0.143)	(0.0334)	(0.928)			(-0.00554)	(0.962)
Percentage of vacant housing units	-0.00472	-0.483	0.000309	0.0558	0.0212	1.21	12	4	0.0132	0.935
	(0.00977)	(0.629)	(0.00553)	(0.956)	(0.0176)	(0.228)			(0.0191)	(0.905)
Percentage of change in number of housing units since last census of total housing units	0.75	1.68	-0.477	-1.11	-0.519	-1.69	12	4	-0.000236	0.333
	(0.447)	(0.0937)	(0.428)	(0.265)	(0.307)	(0.0906)			(-0.000947)	(0.0278)

Table 49. Restrictive bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new under 14 ft bridge (SE)	t value (p value)	new under 14 ft bridge Treatment Variable (SE)	t value (p value)	new under 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.5)	-0.756	-1.37	0.357	1.27	-1.43	-0.748	10	2	0.000846	0.99
	(0.554)	(0.172)	(0.281)	(0.204)	(1.91)	(0.455)			(0.00123)	(0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.886	-1.12	0.524	1.2	-2.19	-0.711	10	2	0.000962	0.991
	(0.787)	(0.261)	(0.438)	(0.231)	(3.09)	(0.477)			(0.0014)	(0.987)
Non-White percentage of total population	-0.0435	-0.935	0.00103	0.135	0.00328	0.0677	10	2	-0.00772	0.958
	(0.0466)	(0.35)	(0.00765)	(0.893)	(0.0486)	(0.946)			(-0.0112)	(0.939)
Black/African American percentage of total population	-0.039	-0.842	-0.00104	-0.142	0.0179	0.372	10	2	-0.00594	0.96
	(0.0463)	(0.4)	(0.00736)	(0.887)	(0.0481)	(0.71)			(-0.00866)	(0.941)
Percentage of Hispanic/Latino of total population	**-0.0109**	**-3.06**	0.00266	1.1	**-0.0121**	**-2.37**	10	2	-0.00631	0.867
	(0.00356)	**(0.00221)**	(0.00242)	(0.272)	**(0.00508)**	**(0.0177)**			(-0.0092)	(0.807)
Percentage of Foreign-born of total population	0.000118	0.0261	-0.00109	-0.348	-0.000466	-0.0663	10	2	0.00402	0.866
	(0.00451)	(0.979)	(0.00315)	(0.728)	(0.00703)	(0.947)			(0.00585)	(0.805)
Percentage of Children under 18 years old of total population	-0.0154	-1.32	0.00611	0.968	-0.0482	-1.47	10	2	0.00527	0.983
	(0.0116)	(0.186)	(0.00631)	(0.333)	(0.0328)	(0.142)			(0.00768)	(0.975)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0795	-1.17	0.0438	1.49	-0.0869	-0.437	10	2	-0.000613	0.985
	(0.0682)	(0.244)	(0.0294)	(0.137)	(0.199)	(0.662)			(-0.000893)	(0.978)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.013	-0.858	0.00488	0.65	**0.0419**	**2.14**	10	2	-0.00182	0.958
	(0.0152)	(0.391)	(0.0075)	(0.516)	**(0.0196)**	**(0.0323)**			(-0.00265)	(0.938)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00123	0.074	-0.00144	-0.136	0.0309	1.09	10	2	-0.00542	0.955
	(0.0166)	(0.941)	(0.0106)	(0.892)	(0.0284)	(0.278)			(-0.00789)	(0.935)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.61)	**-0.627**	**-2.01**	**0.38**	**2.2**	**1.58**	**3.49**	10	2	0.00103	0.955
	(0.311)	**(0.044)**	**(0.173)**	**(0.0279)**	**(0.454)**	**(0.000483)**			(0.0015)	(0.935)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.19)	-0.0303	-0.126	0.074	0.586	-0.544	-0.606	10	2	0.00542	0.989
	(0.239)	(0.899)	(0.126)	(0.558)	(0.898)	(0.545)			(0.00791)	(0.984)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.55)	-0.122	-0.504	0.168	1.4	-0.756	-0.897	10	2	0.00586	0.985
	(0.242)	(0.614)	(0.12)	(0.162)	(0.843)	(0.37)			(0.00853)	(0.978)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.94)	-0.0969	-0.472	0.156	1.47	**-2.21**	**-3.95**	10	2	0.00553	0.983
	(0.205)	(0.637)	(0.106)	(0.141)	**(0.559)**	**(7.92e-05)**			(0.00805)	(0.975)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00695	0.94	-0.00167	-0.44	0.0119	0.927	10	2	-0.00286	0.918
	(0.0074)	(0.347)	(0.00381)	(0.66)	(0.0128)	(0.354)			(-0.00417)	(0.881)
Percentage of Persons 25+ years old who have completed high school but no college	-0.00132	-0.0485	0.00534	0.69	**0.116**	**3.27**	10	2	-0.00128	0.987
	(0.0271)	(0.961)	(0.00774)	(0.49)	**(0.0355)**	**(0.00107)**			(-0.00187)	(0.981)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	**-0.0188**	**-3.24**	0.00317	1.39	0.00196	0.3	10	2	9.49e-05	0.956
	(0.0058)	**(0.00119)**	(0.00228)	(0.164)	(0.00653)	(0.765)			(0.000138)	(0.936)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0278	-0.93	0.0133	1.39	-0.0692	-1.92	10	2	-0.00377	0.96
	(0.0298)	(0.352)	(0.00962)	(0.165)	(0.0361)	(0.0552)			(-0.0055)	(0.942)
Percentage of total persons below the poverty level in past 12 months	-0.0625	-1.22	0.000615	0.0878	0.0795	1.46	10	2	-0.00105	0.931
	(0.0513)	(0.223)	(0.007)	(0.93)	(0.0544)	(0.144)			(-0.00152)	(0.9)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.00137	0.156	2.91e-05	0.005	-0.00119	-0.106	10	2	-0.00213	0.87
	(0.00876)	(0.876)	(0.00582)	(0.996)	(0.0111)	(0.915)			(-0.00311)	(0.81)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-6.08	-0.295	13.8	0.581	-78.9	-1.13	10	2	-0.0394	0.256
	(20.6)	(0.768)	(23.8)	(0.561)	(70.1)	(0.26)			(-0.0575)	(-0.0844)
Percentage of renter-occupied housing units of total housing units	-0.00405	-0.239	0.00807	0.986	0.00795	0.288	10	2	-0.00225	0.976
	(0.0169)	(0.811)	(0.00819)	(0.324)	(0.0276)	(0.774)			(-0.00328)	(0.965)
Percentage of vacant housing units	-0.0134	-1.57	-0.000632	-0.104	**0.0425**	**2.03**	10	2	0.00248	0.924
	(0.00852)	(0.117)	(0.00605)	(0.917)	**(0.021)**	**(0.0429)**			(0.00362)	(0.89)
Percentage of change in number of housing units since last census of total housing units	0.849	1.7	-0.502	-1.15	-0.394	-1.41	10	2	-8.8e-05	0.333
	(0.498)	(0.0885)	(0.436)	(0.249)	(0.28)	(0.16)			(-0.000128)	(0.0287)

Table 49. Restrictive bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new under 14 ft bridge (SE)	t value (p value)	new under 14 ft bridge Treatment Variable (SE)	t value (p value)	new under 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.5)	-0.754	-1.48	0.285	0.886	-2.72	-1.27	12	3	0.000336	0.989
	(0.511)	(0.14)	(0.321)	(0.376)	(2.15)	(0.206)			(0.000483)	(0.984)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.6)	-0.887	-1.17	0.414	0.817	-4.27	-1.22	12	3	0.000314	0.99
	(0.758)	(0.242)	(0.506)	(0.414)	(3.49)	(0.221)			(0.000452)	(0.986)
Non-White percentage of total population	-0.039	-0.827	-0.00155	-0.224	0.0293	0.597	12	3	0.000258	0.966
	(0.0472)	(0.408)	(0.00693)	(0.822)	(0.049)	(0.55)			(0.000355)	(0.951)
Black/African American percentage of total population	-0.0367	-0.784	-0.00266	-0.388	0.0354	0.731	12	3	0.00134	0.967
	(0.0468)	(0.433)	(0.00686)	(0.698)	(0.0484)	(0.465)			(0.00193)	(0.952)
Percentage of Hispanic/Latino of total population	**-0.00957**	**-2.82**	0.00219	0.925	-0.00744	-1.54	12	3	-0.00543	0.868
	(0.00339)	**(0.00481)**	(0.00237)	(0.355)	(0.00484)	(0.124)			(-0.008)	(0.808)
Percentage of Foreign-born of total population	0.000613	0.112	-0.00211	-0.601	0.00246	0.342	12	3	0.00566	0.868
	(0.00549)	(0.911)	(0.0035)	(0.548)	(0.0072)	(0.732)			(0.00816)	(0.808)
Percentage of Children under 18 years old of total population	-0.0114	-0.735	0.00324	0.414	**-0.0943**	**-2.28**	12	3	0.00282	0.981
	(0.0155)	(0.463)	(0.00783)	(0.679)	**(0.0414)**	**(0.0228)**			(0.0041)	(0.972)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.998)	-0.0872	-1.37	0.0411	1.31	-0.15	-0.7	12	3	-0.000453	0.985
	(0.0636)	(0.17)	(0.0314)	(0.191)	(0.214)	(0.484)			(-0.00067)	(0.978)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00758	-0.596	0.00401	0.64	0.033	1.9	12	3	0.00203	0.962
	(0.0127)	(0.551)	(0.00627)	(0.522)	(0.0174)	(0.0579)			(0.00293)	(0.944)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00278	0.15	-0.000611	-0.0631	0.0281	1.03	12	3	-0.000585	0.96
	(0.0185)	(0.881)	(0.00967)	(0.95)	(0.0273)	(0.304)			(-0.000877)	(0.942)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.61)	-0.606	-1.79	0.319	1.95	**1.35**	**2.55**	12	3	0.000434	0.955
	(0.339)	(0.0742)	(0.163)	(0.0508)	**(0.529)**	**(0.0109)**			(0.000605)	(0.934)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.19)	-0.0909	-0.238	0.0907	0.55	-1.6	-1.46	12	3	0.00202	0.986
	(0.382)	(0.812)	(0.165)	(0.583)	(1.1)	(0.145)			(0.00294)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.55)	-0.189	-0.519	0.195	1.31	-1.83	-1.84	12	3	0.003	0.982
	(0.364)	(0.604)	(0.149)	(0.19)	(0.993)	(0.0651)			(0.00436)	(0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 3.94)	-0.213	-0.665	0.215	1.62	**-3.02**	**-4.38**	12	3	0.00373	0.981
	(0.32)	(0.506)	(0.133)	(0.106)	**(0.69)**	**(1.21e-05)**			(0.00543)	(0.972)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00832	1.22	-0.00284	-0.769	0.00805	0.668	12	3	-0.00146	0.92
	(0.00684)	(0.224)	(0.00369)	(0.442)	(0.012)	(0.504)			(-0.00218)	(0.883)
Percentage of Persons 25+ years old who have completed high school but no college	-0.000341	-0.0143	0.00419	0.568	**0.0893**	**2.6**	12	3	-0.000863	0.988
	(0.0238)	(0.989)	(0.00739)	(0.57)	**(0.0343)**	**(0.00934)**			(-0.00127)	(0.982)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	**-0.0177**	**-3.36**	0.00277	1.29	0.00229	0.366	12	3	0.00108	0.957
	(0.00527)	**(0.000792)**	(0.00215)	(0.198)	(0.00627)	(0.715)			(0.00154)	(0.938)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0232	-0.816	0.0109	1.16	-0.0306	-0.947	12	3	-0.000164	0.964
	(0.0284)	(0.414)	(0.00942)	(0.245)	(0.0323)	(0.344)			(-0.00026)	(0.947)
Percentage of total persons below the poverty level in past 12 months	-0.0555	-1.18	-0.000481	-0.0792	0.0725	1.38	12	3	0.00292	0.935
	(0.0473)	(0.24)	(0.00608)	(0.937)	(0.0527)	(0.169)			(0.00422)	(0.905)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.00571	0.632	-0.00141	-0.244	-0.0114	-1.04	12	3	-0.00786	0.864
	(0.00904)	(0.527)	(0.00579)	(0.807)	(0.0109)	(0.299)			(-0.0115)	(0.802)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-9.73	-0.465	14.9	0.602	-35.2	-0.672	12	3	-0.0426	0.253
	(20.9)	(0.642)	(24.7)	(0.547)	(52.4)	(0.501)			(-0.0625)	(-0.0894)
Percentage of renter-occupied housing units of total housing units	-0.0035	-0.185	0.00772	1.03	0.00251	0.0692	12	3	-0.000957	0.977
	(0.0189)	(0.853)	(0.00751)	(0.304)	(0.0363)	(0.945)			(-0.00141)	(0.966)
Percentage of vacant housing units	-0.0131	-1.62	-0.00157	-0.268	0.0173	0.75	12	3	0.00551	0.927
	(0.00812)	(0.106)	(0.00586)	(0.789)	(0.023)	(0.453)			(0.00798)	(0.894)
Percentage of change in number of housing units since last census of total housing units	0.665	1.59	-0.496	-1.17	**-0.6**	**-2.01**	12	3	6.11e-05	0.334
	(0.417)	(0.111)	(0.422)	(0.24)	**(0.298)**	**(0.044)**			(-0.000313)	(0.0285)

Table 50. Non-restrictive bridge treatment effect event study (ES) model CEM results

Dependent Variable	Interaction Estimator for new over 14 ft bridge (SE)	t value (p value)	new over 14 ft bridge Treatment Variable (SE)	t value (p value)	new over 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.0571 (0.144)	0.398 (0.691)	0.00951 (0.108)	0.0879 (0.93)	-0.135 (0.265)	-0.512 (0.609)	12	1	6.39e-07 (-3.17e-06)	0.988 (0.984)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.0393 (0.224)	0.176 (0.861)	-0.0313 (0.16)	-0.196 (0.845)	0.0632 (0.43)	0.147 (0.883)	12	1	1.24e-07 (-3.6e-06)	0.989 (0.985)
Non-White percentage of total population	-0.00462 (0.00378)	-1.22 (0.221)	0.00114 (0.00197)	0.578 (0.564)	0.00955 (0.0111)	0.861 (0.389)	12	1	1.34e-05 (2.18e-06)	0.952 (0.935)
Black/African American percentage of total population	**-0.00746** **(0.00336)**	**-2.22** **(0.0264)**	0.00255 (0.00161)	1.58 (0.114)	0.00278 (0.00599)	0.464 (0.642)	12	1	4.69e-05 (4.92e-05)	0.955 (0.939)
Percentage of Hispanic/Latino of total population	**-0.0038** **(0.00156)**	**-2.44** **(0.0146)**	0.00128 (0.00108)	1.19 (0.233)	0.0127 (0.0102)	1.24 (0.213)	12	1	8.97e-05 (7.18e-05)	0.849 (0.793)
Percentage of Foreign-born of total population	0.00118 (0.00177)	0.665 (0.506)	-0.000976 (0.00106)	-0.922 (0.357)	-0.00345 (0.00424)	-0.815 (0.415)	12	1	1.59e-05 (-1.96e-05)	0.878 (0.832)
Percentage of Children under 18 years old of total population	-0.00403 (0.00401)	-1.01 (0.314)	0.000769 (0.00303)	0.254 (0.799)	-0.0159 (0.00753)	-2.11 (0.0348)	12	1	4.52e-06 (-2.39e-06)	0.975 (0.965)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.986)	0.00627 (0.0147)	0.428 (0.669)	0.00559 (0.0121)	0.462 (0.644)	0.0145 (0.0359)	0.403 (0.687)	12	1	3.54e-06 (-9.68e-07)	0.983 (0.976)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00303 (0.00242)	-1.25 (0.212)	0.00144 (0.00158)	0.913 (0.361)	0.025 (0.013)	1.93 (0.054)	12	1	1.19e-05 (-7.6e-07)	0.95 (0.931)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00314 (0.00291)	-1.08 (0.282)	0.00136 (0.002)	0.68 (0.496)	0.00801 (0.0145)	0.552 (0.581)	12	1	5.96e-06 (-3.37e-06)	0.966 (0.953)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.72)	**-0.486** **(0.0974)**	**-4.99** **(6.28e-07)**	0.0759 (0.0769)	0.988 (0.323)	-0.8 (0.636)	-1.26 (0.209)	12	1	0.000271 (0.000349)	0.936 (0.912)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.0748 (0.0929)	-0.805 (0.421)	-0.0578 (0.0767)	-0.753 (0.451)	0.322 (0.254)	1.27 (0.206)	12	1	1.17e-05 (8.73e-06)	0.979 (0.971)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.74)	0.000544 (0.0893)	0.00609 (0.995)	-0.075 (0.0737)	-1.02 (0.309)	**0.411** **(0.205)**	**2** **(0.045)**	12	1	1.03e-05 (5.8e-06)	0.976 (0.967)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.09)	-0.0534 (0.0794)	-0.673 (0.501)	-0.0577 (0.0656)	-0.879 (0.379)	-0.407 (0.528)	-0.771 (0.441)	12	1	1.49e-05 (1.18e-05)	0.974 (0.965)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00176 (0.00243)	0.722 (0.47)	-0.000175 (0.00142)	-0.123 (0.902)	0.0118 (0.0143)	0.822 (0.411)	12	1	1.26e-05 (-1.86e-05)	0.894 (0.855)
Percentage of Persons 25+ years old who have completed high school but no college	0.0013 (0.00436)	0.299 (0.765)	0.000583 (0.00296)	0.197 (0.844)	-0.00803 (0.0181)	-0.443 (0.658)	12	1	6e-07 (-3.93e-06)	0.986 (0.981)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00148 (0.00134)	-1.1 (0.272)	0.000693 (0.000953)	0.727 (0.467)	0.00446 (0.00622)	0.717 (0.474)	12	1	9.13e-06 (-4.03e-06)	0.951 (0.933)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00435 (0.00586)	0.742 (0.458)	-0.000716 (0.00403)	-0.177 (0.859)	0.0202 (0.0363)	0.557 (0.578)	12	1	4.48e-06 (-7.65e-06)	0.959 (0.944)
Percentage of total persons below the poverty level in past 12 months	0.000967 (0.00429)	0.225 (0.822)	-0.000596 (0.00245)	-0.243 (0.808)	-0.0168 (0.0217)	-0.771 (0.441)	12	1	1.37e-06 (-2.83e-05)	0.911 (0.878)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000618 (0.00231)	0.268 (0.789)	0.000102 (0.00144)	0.071 (0.943)	**-0.0216** **(0.00577)**	**-3.73** **(0.000189)**	12	1	2.28e-06 (-3.8e-05)	0.879 (0.834)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	13.5 (8.34)	1.62 (0.105)	-6.08 (6.63)	-0.917 (0.359)	3.79 (6.39)	0.594 (0.552)	12	1	0.000167 (4.09e-06)	0.337 (0.0895)
Percentage of renter-occupied housing units of total housing units	0.00501 (0.00495)	1.01 (0.312)	-0.0013 (0.00365)	-0.357 (0.721)	**0.0668** **(0.0279)**	**2.4** **(0.0165)**	12	1	5.43e-06 (-4.03e-06)	0.966 (0.954)
Percentage of vacant housing units	0.00633 (0.0039)	1.62 (0.105)	-0.000784 (0.00195)	-0.403 (0.687)	**-0.057** **(0.0269)**	**-2.12** **(0.0342)**	12	1	6.8e-05 (5.6e-05)	0.89 (0.849)
Percentage of change in number of housing units since last census of total housing units	0.407 (0.312)	1.31 (0.191)	0.102 (0.295)	0.347 (0.729)	-1.07 (1.1)	-0.977 (0.329)	12	1	4.78e-05 (-0.000149)	0.37 (0.134)

Table 50. Non-restrictive bridge treatment effect ES model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new over 14 ft bridge (SE)	t value (p value)	new over 14 ft bridge Treatment Variable (SE)	t value (p value)	new over 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.111 (0.132)	0.844 (0.398)	-0.00167 (0.106)	-0.0158 (0.987)	0.215 (0.237)	0.905 (0.365)	10	2	0.00136 (0.00187)	0.989 (0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.117 (0.201)	0.583 (0.56)	-0.0485 (0.15)	-0.323 (0.747)	0.67 (0.399)	1.68 (0.093)	10	2	0.00163 (0.00224)	0.991 (0.987)
Non-White percentage of total population	-0.00417 (0.00407)	-1.02 (0.306)	0.00305 (0.00225)	1.35 (0.177)	-0.00203 (0.0314)	-0.0646 (0.949)	10	2	-0.0114 (-0.0156)	0.941 (0.919)
Black/African American percentage of total population	-0.00661 (0.00346)	-1.91 (0.0559)	**0.0038** **(0.00176)**	**2.16** **(0.031)**	-0.00845 (0.0193)	-0.438 (0.662)	10	2	-0.0084 (-0.0115)	0.947 (0.927)
Percentage of Hispanic/Latino of total population	**-0.00365** **(0.00158)**	**-2.31** **(0.0209)**	0.00132 (0.00108)	1.23 (0.22)	0.00979 (0.0144)	0.681 (0.496)	10	2	-0.00237 (-0.00325)	0.847 (0.79)
Percentage of Foreign-born of total population	0.000807 (0.0018)	0.449 (0.653)	-0.000612 (0.00106)	-0.578 (0.563)	-0.00362 (0.00602)	-0.6 (0.548)	10	2	-0.00184 (-0.00252)	0.876 (0.83)
Percentage of Children under 18 years old of total population	-0.00135 (0.00334)	-0.405 (0.686)	0.001 (0.00251)	0.399 (0.69)	-0.00354 (0.0112)	-0.317 (0.751)	10	2	0.00693 (0.00951)	0.982 (0.975)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.986)	0.00816 (0.0144)	0.565 (0.572)	0.00393 (0.0123)	0.32 (0.749)	0.0353 (0.0335)	1.05 (0.292)	10	2	0.000104 (0.000143)	0.983 (0.977)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00139 (0.00249)	-0.557 (0.577)	0.00122 (0.00156)	0.784 (0.433)	0.0225 (0.018)	1.25 (0.212)	10	2	-1.79e-05 (-2.46e-05)	0.95 (0.931)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00084 (0.00289)	-0.291 (0.771)	0.00137 (0.00193)	0.713 (0.476)	0.00473 (0.0221)	0.214 (0.83)	10	2	0.00109 (0.0015)	0.967 (0.955)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.72)	**-0.44** **(0.0948)**	**-4.64** **(3.51e-06)**	0.0846 (0.074)	1.14 (0.253)	-0.605 (0.658)	-0.919 (0.358)	10	2	0.00189 (0.00259)	0.937 (0.914)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.0176 (0.0709)	-0.249 (0.803)	-0.0605 (0.0603)	-1 (0.316)	**0.628** **(0.178)**	**3.53** **(0.000419)**	10	2	0.00758 (0.0104)	0.986 (0.981)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.74)	0.0605 (0.0701)	0.863 (0.388)	-0.0811 (0.0596)	-1.36 (0.173)	**0.697** **(0.211)**	**3.3** **(0.000975)**	10	2	0.00776 (0.0106)	0.983 (0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.09)	0.00393 (0.0658)	0.0597 (0.952)	-0.0648 (0.0552)	-1.17 (0.241)	-0.177 (0.602)	-0.295 (0.768)	10	2	0.00645 (0.00885)	0.981 (0.974)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.0021 (0.00236)	0.889 (0.374)	0.000131 (0.00139)	0.0945 (0.925)	0.0136 (0.0165)	0.825 (0.409)	10	2	0.000671 (0.000921)	0.895 (0.856)
Percentage of Persons 25+ years old who have completed high school but no college	0.00414 (0.00543)	0.762 (0.446)	-0.00202 (0.0036)	-0.561 (0.575)	-0.0106 (0.026)	-0.407 (0.684)	10	2	-0.00327 (-0.00449)	0.983 (0.976)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00163 (0.00137)	-1.19 (0.234)	0.000283 (0.00098)	0.289 (0.773)	0.00295 (0.00664)	0.445 (0.656)	10	2	-0.00152 (-0.00208)	0.95 (0.931)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.000755 (0.00768)	0.0984 (0.922)	0.00266 (0.00512)	0.519 (0.604)	0.0282 (0.0422)	0.669 (0.504)	10	2	-0.0124 (-0.017)	0.947 (0.927)
Percentage of total persons below the poverty level in past 12 months	0.00266 (0.00414)	0.642 (0.521)	-0.000156 (0.00226)	-0.0691 (0.945)	-0.0165 (0.0296)	-0.559 (0.576)	10	2	0.00593 (0.00814)	0.917 (0.887)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.00102 (0.00223)	0.459 (0.646)	0.000388 (0.00134)	0.289 (0.773)	**-0.0146** **(0.00586)**	**-2.48** **(0.013)**	10	2	0.00662 (0.00909)	0.886 (0.843)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	9.81 (8.6)	1.14 (0.254)	-6.67 (6.92)	-0.964 (0.335)	0.309 (5.8)	0.0534 (0.957)	10	2	-0.0201 (-0.0276)	0.317 (0.0619)
Percentage of renter-occupied housing units of total housing units	0.00837 (0.00484)	1.73 (0.084)	-0.00153 (0.00346)	-0.441 (0.659)	**0.0726** **(0.0363)**	**2** **(0.0455)**	10	2	0.00319 (0.00438)	0.969 (0.958)
Percentage of vacant housing units	**0.00807** **(0.00367)**	**2.2** **(0.0279)**	-0.00103 (0.00188)	-0.547 (0.584)	-0.055 (0.0293)	-1.88 (0.0605)	10	2	0.00503 (0.0069)	0.895 (0.856)
Percentage of change in number of housing units since last census of total housing units	0.437 (0.31)	1.41 (0.158)	0.106 (0.289)	0.367 (0.713)	-1.71 (1.52)	-1.12 (0.262)	10	2	0.000208 (0.000285)	0.37 (0.135)

Table 50. Non-restrictive bridge treatment effect ES model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new over 14 ft bridge (SE)	t value (p value)	new over 14 ft bridge Treatment Variable (SE)	t value (p value)	new over 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.00757 (0.139)	0.0547 (0.956)	0.0443 (0.108)	0.41 (0.682)	0.189 (0.211)	0.898 (0.369)	12	3	0.000911 (0.00125)	0.989 (0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	-0.0644 (0.215)	-0.3 (0.765)	0.0268 (0.158)	0.17 (0.865)	0.615 (0.335)	1.83 (0.0668)	12	3	0.000987 (0.00135)	0.99 (0.986)
Non-White percentage of total population	-0.00265 (0.00391)	-0.677 (0.498)	0.00124 (0.00205)	0.604 (0.546)	0.0122 (0.0134)	0.913 (0.361)	12	3	-0.00324 (-0.00446)	0.949 (0.93)
Black/African American percentage of total population	-0.00565 (0.00338)	-1.67 (0.0946)	0.00223 (0.00164)	1.36 (0.174)	0.0044 (0.00641)	0.686 (0.493)	12	3	-0.000486 (-0.000682)	0.955 (0.938)
Percentage of Hispanic/Latino of total population	**-0.00321 (0.0016)**	**-2.01 (0.0449)**	0.00139 (0.0011)	1.26 (0.206)	0.0131 (0.00989)	1.32 (0.185)	12	3	-0.00947 (-0.013)	0.84 (0.78)
Percentage of Foreign-born of total population	0.00073 (0.00179)	0.408 (0.683)	-0.000595 (0.00107)	-0.558 (0.577)	-0.00361 (0.00421)	-0.857 (0.392)	12	3	-0.000188 (-3e-04)	0.878 (0.832)
Percentage of Children under 18 years old of total population	-0.00559 (0.00356)	-1.57 (0.117)	0.00247 (0.00275)	0.898 (0.369)	-0.000833 (0.0074)	-0.113 (0.91)	12	3	0.00502 (0.00688)	0.98 (0.972)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.986)	0.00416 (0.0145)	0.287 (0.774)	0.00671 (0.012)	0.561 (0.575)	0.0295 (0.0365)	0.81 (0.418)	12	3	0.000354 (0.00048)	0.983 (0.977)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00243 (0.00234)	-1.04 (0.299)	0.0017 (0.00148)	1.14 (0.252)	0.0279 (0.0129)	2.16 (0.0307)	12	3	0.00324 (0.00443)	0.953 (0.935)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00246 (0.00277)	-0.888 (0.375)	0.00165 (0.00183)	0.903 (0.367)	0.013 (0.0118)	1.1 (0.273)	12	3	0.00252 (0.00345)	0.969 (0.957)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.72)	**-0.467 (0.0966)**	**-4.84 (1.34e-06)**	0.0886 (0.0755)	1.17 (0.241)	-0.622 (0.665)	-0.935 (0.35)	12	3	-5.03e-05 (-9.11e-05)	0.935 (0.911)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.136 (0.0825)	-1.65 (0.099)	-0.0254 (0.0692)	-0.367 (0.714)	0.667 (0.262)	2.54 (0.011)	12	3	0.00445 (0.0061)	0.983 (0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.74)	-0.0523 (0.0781)	-0.669 (0.504)	-0.0416 (0.0662)	-0.627 (0.53)	0.734 (0.232)	3.16 (0.00156)	12	3	0.00526 (0.00722)	0.981 (0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.09)	-0.089 (0.0693)	-1.28 (0.199)	-0.0291 (0.058)	-0.502 (0.616)	-0.139 (0.467)	-0.297 (0.766)	12	3	0.00511 (0.00701)	0.98 (0.972)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00163 (0.00239)	0.682 (0.495)	0.000208 (0.00139)	0.149 (0.881)	0.0156 (0.015)	1.03 (0.301)	12	3	0.0037 (0.00505)	0.898 (0.86)
Percentage of Persons 25+ years old who have completed high school but no college	0.00362 (0.00463)	0.781 (0.435)	-0.00107 (0.00308)	-0.347 (0.729)	-0.0029 (0.0279)	-0.104 (0.917)	12	3	-0.000834 (-0.00115)	0.985 (0.98)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00137 (0.00133)	-1.03 (0.304)	0.000387 (0.000937)	0.414 (0.679)	0.00222 (0.00578)	0.385 (0.7)	12	3	0.00138 (0.00188)	0.953 (0.935)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00111 (0.00627)	0.177 (0.86)	0.00157 (0.00418)	0.376 (0.707)	0.0133 (0.047)	0.284 (0.776)	12	3	-0.00166 (-0.0023)	0.958 (0.942)
Percentage of total persons below the poverty level in past 12 months	0.000737 (0.0041)	0.18 (0.857)	0.000382 (0.00221)	0.173 (0.863)	-0.0108 (0.0195)	-0.554 (0.58)	12	3	0.00894 (0.0122)	0.92 (0.891)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000204 (0.00227)	-0.09 (0.928)	0.00103 (0.00136)	0.756 (0.45)	-0.0179 (0.00483)	-3.7 (0.000216)	12	3	0.00483 (0.0066)	0.884 (0.841)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	14.7 (8.44)	1.75 (0.0807)	-7.96 (6.89)	-1.16 (0.248)	-3.21 (9.21)	-0.348 (0.728)	12	3	-0.0184 (-0.0255)	0.318 (0.064)
Percentage of renter-occupied housing units of total housing units	0.00437 (0.00462)	0.946 (0.344)	0.000131 (0.00327)	0.0401 (0.968)	0.0759 (0.019)	4 (6.38e-05)	12	3	0.00396 (0.00542)	0.97 (0.959)
Percentage of vacant housing units	0.00626 (0.00367)	1.7 (0.0887)	-0.000248 (0.00182)	-0.137 (0.891)	-0.052 (0.0252)	-2.07 (0.0387)	12	3	0.00808 (0.0111)	0.898 (0.86)
Percentage of change in number of housing units since last census of total housing units	0.382 (0.304)	1.26 (0.209)	0.0802 (0.285)	0.282 (0.778)	-1.47 (1.33)	-1.1 (0.27)	12	3	0.00201 (0.00254)	0.371 (0.137)

Table 50. Non-restrictive bridge treatment effect ES model CEM results (cont'd)

Dependent Variable	Interaction Estimator for new over 14 ft bridge (SE)	t value (p value)	new over 14 ft bridge Treatment Variable (SE)	t value (p value)	new over 14 ft bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	0.038 (0.13)	0.292 (0.77)	0.00307 (0.101)	0.0303 (0.976)	-0.0535 (0.128)	-0.417 (0.676)	12	4	0.0019 (0.00261)	0.99 (0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.4)	0.0105 (0.202)	0.0518 (0.959)	-0.0439 (0.145)	-0.303 (0.762)	0.255 (0.233)	1.09 (0.274)	12	4	0.00199 (0.00272)	0.991 (0.988)
Non-White percentage of total population	-0.00263 (0.00397)	-0.663 (0.507)	0.00338 (0.0022)	1.54 (0.124)	-0.00279 (0.0155)	-0.18 (0.857)	12	4	-0.00996 (-0.0137)	0.943 (0.921)
Black/African American percentage of total population	-0.00593 (0.00334)	-1.77 (0.076)	**0.00412** **(0.00173)**	**2.38** **(0.0175)**	-0.00688 (0.00895)	-0.77 (0.442)	12	4	-0.00838 (-0.0115)	0.947 (0.927)
Percentage of Hispanic/Latino of total population	-0.00305 (0.00142)	-2.14 (0.0321)	0.0012 (0.000948)	1.27 (0.205)	0.00817 (0.0069)	1.18 (0.236)	12	4	0.0414 (0.0568)	0.891 (0.85)
Percentage of Foreign-born of total population	0.00156 (0.00179)	0.874 (0.382)	-0.000758 (0.00103)	-0.736 (0.462)	-0.00418 (0.00471)	-0.887 (0.375)	12	4	0.00226 (0.00304)	0.88 (0.835)
Percentage of Children under 18 years old of total population	-0.00392 (0.00346)	-1.13 (0.258)	0.000923 (0.00267)	0.345 (0.73)	-0.013 (0.0113)	-1.16 (0.248)	12	4	0.00643 (0.00881)	0.981 (0.974)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 0.986)	0.00444 (0.0142)	0.313 (0.754)	0.00525 (0.0121)	0.434 (0.664)	0.0163 (0.0207)	0.79 (0.43)	12	4	0.000879 (0.0012)	0.984 (0.978)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	-0.00184 (0.00239)	-0.771 (0.441)	0.00152 (0.00151)	1 (0.317)	0.0211 (0.0148)	1.43 (0.154)	12	4	0.00272 (0.0037)	0.952 (0.934)
Percentage of female-headed families with or without own children of total families and subfamilies	-0.00182 (0.00287)	-0.635 (0.526)	0.00156 (0.00197)	0.789 (0.43)	0.00404 (0.0154)	0.262 (0.793)	12	4	0.000706 (0.000951)	0.967 (0.954)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 3.72)	**-0.488** **(0.097)**	**-5.03** **(5.02e-07)**	0.0719 (0.0787)	0.914 (0.361)	-0.737 (0.607)	-1.22 (0.224)	12	4	0.000604 (0.000796)	0.936 (0.912)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.32)	-0.0871 (0.0837)	-1.04 (0.298)	-0.0653 (0.071)	-0.919 (0.358)	**0.439** **(0.113)**	**3.9** **(9.51e-05)**	12	4	0.00522 (0.00715)	0.984 (0.978)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.74)	-0.00773 (0.0802)	-0.0964 (0.923)	-0.0861 (0.0687)	-1.25 (0.21)	0.526 (0.276)	1.9 (0.0572)	12	4	0.00535 (0.00733)	0.981 (0.974)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.09)	-0.0647 (0.069)	-0.937 (0.349)	-0.0668 (0.0601)	-1.11 (0.266)	-0.323 (0.505)	-0.64 (0.522)	12	4	0.00623 (0.00855)	0.981 (0.974)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.00199 (0.00233)	0.853 (0.394)	5.28e-05 (0.00137)	0.0386 (0.969)	0.011 (0.0158)	0.694 (0.488)	12	4	0.00587 (0.008)	0.9 (0.863)
Percentage of Persons 25+ years old who have completed high school but no college	-0.000144 (0.00512)	-0.0282 (0.978)	-0.00101 (0.00337)	-0.299 (0.765)	-0.012 (0.0275)	-0.435 (0.663)	12	4	-0.00194 (-0.00268)	0.984 (0.978)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	-0.00131 (0.00136)	-0.963 (0.335)	0.000211 (0.000979)	0.216 (0.829)	0.00442 (0.00662)	0.668 (0.504)	12	4	-0.00112 (-0.00156)	0.95 (0.932)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	0.00579 (0.00702)	0.825 (0.41)	0.00125 (0.00475)	0.263 (0.793)	0.0307 (0.0506)	0.607 (0.544)	12	4	-0.00714 (-0.00983)	0.952 (0.934)
Percentage of total persons below the poverty level in past 12 months	0.00197 (0.00404)	0.487 (0.626)	-3.05e-05 (0.00231)	-0.0132 (0.989)	-0.0194 (0.0205)	-0.947 (0.344)	12	4	0.00652 (0.0089)	0.918 (0.887)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000418 (0.0023)	0.182 (0.856)	0.000135 (0.00144)	0.0936 (0.925)	**-0.0179** **(0.00591)**	**-3.03** **(0.00248)**	12	4	0.00288 (0.0039)	0.882 (0.838)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	12.4 (8.31)	1.49 (0.136)	-5.43 (6.63)	-0.819 (0.413)	-1.18 (7.13)	-0.166 (0.869)	12	4	-0.000347 (-0.000816)	0.336 (0.0887)
Percentage of renter-occupied housing units of total housing units	0.0061 (0.00484)	1.26 (0.208)	-0.00125 (0.00363)	-0.343 (0.732)	**0.0687** **(0.0251)**	**2.73** **(0.00632)**	12	4	0.00233 (0.00318)	0.969 (0.957)
Percentage of vacant housing units	0.00641 (0.00374)	1.71 (0.0866)	-0.000768 (0.00184)	-0.418 (0.676)	**-0.0578** **(0.028)**	**-2.07** **(0.0388)**	12	4	0.00704 (0.00961)	0.897 (0.859)
Percentage of change in number of housing units since last census of total housing units	0.457 (0.331)	1.38 (0.168)	0.0587 (0.286)	0.205 (0.838)	-1.12 (1.05)	-1.06 (0.289)	12	4	-0.000974 (-0.00166)	0.368 (0.133)

Table 51. All new bridge treatment effect event study model CEM results

Dependent Variable	Interaction Estimator for New bridge (SE)	t value (p value)	New bridge Treatment Variable (SE)	t value (p value)	New bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.361 (0.202)	-1.78 (0.0743)	0.243 (0.215)	1.13 (0.259)	-0.0536 (0.445)	-0.12 (0.904)	12	1	2.07e-05 (2.31e-05)	0.99 (0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.5)	-0.382 (0.22)	-1.74 (0.0822)	0.177 (0.238)	0.745 (0.456)	**-1.66** **(0.725)**	**-2.29** **(0.0222)**	12	1	7.49e-06 (5.63e-06)	0.992 (0.989)
Non-White percentage of total population	0.000302 (0.00499)	0.0605 (0.952)	-0.00122 (0.00388)	-0.314 (0.753)	-0.00543 (0.0272)	-0.199 (0.842)	12	1	1.43e-06 (-1.78e-05)	0.968 (0.954)
Black/African American percentage of total population	0.000379 (0.00439)	0.0863 (0.931)	-0.00034 (0.00329)	-0.103 (0.918)	-0.00992 (0.0267)	-0.372 (0.71)	12	1	1.18e-07 (-1.84e-05)	0.97 (0.957)
Percentage of Hispanic/Latino of total population	**-0.00663** **(0.00297)**	**-2.23** **(0.0259)**	0.00255 (0.00254)	1 (0.316)	-0.0194 (0.0145)	-1.34 (0.182)	12	1	0.00021 (0.000194)	0.833 (0.763)
Percentage of Foreign-born of total population	0.00016 (0.00272)	0.059 (0.953)	0.000947 (0.00239)	0.397 (0.692)	0.00824 (0.0244)	0.339 (0.735)	12	1	1.45e-05 (-4.41e-05)	0.895 (0.851)
Percentage of Children under 18 years old of total population	-0.00746 (0.0051)	-1.46 (0.144)	0.00526 (0.00437)	1.2 (0.229)	0.047 (0.0749)	0.628 (0.53)	12	1	2.42e-05 (2.24e-05)	0.981 (0.973)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.01)	-0.0129 (0.0157)	-0.825 (0.409)	-0.00382 (0.0113)	-0.337 (0.736)	-0.113 (0.0853)	-1.33 (0.184)	12	1	7.23e-06 (3.79e-06)	0.99 (0.985)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00149 (0.00374)	0.398 (0.691)	0.0016 (0.00354)	0.451 (0.652)	**-0.109** **(0.0516)**	**-2.12** **(0.0342)**	12	1	1.69e-05 (-5.52e-06)	0.952 (0.932)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00415 (0.00464)	0.894 (0.372)	0.00105 (0.00418)	0.25 (0.802)	-0.113 (0.0863)	-1.31 (0.19)	12	1	1.86e-05 (8.55e-06)	0.971 (0.959)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 4.39)	-0.0298 (0.128)	-0.233 (0.815)	-0.074 (0.119)	-0.622 (0.534)	1.04 (2.97)	0.352 (0.725)	12	1	2.3e-05 (8.9e-06)	0.962 (0.946)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.42)	-0.0519 (0.131)	-0.397 (0.691)	0.116 (0.116)	0.999 (0.318)	**-3.29** **(0.61)**	**-5.39** **(7.22e-08)**	12	1	1.39e-05 (9.57e-06)	0.984 (0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.81)	0.0147 (0.121)	0.122 (0.903)	0.101 (0.11)	0.914 (0.361)	-0.427 (0.821)	-0.52 (0.603)	12	1	2.13e-05 (1.93e-05)	0.982 (0.975)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.14)	-0.0757 (0.108)	-0.704 (0.482)	0.0444 (0.104)	0.425 (0.671)	**3.61** **(0.463)**	**7.8** **(7.55e-15)**	12	1	4.97e-06 (-6.89e-06)	0.977 (0.968)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.000204 (0.00298)	0.0686 (0.945)	-0.000742 (0.00258)	-0.288 (0.773)	-0.0734 (0.0872)	-0.842 (0.4)	12	1	7.23e-06 (-6.68e-05)	0.875 (0.823)
Percentage of Persons 25+ years old who have completed high school but no college	0.0046 (0.0073)	0.629 (0.529)	-0.00773 (0.00627)	-1.23 (0.218)	-0.147 (0.0889)	-1.66 (0.0976)	12	1	2.05e-05 (1.86e-05)	0.983 (0.976)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	0.00289 (0.00249)	1.16 (0.246)	0.00126 (0.00239)	0.526 (0.599)	0.0362 (0.0302)	1.2 (0.232)	12	1	0.000134 (0.000153)	0.939 (0.914)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.00559 (0.0106)	-0.53 (0.596)	0.0119 (0.00943)	1.26 (0.206)	0.171 (0.164)	1.05 (0.296)	12	1	7.84e-05 (7.94e-05)	0.949 (0.927)
Percentage of total persons below the poverty level in past 12 months	-0.00177 (0.00577)	-0.307 (0.759)	0.00108 (0.00442)	0.244 (0.807)	-0.0243 (0.037)	-0.656 (0.512)	12	1	3.11e-06 (-3.99e-05)	0.928 (0.898)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	0.000267 (0.00321)	0.0834 (0.934)	-0.00188 (0.0025)	-0.752 (0.452)	-0.0342 (0.032)	-1.07 (0.286)	12	1	2.78e-05 (-2.49e-05)	0.895 (0.852)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-9.78 (15.2)	-0.646 (0.519)	-2.07 (11.6)	-0.179 (0.858)	37.5 (60.8)	0.616 (0.538)	12	1	0.00018 (-5.15e-05)	0.501 (0.294)
Percentage of renter-occupied housing units of total housing units	-0.00933 (0.00795)	-1.17 (0.24)	0.0113 (0.00722)	1.56 (0.118)	-0.116 (0.0521)	-2.22 (0.0266)	12	1	4.08e-05 (4.15e-05)	0.974 (0.962)
Percentage of vacant housing units	0.00552 (0.00337)	1.64 (0.101)	-0.0011 (0.00282)	-0.389 (0.697)	-0.00911 (0.0206)	-0.443 (0.658)	12	1	9.56e-05 (7.68e-05)	0.905 (0.865)
Percentage of change in number of housing units since last census of total housing units	-1.53 (1.63)	-0.935 (0.35)	3.68 (3.26)	1.13 (0.259)	-2.54 (4.94)	-0.514 (0.607)	12	1	0.000614 (5e-04)	0.4 (0.151)

Table 51. All new bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for New bridge (SE)	t value (p value)	New bridge Treatment Variable (SE)	t value (p value)	New bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.297	-1.56	0.213	1.05	0.0937	0.521	10	2	-1.07e-05	0.99
	(0.191)	(0.12)	(0.203)	(0.294)	(0.18)	(0.602)			(-1.51e-05)	(0.985)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.5)	-0.299	-1.41	0.149	0.649	-0.205	-0.884	10	2	6.89e-06	0.992
	(0.211)	(0.158)	(0.23)	(0.517)	(0.232)	(0.377)			(9.75e-06)	(0.989)
Non-White percentage of total population	-0.00476	-0.813	0.000192	0.0433	-0.0135	-0.574	10	2	-0.0109	0.957
	(0.00586)	(0.416)	(0.00444)	(0.965)	(0.0235)	(0.566)			(-0.0155)	(0.939)
Black/African American percentage of total population	-0.00322	-0.648	6.38e-05	0.0172	-0.0175	-1.29	10	2	-0.00872	0.961
	(0.00497)	(0.517)	(0.0037)	(0.986)	(0.0136)	(0.197)			(-0.0123)	(0.945)
Percentage of Hispanic/Latino of total population	**-0.00699**	**-2.3**	0.0014	0.516	0.0105	0.983	10	2	-0.00744	0.825
	(0.00304)	**(0.0215)**	(0.00271)	(0.606)	(0.0107)	(0.326)			(-0.0105)	(0.752)
Percentage of Foreign-born of total population	-0.000441	-0.162	0.00101	0.419	0.00501	0.556	10	2	-0.00145	0.894
	(0.00272)	(0.871)	(0.00241)	(0.675)	(0.00901)	(0.578)			(-0.00205)	(0.849)
Percentage of Children under 18 years old of total population	-0.00681	-1.49	0.00541	1.39	-0.0275	-1.84	10	2	0.00289	0.984
	(0.00456)	(0.136)	(0.00391)	(0.166)	(0.0149)	(0.0653)			(0.00409)	(0.977)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.01)	-0.0125	-0.792	-0.00184	-0.163	0.0425	1.47	10	2	-0.000249	0.989
	(0.0158)	(0.428)	(0.0113)	(0.871)	(0.029)	(0.143)			(-0.000352)	(0.985)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.0035	0.907	-0.00179	-0.502	-0.00963	-0.414	10	2	-0.00187	0.95
	(0.00386)	(0.364)	(0.00356)	(0.616)	(0.0232)	(0.679)			(-0.00264)	(0.929)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00604	1.32	-0.00281	-0.684	0.00578	0.303	10	2	-0.00013	0.971
	(0.00457)	(0.187)	(0.00411)	(0.494)	(0.0191)	(0.762)			(-0.000184)	(0.959)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 4.39)	-0.0462	-0.359	-0.0438	-0.366	**-2.35**	**-3.15**	10	2	0.000265	0.962
	(0.129)	(0.72)	(0.12)	(0.714)	**(0.746)**	**(0.00166)**			(0.000375)	(0.946)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.42)	0.0185	0.178	0.07	0.679	-0.104	-0.309	10	2	0.00359	0.987
	(0.104)	(0.858)	(0.103)	(0.497)	(0.336)	(0.757)			(0.00508)	(0.982)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.81)	0.0959	0.958	0.0414	0.407	**-0.824**	**-3.63**	10	2	0.00257	0.985
	(0.1)	(0.338)	(0.102)	(0.684)	**(0.227)**	**(0.000283)**			(0.00364)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.14)	-0.00658	-0.0684	-0.0104	-0.102	-0.37	-1.49	10	2	0.00244	0.98
	(0.0962)	(0.945)	(0.103)	(0.919)	(0.247)	(0.135)			(0.00346)	(0.971)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.00126	-0.43	0.00076	0.293	0.0174	0.539	10	2	-0.00156	0.873
	(0.00292)	(0.667)	(0.00259)	(0.77)	(0.0324)	(0.59)			(-0.00221)	(0.821)
Percentage of Persons 25+ years old who have completed high school but no college	0.0137	1.53	**-0.0201**	**-2.61**	0.0329	0.664	10	2	-0.00463	0.978
	(0.00895)	(0.127)	**(0.00772)**	**(0.00908)**	(0.0496)	(0.507)			(-0.00655)	(0.969)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	0.00367	1.41	-0.00025	-0.1	-0.021	-1.66	10	2	-0.00135	0.938
	(0.00259)	(0.157)	(0.0025)	(0.92)	(0.0126)	(0.0972)			(-0.0019)	(0.912)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0141	-1.05	**0.0266**	**2.27**	-0.0574	-0.924	10	2	-0.0125	0.936
	(0.0135)	(0.296)	**(0.0117)**	**(0.0236)**	(0.0621)	(0.356)			(-0.0177)	(0.91)
Percentage of total persons below the poverty level in past 12 months	-0.00166	-0.305	0.000878	0.208	0.0148	0.835	10	2	0.0015	0.929
	(0.00546)	(0.761)	(0.00422)	(0.835)	(0.0178)	(0.404)			(0.00212)	(0.9)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	8.85e-05	0.0286	-0.000761	-0.313	**0.0229**	**2.42**	10	2	0.00215	0.898
	(0.00309)	(0.977)	(0.00243)	(0.754)	**(0.00947)**	**(0.0157)**			(0.00304)	(0.855)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-16.4	-1.11	6.32	0.541	-15.3	-0.879	10	2	-0.0345	0.467
	(14.8)	(0.269)	(11.7)	(0.589)	(17.4)	(0.379)			(-0.0488)	(0.245)
Percentage of renter-occupied housing units of total housing units	-0.00549	-0.692	0.00756	1.01	**0.159**	**9.97**	10	2	0.00182	0.975
	(0.00794)	(0.489)	(0.00751)	(0.315)	**(0.0159)**	**(3.68e-23)**			(0.00257)	(0.965)
Percentage of vacant housing units	**0.00711**	**2.19**	-0.00303	-1.08	-0.00797	-1.37	10	2	-0.000315	0.904
	(0.00325)	**(0.0288)**	(0.0028)	(0.279)	(0.00582)	(0.171)			(-0.000446)	(0.865)
Percentage of change in number of housing units since last census of total housing units	-0.885	-0.739	2.54	1.05	1.63	1.03	10	2	-0.00326	0.397
	(1.2)	(0.46)	(2.41)	(0.293)	(1.58)	(0.302)			(-0.00461)	(0.146)

Table 51. All new bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for New bridge (SE)	t value (p value)	New bridge Treatment Variable (SE)	t value (p value)	New bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.328	-1.66	0.272	1.35	0.245	0.373	12	3	9.29e-05	0.99
	(0.198)	(0.0976)	(0.202)	(0.178)	(0.658)	(0.709)			(0.000125)	(0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.5)	-0.329	-1.55	0.227	1.04	-1.42	-1.4	12	3	0.000113	0.992
	(0.212)	(0.122)	(0.218)	(0.298)	(1.02)	(0.163)			(0.000155)	(0.989)
Non-White percentage of total population	-0.000638	-0.123	-0.0029	-0.701	-0.0177	-0.666	12	3	-0.00315	0.965
	(0.00517)	(0.902)	(0.00413)	(0.484)	(0.0266)	(0.505)			(-0.00448)	(0.95)
Black/African American percentage of total population	6.05e-07	0.000139	-0.00204	-0.578	-0.0175	-0.726	12	3	-0.000842	0.969
	(0.00436)	(1)	(0.00352)	(0.563)	(0.0242)	(0.468)			(-0.00121)	(0.956)
Percentage of Hispanic/Latino of total population	**-0.00789**	**-2.59**	0.00281	1.02	-0.0181	-1.21	12	3	-0.00913	0.823
	(0.00304)	**(0.00951)**	(0.00275)	(0.306)	(0.015)	(0.228)			(-0.013)	(0.75)
Percentage of Foreign-born of total population	-9.36e-05	-0.0343	0.000708	0.295	0.00341	0.148	12	3	-0.00157	0.893
	(0.00273)	(0.973)	(0.0024)	(0.768)	(0.023)	(0.882)			(-0.00228)	(0.849)
Percentage of Children under 18 years old of total population	-0.00719	-1.42	0.00747	1.75	0.0595	1.16	12	3	0.00211	0.983
	(0.00505)	(0.155)	(0.00426)	(0.0794)	(0.0515)	(0.248)			(0.00298)	(0.976)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.01)	-0.0133	-0.847	0.00213	0.187	-0.123	-1.29	12	3	-1.81e-05	0.99
	(0.0158)	(0.397)	(0.0114)	(0.852)	(0.0954)	(0.197)			(-3.21e-05)	(0.985)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00218	0.584	0.0015	0.423	**-0.099**	**-1.97**	12	3	5.67e-05	0.952
	(0.00373)	(0.559)	(0.00354)	(0.672)	**(0.0502)**	**(0.0488)**			(5.08e-05)	(0.932)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00474	1.07	0.000649	0.163	-0.0984	-1.43	12	3	0.000317	0.971
	(0.00445)	(0.287)	(0.00398)	(0.87)	(0.0687)	(0.152)			(0.000431)	(0.959)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 4.39)	-0.0282	-0.22	-0.0561	-0.473	1.46	0.5	12	3	-6.08e-05	0.962
	(0.128)	(0.826)	(0.119)	(0.636)	(2.92)	(0.617)			(-0.00011)	(0.946)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.42)	0.0187	0.156	0.114	0.991	**-3.35**	**-3.49**	12	3	0.00312	0.987
	(0.12)	(0.876)	(0.115)	(0.322)	**(0.959)**	**(0.000479)**			(0.00441)	(0.981)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.81)	0.0789	0.713	0.103	0.951	-0.406	-0.36	12	3	0.00281	0.985
	(0.111)	(0.476)	(0.108)	(0.342)	(1.13)	(0.719)			(0.00396)	(0.979)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.14)	-0.00866	-0.0868	0.0422	0.415	**3.7**	**2.78**	12	3	0.00382	0.981
	(0.0998)	(0.931)	(0.102)	(0.678)	**(1.33)**	**(0.00539)**			(0.00539)	(0.973)
Percentage of Persons 25+ years old who have completed 0-8 years of school	-0.000571	-0.2	0.000229	0.092	-0.0658	-0.72	12	3	0.00428	0.879
	(0.00285)	(0.841)	(0.00249)	(0.927)	(0.0914)	(0.472)			(0.00598)	(0.829)
Percentage of Persons 25+ years old who have completed high school but no college	0.00725	0.961	-0.011	-1.69	-0.117	-1.11	12	3	-0.00143	0.982
	(0.00754)	(0.337)	(0.00649)	(0.0908)	(0.106)	(0.268)			(-0.00204)	(0.974)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	0.00234	0.955	0.00123	0.522	0.0359	1.07	12	3	0.00191	0.941
	(0.00245)	(0.34)	(0.00236)	(0.602)	(0.0335)	(0.283)			(0.00267)	(0.917)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.00627	-0.569	0.0141	1.46	0.137	0.758	12	3	-0.00215	0.946
	(0.011)	(0.569)	(0.00966)	(0.144)	(0.181)	(0.449)			(-0.00308)	(0.924)
Percentage of total persons below the poverty level in past 12 months	-0.00112	-0.207	0.0017	0.393	-0.0169	-0.603	12	3	0.0022	0.93
	(0.0054)	(0.836)	(0.00432)	(0.694)	(0.028)	(0.547)			(0.00307)	(0.901)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	3.65e-05	0.0115	-0.000509	-0.202	-0.0309	-1.15	12	3	0.000479	0.896
	(0.00318)	(0.991)	(0.00252)	(0.84)	(0.0269)	(0.251)			(0.000614)	(0.853)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-13.8	-0.906	2.16	0.184	17.2	0.312	12	3	-0.0279	0.473
	(15.2)	(0.365)	(11.7)	(0.854)	(55.3)	(0.755)			(-0.0398)	(0.254)
Percentage of renter-occupied housing units of total housing units	-0.00578	-0.788	0.0113	1.68	-0.0955	-1.58	12	3	0.00272	0.976
	(0.00734)	(0.431)	(0.00675)	(0.0938)	(0.0602)	(0.113)			(0.00384)	(0.966)
Percentage of vacant housing units	0.00577	1.75	-0.000714	-0.252	-0.00178	-0.129	12	3	0.00128	0.906
	(0.00329)	(0.0798)	(0.00283)	(0.801)	(0.0138)	(0.897)			(0.00175)	(0.867)
Percentage of change in number of housing units since last census of total housing units	-1.71	-0.973	3.48	1.12	0.333	0.0631	12	3	0.000389	0.4
	(1.76)	(0.331)	(3.09)	(0.261)	(5.27)	(0.95)			(0.000182)	(0.151)

Table 51. All new bridge treatment effect event study model CEM results (cont'd)

Dependent Variable	Interaction Estimator for New bridge (SE)	t value (p value)	New bridge Treatment Variable (SE)	t value (p value)	New bridge Group Dummy Variable (SE)	t value (p value)	# Other Controls	Set	R2 (Adj. R2) diff w/o New Variables	R2 (Adj. R2)
Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US, mean = 11.4)	-0.309	-1.54	0.195	0.838	-0.00229	-0.00824	12	4	0.000266	0.99
	(0.2)	(0.123)	(0.233)	(0.402)	(0.278)	(0.993)			(0.000371)	(0.986)
Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US, mean = 18.5)	-0.31	-1.4	0.116	0.433	-0.271	-0.816	12	4	0.000182	0.992
	(0.221)	(0.161)	(0.268)	(0.665)	(0.332)	(0.414)			(0.00025)	(0.989)
Non-White percentage of total population	0.000506	0.0869	-0.00204	-0.444	-0.0184	-1.01	12	4	-0.0111	0.957
	(0.00582)	(0.931)	(0.00461)	(0.657)	(0.0183)	(0.315)			(-0.0157)	(0.939)
Black/African American percentage of total population	0.000369	0.0738	-0.00144	-0.365	**-0.0227**	**-2.29**	12	4	-0.00954	0.96
	(0.005)	(0.941)	(0.00395)	(0.715)	**(0.0099)**	**(0.0219)**			(-0.0135)	(0.944)
Percentage of Hispanic/Latino of total population	-0.00349	-1.29	0.00087	0.298	0.00514	0.444	12	4	0.034	0.867
	(0.00269)	(0.195)	(0.00292)	(0.765)	(0.0116)	(0.657)			(0.0479)	(0.811)
Percentage of Foreign-born of total population	0.000179	0.0667	0.00108	0.452	0.00623	0.74	12	4	0.000924	0.896
	(0.00267)	(0.947)	(0.00239)	(0.651)	(0.00842)	(0.459)			(0.00121)	(0.853)
Percentage of Children under 18 years old of total population	-0.00459	-0.993	0.00334	0.863	**-0.0334**	**-3.59**	12	4	0.00278	0.983
	(0.00462)	(0.321)	(0.00387)	(0.388)	**(0.0093)**	**(0.000329)**			(0.00392)	(0.976)
Inverse Hyperbolic Sine Transformation of Ratio of adults 18+ years old to children under 18 years old (adults/children, mean = 1.01)	-0.0118	-0.75	-0.00625	-0.547	0.04	1.34	12	4	0.000198	0.99
	(0.0157)	(0.454)	(0.0114)	(0.584)	(0.0299)	(0.181)			(0.00027)	(0.985)
Percentage of single-parent families with own children under 18 years old of total families and subfamilies	0.00604	1.62	-0.00334	-0.965	-0.0201	-1.06	12	4	0.000564	0.953
	(0.00373)	(0.106)	(0.00347)	(0.335)	(0.019)	(0.291)			(0.000754)	(0.933)
Percentage of female-headed families with or without own children of total families and subfamilies	0.00849	1.77	-0.00373	-0.87	-0.0044	-0.267	12	4	-0.00138	0.97
	(0.00479)	(0.0763)	(0.00429)	(0.385)	(0.0165)	(0.789)			(-0.00198)	(0.957)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included mean = 4.39)	-0.0236	-0.181	-0.0536	-0.445	**-2.5**	**-3.76**	12	4	-2.36e-05	0.962
	(0.131)	(0.857)	(0.121)	(0.657)	**(0.665)**	**(0.000175)**			(-6.88e-05)	(0.946)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes (mean = 5.42)	0.0249	0.208	0.0297	0.245	-0.034	-0.104	12	4	0.00291	0.987
	(0.12)	(0.835)	(0.121)	(0.807)	(0.327)	(0.917)			(0.00411)	(0.981)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes (mean = 4.81)	0.0901	0.77	0.0225	0.19	**-0.759**	**-2.62**	12	4	0.00175	0.984
	(0.117)	(0.441)	(0.118)	(0.849)	**(0.289)**	**(0.00871)**			(0.00247)	(0.977)
Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes (mean = 4.14)	0.0115	0.112	-0.0433	-0.399	-0.413	-1.65	12	4	0.00341	0.981
	(0.103)	(0.911)	(0.108)	(0.69)	(0.25)	(0.0986)			(0.00481)	(0.973)
Percentage of Persons 25+ years old who have completed 0-8 years of school	0.000942	0.33	-0.000577	-0.218	0.0123	0.392	12	4	0.00486	0.88
	(0.00285)	(0.741)	(0.00265)	(0.828)	(0.0314)	(0.695)			(0.00677)	(0.83)
Percentage of Persons 25+ years old who have completed high school but no college	0.0157	1.83	**-0.0212**	**-2.82**	0.0113	0.256	12	4	-0.0031	0.98
	(0.00855)	(0.0669)	**(0.00751)**	**(0.00484)**	(0.0443)	(0.798)			(-0.00441)	(0.972)
Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	0.00295	1.15	0.000385	0.154	**-0.0214**	**-1.65**	12	4	-0.000315	0.939
	(0.00257)	(0.251)	(0.0025)	(0.877)	**(0.013)**	**(0.0991)**			(-0.000503)	(0.913)
Percentage of Persons 25+ years old who have a bachelor's or graduate/professional degree	-0.0206	-1.61	**0.0303**	**2.66**	-0.0203	-0.409	12	4	-0.00672	0.942
	(0.0128)	(0.108)	**(0.0114)**	**(0.00783)**	(0.0496)	(0.682)			(-0.00956)	(0.918)
Percentage of total persons below the poverty level in past 12 months	-0.000451	-0.0788	0.00105	0.235	0.00881	0.435	12	4	0.00153	0.929
	(0.00573)	(0.937)	(0.00446)	(0.814)	(0.0203)	(0.664)			(0.0021)	(0.9)
Percentage of households with public assistance inc. (incl. SSI) last year of total households	-0.000379	-0.118	-0.000639	-0.253	**0.0239**	**3.01**	12	4	0.00197	0.897
	(0.00322)	(0.906)	(0.00253)	(0.801)	**(0.00794)**	**(0.00265)**			(0.0027)	(0.855)
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	-13.3	-0.875	-0.242	-0.0212	-10.1	-0.453	12	4	-0.00281	0.498
	(15.2)	(0.382)	(11.4)	(0.983)	(22.2)	(0.651)			(-0.00443)	(0.289)
Percentage of renter-occupied housing units of total housing units	-0.00463	-0.553	0.00663	0.847	**0.149**	**14.3**	12	4	0.000323	0.974
	(0.00837)	(0.58)	(0.00784)	(0.397)	**(0.0104)**	**(3.92e-45)**			(0.000434)	(0.963)
Percentage of vacant housing units	**0.00796**	**2.42**	-0.00431	-1.43	**-0.0125**	**-2.2**	12	4	0.00135	0.906
	(0.00329)	**(0.0157)**	(0.00301)	(0.152)	**(0.00571)**	**(0.0282)**			(0.00182)	(0.867)
Percentage of change in number of housing units since last census of total housing units	-0.832	-0.738	2.6	1.06	-0.274	-0.231	12	4	-0.00345	0.396
	(1.13)	(0.46)	(2.45)	(0.289)	(1.18)	(0.817)			(-0.00544)	(0.145)

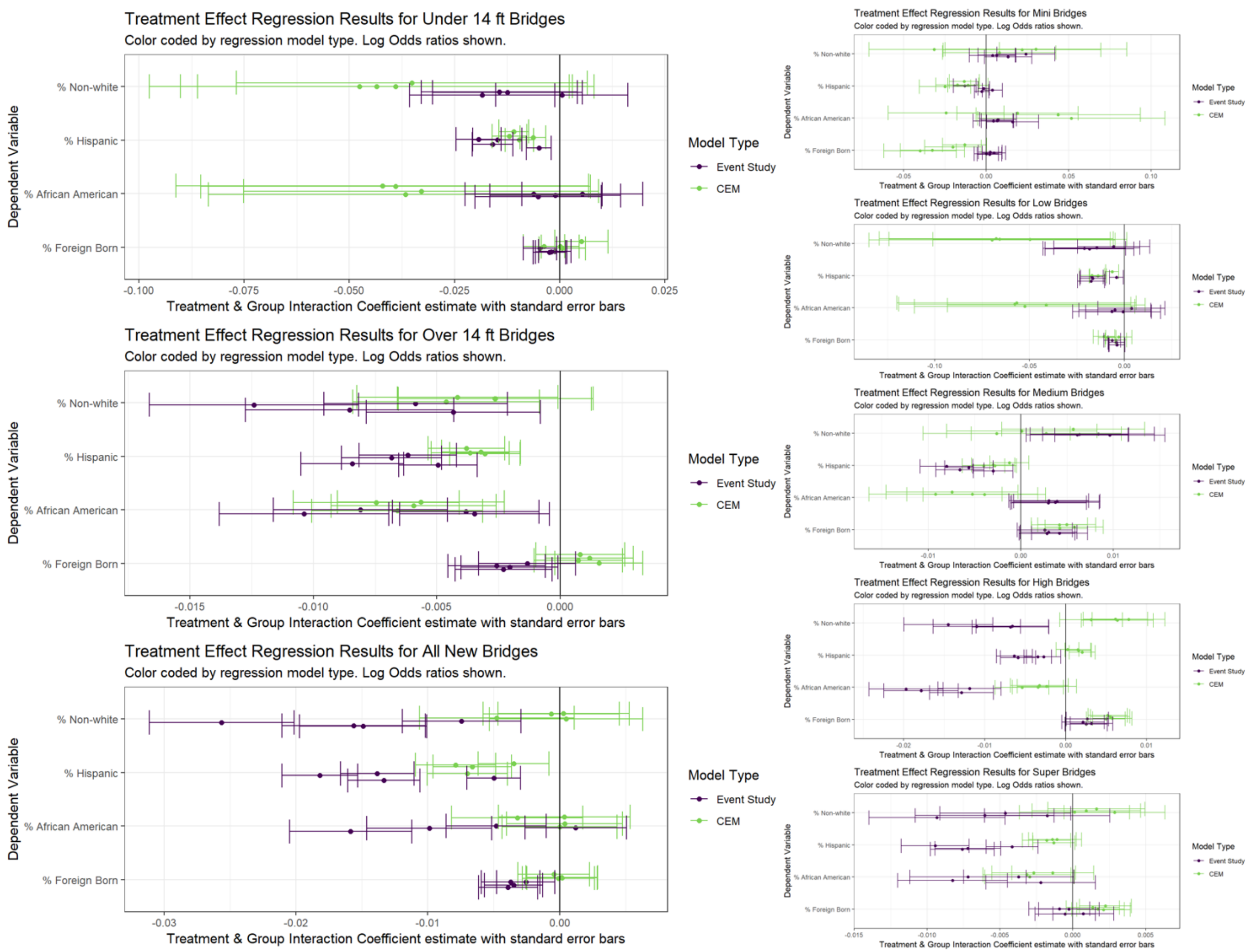

Fig. 34. Graphic depicting demographic variables in treatment effect models

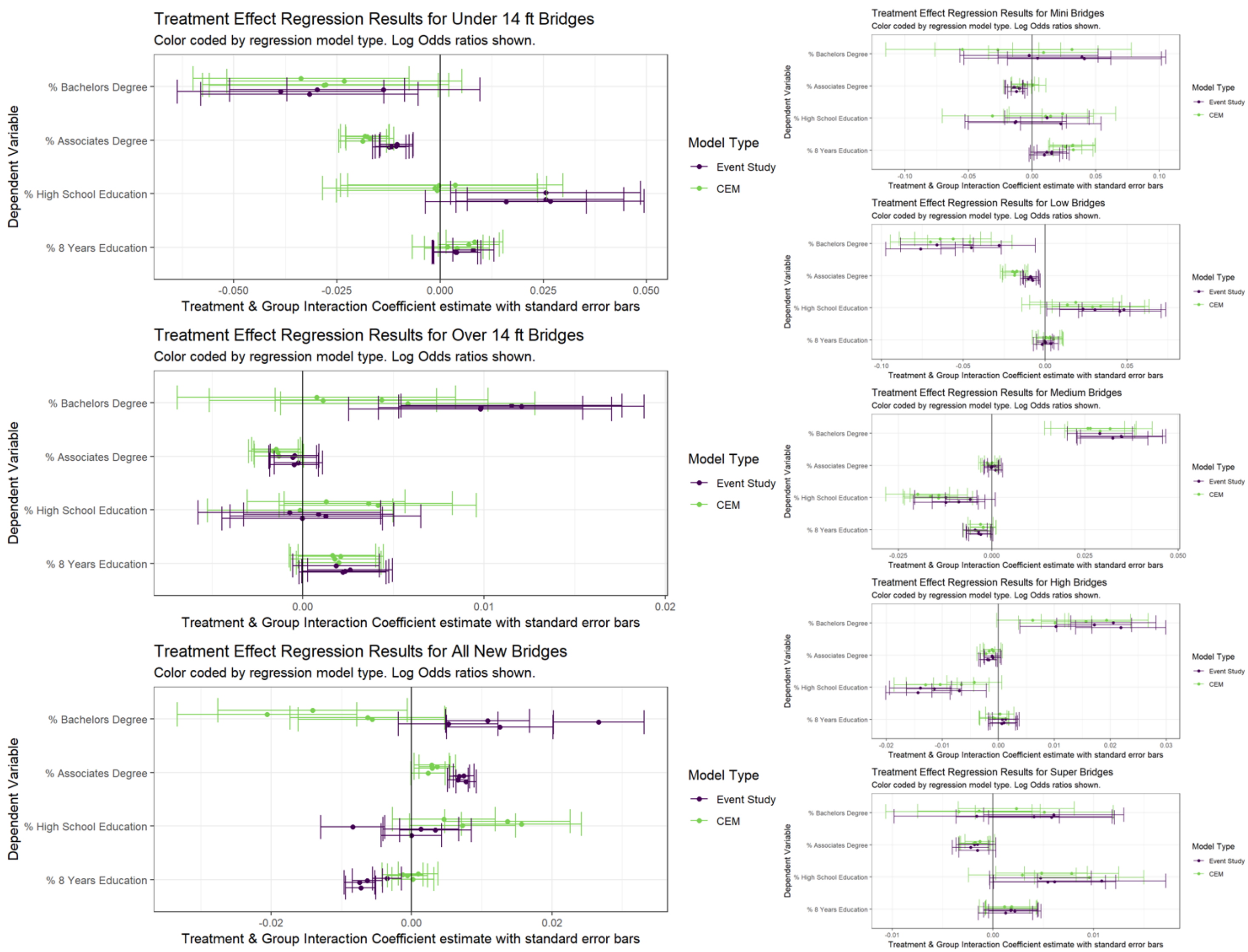

Fig. 35. Graphic depicting education variables in treatment effect models

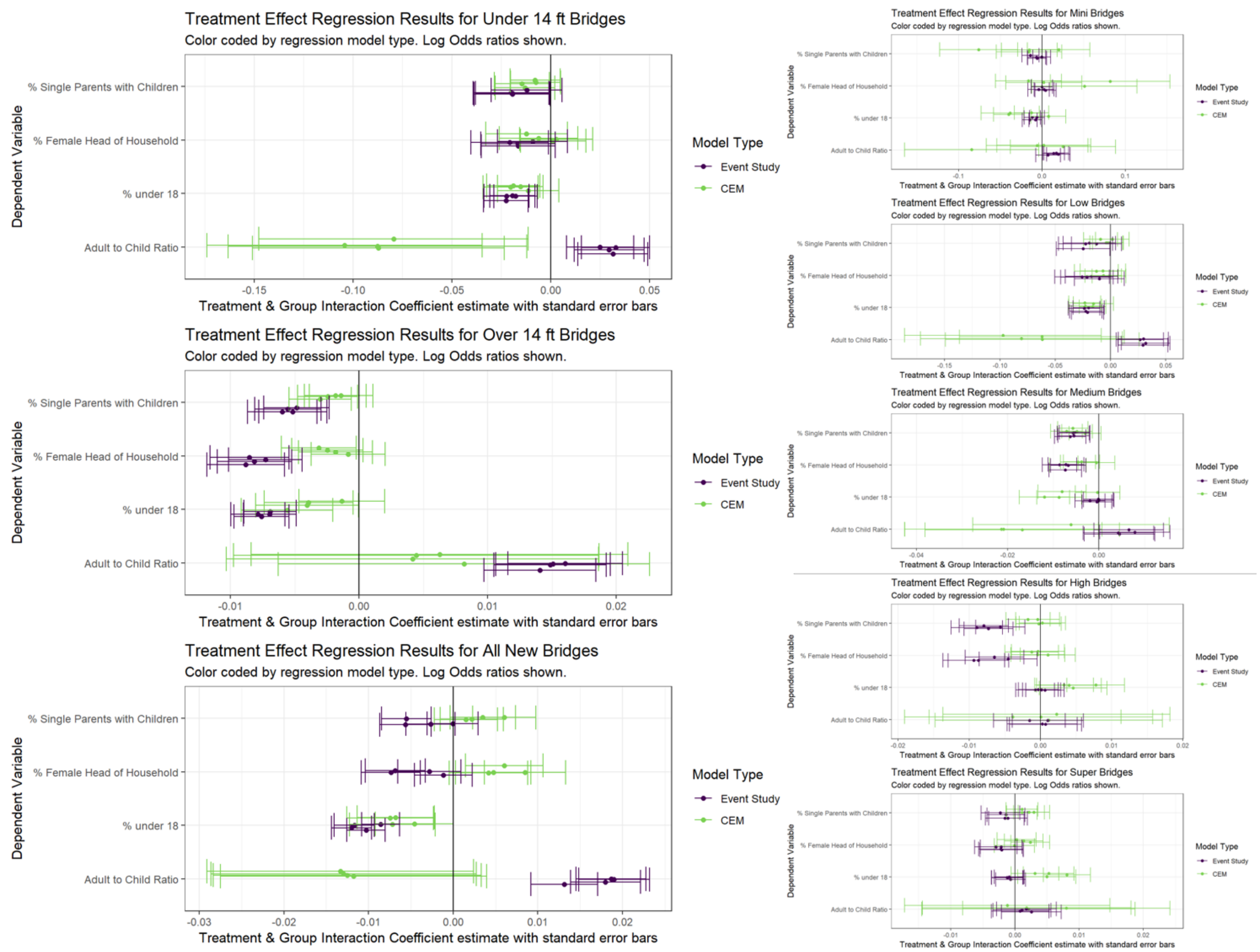

Fig. 36. Graphic depicting family variables in treatment effect models

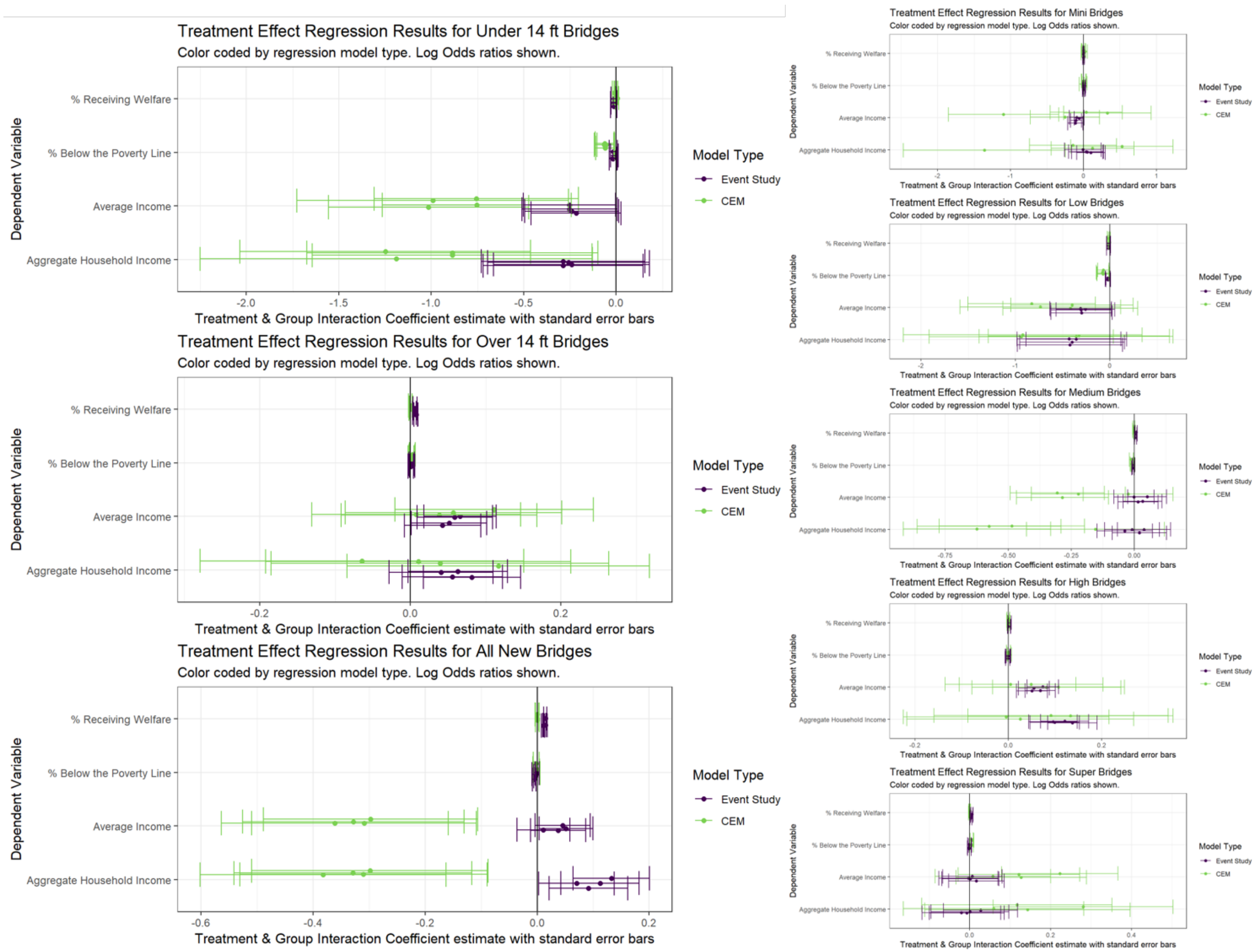

Fig. 37. Graphic depicting financial variables in treatment effect models

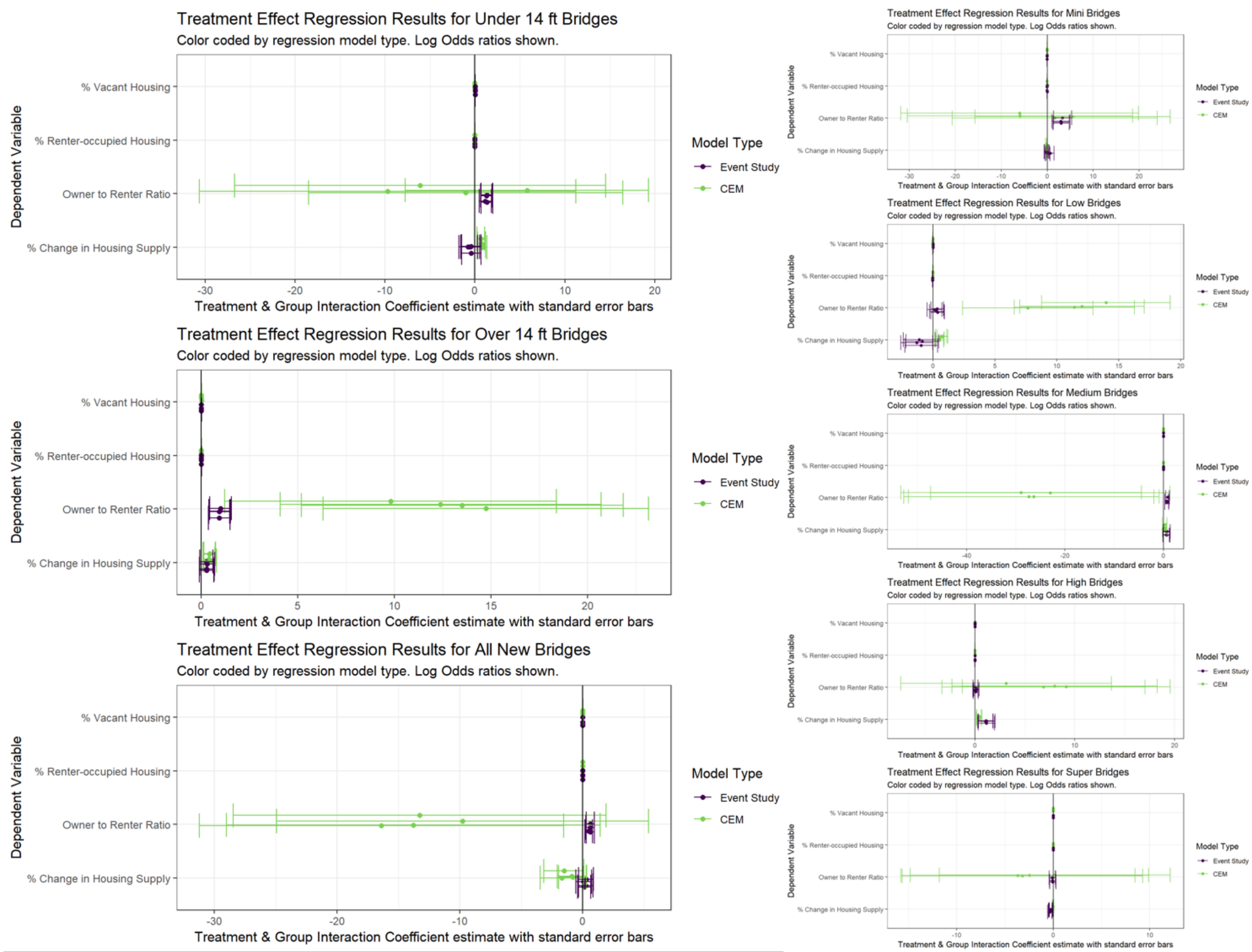

Fig. 38. Graphic depicting housing variables in treatment effect models

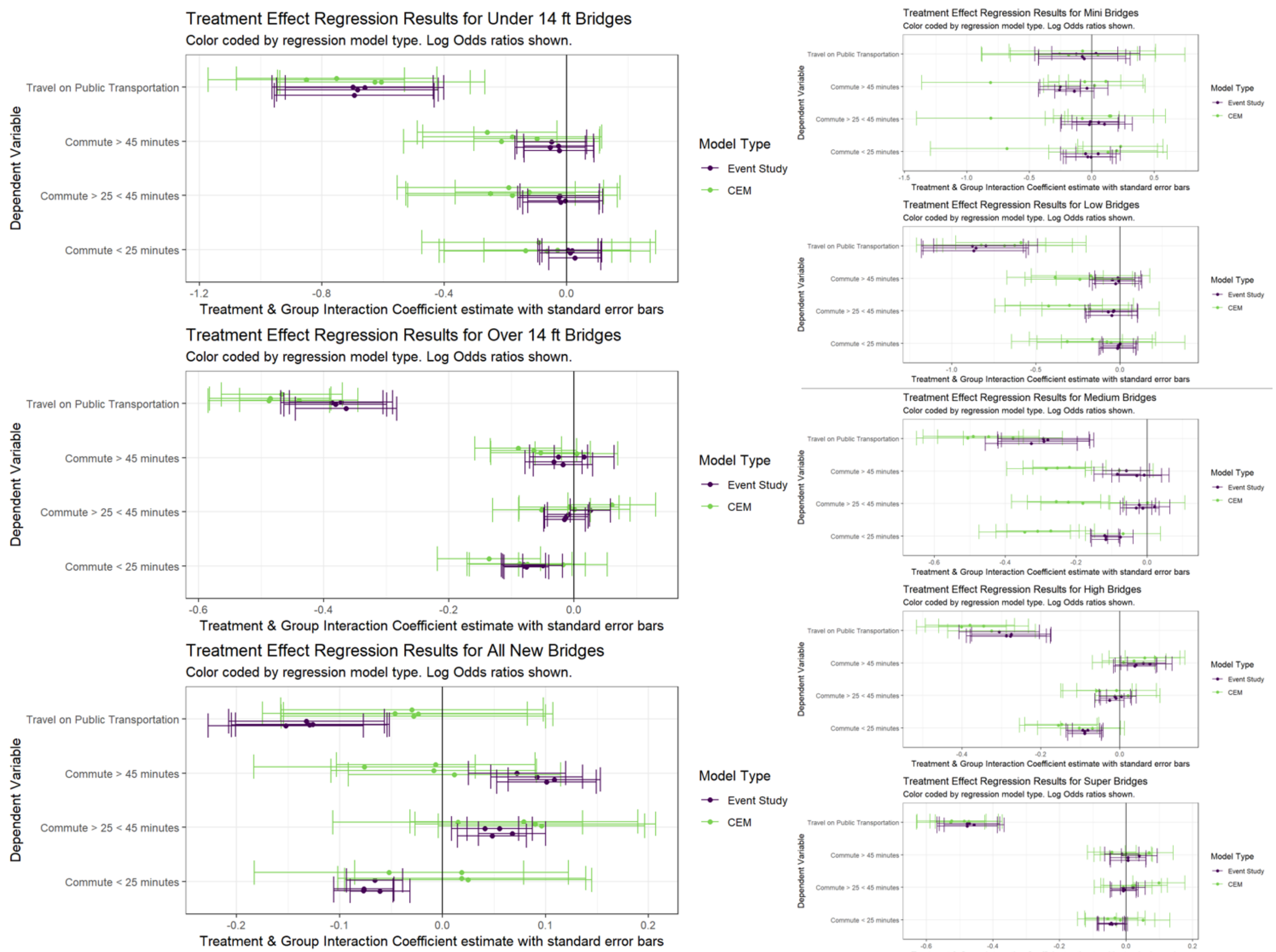

Fig. 39. Graphic depicting transportation variables in treatment effect models

Section G Robustness checks

Selection Effect Models

Even though the authors recognized, based on the data, that a logistic model would likely be the most appropriate model, the authors began by using very simple methods to test if there is a measurable effect that warrants more sophisticated methods. For the selection effect hypotheses, the authors started with a simple linear probability model and then tested for out of range predictions. The same model was used as an OLS model by using the count of new restrictive bridges instead of a dichotomous dummy variable as the dependent variable.

Equation 6. Linear Probability and OLS Selection Effect Models Specification

$$y_{i,t} = \beta_0 + \gamma_k X_{k,i,t-1} + \delta_t + f_i + e_{i,t}$$

where y is a either a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years or the count of such bridges, in tract i, in census year t, γ_k is a vector of control variable coefficients, X is a vector of variables of social interest, δ is a fixed effect for each census year, and f is a time-invariant tract fixed effect.

The linear probability model was not a good model as the predictions were out of range for over 65% of the predictions. The results varied in magnitude but not direction from the logistic regression model (see Section F Tables S24, S25, and S26 for results.)

Due to the nature of census data primarily consisting of counts of various aspects of life, a Poisson regression model was also developed.

Equation 7. Poisson Regression Selection Effect Model Specification

$$\log(\mu) = \beta_0 + \gamma_k X_{k,i,t-1} + \delta_t + e_{i,t}$$

where $\log(\mu)$ is a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years, in tract i, in census year t, X is a vector of variables of social interest, and δ is a fixed effect for each census year.

The Poisson model was found to have slightly worse goodness of fit (AIC and BIC) measures than the logistic regression model. The results varied slightly, but the results were consistent with the logit link logistic model (see Section F, Table 24 for results.)

Treatment Effect Models

For the treatment effect model the authors use a fixed effects regression model.

Equation 8. Fixed effects regression treatment effect model specification

$$z_{i,t} = \beta_0 + \beta_1 x_{i,t} + \beta_2 g_{i,t} + \gamma_k C_{k,i,t-1} + \delta_t + f_i + e_{i,t}$$

where z is a social equity variable of interest, in tract i, in year t, x is a dummy variable designating the tract received a new restrictive bridge treatment, g is a dummy variable designating the tract as receiving a new restrictive bridge at any time, γ_k is a vector of control variable coefficients, C is a vector of lagged control variables, δ is a fixed effect for each census year, and f is a time-invariant tract fixed effect.

This model produced some associative results, but the results were not very consistent or robust.

A difference in difference model was developed to discover the treatment effects:

Equation 9. Difference in difference treatment effect model specification

$$z_{i,t} = \beta_0 + \beta_1 d_{i,t} + \gamma_k C_{k,i,t-1} + \delta_t + f_i + e_{i,t}$$

where z is a social equity variable of interest, in tract i, in year t, d is a dichotomous variable designating the interaction of the group and treatment variables, γ_k is a vector of control variable coefficients, C is a vector of lagged control variables, δ is a fixed effect for each census year, and f is a time-invariant tract fixed effect.

One of the key assumptions of a difference in difference model is the parallel trends assumption. In order to provide evidence of this assumption event study methods were used.

The authors also consider more granular measures for underclearance height ("mini": 3-3.65 m or 9.8-12 ft, "low": 3.65-4.27 m or 12-14 ft, "medium": 4.27-4.87 m or 14-16 ft, "high": 4.88-

5.48 m or 16-18 ft, and "super": 5.49 m or 18 ft and over). Given case study data resolution may be too coarse for such granular demarcations, the authors report the results from these more refined height distinctions here.

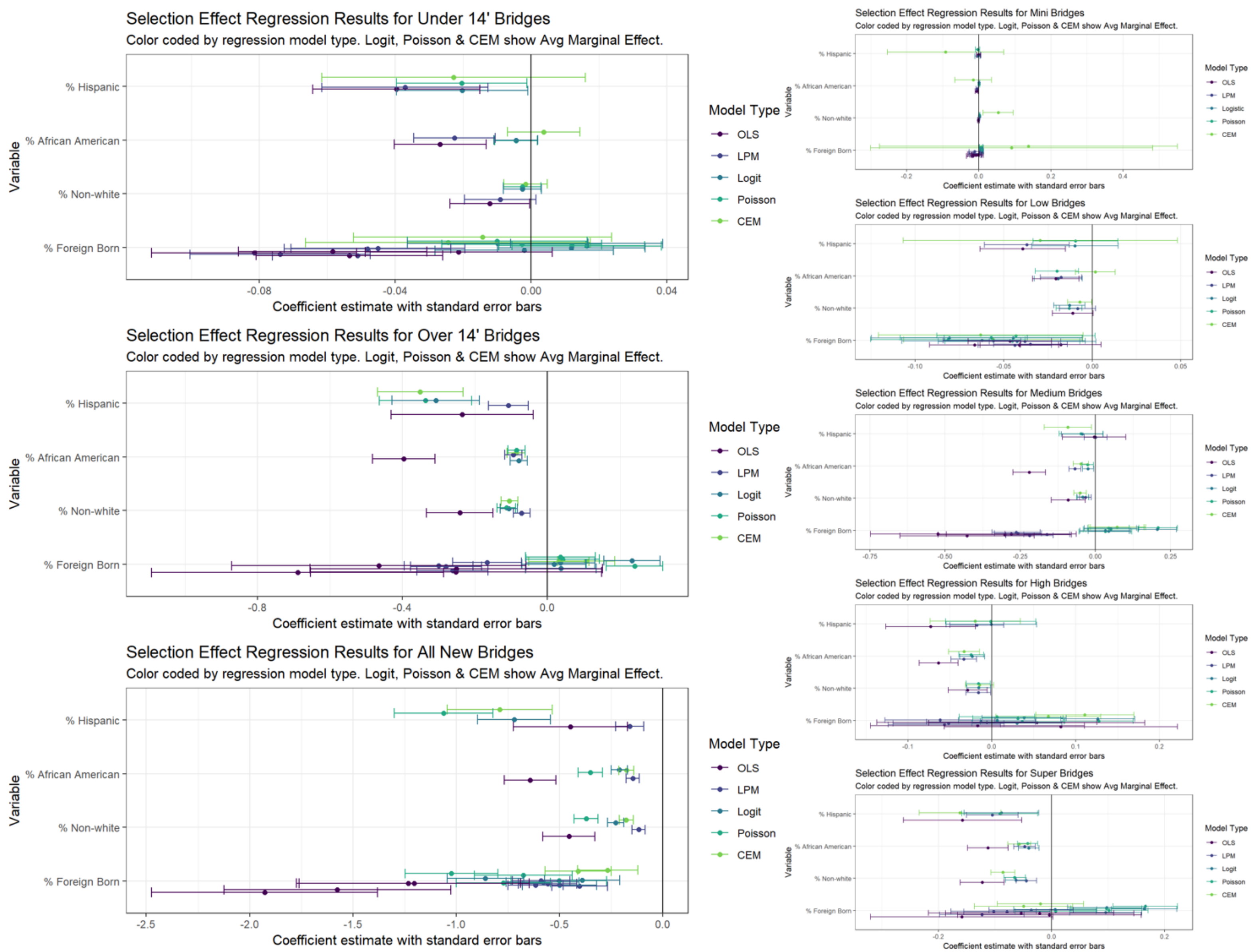

Fig. 40. Selection effect model average marginal effect results for demographics variables

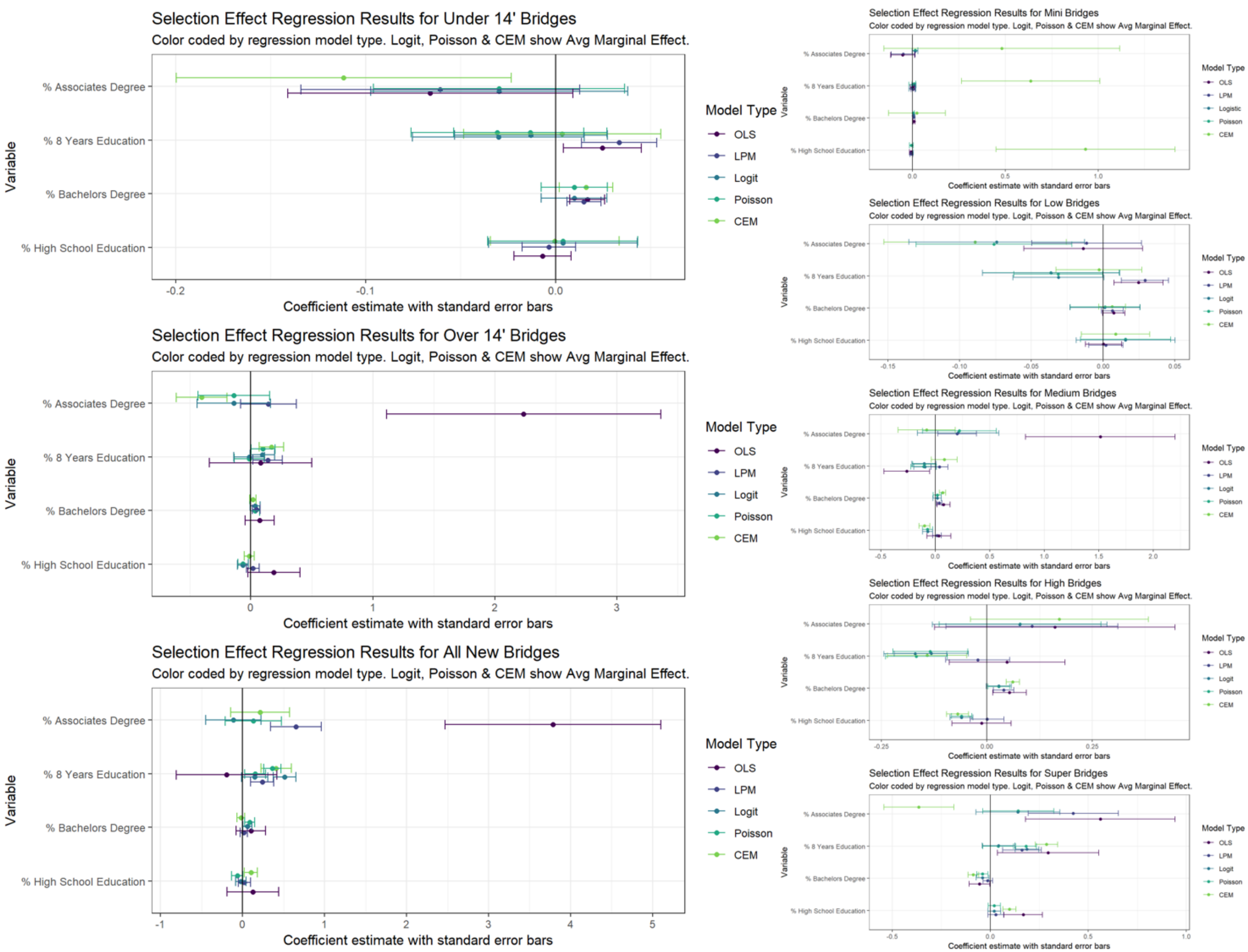

Fig. 41. Selection effect model average marginal effect results for education variables

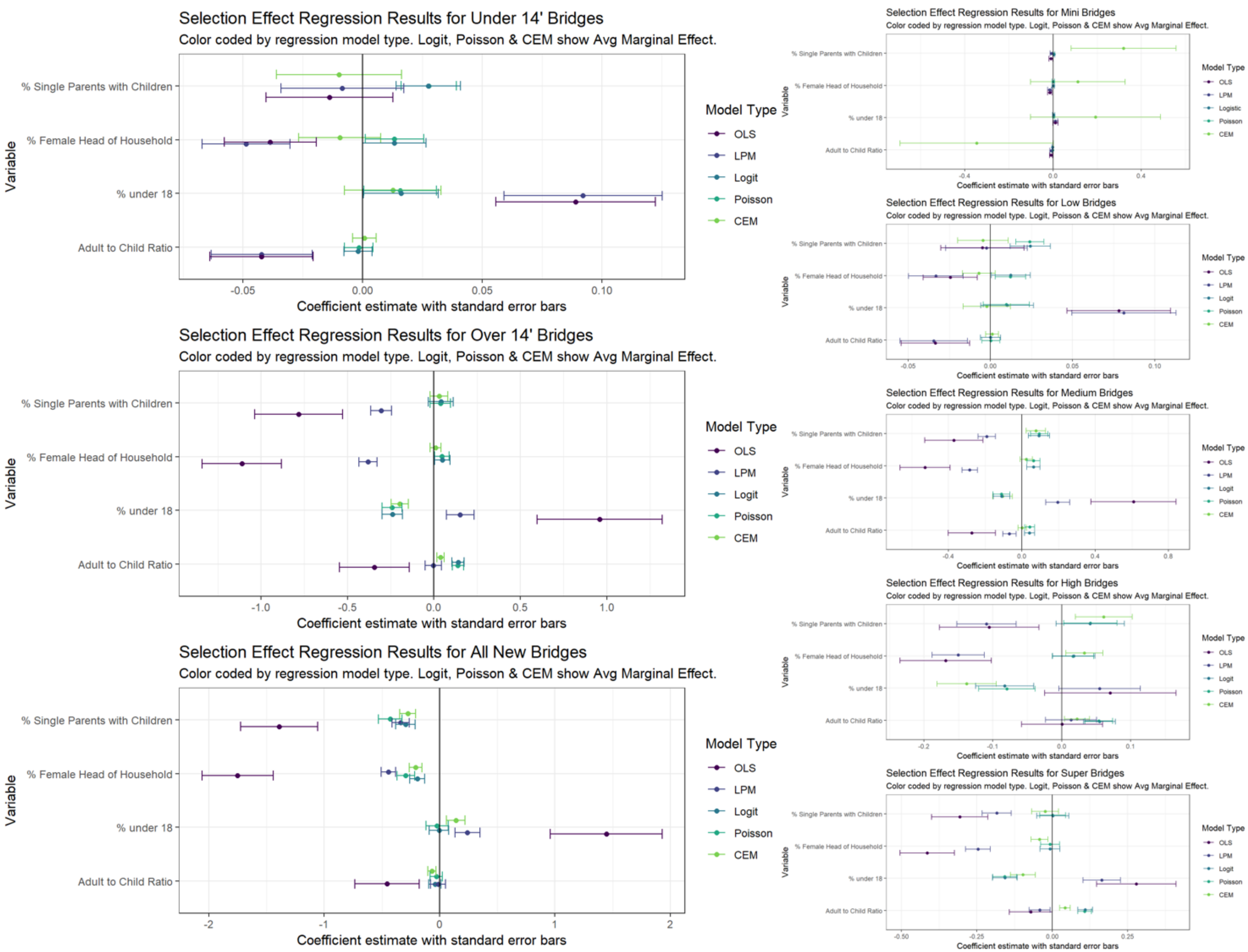

Fig. 42. Selection effect model average marginal effect results for family variables

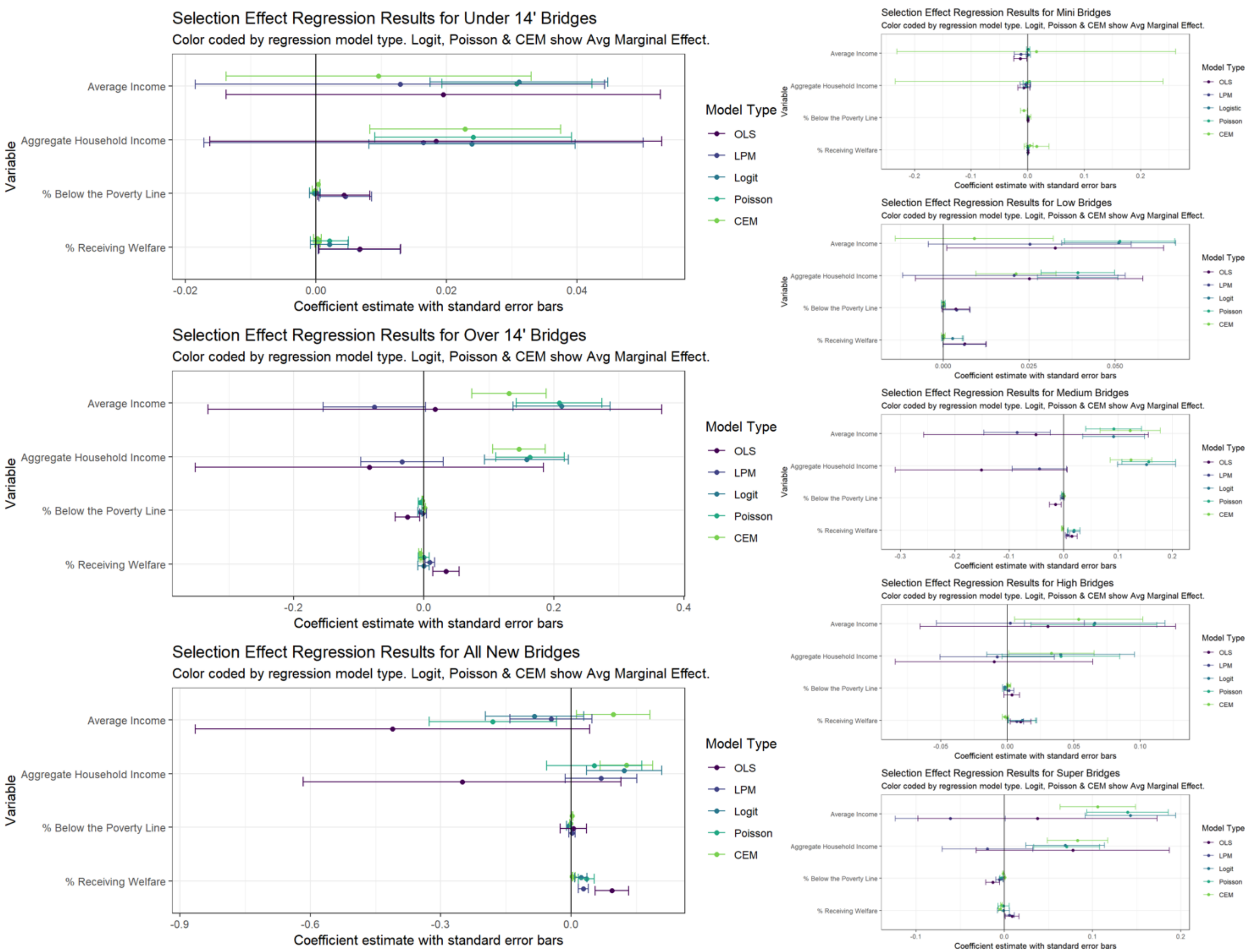

Fig. 43. Selection effect model average marginal effect results for finance variables

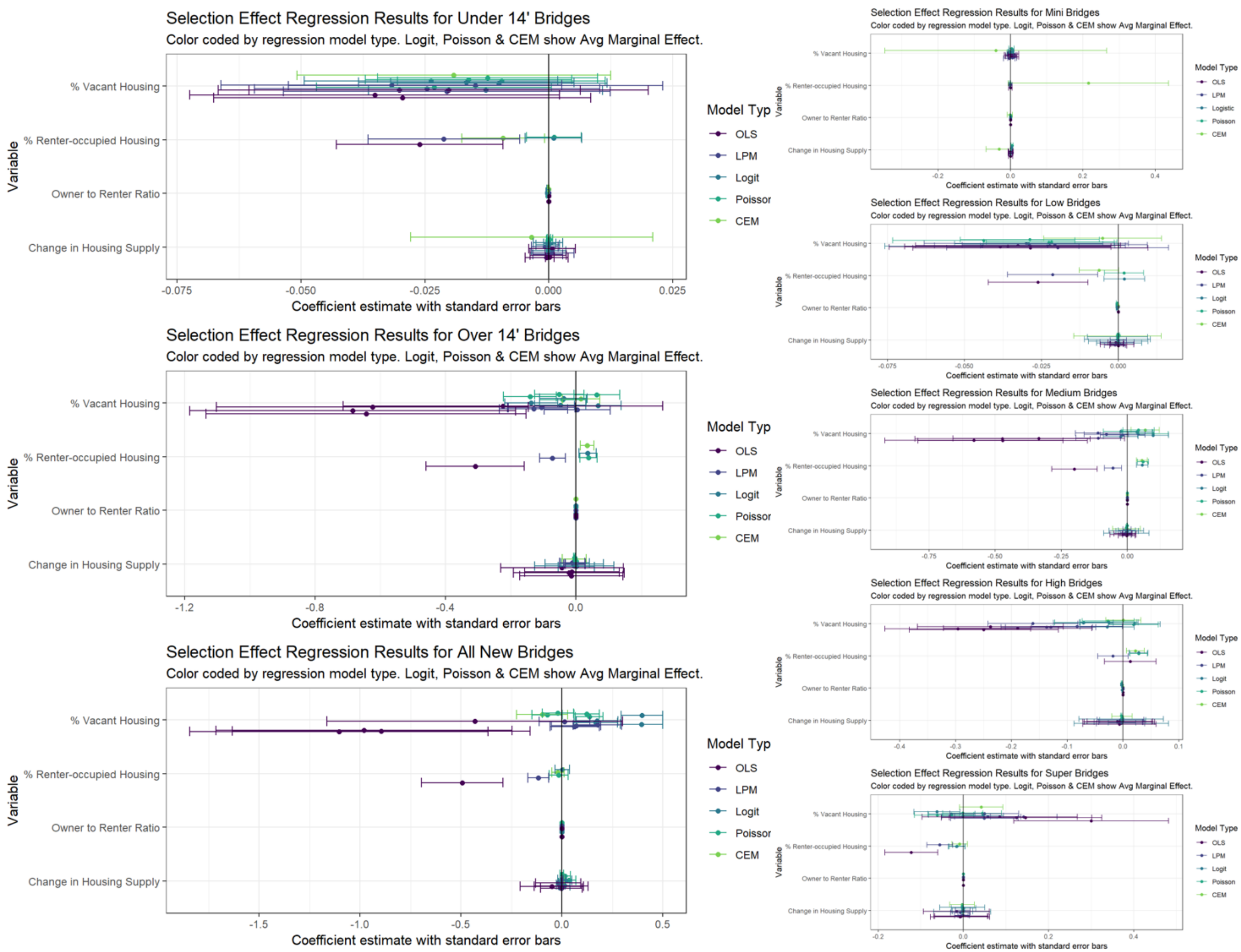

Fig. 44. Selection effect model average marginal effect results for housing variables

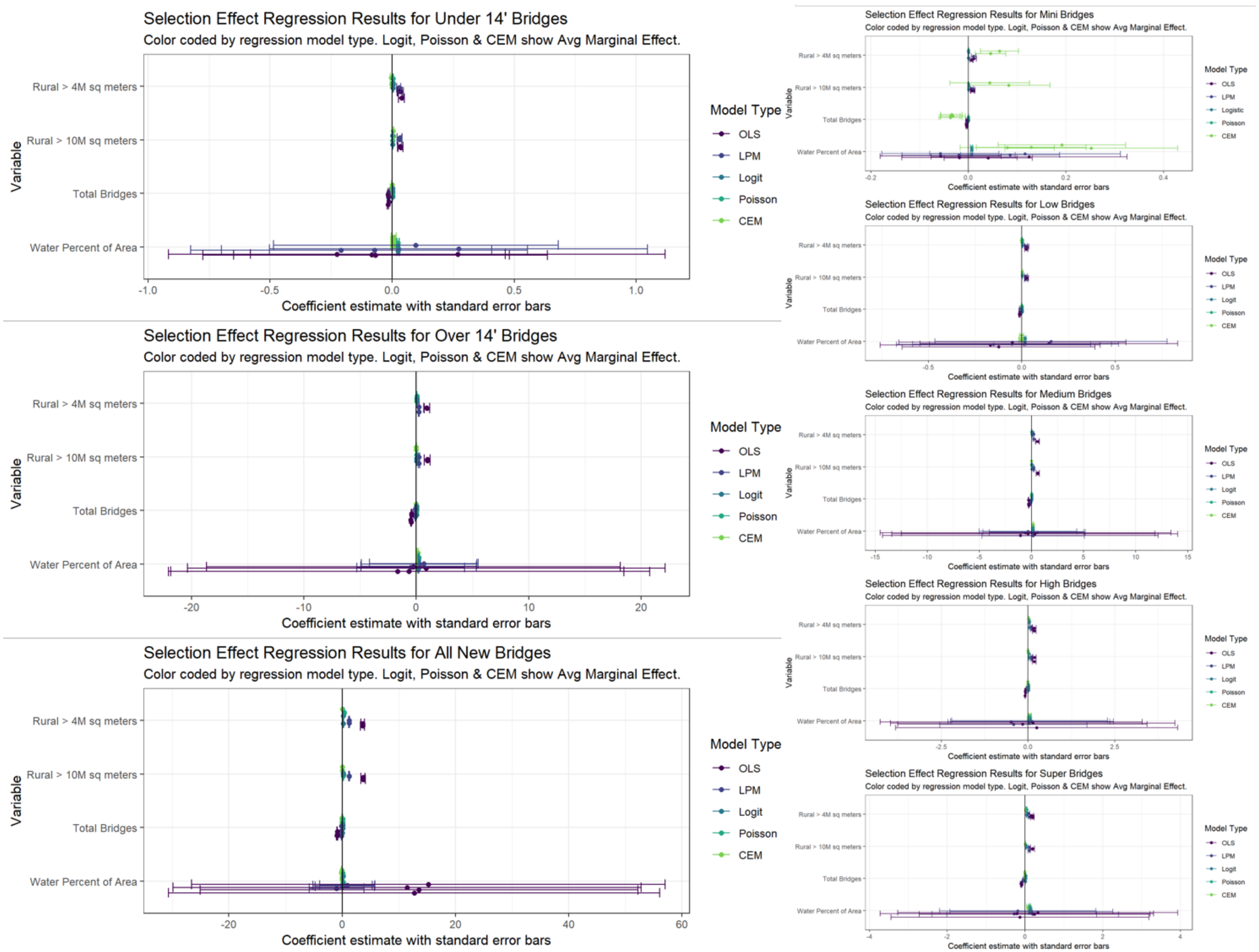

Fig. 45. Selection effect model average marginal effect results for physical variables

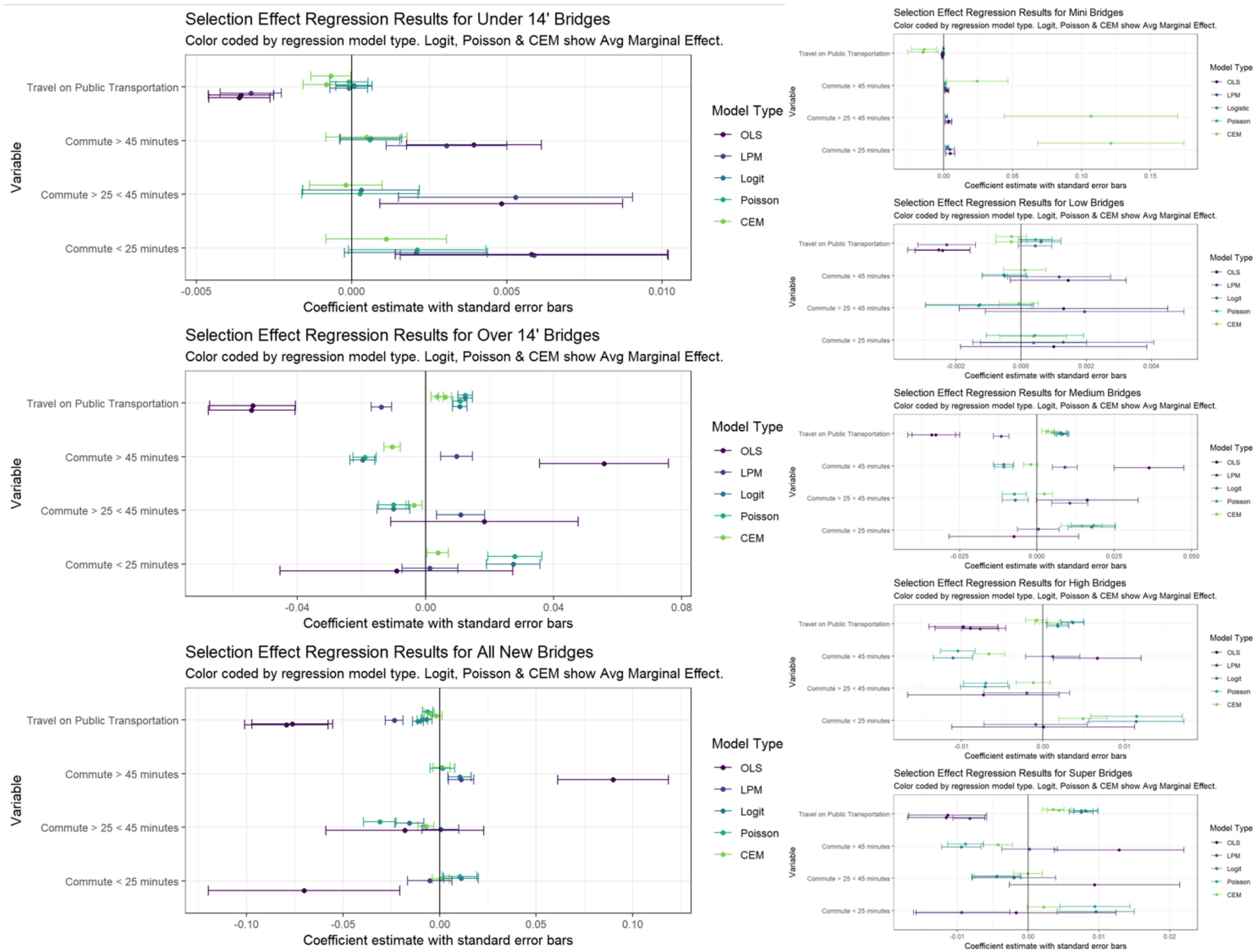

Fig. 46. Selection effect model average marginal effect results for transportation variables

Supplementary Analyses – Possible Moderating Factors

Undoubtedly, bridges do not operate in isolation. In fact, the prior literature contends that the built environment acts as a conduit for both intended and unintended social connections (Audretsch et al. 2015; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). If so, then our findings may work in concert with other infrastructure systems and local policies. To gauge this possibility, we ran three supplementary analyses. First, we assessed whether road networks may work in concert with bridges. To assess this, we re-ran our analyses on restrictive bridges by splitting tracts based on whether they were above or below the median observed lane road miles. The overall trend of note from these analyses (see Tables S34-S36) is that while the effect sizes are not generally different between those tracts with more or less mileage, the results for tracts with less mileage were more significant, if statistical significance was achieved. In particular, these results suggested the negative associations for new and non-restrictive bridges found for non-white, African American, and Hispanic populations in the main analysis were more statistically significant for tracts with less mileage. This perhaps suggests that restrictions were more likely when fewer alternative routes exist in a locale.

Second, we assessed whether public transportation may work in concert with bridges. To assess this, we re-ran our analyses on restrictive bridges by splitting tracts based on whether they were above or below the median observed levels of population using public transportation. The overall trend of note from these analyses (see Tables S37-S39) is that while the effect sizes are not generally different between those tracts with more or less public transportation ridership, the results for tracts with more public transportation usage were more significant, if statistical significance was achieved. In particular, these results generally suggested the negative associations for new and non-restrictive bridges found for non-white, African American, and Hispanic populations in the main analysis were more statistically significant for tracts with more public transportation usage. As with prior research (Winner 1980) this perhaps suggests that restrictive bridges especially constrict where those who rely on public transportation have access.

Third, we assessed whether local community salience to infrastructure may work in concert with bridges. In other words, this more generally assesses whether social and physical infrastructure act in concert. To assess this, we re-ran our analyses on restrictive bridges by splitting the sample tracts based on whether they were above or below the median observed levels of Nationally Registered Historic Places (NRHP). Prior studies note that such registration often arise due to local collective action to petition for a place to be given such historical significance (Desai 2018). Thus, this suggests that a community with more nationally registered places have greater salience, and perhaps more local policies, on its infrastructure. The overall trend of note from these analyses (see Tables S40-S42) is that while the effect sizes are not generally different between those tracts with more or less NRHP, the results for tracts with fewer NHRP were more significant, if statistical significance was achieved. In particular, these results generally suggested the negative associations for new and non-restrictive bridges found for Hispanic populations in the main analysis were more statistically significant for tracts with fewer NHRP. This suggests when infrastructure is less salient, and thus more taken-for-granted, to a local community, these deleterious effects are perhaps more pronounced (Carless 2018; Winner 1980).

Table 52. Lane Road Miles Split Dataset Selection Effect Results for Restrictive Bridges

	DV: Dummy variable denoting that a new restrictive bridge was built in this tract in the last 10 years											
	Full 1	**Road=Hi 1**	**Road=Low 1**	**Full 2**	**Road=Hi 2**	**Road=Low 2**	**Full 3**	**Road=Hi 3**	**Road=Low 3**	**Full 4**	**Road=Hi 4**	**Road=Low 4**
% Water Area	1.078	-4.983	1.049	0.86	-11.743	1.231	1.142	-7.087	1.394	1.179	-8.59	1.312
	(2.057)	(1.694)	(1.728)	(1.720)	(16.571)	(15.821)	(17.402)	(13.023)	(2.511)	(2.007)	(2.044)	(1.876)
Rural tract indicator > 10M sq. meters	0.891	1.364	-17.101				0.806	1.271	-17.001***			
	(0.558)	(0.643)	(0.557)				(0.860)	(1.244)	(0.734)			
Rural tract indicator > 4M sq. meters				-0.424	-1.382	-0.579				-0.529	-1.156***	-0.678
				(0.582)	(0.946)	(1.343)				(1.363)	(0.650)	(1.230)
Lagged IHS-transformed Total bridges	-0.318	-0.495	-0.145	-0.066	0.189	-0.266	-0.317	-0.435	-0.182	-0.141	0.066	-0.322
	(0.179)	(0.193)	(0.183)	(0.187)	(0.320)	(0.454)	(0.299)	(0.401)	(0.261)	(0.306)	(0.267)	(0.283)
Lagged IHS-transformed Real Average Income	0.054	0.054	0.015				0.039	0.108	0.02			
	(0.075)	(0.070)	(0.106)				(0.211)	(0.075)	(0.118)			
Lagged IHS-transformed Real Aggregate Household Income				-0.02	-0.145	-0.02				0.051	0.058	0.001
				(0.047)	(0.113)	(0.142)				(0.087)	(0.130)	(0.070)
Lagged Population Percentage of Below the Poverty Line	4.097	7.298	4.453									
	(2.353)	(0.317)	(0.203)									
Lagged Population Percentage of Receiving Welfare							1.68	9.197	2.967			
							(5.856)	(4.654)	(6.912)			
Lagged Non-white Population Percentage of	-0.288	-7.123	0.118									
	(1.130)	(6.733)	(1.841)									
Lagged African American Population Percentage of							0.66	-5.955	1.139			
							(5.773)	(25.701)	(1.185)			
Lagged Hispanic Population Percentage of										-3.597	-11.662	-4.471
										(13.194)	(2.043)	(8.287)
Lagged Population Percentage of Foreign-born				-4	9.54	-7.962				-2.247	10.602	-6.769
				(6.079)	(5.900)	(11.882)				(4.312)	(0.892)	(11.645)
Lagged Population Percentage of under 18				2.066	8.158	0.28						
				(5.903)	(0.185)	(6.304)						
Lagged IHS-transformed Adult to Child Ratio							0.123	-1.2	-0.012			
							(1.862)	(9.488)	(0.196)			
Lagged Percentage of single parents with Children				-1.611	-1.187	1.314						
				(2.644)	(3.876)	(5.761)						
Lagged Percentage of female Head of Household										-1.511	-2.83	0.307
										(6.544)	(5.125)	(4.114)
Lagged IHS-transformed Population Travel on Public Transportation	-0.12	-0.122	-0.158							-0.128	-0.121	-0.078
	(0.121)	(3.270)	(0.865)							(0.353)	(0.323)	(0.238)
Lagged IHS-transformed Population with Commute < 25 minutes				0.183	1.050*	-0.18						
				(0.123)	(3.318)	(0.935)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.032	0.038	-0.25			
							(0.274)	(0.141)	(3.734)			
										0.077	0.067	-0.148

Lagged IHS-transformed Population with Commute > 45 minutes										(23.518)	(21.546)	(0.359)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										0.552	-0.945	4.065
										(4.878)	(1.781)	(6.872)
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.058	-4.415	8.076			
							(6.165)	(0.228)	(0.006)			
Lagged percentage of over 25-yr-olds with Associate Degree				-18.271	-42.045	5.684						
				(0.209)	(0.064)	(23.517)						
Lagged percentage of over 25-yr-olds with bachelor's degree	2.89	6.389	-12.629									
	(2.482)	(4.200)	(4.143)									
Lagged Owner to Renter Ratio	-0.012	-0.055	-0.006									
	(0.023)	(14.222)	(5.921)									
Lagged Percentage of Housing Units Renter-occupied							-1.614	-0.145	-2.671			
							(1.968)	(9.812)	(8.396)			
Lagged Percentage of Housing Units Vacant	-3.432	0.37	-5.175									
	(5.563)	(3.969)	(1.411)									
Lagged Percent Change in Housing Unit Supply				-0.57	0.164	-0.472						
				(8.205)	(6.879)	(1.049)						
AIC	354.579	227.544	138.087	355.932	228.444	138.435	360.186	231.97	138.919	359.615	233.854	142.679
BIC	450.44	307.487	228.533	451.793	308.386	228.881	456.047	311.913	229.365	455.476	313.797	233.125
Log Likelihood	-163.29	-99.772	-55.044	-163.97	-100.222	-55.217	-166.09	-101.985	-55.46	-165.81	-102.927	-57.34
Deviance	339.259	203.063	119.27	345.278	204.389	123.455	345.023	207.051	120.811	346.241	210.057	125.548
Num. obs.	6955	2231	4724	6955	2231	4724	6955	2231	4724	6955	2231	4724

***p < 0.001, **p < 0.01, *p < 0.05

Table 53. Lane Road Miles Split Dataset Selection Effect Results for Non-restrictive Bridges

	Road Lane Miles DV: Dummy variable denoting that a new non-restrictive bridge was built in this tract in the last 10 years											
	Full 1	**Road=Hi 1**	**Road=Low 1**	**Full 2**	**Road=Hi 2**	**Road=Low 2**	**Full 3**	**Road=Hi 3**	**Road=Low 3**	**Full 4**	**Road=Hi 4**	**Road=Low 4**
% Water Area	1.925*	0.043***	2.208*	2.555***	0.553	2.687	1.817	-0.34	2.217**	2.496***	-0.463**	2.762***
	(0.768)	(0.743)	(0.764)	(0.748)	(2.112)	(2.095)	(2.157)	(2.240)	(0.825)	(0.809)	(0.809)	(0.806)
Rural tract indicator > 10M sq. meters	-0.004	0.489**	-1.234				-0.008**	0.466***	-1.139***			
	(0.126)	(0.141)	(0.123)				(0.171)	(0.192)	(0.270)			
Rural tract indicator > 4M sq. meters				0.449***	0.804**	0.035***				0.472	0.922***	-0.031
				(0.136)	(0.168)	(0.192)				(0.221)	(0.265)	(0.205)
Lagged IHS-transformed Total bridges	-0.067	-0.292**	0.059	-0.154**	-0.313***	-0.034***	-0.056***	-0.275***	0.075	-0.154	-0.31	-0.047
	(0.045)	(0.050)	(0.046)	(0.052)	(0.068)	(0.066)	(0.070)	(0.068)	(0.061)	(0.073)	(0.060)	(0.074)
Lagged IHS-transformed Real Average Income	-0.063***	-0.093	-0.006**				-0.082	-0.079***	-0.059			
	(0.018)	(0.015)	(0.029)				(0.045)	(0.014)	(0.038)			
Lagged IHS-transformed Real Aggregate Household Income				0.021**	-0.006***	0.035				-0.032	-0.052	-0.013
				(0.011)	(0.023)	(0.022)				(0.025)	(0.047)	(0.024)
Lagged Population Percentage of Below the Poverty Line	2.171***	4.016	1.397									
	(0.595)	(0.049)	(0.038)									
Lagged Population Percentage of Receiving Welfare							1.934**	5.154*	1.122			
							(1.834)	(1.114)	(0.497)			
Lagged Non-white Population Percentage of	-1.551***	-1.184	-1.188***									
	(0.340)	(1.227)	(0.369)									
Lagged African American Population Percentage of							-1.286	-1.43	-0.912**			
							(1.238)	(5.497)	(0.383)			
Lagged Hispanic Population Percentage of										-5.224	-6.347*	-4.368**
										(1.522)	(0.402)	(1.579)
Lagged Population Percentage of Foreign-born				0.463**	2.087	0.211				1.590**	3.933	1.681
				(1.752)	(1.016)	(2.751)				(0.983)	(0.447)	(1.377)
Lagged Population Percentage of under 18				-2.942	-2.047*	-2.98						
				(1.168)	(0.041)	(1.177)						
Lagged IHS-transformed Adult to Child Ratio							0.576	0.315	0.772			
							(0.464)	(3.241)	(0.040)			
Lagged Percentage of single parents with Children				0.45	1.832	0.337						
				(0.479)	(0.650)	(1.493)						
Lagged Percentage of female Head of Household										0.136	2.627	-0.235
										(0.948)	(1.104)	(0.621)
Lagged IHS-transformed Population Travel on Public Transportation	0.054	0.098***	-0.012							0.091	0.099	0.067
	(0.028)	(0.747)	(0.311)							(0.124)	(0.072)	(0.046)
Lagged IHS-transformed Population with Commute < 25 minutes				0.057**	0.033***	0.075						
				(0.031)	(1.123)	(0.049)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.054	-0.089*	-0.035			
							(0.048)	(0.043)	(0.820)			

Lagged IHS-transformed Population with Commute > 45 minutes										-0.154	-0.182	-0.145*
										(4.306)	(0.839)	(0.060)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										2.511	3.681	0.759
										(1.055)	(0.414)	(2.376)
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.216	-1.029***	-0.268			
							(0.975)	(0.052)	(0.002)			
Lagged percentage of over 25-yr-olds with Associate Degree				-5.994***	-7.323	-5.35						
				(0.038)	(0.001)	(4.591)						
Lagged percentage of over 25-yr-olds with bachelor's degree	0.271	0.301	0.540*									
	(0.389)	(0.754)	(0.845)									
Lagged Owner to Renter Ratio	-0.001	0	-0.001									
	(0.001)	(3.104)	(0.604)									
Lagged Percentage of Housing Units Renter-occupied							0.501	0.86	0.255			
							(0.600)	(2.134)	(1.548)			
Lagged Percentage of Housing Units Vacant	0.222	-0.904	1.862									
	(0.848)	(0.544)	(0.311)									
Lagged Percent Change in Housing Unit Supply				-0.073	-0.467	-0.058						
				(1.507)	(1.200)	(0.319)						
AIC	4713.531	2726.079	1963.851	4708.67	2729.963	1987.499	4711.262	2724.223	1964.216	4700.148	2710.54	1988.621
BIC	4814.968	2814.745	2058.099	4810.107	2818.628	2081.747	4812.699	2812.889	2058.464	4801.586	2799.206	2082.868
Log Likelihood	-2342.77	-1349.039	-967.925	-2340.34	-1350.981	-979.749	-2341.63	-1348.112	-968.108	-2336.07	-1341.27	-980.31
Deviance	4924.773	2748.852	2118.044	4917.775	2749.133	2145.03	4925.182	2749.405	2119.353	4909.864	2730.11	2146.672
Num. obs.	10358	4160	6198	10358	4160	6198	10358	4160	6198	10358	4160	6198

***p < 0.001, **p < 0.01, *p < 0.05

Table 54. Lane Road Miles Split Dataset Selection Effect Results for All New Bridges

	DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years											
	Full 1	Road=Hi 1	Road=Low 1	Full 2	Road=Hi 2	Road=Low 2	Full 3	Road=Hi 3	Road=Low 3	Full 4	Road=Hi 4	Road=Low 4
% Water Area	-1.044	2.164	-2.205	-0.413	2.794	-1.48	-1.005	1.934	-2.168	-0.479	2.674	-1.62
	(1.09)	(1.08)	(1.09)	(1.09)	(2.37)	(2.37)	(2.43)	(2.35)	(1.43)	(1.42)	(1.42)	(1.43)
Rural tract indicator > 10M sq. meters	0.401	1.009*	-0.398				0.421*	1.044	-0.315			
	(0.35)	(0.13)	(0.34)				(0.45)	(0.19)	(0.60)			
Rural tract indicator > 4M sq. meters				0.327*	0.279*	0.401				0.315*	0.258	0.395*
				(0.13)	(0.44)	(0.19)				(0.19)	(0.60)	(0.19)
Lagged IHS-transformed Total bridges	-0.322***	-0.529***	-0.218***	-0.364***	-0.538***	-0.273***	-0.304***	-0.529***	-0.193**	-0.390***	-0.534**	-0.319***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)	(0.08)
Lagged IHS-transformed Real Average Income	0.028	-0.017	0.101*				0.073	-0.012	0.169*			
	(0.02)	(0.02)	(0.04)				(0.07)	(0.02)	(0.04)			
Lagged IHS-transformed Real Aggregate Household Income				-0.007	-0.003	0.02				0.03	-0.011**	0.080**
				(0.02)	(0.03)	(0.03)				(0.03)	(0.05)	(0.03)
Lagged Population Percentage of Below the Poverty Line	1.443*	0.706	1.894									
	(0.68)	(0.05)	(0.05)									
Lagged Population Percentage of Receiving Welfare							1.089	3.236	0.224			
							(2.49)	(1.52)	(0.56)			
Lagged Non-white Population Percentage of	-2.000***	-0.819**	-1.859***									
	(0.39)	(1.80)	(0.41)									
Lagged African American Population Percentage of							-1.977	-1.244	-1.830***			
							(1.63)	(5.28)	(0.42)			
Lagged Hispanic Population Percentage of										-9.095	-4.594***	-10.619**
										(2.02)	(0.44)	(3.57)
Lagged Population Percentage of Foreign-born				-4.647**	-3.763	-3.539				-3.074*	-2.593*	-2.406
				(2.92)	(1.44)	(4.26)				(1.13)	(0.55)	(1.87)
Lagged Population Percentage of under 18				1.584	-0.3	2.418						
				(1.68)	(0.05)	(1.80)						
Lagged IHS-transformed Adult to Child Ratio							-0.73	-0.015	-1.189**			
							(0.79)	(4.51)	(0.03)			
Lagged Percentage of single parents with Children				-3.134***	1.537	-3.941						
				(0.61)	(1.41)	(1.85)						
Lagged Percentage of female Head of Household										-2.398***	-0.658	-2.496***
										(0.92)	(1.15)	(0.72)
Lagged IHS-transformed Population Travel on Public Transportation	-0.060*	0.022	-0.096							-0.021	0.046*	-0.058
	(0.03)	(0.90)	(0.40)							(0.09)	(0.07)	(0.05)
Lagged IHS-transformed Population with Commute < 25 minutes				0.008	0.029	-0.042						
				(0.04)	(1.60)	(0.07)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.079	-0.007	-0.161*			
							(0.07)	(0.06)	(0.76)			

Lagged IHS-transformed Population with Commute > 45 minutes										0.012	0.02	-0.026
										(4.97)	(1.01)	(0.07)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										4.709	9.316	2.573
										(0.13)	(0.41)	(2.65)
Lagged percentage of over 25-yr-olds with at Least High School Education							1.147	1.622	0.78			
							(1.99)	(0.08)	(0.00)			
Lagged percentage of over 25-yr-olds with Associate Degree				2.428	-1.82	4.545						
				(0.05)	0.00	(8.18)						
Lagged percentage of over 25-yr-olds with bachelor's degree	-0.232	-1.340***	-0.104									
	(0.51)	(0.77)	(0.95)									
Lagged Owner to Renter Ratio	0	0	-0.001									
	0.00	(4.09)	(0.89)									
Lagged Percentage of Housing Units Renter-occupied							-0.219	0.126*	-0.125			
							(0.75)	(4.31)	(2.20)			
Lagged Percentage of Housing Units Vacant	-1.103	0.643	-3.472									
	(1.44)	(0.11)	(0.34)									
Lagged Percent Change in Housing Unit Supply				0.009*	-0.096	-0.001						
				(2.12)	(2.02)	(0.40)						
AIC	3587.598	1275.485	2312.885	3599.245	1282.944	2317.874	3588.673	1272.581	2317.658	3580.556	1275.803	2303.781
BIC	3682.779	1350.266	2404.353	3694.426	1357.725	2409.343	3683.853	1347.362	2409.127	3675.736	1350.584	2395.249
Log Likelihood	-1779.8	-623.742	-1142.442	-1785.62	-627.472	-1144.937	-1780.34	-622.29	-1144.829	-1776.28	-623.902	-1137.89
Deviance	3806.165	1304.847	2461.779	3816.145	1309.43	2469.1	3810.28	1302.312	2469.135	3789.159	1303.093	2449.137
Num. obs.	6625	1543	5082	6625	1543	5082	6625	1543	5082	6625	1543	5082

***p < 0.001, **p < 0.01, *p < 0.05

Table 55. Access to Public Transportation Proxy Split Dataset Selection Effect Results for Restrictive Bridges

	DV: Dummy variable denoting that a new restrictive bridge was built in this tract in the last 10 years											
	Full 1	**PT=Hi 1**	**PT=Low 1**	**Full 2**	**PT=Hi 2**	**PT=Low 2**	**Full 3**	**PT=Hi 3**	**PT=Low 3**	**Full 4**	**PT=Hi 4**	**PT=Low 4**
% Water Area	1.078	1.148	0.905	0.86	0.411	2.013	1.142	0.7	-1.082	1.179	0.816	2.824
	(2.057)	(1.694)	(1.728)	(1.720)	(3.635)	(3.472)	(3.173)	(3.308)	(4.199)	(4.190)	(5.166)	(3.368)
Rural tract indicator > 10M sq. meters	0.891	1.392	1.202				0.806	0.777	1.237			
	(0.558)	(0.643)	(0.557)				(0.787)	(1.095)	(1.029)			
Rural tract indicator > 4M sq. meters				-0.424	-0.74	-0.675				-0.529	-0.179	-0.478
				(0.582)	(0.805)	(1.039)				(1.071)	(1.285)	(0.884)
Lagged IHS-transformed Total bridges	-0.318	-0.304	-0.353	-0.066	-0.117	-0.016	-0.317	-0.367	-0.429	-0.141	-0.154	-0.106
	(0.179)	(0.193)	(0.183)	(0.187)	(0.258)	(0.291)	(0.269)	(0.301)	(0.308)	(0.330)	(0.406)	(0.297)
Lagged IHS-transformed Real Average Income	0.054	-0.375	0.108				0.039	-0.121*	0.071			
	(0.075)	(0.070)	(0.106)				(0.175)	(0.105)	(0.106)			
Lagged IHS-transformed Real Aggregate Household Income				-0.02	-0.129	-0.016				0.051	-0.212	0.085
				(0.047)	(0.206)	(0.113)				(0.108)	(0.178)	(0.057)
Lagged Population Percentage of Below the Poverty Line	4.097	-8.579	5.013									
	(2.353)	(0.317)	(0.203)									
Lagged Population Percentage of Receiving Welfare							1.68	3.436	4.691			
							(3.888)	(4.247)	(6.427)			
Lagged Non-white Population Percentage of	-0.288	0.262	1.181									
	(1.130)	(6.733)	(1.841)									
Lagged African American Population Percentage of							0.66	-0.688	4.508			
							(1.534)	(25.848)	(2.826)			
Lagged Hispanic Population Percentage of										-3.597	-22.346	6.014
										(27.336)	(3.858)	(4.058)
Lagged Population Percentage of Foreign-born				-4	2.586	-16.782				-2.247	-0.795	-15.334
				(6.079)	(1.083)	(3.836)				(4.747)	(1.557)	(24.316)
Lagged Population Percentage of under 18				2.066	1.909**	3.822						
				(5.903)	(0.244)	(4.722)						
Lagged IHS-transformed Adult to Child Ratio							0.123	0.033	-0.41			
							(2.206)	(5.163)	(0.178)			
Lagged Percentage of single parents with Children				-1.611	-2.767	1.753						
				(2.644)	(4.082)	(6.797)						
Lagged Percentage of female Head of Household										-1.511	-2.758	0.282
										(9.190)	(6.152)	(3.568)
Lagged IHS-transformed Population Travel on Public Transportation	-0.12	0.637	-0.251							-0.128	0.506	-0.244
	(0.121)	(3.270)	(0.865)							(0.301)	(0.226)	(0.176)
Lagged IHS-transformed Population with Commute < 25 minutes				0.183	1.835	0.089*						
				(0.123)	(7.420)	(0.713)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.032	0.435*	0.030*			
							(1.290)	(0.238)	(2.428)			
Lagged IHS-transformed Population with Commute > 45 minutes										0.077	0.227	0.072
										(20.024)	(6.789)	(0.203)
Lagged percentage of										0.552	-116.99	1.925
										(5.728)	(2.657)	(9.470)

over 25-yr-olds with at Least 8 Years Education												
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.058*	-16.37	3.851			
							(7.077)	(0.619)	(0.086)			
Lagged percentage of over 25-yr-olds with Associate Degree				-18.271	15.588	-31.346						
				(0.209)	(0.039)	(9.078)						
Lagged percentage of over 25-yr-olds with bachelor's degree	2.89	5.472	1.583									
	(2.482)	(4.200)	(4.143)									
Lagged Owner to Renter Ratio	-0.012	-0.018	-0.035									
	(0.023)	(14.222)	(5.921)									
Lagged Percentage of Housing Units Renter-occupied							-1.614	-1.755***	-0.62			
							(2.000)	(30.571)	(6.223)			
Lagged Percentage of Housing Units Vacant	-3.432	2.907	-1.579									
	(5.563)	(3.969)	(1.411)									
Lagged Percent Change in Housing Unit Supply				-0.57	-0.929	-0.672						
				(8.205)	(8.510)	(2.586)						
AIC	354.579	158.29	204.775	355.932	163.49	205.627	360.186	163.219	208.095	359.615	159.07	212.449
BIC	450.44	247.72	286.66	451.793	252.92	287.513	456.047	252.645	289.981	455.476	248.5	294.334
Log Likelihood	-163.29	-65.146	-88.387	-163.97	-67.745	-88.814	-166.09	-67.61	-90.048	-165.81	-65.537	-92.224
Deviance	339.259	139.86	180.111	345.278	145.83	186.275	345.023	144.054	183.783	346.241	141.13	189.343
Num. obs.	6955	4392	2563	6955	4392	2563	6955	4392	2563	6955	4392	2563

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 56. Access to Public Transportation Proxy Split Dataset Selection Effect Results for Non-restrictive Bridges

	Access to Public Transportation DV: Dummy variable denoting that a new non-restrictive bridge was built in this tract in the last 10 years											
	Full 1	**PT=Hi 1**	**PT=Low 1**	**Full 2**	**PT=Hi 2**	**PT=Low 2**	**Full 3**	**PT=Hi 3**	**PT=Low 3**	**Full 4**	**PT=Hi 4**	**PT=Low 4**
% Water Area	1.925*	2.685***	-0.691*	2.555***	2.922***	0.742***	1.817**	2.450***	-0.451	2.496	3.023	-0.352
	(0.77)	(0.74)	(0.76)	(0.75)	(0.80)	(0.82)	(0.81)	(0.80)	(2.19)	(2.19)	(2.11)	(2.31)
Rural tract indicator > 10M sq. meters	-0.004	-0.041**	0.091				-0.008	0.025	0.145			
	(0.13)	(0.14)	(0.12)				(0.19)	(0.18)	(0.19)			
Rural tract indicator > 4M sq. meters				0.449***	0.268	0.669				0.472***	0.225	0.774***
				(0.14)	(0.20)	(0.19)				(0.20)	(0.20)	(0.20)
Lagged IHS-transformed Total bridges	-0.067	-0.021**	-0.134	-0.154**	-0.035	-0.279	-0.056	0.009	-0.141	-0.154***	-0.045	-0.263***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)
Lagged IHS-transformed Real Average Income	-0.063***	-0.125	-0.081**				-0.082***	-0.171**	-0.063***			
	(0.02)	(0.02)	(0.03)				(0.05)	(0.03)	(0.02)			
Lagged IHS-transformed Real Aggregate Household Income				0.021**	-0.044**	0.015				-0.032	-0.078	-0.039**
				(0.01)	(0.04)	(0.03)				(0.02)	(0.04)	(0.01)
Lagged Population Percentage of Below the Poverty Line	2.171***	1.097	3.23									
	(0.60)	(0.05)	(0.04)									
Lagged Population Percentage of Receiving Welfare							1.934*	2.15	2.27			
							(1.07)	(0.62)	(0.70)			
Lagged Non-white Population Percentage of	-1.551***	-1.099	-1.072***									
	(0.34)	(1.23)	(0.37)									
Lagged African American Population Percentage of							-1.286***	-1.317*	-0.144			
							(0.39)	(1.61)	(0.95)			
Lagged Hispanic Population Percentage of										-5.224	-3.179	-10.587
										(3.03)	(1.27)	(5.60)
Lagged Population Percentage of Foreign-born				0.463**	1.814**	-1.855				1.590*	2.689	-1.011
				(1.75)	(0.39)	(1.43)				(1.11)	(0.38)	(3.70)
Lagged Population Percentage of under 18				-2.942	-2.248	-2.508*						
				(1.17)	(0.06)	(1.04)						
Lagged IHS-transformed Adult to Child Ratio							0.576	0.735*	0.357**			
							(0.55)	(1.30)	(0.05)			
Lagged Percentage of single parents with Children				0.45	0.627	1.253						
				(0.48)	(0.50)	(0.90)						
Lagged Percentage of female Head of Household										0.136	0.002	2.140*
										(1.47)	(1.67)	(0.99)
Lagged IHS-transformed Population Travel on Public Transportation	0.054	0.020***	0.119							0.091	0.036*	0.164***
	(0.03)	(0.75)	(0.31)							(0.06)	(0.05)	(0.05)
Lagged IHS-transformed Population with Commute < 25 minutes				0.057**	0.494	-0.001***						
				(0.03)	(0.69)	(0.14)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.054	0.064	-0.101**			
							(0.09)	(0.06)	(0.99)			

Lagged IHS-transformed Population with Commute > 45 minutes										-0.154	-0.107	-0.208***
										(4.68)	(0.95)	(0.05)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										2.511	-0.182	3.102
										(0.79)	(0.60)	(2.08)
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.216	-0.694	-0.364			
							(0.90)	(0.08)	(0.00)			
Lagged percentage of over 25-yr-olds with Associate Degree				-5.994***	-5.115	-6.842						
				(0.04)	(0.00)	(4.33)						
Lagged percentage of over 25-yr-olds with bachelor's degree	0.271	0.919	-0.183*									
	(0.39)	(0.75)	(0.85)									
Lagged Owner to Renter Ratio	-0.001	-0.002	0									
	(0.00)	(3.10)	(0.60)									
Lagged Percentage of Housing Units Renter-occupied							0.501	0.421	0.542			
							(0.42)	(2.47)	(1.45)			
Lagged Percentage of Housing Units Vacant	0.222	1.019	-0.332									
	(0.85)	(0.54)	(0.31)									
Lagged Percent Change in Housing Unit Supply				-0.073	-0.451	-0.068						
				(1.51)	(1.09)	(0.38)						
AIC	4713.531	2257.129	2457.018	4708.67	2242.269	2460.579	4711.262	2252.218	2465.149	4700.148	2259.147	2430.274
BIC	4814.968	2351.112	2546.069	4810.107	2336.252	2549.63	4812.699	2346.201	2554.199	4801.586	2353.13	2519.325
Log Likelihood	-2342.77	-1114.56	-1214.51	-2340.34	-1107.13	-1216.29	-2341.63	-1112.11	-1218.57	-2336.07	-1115.57	-1201.14
Deviance	4924.773	2396.273	2501.07	4917.775	2380.175	2501.362	4925.182	2391.859	2510.894	4909.864	2398.035	2473.058
Num. obs.	10358	6082	4276	10358	6082	4276	10358	6082	4276	10358	6082	4276

***p < 0.001, **p < 0.01, *p < 0.05

Table 57. Access to Public Transportation Proxy Split Dataset Selection Effect Results for All New Bridges

	Access to Public Transportation DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years											
	Full 1	**PT=Hi 1**	**PT=Low 1**	**Full 2**	**PT=Hi 2**	**PT=Low 2**	**Full 3**	**PT=Hi 3**	**PT=Low 3**	**Full 4**	**PT=Hi 4**	**PT=Low 4**
% Water Area	-1.044	-1.368	-1.092	-0.413	0.056	-1.013	-1.005	-0.944	-1.106	-0.479	-0.507	-1.134
	(1.09)	(1.08)	(1.09)	(1.09)	(1.30)	(1.18)	(1.25)	(1.26)	(2.12)	(2.23)	(2.13)	(2.23)
Rural tract indicator > 10M sq. meters	0.401	1.159*	0.433				0.421*	1.257*	0.401			
	(0.35)	(0.13)	(0.34)				(0.58)	(0.18)	(0.41)			
Rural tract indicator > 4M sq. meters				0.327*	0.45	0.101*				0.315	0.418	0.101
				(0.13)	(0.59)	(0.18)				(0.20)	(0.41)	(0.20)
Lagged IHS-transformed Total bridges	-0.322***	-0.166***	-0.553***	-0.364***	-0.187*	-0.627*	-0.304	-0.123**	-0.579***	-0.390***	-0.234***	-0.604***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.07)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
Lagged IHS-transformed Real Average Income	0.028	0.076	-0.008*				0.073	0.044	0.083			
	(0.02)	(0.02)	(0.04)				(0.07)	(0.03)	(0.03)			
Lagged IHS-transformed Real Aggregate Household Income				-0.007	-0.057	-0.007				0.03	0.044	0.024
				(0.02)	(0.05)	(0.03)				(0.03)	(0.05)	(0.02)
Lagged Population Percentage of Below the Poverty Line	1.443*	0.764	2.5									
	(0.68)	(0.05)	(0.05)									
Lagged Population Percentage of Receiving Welfare							1.089	-0.07	3.453			
							(1.19)	(0.71)	(1.08)			
Lagged Non-white Population Percentage of	-2.000***	-1.244**	-2.544***									
	(0.39)	(1.80)	(0.41)									
Lagged African American Population Percentage of							-1.977***	-1.722***	-1.708*			
							(0.42)	(3.81)	(1.16)			
Lagged Hispanic Population Percentage of										-9.095**	-13.262	-0.878
										(5.38)	(1.41)	(3.29)
Lagged Population Percentage of Foreign-born				-4.647**	-2.108**	-15.604				-3.074	-0.255	-15.594**
				(2.92)	(0.45)	(1.93)				(1.46)	(0.50)	(5.32)
Lagged Population Percentage of under 18				1.584	1.646***	2.561						
				(1.68)	(0.05)	(1.17)						
Lagged IHS-transformed Adult to Child Ratio							-0.73	-1.139	-0.66			
							(0.69)	(1.65)	(0.06)			
Lagged Percentage of single parents with Children				-3.134***	-3.104	-1.056**						
				(0.61)	(0.61)	(0.95)						
Lagged Percentage of female Head of Household										-2.398	-1.351	-2.116
										(1.80)	(2.38)	(1.39)
Lagged IHS-transformed Population Travel on Public Transportation	-0.060*	-0.241	0.02							-0.021	-0.219	0.091
	(0.03)	(0.90)	(0.40)							(0.06)	(0.07)	(0.06)
Lagged IHS-transformed Population with Commute < 25 minutes				0.008	0.068	-0.044						
				(0.04)	(0.79)	(0.12)						
Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.079	-0.046***	-0.115			
							(0.11)	(0.07)	(1.39)			
										0.012	0.03	-0.029

Lagged IHS-transformed Population with Commute > 45 minutes										(6.82)	(1.75)	(0.07)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										4.709	1.95	6.451
										(0.30)	(0.70)	(3.52)
Lagged percentage of over 25-yr-olds with at Least High School Education							1.147	0.597	1.547			
							(1.11)	(0.10)	0.00			
Lagged percentage of over 25-yr-olds with Associate Degree				2.428	6.875	-1.763						
				(0.05)	(0.00)	(5.42)						
Lagged percentage of over 25-yr-olds with bachelor's degree	-0.232	0.239***	-1.143									
	(0.51)	(0.77)	(0.95)									
Lagged Owner to Renter Ratio	0	-0.002	0									
	0.00	(4.09)	(0.89)									
Lagged Percentage of Housing Units Renter-occupied							-0.219	0.142	-0.925			
							(0.44)	(2.80)	(3.07)			
Lagged Percentage of Housing Units Vacant	-1.103	-1.555	-0.903									
	(1.44)	(0.11)	(0.34)									
Lagged Percent Change in Housing Unit Supply				0.009*	0.582	-0.042						
				(2.12)	(1.62)	(0.43)						
AIC	3587.598	2146.487	1428.761	3599.245	2157.069	1426.817	3588.673	2165.281	1428.823	3580.556	2134.54	1422.65
BIC	3682.779	2236.82	1506.74	3694.426	2247.402	1504.796	3683.853	2255.613	1506.802	3675.736	2224.873	1500.629
Log Likelihood	-1779.8	-1059.24	-700.38	-1785.62	-1064.53	-699.409	-1780.34	-1068.64	-700.412	-1776.28	-1053.27	-697.325
Deviance	3806.165	2277.142	1479.242	3816.145	2285.717	1475.891	3810.28	2301.061	1477.483	3789.159	2257	1472.75
Num. obs.	6625	4686	1939	6625	4686	1939	6625	4686	1939	6625	4686	1939

***p < 0.001, **p < 0.01, *p < 0.05

Table 58. National Registry of Historic Places Proxy Split Dataset Selection Effect Results for Restrictive Bridges

	DV: Dummy variable denoting that a new restrictive bridge was built in this tract in the last 10 years											
	Full 1	NRHP=Hi 1	NRHP=Low 1	Full 2	NRHP=Hi 2	NRHP=Low 2	Full 3	NRHP=Hi 3	NRHP=Low 3	Full 4	NRHP=Hi 4	NRHP=Low 4
% Water Area	1.078	4.082	0.997	0.86	6.485	0.376	1.142	4.832	0.872	1.179	14.005	1.09
	(2.057)	(1.694)	(1.728)	(1.720)	(32.559)	(10.813)	(14.022)	(14.024)	(2.473)	(2.517)	(2.408)	(2.242)
Rural tract indicator > 10M sq. meters	0.891	1.569	0.689				0.806	0.678	0.68			
	(0.558)	(0.643)	(0.557)				(0.932)	(4.177)	(0.649)			
Rural tract indicator > 4M sq. meters				-0.424	-2.217	-0.277				-0.529	-4.613	-0.478
				(0.582)	(2.533)	(1.752)				(0.739)	(0.651)	(0.626)
Lagged IHS-transformed Total bridges	-0.318	-0.556	-0.272	-0.066	0.137	-0.07	-0.317	-0.509	-0.282	-0.141	-0.074	-0.127
	(0.179)	(0.193)	(0.183)	(0.187)	(0.871)	(0.713)	(0.684)	(0.861)	(0.208)	(0.211)	(0.214)	(0.207)
Lagged IHS-transformed Real Average Income	0.054	0.355	0.041				0.039*	1.129	-0.025			
	(0.075)	(0.070)	(0.106)				(0.482)	(1.141)	(0.080)			
Lagged IHS-transformed Real Aggregate Household Income				-0.02	1.267	0.023				0.051	0.874	0.039
				(0.047)	(0.232)	(1.452)				(0.068)	(0.099)	(0.046)
Lagged Population Percentage of Below the Poverty Line	4.097	-4.874	4.879									
	(2.353)	(0.317)	(0.203)									
Lagged Population Percentage of Receiving Welfare							1.68	19.743	1.514			
							(15.345)	(37.317)	(4.918)			
Lagged Non-white Population Percentage of	-0.288	2.009	-0.443									
	(1.130)	(6.733)	(1.841)									
Lagged African American Population Percentage of							0.66	-11.424	1.488			
							(6.919)	(31.470)	(1.211)			
Lagged Hispanic Population Percentage of										-3.597	39.559	-9.63
										(8.097)	(1.956)	(11.444)
Lagged Population Percentage of Foreign-born				-4	7.158	-5.265				-2.247	12.509	-1.667
				(6.079)	(4.862)	(11.328)				(3.257)	(0.737)	(7.541)
Lagged Population Percentage of under 18				2.066	26.516	-0.894						
				(5.903)	(0.994)	(15.076)						
Lagged IHS-transformed Adult to Child Ratio							0.123	-15.413	0.765			
							(8.306)	(21.325)	(0.133)			
Lagged Percentage of single parents with Children				-1.611	-10.261	1.549						
				(2.644)	(15.060)	(5.872)						
Lagged Percentage of female Head of Household										-1.511	-41.057	0.702
										(4.473)	(5.272)	(2.924)
Lagged IHS-transformed Population Travel on Public Transportation	-0.12	-1.021	-0.095							-0.128	-1.429	-0.119
	(0.121)	(3.270)	(0.865)							(0.359)	(0.223)	(0.145)
Lagged IHS-transformed Population with Commute < 25 minutes				0.183	0.752	0.201						
				(0.123)	(7.164)	(3.887)						

Lagged IHS-transformed Population with Commute > 25 < 45 minutes							-0.032	0.176	0.038			
							(1.759)	(0.933)	(2.795)			
Lagged IHS-transformed Population with Commute > 45 minutes										0.077	3.566	0.014
										(17.850)	(6.006)	(0.206)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										0.552	-78.561	5.665
										(4.943)	(1.628)	(6.060)
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.058	-24.94	8.01			
							(17.608)	(2.910)	(0.049)			
Lagged percentage of over 25-yr-olds with Associate Degree				-18.271	-4.61	-27.193						
				(0.209)	(0.035)	(60.976)						
Lagged percentage of over 25-yr-olds with bachelor's degree	2.89	18.529	-1.787									
	(2.482)	(4.200)	(4.143)									
Lagged Owner to Renter Ratio	-0.012	0.002	-0.017									
	(0.023)	(14.222)	(5.921)									
Lagged Percentage of Housing Units Renter-occupied							-1.614	0.069	-1.053			
							(3.753)	(52.367)	(4.911)			
Lagged Percentage of Housing Units Vacant	-3.432	-19.624	-1.529									
	(5.563)	(3.969)	(1.411)									
Lagged Percent Change in Housing Unit Supply				-0.57	3.431	-0.723						
				(8.205)	(60.276)	(1.915)						
AIC	354.579	52.275	311.756	355.932	56.44	310.231	360.186	53.557	313.009	359.615	51.333	316.761
BIC	450.44	120.572	405.512	451.793	124.736	403.986	456.047	121.854	406.765	455.476	119.629	410.517
Log Likelihood	-163.289	-12.137	-141.878	-163.966	-14.22	-141.115	-166.093	-12.779	-142.505	-165.807	-11.666	-144.38
Deviance	339.259	24.658	295.646	345.278	29.631	300.051	345.023	26.693	297.701	346.241	24.017	302.476
Num. obs.	6955	971	5984	6955	971	5984	6955	971	5984	6955	971	5984

***p < 0.001, **p < 0.01, *p < 0.05

Table 59. National Registry of Historic Places Proxy Split Dataset Selection Effect Results for Non-restrictive Bridges

	National Register of Historic Places Proxy DV: Dummy variable denoting that a new non-restrictive bridge was built in this tract in the last 10 years											
	Full 1	**NRHP= Hi 1**	**NRHP=Low 1**	**Full 2**	**NRHP= Hi 2**	**NRHP=Low 2**	**Full 3**	**NRHP= Hi 3**	**NRHP=Low 3**	**Full 4**	**NRHP= Hi 4**	**NRHP=Low 4**
% Water Area	1.925*	3.628***	0.814*	2.555***	5.199**	1.306***	1.817**	3.535***	0.669	2.496	5.031	1.119
	(0.77)	(0.74)	(0.76)	(0.75)	(1.20)	(1.25)	(1.21)	(1.21)	(1.06)	(1.02)	(1.04)	(1.04)
Rural tract indicator > 10M sq. meters	-0.004	-0.253**	0.046				-0.008	-0.372	0.052			
	(0.13)	(0.14)	(0.12)				(0.41)	(0.47)	(0.13)			
Rural tract indicator > 4M sq. meters				0.449***	0.608	0.429				0.472**	0.548	0.466**
				(0.14)	(0.42)	(0.51)				(0.15)	(0.13)	(0.14)
Lagged IHS-transformed Total bridges	-0.067	-0.185**	-0.053	-0.154**	-0.331	-0.132*	-0.056	-0.206*	-0.037	-0.154*	-0.315	-0.137*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)	(0.14)	(0.13)	(0.14)	(0.05)	(0.06)	(0.05)	(0.06)
Lagged IHS-transformed Real Average Income	-0.063***	-0.127	-0.056**				-0.082	-0.041*	-0.086**			
	(0.02)	(0.02)	(0.03)				(0.09)	(0.03)	(0.02)			
Lagged IHS-transformed Real Aggregate Household Income				0.021**	-0.037*	0.03				-0.032	-0.072**	-0.027*
				(0.01)	(0.05)	(0.04)				(0.02)	(0.03)	(0.01)
Lagged Population Percentage of Below the Poverty Line	2.171***	1.805	2.083									
	(0.60)	(0.05)	(0.04)									
Lagged Population Percentage of Receiving Welfare							1.934	3.327	1.471			
							(2.40)	(1.12)	(0.43)			
Lagged Non-white Population Percentage of	-1.551***	-1.924	-1.502***									
	(0.34)	(1.23)	(0.37)									
Lagged African American Population Percentage of							-1.286**	-2.071	-1.189***			
							(0.75)	(2.43)	(0.43)			
Lagged Hispanic Population Percentage of										-5.224	1.298*	-8.735***
										(1.40)	(0.48)	(2.28)
Lagged Population Percentage of Foreign-born				0.463**	3.105**	0.171				1.590***	2.523*	1.551
				(1.75)	(0.63)	(2.74)				(0.86)	(0.33)	(1.41)
Lagged Population Percentage of under 18				-2.942	-1.971	-3.138						
				(1.17)	(0.08)	(1.83)						
Lagged IHS-transformed Adult to Child Ratio							0.576	-0.598	0.704			
							(0.90)	(2.42)	(0.03)			
Lagged Percentage of single parents with Children				0.45	1.365	-0.08						
				(0.48)	(1.11)	(1.47)						
Lagged Percentage of female Head of Household										0.136	0.223	0.06
										(0.92)	(0.90)	(0.55)
Lagged IHS-transformed Population Travel on Public Transportation	0.054	0.111***	0.047							0.091	0.093	0.092**
	(0.03)	(0.75)	(0.31)							(0.05)	(0.04)	(0.03)
Lagged IHS-transformed Population with Commute < 25 minutes				0.057**	0.027	0.061						
				(0.03)	(1.38)	(0.11)						
Lagged IHS-transformed Population							-0.054	-0.043	-0.062**			
							(0.11)	(0.08)	(0.68)			

with Commute > 25 < 45 minutes												
Lagged IHS-transformed Population with Commute > 45 minutes										-0.154*	-0.101	-0.167***
										(3.28)	(0.65)	(0.04)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										2.511	-2.54	3.120*
										(0.63)	(0.35)	(1.57)
Lagged percentage of over 25-yr-olds with at Least High School Education							-0.216	0.155	-0.719			
							(2.07)	(0.10)	(0.00)			
Lagged percentage of over 25-yr-olds with Associate Degree				-5.994***	2.805	-8.293						
				(0.04)	(0.00)	(11.42)						
Lagged percentage of over 25-yr-olds with bachelor's degree	0.271	-0.015	0.514*									
	(0.39)	(0.75)	(0.85)									
Lagged Owner to Renter Ratio	-0.001	0	-0.001									
	(0.00)	(3.10)	(0.60)									
Lagged Percentage of Housing Units Renter-occupied							0.501	0.665	0.549			
							(0.76)	(4.75)	(0.95)			
Lagged Percentage of Housing Units Vacant	0.222	0.953	0.216									
	(0.85)	(0.54)	(0.31)									
Lagged Percent Change in Housing Unit Supply				-0.073	-0.112	-0.066						
				(1.51)	(2.27)	(0.64)						
AIC	4713.531	642.71	4072.024	4708.67	647.549	4060.253	4711.262	641.365	4068.119	4700.148	646.755	4047.752
BIC	4814.968	716.407	4171.384	4810.107	721.246	4159.613	4812.699	715.061	4167.479	4801.586	720.451	4147.112
Log Likelihood	-2342.77	-307.355	-2022.012	-2340.34	-309.775	-2016.126	-2341.63	-306.683	-2020.059	-2336.07	-309.377	-2009.876
Deviance	4924.773	657.992	4238.975	4917.775	663.209	4225.004	4925.182	657.136	4237.495	4909.864	662.453	4212.54
Num. obs.	10358	1428	8930	10358	1428	8930	10358	1428	8930	10358	1428	8930

***p < 0.001, **p < 0.01, *p < 0.05

Table 60. National Registry of Historic Places Proxy Split Dataset Selection Effect Results for All New Bridges

	National Register of Historic Places Proxy DV: Dummy variable denoting that a new bridge was built in this tract in the last 10 years											
	Full 1	**NRHP= Hi 1**	**NRHP=Low 1**	**Full 2**	**NRHP= Hi 2**	**NRHP=Low 2**	**Full 3**	**NRHP= Hi 3**	**NRHP=Low 3**	**Full 4**	**NRHP= Hi 4**	**NRHP=Low 4**
% Water Area	-1.044	2.923	-1.595	-0.413	4.826	-1.197	-1.005	2.999	-1.663	-0.479	4.564	-1.229
	(1.09)	(1.08)	(1.09)	(1.09)	(3.33)	(3.40)	(3.45)	(3.41)	(1.18)	(1.18)	(1.19)	(1.18)
Rural tract indicator > 10M sq. meters	0.401	-0.972*	0.688				0.421	-1.119	0.711			
	(0.35)	(0.13)	(0.34)				(1.45)	(0.52)	(0.35)			
Rural tract indicator > 4M sq. meters				0.327*	0.288	0.347				0.315*	0.290*	0.337*
				(0.13)	(1.49)	(0.57)				(0.14)	(0.35)	(0.14)
Lagged IHS-transformed Total bridges	-0.322***	-0.230***	-0.329***	-0.364***	-0.273	-0.38	-0.304	-0.229	-0.305***	-0.390***	-0.280***	-0.404***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.20)	(0.18)	(0.20)	(0.19)	(0.06)	(0.07)	(0.06)	(0.07)
Lagged IHS-transformed Real Average Income	0.028	-0.056	0.033*				0.073	0.028	0.081			
	(0.02)	(0.02)	(0.04)				(0.12)	(0.05)	(0.02)			
Lagged IHS-transformed Real Aggregate Household Income				-0.007	-0.069	0				0.03	-0.006*	0.032
				(0.02)	(0.08)	(0.06)				(0.02)	(0.04)	(0.02)
Lagged Population Percentage of Below the Poverty Line	1.443*	0.313	1.502									
	(0.68)	(0.05)	(0.05)									
Lagged Population Percentage of Receiving Welfare							1.089	2.133	0.86			
							(3.48)	(1.58)	(0.56)			
Lagged Non-white Population Percentage of	-2.000***	-2.448**	-1.796***									
	(0.39)	(1.80)	(0.41)									
Lagged African American Population Percentage of							-1.977**	-3.085	-1.671***			
							(0.97)	(5.06)	(0.45)			
Lagged Hispanic Population Percentage of										-9.095*	-8.577***	-8.959**
										(2.01)	(0.48)	(3.12)
Lagged Population Percentage of Foreign-born				-4.647**	-0.532**	-5.105				-3.074	0.027	-3.547
				(2.92)	(0.77)	(3.51)				(0.99)	(0.42)	(1.92)
Lagged Population Percentage of under 18				1.584	1.694	1.532						
				(1.68)	(0.13)	(2.72)						
Lagged IHS-transformed Adult to Child Ratio							-0.73	-1.221	-0.708*			
							(1.55)	(2.70)	(0.03)			
Lagged Percentage of single parents with Children				-3.134***	-3.056	-2.813						
				(0.61)	(1.68)	(2.10)						
Lagged Percentage of female Head of Household										-2.398**	-2.607	-2.200**
										(0.88)	(0.98)	(0.71)
Lagged IHS-transformed Population Travel on Public Transportation	-0.060*	0.023	-0.064							-0.021	-0.075*	-0.01
	(0.03)	(0.90)	(0.40)							(0.05)	(0.05)	(0.04)
Lagged IHS-transformed Population with Commute < 25 minutes				0.008	0.239	-0.016						
				(0.04)	(2.27)	(0.32)						
Lagged IHS-transformed Population							-0.079	0.168	-0.104*			
							(0.24)	(0.12)	(0.71)			

with Commute > 25 < 45 minutes												
Lagged IHS-transformed Population with Commute > 45 minutes										0.012	0.194	-0.01
										(4.31)	(0.97)	(0.06)
Lagged percentage of over 25-yr-olds with at Least 8 Years Education										4.709	9.035	4.385
										(0.11)	(0.37)	(2.28)
Lagged percentage of over 25-yr-olds with at Least High School Education							1.147	0.845	0.865			
							(2.75)	(0.16)	0.00			
Lagged percentage of over 25-yr-olds with Associate Degree				2.428	5.922	1.442						
				(0.05)	(0.00)	(13.32)						
Lagged percentage of over 25-yr-olds with bachelor's degree	-0.232	-1.551***	0.062									
	(0.51)	(0.77)	(0.95)									
Lagged Owner to Renter Ratio	0	0	0									
	0.00	(4.09)	(0.89)									
Lagged Percentage of Housing Units Renter-occupied							-0.219	0.183	-0.199			
							(1.26)	(7.00)	(1.51)			
Lagged Percentage of Housing Units Vacant	-1.103	-0.396	-0.998									
	(1.44)	(0.11)	(0.34)									
Lagged Percent Change in Housing Unit Supply				0.009*	0.894	-0.009						
				(2.12)	(4.22)	(0.78)						
AIC	3587.598	328.224	3268.13	3599.245	332.047	3271.981	3588.673	326.028	3268.959	3580.556	331.649	3256.404
BIC	3682.779	395.917	3361.192	3694.426	399.739	3365.044	3683.853	393.72	3362.022	3675.736	399.342	3349.467
Log Likelihood	-1779.8	-150.112	-1620.065	-1785.62	-152.023	-1621.991	-1780.34	-149.014	-1620.479	-1776.28	-151.824	-1614.202
Deviance	3806.165	325.326	3460.416	3816.145	329.164	3462.468	3810.28	321.859	3465.194	3789.159	328.196	3439.438
Num. obs.	6625	930	5695	6625	930	5695	6625	930	5695	6625	930	5695

***p < 0.001, **p < 0.01, *p < 0.05

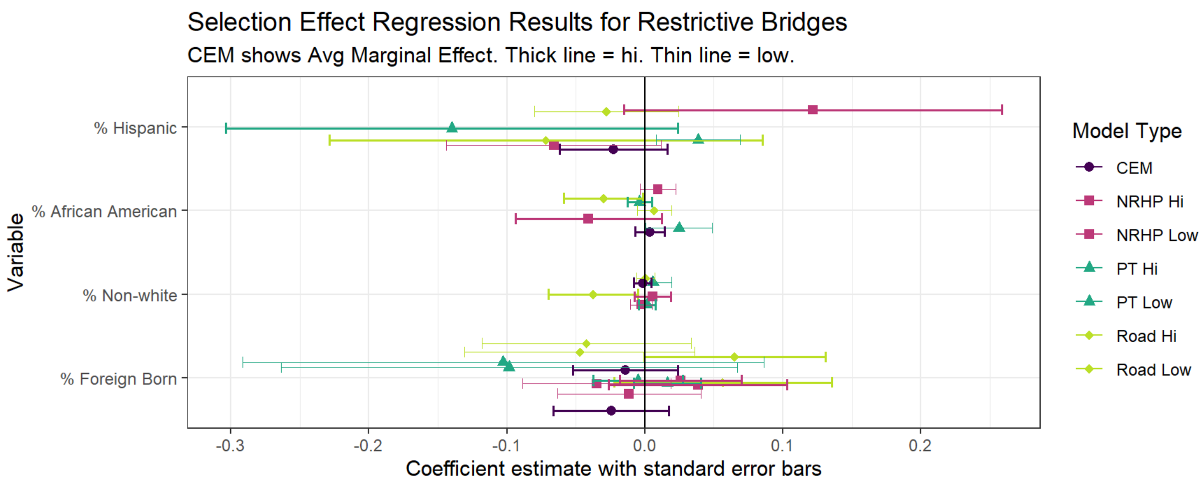

Fig. 47. Demographic Variables Split Dataset Selection Effect Results for Restrictive Bridges

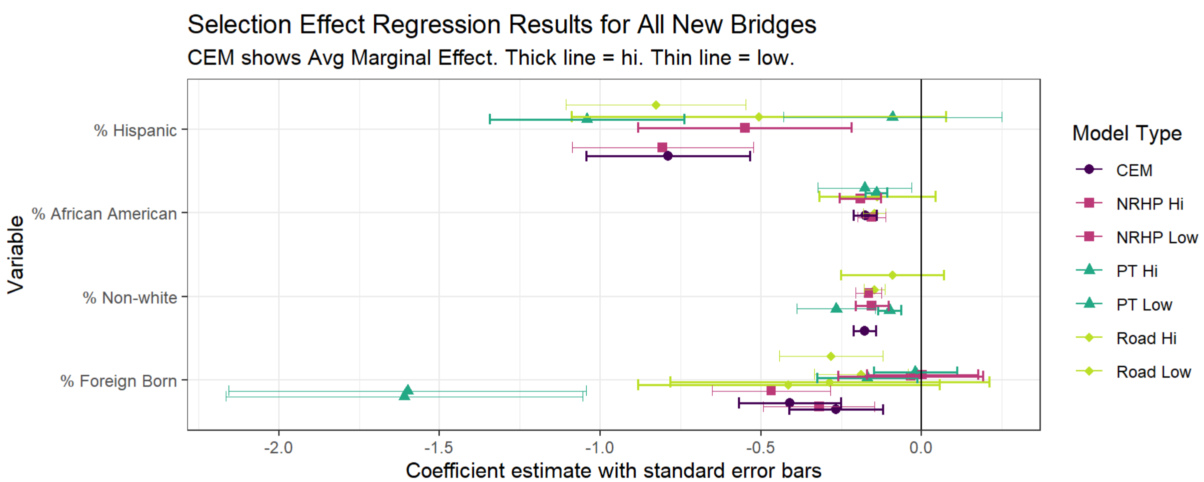

Fig. 48. Demographic Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

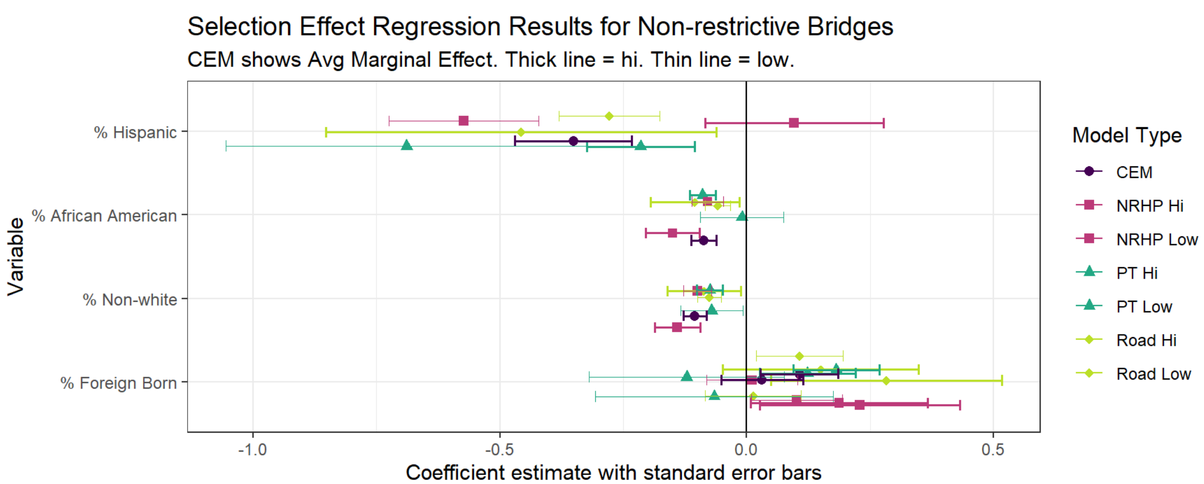

Fig. 49. Demographic Variables Split Dataset Selection Effect Results for All New Bridges

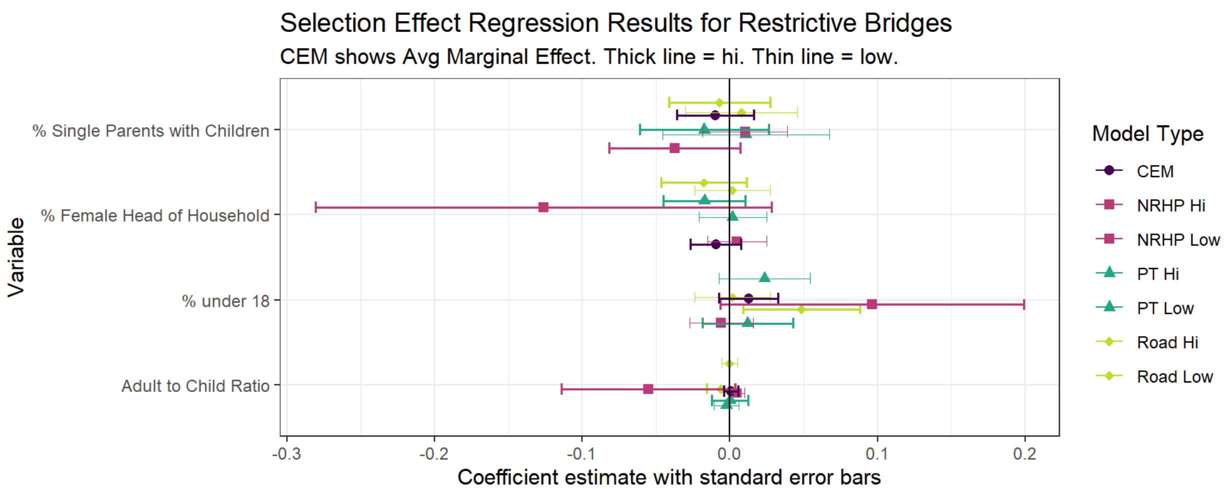

Fig. 50. Family Variables Split Dataset Selection Effect Results for Restrictive Bridges

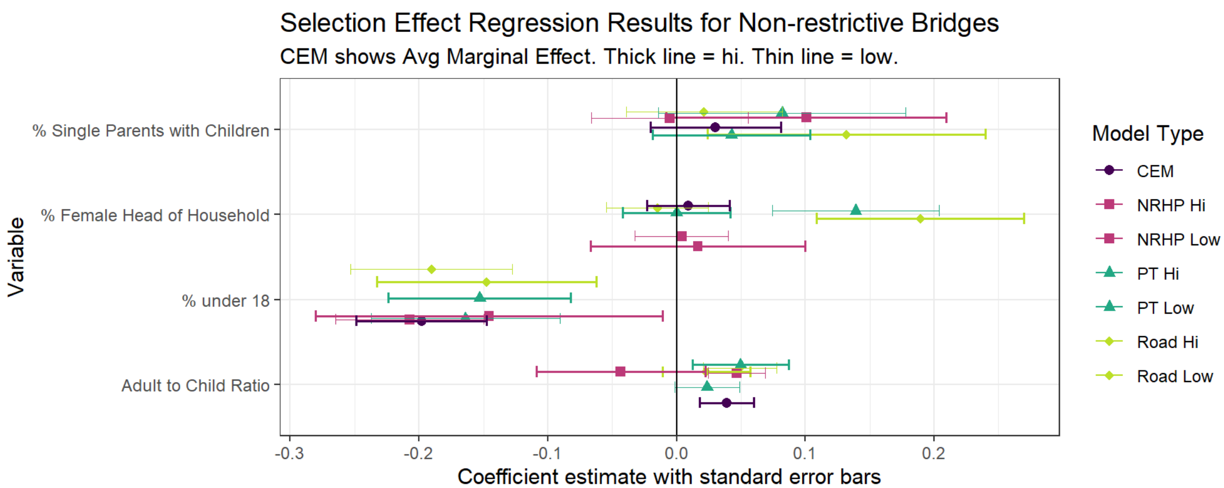

Fig. 51. Family Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

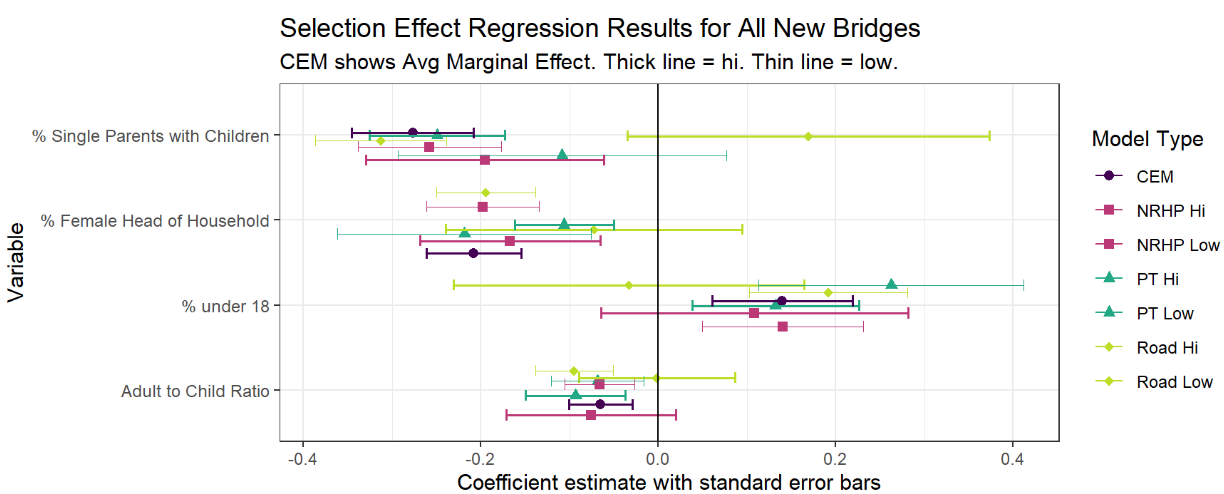

Fig. 52. Family Variables Split Dataset Selection Effect Results for All New Bridges

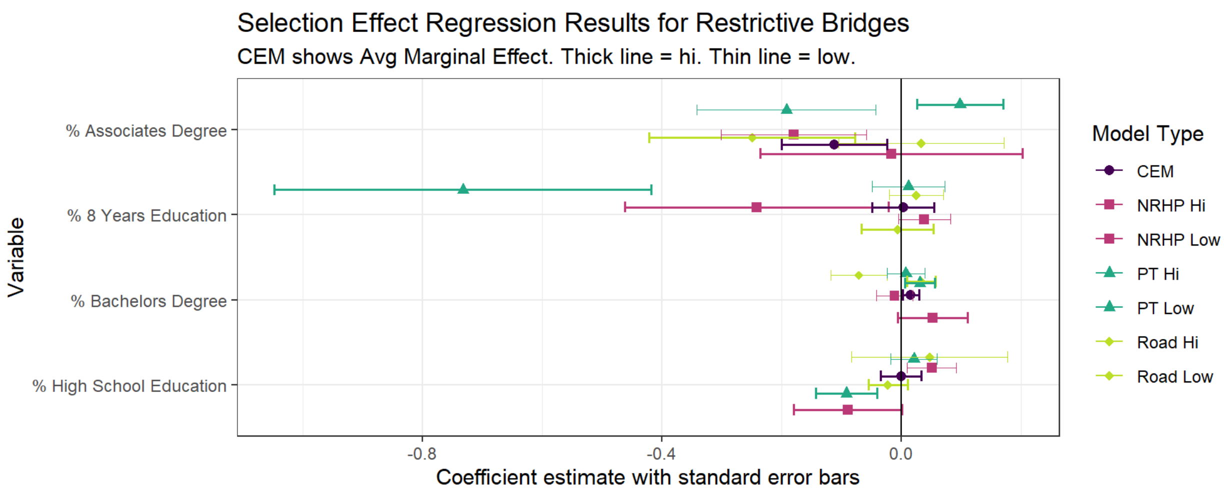

Fig. 53. Education Variables Split Dataset Selection Effect Results for Restrictive Bridges

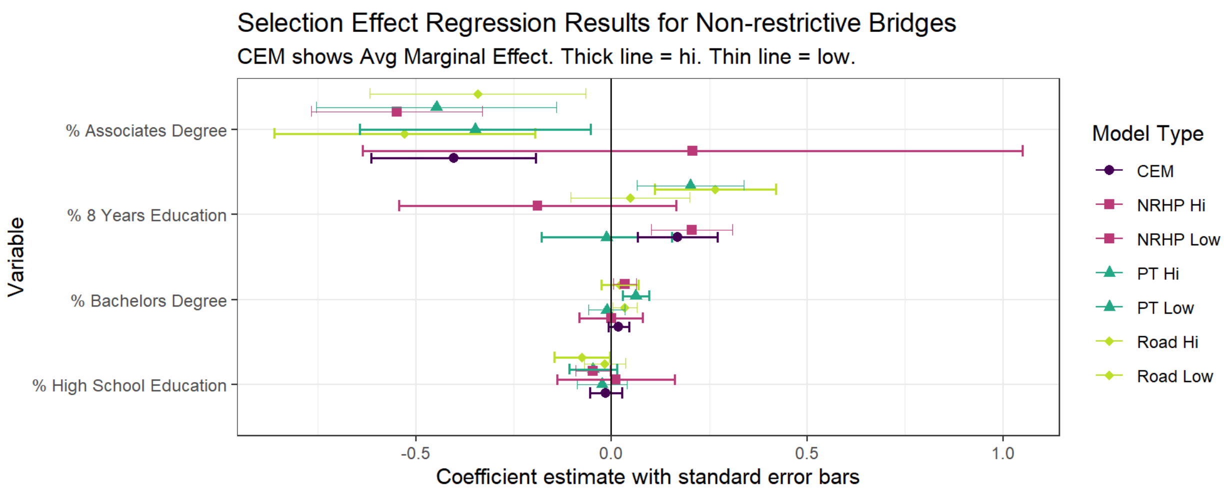

Fig. 54. Education Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

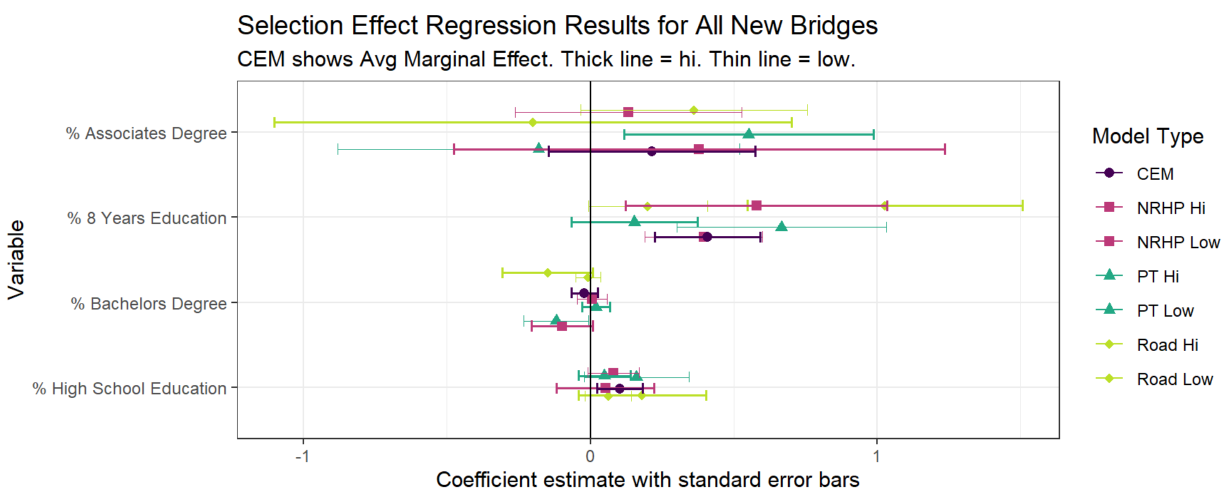

Fig. 55. Education Variables Split Dataset Selection Effect Results for All New Bridges

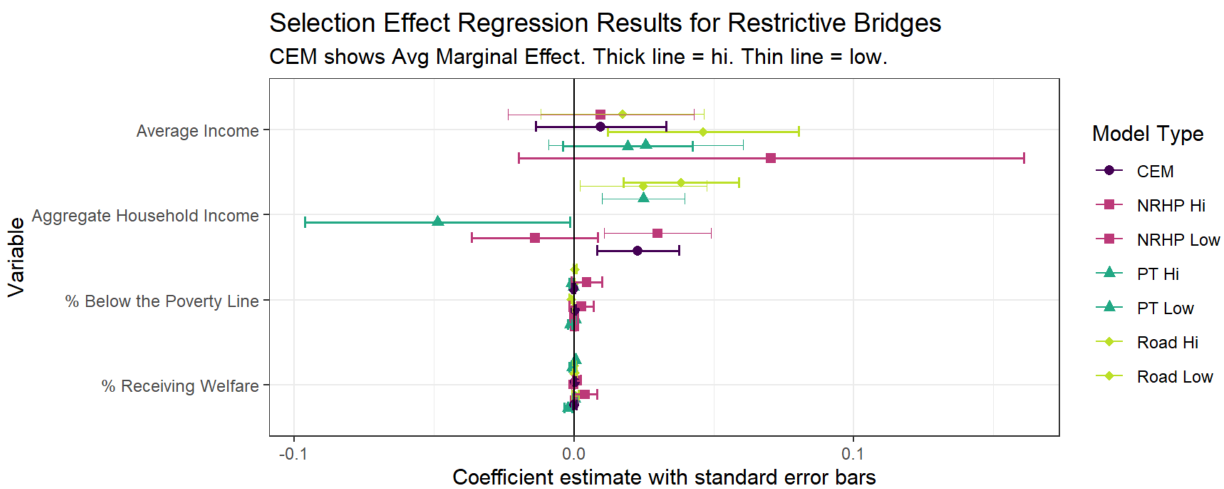

Fig. 56. Financial Variables Split Dataset Selection Effect Results for Restrictive Bridges

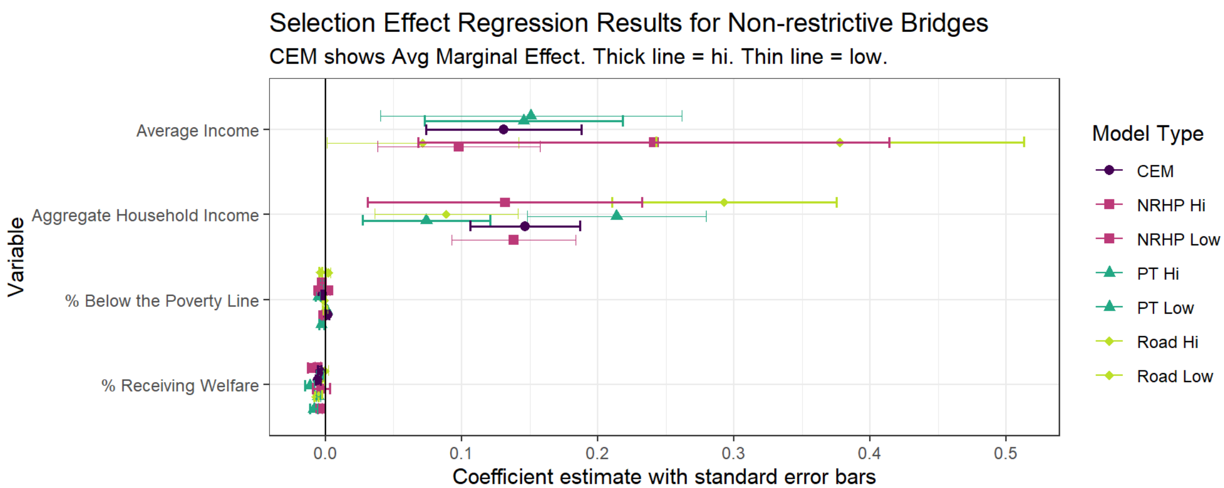

Fig. 57. Financial Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

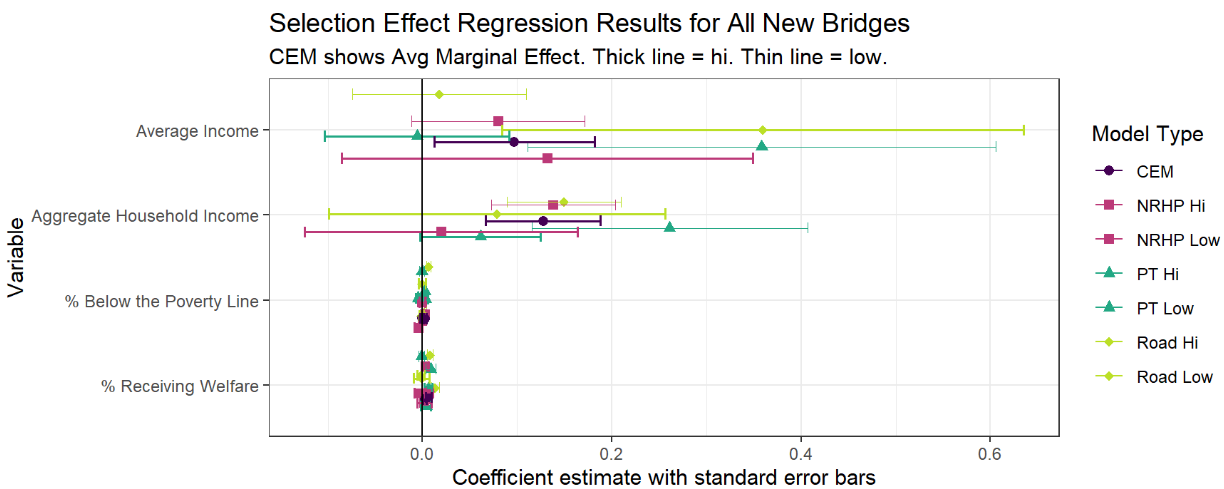

Fig. 58. Financial Variables Split Dataset Selection Effect Results for All New Bridges

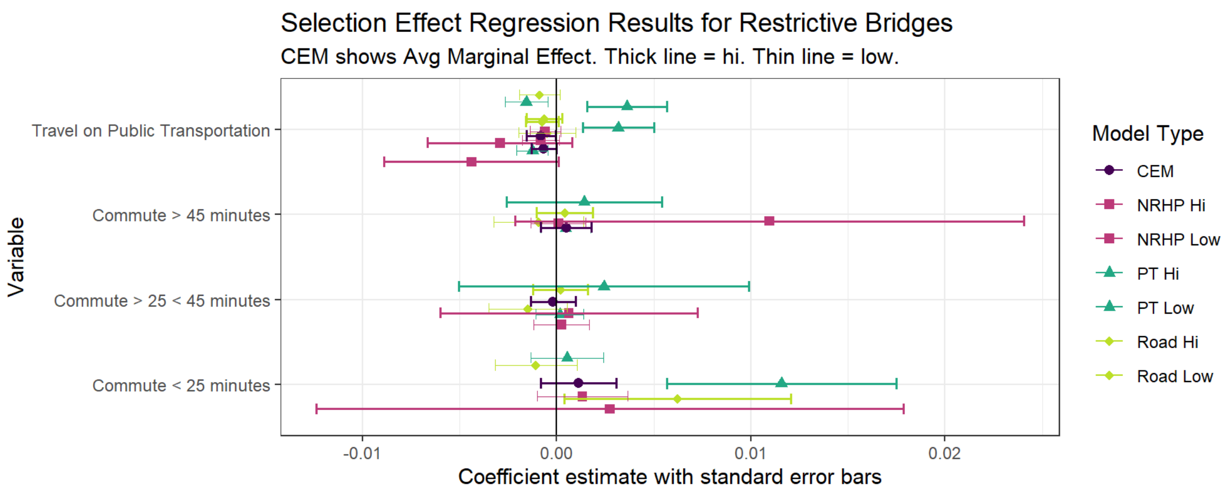

Fig. 59. Transportation Variables Split Dataset Selection Effect Results for Restrictive Bridges

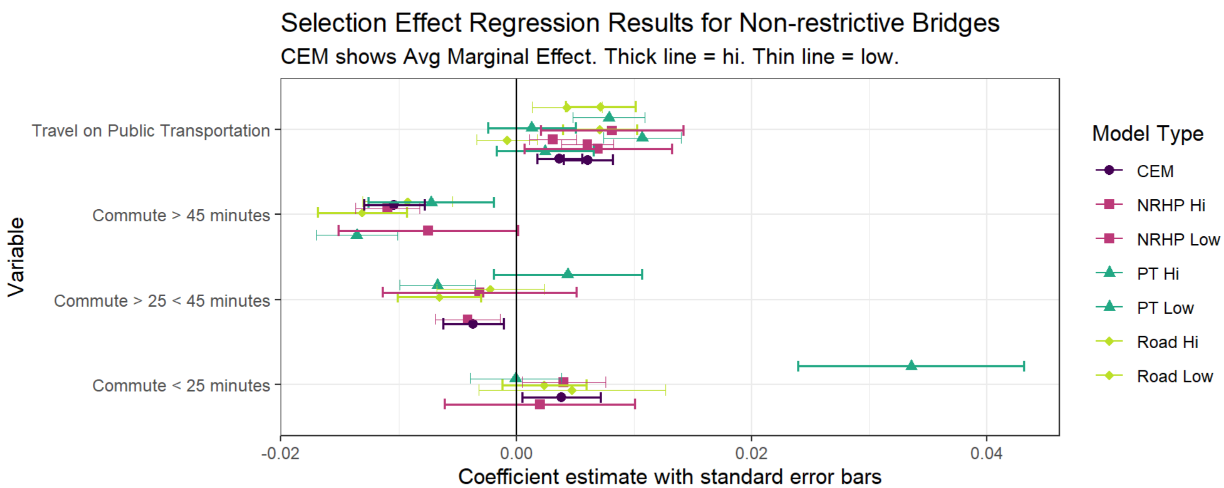

Fig. 60. Transportation Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

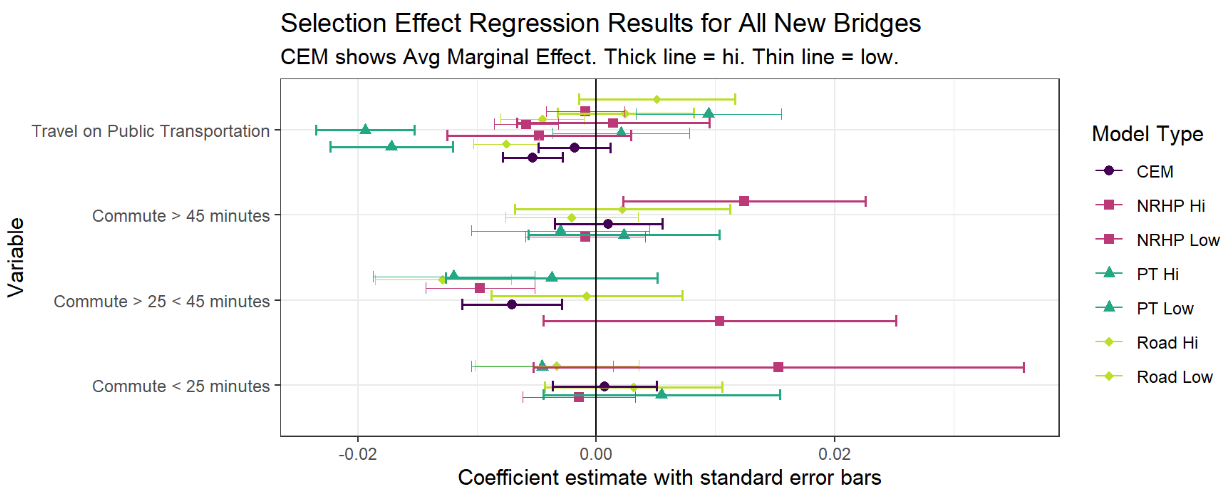

Fig. 61. Transportation Variables Split Dataset Selection Effect Results for All New Bridges

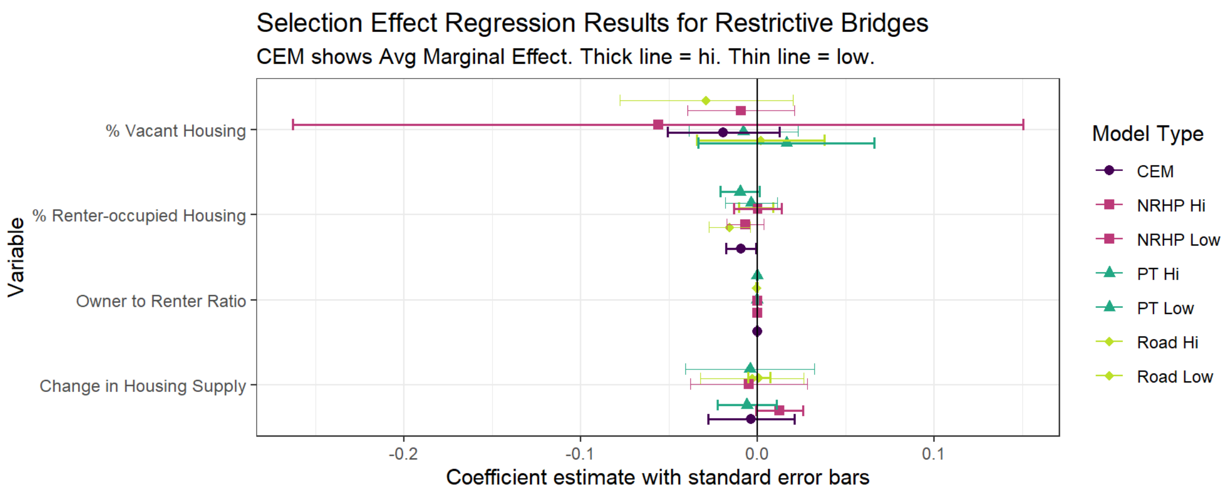

Fig. 62. Housing Variables Split Dataset Selection Effect Results for Restrictive Bridges

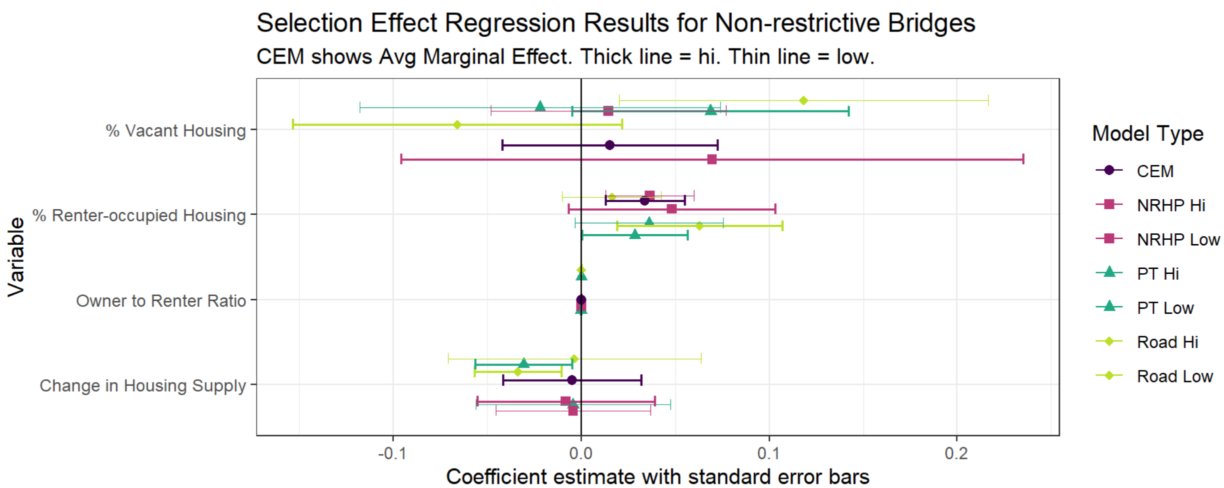

Fig. 63. Housing Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

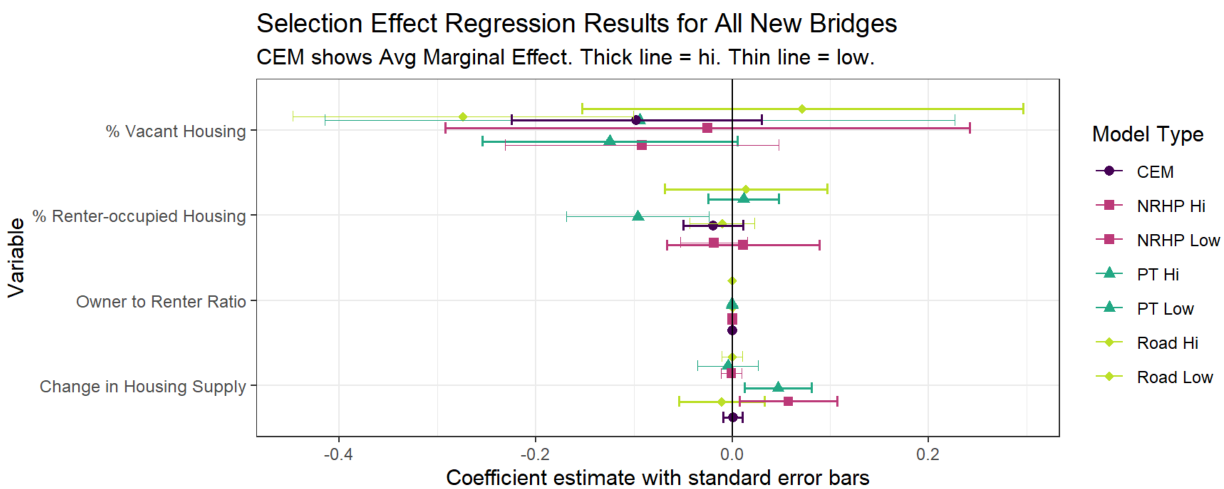

Fig. 64. Housing Variables Split Dataset Selection Effect Results for All New Bridges

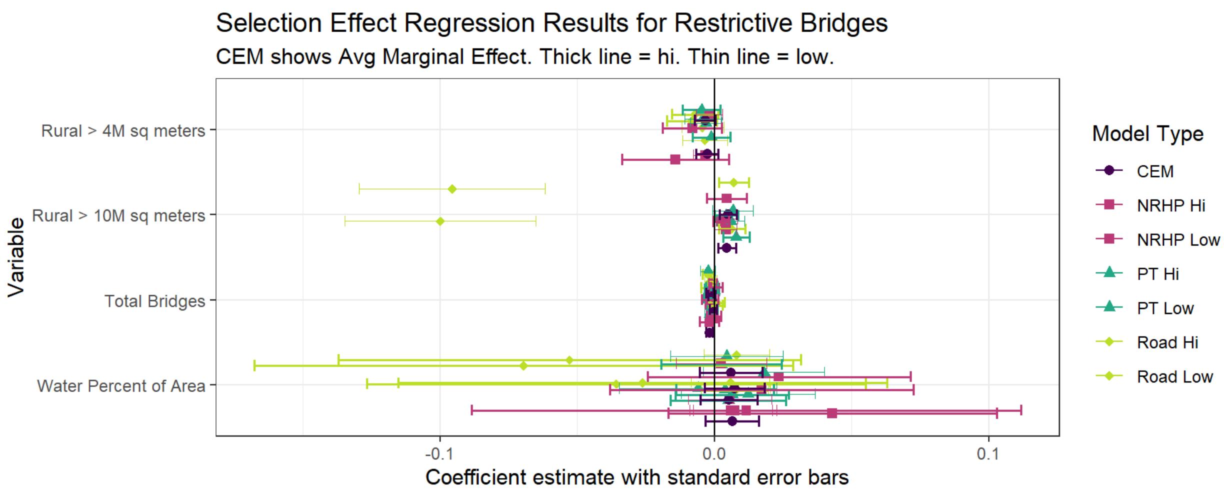

Fig. 65. Physical Variables Split Dataset Selection Effect Results for Restrictive Bridges

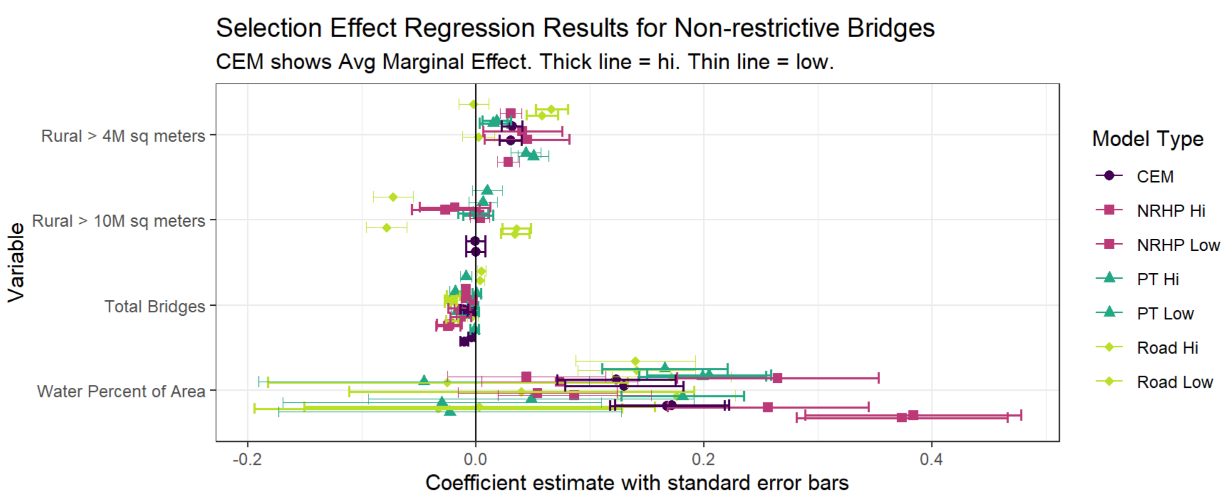

Fig. 66. Physical Variables Split Dataset Selection Effect Results for Non-restrictive Bridges

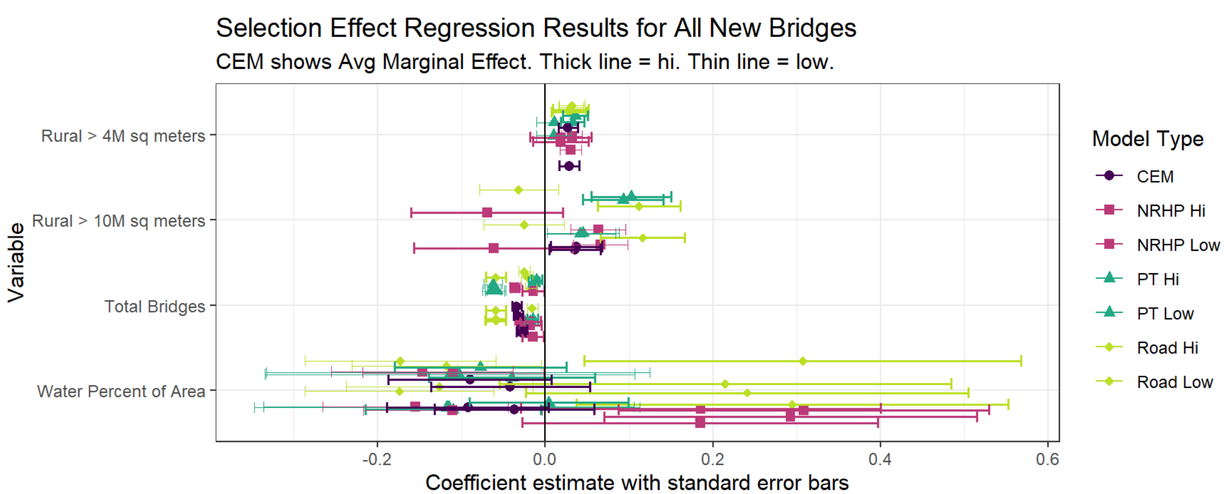

Fig. 67. Physical Variables Split Dataset Selection Effect Results for All New Bridges

Section H Literature Review

That literature which specifically focuses on bridges primarily describes optimizing limited funds to maintain bridges, and the impacts of construction or maintenance of bridges on the local populace that uses the bridge. The literature on maintaining bridges describes how government institutions can maximize resources to optimize maintenance of the greatest number of bridges (Chengalur-Smith et al. 1997; Mohammadi Jamshid et al. 1995). These studies primarily use cost as the outcome and have technical measures as the explanatory factors such as: condition ratings, structural safety requirements, and age of bridge. Their primary concern is to rank-order the bridges for maintenance priority. When researchers do take user cost factors into consideration, they tend to focus on factors affected only during construction or rehabilitation such as detour lengths, traffic delays, and congestion (Liu and Frangopol 2005; Liu Min and Frangopol Dan M. 2006; Liu Ming and Frangopol Dan M. 2006; Twumasi-Boakye and Sobanjo 2017). This literature is primarily concerned with technical engineering factors only before and during construction or maintenance (Amini, Nikraz, and Fathizadeh, 2016), and the main consideration given to social factors is the impact on the bridge users during those same periods. Much progress has even been made in minimizing social impacts during construction as demonstrated by Accelerated Bridge Construction(ABC) which greatly minimizes user impact. Understanding wider social impacts of infrastructure, such as bridges, is still generally understudied and the motivation of this work.

The literature around society and the built environment has the following foci. The first and predominant focus contends that the built environment acts as a conduit for both intended and unintended social connections (Audretsch et al. 2015; Joerges 1999; Pinch and Bijker 2012; Schindler 2015; Shilton 2013; Star 1999; Winner 1980; Woolgar and Cooper 1999). As Howe and colleagues (2016) write, “Infrastructural deficiencies can both index preexisting inequalities, just as they may, simultaneously, deepen those inequalities” (Howe et al. 2016 p. 551).

On the one hand, infrastructure improves the flow of goods and services such that it can help recognize market opportunities. In an infrastructure study from 2001-2005, the researchers found the impact of infrastructure on new startup activity varies by type and industry (Audretsch et al. 2015). Knowledge and broadband infrastructure increased startup activity in information-intensive industries such as technology oriented services, while railway and the efficient movement of goods and services increases startup activity in consumer-related services and retail trade (Audretsch et al. 2015).

On the other hand, while those using the focal infrastructure may see benefits, the populations living near the infrastructure may experience harm. These deleterious effects may have disproportionately negative effects on the poor and marginalized (Epting 2016; Faoziyah 2016; Grabowski et al. 2017; Star 1999). A marginalized population is one which is "excluded from mainstream social, economic, cultural, or political life (Cook 2008)." A study that simulated the effect of a bridge linking two populations centers in Indonesia concluded that while the bridge was expected to equalize benefits between the districts, the majority of benefits actually accrued to the already more developed population (Faoziyah 2016).

Studies have observed deleterious and segregational effects of transportation infrastructure (Grannis, 1998, Reardon et al, 2008). In two cities, size and speed of road networks were better predictors of racial contiguity than geographic closeness and larger streets with higher speeds acted as boundaries to neighborhoods (Grannis 1998). In a study emphasizing the importance of scale on segregation patterns, the researchers posit that "It seems plausible that the built environment (including highways, street networks, railroads, and public transportation systems) may influence residential segregation patterns (and vice versa)" (Reardon et al. 2008 p. 509). In a legal review, Schindler (2015) noted that infrastructure's accessibility "can shape the demographics of a city and isolate a neighborhood from those surrounding it, often intentionally" (Schindler 2015 p. 1939). Schindler goes on to note that the built environment controls human behavior by constraining physical movement (Schindler 2015). Restrictive bridges constrain physical movement and are therefore of interest to this study.

The second focus argues that in the perception of the built environment as technical engineering objects, social values are often taken for granted (Grabowski et al. 2017; Leonardi and Barley 2010; Star 1999; Star and Bowker 2006). A theoretical study chronicling internet infrastructure argues the taken-for-granted assumption is that it will "democratize" knowledge by extending the reach and access of knowledge, but they observe that internet infrastructure often fails in low-income and developing contexts. Even with advances in the internet there are unforeseen access and usability barriers that were not known until these breakdowns were prominent (DiMaggio et al. 2001; Star and Bowker 2006). When national and local governments differ about the aim of infrastructure, such conflicts can lead to variation in bridge design (Desai and Armanios 2018). Generally speaking, this literature is comprised of a rich set of detailed qualitative studies, with few large-scale quantitative analyses (Desai and Armanios 2018, as a rare exception). It is not yet clear how widespread are the social impacts from the built environment, especially the scope to which the built environment affects marginalized populations. In fact, prior studies have noted this is largely ignored and not subject to the same breadth and depth of public and governmental review (Schindler 2015). Recent studies utilizing social network analysis have attempted to develop frameworks to quantify social sustainability and satisfaction perceptions, but both note the prohibitive costs in time and resources to properly map social networks and the likelihood that results are specific to the community of study (Doloi 2018; Wang et al. 2018). Both studies focused on the perceptions of the value of the built environment and not on their actual effects.

Section I Coarsened Exact Matching Statistics

Coarsened Exact Matching (CEM) is a preprocessing algorithm used to eliminate individuals in a treated and control group based on their dissimilarity from an identified attribute. The algorithm follows three steps: 1) temporarily coarsens a variable by dividing the values of that variable into sub strata based on defined cut-offs or a number of sub strata similar to a histogram, 2) sort all individuals into these strata based on the values of that variable, and 3) remove from the data any individuals without a at least one individual in the control and treated groups (Iacus et al. 2009).

Table 61. Pre- and post-coarsened exact matching statistics for five types of bridges

	New Mini Bridges		New Low Bridges		New Medium Bridges		New High Bridges		New Super Bridges	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Original	12784	84	12624	244	10028	2840	10716	2152	10232	2636
Matched	617	42	6052	166	7897	1989	8890	1472	8310	1708
Not-matched	12167	42	6572	78	2131	851	1826	680	1922	928
% Matched	4.8%	50.0%	47.9%	68.0%	78.7%	70.0%	83.0%	68.4%	81.2%	64.8%
% Not-matched	95.2%	50.0%	52.1%	32.0%	21.3%	30.0%	17.0%	31.6%	18.8%	35.2%

Table 62. Pre- and post-coarsened exact matching statistics for two types of bridges and all bridges

	New Under 14-ft Bridges		New Over 14-ft Bridges		All New Bridges	
	Control	Treatment	Control	Treatment	Control	Treatment
Original	12548	320	8628	4240	4528	8340
Matched	6739	216	7406	2952	4320	2305
Not-matched	5809	104	1222	1288	208	6035
% Matched	53.7%	67.5%	85.8%	69.6%	95.4%	27.6%
% Not-matched	46.3%	32.5%	14.2%	30.4%	4.6%	72.4%

Table 63. CEM pre-match statistics for restricted bridges

	All New Bridges Pre-match Statistics				
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	320	320	320	320	320
Control Sample Size	12548	12548	12548	12548	12548
statistic	-20882413	-412242	83.911	-11.395	-12.149
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.407	0.304
min	-463151	0.000	0.000	0.000	0.000
25%	-1424389	-27974.000	296.000	-8.000	-20.000
50%	-8595211	-226349	-116	-13	-10
75%	-57608686	-601166	74	-16	-10
max	621328291	18986580	2045	56	0
Overall Multivariate Imbalance Measure	0.969	0.969	0.969	0.969	0.969
Local Common Support (%)	1.045	1.045	1.045	1.045	1.045
T-Test: Statistic	-4.272	-4.549	0.731	-11.533	-13.668
T-Test: P-Value	0.000	0.000	0.465	< 2.22e-16	< 2.22e-16
KS-Test: Statistic	0.208	0.322	0.095	0.423	0.304
KS-Test: P-Value	0.000	< 2.22e-16	0.007	< 2.22e-16	< 2.22e-16
BEST: Stat Diff	-3942986	-132312	80	-12.496	-12.174
BEST: Sigma Diff	-6758625	-193481	-360	-5.398	2.369
BEST: Effect Size	-0.541	-0.912	0.043	-1.895	-0.722

Table 64. CEM post-match statistics for restricted bridges

	All New Bridges Post-match Statistics				
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	216	216	216	216	216
Control Sample Size	6739	6739	6739	6739	6739
statistic	-20573679	-242527	-421.703	-11.872	-6.097
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.624	0.165
min	-463151	0.000	0.000	0.000	0.000
25%	-971009	-2773.000	-86.000	-6.000	-10.000
50%	-2862736	-104010.000	-623.000	-11.000	-10.000
75%	-17348089	-300766	-663.000	-16.000	-10.000
max	8494504	-327394	-700.000	1.000	0.000
Overall Multivariate Imbalance Measure (L1)	0.993	0.993	0.993	0.993	0.993
Local Common Support (%)	0.530	0.530	0.530	0.530	0.530
T-Test: Statistic	0.185	0.209	0.177	-0.703	0.000
T-Test: P-Value	0.853	0.835	0.859	0.482	1.000
KS-Test: Statistic	0.178	0.129	0.069	0.178	0.000
KS-Test: P-Value	0.081	0.373	0.969	0.081	1.000
BEST: Stat Diff	-3297184	-55138.430	-2936	-10.891	-14.123
BEST: Sigma Diff	-4001057	-86201.992	-615	-5.829	-6.035
BEST: Effect Size	-1.073	-0.871	-3.572	-2.515	-1.884

Table 65. CEM pre-match statistics for non-restricted bridges

All New Bridges Pre-match Statistics					
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	4240	4240	4240	4240	4240
Control Sample Size	8628	8628	8628	8628	8628
statistic	-21000021	-217380	-242.186	-10.254	-9.167
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.458	0.229
min	-121572	0.000	0.000	0.000	0.000
25%	-2341801	0.000	-187.000	-5.000	-10.000
50%	-10055025	-99077	-351	-10	-10
75%	-44677997	-387943	-371	-15	-10
max	51715434	12236365	-256	41	0
Overall Multivariate Imbalance Measure	0.816	0.816	0.816	0.816	0.816
Local Common Support (%)	8.553	8.553	8.553	8.553	8.553
T-Test: Statistic	-13.173	-7.542	-7.412	-35.394	-27.696
T-Test: P-Value	< 2.22e-16	0.000	0.000	< 2.22e-16	< 2.22e-16
KS-Test: Statistic	0.322	0.250	0.088	0.465	0.229
KS-Test: P-Value	< 2.22e-16	< 2.22e-16	< 2.22e-16	< 2.22e-16	< 2.22e-16
BEST: Stat Diff	-5677023	-41670	-251	-9.333	-9.197
BEST: Sigma Diff	-8243709	-90122	-157	-5.524	0.621
BEST: Effect Size	-0.791	-0.642	-0.150	-1.843	-0.520

Table 66. CEM post-match statistics for non-restricted bridges

	All New Bridges Post-match Statistics				
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	2952	2952	2952	2952	2952
Control Sample Size	7406	7406	7406	7406	7406
statistic	-8637346	-98227	-134.606	-5.977	-6.616
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.503	0.175
min	-121572	0.000	0.000	0.000	0.000
25%	-1388822	0.000	-136.000	-4.000	-10.000
50%	-4297392	-27974.000	-242.000	-7.000	0.000
75%	-12755394	-145372	-159.000	-9.000	0.000
max	7833782	72667	496.000	2.000	0.000
Overall Multivariate Imbalance Measure (L1)	0.868	0.868	0.868	0.868	0.868
Local Common Support (%)	7.234	7.234	7.234	7.234	7.234
T-Test: Statistic	1.584	-1.299	0.346	-1.658	0.000
T-Test: P-Value	0.113	0.194	0.729	0.097	1.000
KS-Test: Statistic	0.099	0.079	0.030	0.139	0.000
KS-Test: P-Value	0.705	0.909	1.000	0.286	1.000
BEST: Stat Diff	-3696689	-9494.779	-2325	-6.764	-11.786
BEST: Sigma Diff	-3550751	-27138.878	-413	-3.641	-4.974
BEST: Effect Size	-1.282	-0.482	-2.952	-2.390	-1.206

Table 67. CEM pre-match statistics for all bridges

All New Bridges CEM Pre-match Statistics					
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	8340	8340	8340	8340	8340
Control Sample Size	4528	4528	4528	4528	4528
statistic	52774263	598331	237.493	14.620	13.445
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.689	0.336
min	121572	0.000	0.000	0.000	0.000
25%	3063833	0.000	223.000	4.000	20.000
50%	13727566	93310	384	10	20
75%	60877935	510717	464	20	10
max	980935185	11688321	256	125	0
Overall Multivariate Imbalance Measure	0.811	0.811	0.811	0.811	0.811
Local Common Support (%)	7.078	7.078	7.078	7.078	7.078
T-Test: Statistic	-50.129	-25.765	-7.885	-80.600	-42.074
T-Test: P-Value	< 2.22e-16	< 2.22e-16	0.000	< 2.22e-16	< 2.22e-16
KS-Test: Statistic	0.657	0.437	0.099	0.756	0.336
KS-Test: P-Value	< 2.22e-16	< 2.22e-16	< 2.22e-16	< 2.22e-16	< 2.22e-16
BEST: Stat Diff	-7528355	-36954	-259	-8.262	-13.498
BEST: Sigma Diff	-11450446	-84422	-190	-6.227	2.429
BEST: Effect Size	-0.889	-0.607	-0.160	-1.872	-0.800

Table 68. CEM post-match statistics for all bridges

All New Bridges CEM Post-match Statistics					
Variables	Land Area	Water Area	Tract Population	Total Bridges	Treatment Time
Treated Sample Size	2305	2305	2305	2305	2305
Control Sample Size	4320	4320	4320	4320	4320
statistic	1505654	24265	-21.416	2.018	5.115
type	(diff)	(diff)	(diff)	(diff)	(diff)
L1	0.000	0.000	0.000	0.598	0.100
min	121572	0.000	0.000	0.000	0.000
25%	852300	0.000	66.000	1.000	10.000
50%	1418126	0.000	34.000	2.000	10.000
75%	1944250	38284	34.000	3.000	0.000
max	-3173709	327394	-90.000	0.000	0.000
Overall Multivariate Imbalance Measure (L1)	0.923	0.923	0.923	0.923	0.923
Local Common Support (%)	4.907	4.907	4.907	4.907	4.907
T-Test: Statistic	-1.803	0.262	0.125	-1.283	0.000
T-Test: P-Value	0.071	0.793	0.900	0.199	1.000
KS-Test: Statistic	0.158	0.040	0.040	0.168	0.000
KS-Test: P-Value	0.159	1.000	1.000	0.114	1.000
BEST: Stat Diff	-1924188	-1.570	-2121	-2.155	-9.590
BEST: Sigma Diff	-817346	-1.599	-404	-1.078	-6.486
BEST: Effect Size	-2.607	-0.005	-2.863	-2.806	-1.011

Table 69. CEM pre-match statistics for five types of bridges

	Pre-match Statistics															
Variables	Treated Sample Size	Control Sample Size	statistic	type	L1	min	25%	50%	75%	max	Overall Multivariate Imbalance Measure	Local Common Support (%)	T-Test: Statistic	T-Test: P-Value	KS-Test: Statistic	KS-Test: P-Value
New Mini Bridges																
Land Area	84	12784	-2.29E+06	(diff)	5.55E-17	-6.23E+05	-2.99E+05	-4.56E+05	-3.11E+07	7.84E+08	9.83E-01	5.43E-01	-3.37E-01	7.37E-01	1.50E-01	4.59E-02
Water Area	84	12784	-6.92E-02	(diff)	5.55E-17	0.00E+00	-1.69E-03	-1.38E-02	-1.60E-01	3.49E-01	9.83E-01	5.43E-01	-4.71E+00	9.63E-06	2.99E-01	6.36E-07
Population Density	84	12784	1.08E+03	(diff)	5.55E-17	0.00E+00	7.00E+01	6.20E+02	9.11E+02	2.04E+04	9.83E-01	5.43E-01	8.93E+00	4.29E-14	1.98E-01	2.79E-03
Total Bridges	84	12784	-6.61E+00	(diff)	4.28E-01	0.00E+00	-6.00E+00	-8.00E+00	-9.00E+00	8.20E+01	9.83E-01	5.43E-01	-4.24E+00	5.72E-05	4.60E-01	8.88E-16
Time Period	84	12784	-8.76E+00	(diff)	2.19E-01	-1.00E+01	-1.00E+01	0.00E+00	-1.00E+01	0.00E+00	9.83E-01	5.43E-01	-5.36E+00	7.05E-07	2.19E-01	6.72E-04
New Low Bridges																
Land Area	244	12624	-2.93E+07	(diff)	0.00E+00	-4.63E+05	-2.09E+06	-1.17E+07	-6.69E+07	6.21E+08	9.55E-01	1.71E+00	-4.80E+00	2.69E-06	2.47E-01	3.76E-13
Water Area	244	12624	-2.70E-02	(diff)	0.00E+00	0.00E+00	-1.29E-03	-6.09E-03	-1.08E-02	3.50E-01	9.55E-01	1.71E+00	-4.18E+00	4.10E-05	2.94E-01	< 2.22e-16
Population Density	244	12624	1.34E+03	(diff)	0.00E+00	0.00E+00	7.49E+01	6.23E+02	1.54E+03	2.17E+04	9.55E-01	1.71E+00	2.18E+01	< 2.22e-16	2.65E-01	4.89E-15
Total Bridges	244	12624	-1.31E+01	(diff)	4.16E-01	0.00E+00	-9.00E+00	-1.50E+01	-1.90E+01	5.60E+01	9.55E-01	1.71E+00	-1.12E+01	< 2.22e-16	4.36E-01	< 2.22e-16
Time Period	244	12624	-1.26E+01	(diff)	3.14E-01	0.00E+00	-2.00E+01	-1.00E+01	-1.00E+01	0.00E+00	9.55E-01	1.71E+00	-1.21E+01	< 2.22e-16	3.14E-01	< 2.22e-16
New Medium Bridges																
Land Area	2840	10028	-1.56E+07	(diff)	5.55E-17	-1.22E+05	-2.27E+06	-1.05E+07	-3.65E+07	3.21E+08	7.76E-01	1.31E+01	-8.92E+00	< 2.22e-16	2.89E-01	< 2.22e-16
Water Area	2840	10028	-1.35E-02	(diff)	5.55E-17	0.00E+00	-1.73E-04	-5.50E-03	-9.71E-03	1.58E-01	7.76E-01	1.31E+01	-9.01E+00	< 2.22e-16	2.34E-01	< 2.22e-16
Population Density	2840	10028	1.46E+03	(diff)	5.55E-17	0.00E+00	6.97E+01	8.29E+02	1.89E+03	8.56E+03	7.76E-01	1.31E+01	3.45E+01	< 2.22e-16	2.84E-01	< 2.22e-16
Total Bridges	2840	10028	-1.06E+01	(diff)	4.64E-01	0.00E+00	-6.00E+00	-1.10E+01	-1.50E+01	4.70E+01	7.76E-01	1.31E+01	-3.10E+01	< 2.22e-16	4.62E-01	< 2.22e-16
Time Period	2840	10028	-1.17E+01	(diff)	2.92E-01	0.00E+00	-2.00E+01	-1.00E+01	-1.00E+01	0.00E+00	7.76E-01	1.31E+01	-3.35E+01	< 2.22e-16	2.92E-01	< 2.22e-16
New High Bridges																
Land Area	2152	10716	-2.96E+07	(diff)	0.00E+00	-1.22E+05	-4.25E+06	-1.64E+07	-6.22E+07	3.02E+08	7.86E-01	1.11E+01	-1.36E+01	< 2e-16	3.67E-01	< 2.22e-16
Water Area	2152	10716	-2.43E-03	(diff)	0.00E+00	0.00E+00	-2.27E-04	-4.51E-03	-3.04E-03	1.88E-01	7.86E-01	1.11E+01	-1.74E+00	8.20E-02	2.28E-01	< 2.22e-16
Population Density	2152	10716	1.64E+03	(diff)	0.00E+00	0.00E+00	9.66E+01	9.14E+02	2.15E+03	8.56E+03	7.86E-01	1.11E+01	4.10E+01	< 2e-16	3.63E-01	< 2.22e-16
Total Bridges	2152	10716	-1.34E+01	(diff)	4.78E-01	0.00E+00	-8.00E+00	-1.40E+01	-1.90E+01	4.10E+01	7.86E-01	1.11E+01	-3.21E+01	< 2e-16	4.77E-01	< 2.22e-16
Time Period	2152	10716	-4.55E+00	(diff)	1.17E-01	0.00E+00	-1.00E+01	0.00E+00	0.00E+00	0.00E+00	7.86E-01	1.11E+01	-9.99E+00	< 2e-16	1.15E-01	< 2.22e-16
New Super Bridges																
Land Area	2636	10232	-2.69E+07	(diff)	5.55E-17	-2.62E+05	-2.96E+06	-1.38E+07	-5.15E+07	5.17E+07	7.58E-01	1.28E+01	-1.32E+01	< 2.22e-16	3.29E-01	< 2.22e-16
Water Area	2636	10232	-8.36E-03	(diff)	5.55E-17	0.00E+00	-1.64E-04	-4.79E-03	-8.65E-03	1.58E-01	7.58E-01	1.28E+01	-5.76E+00	8.99E-09	2.26E-01	< 2.22e-16
Population Density	2636	10232	1.59E+03	(diff)	5.55E-17	0.00E+00	9.55E+01	9.28E+02	2.07E+03	8.56E+03	7.58E-01	1.28E+01	3.88E+01	< 2.22e-16	3.30E-01	< 2.22e-16
Total Bridges	2636	10232	-1.12E+01	(diff)	4.43E-01	0.00E+00	-7.00E+00	-1.30E+01	-1.60E+01	4.10E+01	7.58E-01	1.28E+01	-3.14E+01	< 2.22e-16	4.47E-01	< 2.22e-16
Time Period	2636	10232	-5.29E+00	(diff)	1.32E-01	0.00E+00	-1.00E+01	0.00E+00	0.00E+00	0.00E+00	7.58E-01	1.28E+01	-1.35E+01	< 2.22e-16	1.32E-01	< 2.22e-16

Table 70. CEM post-match statistics for five types of bridges

	Post-match Statistics															
Variables	Treated Sample Size	Control Sample Size	statistic	type	L1	min	25%	50%	75%	max	Overall Multivariate Imbalance Measure	Local Common Support (%)	T-Test: Statistic	T-Test: P-Value	KS-Test: Statistic	KS-Test: P-Value
New Mini Bridges																
Land Area	42	617	-3.71E+06	(diff)	0.00E+00	-4.97E+05	-3.15E+05	4.66E+05	-1.10E+06	2.73E+06	9.87E-01	1.62E+00	1.07E-01	0.92	2.87E-01	0.00
Water Area	42	617	-1.78E+05	(diff)	0.00E+00	0.00E+00	0.00E+00	-1.04E+05	-4.53E+05	1.25E+05	9.87E-01	1.62E+00	-4.77E-02	0.96	1.19E-01	0.47
Population Density	42	617	1.41E+03	(diff)	0.00E+00	0.00E+00	1.04E+03	2.30E+03	1.71E+03	1.18E+02	9.87E-01	1.62E+00	1.13E-01	0.91	7.92E-02	0.91
Total Bridges	42	617	-4.57E+00	(diff)	3.56E-01	0.00E+00	-5.00E+00	-4.00E+00	-4.00E+00	0.00E+00	9.87E-01	1.62E+00	-5.91E-01	0.55	1.68E-01	0.11
Time Period	42	617	-4.27E+00	(diff)	1.41E-01	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	9.87E-01	1.62E+00	0.00E+00	1.00	0.00E+00	1.00
New Low Bridges																
Land Area	166	6052	-2.17E+07	(diff)	0.00E+00	-4.63E+05	-1.93E+06	-5.74E+06	-1.74E+07	8.49E+06	9.91E-01	4.72E-01	7.41E-02	0.94	1.58E-01	0.16
Water Area	166	6052	-2.77E+05	(diff)	0.00E+00	0.00E+00	-5.23E+03	-8.27E+04	-3.29E+05	4.99E+05	9.91E-01	4.72E-01	5.45E-01	0.59	1.29E-01	0.37
Population Density	166	6052	-7.30E+02	(diff)	0.00E+00	0.00E+00	-3.37E+02	-9.14E+02	-1.02E+03	-2.47E+02	9.91E-01	4.72E-01	1.63E-01	0.87	5.94E-02	0.99
Total Bridges	166	6052	-1.24E+01	(diff)	6.31E-01	0.00E+00	-8.00E+00	-1.30E+01	-1.80E+01	2.00E+00	9.91E-01	4.72E-01	-4.81E-01	0.63	1.39E-01	0.29
Time Period	166	6052	-6.02E+00	(diff)	1.13E-01	0.00E+00	-1.00E+01	-1.00E+01	-1.00E+01	0.00E+00	9.91E-01	4.72E-01	0.00E+00	1.00	0.00E+00	1.00
New Medium Bridges																
Land Area	1989	7897	1.06E+07	(diff)	5.55E-17	1.22E+05	1.41E+06	4.52E+06	1.40E+07	-1.85E+07	9.10E-01	5.52E+00	1.61E+00	0.11	9.90E-02	0.71
Water Area	1989	7897	1.20E+05	(diff)	5.55E-17	0.00E+00	0.00E+00	4.62E+04	1.89E+05	-8.19E+05	9.10E-01	5.52E+00	-8.97E-01	0.37	7.92E-02	0.91
Population Density	1989	7897	1.24E+02	(diff)	5.55E-17	0.00E+00	1.55E+02	1.63E+02	1.62E+02	-1.28E+02	9.10E-01	5.52E+00	2.17E-01	0.83	1.98E-02	1.00
Total Bridges	1989	7897	7.32E+00	(diff)	5.36E-01	0.00E+00	5.00E+00	8.00E+00	1.10E+01	-1.00E+00	9.10E-01	5.52E+00	-1.21E+00	0.23	1.19E-01	0.47
Time Period	1989	7897	8.66E+00	(diff)	2.34E-01	0.00E+00	2.00E+01	1.00E+01	1.00E+01	0.00E+00	9.10E-01	5.52E+00	0.00E+00	1.00	0.00E+00	1.00
New High Bridges																
Land Area	1472	8890	-1.53E+07	(diff)	1.11E-16	-1.22E+05	-2.24E+06	-6.99E+06	-2.08E+07	-8.22E+06	9.23E-01	3.38E+00	1.43E+00	0.15	1.19E-01	0.47
Water Area	1472	8890	-1.48E+05	(diff)	1.11E-16	0.00E+00	0.00E+00	-5.80E+04	-1.89E+05	9.80E+05	9.23E-01	3.38E+00	-1.36E-01	0.89	3.96E-02	1.00
Population Density	1472	8890	-1.64E+02	(diff)	1.11E-16	0.00E+00	-1.57E+02	-2.13E+02	-1.74E+02	3.77E+02	9.23E-01	3.38E+00	2.65E-01	0.79	2.97E-02	1.00
Total Bridges	1472	8890	-8.19E+00	(diff)	5.21E-01	0.00E+00	-6.00E+00	-9.00E+00	-1.10E+01	3.00E+00	9.23E-01	3.38E+00	-6.80E-01	0.50	6.93E-02	0.97
Time Period	1472	8890	-2.26E+00	(diff)	7.02E-02	0.00E+00	0.00E+00	-1.00E+01	0.00E+00	0.00E+00	9.23E-01	3.38E+00	1.25E-15	1.00	0.00E+00	1.00
New Super Bridges																
Land Area	1708	8310	-1.17E+07	(diff)	0.00E+00	-2.62E+05	-1.78E+06	-5.10E+06	-1.73E+07	3.73E+06	9.01E-01	5.30E+00	1.16E+00	0.25	8.91E-02	0.82
Water Area	1708	8310	-1.11E+05	(diff)	0.00E+00	0.00E+00	0.00E+00	-4.01E+04	-1.72E+05	7.27E+04	9.01E-01	5.30E+00	-1.47E+00	0.14	7.92E-02	0.91
Population Density	1708	8310	-2.26E+02	(diff)	0.00E+00	0.00E+00	-1.76E+02	-3.38E+02	-2.60E+02	-2.58E+02	9.01E-01	5.30E+00	2.13E-01	0.83	3.96E-02	1.00
Total Bridges	1708	8310	-7.03E+00	(diff)	4.97E-01	0.00E+00	-4.00E+00	-8.00E+00	-1.00E+01	2.00E+00	9.01E-01	5.30E+00	-1.05E+00	0.29	1.09E-01	0.59
Time Period	1708	8310	-3.36E+00	(diff)	6.91E-02	0.00E+00	-1.00E+01	0.00E+00	0.00E+00	0.00E+00	9.01E-01	5.30E+00	0.00E+00	1.00	0.00E+00	1.00

Section J Dijkstra's algorithm

Dijkstra's shortest path algorithm was first published in 1959. The algorithm finds the shortest path between nodes in a graph. A common variant as employed in this paper fixes one node as the source and calculates distances from that node. ("Algorithms used by the ArcGIS Network Analyst extension—Help | ArcGIS Desktop" n.d.)

Pseudocode (Yan 2013)

$dist[s] \leftarrow 0$ (distance to source vertex is zero)

for all $v \in V - s$

do $dist[v] \leftarrow \infty$ (set all other distances to infinity)

$S \leftarrow \emptyset$ (S, the set of visited vertices is initially empty)

$Q \leftarrow V$ (Q, the queue initially contains all vertices)

while $Q \neq \emptyset$ (while the queue is not empty)

do $u \leftarrow mindistance(Q, dist)$ (select the element of Q with the min. distance)

$S \leftarrow S \cup \{u\}$ (add u to list of visited vertices)

for all $v \in neighbors[u]$

do if $dist[v] > dist[u] + w(u, v)$ (if new shortest path found)

then $d[v] \leftarrow d[u] + w(u, v)$ (set new value of shortest path)

return $dist$

Section K CEM algorithm

Coarsened exact matching is a data preprocessing method. The goal of the algorithm is to minimize the differences between a treatment and control group based on pre-treatment covariates. (Iacus et al. 2009) To do this, the authors use a set of matching controls that are designed to rule out other reasons for bridge placement beyond the socioeconomic variables of interest. These include physical impediments and terrain (water and land area), demand (population), overall construction trends (total bridges), and time (time period) as pre-treatment covariates. With the exception of time period, these four variables were found to have high correlation with most of the independent variables used in this analysis. These variables were selected in order to find tracts that were similar in geophysical, population, and infrastructure. By matching on these similarities, the authors goal is to minimize differences between the control and treatment groups. The authors then contrast the treatment and control groups before and after the match was conducted. The t-tests and ks-tests were no longer significant, and the Bayesian tests also saw a move toward a more unified distribution which indicates greater treatment-control group balance.

Algorithm Steps

"1. Temporarily coarsen each control variable in X as much as you are willing, for the purposes of matching. For example, years of education might be coarsened into grade school, middle school, high school, college, graduate school. Most researchers are intimately familiar with the concept and practice of coarsening, as it is widely used in applied data analyses in many fields, although unlike its present use coarsening for data analysis involves a permanent removal of information from the analysis and ultimate estimates.

"2. Sort all units into strata, each of which has the same values of the coarsened X.

"3. Prune from the data set the units in any stratum that do not include at least one treated and one control unit." (Iacus et al. 2009)

Notation

The following symbols are used in this paper:

$\boldsymbol{C}$ = a vector of lagged control variables;

d = a dichotomous variable designating the interaction of the group and treatment variables;

e = the error term;

f = a time-invariant tract fixed effect;

g = a dummy variable designating the tract as receiving a new bridge at any time (group term);

i = the tract index;

k = the index for a particular variable;

logit(p(x)) = the probability that a variable designating a new bridge was built in the preceding 10 years;

t = the year index;

$\boldsymbol{X}$ = a vector of variables of social interest;

x = a dummy variable designating the tract received a new bridge treatment (treatment term);

y = either a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years or the count of such bridges;

z = a social equity variable of interest;

β_0 = the intercept;

β_1 = the event study coefficient for the treatment and group interaction term;

β_2 = the coefficient for the treatment term;

β_3 = the coefficient for the group term;

$\boldsymbol{\gamma_k}$ = a vector of control variable coefficients;

δ = a fixed effect for each census year;

λ = Lagrange multiplier that balances the tradeoff between the squared error loss and the L_1 penalty

Appendix II: Methodological Framework and Feasibility Study to Assess Social Equity Impacts of the Built Environment Supplemental Information

Section A Correlation Matrix and Graphics

Table 71. Correlation matrix for all variables

	newbridge	newbridge.over14	newbridge.under14.mod	bridge.new.total	bridge.new.over14	bridge.new.under14.mod	rur10m	rur4m	SHRWHTN.pct.lag	SHRBLKN.pct.lag	SHRAMIN.pct.lag	SHRAPIN.pct.lag	SHRHSPN.pct.lag	OUTBORN.ihs.lag	FORBORN.ihs.lag	FHHTOT.pct.lag	MCWKID.pct.lag	MHWKID.ihs.lag	MHNKID.ihs.lag	CHILD.pct.lag	COMMUT2.lag	COMMUT4.lag	COMMUTX.lag	TRVLPBN.ihs.lag	EDUC8.lag	EDUC15.pct.lag	WKHOME.ihs.lag	WRCNTYN.lag	OCC5.lag	OCC9.ihs.lag	ARMFRM.ihs.lag	ARMFRF.ihs.lag	AVHHIN.2010real.ihs.lag	AVHHINN.2010real.ihs.lag	POVRATN.pct.lag	WELFARN.pct.lag	VACHU.pct.lag	VACOCC.lag	NEWHOUS.pct.lag	OWNRNT.pct.lag	YEAR
newbridge	1.00	0.59	0.11	0.82	0.50	0.11	0.06	0.15	0.07	-0.10	-0.05	-0.03	-0.07	-0.07	-0.07	-0.13	0.08	-0.04	-0.08	0.01	-0.01	-0.04	-0.05	-0.11	-0.02	-0.05	0.02	-0.02	0.01	0.04	0.00	-0.02	-0.03	-0.04	-0.08	-0.08	-0.08	-0.01	0.02	0.01	-0.06
newbridge.over14	0.59	1.00	0.14	0.66	0.86	0.14	0.02	0.04	0.03	-0.04	-0.04	0.00	-0.04	-0.04	-0.02	-0.05	0.02	-0.03	-0.02	0.00	-0.03	-0.05	-0.06	-0.01	0.02	-0.04	-0.01	-0.01	-0.01	-0.01	0.00	0.01	-0.03	-0.03	-0.02	-0.02	-0.02	-0.01	-0.01	0.00	-0.06
newbridge.under14.mod	0.11	0.14	1.00	0.24	0.16	1.00	0.00	0.01	-0.02	0.01	-0.01	-0.01	-0.01	-0.01	-0.03	-0.01	-0.01	-0.02	-0.02	-0.01	-0.02	-0.01	-0.02	-0.01	0.01	-0.03	-0.03	-0.02	-0.01	0.00	-0.01	0.01	-0.02	-0.03	0.03	0.00	0.00	0.00	-0.04	0.00	-0.03
bridge.new.total	0.82	0.66	0.24	1.00	0.77	0.24	0.04	0.11	0.04	-0.08	-0.04	-0.02	-0.06	-0.07	-0.07	-0.11	0.05	-0.04	-0.07	0.00	-0.03	-0.05	-0.06	-0.09	0.00	-0.07	0.00	-0.02	0.00	0.02	0.01	0.00	-0.05	-0.06	-0.06	-0.07	-0.07	-0.01	0.00	0.01	-0.07
bridge.new.over14	0.50	0.86	0.16	0.77	1.00	0.16	0.01	0.02	0.02	-0.04	-0.03	0.01	-0.04	-0.04	-0.03	-0.04	0.01	-0.04	-0.02	-0.01	-0.04	-0.06	-0.06	-0.02	0.02	-0.05	-0.02	-0.01	-0.01	-0.01	0.01	0.02	-0.04	-0.04	-0.01	-0.02	-0.02	-0.01	-0.02	0.00	-0.06
bridge.new.under14.mod	0.11	0.14	1.00	0.24	0.16	1.00	0.00	0.01	-0.02	0.01	-0.01	-0.01	-0.01	-0.01	-0.03	-0.01	-0.01	-0.02	-0.02	-0.01	-0.02	-0.01	-0.02	-0.01	0.01	-0.03	-0.03	-0.02	-0.01	0.00	-0.01	0.01	-0.02	-0.03	0.03	0.00	0.00	0.00	-0.04	0.00	-0.03
rur10m	0.06	0.02	0.00	0.04	0.01	0.00	1.00	0.28	0.05	-0.05	-0.01	-0.02	-0.01	-0.01	-0.03	-0.08	0.10	-0.01	-0.04	0.05	0.00	-0.01	-0.02	-0.08	-0.03	-0.01	0.04	-0.04	0.01	0.10	0.00	-0.01	0.02	0.01	-0.06	-0.06	-0.05	0.08	0.01	-0.01	-0.03
rur4m	0.15	0.04	0.01	0.11	0.02	0.01	0.28	1.00	0.10	-0.15	-0.06	-0.02	-0.07	-0.04	-0.06	-0.25	0.22	-0.06	-0.17	0.06	0.08	0.01	-0.01	-0.21	-0.11	-0.04	0.08	0.00	0.03	0.13	0.03	-0.01	0.00	-0.02	-0.21	-0.19	-0.16	0.05	0.06	0.06	-0.06
SHRWHTN.pct.lag	0.07	0.03	-0.02	0.04	0.02	-0.02	0.05	0.10	1.00	-0.77	-0.17	-0.08	-0.19	0.07	0.39	-0.51	0.63	-0.01	0.13	0.13	0.25	0.03	-0.15	-0.04	0.02	-0.02	0.41	0.25	0.32	0.17	0.10	-0.05	0.51	0.48	-0.44	-0.51	-0.34	0.02	0.08	-0.16	-0.04
SHRBLKN.pct.lag	-0.10	-0.04	0.01	-0.08	-0.04	0.01	-0.05	-0.15	-0.77	1.00	0.21	0.02	0.08	0.06	-0.02	0.77	-0.36	0.25	0.23	0.24	-0.15	0.10	0.28	0.38	0.14	0.13	-0.14	-0.02	-0.16	-0.07	0.00	0.10	0.03	0.06	0.60	0.67	0.52	0.01	-0.07	-0.04	0.13
SHRAMIN.pct.lag	-0.05	-0.04	-0.01	-0.04	-0.03	-0.01	-0.01	-0.06	-0.17	0.21	1.00	0.11	0.24	0.14	0.03	0.29	-0.16	0.17	0.08	0.02	0.11	0.09	0.14	0.05	-0.10	0.21	-0.03	-0.02	-0.01	0.01	-0.05	0.04	0.05	0.06	0.26	0.26	0.26	0.03	0.00	-0.03	0.27
SHRAPIN.pct.lag	-0.03	0.00	-0.01	-0.02	0.01	-0.01	-0.02	-0.02	-0.08	0.02	0.11	1.00	0.13	0.20	0.31	0.07	-0.05	0.07	0.05	-0.13	0.20	0.17	0.21	0.13	-0.14	0.25	0.10	0.06	0.00	0.00	-0.03	0.04	0.08	0.09	0.17	0.03	0.10	0.08	0.00	-0.03	0.32
SHRHSPN.pct.lag	-0.07	-0.04	-0.01	-0.06	-0.04	-0.01	-0.01	-0.07	-0.19	0.08	0.24	0.13	1.00	0.50	0.17	0.31	-0.08	0.22	0.12	0.20	0.04	0.01	0.05	0.10	0.08	0.07	-0.04	-0.02	0.06	0.11	-0.03	-0.01	0.03	0.05	0.39	0.42	0.26	0.04	-0.03	-0.03	0.19
OUTBORN.ihs.lag	-0.07	-0.04	-0.01	-0.07	-0.04	-0.01	-0.01	-0.04	0.07	0.06	0.14	0.20	0.50	1.00	0.49	0.20	0.14	0.36	0.35	0.26	0.26	0.15	0.17	0.31	0.20	0.15	0.31	0.37	0.32	0.19	0.15	0.07	0.35	0.39	0.23	0.18	0.13	0.07	0.01	-0.01	0.18
FORBORN.ihs.lag	-0.07	-0.02	-0.03	-0.07	-0.03	-0.03	-0.03	-0.06	0.39	-0.02	0.03	0.31	0.17	0.49	1.00	0.10	0.40	0.33	0.57	0.33	0.26	0.35	0.32	0.63	0.34	0.07	0.49	0.55	0.43	0.15	0.17	0.06	0.63	0.67	0.07	0.02	0.01	0.09	0.01	-0.22	0.08
FHHTOT.pct.lag	-0.13	-0.05	-0.01	-0.11	-0.04	-0.01	-0.08	-0.25	-0.51	0.77	0.29	0.07	0.31	0.20	0.10	1.00	-0.42	0.37	0.37	0.26	0.04	0.12	0.26	0.38	0.12	0.27	-0.09	0.02	-0.06	-0.01	-0.04	0.05	0.16	0.21	0.80	0.85	0.69	0.03	-0.14	-0.11	0.36
MCWKID.pct.lag	0.08	0.02	-0.01	0.05	0.01	-0.01	0.10	0.22	0.63	-0.36	-0.16	-0.05	-0.08	0.14	0.40	-0.42	1.00	0.04	0.11	0.64	-0.06	-0.01	-0.08	0.12	0.17	-0.21	0.33	0.22	0.33	0.17	0.18	0.00	0.51	0.47	-0.38	-0.36	-0.34	-0.04	0.08	-0.15	-0.30
MHWKID.ihs.lag	-0.04	-0.03	-0.02	-0.04	-0.04	-0.02	-0.01	-0.06	-0.01	0.25	0.17	0.07	0.22	0.36	0.33	0.37	0.04	1.00	0.47	0.34	0.32	0.27	0.33	0.27	0.17	0.30	0.23	0.40	0.46	0.15	0.12	0.08	0.31	0.37	0.25	0.31	0.26	0.07	0.01	-0.13	0.35
MHNKID.ihs.lag	-0.08	-0.02	-0.02	-0.07	-0.02	-0.02	-0.04	-0.17	0.13	0.23	0.08	0.05	0.12	0.35	0.57	0.37	0.11	0.47	1.00	0.35	0.25	0.31	0.32	0.55	0.42	0.15	0.32	0.53	0.46	0.13	0.15	0.08	0.47	0.55	0.25	0.30	0.22	0.07	0.01	-0.19	0.17
CHILD.pct.lag	0.01	0.00	-0.01	0.00	-0.01	-0.01	0.05	0.06	0.13	0.24	0.02	-0.13	0.20	0.26	0.33	0.26	0.64	0.34	0.35	1.00	-0.19	-0.04	0.03	0.35	0.34	-0.14	0.15	0.16	0.32	0.11	0.14	0.01	0.48	0.48	0.17	0.31	0.10	-0.05	0.02	-0.17	-0.19
COMMUT2.lag	-0.01	-0.03	-0.02	-0.03	-0.04	-0.02	0.00	0.08	0.25	-0.15	0.11	0.20	0.04	0.26	0.26	0.04	-0.06	0.32	0.25	-0.19	1.00	0.53	0.41	-0.03	-0.27	0.53	0.32	0.52	0.37	0.29	0.04	0.08	0.24	0.29	-0.04	-0.05	0.04	0.10	0.06	-0.09	0.62
COMMUT4.lag	-0.04	-0.05	-0.01	-0.05	-0.06	-0.01	-0.01	0.01	0.03	0.10	0.09	0.17	0.01	0.15	0.35	0.12	-0.01	0.27	0.31	-0.04	0.53	1.00	0.79	0.34	-0.08	0.19	0.18	0.45	0.31	0.19	0.03	0.09	0.21	0.27	-0.06	0.07	0.04	0.06	0.03	-0.07	0.34
COMMUTX.lag	-0.05	-0.06	-0.02	-0.06	-0.06	-0.02	-0.02	-0.01	-0.15	0.28	0.14	0.21	0.05	0.17	0.32	0.26	-0.08	0.33	0.32	0.03	0.41	0.79	1.00	0.35	-0.11	0.37	0.15	0.36	0.30	0.10	0.04	0.10	0.18	0.23	0.05	0.17	0.12	0.07	0.01	-0.06	0.44
TRVLPBN.ihs.lag	-0.11	-0.01	-0.01	-0.09	-0.02	-0.01	-0.08	-0.21	-0.04	0.38	0.05	0.13	0.10	0.31	0.63	0.38	0.12	0.27	0.55	0.35	-0.03	0.34	0.35	1.00	0.39	-0.04	0.24	0.44	0.21	0.01	0.15	0.07	0.42	0.48	0.26	0.28	0.19	0.02	-0.07	-0.16	-0.07
EDUC8.lag	-0.02	0.02	0.01	0.00	0.02	0.01	-0.03	-0.11	0.02	0.14	-0.10	-0.14	0.08	0.20	0.34	0.12	0.17	0.17	0.42	0.34	-0.27	-0.08	-0.11	0.39	1.00	-0.47	0.14	0.39	0.35	0.06	0.18	0.03	0.11	0.20	0.19	0.21	0.01	0.00	-0.01	-0.07	-0.50
EDUC15.pct.lag	-0.05	-0.04	-0.03	-0.07	-0.05	-0.03	-0.01	-0.04	-0.02	0.13	0.21	0.25	0.07	0.15	0.07	0.27	-0.21	0.30	0.15	-0.14	0.53	0.19	0.37	-0.04	-0.47	1.00	0.18	0.11	0.10	0.04	-0.04	0.06	0.21	0.20	0.10	0.08	0.25	0.07	0.00	-0.07	0.87
WKHOME.ihs.lag	0.02	-0.01	-0.03	0.00	-0.02	-0.03	0.04	0.08	0.41	-0.14	-0.03	0.10	-0.04	0.31	0.49	-0.09	0.33	0.23	0.32	0.15	0.32	0.18	0.15	0.24	0.14	0.18	1.00	0.46	0.31	0.20	0.16	0.04	0.46	0.48	-0.10	-0.17	-0.08	0.10	0.03	-0.15	0.13
WRCNTYN.lag	-0.02	-0.01	-0.02	-0.02	-0.01	-0.02	-0.04	0.00	0.25	-0.02	-0.02	0.06	-0.02	0.37	0.55	0.02	0.22	0.40	0.53	0.16	0.52	0.45	0.36	0.44	0.39	0.11	0.46	1.00	0.65	0.20	0.21	0.09	0.35	0.45	-0.04	-0.06	-0.08	0.08	0.02	-0.14	0.09
OCC5.lag	0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.01	0.03	0.32	-0.16	-0.01	0.00	0.06	0.32	0.43	-0.06	0.33	0.46	0.46	0.32	0.37	0.31	0.30	0.21	0.35	0.10	0.31	0.65	1.00	0.16	0.16	0.06	0.27	0.35	-0.15	-0.09	-0.14	0.02	0.02	-0.11	0.11
OCC9.ihs.lag	0.04	-0.01	0.00	0.02	-0.01	0.00	0.10	0.13	0.17	-0.07	0.01	0.00	0.11	0.19	0.15	-0.01	0.17	0.15	0.13	0.11	0.29	0.19	0.10	0.01	0.06	0.04	0.20	0.20	0.16	1.00	0.13	0.08	0.18	0.20	0.01	0.00	0.00	0.01	0.06	-0.08	0.03
ARMFRM.ihs.lag	0.00	0.00	-0.01	0.01	0.01	-0.01	0.00	0.03	0.10	0.00	-0.05	-0.03	-0.03	0.15	0.17	-0.04	0.18	0.12	0.15	0.14	0.04	0.03	0.04	0.15	0.18	-0.04	0.16	0.21	0.16	0.13	1.00	0.14	0.13	0.15	-0.03	-0.05	-0.06	0.02	0.02	-0.05	-0.12
ARMFRF.ihs.lag	-0.02	0.01	0.01	0.00	0.02	0.01	-0.01	-0.01	-0.05	0.10	0.04	0.04	-0.01	0.07	0.06	0.05	0.00	0.08	0.08	0.01	0.08	0.09	0.10	0.07	0.03	0.06	0.04	0.09	0.06	0.08	0.14	1.00	0.04	0.05	0.03	0.03	0.04	0.01	0.01	-0.02	0.03
AVHHIN.2010real.ihs.lag	-0.03	-0.03	-0.02	-0.05	-0.04	-0.02	0.02	0.00	0.51	0.03	0.05	0.08	0.03	0.35	0.63	0.16	0.51	0.31	0.47	0.48	0.24	0.21	0.18	0.42	0.11	0.21	0.46	0.35	0.27	0.18	0.13	0.04	1.00	0.98	0.08	0.06	0.13	0.06	0.03	0.01	0.22
AVHHINN.2010real.ihs.lag	-0.04	-0.03	-0.03	-0.06	-0.04	-0.03	0.01	-0.02	0.48	0.06	0.06	0.09	0.05	0.39	0.67	0.21	0.47	0.37	0.55	0.48	0.29	0.27	0.23	0.48	0.20	0.20	0.48	0.45	0.35	0.20	0.15	0.05	0.98	1.00	0.12	0.11	0.14	0.07	0.04	0.03	0.23
POVRATN.pct.lag	-0.08	-0.02	0.03	-0.06	-0.01	0.03	-0.06	-0.21	-0.44	0.60	0.26	0.17	0.39	0.23	0.07	0.80	-0.38	0.25	0.25	0.17	-0.04	-0.06	0.05	0.26	0.19	0.10	-0.10	-0.04	-0.15	0.01	-0.03	0.03	0.08	0.12	1.00	0.83	0.68	0.06	-0.05	-0.09	0.21
WELFARN.pct.lag	-0.08	-0.02	0.00	-0.07	-0.02	0.00	-0.06	-0.19	-0.51	0.67	0.26	0.03	0.42	0.18	0.02	0.85	-0.36	0.31	0.30	0.31	-0.05	0.07	0.17	0.28	0.21	0.08	-0.17	-0.06	-0.09	0.00	-0.05	0.03	0.06	0.11	0.83	1.00	0.67	0.03	-0.11	-0.08	0.21
VACHU.pct.lag	-0.08	-0.02	0.00	-0.07	-0.02	0.00	-0.05	-0.16	-0.34	0.52	0.26	0.10	0.26	0.13	0.01	0.69	-0.34	0.26	0.22	0.10	0.04	0.04	0.12	0.19	0.01	0.25	-0.08	-0.08	-0.14	0.00	-0.06	0.04	0.13	0.14	0.68	0.67	1.00	0.22	-0.03	-0.09	0.35
VACOCC.lag	-0.01	-0.01	0.00	-0.01	-0.01	0.00	0.08	0.05	0.02	0.01	0.03	0.08	0.04	0.07	0.09	0.03	-0.04	0.07	0.07	-0.05	0.10	0.06	0.07	0.02	0.00	0.07	0.10	0.08	0.02	0.01	0.02	0.01	0.06	0.07	0.06	0.03	0.22	1.00	0.02	-0.03	0.11
NEWHOUS.pct.lag	0.02	-0.01	-0.04	0.00	-0.02	-0.04	0.01	0.06	0.08	-0.07	0.00	0.00	-0.03	0.01	0.01	-0.14	0.08	0.01	0.01	0.02	0.06	0.03	0.01	-0.07	-0.01	0.00	0.03	0.02	0.02	0.06	0.02	0.01	0.03	0.04	-0.05	-0.11	-0.03	0.02	1.00	0.00	0.00
OWNRNT.pct.lag	0.01	0.00	0.00	0.01	0.00	0.00	-0.01	0.06	-0.16	-0.04	-0.03	-0.03	-0.03	-0.01	-0.22	-0.11	-0.15	-0.13	-0.19	-0.17	-0.09	-0.07	-0.06	-0.16	-0.07	-0.07	-0.15	-0.14	-0.11	-0.08	-0.05	-0.02	0.01	0.03	-0.09	-0.08	-0.09	-0.03	0.00	1.00	-0.04
YEAR	-0.06	-0.06	-0.03	-0.07	-0.06	-0.03	-0.03	-0.06	-0.04	0.13	0.27	0.32	0.19	0.18	0.08	0.36	-0.30	0.35	0.17	-0.19	0.62	0.34	0.44	-0.07	-0.50	0.87	0.13	0.09	0.11	0.03	-0.12	0.03	0.22	0.23	0.21	0.21	0.35	0.11	0.00	-0.04	1.00

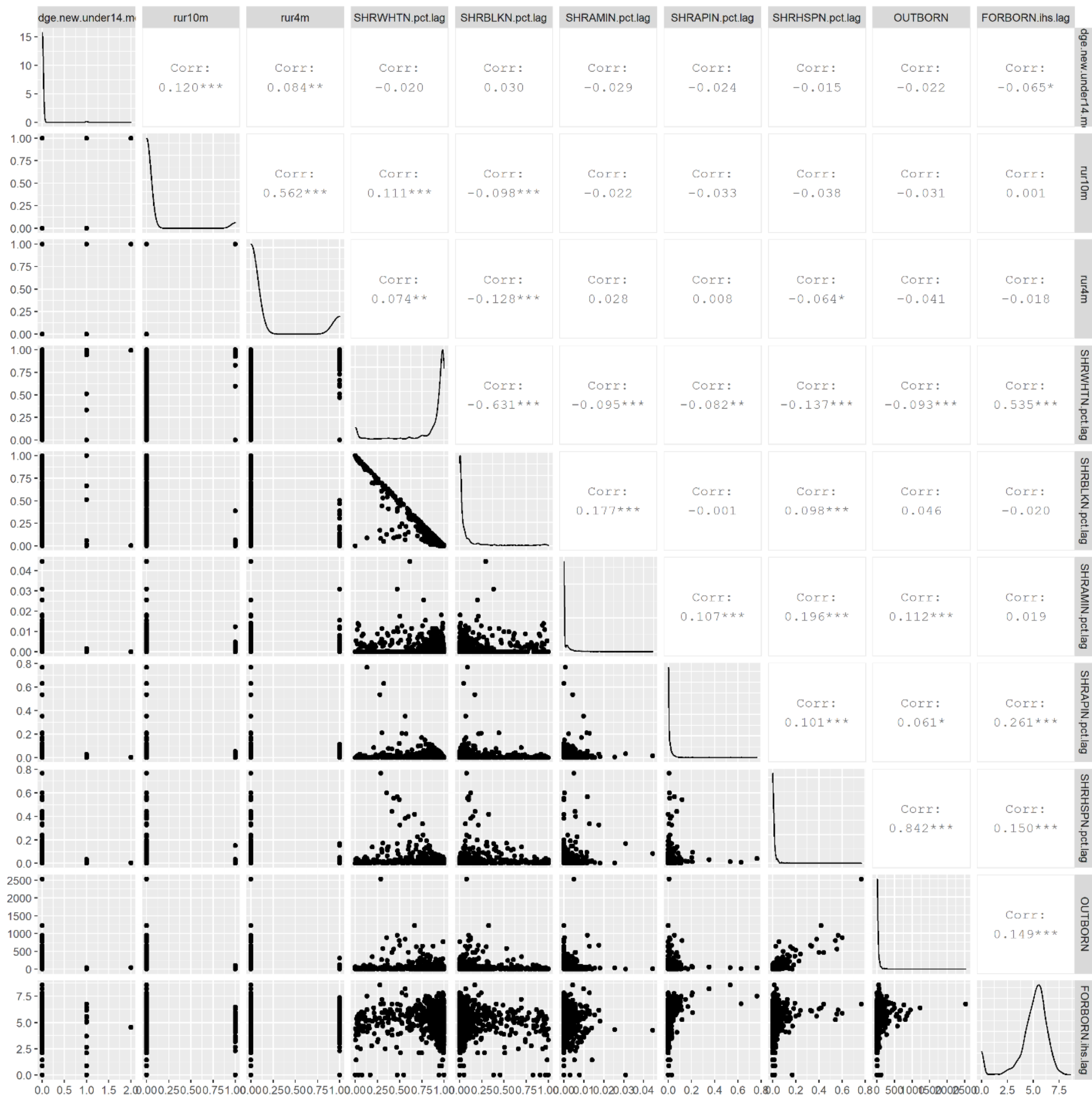

Fig. 68. Restrictive bridge demographic variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

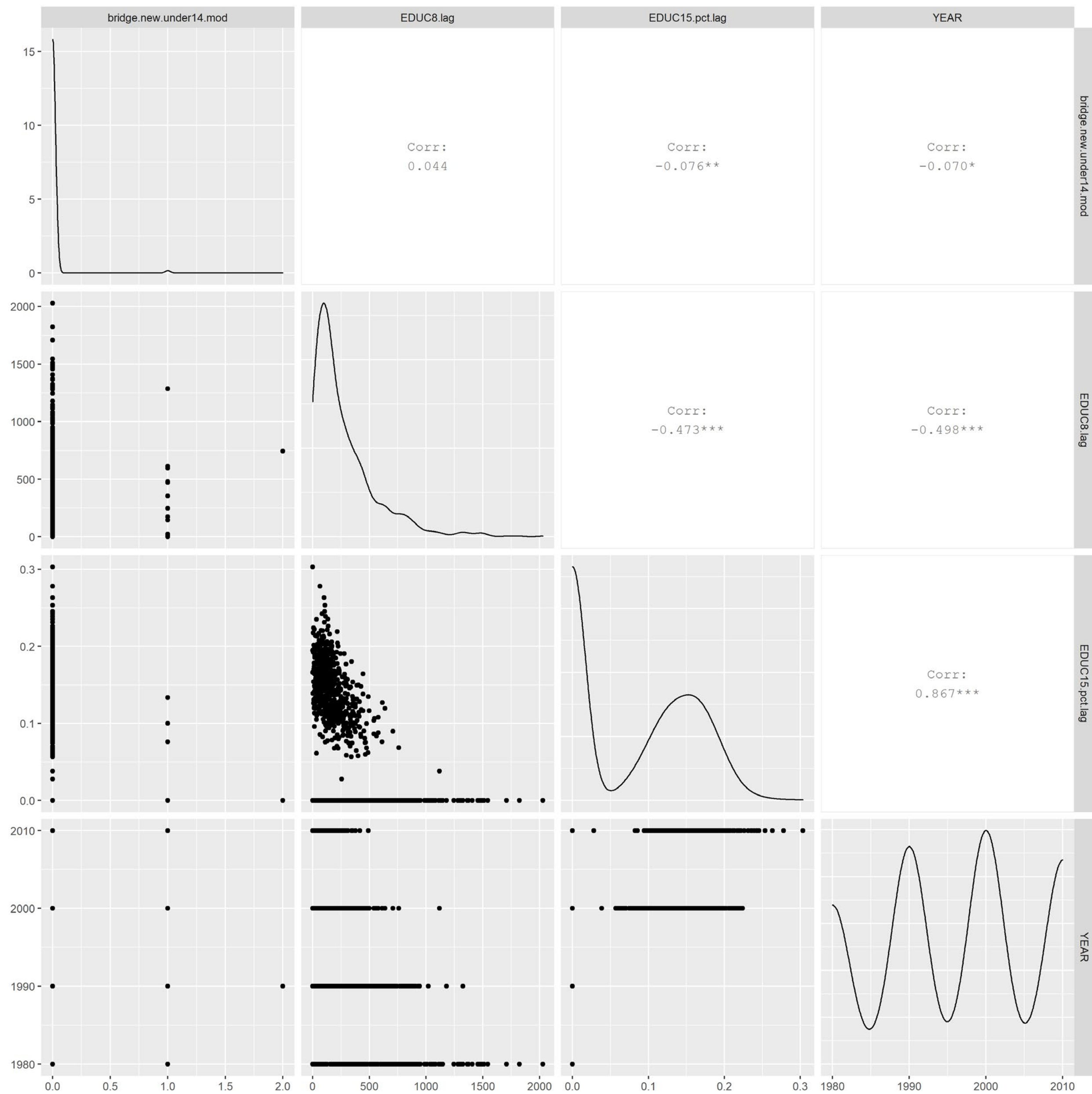

Fig. 69. Restrictive bridge education variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

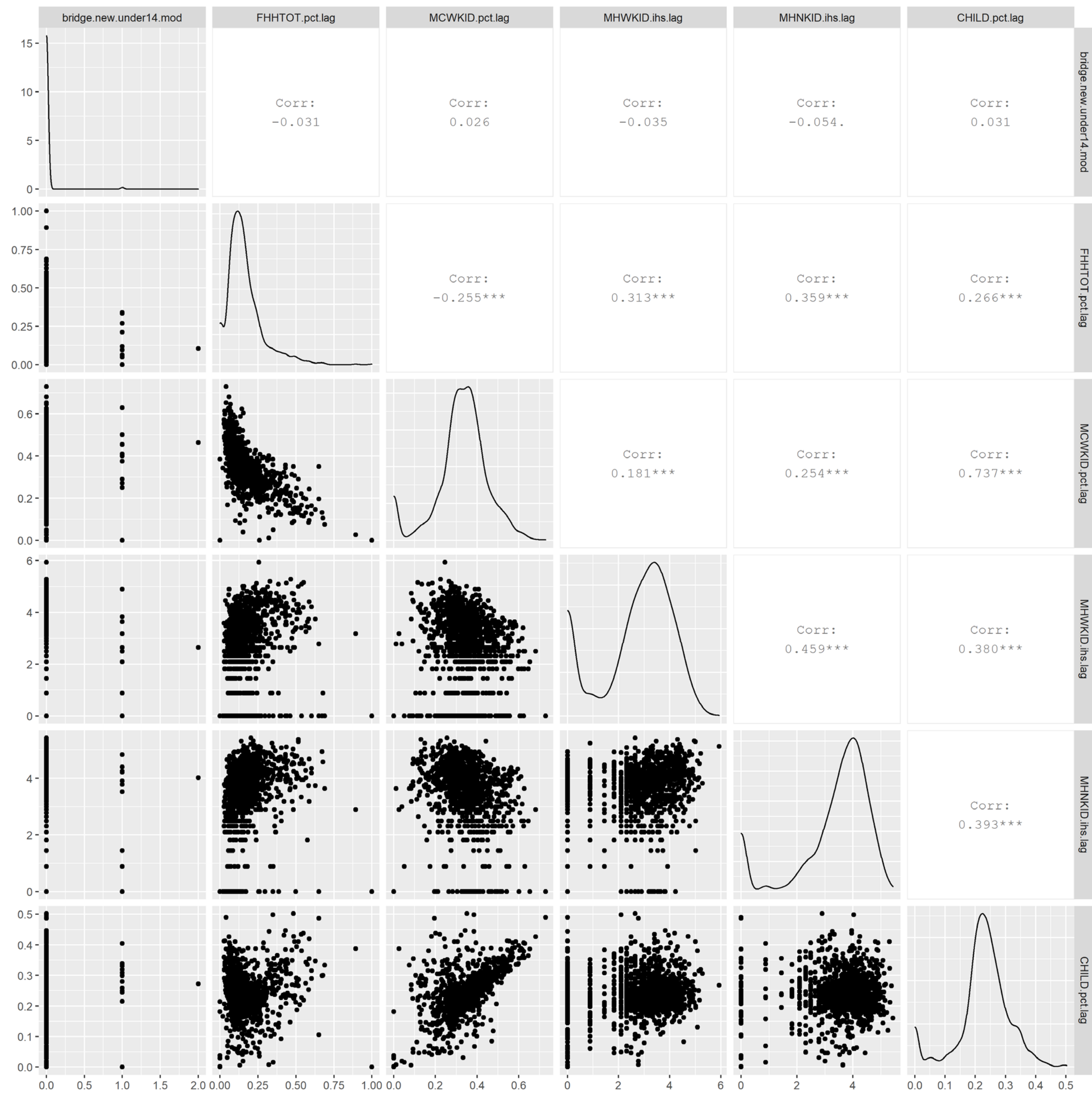

Fig. 70. Restrictive bridge family variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

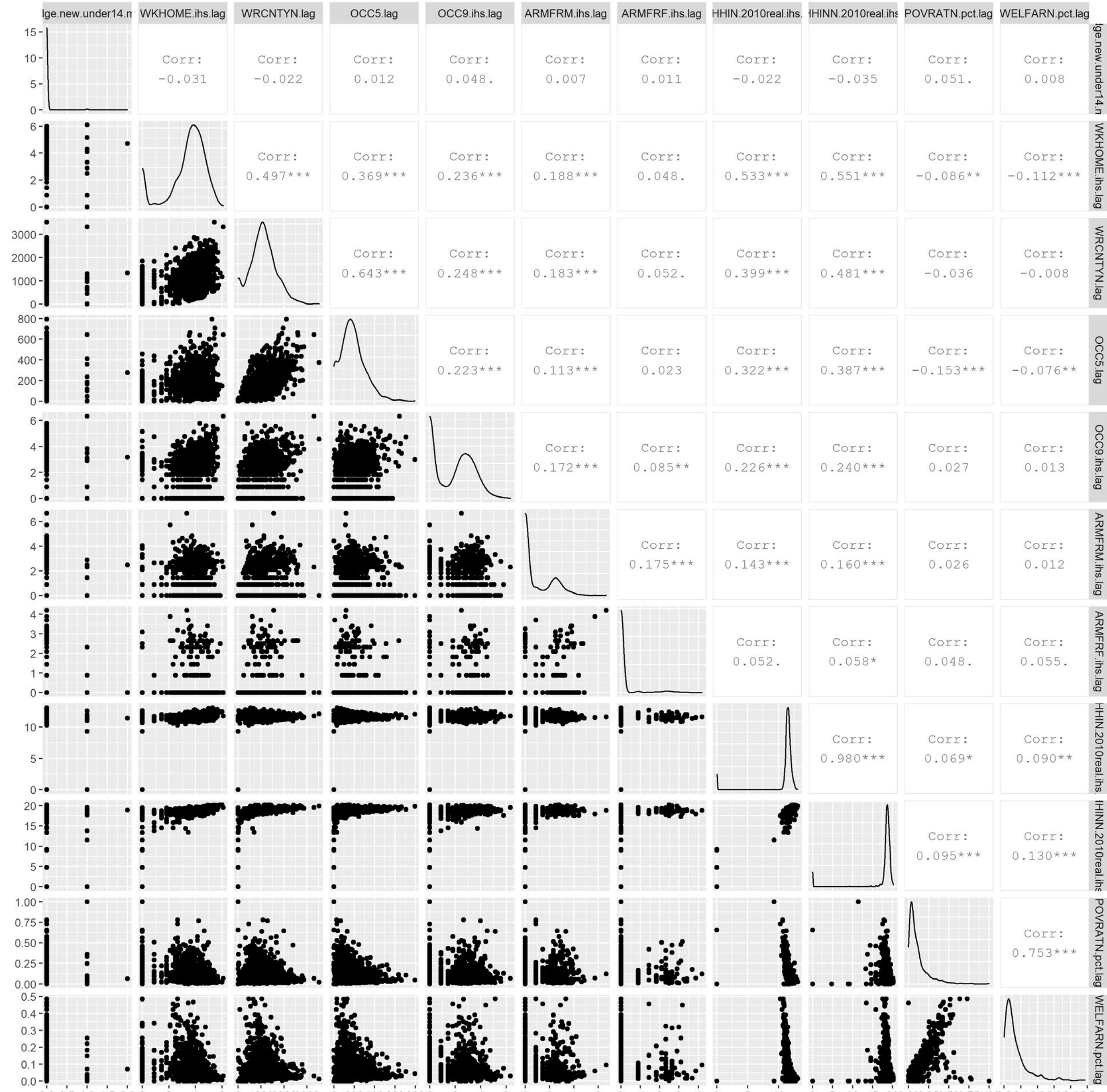

Fig. 71. Restrictive bridge finance variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

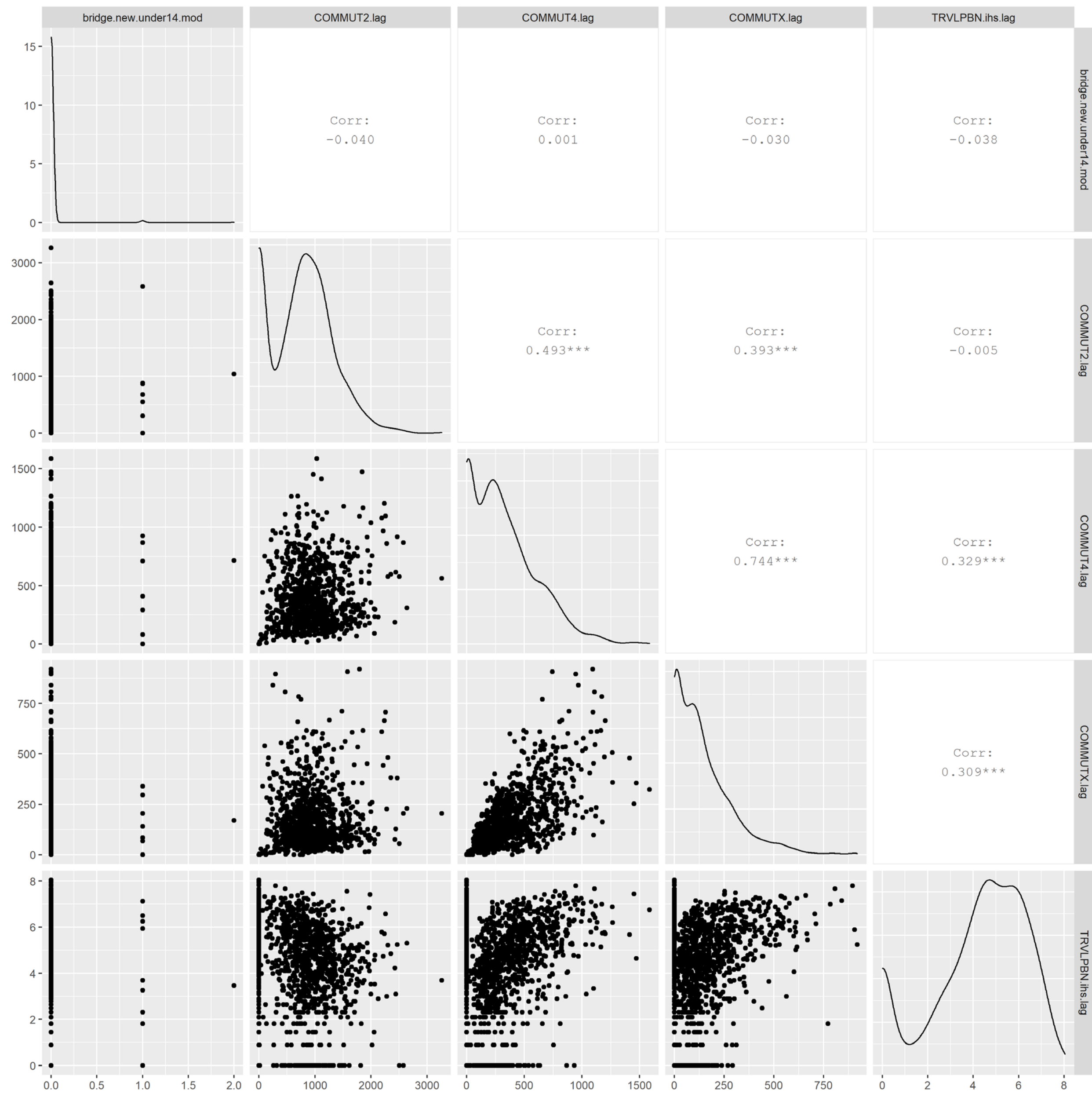

Fig. 72. Restrictive bridge transportation variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

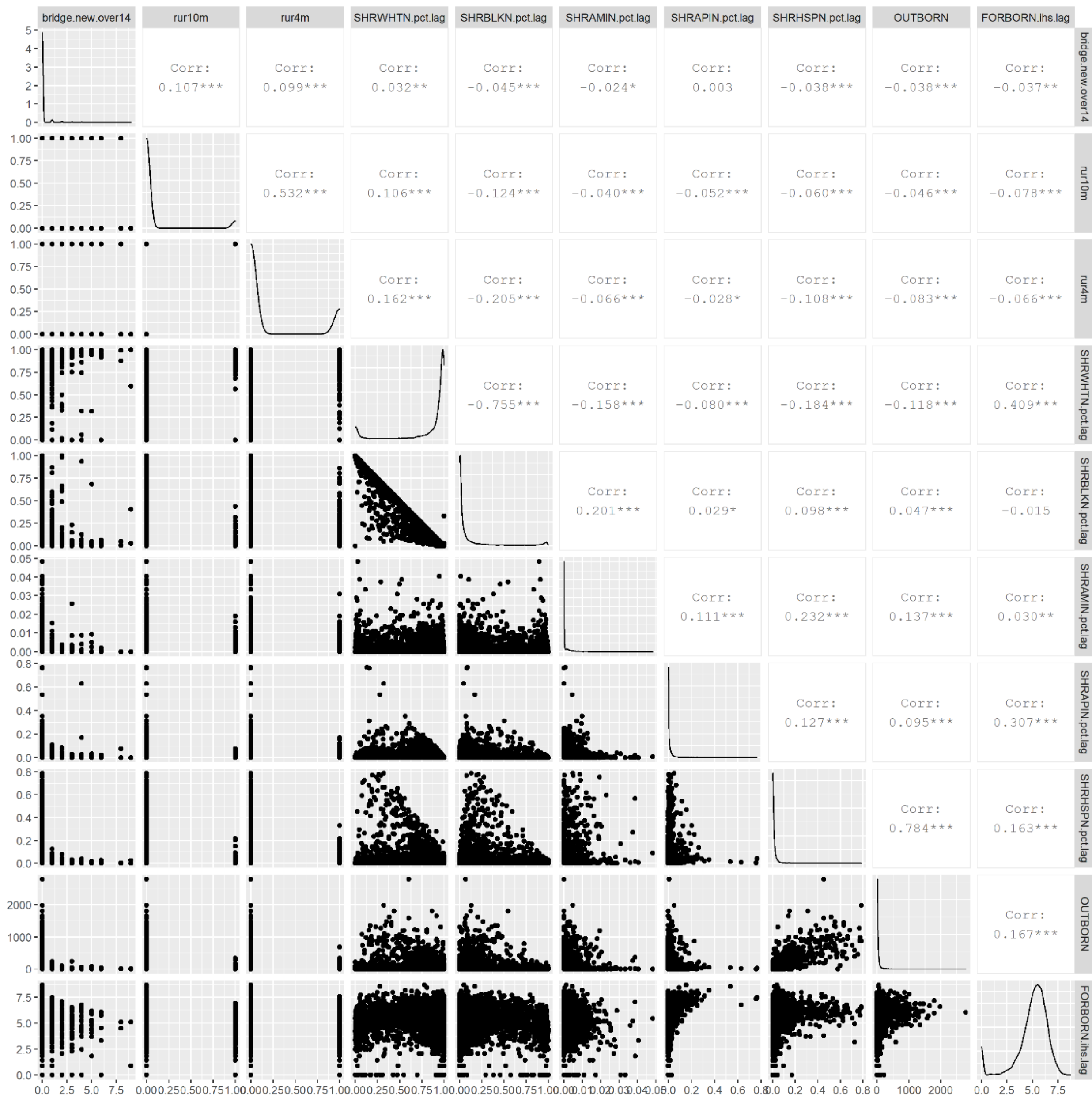

Fig. 73. Non-restrictive bridge demographic variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

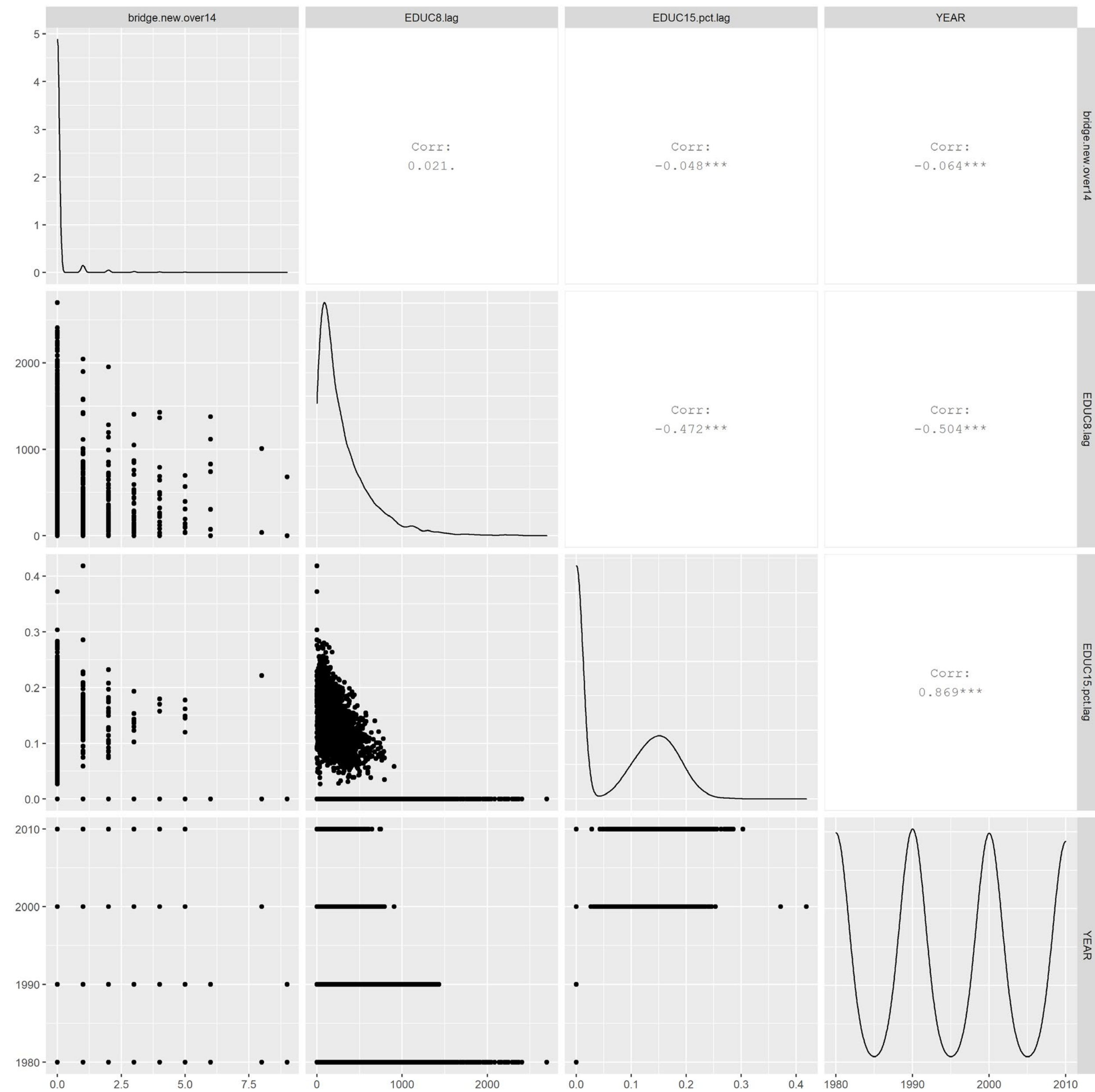

Fig. 74. Non-restrictive bridge education variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

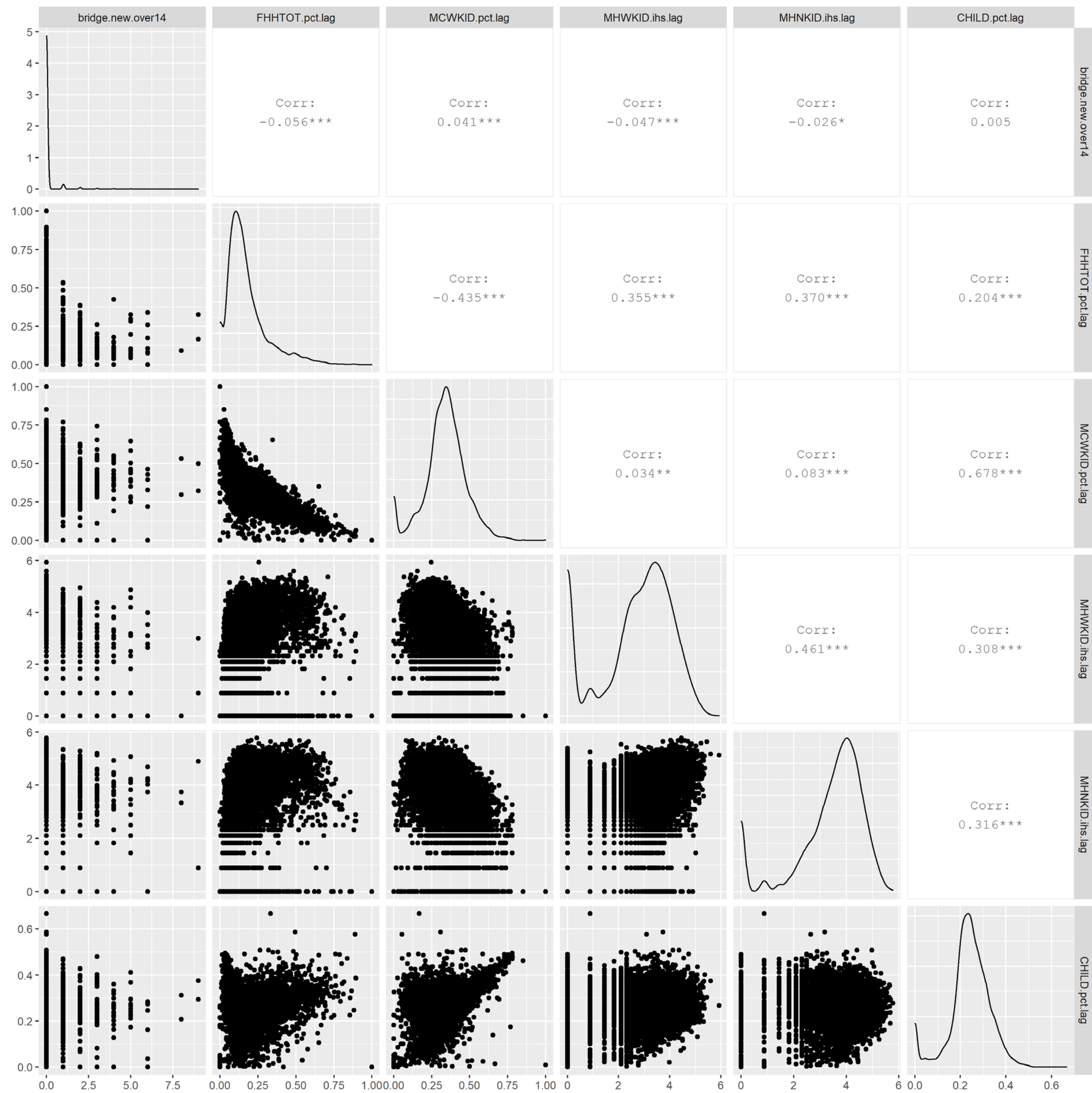

Fig. 75. Non-restrictive bridge family variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

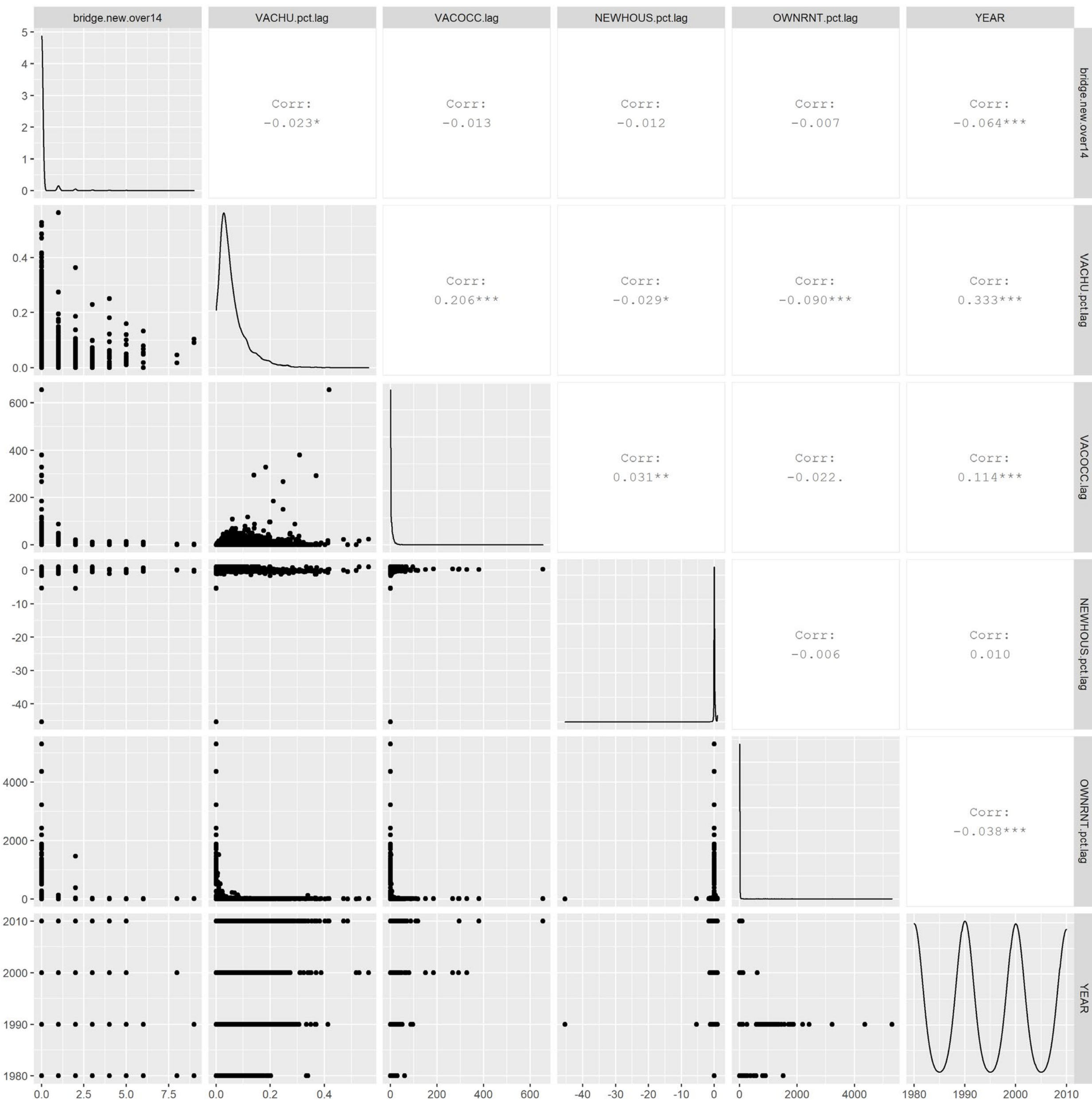

Fig. 76. Non-restrictive bridge housing variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

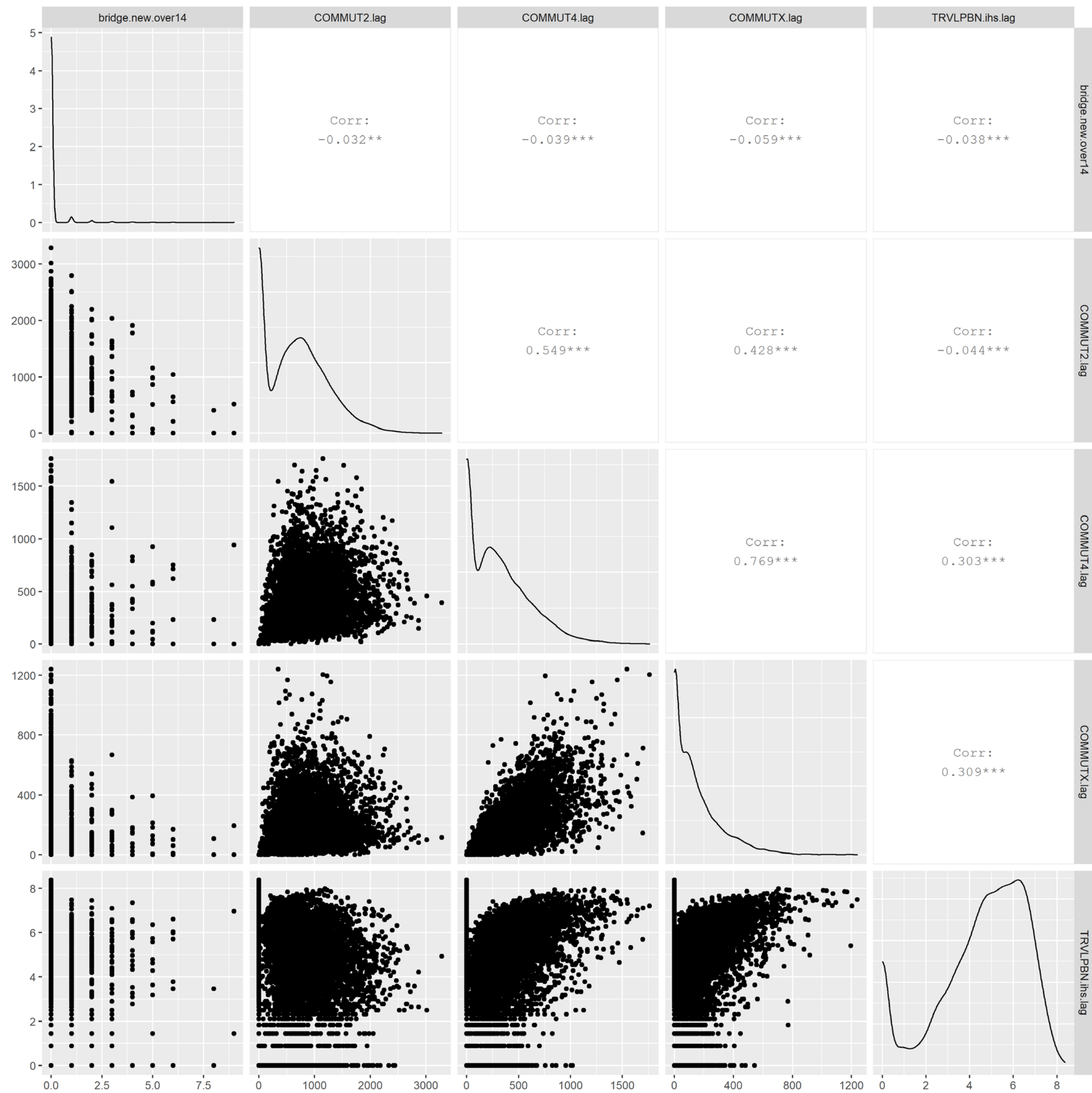

Fig. 77. Non-restrictive bridge transportation variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

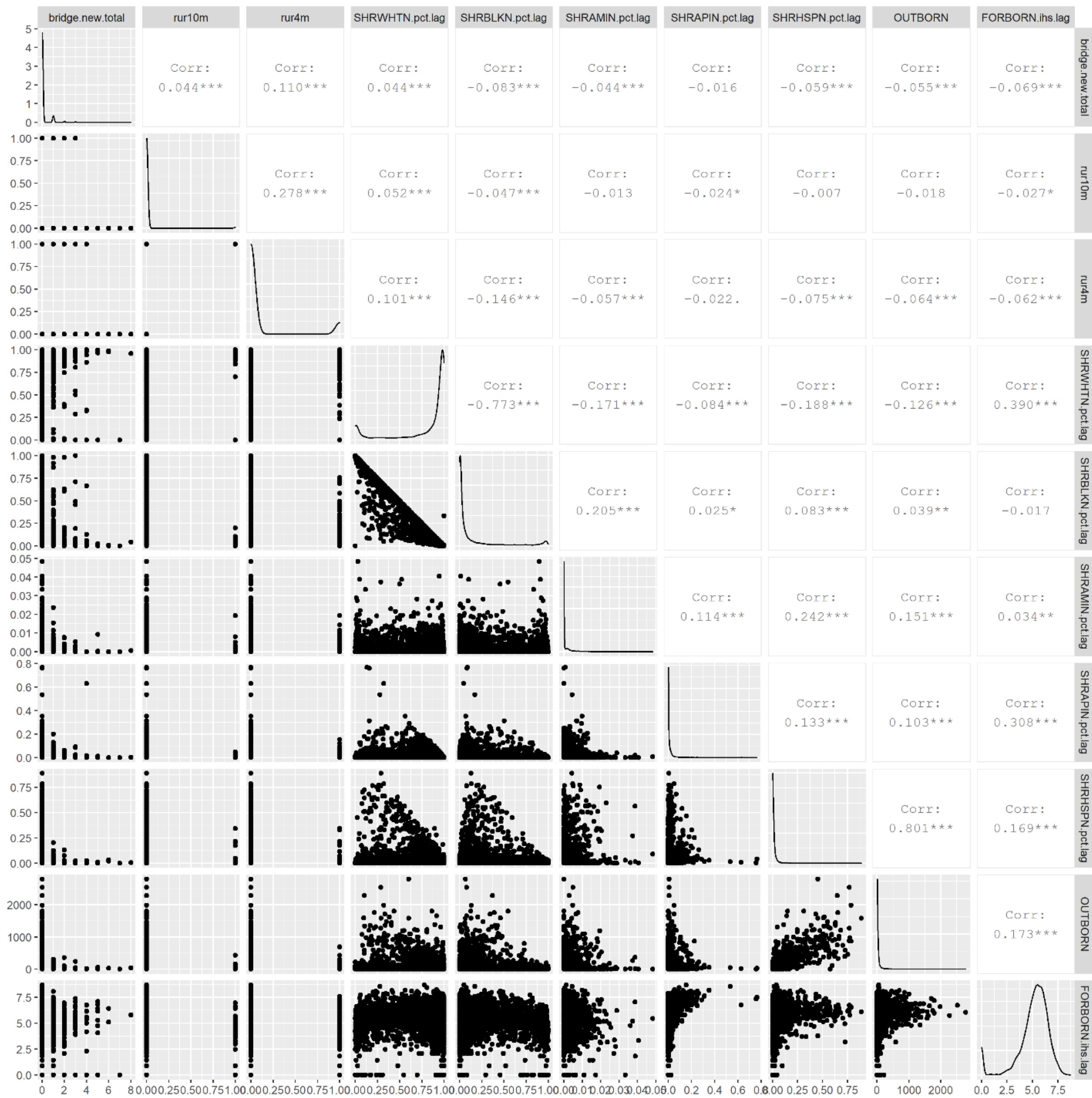

Fig. 78. All new bridge demographic variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

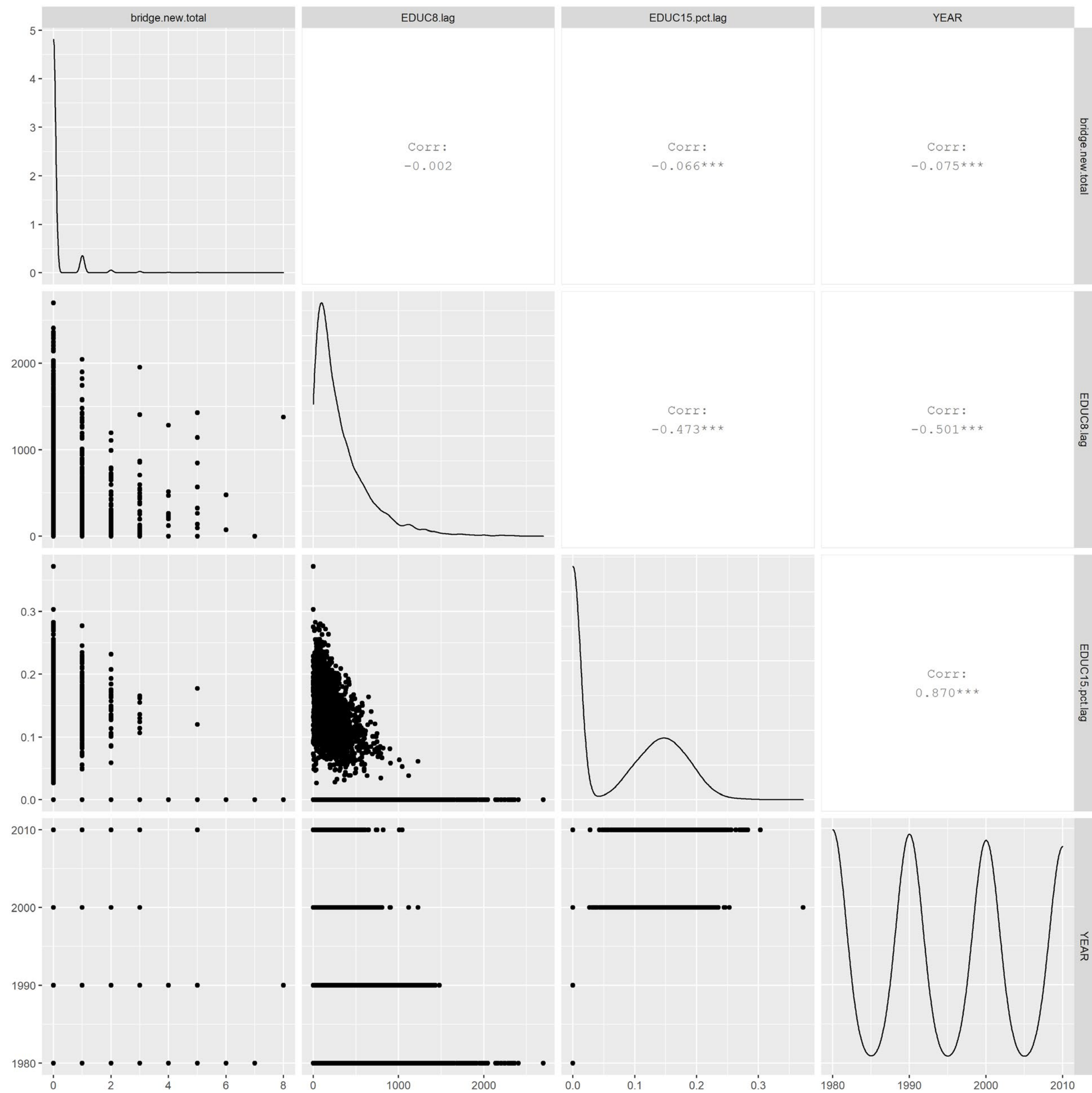

Fig. 79. All new bridge education variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

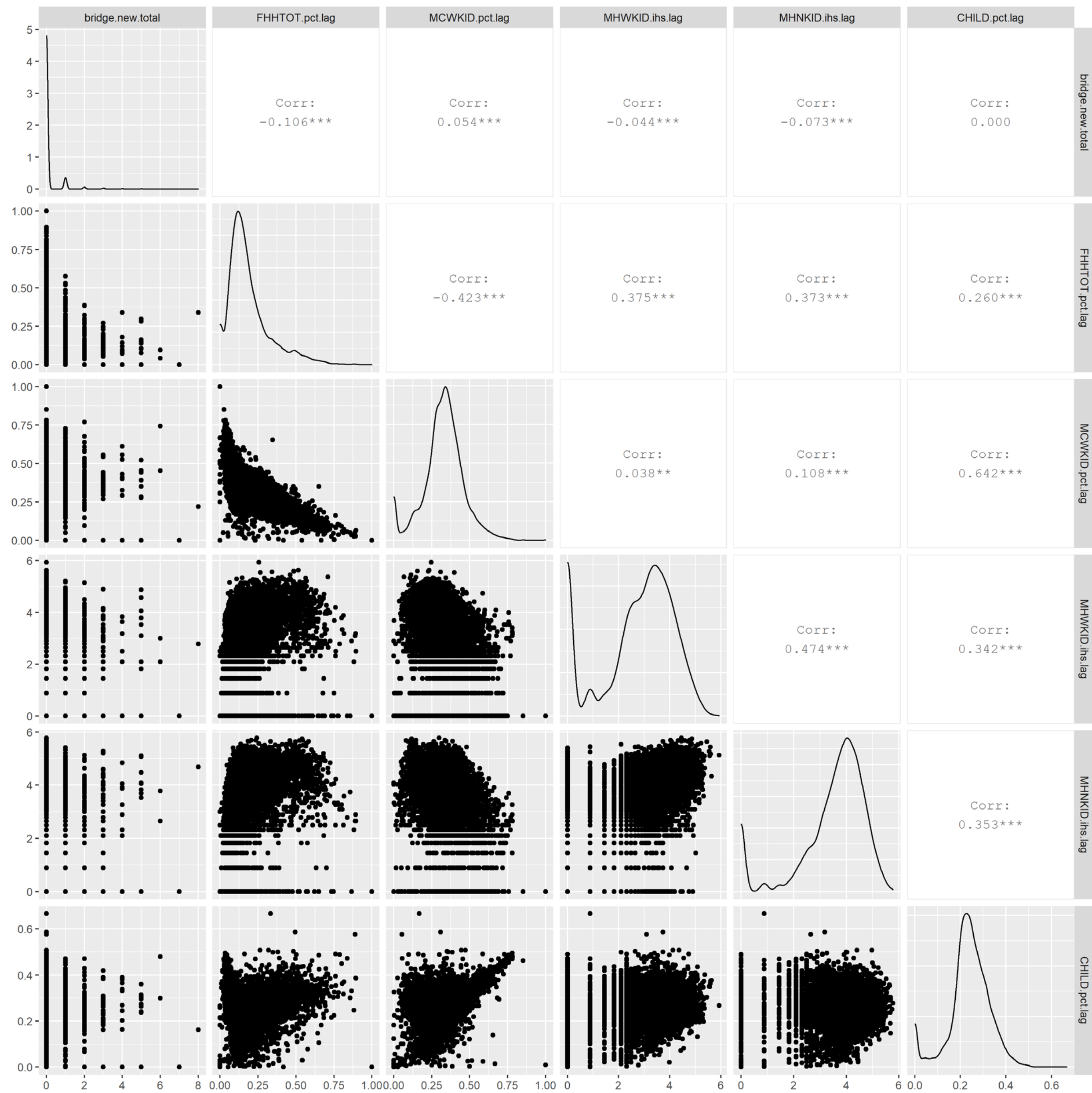

Fig. 80. All new bridge family variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

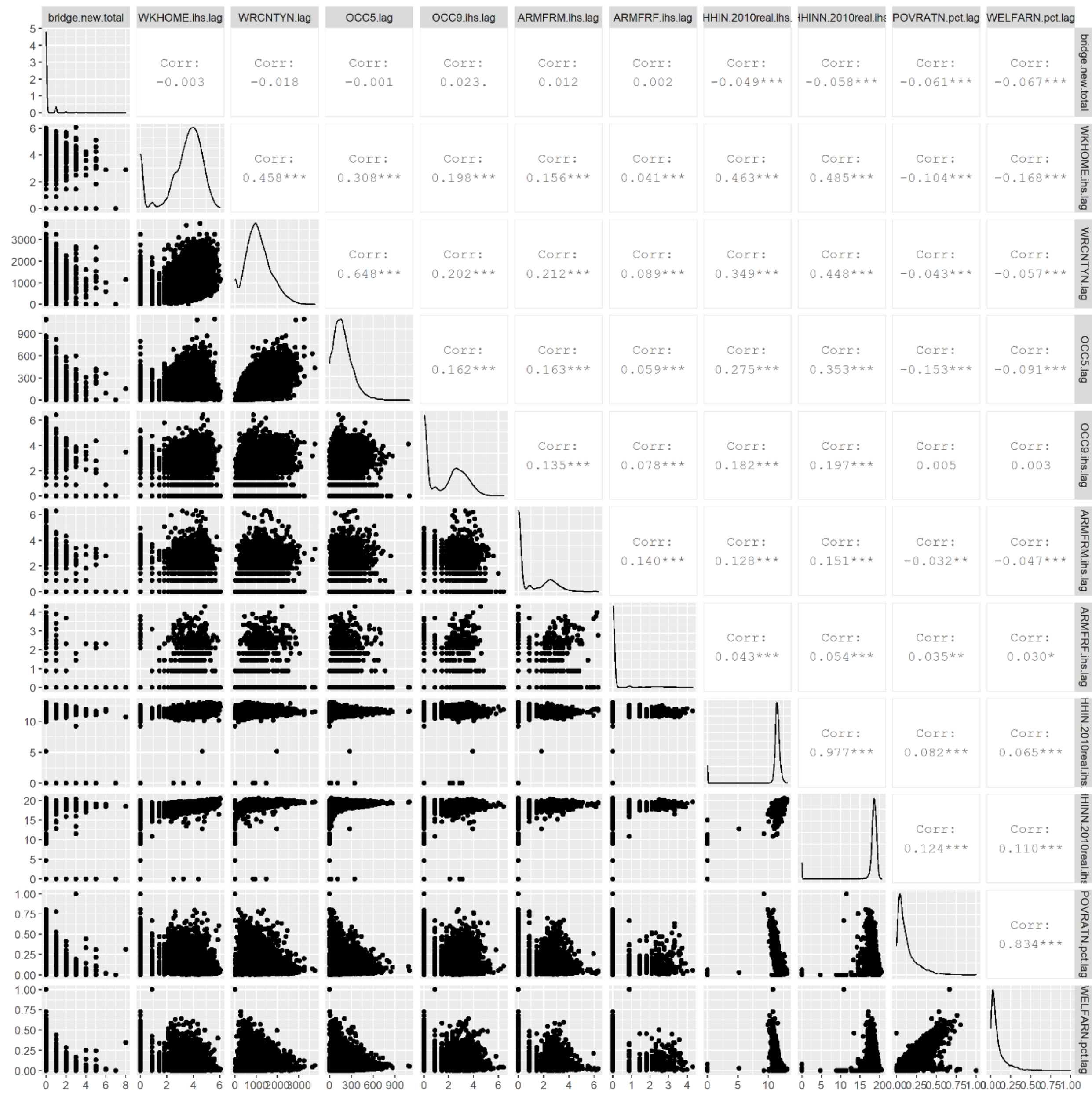

Fig. 81. All new bridge finance variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

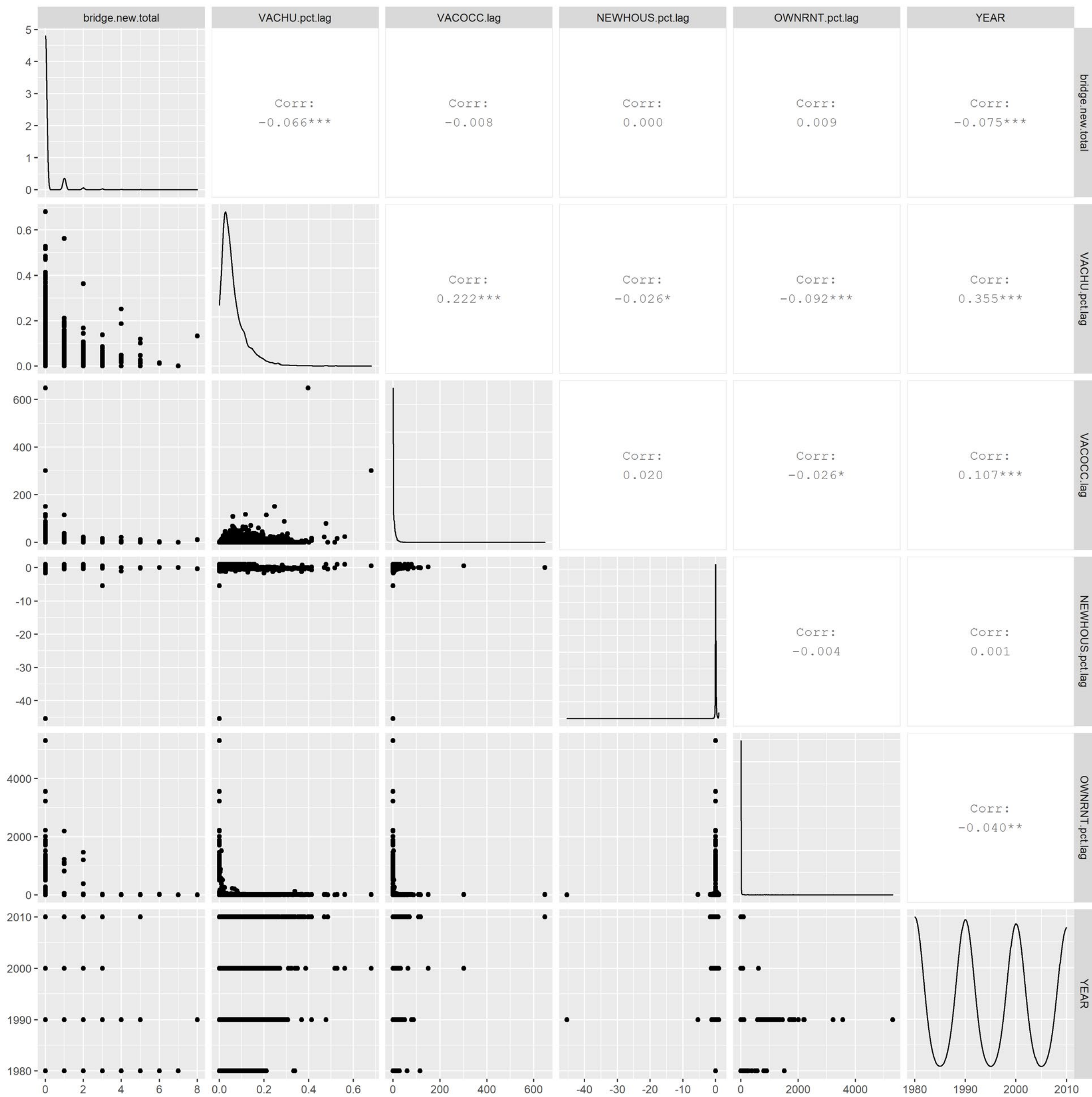

Fig. 82. All new bridge housing variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

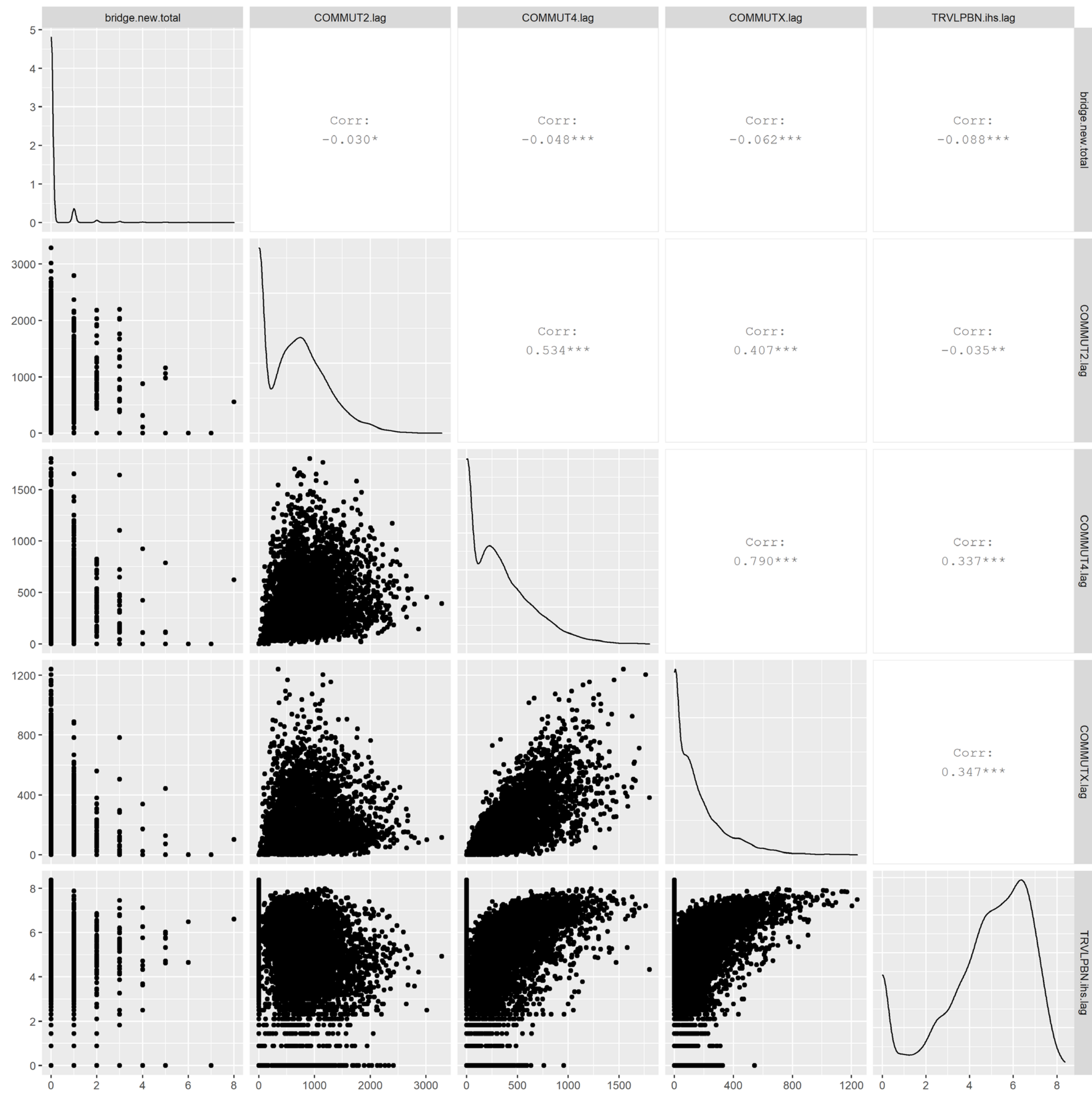

Fig. 83. All new bridge transportation variable scatterplots in lower left triangle. Diagonal contains distribution plots. Upper right triangle is correlation between variables.

Section B Variables

Table 72. List of variables considered by LASSO and MB-search

Variable	Units
Dummy variable denoting that a new bridge was built in this tract in the last 10 years	binary
Dummy variable denoting that a new bridge was built in this tract in any previous time period	binary
Dummy variable denoting that a new bridge was built in this tract in any time period	binary
Variable denoting how many years since a new bridge was built in this tract	binary
Total number of bridges in and near the tract built in the last 10 years	# bridges
Dummy variable denoting that a new bridge with an underclearance under 13.5 ft & over 9.8 ft was built in this tract in the last 10 years	binary
Dummy variable denoting that a new bridge with an underclearance under 13.5 ft & over 9.8 ft was built in this tract in this or a previous time period	binary
Dummy variable denoting that a new bridge with an underclearance under 13.5 ft & over 9.8 ft was built in this tract in any time period	binary
Dummy variable denoting that a new bridge with an underclearance under 13.5 ft & over 9.8 ft was built in this tract in the last 10 years	binary
Total number of bridges in and near the tract with underclearance under 13.5 ft & over 9.8 ft built in the last 10 years	#bridges
Variable denoting how many years since a new restrictive bridge was built in this tract	binary
Dummy variable denoting that a new bridge with an underclearance over 14 ft was built in this tract in this or a previous time period	binary
Dummy variable denoting that a new bridge with an underclearance over 14 ft was built in this tract in any time period	binary
Variable denoting how many years since a new non-restrictive bridge was built in this tract	binary
Total number of bridges in and near the tract with underclearance over 13.5 ft built in the last 10 years	# bridges
Total number of bridges in and near the tract	# bridges
Year	Year
Area (Land)	Square meters
Area (Water)	Square meters
Total population	# of people
Rural indicator for tracts greater than 10M sq. meters	rural tract
Rural indicator for tracts greater than 4M sq. meters (median area)	rural tract
Lagged Total population	# of people

Variable	Units
Lagged Log(1+ Total population)	Log
Lagged Inverse Hyperbolic Sine Transformation of Total population	Inverse Hyperbolic Sine
Lagged Tract Population Density (people per square kilometer)	people/sq. km
Lagged Inverse Hyperbolic Sine Transformation of Tract Population Density - people/sq. km	Inverse Hyperbolic Sine
Lagged Unweighted sample count of persons (long form)	# of people
Lagged Inverse hyperbolic sine transformation unweighted sample count of persons (long form)	# of people
Lagged Total number of non-White persons	# of non-White persons
Lagged Inverse Hyperbolic Sine Transformation of Total number of non-white persons	Inverse Hyperbolic Sine
Lagged Non-White percentage of total population	% non-White minorities
Lagged Total White population	# of people
Lagged Inverse Hyperbolic Sine Transformation of Total White population	Inverse Hyperbolic Sine
White percentage of total population	% White population
Lagged Total Black/African American population	# of people
Black/African American percentage of total population	%
Lagged Black/African American percentage of total population	% Black population
Lagged Total American Indian/Alaska Native population	# of people
Lagged Inverse Hyperbolic Sine Transformation of Total American Indian/Alaska Native population	Inverse Hyperbolic Sine
American Indian/Alaska Native percentage of total population	% American Indian population
Lagged Total Asian, Native Hawaiian and other Pacific Islander population	# of people
Lagged Inverse Hyperbolic Sine Transformation of Total Asian, Native Hawaiian and other Pacific Islander population	Inverse Hyperbolic Sine
Percentage Asian, Native Hawaiian and other Pacific Islander of total population	% Asian population
Lagged Total Hispanic/Latino population	# of people
Lagged Inverse Hyperbolic Sine Transformation of Total Hispanic/Latino population	Inverse Hyperbolic Sine
Percentage Hispanic/Latino of total population	% Hispanic population
Lagged Persons not of Hispanic/Latino origin	# of people
Lagged inverse hyperbolic sine transformed persons not of Hispanic/Latino origin	# of people
Lagged Native born population	# of people
Lagged Population born outside the U.S., not foreign born	# of people

Variable	Units
inverse hyperbolic sine transformed population born outside the U.S., not foreign born	# of people
Lagged foreign-born population	# of people
Inverse Hyperbolic Sine Transformation of foreign-born population	Inverse Hyperbolic Sine
Lagged Percentage foreign-born of total population	% foreign-born
Lagged total households	# of households
Lagged inverse hyperbolic sine transformed total households	# of households
Lagged total persons 15+ years old	# of people
Lagged inverse hyperbolic sine transformed Total persons 15+ years old	# of people
Lagged Males 15+ years old	# of people
Lagged inverse hyperbolic sine transformed Males 15+ years old	# of people
Lagged Females 15+ years old	# of people
Lagged inverse hyperbolic sine transformed Females 15+ years old	# of people
Lagged Males 16-34 years old	# of people
Lagged inverse hyperbolic sine transformed males 16-34 years old	# of people
Lagged Females 16-34 years old	# of people
Lagged inverse hyperbolic sine transformed females 16-34 years old	# of people
Lagged Calculated total families and subfamilies from sub-categories	# families
Lagged Inverse Hyperbolic Sine Transformation of Total families and subfamilies	Inverse Hyperbolic Sine
Lagged Female-headed families with or without own children	# female-headed families
Lagged Inverse Hyperbolic Sine Transformation of Female-headed families with or without own children	Inverse Hyperbolic Sine
Percentage female-headed families with or without own children of total families and subfamilies	% female-headed families
Lagged Female-headed families with own children under 18 years old	# of families
Lagged Inverse Hyperbolic Sine Transformation of Female-headed families with own children under 18 years old	Inverse Hyperbolic Sine
Lagged Percentage female-headed families with own children under 18 years old of total families and subfamilies	% female-headed families with kids
Lagged Female-headed families without own children under 18 years old	# of families
Lagged Inverse Hyperbolic Sine Transformation Female-headed families without own children under 18 years old	# of families
Lagged Female-headed families and subfamilies with own children	# of families
Lagged Inverse Hyperbolic Sine Transformation Female-headed families and subfamilies with own children	# of families
Lagged Total families and subfamilies with own children	# of families
Lagged Inverse Hyperbolic Sine Transformation Total families and subfamilies with own children	# of families

Variable	**Units**
Lagged Married-couple families with own children under 18 years old	# of families
Lagged Inverse Hyperbolic Sine Transformation of Married-couple families with own children under 18 years old	Inverse Hyperbolic Sine
Percentage married-couple families with own children under 18 years old of total families and subfamilies	% married-couple families with kids
Lagged Married-couple families without own children under 18 years old	# of families
Lagged Inverse Hyperbolic Sine Transformation Married-couple families without own children under 18 years old	# of families
Lagged Male-headed families with own children under 18 years old	# of families
Lagged Inverse Hyperbolic Sine Transformation of Male-headed families with own children under 18 years old	Inverse Hyperbolic Sine
Lagged Percentage male-headed families with own children under 18 years old of total families and subfamilies	% male-headed families with kids
Lagged Male-headed families without own children under 18 years old	# of families
Inverse Hyperbolic Sine Transformation Male-headed families without own children under 18 years old	# of families
Lagged Single parent families with own children under 18 years old (sum of male-headed and female-headed families with children)	# single parent families with kids
Lagged Inverse Hyperbolic Sine Transformation of Single parent families with own children under 18 years old	Inverse Hyperbolic Sine
Lagged Percentage single parent families with own children under 18 years old of total families and subfamilies	% single parent families with kids
Percentage Children under 18 years old of total population	% children
Children under 5 years old	# of people
Children under 5 years old	# of people
Lagged Workers 16+ years old traveling to work by car, truck, or van	# of people
Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work by car, truck, or van	Inverse Hyperbolic Sine
Workers 16+ years old with travel time to work less than 25 minutes	# of people
Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work less than 25 minutes or work at home	Inverse Hyperbolic Sine
Lagged Workers 16+ years old with travel time to work 25 to 44 minutes	# of people
Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work 25 to 44 minutes	Inverse Hyperbolic Sine
Workers 16+ years old with travel time to work more than 45 minutes	# of people
Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old with travel time to work more than 45 minutes	Inverse Hyperbolic Sine
Lagged Workers 16+ years old traveling to work on public transportation (taxi not included)	# of people

Variable	Units
Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work on public transportation (taxi not included)	Inverse Hyperbolic Sine
Lagged Workers 16+ years old working outside the home	# of people
Lagged Inverse Hyperbolic Sine Transformation Workers 16+ years old working outside the home	# of people
Lagged Workers 16+ years old traveling to work by walking or other means (includes taxi)	# of people
Lagged Inverse Hyperbolic Sine Transformation of Workers 16+ years old traveling to work by walking or other means (includes taxi)	Inverse Hyperbolic Sine
Persons 25+ years old who have completed 0-8 years of school	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have completed 0-8 years of school	Inverse Hyperbolic Sine
Lagged Percentage of Persons 25+ years old who have completed 0-8 years of school	% of people
Lagged Persons 25+ years old who have completed 9-12 years of school but no diploma	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have completed 9-12 years of school but no diploma	Inverse Hyperbolic Sine
Lagged Percentage of Persons 25+ years old who have completed 9-12 years of school but no diploma	% of people
Lagged Persons 25+ years old who have completed high school but no college	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have completed high school but no college	Inverse Hyperbolic Sine
Lagged Percentage of Persons 25+ years old who have completed high school but no college	% of people
Lagged Persons 25+ years old who have completed some college but no degree	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have completed some college but no degree	Inverse Hyperbolic Sine
Percentage of Persons 25+ years old who have completed some college but no degree	% of people
Lagged Persons 25+ years old who have an associate degree but no bachelor's degree	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have an associate degree but no bachelor's degree	Inverse Hyperbolic Sine
Lagged Percentage of Persons 25+ years old who have an associate degree but no bachelor's degree	% of people
Lagged Persons 25+ years old who have a bachelors or graduate/professional degree	# of people
Lagged Inverse Hyperbolic Sine Transformation of Persons 25+ years old who have a bachelors or graduate/professional degree	Inverse Hyperbolic Sine
Lagged Percentage of Persons 25+ years old who have a bachelors or graduate/professional degree	% of people
Lagged Persons 25+ years old	# of people

Variable	Units
Lagged Inverse Hyperbolic Sine Transformation Persons 25+ years old	# of people
Lagged Workers 16+ years old working at home	# of people
Inverse Hyperbolic Sine Transformation Workers 16+ years old working at home	# of people
Workers 16+ years old working within their county of residence	# of people
Workers 16+ years old working within their county of residence	# of people
Workers 16+ years old	# of people
Workers 16+ years old	# of people
Workers 16+ years old working within their metro area of residence	# of people
Workers 16+ years old working within their metro area of residence	# of people
Persons 16+ years old employed in manufacturing, transportation and public administration	# of people
Persons 16+ years old employed in manufacturing, transportation and public administration	# of people
Civilian employed persons 16+ years old	# of people
Civilian employed persons 16+ years old	# of people
Persons 16+ years old employed as operators, assemblers, transportation, material moving, nonfarm laborers, and service workers	# of people
Persons 16+ years old employed as operators, assemblers, transportation, material moving, nonfarm laborers, and service workers	# of people
Persons 16+ years old employed in professional and technical occupations	# of people
Persons 16+ years old employed in professional and technical occupations	# of people
Persons 16+ years old employed as executives, managers, and administrators (excl. farms)	# of people
Persons 16+ years old employed as executives, managers, and administrators (excl. farms)	# of people
Persons 16+ years old employed as sales workers	# of people
Persons 16+ years old employed as sales workers	# of people
Persons 16+ years old employed as administrative support and clerical workers	# of people
Persons 16+ years old employed as administrative support and clerical workers	# of people
Persons 16+ years old employed as precision production, craft, and repair workers	# of people
Persons 16+ years old employed as precision production, craft, and repair workers	# of people
Persons 16+ years old employed as operators, assemblers, transportation, and material moving workers	# of people
Persons 16+ years old employed as operators, assemblers, transportation, and material moving workers	# of people
Persons 16+ years old employed as nonfarm laborers	# of people
Persons 16+ years old employed as nonfarm laborers	# of people
Persons 16+ years old employed as service workers	# of people

Variable	Units
Persons 16+ years old employed as service workers	# of people
Persons 16+ years old employed as farm workers or in forestry and fishing	# of people
Inverse hyperbolic sine transformation of persons 16+ years old employed as farm workers or in forestry and fishing	# of people
Lagged Persons 16+ years old employed in professional, managerial or administrative occupations (sum of OCC1, OCC2, & OCC4)	# professionals, managers & admin
Lagged Inverse Hyperbolic Sine Transformation of Persons 16+ years old employed in professional, managerial or administrative occupations	Inverse Hyperbolic Sine
Lagged Percentage persons employed in professional, managerial or administrative occupations of civilian employed persons 16+ years old	% professionals, managers & admin
Males 16+ years old in the armed forces	# of people
Males 16+ years old in the armed forces	# of people
Females 16+ years old in the armed forces	# of people
Females 16+ years old in the armed forces	# of people
Lagged Aggregate household income in past 12 months (2010 Constant $ US)	2010 Constant $ (US)
Lagged Inverse Hyperbolic Sine Transformation of Aggregate household income in past 12 months (2010 Constant $ US)	Inverse Hyperbolic Sine
Lagged Average household income in past 12 months (2010 Constant $ US)	2010 Constant $ (US)
Lagged Inverse Hyperbolic Sine Transformation of Average household income in past 12 months (2010 Constant $ US)	Inverse Hyperbolic Sine
Lagged Total persons below the poverty level in past 12 months	# of people
Lagged Inverse Hyperbolic Sine Transformation of Total persons below the poverty level in past 12 months	Inverse Hyperbolic Sine
Percentage of total persons below the poverty level in past 12 months	% of people
Total population with poverty status determined	# of people
Total population with poverty status determined	# of people
White persons below the poverty level in past 12 months	# of people
White persons below the poverty level in past 12 months	# of people
White population with poverty status determined	# of people
White population with poverty status determined	# of people
Lagged Households with public assistance inc. (incl. SSI) last year	# of households
Lagged Inverse Hyperbolic Sine Transformation of Households with public assistance inc. (incl. SSI) last year	Inverse Hyperbolic Sine
Percentage households with public assistance inc. (incl. SSI) last year of total households	% welfare households
Total households	# of households

Variable	Units
Total households	# of households
Total nonelderly persons under 65 years old below the poverty level in the past 12 months	# of people
Total nonelderly persons under 65 years old below the poverty level in the past 12 months	# of people
Persons under 65 years old with poverty status determined	# of people
Persons under 65 years old with poverty status determined	# of people
Elderly persons 65+ years old below the poverty level in past 12 months	# of people
Elderly persons 65+ years old below the poverty level in past 12 months	# of people
Elderly persons 65+ years old with poverty status determined	# of people
Elderly persons 65+ years old with poverty status determined	# of people
Lagged Total housing units	# housing units
Lagged Inverse Hyperbolic Sine Transformation of Total housing units	Inverse Hyperbolic Sine
Unweighted sample count of housing units (long form)	# housing units
Unweighted sample count of housing units (long form)	# housing units
Total occupied housing units	# housing units
Total occupied housing units	# housing units
Lagged Total vacant housing units	# housing units
Lagged Inverse Hyperbolic Sine Transformation of Total vacant housing units	Inverse Hyperbolic Sine
Percentage of vacant housing units	% of vacant housing units
Vacant housing units for rent	# housing units
Vacant housing units for rent	# housing units
Vacant housing units for sale only	# housing units
Vacant housing units for sale only	# housing units
Vacant housing units for seasonal, recreational or occasional use	# housing units
Vacant housing units for seasonal, recreational or occasional use	# housing units
Vacant housing units, other vacant (1990 def.)	# housing units
Vacant housing units, other vacant (1990 def.)	# housing units
Lagged Total renter-occupied housing units	# housing units
Lagged Inverse Hyperbolic Sine Transformation of Total renter-occupied housing units	Inverse Hyperbolic Sine
Lagged Percentage renter-occupied housing units of total housing units	% renter-occupied housing units
Total owner-occupied housing units	# housing units

Variable	Units
Total owner-occupied housing units	# housing units
Total owner-occupied housing units	# housing units
Total specified renter-occupied housing units	# housing units
Total specified renter-occupied housing units	# housing units
Total specified owner-occupied housing units	# housing units
Total specified owner-occupied housing units	# housing units
Persons in occupied rental units	# housing units
Persons in occupied rental units	# housing units
Lagged Change in number of housing units since last census	# new housing units
Lagged Inverse Hyperbolic Sine Transformation of Change in number of housing units since last census	Inverse Hyperbolic Sine
Percentage of change in number of housing units since last census of total housing units	% new housing units
Ratio of Owner-Occupied housing units to Renter Occupied Housing units	% owner housing/(1 + renter housing)

Section C Bridge Siting Model Results

Table 73. Restrictive bridge siting logistic model post-CEM results

DV: Dummy variable denoting that a new restrictive bridge was built in this tract in the last 10 years

	Set 1	**Set 2**	**Set 3**	**Set 4**
Rural tract indicator > 10M sq. meters	-0.124		-0.083	
	(0.426)		(0.425)	
Rural tract indicator > 4M sq. meters		-1.289*		-1.086*
		(0.601)		(0.483)
Lagged African American Population percentage		-0.040		
		(0.853)		
Lagged Hispanic Population Percentage				-2.490
				(4.375)
Lagged Native Americans percentage			-116.283	
			(137.095)	
Lagged Asian, Native Hawaiian and other percentage			-9.433	
			(18.601)	
Lagged Percentage of White Population	-0.640			
	(1.316)			
Lagged IHS-transformed Population Born Outside U.S.	-0.084		0.019	
	(0.143)		(0.146)	
Lagged IHS-transformed Population Foreign Born		-0.365		-0.406
		(0.256)		(0.243)
Lagged % female-headed families	-1.664			
	(3.880)			
Lagged Percentage Married Couples with Children		1.840		
		(2.136)		
Lagged IHS-transformed male-headed families w/kids				0.067
				(0.214)
Lagged IHS-transformed Male Single Parent w/o Children			-0.248	
			(0.320)	
Lagged Population Percentage under 18			0.434	
			(2.496)	
Lagged Population with Commute < 25 minutes	0.001			
	(0.000)			
Lagged Commute 25-45 minutes		0.001		
		(0.001)		
Lagged Population with Commute > 45 minutes			0.001	
			(0.001)	
Lagged IHS-transformed Population Travel on Public Transportation				-0.068
				(0.115)
Lagged over 25-yr-olds with at Least 8 Years Education	-0.000		0.001	
	(0.001)		(0.001)	
Lagged percentage of over 25-yr-olds with Some College		-23.331*		-26.024**
		(9.223)		(8.515)
Lagged IHS-transformed Population Work at home	-0.300		-0.169	

	(0.159)		(0.167)	
Lagged Population Work in county		0.001		0.001
		(0.001)		(0.001)
Lagged Precision crafters	0.005			
	(0.003)			
Lagged IHS-transformed Farm, fishery and forestry workers		0.144		
		(0.137)		
Lagged IHS-transformed Military females				0.412
				(0.216)
Lagged IHS-transformed Military males			0.004	
			(0.154)	
Lagged IHS-transformed real average income	0.079		0.062	
	(0.134)		(0.092)	
Lagged IHS-transformed real aggregate income		-0.027		0.079
		(0.082)		(0.074)
Lagged Population Percentage Below the Poverty Line	5.639	3.914		
	(3.124)	(3.480)		
Lagged Population Percentage Receiving Welfare			2.408	0.402
			(3.044)	(3.653)
Lagged Percentage Housing Units Vacant	-0.202			
	(3.587)			
Lagged Vacant housing for occasional use		0.003		
		(0.003)		
Lagged Percent Change in Housing Unit Supply			-0.491	
			(1.784)	
Lagged Owner to Renter Ratio				-0.008
				(0.007)
AIC	316.798	307.564	328.063	312.697
BIC	417.939	408.705	442.690	413.838
Log Likelihood	-143.399	-138.782	-147.032	-141.349
Deviance	293.445	287.456	304.710	291.566
Num. obs.	6265	6265	6265	6265

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 74. Non-restrictive bridge siting logistic model post-CEM results

DV: Dummy variable denoting that a new non-restrictive bridge was built in this tract in the last 10 years

	Set 1	**Set 2**	**Set 3**	**Set 4**
Rural tract indicator > 10M sq. meters	-0.105		-0.066	
	(0.103)		(0.103)	
Rural tract indicator > 4M sq. meters		0.265*		0.101
		(0.112)		(0.102)
Lagged African American Population percentage		-0.990**		
		(0.313)		
Lagged Hispanic Population Percentage				-3.996**
				(1.457)
Lagged Native Americans percentage			-32.675	
			(23.672)	
Lagged Asian, Native Hawaiian and other percentage			2.177	
			(1.558)	
Lagged Percentage of White Population	0.764*			
	(0.330)			
Lagged IHS-transformed Population Born Outside U.S.	-0.065*		-0.038	
	(0.033)		(0.033)	
Lagged IHS-transformed Population Foreign Born		0.033		0.025
		(0.046)		(0.055)
Lagged % female-headed families	-0.571			
	(0.835)			
Lagged Percentage Married Couples with Children		-0.526		
		(0.519)		
Lagged IHS-transformed male-headed families w/kids				-0.085*
				(0.037)
Lagged IHS-transformed Male Single Parent w/o Children			0.064	
			(0.051)	
Lagged Population Percentage under 18			-2.190**	
			(0.728)	
Lagged Population with Commute < 25 minutes	0.001***			
	(0.000)			
Lagged Commute 25-45 minutes		-0.001***		
		(0.000)		
Lagged Population with Commute > 45 minutes			-0.002***	
			(0.000)	
Lagged IHS-transformed Population Travel on Public Transportation				0.042
				(0.031)
Lagged over 25-yr-olds with at Least 8 Years Education	0.001**		0.000	
	(0.000)		(0.000)	
Lagged percentage of over 25-yr-olds with Some College		0.247		-2.597
		(1.967)		(2.032)
Lagged IHS-transformed Population Work at home	-0.129**		-0.016	
	(0.041)		(0.044)	
Lagged Population Work in county		0.000***		0.000**

		(0.000)		(0.000)
Lagged Precision crafters	-0.002**			
	(0.000)			
Lagged IHS-transformed Farm, fishery and forestry workers		-0.084**		
		(0.032)		
Lagged IHS-transformed Military females				0.094
				(0.077)
Lagged IHS-transformed Military males			0.054	
			(0.036)	
Lagged IHS-transformed real average income	-0.055		0.012	
	(0.036)		(0.027)	
Lagged IHS-transformed real aggregate income		-0.026		-0.046**
		(0.018)		(0.017)
Lagged Population Percentage Below the Poverty Line	1.488	1.859**		
	(0.769)	(0.591)		
Lagged Population Percentage Receiving Welfare			0.685	2.111**
			(0.779)	(0.699)
Lagged Percentage Housing Units Vacant	0.878			
	(0.851)			
Lagged Vacant housing for occasional use		-0.001		
		(0.001)		
Lagged Percent Change in Housing Unit Supply			-0.051	
			(0.386)	
Lagged Owner to Renter Ratio				-0.001
				(0.001)
AIC	4698.235	4710.482	4703.693	4746.432
BIC	4806.918	4819.165	4826.866	4855.115
Log Likelihood	-2334.118	-2340.241	-2334.846	-2358.216
Deviance	4890.718	4889.808	4907.710	4930.341
Num. obs.	10358	10358	10358	10358

***p < 0.001, **p < 0.01, *p < 0.05

Table 75. All new bridge siting logistic model post-CEM results

DV: Dummy variable denoting that any new bridge was built in this tract in the last 10 years

	Set 1	Set 2	Set 3	Set 4
Rural tract indicator > 10M sq. meters	0.912***		0.960***	
	(0.198)		(0.185)	
Rural tract indicator > 4M sq. meters		0.926***		0.948***
		(0.107)		(0.105)
Lagged African American Population percentage		-2.417***		
		(0.473)		
Lagged Hispanic Population Percentage				-8.351**
				(2.600)
Lagged Native Americans percentage			-6.097	
			(19.715)	
Lagged Asian, Native Hawaiian and other percentage			0.438	
			(1.918)	
Lagged Percentage of White Population	0.760**			
	(0.282)			
Lagged IHS-transformed Population Born Outside U.S.	-0.119***		-0.133***	
	(0.035)		(0.032)	
Lagged IHS-transformed Population Foreign Born		-0.162***		-0.116*
		(0.048)		(0.058)
Lagged % female-headed families	-3.111***			
	(0.783)			
Lagged Percentage Married Couples with Children		1.131*		
		(0.509)		
Lagged IHS-transformed male-headed families w/kids				0.014
				(0.041)
Lagged IHS-transformed Male Single Parent w/o Children			-0.162***	
			(0.044)	
Lagged Population Percentage under 18			1.627*	
			(0.695)	
Lagged Population with Commute < 25 minutes	-0.000			
	(0.000)			
Lagged Commute 25-45 minutes		0.000		
		(0.000)		
Lagged Population with Commute > 45 minutes			0.000	
			(0.000)	
Lagged IHS-transformed Population Travel on Public Transportation				-0.010
				(0.033)
Lagged over 25-yr-olds with at Least 8 Years Education	-0.000		0.000	
	(0.000)		(0.000)	
Lagged percentage of over 25-yr-olds with Some College		-0.572		-2.941
		(1.999)		(2.057)
Lagged IHS-transformed Population Work at home	0.052		0.097*	
	(0.043)		(0.043)	
Lagged Population Work in county		0.000		0.000

		(0.000)		(0.000)
Lagged Precision crafters	0.000			
	(0.000)			
Lagged IHS-transformed Farm, fishery and forestry workers		0.004		
		(0.040)		
Lagged IHS-transformed Military females				-0.252
				(0.153)
Lagged IHS-transformed Military males			0.065	
			(0.037)	
Lagged IHS-transformed real average income	-0.037		-0.014	
	(0.032)		(0.027)	
Lagged IHS-transformed real aggregate income		-0.001		0.027
		(0.019)		(0.018)
Lagged Population Percentage Below the Poverty Line	1.599*	1.838**		
	(0.652)	(0.630)		
Lagged Population Percentage Receiving Welfare			-2.384**	-1.848*
			(0.797)	(0.862)
Lagged Percentage Housing Units Vacant	-0.708			
	(1.439)			
Lagged Vacant housing for occasional use		-0.003		
		(0.003)		
Lagged Percent Change in Housing Unit Supply			0.002	
			(0.090)	
Lagged Owner to Renter Ratio				-0.000
				(0.000)
AIC	6061.537	5961.025	6080.875	5998.556
BIC	6166.511	6065.999	6199.845	6103.530
Log Likelihood	-3015.769	-2965.513	-3023.437	-2984.278
Deviance	5993.579	5900.512	6008.472	5936.287
Num. obs.	8089	8089	8089	8089

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

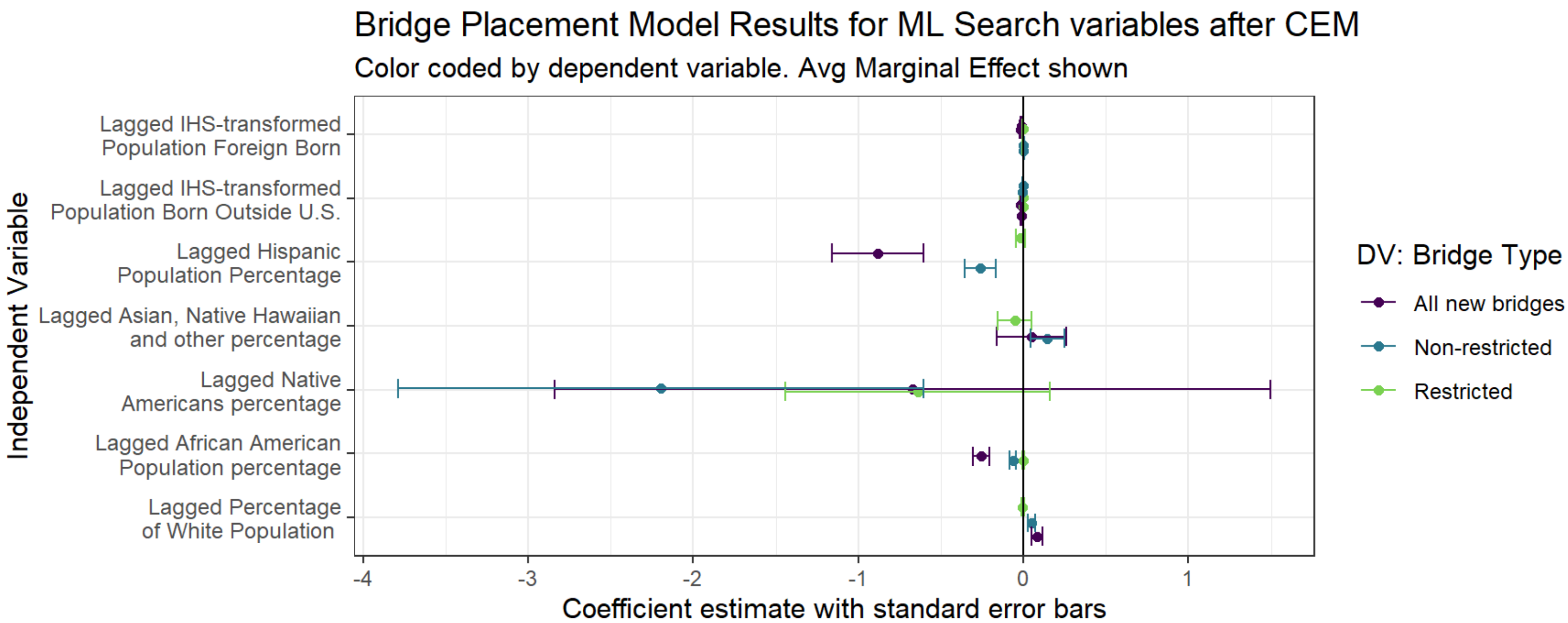

Fig. 84. Graphic depicting demographic variables in bridge siting models

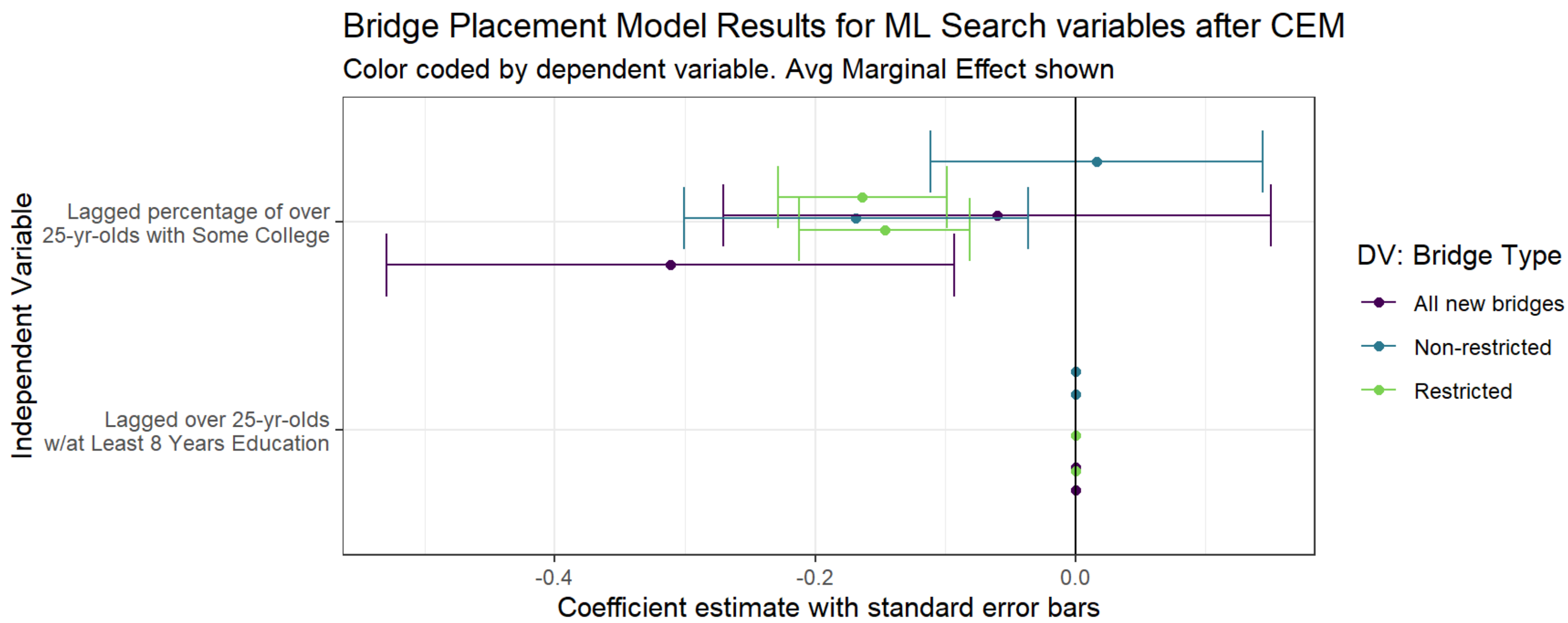

Fig. 85. Graphic depicting education variables in bridge siting models

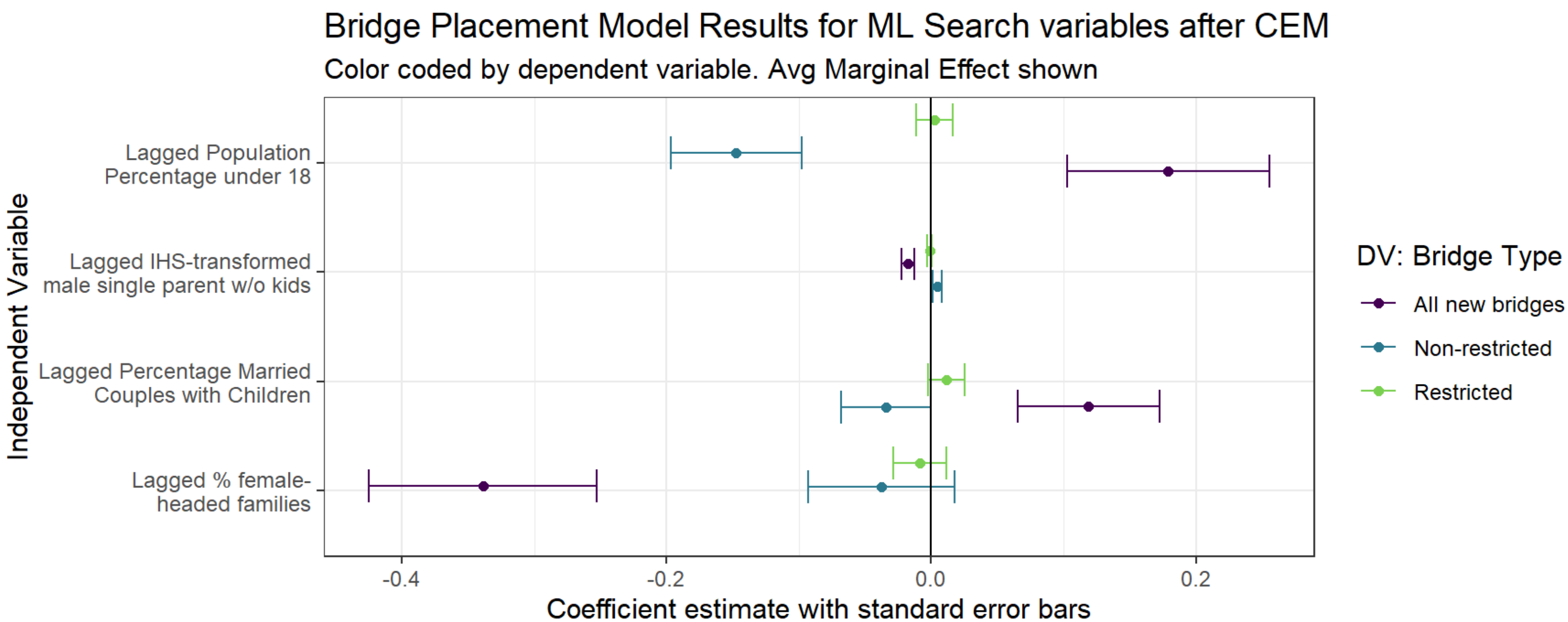

Fig. 86. Graphic depicting family variables in bridge siting models

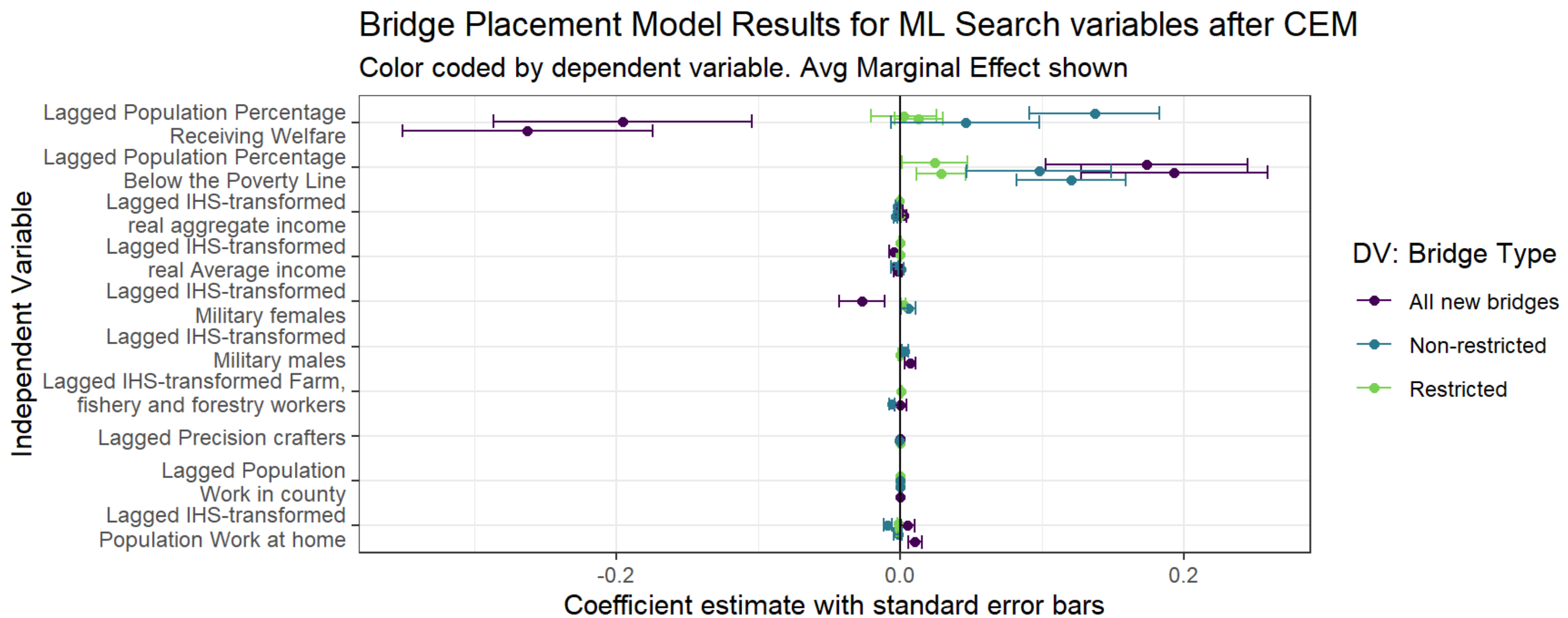

Fig. 87. Graphic depicting financial variables in bridge siting models

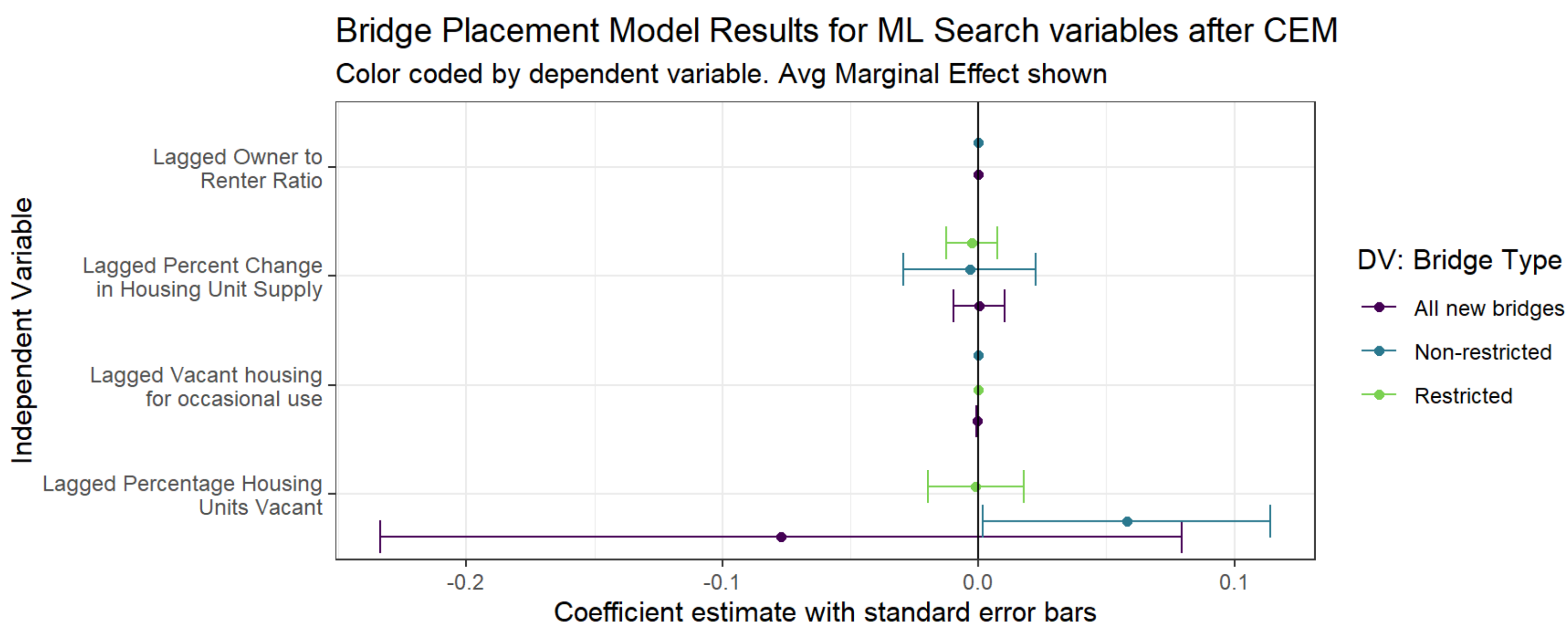

Fig. 88. Graphic depicting housing variables in bridge siting models

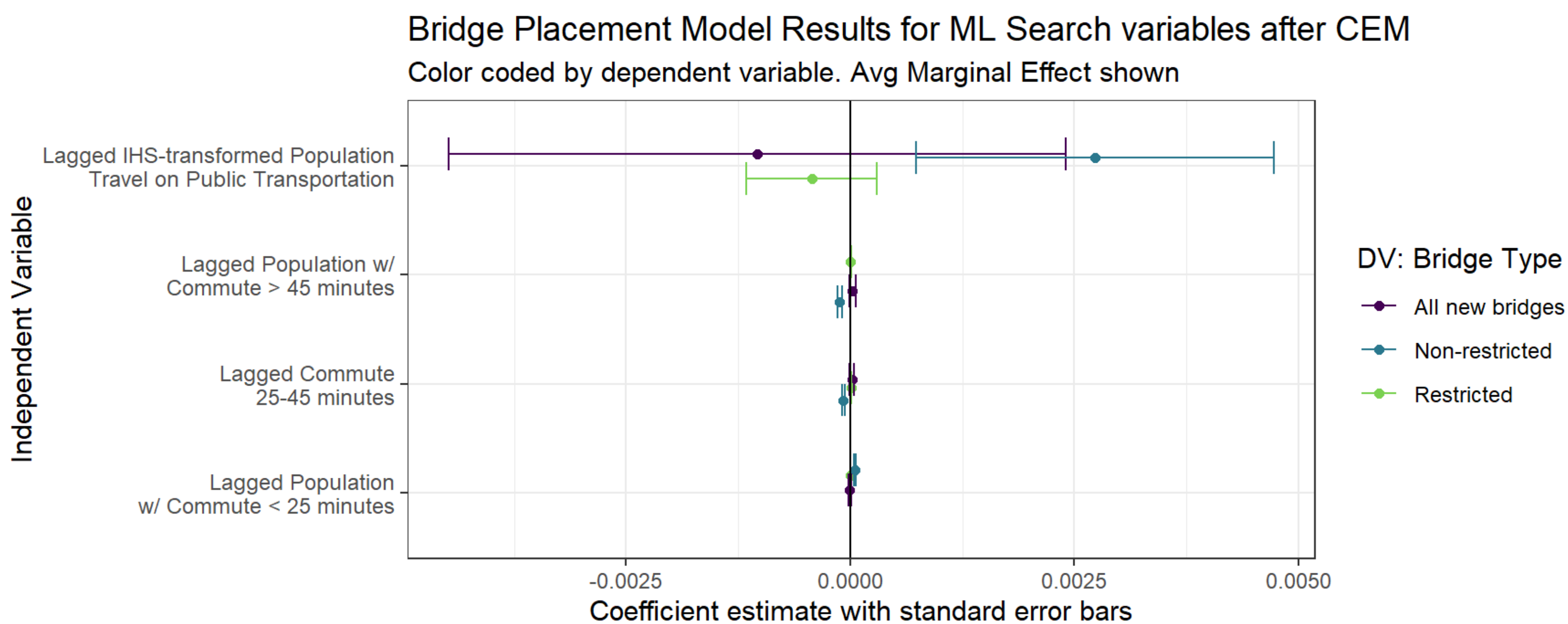

Fig. 89. Graphic depicting transportation variables in bridge siting models

Section D LASSO results

The Least Absolute Shrinkage and Selection Operator (LASSO) algorithm is designed to be a sparse variable selector (James et al. 2013; Tibshirani 1996). The LASSO uses an L_1 penalty which is used to shrink coefficient estimates towards zero. As it does so, only the most influential variables maintain a non-zero coefficient (see Fig. 90 for a graphical representation of this process). The minimization of the overall loss function can be seen in Equation 10:

Equation 10. LASSO minimization of overall loss function

$$\hat{\beta} \leftarrow \underset{\beta}{argmin}\left\{\sum_{i=1}^{n}\left(y_i - \beta - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2\right\} + \lambda\|\beta\|_1$$

where $\{x_i, y_i\}_{i=1}^{n}$ is the training data, β the intercept and λ is the Lagrange multiplier that balances the tradeoff between the squared error loss and the L_1 penalty $\|\beta\|_1$ (Jain et al. 2014).

In this work the authors used two values of lambda. The first is the minimum value of lambda and the second is one standard error above the minimum lambda (an example can be seen in Fig. 91). By taking agreement between these two values of lambda for both OLS and logistic regressions, the authors were able to narrow down the list of variables from 214 down to 17.

Table 76. Results of LASSO optimization using all variables for any new bridge regardless of underclearance height

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
AREALAND	0.000	0.000	0.000	0.000	0.000	0.000
AREAWATR	0.000	NA	NA	NA	NA	NA
rur10m	0.365	0.406	0.396	0.172	0.202	0.222
rur4m	0.198	0.220	0.041	0.129	0.153	0.155
TRCTPOP.lag	NA	NA	NA	NA	NA	NA
TPOPDENS.lag	0.000	0.000	NA	0.000	0.000	0.000
SMPPRS.lag	0.000	0.000	NA	0.000	0.000	0.000
MINORITY.lag	0.000	NA	NA	NA	NA	NA
SHRWHTN.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.lag	0.000	NA	NA	NA	NA	NA
SHRAPIN.lag	NA	NA	NA	NA	NA	NA
NONHISP.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.lag	0.000	NA	NA	0.000	0.000	NA
ADULTN.lag	NA	NA	NA	NA	NA	NA
AD2CHILD.lag	0.038	NA	NA	NA	NA	NA
CHILDN.lag	NA	NA	NA	NA	NA	NA
OLDN.lag	NA	NA	NA	0.000	NA	NA
KIDSN.lag	NA	NA	NA	0.000	NA	NA
NATBORN.lag	NA	NA	NA	NA	NA	NA
OUTBORN.lag	NA	NA	NA	NA	NA	NA
FORBORN.lag	0.000	NA	NA	0.000	0.000	NA
NUMHHS.lag	NA	NA	NA	NA	NA	NA
PERS15P.lag	NA	NA	NA	NA	NA	NA
MEN15P.lag	0.000	NA	NA	0.000	NA	NA
FEM15P.lag	NA	NA	NA	NA	NA	NA
MGMKTN.lag	NA	NA	NA	0.000	NA	NA
MGMKTD.lag	NA	NA	NA	NA	NA	NA
FAMSUB.lag	0.001	NA	NA	0.000	NA	NA
FFHN.lag	NA	NA	NA	NA	NA	NA
FFHD.lag	NA	NA	NA	NA	NA	NA
MCWKID.lag	NA	NA	NA	NA	NA	NA
MCNKID.lag	NA	NA	NA	NA	NA	NA
MHWKID.lag	NA	NA	NA	0.000	NA	NA
MHNKID.lag	NA	NA	NA	0.000	NA	NA
FHWKID.lag	NA	NA	NA	NA	NA	NA
FHNKID.lag	0.000	NA	NA	0.000	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
FHNKID.ihs.lag	-0.001	NA	NA	-0.002	NA	NA
TRVLPBN.lag	NA	NA	NA	0.000	NA	NA
TRVLPBD.lag	NA	NA	NA	NA	NA	NA
WKHOME.lag	0.000	NA	NA	NA	NA	NA
AUTO.lag	NA	NA	NA	NA	NA	NA
COMMUT2.lag	0.000	NA	NA	NA	NA	NA
COMMUT4.lag	0.000	NA	NA	NA	NA	NA
COMMUTX.lag	0.000	NA	NA	0.000	NA	NA
TRVLOTN.lag	0.000	NA	NA	0.000	NA	NA
EDUC8.lag	NA	NA	NA	0.000	0.000	NA
EDUC11.lag	0.000	NA	NA	NA	NA	NA
EDUC12.lag	NA	NA	NA	NA	NA	NA
EDUC15.lag	NA	NA	NA	NA	NA	NA
EDUCA.lag	NA	NA	NA	NA	NA	NA
EDUC16.lag	NA	NA	NA	NA	NA	NA
EDUCPP.lag	NA	NA	NA	NA	NA	NA
WRCNTYN.lag	0.000	0.000	NA	0.000	0.000	NA
WRCNTYD.lag	NA	NA	NA	NA	NA	NA
WRKSMN.lag	0.000	NA	NA	0.000	NA	NA
PRFEMP.lag	NA	NA	NA	NA	NA	NA
INDEMP.lag	NA	NA	NA	NA	NA	NA
USKOCC.lag	NA	NA	NA	NA	NA	NA
OCC1.lag	NA	NA	NA	0.000	NA	NA
OCC2.lag	0.000	NA	NA	0.000	NA	NA
OCC3.lag	0.000	NA	NA	0.000	NA	NA
OCC4.lag	-0.001	NA	NA	0.000	NA	NA
OCC5.lag	NA	NA	NA	0.000	0.000	NA
OCC6.lag	0.000	NA	NA	0.000	NA	NA
OCC7.lag	NA	NA	NA	0.000	NA	NA
OCC8.lag	NA	NA	NA	NA	NA	NA
OCC9.lag	0.002	0.003	NA	0.000	0.001	0.001
OCCPRO.lag	NA	NA	NA	NA	NA	NA
OCCPRO.ihs.lag	NA	NA	NA	NA	NA	NA
ARMFRM.lag	0.000	NA	NA	0.000	NA	NA
ARMFRF.lag	-0.003	NA	NA	0.000	NA	NA
AVHHINN.2010real.lag	0.000	NA	NA	0.000	NA	NA
AVHHIN.2010real.lag	NA	NA	NA	NA	NA	NA
POVRATN.lag	NA	NA	NA	NA	NA	NA
POVRATD.lag	NA	NA	NA	NA	NA	NA
POVRATD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRN.lag	0.000	0.000	NA	0.000	0.000	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
WELFARN.lag	0.000	NA	NA	0.000	NA	NA
WELFARD.lag	NA	NA	NA	NA	NA	NA
NELPOON.lag	NA	NA	NA	0.000	NA	NA
NELPOOD.lag	NA	NA	NA	NA	NA	NA
ELDPOON.lag	0.000	NA	NA	0.000	NA	NA
ELDPOOD.lag	NA	NA	NA	0.000	NA	NA
WHTPRD.lag	0.000	NA	NA	NA	NA	NA
TOTHSUN.lag	NA	NA	NA	NA	NA	NA
SMPHSU.lag	NA	NA	NA	NA	NA	NA
OCCHU.lag	NA	NA	NA	NA	NA	NA
VACHU.lag	NA	NA	NA	NA	NA	NA
VACRT.lag	NA	NA	NA	NA	NA	NA
VACFS.lag	0.001	NA	NA	0.000	NA	NA
VACOCC.lag	0.000	0.000	NA	0.000	0.000	NA
VACOTH.lag	NA	NA	NA	0.000	NA	NA
RNTOCC.lag	NA	NA	NA	NA	NA	NA
OWNOCC.lag	NA	NA	NA	NA	NA	NA
SPRNTOC.lag	0.000	NA	NA	0.000	NA	NA
SPOWNOC.lag	-0.001	NA	NA	0.000	NA	NA
PRSRNTU.lag	NA	NA	NA	NA	NA	NA
NEWHOUS.lag	0.000	NA	NA	NA	NA	NA
MINORITY.pct.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.pct.lag	NA	NA	NA	0.054	0.024	NA
SHRBLKN.pct.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.pct.lag	22.843	NA	NA	0.564	NA	NA
SHRAPIN.pct.lag	1.270	NA	NA	0.333	NA	NA
SHRHSPN.pct.lag	NA	NA	NA	NA	-0.008	NA
CHILD.pct.lag	-0.273	NA	NA	NA	NA	NA
FORBORN.pct.lag	0.575	NA	NA	NA	NA	NA
MCWKID.pct.lag	NA	NA	NA	NA	0.033	NA
SPWKID.pct.lag	NA	NA	NA	NA	NA	NA
MHWKID.pct.lag	NA	NA	NA	-0.199	NA	NA
FHHTOT.pct.lag	NA	NA	NA	-0.041	NA	NA
FHWKID.pct.lag	NA	NA	NA	NA	NA	NA
EDUC8.pct.lag	-0.737	NA	NA	NA	NA	NA
EDUC11.pct.lag	-0.105	NA	NA	NA	NA	NA
EDUC12.pct.lag	NA	NA	NA	NA	NA	NA
EDUC15.pct.lag	-0.025	-0.081	NA	NA	NA	NA
EDUCA.pct.lag	-0.571	NA	NA	-0.091	NA	NA
EDUC16.pct.lag	NA	NA	NA	NA	NA	NA
OCCPRO.pct.lag	0.452	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
POVRATN.pct.lag	0.077	NA	NA	0.130	0.059	NA
WELFARN.pct.lag	0.571	NA	NA	0.094	NA	NA
VACHU.pct.lag	-0.578	NA	NA	-0.392	-0.023	NA
OWNOCC.pct.lag	0.237	NA	NA	NA	NA	NA
RNTOCC.pct.lag	NA	NA	NA	NA	NA	NA
OWNRNT.pct.lag	0.000	NA	NA	0.000	0.000	NA
NEWHOUS.pct.lag	-0.018	NA	NA	-0.004	NA	NA
TRCTPOP.ihs.lag	NA	NA	NA	NA	NA	NA
MINORITY.ihs.lag	NA	NA	NA	NA	NA	NA
SMPPRS.ihs.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.ihs.lag	NA	NA	NA	0.003	NA	NA
SHRBLKN.ihs.lag	0.017	NA	NA	0.004	NA	NA
SHRAMIN.ihs.lag	-0.041	NA	NA	NA	NA	NA
SHRAPIN.ihs.lag	-0.006	NA	NA	-0.005	0.000	NA
NONHISP.ihs.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.ihs.lag	-0.007	NA	NA	-0.002	-0.002	NA
ADULTN.ihs.lag	NA	NA	NA	NA	NA	NA
CHILDN.ihs.lag	NA	NA	NA	NA	NA	NA
OLDN.ihs.lag	NA	NA	NA	NA	NA	NA
KIDSN.ihs.lag	NA	NA	NA	NA	NA	NA
NATBORN.ihs.lag	NA	NA	NA	NA	NA	NA
OUTBORN.ihs.lag	-0.002	NA	NA	-0.005	-0.004	NA
FORBORN.ihs.lag	-0.037	NA	NA	-0.015	-0.005	NA
NUMHHS.ihs.lag	NA	NA	NA	NA	NA	NA
PERS15P.ihs.lag	NA	NA	NA	NA	NA	NA
MEN15P.ihs.lag	NA	NA	NA	NA	NA	NA
FEM15P.ihs.lag	NA	NA	NA	0.002	NA	NA
MGMKTN.ihs.lag	NA	NA	NA	NA	NA	NA
MGMKTD.ihs.lag	NA	NA	NA	NA	NA	NA
FAMSUB.ihs.lag	NA	NA	NA	-0.004	NA	NA
FFHN.ihs.lag	NA	NA	NA	NA	NA	NA
FFHD.ihs.lag	NA	NA	NA	NA	NA	NA
MCWKID.ihs.lag	NA	NA	NA	NA	NA	NA
MCNKID.ihs.lag	NA	NA	NA	NA	NA	NA
MHWKID.ihs.lag	NA	NA	NA	NA	NA	NA
MHNKID.ihs.lag	NA	NA	NA	NA	NA	NA
FHWKID.ihs.lag	NA	NA	NA	NA	NA	NA
WRCNTYN.ihs.lag	NA	NA	NA	NA	NA	NA
WRCNTYD.ihs.lag	NA	NA	NA	NA	NA	NA
WRKSMN.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBN.ihs.lag	0.028	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
TRVLPBD.ihs.lag	NA	NA	NA	NA	NA	NA
WKHOME.ihs.lag	NA	NA	NA	0.004	0.004	NA
AUTO.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT2.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT4.ihs.lag	NA	NA	NA	0.000	NA	NA
COMMUTX.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLOTN.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC8.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC11.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC12.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC15.ihs.lag	NA	NA	NA	NA	NA	NA
EDUCA.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC16.ihs.lag	NA	NA	NA	NA	NA	NA
EDUCPP.ihs.lag	NA	NA	NA	0.010	NA	NA
PRFEMP.ihs.lag	NA	NA	NA	NA	NA	NA
INDEMP.ihs.lag	NA	NA	NA	NA	NA	NA
USKOCC.ihs.lag	NA	NA	NA	NA	NA	NA
OCC1.ihs.lag	NA	NA	NA	0.014	NA	NA
OCC2.ihs.lag	NA	NA	NA	NA	NA	NA
OCC3.ihs.lag	NA	NA	NA	NA	NA	NA
OCC4.ihs.lag	NA	NA	NA	NA	NA	NA
OCC5.ihs.lag	NA	NA	NA	NA	NA	NA
OCC6.ihs.lag	NA	NA	NA	NA	NA	NA
OCC7.ihs.lag	NA	NA	NA	NA	NA	NA
OCC8.ihs.lag	NA	NA	NA	NA	NA	NA
OCC9.ihs.lag	NA	NA	NA	0.002	0.003	NA
ARMFRM.ihs.lag	0.022	NA	NA	0.004	0.000	NA
ARMFRF.ihs.lag	0.027	NA	NA	NA	NA	NA
POVRATN.ihs.lag	NA	NA	NA	NA	NA	NA
POVRATD.ihs.lag.1	NA	NA	NA	NA	NA	NA
WHTPRN.ihs.lag	NA	NA	NA	NA	NA	NA
WELFARN.ihs.lag	NA	NA	NA	-0.007	NA	NA
WELFARD.ihs.lag	NA	NA	NA	NA	NA	NA
NELPOON.ihs.lag	NA	NA	NA	NA	NA	NA
NELPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
ELDPOON.ihs.lag	-0.001	NA	NA	-0.005	NA	NA
ELDPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRD.ihs.lag	NA	NA	NA	NA	NA	NA
TOTHSUN.ihs.lag	NA	NA	NA	NA	NA	NA
SMPHSU.ihs.lag	-0.067	NA	NA	-0.024	NA	NA
OCCHU.ihs.lag	NA	NA	NA	0.001	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
VACHU.ihs.lag	NA	NA	NA	0.018	NA	NA
VACRT.ihs.lag	0.010	NA	NA	NA	NA	NA
VACFS.ihs.lag	NA	NA	NA	-0.004	NA	NA
VACOCC.ihs.lag	-0.022	NA	NA	-0.002	NA	NA
VACOTH.ihs.lag	0.020	NA	NA	0.000	NA	NA
RNTOCC.ihs.lag	NA	NA	NA	NA	NA	NA
OWNOCC.ihs.lag	NA	NA	NA	0.000	NA	NA
SPRNTOC.ihs.lag	0.092	NA	NA	0.014	0.003	NA
SPOWNOC.ihs.lag	NA	NA	NA	NA	NA	NA
PRSRNTU.ihs.lag	NA	NA	NA	0.007	NA	NA
TPOPDENS.ihs.lag	-0.076	-0.023	NA	-0.047	-0.021	-0.011
NEWHOUS.ihs.lag	-0.004	NA	NA	-0.002	NA	NA
AVHHINN.2010real.ihs.lag	NA	NA	NA	NA	NA	NA
AVHHIN.2010real.ihs.lag	NA	NA	NA	0.005	NA	NA
factor(YEAR)1980	0.535	0.078	NA	NA	NA	NA
factor(YEAR)1990	NA	NA	NA	0.017	0.005	NA
factor(YEAR)2000	-0.092	-0.037	NA	-0.023	-0.023	NA
factor(YEAR)2010	NA	NA	NA	NA	NA	NA

Table 77. Results of LASSO optimization using All variables for new non-restrictive bridges

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
AREALAND	0.000	NA	NA	0.000	NA	NA
AREAWATR	0.000	NA	NA	NA	NA	NA
rur10m	0.113	0.111	NA	0.014	0.007	NA
rur4m	0.043	0.086	0.000	0.045	0.047	0.028
TRCTPOP.lag	NA	NA	NA	NA	NA	NA
TPOPDENS.lag	0.000	0.000	NA	0.000	0.000	NA
SMPPRS.lag	NA	NA	NA	NA	NA	NA
MINORITY.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.lag	-0.003	NA	NA	NA	NA	NA
SHRAPIN.lag	NA	NA	NA	NA	NA	NA
NONHISP.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.lag	0.000	NA	NA	0.000	NA	NA
ADULTN.lag	NA	NA	NA	NA	NA	NA
AD2CHILD.lag	0.065	NA	NA	0.016	NA	NA
CHILDN.lag	NA	NA	NA	NA	NA	NA
OLDN.lag	0.000	NA	NA	NA	NA	NA
KIDSN.lag	NA	NA	NA	NA	NA	NA
NATBORN.lag	NA	NA	NA	NA	NA	NA
OUTBORN.lag	0.000	NA	NA	NA	NA	NA
FORBORN.lag	0.000	NA	NA	0.000	NA	NA
NUMHHS.lag	NA	NA	NA	NA	NA	NA
PERS15P.lag	NA	NA	NA	NA	NA	NA
MEN15P.lag	0.000	NA	NA	NA	NA	NA
FEM15P.lag	NA	NA	NA	NA	NA	NA
MGMKTN.lag	NA	NA	NA	0.000	NA	NA
MGMKTD.lag	NA	NA	NA	NA	NA	NA
FAMSUB.lag	0.000	NA	NA	NA	NA	NA
FFHN.lag	NA	NA	NA	NA	NA	NA
FFHD.lag	NA	NA	NA	NA	NA	NA
MCWKID.lag	NA	NA	NA	NA	NA	NA
MCNKID.lag	NA	NA	NA	NA	NA	NA
MHWKID.lag	0.000	NA	NA	NA	NA	NA
MHNKID.lag	NA	NA	NA	NA	NA	NA
FHWKID.lag	NA	NA	NA	NA	NA	NA
FHNKID.lag	NA	NA	NA	NA	NA	NA
FHNKID.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBN.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
TRVLPBD.lag	NA	NA	NA	NA	NA	NA
WKHOME.lag	NA	NA	NA	NA	NA	NA
AUTO.lag	NA	NA	NA	NA	NA	NA
COMMUT2.lag	0.000	0.000	NA	0.000	NA	NA
COMMUT4.lag	0.000	NA	NA	0.000	NA	NA
COMMUTX.lag	0.000	0.000	NA	0.000	0.000	NA
TRVLOTN.lag	0.000	NA	NA	0.000	NA	NA
EDUC8.lag	NA	NA	NA	0.000	NA	NA
EDUC11.lag	0.000	NA	NA	0.000	NA	NA
EDUC12.lag	NA	NA	NA	NA	NA	NA
EDUC15.lag	0.000	NA	NA	0.000	NA	NA
EDUCA.lag	0.000	NA	NA	NA	NA	NA
EDUC16.lag	NA	NA	NA	NA	NA	NA
EDUCPP.lag	NA	NA	NA	NA	NA	NA
WRCNTYN.lag	0.000	0.000	NA	0.000	0.000	NA
WRCNTYD.lag	NA	NA	NA	NA	NA	NA
WRKSMN.lag	0.000	NA	NA	0.000	NA	NA
PRFEMP.lag	0.000	NA	NA	NA	NA	NA
INDEMP.lag	NA	NA	NA	NA	NA	NA
USKOCC.lag	NA	NA	NA	NA	NA	NA
OCC1.lag	0.000	NA	NA	NA	NA	NA
OCC2.lag	0.001	NA	NA	0.000	NA	NA
OCC3.lag	NA	NA	NA	NA	NA	NA
OCC4.lag	0.000	NA	NA	NA	NA	NA
OCC5.lag	NA	NA	NA	NA	NA	NA
OCC6.lag	0.000	NA	NA	0.000	NA	NA
OCC7.lag	NA	NA	NA	NA	NA	NA
OCC8.lag	NA	NA	NA	NA	NA	NA
OCC9.lag	-0.001	0.000	NA	0.000	NA	NA
OCCPRO.lag	NA	NA	NA	NA	NA	NA
OCCPRO.ihs.lag	NA	NA	NA	NA	NA	NA
ARMFRM.lag	0.000	NA	NA	0.000	NA	NA
ARMFRF.lag	-0.002	NA	NA	NA	NA	NA
AVHHINN.2010real.lag	0.000	NA	NA	NA	NA	NA
AVHHIN.2010real.lag	NA	NA	NA	NA	NA	NA
POVRATN.lag	NA	NA	NA	NA	NA	NA
POVRATD.lag	NA	NA	NA	NA	NA	NA
POVRATD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRN.lag	0.000	0.000	NA	0.000	0.000	NA
WELFARN.lag	NA	NA	NA	NA	NA	NA
WELFARD.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
NELPOON.lag	NA	NA	NA	NA	NA	NA
NELPOOD.lag	NA	NA	NA	NA	NA	NA
ELDPOON.lag	0.000	NA	NA	NA	NA	NA
ELDPOOD.lag	NA	NA	NA	NA	NA	NA
WHTPRD.lag	NA	NA	NA	NA	NA	NA
TOTHSUN.lag	NA	NA	NA	NA	NA	NA
SMPHSU.lag	0.000	NA	NA	NA	NA	NA
OCCHU.lag	NA	NA	NA	NA	NA	NA
VACHU.lag	NA	NA	NA	NA	NA	NA
VACRT.lag	0.000	NA	NA	NA	NA	NA
VACFS.lag	0.000	NA	NA	0.000	NA	NA
VACOCC.lag	0.000	0.000	NA	0.000	0.000	NA
VACOTH.lag	0.000	NA	NA	NA	NA	NA
RNTOCC.lag	NA	NA	NA	NA	NA	NA
OWNOCC.lag	NA	NA	NA	NA	NA	NA
SPRNTOC.lag	0.000	NA	NA	0.000	NA	NA
SPOWNOC.lag	0.000	NA	NA	0.000	NA	NA
PRSRNTU.lag	0.000	NA	NA	NA	NA	NA
NEWHOUS.lag	0.000	0.000	NA	0.000	0.000	NA
MINORITY.pct.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.pct.lag	0.174	NA	NA	0.012	NA	NA
SHRBLKN.pct.lag	0.183	NA	NA	NA	NA	NA
SHRAMIN.pct.lag	26.165	2.699	NA	0.456	NA	NA
SHRAPIN.pct.lag	1.099	0.033	NA	0.101	NA	NA
SHRHSPN.pct.lag	0.323	NA	NA	NA	NA	NA
CHILD.pct.lag	-0.686	-0.183	NA	-0.038	-0.034	NA
FORBORN.pct.lag	0.212	NA	NA	NA	NA	NA
MCWKID.pct.lag	0.128	NA	NA	NA	NA	NA
SPWKID.pct.lag	NA	NA	NA	NA	NA	NA
MHWKID.pct.lag	NA	NA	NA	NA	NA	NA
FHHTOT.pct.lag	NA	NA	NA	NA	NA	NA
FHWKID.pct.lag	NA	NA	NA	NA	NA	NA
EDUC8.pct.lag	NA	NA	NA	NA	NA	NA
EDUC11.pct.lag	-0.441	NA	NA	NA	NA	NA
EDUC12.pct.lag	0.015	NA	NA	NA	NA	NA
EDUC15.pct.lag	NA	NA	NA	NA	NA	NA
EDUCA.pct.lag	NA	NA	NA	-0.013	NA	NA
EDUC16.pct.lag	-0.049	NA	NA	NA	NA	NA
OCCPRO.pct.lag	0.366	NA	NA	0.015	NA	NA
POVRATN.pct.lag	NA	0.050	NA	0.024	NA	NA
WELFARN.pct.lag	0.703	0.294	NA	0.097	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
VACHU.pct.lag	NA	NA	NA	NA	NA	NA
OWNOCC.pct.lag	0.086	NA	NA	NA	NA	NA
RNTOCC.pct.lag	NA	NA	NA	NA	NA	NA
OWNRNT.pct.lag	0.000	NA	NA	0.000	NA	NA
NEWHOUS.pct.lag	-0.012	-0.004	NA	-0.004	-0.001	NA
TRCTPOP.ihs.lag	NA	NA	NA	NA	NA	NA
MINORITY.ihs.lag	NA	NA	NA	NA	NA	NA
SMPPRS.ihs.lag	-0.010	NA	NA	NA	NA	NA
SHRWHTN.ihs.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.ihs.lag	0.003	0.000	NA	0.002	NA	NA
SHRAMIN.ihs.lag	-0.032	-0.001	NA	NA	NA	NA
SHRAPIN.ihs.lag	-0.004	NA	NA	NA	NA	NA
NONHISP.ihs.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.ihs.lag	-0.001	NA	NA	-0.002	NA	NA
ADULTN.ihs.lag	NA	NA	NA	NA	NA	NA
CHILDN.ihs.lag	NA	NA	NA	NA	NA	NA
OLDN.ihs.lag	NA	NA	NA	NA	NA	NA
KIDSN.ihs.lag	-0.008	NA	NA	NA	NA	NA
NATBORN.ihs.lag	NA	NA	NA	NA	NA	NA
OUTBORN.ihs.lag	-0.001	NA	NA	-0.003	NA	NA
FORBORN.ihs.lag	NA	NA	NA	NA	NA	NA
NUMHHS.ihs.lag	NA	NA	NA	NA	NA	NA
PERS15P.ihs.lag	NA	NA	NA	NA	NA	NA
MEN15P.ihs.lag	NA	NA	NA	NA	NA	NA
FEM15P.ihs.lag	NA	NA	NA	NA	NA	NA
MGMKTN.ihs.lag	NA	NA	NA	NA	NA	NA
MGMKTD.ihs.lag	NA	NA	NA	NA	NA	NA
FAMSUB.ihs.lag	NA	NA	NA	NA	NA	NA
FFHN.ihs.lag	NA	NA	NA	NA	NA	NA
FFHD.ihs.lag	NA	NA	NA	NA	NA	NA
MCWKID.ihs.lag	NA	NA	NA	NA	NA	NA
MCNKID.ihs.lag	NA	NA	NA	NA	NA	NA
MHWKID.ihs.lag	NA	NA	NA	-0.001	NA	NA
MHNKID.ihs.lag	0.001	NA	NA	NA	NA	NA
FHWKID.ihs.lag	0.019	NA	NA	NA	NA	NA
WRCNTYN.ihs.lag	NA	NA	NA	NA	NA	NA
WRCNTYD.ihs.lag	NA	NA	NA	NA	NA	NA
WRKSMN.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBN.ihs.lag	0.033	0.001	NA	0.007	NA	NA
TRVLPBD.ihs.lag	NA	NA	NA	NA	NA	NA
WKHOME.ihs.lag	-0.001	NA	NA	-0.001	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
AUTO.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT2.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT4.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUTX.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLOTN.ihs.lag	-0.002	NA	NA	NA	NA	NA
EDUC8.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC11.ihs.lag	0.037	NA	NA	NA	NA	NA
EDUC12.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC15.ihs.lag	-0.038	NA	NA	NA	NA	NA
EDUCA.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC16.ihs.lag	NA	NA	NA	NA	NA	NA
EDUCPP.ihs.lag	NA	NA	NA	NA	NA	NA
PRFEMP.ihs.lag	NA	NA	NA	NA	NA	NA
INDEMP.ihs.lag	NA	NA	NA	NA	NA	NA
USKOCC.ihs.lag	NA	NA	NA	NA	NA	NA
OCC1.ihs.lag	NA	NA	NA	NA	NA	NA
OCC2.ihs.lag	NA	NA	NA	NA	NA	NA
OCC3.ihs.lag	NA	NA	NA	NA	NA	NA
OCC4.ihs.lag	NA	NA	NA	NA	NA	NA
OCC5.ihs.lag	-0.021	NA	NA	NA	NA	NA
OCC6.ihs.lag	NA	NA	NA	NA	NA	NA
OCC7.ihs.lag	0.009	NA	NA	NA	NA	NA
OCC8.ihs.lag	NA	NA	NA	NA	NA	NA
OCC9.ihs.lag	0.000	NA	NA	-0.002	NA	NA
ARMFRM.ihs.lag	0.015	0.005	NA	0.003	NA	NA
ARMFRF.ihs.lag	0.032	0.001	NA	0.004	NA	NA
POVRATN.ihs.lag	0.006	NA	NA	NA	NA	NA
POVRATD.ihs.lag.1	NA	NA	NA	NA	NA	NA
WHTPRN.ihs.lag	NA	NA	NA	NA	NA	NA
WELFARN.ihs.lag	NA	NA	NA	NA	NA	NA
WELFARD.ihs.lag	NA	NA	NA	NA	NA	NA
NELPOON.ihs.lag	0.000	NA	NA	NA	NA	NA
NELPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
ELDPOON.ihs.lag	-0.010	NA	NA	NA	NA	NA
ELDPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRD.ihs.lag	NA	NA	NA	NA	NA	NA
TOTHSUN.ihs.lag	NA	NA	NA	NA	NA	NA
SMPHSU.ihs.lag	-0.017	NA	NA	-0.003	NA	NA
OCCHU.ihs.lag	NA	NA	NA	NA	NA	NA
VACHU.ihs.lag	0.000	NA	NA	NA	NA	NA
VACRT.ihs.lag	0.006	NA	NA	0.002	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
VACFS.ihs.lag	NA	NA	NA	NA	NA	NA
VACOCC.ihs.lag	-0.008	NA	NA	NA	NA	NA
VACOTH.ihs.lag	0.014	NA	NA	0.001	NA	NA
RNTOCC.ihs.lag	0.007	NA	NA	NA	NA	NA
OWNOCC.ihs.lag	NA	NA	NA	NA	NA	NA
SPRNTOC.ihs.lag	0.034	NA	NA	0.003	NA	NA
SPOWNOC.ihs.lag	NA	NA	NA	NA	NA	NA
PRSRNTU.ihs.lag	0.004	NA	NA	NA	NA	NA
TPOPDENS.ihs.lag	-0.080	-0.003	NA	-0.011	0.000	NA
NEWHOUS.ihs.lag	-0.003	NA	NA	-0.001	NA	NA
AVHHINN.2010real.ihs.lag	NA	NA	NA	NA	NA	NA
AVHHIN.2010real.ihs.lag	NA	NA	NA	NA	NA	NA
factor(YEAR)1980	0.343	0.127	NA	0.034	0.009	NA
factor(YEAR)1990	NA	NA	NA	NA	-0.004	NA
factor(YEAR)2000	-0.034	NA	NA	-0.002	NA	NA
factor(YEAR)2010	NA	NA	NA	NA	NA	NA

Table 78. Results of LASSO optimization using all variables for new restricted bridges

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
AREALAND	0.000	0.000	0.000	NA	NA	NA
AREAWATR	NA	NA	NA	NA	NA	NA
rur10m	NA	NA	NA	NA	NA	NA
rur4m	NA	NA	NA	NA	NA	NA
TRCTPOP.lag	NA	NA	NA	NA	NA	NA
TPOPDENS.lag	NA	NA	NA	NA	NA	NA
SMPPRS.lag	NA	NA	NA	NA	NA	NA
MINORITY.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.lag	NA	NA	NA	NA	NA	NA
SHRAPIN.lag	NA	NA	NA	NA	NA	NA
NONHISP.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.lag	NA	NA	NA	NA	NA	NA
ADULTN.lag	NA	NA	NA	NA	NA	NA
AD2CHILD.lag	NA	NA	NA	NA	NA	NA
CHILDN.lag	NA	NA	NA	NA	NA	NA
OLDN.lag	NA	NA	NA	NA	NA	NA
KIDSN.lag	NA	NA	NA	NA	NA	NA
NATBORN.lag	NA	NA	NA	NA	NA	NA
OUTBORN.lag	NA	NA	NA	NA	NA	NA
FORBORN.lag	NA	NA	NA	NA	NA	NA
NUMHHS.lag	NA	NA	NA	NA	NA	NA
PERS15P.lag	NA	NA	NA	NA	NA	NA
MEN15P.lag	NA	NA	NA	NA	NA	NA
FEM15P.lag	NA	NA	NA	NA	NA	NA
MGMKTN.lag	NA	NA	NA	NA	NA	NA
MGMKTD.lag	NA	NA	NA	NA	NA	NA
FAMSUB.lag	NA	NA	NA	NA	NA	NA
FFHN.lag	NA	NA	NA	NA	NA	NA
FFHD.lag	NA	NA	NA	NA	NA	NA
MCWKID.lag	NA	NA	NA	NA	NA	NA
MCNKID.lag	NA	NA	NA	NA	NA	NA
MHWKID.lag	NA	NA	NA	NA	NA	NA
MHNKID.lag	NA	NA	NA	NA	NA	NA
FHWKID.lag	NA	NA	NA	NA	NA	NA
FHNKID.lag	NA	NA	NA	NA	NA	NA
FHNKID.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBN.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
TRVLPBD.lag	NA	NA	NA	NA	NA	NA
WKHOME.lag	NA	NA	NA	NA	NA	NA
AUTO.lag	NA	NA	NA	NA	NA	NA
COMMUT2.lag	NA	NA	NA	NA	NA	NA
COMMUT4.lag	NA	NA	NA	NA	NA	NA
COMMUTX.lag	NA	NA	NA	NA	NA	NA
TRVLOTN.lag	NA	NA	NA	NA	NA	NA
EDUC8.lag	NA	NA	NA	NA	NA	NA
EDUC11.lag	NA	NA	NA	NA	NA	NA
EDUC12.lag	NA	NA	NA	NA	NA	NA
EDUC15.lag	NA	NA	NA	NA	NA	NA
EDUCA.lag	NA	NA	NA	NA	NA	NA
EDUC16.lag	NA	NA	NA	NA	NA	NA
EDUCPP.lag	NA	NA	NA	NA	NA	NA
WRCNTYN.lag	NA	NA	NA	NA	NA	NA
WRCNTYD.lag	NA	NA	NA	NA	NA	NA
WRKSMN.lag	NA	NA	NA	NA	NA	NA
PRFEMP.lag	NA	NA	NA	NA	NA	NA
INDEMP.lag	NA	NA	NA	NA	NA	NA
USKOCC.lag	NA	NA	NA	NA	NA	NA
OCC1.lag	NA	NA	NA	NA	NA	NA
OCC2.lag	NA	NA	NA	NA	NA	NA
OCC3.lag	NA	NA	NA	NA	NA	NA
OCC4.lag	NA	NA	NA	NA	NA	NA
OCC5.lag	NA	NA	NA	NA	NA	NA
OCC6.lag	NA	NA	NA	NA	NA	NA
OCC7.lag	NA	NA	NA	NA	NA	NA
OCC8.lag	NA	NA	NA	NA	NA	NA
OCC9.lag	NA	NA	NA	NA	NA	NA
OCCPRO.lag	NA	NA	NA	NA	NA	NA
OCCPRO.ihs.lag	NA	NA	NA	NA	NA	NA
ARMFRM.lag	NA	NA	NA	NA	NA	NA
ARMFRF.lag	NA	NA	NA	NA	NA	NA
AVHHINN.2010real.lag	NA	NA	NA	NA	NA	NA
AVHHIN.2010real.lag	NA	NA	NA	NA	NA	NA
POVRATN.lag	NA	NA	NA	NA	NA	NA
POVRATD.lag	NA	NA	NA	NA	NA	NA
POVRATD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRN.lag	NA	NA	NA	NA	NA	NA
WELFARN.lag	NA	NA	NA	NA	NA	NA
WELFARD.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
NELPOON.lag	NA	NA	NA	NA	NA	NA
NELPOOD.lag	NA	NA	NA	NA	NA	NA
ELDPOON.lag	NA	NA	NA	NA	NA	NA
ELDPOOD.lag	NA	NA	NA	NA	NA	NA
WHTPRD.lag	NA	NA	NA	NA	NA	NA
TOTHSUN.lag	NA	NA	NA	NA	NA	NA
SMPHSU.lag	NA	NA	NA	NA	NA	NA
OCCHU.lag	NA	NA	NA	NA	NA	NA
VACHU.lag	NA	NA	NA	NA	NA	NA
VACRT.lag	NA	NA	NA	NA	NA	NA
VACFS.lag	NA	NA	NA	NA	NA	NA
VACOCC.lag	NA	NA	NA	NA	NA	NA
VACOTH.lag	NA	NA	NA	NA	NA	NA
RNTOCC.lag	NA	NA	NA	NA	NA	NA
OWNOCC.lag	NA	NA	NA	NA	NA	NA
SPRNTOC.lag	NA	NA	NA	NA	NA	NA
SPOWNOC.lag	NA	NA	NA	NA	NA	NA
PRSRNTU.lag	NA	NA	NA	NA	NA	NA
NEWHOUS.lag	NA	NA	NA	NA	NA	NA
MINORITY.pct.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.pct.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.pct.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.pct.lag	NA	NA	NA	NA	NA	NA
SHRAPIN.pct.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.pct.lag	NA	NA	NA	NA	NA	NA
CHILD.pct.lag	NA	NA	NA	NA	NA	NA
FORBORN.pct.lag	NA	NA	NA	NA	NA	NA
MCWKID.pct.lag	NA	NA	NA	NA	NA	NA
SPWKID.pct.lag	NA	NA	NA	NA	NA	NA
MHWKID.pct.lag	NA	NA	NA	NA	NA	NA
FHHTOT.pct.lag	NA	NA	NA	NA	NA	NA
FHWKID.pct.lag	NA	NA	NA	NA	NA	NA
EDUC8.pct.lag	NA	NA	NA	NA	NA	NA
EDUC11.pct.lag	NA	NA	NA	NA	NA	NA
EDUC12.pct.lag	NA	NA	NA	NA	NA	NA
EDUC15.pct.lag	NA	NA	NA	0.000	0.000	0.000
EDUCA.pct.lag	NA	NA	NA	NA	NA	NA
EDUC16.pct.lag	NA	NA	NA	NA	NA	NA
OCCPRO.pct.lag	NA	NA	NA	NA	NA	NA
POVRATN.pct.lag	NA	NA	NA	NA	NA	NA
WELFARN.pct.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
VACHU.pct.lag	NA	NA	NA	NA	NA	NA
OWNOCC.pct.lag	NA	NA	NA	NA	NA	NA
RNTOCC.pct.lag	NA	NA	NA	NA	NA	NA
OWNRNT.pct.lag	NA	NA	NA	NA	NA	NA
NEWHOUS.pct.lag	NA	NA	NA	NA	NA	NA
TRCTPOP.ihs.lag	NA	NA	NA	NA	NA	NA
MINORITY.ihs.lag	NA	NA	NA	NA	NA	NA
SMPPRS.ihs.lag	NA	NA	NA	NA	NA	NA
SHRWHTN.ihs.lag	NA	NA	NA	NA	NA	NA
SHRBLKN.ihs.lag	NA	NA	NA	NA	NA	NA
SHRAMIN.ihs.lag	NA	NA	NA	NA	NA	NA
SHRAPIN.ihs.lag	NA	NA	NA	NA	NA	NA
NONHISP.ihs.lag	NA	NA	NA	NA	NA	NA
SHRHSPN.ihs.lag	NA	NA	NA	NA	NA	NA
ADULTN.ihs.lag	NA	NA	NA	NA	NA	NA
CHILDN.ihs.lag	NA	NA	NA	NA	NA	NA
OLDN.ihs.lag	NA	NA	NA	NA	NA	NA
KIDSN.ihs.lag	NA	NA	NA	NA	NA	NA
NATBORN.ihs.lag	NA	NA	NA	NA	NA	NA
OUTBORN.ihs.lag	NA	NA	NA	NA	NA	NA
FORBORN.ihs.lag	NA	NA	NA	NA	NA	NA
NUMHHS.ihs.lag	NA	NA	NA	NA	NA	NA
PERS15P.ihs.lag	NA	NA	NA	NA	NA	NA
MEN15P.ihs.lag	NA	NA	NA	NA	NA	NA
FEM15P.ihs.lag	NA	NA	NA	NA	NA	NA
MGMKTN.ihs.lag	NA	NA	NA	NA	NA	NA
MGMKTD.ihs.lag	NA	NA	NA	NA	NA	NA
FAMSUB.ihs.lag	NA	NA	NA	NA	NA	NA
FFHN.ihs.lag	NA	NA	NA	NA	NA	NA
FFHD.ihs.lag	NA	NA	NA	NA	NA	NA
MCWKID.ihs.lag	NA	NA	NA	NA	NA	NA
MCNKID.ihs.lag	NA	NA	NA	NA	NA	NA
MHWKID.ihs.lag	NA	NA	NA	NA	NA	NA
MHNKID.ihs.lag	NA	NA	NA	NA	NA	NA
FHWKID.ihs.lag	NA	NA	NA	NA	NA	NA
WRCNTYN.ihs.lag	NA	NA	NA	NA	NA	NA
WRCNTYD.ihs.lag	NA	NA	NA	NA	NA	NA
WRKSMN.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBN.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLPBD.ihs.lag	NA	NA	NA	NA	NA	NA
WKHOME.ihs.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
AUTO.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT2.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUT4.ihs.lag	NA	NA	NA	NA	NA	NA
COMMUTX.ihs.lag	NA	NA	NA	NA	NA	NA
TRVLOTN.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC8.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC11.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC12.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC15.ihs.lag	NA	NA	NA	NA	NA	NA
EDUCA.ihs.lag	NA	NA	NA	NA	NA	NA
EDUC16.ihs.lag	NA	NA	NA	NA	NA	NA
EDUCPP.ihs.lag	NA	NA	NA	NA	NA	NA
PRFEMP.ihs.lag	NA	NA	NA	NA	NA	NA
INDEMP.ihs.lag	NA	NA	NA	NA	NA	NA
USKOCC.ihs.lag	NA	NA	NA	NA	NA	NA
OCC1.ihs.lag	NA	NA	NA	NA	NA	NA
OCC2.ihs.lag	NA	NA	NA	NA	NA	NA
OCC3.ihs.lag	NA	NA	NA	NA	NA	NA
OCC4.ihs.lag	NA	NA	NA	NA	NA	NA
OCC5.ihs.lag	NA	NA	NA	NA	NA	NA
OCC6.ihs.lag	NA	NA	NA	NA	NA	NA
OCC7.ihs.lag	NA	NA	NA	NA	NA	NA
OCC8.ihs.lag	NA	NA	NA	NA	NA	NA
OCC9.ihs.lag	NA	NA	NA	NA	NA	NA
ARMFRM.ihs.lag	NA	NA	NA	NA	NA	NA
ARMFRF.ihs.lag	NA	NA	NA	NA	NA	NA
POVRATN.ihs.lag	NA	NA	NA	NA	NA	NA
POVRATD.ihs.lag.1	NA	NA	NA	NA	NA	NA
WHTPRN.ihs.lag	NA	NA	NA	NA	NA	NA
WELFARN.ihs.lag	NA	NA	NA	NA	NA	NA
WELFARD.ihs.lag	NA	NA	NA	NA	NA	NA
NELPOON.ihs.lag	NA	NA	NA	NA	NA	NA
NELPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
ELDPOON.ihs.lag	NA	NA	NA	NA	NA	NA
ELDPOOD.ihs.lag	NA	NA	NA	NA	NA	NA
WHTPRD.ihs.lag	NA	NA	NA	NA	NA	NA
TOTHSUN.ihs.lag	NA	NA	NA	NA	NA	NA
SMPHSU.ihs.lag	NA	NA	NA	NA	NA	NA
OCCHU.ihs.lag	NA	NA	NA	NA	NA	NA
VACHU.ihs.lag	NA	NA	NA	NA	NA	NA
VACRT.ihs.lag	NA	NA	NA	NA	NA	NA

Variable	OLS % Min Lambda	OLS % Mid Lambda	OLS % 1se Lambda	Log % Min Lambda	Log % Mid Lambda	Log % 1se Lambda
VACFS.ihs.lag	NA	NA	NA	NA	NA	NA
VACOCC.ihs.lag	NA	NA	NA	NA	NA	NA
VACOTH.ihs.lag	NA	NA	NA	NA	NA	NA
RNTOCC.ihs.lag	NA	NA	NA	NA	NA	NA
OWNOCC.ihs.lag	NA	NA	NA	NA	NA	NA
SPRNTOC.ihs.lag	NA	NA	NA	NA	NA	NA
SPOWNOC.ihs.lag	NA	NA	NA	NA	NA	NA
PRSRNTU.ihs.lag	NA	NA	NA	NA	NA	NA
TPOPDENS.ihs.lag	NA	NA	NA	NA	NA	NA
NEWHOUS.ihs.lag	NA	NA	NA	NA	NA	NA
AVHHINN.2010real.ihs.lag	NA	NA	NA	NA	NA	NA
AVHHIN.2010real.ihs.lag	NA	NA	NA	NA	NA	NA
factor(YEAR)1980	NA	NA	NA	NA	NA	NA
factor(YEAR)1990	NA	NA	NA	NA	NA	NA
factor(YEAR)2000	NA	NA	NA	NA	NA	NA
factor(YEAR)2010	NA	NA	NA	NA	NA	NA

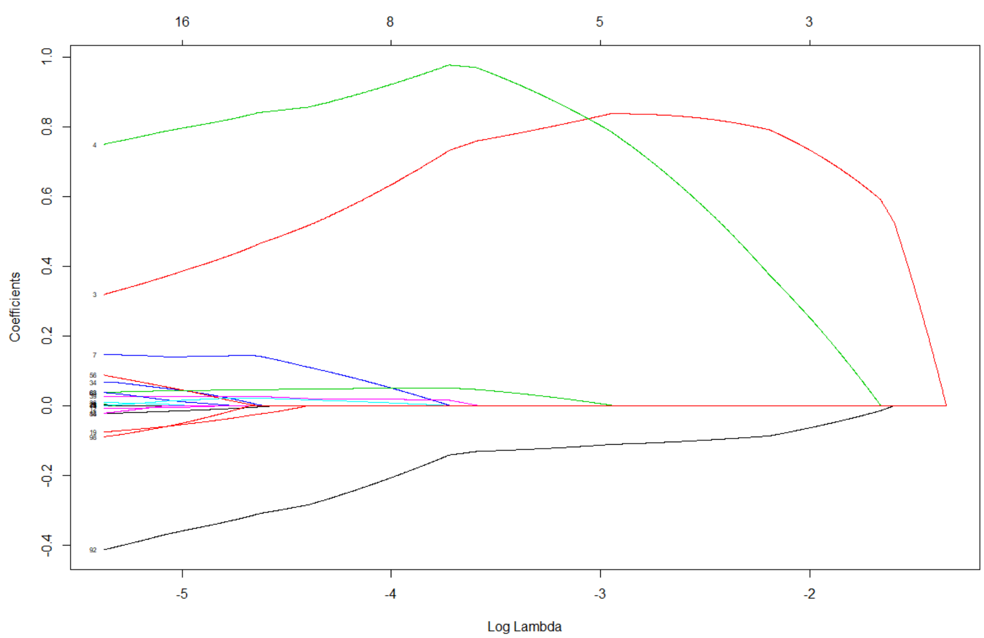

Fig. 90. Illustration of how variables shrink to zero as lambda changes – number of variables with a non-zero coefficient are listed across the top axis

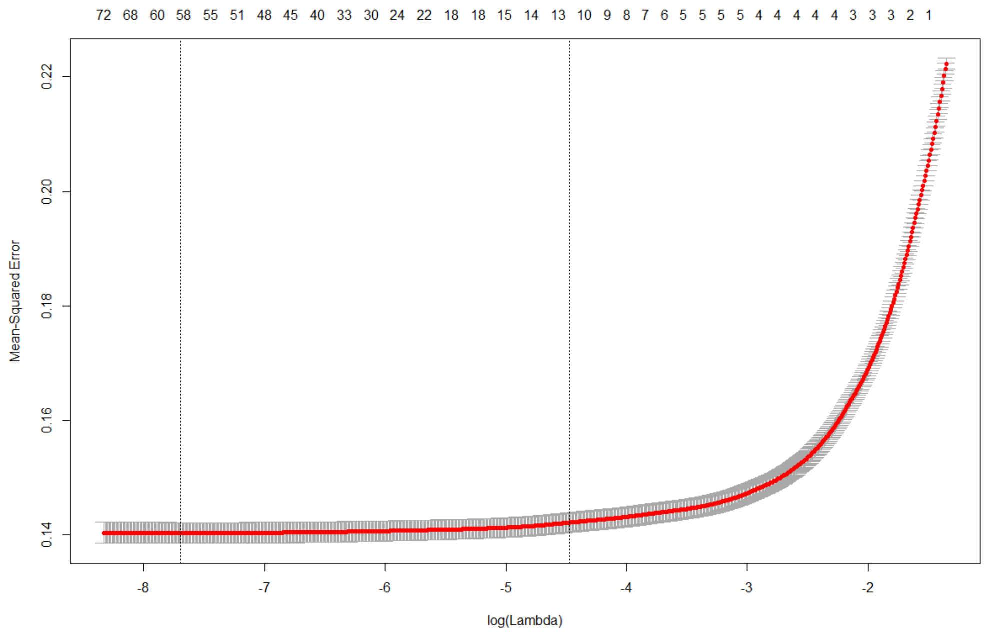

Fig. 91. Log lambda vs. MSE with number of non-zero variables across the top. Dashed line on left is the minimum lambda and the right dashed line is lambda within one standard error

Section E Machine learning causal search algorithms

These machine learning causal search algorithms are based in information theory. Most of them use mutual information and Bayesian statistical methods to discover statistical and causal relationships between variables within data sets. This information is then presented in a graph form. Depending on the causal relationships of the variables, the graphs may consist of directed or undirected edges. A directed edge signifies that the causal relationship is known between the 2 variables, while an undirected edge signifies that the direction of the causal influence is unknown (i.e. from A to B or from B to A). For readers unfamiliar with these methods, it is important to gain an understanding of Markov Causal and Faithfulness assumptions (sometimes called conditions) and the authors recommend Spirtes, et al (1993) for more information.

Markov Blanket Fan Search (MBFS) Algorithm

This algorithm was specifically designed to discover causal relationships of a target variable in high dimensional datasets. Using a Markov Blanket in the selection of this subset of variables is optimal (Ramsey 2006). A Markov Blanket of a target (t) includes the parents (influencers) of the target variable, the children (influenced by) of the target variable and the parents of the children of the target variable (Ramsey 2006). The Markov Blanket in essence is a superset of the variables that could either directly influence or be directly influenced by the target variable.

The MBFS algorithm follows the same method for adjacency search as the PC algorithm (Peter [Spirtes] and Clark [Glymour] algorithm), but in a novel arrangement (Ramsey 2006). The MBFS algorithm is divided into 3 stages: an adjacency search phase, an edge orientation phase, and a graph trimming phase (Ramsey 2006). During the adjacency search, the algorithm constructs an edge from the target variable to every other variable that is not unconditionally independent of the target variable. Then for each variable with an edge, the algorithm finds all variables that are not unconditionally independent. This is what Ramsey calls a fan (2006). At the end of the fan search, all found variables will be connected to the target variable by no more than 2 steps (i.e. all variables will be connected to the target variable with no more than one intermediate variable). The edge orientation phase first orients colliders and then applies the Meek-Orient procedure. Finally, the graph is trimmed using Trim-To-MBP creating the final Markov Blanket. The pseudo-code for the algorithm follows using G (a graph, to be constructed), A (a list of variables visited by the Construct-Fan method), t, v, w, and y (variables in V), and T (a set of variables in V) (Ramsey 2006).

MBFS(V, I, t, d_{max}):

1. G ← Ø, A ← Ø
2. Add t to G
3. **do** Construct-Fan(t, V, I, G, A, d_{max})
4. **for** each v in adj(t)
5. **do** Construct-Fan(v, V, I, G, A, d_{max})
6. **for** each win adj(adj(t)) \ A
7. **do** Construct-Fan(w, V, I, G, A, d_{max})
8. **do** Orient-Colliders(G, A)
9. **do** Meek-Orient(G, t, A)
10. **do** Trim-To-MBP(G, t)
11. **return** G

Fast Greedy Equivalence Search (FGES) algorithm

FGES is based on the GES algorithm originally developed by Meek (1995) and further developed by Chickering (2002). Meek developed the Greedy Equivalence Search (GES) algorithm to specifically answer the following 2 questions: “Does there exists a complete causal explanation for a list of conditional independence statements *M* consistent with background knowledge *K*?” and “Given that there is a complete causal explanation for *M* what are the causal relationships common to every complete causal explanation consist with respect to background knowledge *K*?” (1995 p. 404) GES is a Bayesian algorithm that searches the space by starting with an empty graph and scoring it after each change. The forward pass adds edges until the score no longer increases due to any single edge addition. The backward pass removes single edges until the score no longer increases. (Glymour et al. 2017)

Chickering provided elements of and proofs for GES, but did not include the precise algorithm (2002). Meek, however, provided the algorithm for GES, FGES is an extension that imposes background information first, includes the following 4 phases (1995 p. 404):

I. Examine independence statements in *M* and try to construct the pattern of some directed acyclic graph (DAG) *G*. Let Π_{I} be the result of Phase I.
II. Try to extend Π_{I} with the background knowledge *K*. Let Π_{II} be the result of Phase II.
III. Try to find a graph Π_{III} which is a consistent DAG extension of Π_{II}.
IV. Check whether Π_{III} is a complete causal explanation for *M*.

The FGES improves upon the original GES algorithm by parallelizing and optimizing the process (Glymour et al. 2017). Specifically, FGES does this with the following 4 changes: scores are cached so that changes to a graph can be updated with each addition or subtraction of an edge, each step has been parallelized, if BIC is used the penalty can be increased, and a limited faithfulness assumption is implemented whereby if an edge has been found to be uncorrelated it will not be added at any future step in the forward search (Ramsey et al. 2017). These changes are the keys to speeding the process and allowing GES to function on large data sets.

Fast Greedy Equivalent Search-Markov Blanket (FGES-MB) algorithm

This is a modification and restriction of the FGES algorithm. This algorithm restricts the search space of the FGES algorithm to the Markov Blanket of a target variable. The process is as follows (Ramsey et al. 2017):

1. For the Markov blanket search, one calculates a set A of adjacencies *x–y* about *t* as follows.
2. First, given a score *I (a, b, C)*, one finds the set of variables *x* such that

$I(x, t, \emptyset) > 0$ and adds $x–t$ to A for each x found.

3. Then for each such variable x found, one finds the set of variables y such that $I(y, x, \emptyset) > 0$ and adds $y–x$ to A for each such y found. The general form of this calculation is familiar for Markov blanket searches, though in this case it is carried out using a score difference function.
4. One then simply runs the rest of FGES, restricting adjacencies used in the search to the adjacencies in A in the first pass and then marrying parents as necessary and re-running the backward search to get the remaining unshielded colliders, inferring additional orientations as necessary.
5. The resulting graph may then simply be trimmed to the variables in A and returned.

Section F FGES search results

Table 79. FGES graph results for ML-search identified subset of variables for 1,000 bootstraps with 80% of data for all variables – only showing variables where one node is a bridge and the other node is not

Node1	Int	Node2	Ensemble	No Edge	-->	<--
IHS new total bridges	<--	Rural tract ind (10M)	0.167	0.833		0.167
Total bridges	-->	Rural tract ind (10M)	0.667	0.333	0.667	
IHS total bridges	-->	Rural tract ind (10M)	0.833	0	0.833	0.167
newbridge.under14	<--	Rural tract ind (10M)	0.333	0.667		0.333
IHS total bridges	-->	Rural tract ind (4M)	1	0	1	
Owner occupied housing	-->	New total bridges	0.167	0.833	0.167	
Log foreign born	-->	New restrictive bridges	0.167	0.833	0.167	
Log Male head of house w/kids	-->	New restrictive bridges	0.167	0.833	0.167	
IHS real average income	-->	IHS total bridges	0.167	0.833	0.167	
IHS real aggregate income	-->	IHS total bridges	0.333	0.667	0.333	
Log real average income	-->	IHS total bridges	0.167	0.833	0.167	
% Male head of house w/kids	-->	IHS total bridges	0.333	0.667	0.333	
Population density	-->	IHS total bridges	0.5	0.333	0.5	0.167
Some college	-->	Total non-restrictive bridges	0.167	0.833	0.167	
Commute < 25 min	<--	Restrictive bridges	0.167	0.833		0.167
Commute 25-45 min	<--	Restrictive bridges	0.167	0.833		0.167
% Some college	<--	Restrictive bridges	0.167	0.833		0.167
Female head of house	<--	Restrictive bridges	0.167	0.833		0.167
% Female head of house	<--	Restrictive bridges	0.167	0.833		0.167
IHS new houses	<--	Restrictive bridges	0.167	0.833		0.167
IHS Native American	<--	Restrictive bridges	0.167	0.833		0.167
Log vacant housing	<--	Restrictive bridges	0.167	0.833		0.167
Welfare	<--	Restrictive bridges	0.167	0.833		0.167

Table 80. FGES search results for literature review identified subset of variables – only showing variables where one node is a bridge and the other node is not

Node1	Interaction	Node2	Ensemble	No edge	-->	<--	---
"AREALAND"	-->	"bridge.new.total"	0.862	0.111	0.86	0.03	
"AREALAND"	<--	"bridge.total.ihs"	0.622	0.155	0.22	0.62	0
"TRVLPBN.ihs"	<--	"bridge.total.ihs"	0.594	0.406		0.59	
"bridge.total.ihs"	-->	"rur10m"	0.422	0.025	0.42	0.3	0.25

Notation

The following symbols are used in this paper:

C = a vector of lagged control variables;

d = a dichotomous variable designating the interaction of the group and treatment variables;

e = the error term;

f = a time-invariant tract fixed effect;

g = a dummy variable designating the tract as receiving a new bridge at any time (group term);

i = the tract index;

k = the index for a particular variable;

logit(p(x)) = the probability that a variable designating a new bridge was built in the preceding 10 years;

t = the year index;

X = a vector of variables of social interest;

x = a dummy variable designating the tract received a new bridge treatment (treatment term);

y = either a dichotomous variable designating a new restrictive bridge was built in the preceding 10 years or the count of such bridges;

z = a social equity variable of interest;

β_0 = the intercept;

β_1 = the event study coefficient for the treatment and group interaction term;

β_2 = the coefficient for the treatment term;

β_3 = the coefficient for the group term;

γ_k = a vector of control variable coefficients;

δ = a fixed effect for each census year;

λ = he Lagrange multiplier that balances the tradeoff between the squared error loss and the L_1 penalty;

Appendix III: Machine Learning Methods to Predict Air Pollution Concentration for Policymakers Supplemental Information

Section A Additional details from literature review

Air pollution effects on human health

Stieb et al (2002) conducted a comprehensive, systematic synthesis of 109 time-series studies on epidemiological link between air pollution and mortality. They found effect sizes were generally reduced in multi-pollutant models, but significantly different than zero for PM_{10} and SO_2. Respiratory mortality had larger effect sizes for all pollutants except O_3. They also found that results were robust to the different methodologies used by the various studies. They note further work is need in isolating effects of individual pollutants, effect thresholds, and susceptibility of different populations. A possibly important finding by Fiore et al (2003) is that as ozone simulations become more coarse in the spatial resolution they capture averages better but not because the predictions are more accurate. Using PMCAMx, Karydis et al (2007) evaluated the efficacy of this CTM for the Eastern United States for all four seasons. Among other findings, they discovered that the $PM_{2.5}$ predictions were encouraging but not great, nitrate was underpredicted, wet deposition was inaccurate, ammonium was overpredicted, but elemental carbon predictions were particularly good. Peng et al (2017) first simulated and then applied several modelling methods developed for dealing with confounders in time-series datasets to the National Morbidity, Mortality, and Air Pollution Study (NMMAPS). By doing so, they quantified and characterized the uncertainty of each model type. These models used several methods for adjusting for seasonal and long-term trends in air pollution epidemiology. They found that regardless of the strengths or weaknesses of any particular model, it was clear that there is a link between PM_{10} and mortality.

Reduced complexity models are useful

Muller et al (2011) use the Air Pollution Emission Experiments and Policy (APEEP) RCM model to estimate damages from six major pollutants by industry. This is a good example of an RCM for use by policymakers. Using this model Muller et al (2011) calculate damages by industry and delineate which provide a greater ratio of gross external damages to value added. The Estimating Air pollution Social Impact Using Regression (EASIUR) model was developed to specifically estimate public health costs of fine particulate matter ($PM_{2.5}$). Using their EASIUR RCM, Heo et al (2016) were able to demonstrate results with fractional errors which are similar to or less than CTM's performance. Gilmore et al (2019) compared several chemical transport models (CTM) with reduced complexity models (RCM) and found that the reduced complexity models predicted $PM_{2.5}$ with only a modest reduction in accuracy. The RCMs predictions were within a factor of two to three which is usually less sensitive than the value of a statistical life (VSL) and other uncertainties. Therefore, these findings support using RCMs as valid tools for policy formulation and analysis.

Machine Learning Techniques are being Employed in Air Pollution Studies

Bellinger et al. (2017) conducted a systematic review of machine learning techniques used in air pollution epidemiology literature. They reviewed methods from 47 relevant articles from a search that discovered 400 potential research articles. They divided the articles into three areas of interest "1) source apportionment; 2) forecasting/prediction of air pollution/quality or exposure; and 3) generating hypotheses (Bellinger et al. 2017 p. 1)." They found researchers had employed neural networks, decision trees, support vector machines, k-means clustering and the APRIORI algorithm (a commonly used association mining technique). They also identified potential areas for future work including deep learning and geo-spatial pattern mining. Based on the objectives of the articles identified during their review, none of the reviewed articles had the same objective or methods as those the authors are considering. There are several that share similarities with the goals and methods and the authors plan to review these articles in depth in order to better delineate commonalities and differences.

As specific examples of what has been attempted in this space, the authors share details about the following works. Feng et al (2015) created a hybrid model using wavelet transformations with a neural network to predict course $PM_{2.5}$ levels up to two days in advance in China based on temperatures, wind, humidity, general conditions, day of year and day of week. Kleine Deters et al (2017) developed a neural network to predict $PM_{2.5}$ concentrations solely based on wind and precipitation levels in Quito, Ecuador. This method is computationally less expensive than CTMs. They make the case that weather sensors are both more accurate and less expensive than $PM_{2.5}$ sensors. Their technique also demonstrated limitations of using only weather data with a neural net to predict air pollution. Kelp et al (2019) developed a neural network to emulate the carbon bond mechanism Z (CBM-Z) gas-phase chemical mechanism. This model predicted the hourly concentrations of 77 chemical species with a root mean square error (RMSE) of 1.97 ppb. Using GPUs, this model was able to achieve speedup of 4,250 times compared to a CTM. The model requires more work in order to constrain propagation errors that compound over time. Kelp et al (2020) next attempt to increase the length of time for which accurate forecasts can be made and explore the parameter space to create a more stable, general air chemistry model. Xue et al (Xue et al. 2019) combined inputs from satellites, CTMs, and in-situ readings to develop a machine learning model to predict $PM_{2.5}$. The model was trained using data from 2013-2016. The model was then applied to sometimes the time period from 2000-2012 which is known for having missing measurements. Their model produced rather good predictions for daily, monthly and annual averages. They then added a generalized additive model to interpolate missing predictions due to missing satellite data. This two-stage estimation technique sacrificed daily prediction accuracy but significantly improved monthly and annual prediction accuracy. Their predictions found increasing pollution during the period from 2000-2007 and decreased pollution thereafter. They offer these data in the hope that others will use them to perform large-scale epidemiological studies.

General Machine Learning Efficacy

Hornik et al. (1991; 1989) show how feedforward neural networks are universal approximators. Since that time, many applications have established this principle and a plethora of feedforward network architectures have been developed. Huang et al (2016) build upon that architecture and demonstrated deep neural network advantages including: less prone to overfitting, ease of training and regularizing effects.

Section B Data

The data for this project covers three calendar years in 1990, 2001 and 2010. These three years were chosen due to data availability. Carnegie Mellon University's Center for Atmospheric Particle Studies (CAPS) has already simulated three full years (excepting 4 days) (Xing et al. 2013). CAPS researchers modeled these three years due to availability of the U.S. EPA's National Emission Inventory (NEI). The NEI data was formatted to be used as the input for the Particulate Matter Comprehensive Air Quality Model with Extensions (PMCAMx). The data consist of three general categories: pollution sources, meteorological conditions, and resultant concentrations. Pollution sources and meteorological condition files are the input and resultant concentrations are the output. With the exception of the point pollution sources, the data are hourly measurements covering the continental United States (CONUS) divided into 36 km x 36 km cells (see Fig. 15). The point pollution sources by contrast are hourly measurements of individual pollution sources including physical characteristics, temperature at discharge point, and discharge volume rates. The model developed in this work only uses the resultant concentrations and the area pollution sources. For this work, as previously noted, the authors concentrate on the well-understood EC species. The authors chose to divide EC (and other species) particulate matter into two regulated size categories with the smaller size shown to have health effects: one for fine ($PM_{2.5}$) EC and one for coarse (PM_C) EC. Hereafter, the authors refer to fine EC as $EC_{2.5}$ and coarse EC as EC_C. The authors use the EPA's definition for fine and coarse (US EPA 2014). Fine particulate matter is $\leq 2.5\mu m$. Course particulate matter is $\leq 10\mu m$ and $> 2.5\mu m$.

Table 81 Data characteristics of file types representing one day of measurements

Data Type	Layers	Rows	Columns	Variables	Time Steps
Output Files					
Daily Hourly Output	1	82	132	509	24
Meteorology Input Files					
Vertical Diffusivity	14	82	132	1	24
Land Use	1	82	132	11	1
Water Vapor	14	82	132	1	24
Temperature	14	82	132	2	24
Wind Speed	14	82	132	2	24
Height Pressure	14	82	132	2	24
Cloud/Rain	14	82	132	3	24
Snow	1	82	132	1	1
Emission Source Input Files					
Area - On Road Pollution	1	116	152	114	24
Area - Non-road Pollution	1	116	152	114	24
Point - Electricity Generating Units (EGU) pollution	1	8304	(x, y, z, coords included in	128	24
Point - Non-Integrated Planning Module (IPM)	1	102951	(x, y, z, coords included in	128	24

Section C Preliminary analysis and exploration

VAR

VAR is a multivariate algorithm used to analyze how multiple time series interact. This method is used to determine how much information is contained in the past. It is considered autoregressive because it is concerned with how past measurements influence the present measurement. The authors only used the output data for this method. To ensure VAR is a suitable method for the data, some preliminary tests were run including: stationarity, Granger causality (Granger 1969), Johansen's co-integration (Johansen 1991), and order selection. (See Appendix III, Section C for more information on these tests.) Each variable is modeled as a function of past variables where:

Equation 11. VAR in context of geographic-based measurements

$$y_{i,x,y,t} = \alpha + \boldsymbol{\beta}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{\beta}_p \boldsymbol{Y}_{t-p} + \epsilon_t$$

$$\epsilon_t \sim Normal(0, \Sigma_u)$$

where i is the measure of concentration of either $PEC_{2.5}$ or PEC_C, x and y are the grid coordinates of a variable, t is the time (format: year-month-day-hour) of the measurement, α is the intercept, $\boldsymbol{\beta}$ are coefficients of the lags of $\boldsymbol{Y}$ vectors (including all x, y and i variables in that t) until order p, and ϵ_t is the error. Here is an example or snapshot in the process:

Equation 12. VAR example from sample 3 x 3 grid with order 4 time lag

$$y_{PM2.5,33,14,1990-01-15-08:00:00} = \alpha + \boldsymbol{\beta}_1 \boldsymbol{Y}_{1990-01-15-07:00:00} + \cdots + \boldsymbol{\beta}_4 \boldsymbol{Y}_{1990-01-15-04:00:00} + \epsilon_t$$

In this example, 4 lags (order 4) were calculated to be the best fit for our 9-cell grid located over land in Mexico (locations [32,13] to [34,15] in the Lambert Conformal Projection grid-numbering system used by PMCAMx, see Fig. 15). As the algorithm fits the coefficients, it examines the concentration of $PEC_{2.5}$ in the grid cell located at [33, 14] at 0800 on January 15, 1990. On the right-hand side, the algorithm is looking at the concentration of $PEC_{2.5}$ and PEC_C in all 9 grid cells from 0700 to 0400 on January 15, 1990. After training on the entire 3 years of hourly data, the model can be used to generate predictions with only the number of lag measurements as input. See Appendix III, Table 82 (shows overall results and only the coefficients for the grid cell in the example truncated to a single page and does not include the correlation matrix of residuals). Fig. 92 shows a graphical representation of results for the 11 x 11 cell grid.

After fitting the model, the authors checked to see if there was a leftover pattern in the residuals. If there was, that would mean there is some other phenomena that should be identifiable and accounted for in the model (other predictors or a different model). To check for serial correlation, the authors used Durbin Watson's Statistic. The statistic varies from 0 to 4. As it approaches 0, there is a positive serial correlation; as it approaches 4, there is a negative serial correlation; as it approaches 2, there is no significant serial correlation. The specific implementation is from the Statsmodels module for Python. See Appendix III, Table 82 for a sample of results. No additional serial correlations were found in the residuals.

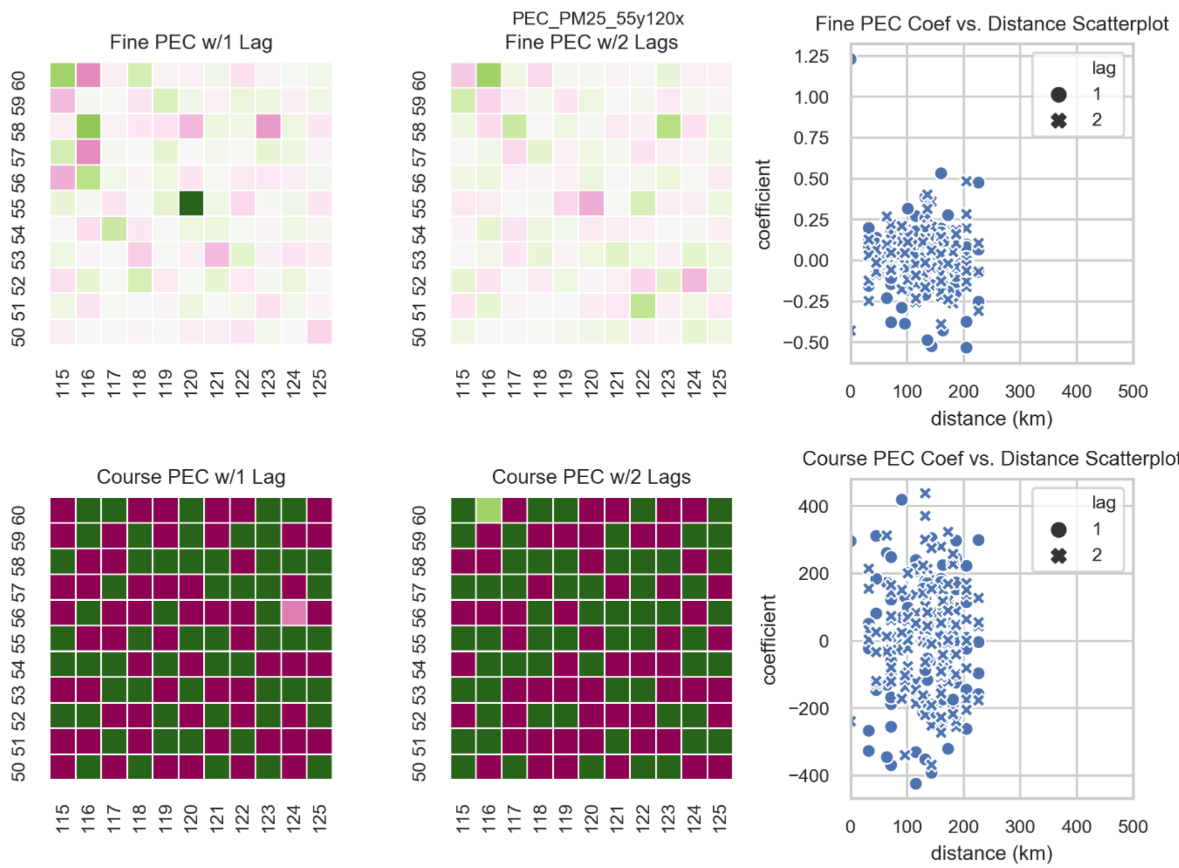

Fig. 92. VAR results for $PEC_{2.5}$ in grid cell 120, 55. Top row shows $PEC_{2.5}$ coefficients and bottom row shows PEC_C coefficients.

Pre-processing Analysis to ensure VAR is a reasonable method

Prior to running the VAR model there are several pre-processing steps required to ensure that a VAR model is reasonable. The steps and reasons are provided below.

Stationarity test. Many of the other pre-processing steps and VAR require the time series data to be stationary, that is that the joint probability distribution (and by extension the mean and variance) do not change over time. The specific test is the Augmented Dickey-Fuller test that comes from the Python statsmodels module. The null hypothesis is that there is a unit root meaning that the distribution is not stationary. If the value returned is less that a desired p-value, the series is stationary. Almost without exception all data tested was found to be stationary. If the data were not stationary, we could use differencing to make the data stationary. See Table *84* for results from the 9-grid dataset overland in Mexico.

Granger Causality test (Granger 1969). This is a statistical hypothesis test that tries to determine if one time-series is useful in forecasting another time series. Therefore, a time series X is said to Granger-cause time series Y if it can be shown that X provides statistically significant information about future values of Y. The specific test used comes from the Python statsmodels module which tests the null hypothesis that the two time series do not Granger-cause each other. The hypothesis can be rejected if the p-value is below the desired threshold. I tested up to 48 lags and found that the null hypothesis was rejected for our data meaning that our variables' past values were found to Granger-cause present values. See Table *85* for a small sample of results from the 9-grid dataset overland in Mexico.

Table 82. Sample results from VAR analysis of for PEC $PM_{2.5}$ in grid cell 33, 14 located in Mexico over land

```
Summary of Regression Results
==================================
Model:                 VAR
Method:                OLS
Date:         Sat, 14, Mar, 2020
Time:                00:04:35
--------------------------------------------------------------------
No. of Equations:        18.0000    BIC:              -308.205
Nobs:                 26180.0    HQIC:             -308.483
Log likelihood:      3.37243e+06    FPE:           9.33310e-135
AIC:                  -308.615    Det(Omega_mle):   8.87684e-135
--------------------------------------------------------------------
Results for equation PEC_PM25_14y33x
=====================================================================================
                    coefficient     std. error        t-stat         prob
-------------------------------------------------------------------------------------
const                  0.000356       0.000073          4.869        0.000
L1.PEC_PM25_13y32x    -0.010401       0.011095         -0.938        0.348
L1.PEC_PM25_13y33x     0.185286       0.014969         12.378        0.000
L1.PEC_PM25_13y34x     0.082247       0.012286          6.694        0.000
L1.PEC_PM25_14y32x     0.182803       0.015665         11.670        0.000
L1.PEC_PM25_14y33x     1.161150       0.019076         60.870        0.000
L1.PEC_PM25_14y34x     0.035414       0.015663          2.261        0.024
L1.PEC_PM25_15y32x    -0.089695       0.012756         -7.032        0.000
L1.PEC_PM25_15y33x     0.157815       0.016544          9.539        0.000
L1.PEC_PM25_15y34x     0.073918       0.011383          6.494        0.000
L1.PEC_PMC_13y32x     -4.700337       0.992159         -4.737        0.000
L1.PEC_PMC_13y33x      2.175567       1.195714          1.819        0.069
L1.PEC_PMC_13y34x     -4.145302       1.189662         -3.484        0.000
L1.PEC_PMC_14y32x      2.469024       1.371109          1.801        0.072
L1.PEC_PMC_14y33x      2.121705       1.414384          1.500        0.134
L1.PEC_PMC_14y34x     -1.599624       1.532338         -1.044        0.297
L1.PEC_PMC_15y32x     -2.373465       1.215327         -1.953        0.051
L1.PEC_PMC_15y33x     -3.776709       1.357299         -2.783        0.005
L1.PEC_PMC_15y34x     -4.029115       1.214434         -3.318        0.001
...               ...        ...        ...          ...
L4.PEC_PM25_14y32x     0.025249       0.015736          1.605        0.109
L4.PEC_PM25_14y33x    -0.063831       0.018351         -3.478        0.001
L4.PEC_PM25_14y34x     0.010234       0.015682          0.653        0.514
L4.PEC_PM25_15y32x     0.051091       0.013069          3.909        0.000
L4.PEC_PM25_15y33x     0.036633       0.015991          2.291        0.022
L4.PEC_PM25_15y34x    -0.002773       0.011995         -0.231        0.817
L4.PEC_PMC_13y32x      0.002796       0.935159          0.003        0.998
L4.PEC_PMC_13y33x      1.672722       1.213486          1.378        0.168
L4.PEC_PMC_13y34x     -2.822515       1.288663         -2.190        0.029
L4.PEC_PMC_14y32x     -0.849890       1.350372         -0.629        0.529
L4.PEC_PMC_14y33x     -2.058806       1.407345         -1.463        0.143
L4.PEC_PMC_14y34x      2.298493       1.543369          1.489        0.136
L4.PEC_PMC_15y32x     -0.061571       1.126642         -0.055        0.956
L4.PEC_PMC_15y33x     -0.437012       1.322562         -0.330        0.741
L4.PEC_PMC_15y34x     -3.074512       1.285940         -2.391        0.017
=====================================================================================
```

Table 83. Durbin Watson's Statistic for VAR model residuals for the 3 x 3 grid sample located in Mexico

```
Durbin Watson Residual Serial Correlation Test
PEC_PM25_13y32x: 2.0
PEC_PM25_13y33x: 2.006
PEC_PM25_13y34x: 2.0
PEC_PM25_14y32x: 2.002
PEC_PM25_14y33x: 2.005
PEC_PM25_14y34x: 2.003
PEC_PM25_15y32x: 2.003
PEC_PM25_15y33x: 2.008
PEC_PM25_15y34x: 2.004
PEC_PMC_13y32x: 2.007
PEC_PMC_13y33x: 2.006
PEC_PMC_13y34x: 2.01
PEC_PMC_14y32x: 2.003
PEC_PMC_14y33x: 2.002
PEC_PMC_14y34x: 2.009
PEC_PMC_15y32x: 2.004
PEC_PMC_15y33x: 2.0
PEC_PMC_15y34x: 2.001
```

Table 84. Sample results from Augmented Dickey-Fuller stationarity test

```
Augmented Dickey-Fuller Test on "PEC_PM25_13y32x"
-----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    =   0.05
 Test Statistic        = -16.4242
 No. Lags Chosen       =  24
 Critical value 1%     =  -3.431
 Critical value 5%     =  -2.862
 Critical value 10%    =  -2.567
 => P-Value = 0.0. Rejecting Null Hypothesis.
 => Series is Stationary.
```

Table 85. Sample of results from Granger Causality Tests for 3 grid cells (columns Granger-cause rows if reported p-value is less than 0.05)

	PEC_PM25_13y32x_x	PEC_PM25_13y33x_x	PEC_PM25_13y34x_x
PEC_PM25_13y32x_y	1	0	0
PEC_PM25_13y33x_y	0	1	0
PEC_PM25_13y34x_y	0	0	1

Johansen Co-integration test (Johansen 1991). Two or more time series are considered to be co-integrated if there exists a linear combination of them that has an order of integration less than that of the individual series. The specific test used also comes from the Python statsmodels module and is limited to testing up to 12 time series. As a result of this limitation, fine and course PEC variables were tested separately (i.e. fine with fine and course with course). See Table 86 for results from the 9-grid dataset overland in Mexico.

Table 86. Sample results of Johansen Co-integration tests for fine and course PEC

```
Name          ::  Test Stat > C(95%)   =>   Significant?
----------------------------------------------------------
PEC_PM25_13y32x::  16272.93  > 179.5199  =>   True
PEC_PM25_13y33x::  13106.63  > 143.6691  =>   True
PEC_PM25_13y34x::  10351.05  > 111.7797  =>   True
PEC_PM25_14y32x::  7960.74   > 83.9383   =>   True
PEC_PM25_14y33x::  5769.98   > 60.0627   =>   True
PEC_PM25_14y34x::  3866.65   > 40.1749   =>   True
PEC_PM25_15y32x::  2156.88   > 24.2761   =>   True
PEC_PM25_15y33x::  1030.3    > 12.3212   =>   True
PEC_PM25_15y34x::  26.72     > 4.1296    =>   True
----------------------------------------------------------
PEC_PMC_13y32x  ::  17127.27  > 179.5199  =>   True
PEC_PMC_13y33x  ::  14028.51  > 143.6691  =>   True
PEC_PMC_13y34x  ::  11140.55  > 111.7797  =>   True
PEC_PMC_14y32x  ::  8674.26   > 83.9383   =>   True
PEC_PMC_14y33x  ::  6432.9    > 60.0627   =>   True
PEC_PMC_14y34x  ::  4465.64   > 40.1749   =>   True
PEC_PMC_15y32x  ::  2624.48   > 24.2761   =>   True
PEC_PMC_15y33x  ::  1121.89   > 12.3212   =>   True
PEC_PMC_15y34x  ::  152.81    > 4.1296    =>   True
```

Order selection. A critical parameter of a VAR is the order of the model. The order is how many lags should be analyzed by the model. The VAR function comes with a select order sub-function. I provided a maximum lag of 48 hours to the function and it returned a list of goodness of fit measures (AIC, BIC, FPE and HQIC) and selected the order (number of lags) deemed optimal for the data. The default goodness of fit measure used to select the order is BIC. Depending on the number of grid cells provided, the order selected changes. For the 3 x 3 grid over Mexico, order 4 was selected. For the 11 x 11 grid centered on New York City, order 2 was selected. For the entire CONUS, order 2 was also selected. See for results from the 9-grid dataset overland in Mexico.

Table 87. Sample of VAR order selection results

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	-261.8	-261.8	1.984e-114	-261.8
1	-298.9	-298.8	1.606e-130	-298.8
2	-307.4	-307.2	3.072e-134	-307.4
3	-308.4	-308.1	1.124e-134	-308.3
4	-308.6	-308.2*	9.611e-135	-308.5
5	-308.7	-308.1	8.976e-135	-308.5
6	-308.7	-308.1	8.658e-135	-308.5*
7	-308.7	-308.0	8.386e-135	-308.5
8	-308.8	-307.9	8.131e-135	-308.5
9	-308.8	-307.9	7.923e-135	-308.5
...	...	...	...	
47	-309.2	-304.5	5.043e-135	-307.7
48	-309.2*	-304.4	4.997e-135*	-307.7

LASSO

Least Absolute Shrinkage and Selection Operator (LASSO)

VAR analysis determined the optimal order (number of lags) of the output data. To test for variable importance and geographic adjacency dependencies, the authors used the LASSO algorithm. LASSO (also sometimes written lasso) was developed by Tibshirani (1996). Originally developed for ordinary least square (OLS) as an alternative to subset selection and ridge regression techniques. LASSO effectively performs both functions at the same time. LASSO shrinks some variable coefficients and sets others to 0 effectively subsetting the data.

$$(\hat{\alpha}, \hat{\beta}) = arg \min \left\{ \sum_{i=1}^{N} \left(y_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 \right\}$$

subject to

$$\sum_j |\beta_j| \leq t$$

The parameter $t \geq 0$ controls the amount of shrinkage applied to estimates.

For this specific application, the authors used the Least Angle Regression (LARS) algorithm with LASSO modification and 10-fold cross-validation via the Sci-Kit Learn package for Python (Efron et al. 2004). This method was selected due to its computational efficiency. To compare computational speeds, the authors compared “pure” LASSO, LARS and LARS with LASSO with 10-fold cross validation on a 3 x 3 cell grid sample on a PC. The analysis took (mm:ss): 22:28, 1:55 and 0:46 respectively. These results demonstrate that the LARS with LASSO modification is the most efficient computationally.

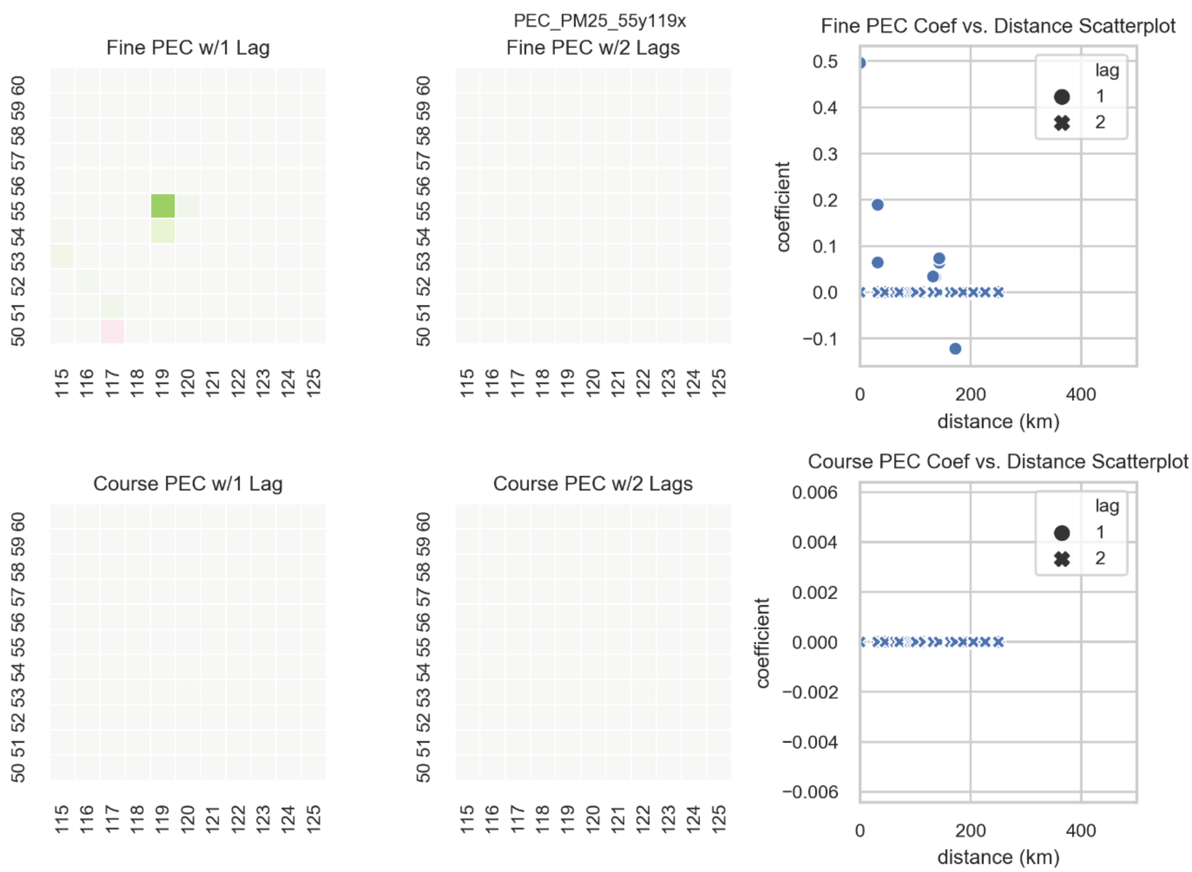

Fig. 93. VAR results for $PEC_{2.5}$ in grid cell 120, 55. Top row shows PEC $PM_{2.5}$ coefficients and bottom row shows PEC_C coefficients.

Assuming that there are no instantaneous effects (within the same hourly measurement) between grid cells, each cell had both $PEC_{2.5}$ and PEC_C variables set as the y variable and then LASSO analyzed all lagged variables for importance. For example, if a 3 x 3 grid cell was run with 4 lags as was the case for the sample over land in Mexico, LASSO was run 18 times (once per grid cell for both $PEC_{2.5}$ and PEC_C) and considered 72 lagged variables (four per grid cell for both $PEC_{2.5}$ and PEC_C). This analysis quickly ramps up as the sample size increases. The authors also ran LASSO for the 11 x 11 grid centered on New York City with 2 lags. This ran LASSO 242 times and considered 484 lagged variables. This case takes substantially longer to run: 1:49:32 on a PC (LARS took 26:48:12 for the same data).

The LASSO algorithm does not automatically generate lags. Therefore, lagged variables were added to the dataset. The number of lags were selected by the Vector Autoregression (VAR) analysis. Each variable is lagged by 1 or more hours depending on the number of lags determined to be optimal (i.e., if 2 lags were determined to be optimal, all variables would be lagged by 1 hour and 2 hours, effectively tripling the number of variables).

The algorithm returns a parsimonious set of coefficients for each size of PEC in each grid cell. See Table 88 for a sample of results. See **Error! Reference source not found.** for a graphical depiction of the results.

Table 88. Sample results from LASSO analysis of $PEC_{2.5}$ in grid cell 119, 55 located near New York City

PEC_PM25_55y119x	
PEC_PM25_50y117x.L1	-0.122165
PEC_PM25_51y117x.L1	0.063757
PEC_PM25_52y116x.L1	0.033179
PEC_PM25_53y115x.L1	0.073355
PEC_PM25_54y115x.L1	0.034095
PEC_PM25_54y119x.L1	0.189275
PEC_PM25_55y119x.L1	0.495967
PEC_PM25_55y120x.L1	0.064406
training data MSE	0.073214
test data MSE	0.067137
training data R-square	0.858740
test data R-square	0.864024

CD-NOD

A common assumption made in order to use many causal discovery algorithms is that the data provided are stationary, that is the joint probability distribution (and by extension the mean and variance) do not change over time. Unfortunately, real-world data is not always stationary. The CD-NOD algorithm's purpose is to detect non-stationarity and use that information to build a causal structure in the form of a directed acyclic graph (DAG) (Zhang et al. 2017). CD-NOD explicitly identifies which nodes (variables) in the graph have non-stationarity and use that information to better detect the causal structural skeleton of the graph.

The data provided to the CD-NOD algorithm also has a number of lags selected by the Vector Autoregression (VAR) analysis. Each variable is lagged by 1 or more hours depending on the number of lags determined to be optimal (i.e. if 2 lags were determined to be optimal, all variables would be lagged by 1 hour and 2 hours, effectively tripling the number of variables). This data set has 4 lags. Due to the computational costs of this algorithm, I also used LASSO to find a more parsimonious set of lagged variables in order to eliminate any lagged variables that were not influential on the non-lagged variables. Of the 72 lagged variables, LASSO determined 22 were important. Finally, I then selected a two-month period of transition between seasons (February and March of 1990) to use as a test case. This resulted in a dataset containing 1,344 hourly time periods of 40 variables (18 non-lagged concentration measurements and 22 lagged concentration measurements).

Other Assumptions

Zhang, et al. (2017) make several assumptions for their algorithm to function. First, they do not assume causal sufficiency for the observed variables, but do assume that if there are unobserved confounders, they can be written as smooth functions of time or domain. Therefore, the values of the confounders are fixed in each time or domain. They call this set a "pseudo causal sufficiency" assumption (Zhang et al. 2017 p. 1348). Further, they assume that the data are independent but not identically distributed. This is specifically due to the non-stationary nature of the problem the algorithm is meant to solve.

Algorithm S1. Detection of Changing Modules and Recovery of Causal Skeleton	
1.	Build a complete undirected graph U_C on the variable set $V \cup \{C\}$.
2.	(Detection of changing modules) For each i, test for the marginal and conditional independence between V_i and C. If they are independent given a subset of $\{V_k \mid k \neq i\}$, remove the edge between V_i and C in U_C.
3.	(Recovery of causal skeleton) For every i $\neq j$, test for the marginal and conditional independence between V_i and V_j . If they are independent given a subset of $\{V_k \mid k \neq i, k \neq j\} \cup \{C\}$, remove the edge between V_i and V_j in U_C.

Table 89. Sample results from CD-NOD analysis of $PEC_{2.5}$ and PEC_C in 3 x 3 grid. This represents a recovered graph structure. "1" signifies that the row was found to cause the column variable. "-1" signifies that a causal link exists between the two variables, but the direction is uncertain. Connection of nonstationarity indicator CNI(C) with a "1" signifies that the column variable was found to be non-stationary.

	EC_25_13y32x	EC_25_13y33x	EC_25_13y34x	EC_25_14y32x	EC_25_14y33x	EC_25_14y34x	EC_25_15y32x	EC_25_15y33x	EC_25_15y34x	EC_C_13y32x	EC_C_13y33x	EC_C_13y34x	EC_C_14y32x	EC_C_14y33x	EC_C_14y34x	EC_C_15y32x	EC_C_15y33x	EC_C_15y34x	EC_25_13y32x.L1	EC_25_13y33x.L1	EC_25_13y34x.L1	EC_25_14y32x.L1	EC_25_14y33x.L1	EC_25_14y34x.L1	EC_25_15y32x.L1	EC_25_15y33x.L1	EC_25_15y34x.L1	EC_C_13y32x.L1	EC_C_13y33x.L1	EC_C_13y34x.L1	EC_C_14y32x.L1	EC_C_14y34x.L1	EC_C_15y32x.L1	EC_C_15y33x.L1	EC_C_15y34x.L1	EC_25_13y34x.L2	EC_25_14y34x.L2	EC_25_15y32x.L2	EC_25_15y33x.L2	EC_C_13y32x.L2
EC_25_13y32x	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_13y33x	**1**	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_13y34x	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_14y32x	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_14y33x	0	**1**	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0
EC_25_14y34x	0	0	**1**	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_15y32x	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0
EC_25_15y33x	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_15y34x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_13y32x	0	0	0	0	0	0	0	0	0	0	**1**	0	**1**	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0
EC_C_13y33x	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0
EC_C_13y34x	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	**1**	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_14y32x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0
EC_C_14y33x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_14y34x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0
EC_C_15y32x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0
EC_C_15y33x	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_15y34x	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0
EC_25_13y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	**1**	**1**	0	0	0	**1**	0	0	0	**1**	0	0	0	0	0	0	0	0	0
EC_25_13y33x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**1**	0	0	**1**	0	0	0	0	0	0	0	0
EC_25_13y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0
EC_25_14y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	**1**	0	**1**	0	0	0	**1**	0	0	0	0	0	0	0
EC_25_14y33x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_14y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0
EC_25_15y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0
EC_25_15y33x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0
EC_25_15y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_13y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**
EC_C_13y33x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0
EC_C_13y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	**1**	0	0	0	0	0	0
EC_C_14y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0
EC_C_14y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0
EC_C_15y32x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0
EC_C_15y33x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_15y34x.L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	**1**	0	0	**1**	0	0	0	0	0	0	0
EC_25_13y34x.L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_14y34x.L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_15y32x.L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_25_15y33x.L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC_C_13y32x.L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**-1**	0	0	0	0	0	0	0	0	0	0	0	0
CNI (C)	**1**	**1**	**1**	**1**	0	0	0	0	0	**1**	**1**	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0

Section D Hyperparameter tuning

Generally speaking, the hyperparameter tuning was accomplished using the 11x11 grid centered on New York City. Initial testing of loss functions and optimizers was performed using the much smaller 3x3 grid sample from Mexico. The various configurations were tested using the validation set and run on a personal computer with a modest GPU. The test data set was never used for hyperparameter tuning. The exception to this is when the data was run for the entire CONUS. Then the model was trained on a server with a Tesla T4 GPU.

As seen below, the combination with the lowest loss is the Adam optimizer with the Huber (L1) loss function. This combination was used for all other hyperparameter tuning. Hyperparameter tuning generally focused on the number of units within the hidden layers and the number of hidden layers. While modest gains in loss were sometimes realized with deeper and wider networks, the authors generally found that a 5-layer network with approximately the same number of hidden units as output variables plus double the number of time variables.

Table 90. LinVARNN hyperparameter tuning to determine optimal pairing of loss function and optimizer with 3x3 Mexico PEC subset

Loss		Optimizer			Final	hh:mm:ss
Huber	**MSE**	**RMSProp**	**Adam**	**SGD**	**Validation Loss**	**Time to train 1k**
X		X			0.00002519	00:06:42
	X	X			0.00005232	00:06:09
X			X		0.00001754	00:06:41
	X		X		0.00003841	00:06:08
X				X	0.00836772	00:07:19
	X			X	0.00814624	00:06:41

Table 91. VARNN hyperparameter tuning to determine number of neurons per layer with 11x11 New York City PEC subset

Hidden Layers	H dim	Validation Loss	Time to train 1k	Time to predict 3 yrs
3	None	0.00152550	00:09:53	00:00:01
3	121	0.00166669	00:08:45	00:00:01
3	242	0.00131906	00:12:58	00:00:01

Table 92. HyVARNN hyperparameter tuning to determine number hidden layers and number of neurons per layer with 11x11 New York City PEC subset

Hidden Layers	H dim	Validation Loss	Time to train 1k	Time to predict 3 yrs
3	121	n/a	n/a	n/a
3	242	0.00232673	00:27:43	00:00:03
5	242	0.00296003	00:14:32	00:00:01
10	242	0.0177	n/a	n/a
15	242	0.001795341	00:29:49	00:00:01

Table 93. VARNN hyperparameter tuning to determine number hidden layers and number of neurons per layer with 11x11 New York City SO_2 and PSO_4 subset

Hidden Layers	H dim	Validation Loss	Time to train 1k	Time to predict 3 yrs
3	363	0.001499492	00:11:50	00:00:01
3	121	0.01719851	00:11:19	00:00:01

Table 94. VARNN hyperparameter tuning to determine number hidden layers and number of neurons per layer with CONUS PEC subset

Hidden Layers	H dim	Validation Loss	MSE	Time to train 1k	Time to predict 3 yrs
3	5412	0.00167469	n/a		00:00:41
5	10824		0.00337	00:19:41	00:00:00

Table 95. HyVARNN-T hyperparameter tuning to determine number hidden layers and number of neurons per layer with 11x11 New York City PEC subset with 6 time variables

Hidden Layers	H dim	Test Loss	MSE	Time to train 1k	Time to predict 3 yrs
5	121			00:19:41	00:00:00
5	248	0.0118	0.0248	00:21:14	00:00:00
5	484			00:31:26	00:00:00
10	248			00:25:42	
15	242			00:27:19	00:00:00

Table 96. Lag order for each region

Grid size	Order
3 x 3	7
11 x 11	4
15 x 15	2
25 x 25	2
82 x 132	1

Section E graphical results for VARNNmodel

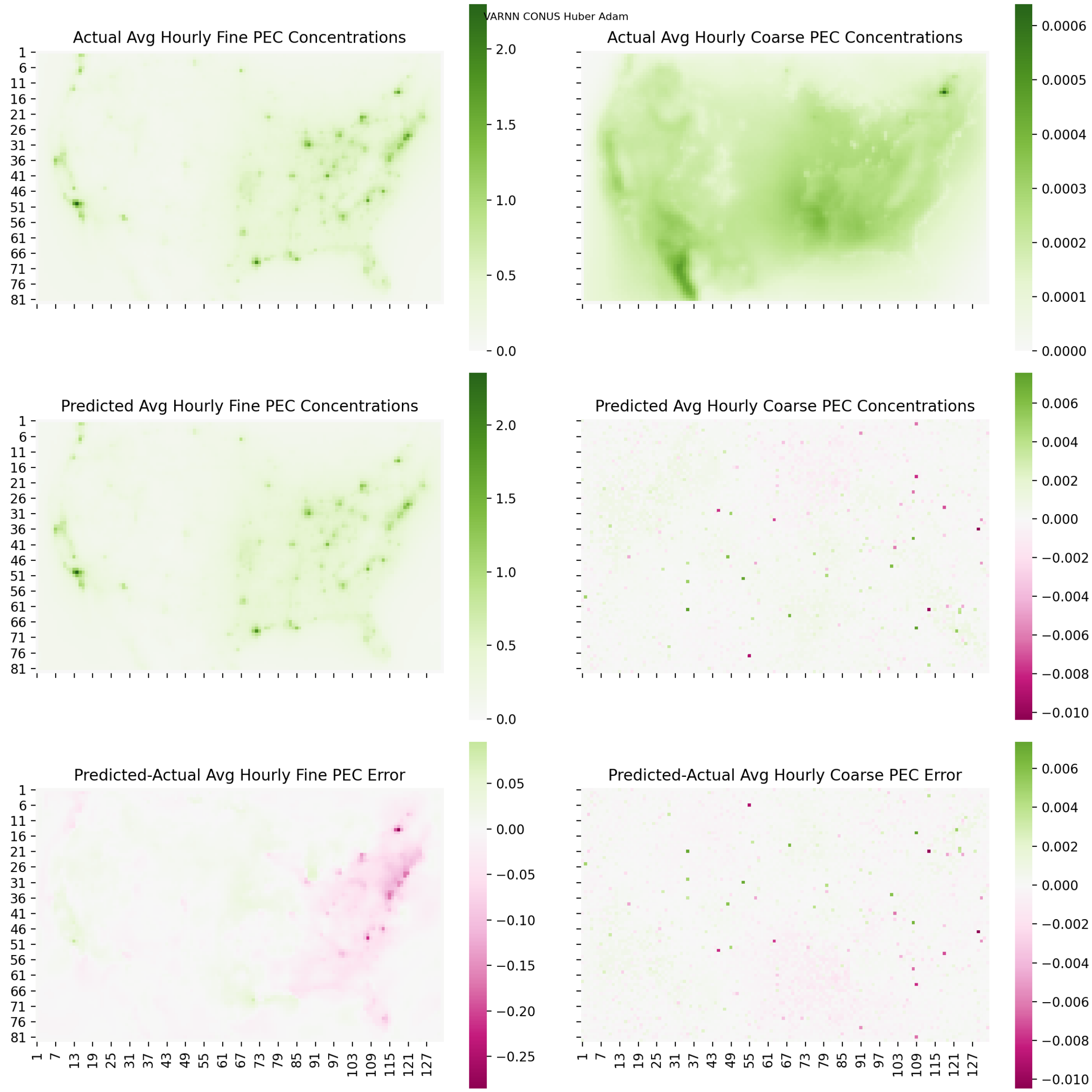

Fig. 94. Average hourly measurements for continental United States. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from VARNN and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

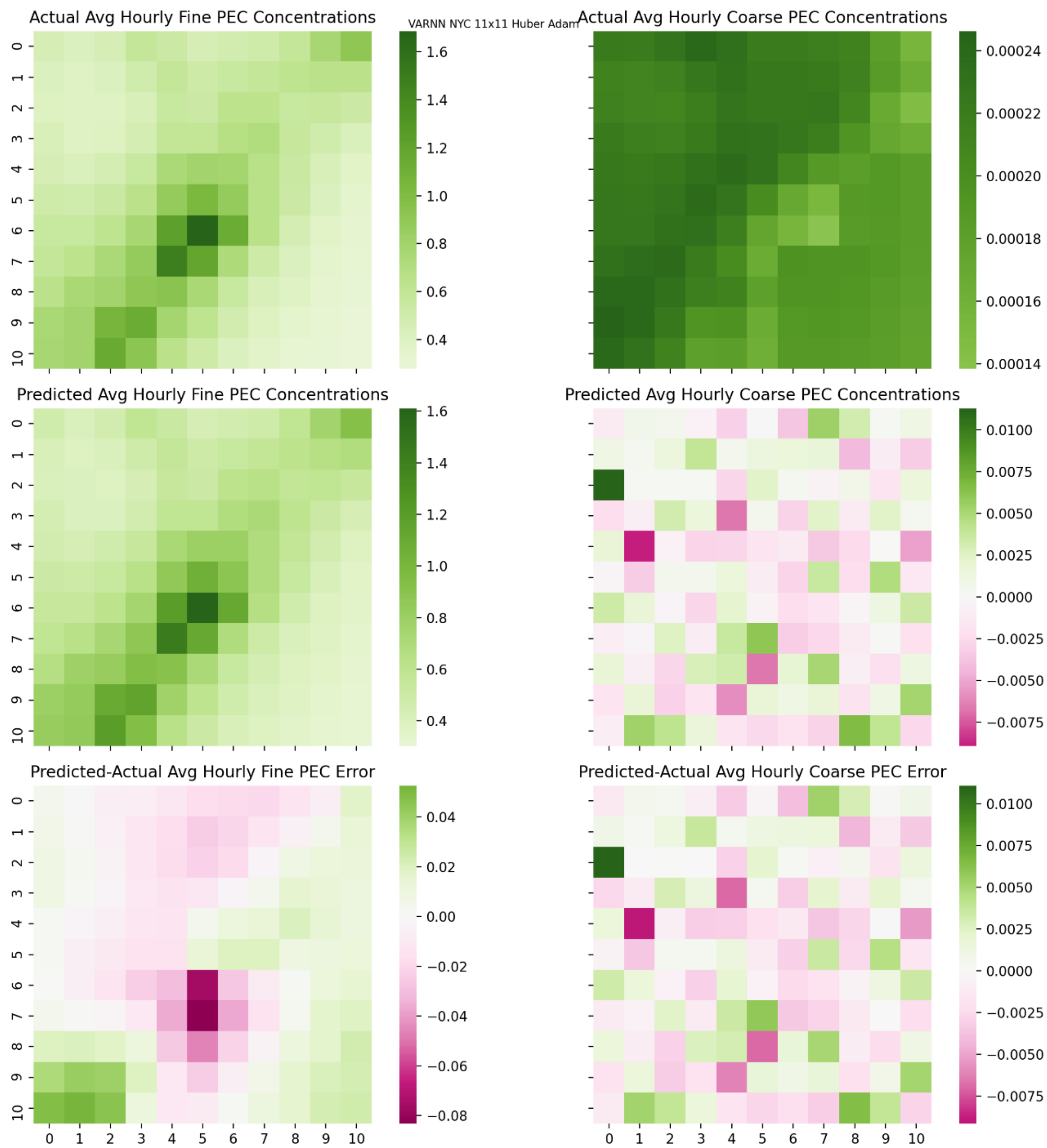

Fig. 95. Average hourly measurements for the 11x11 grid region in New York state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from VARNN and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

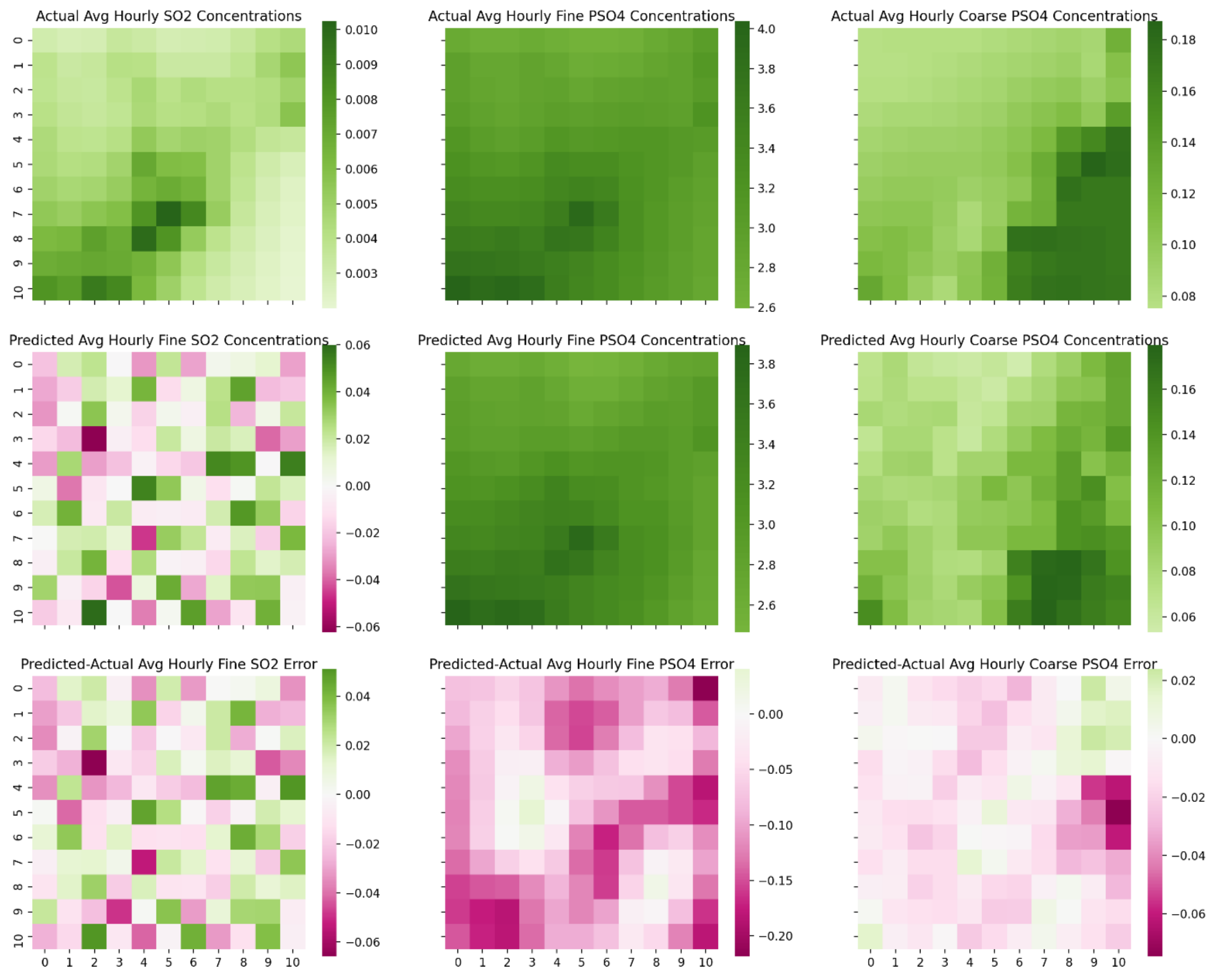

Fig. 96. Average hourly measurements for the 11x11 grid region in New York state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from VARNN and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

Graphical Results for HyVARNN Model

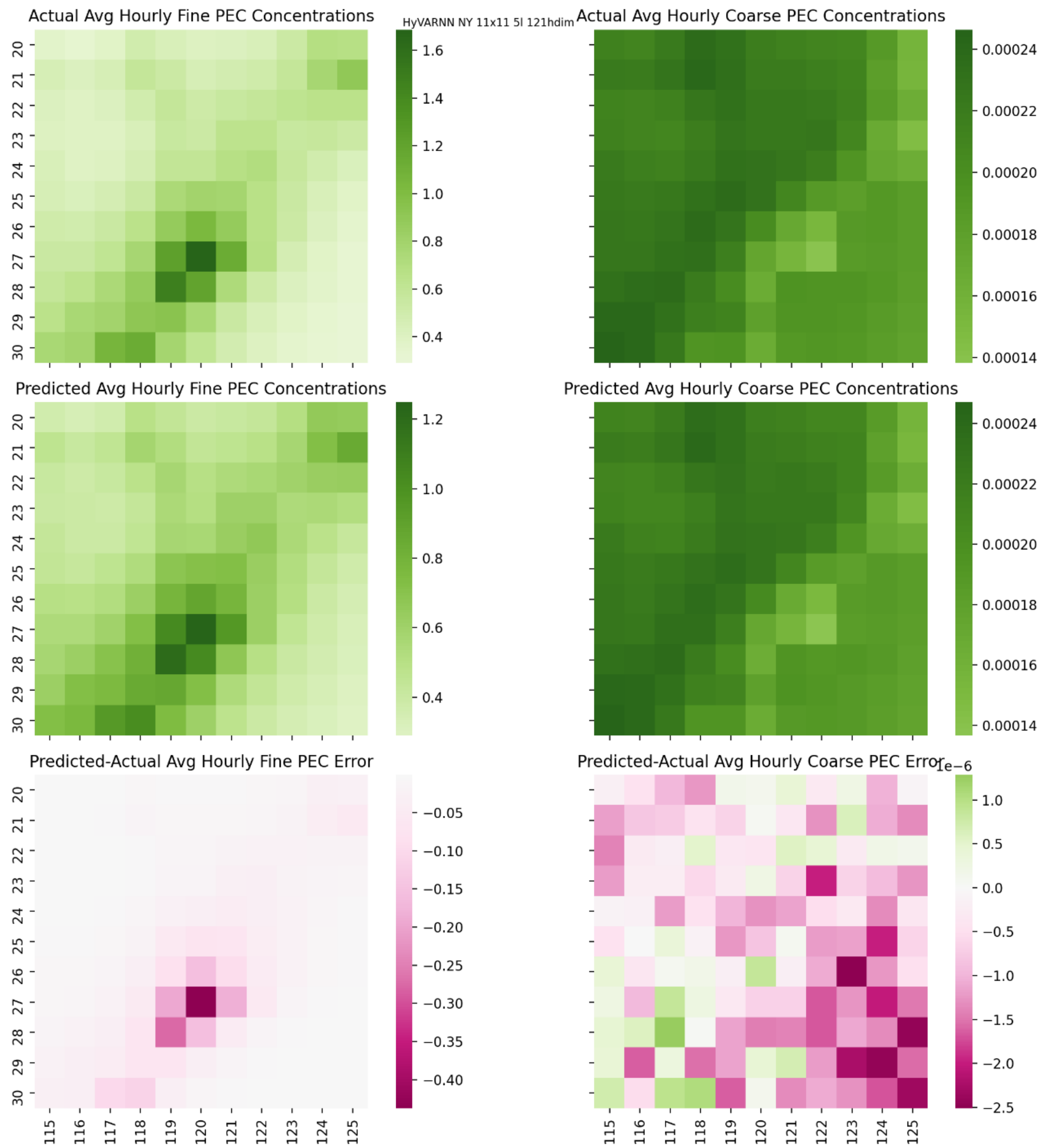

Fig. 97. Average hourly measurements for the 11x11 grid region in New York state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

Actual, prediction and error graphical results for HyVARNN-T model

Fig. 98. Test set average hourly measurements for the 15x15 grid region in California state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

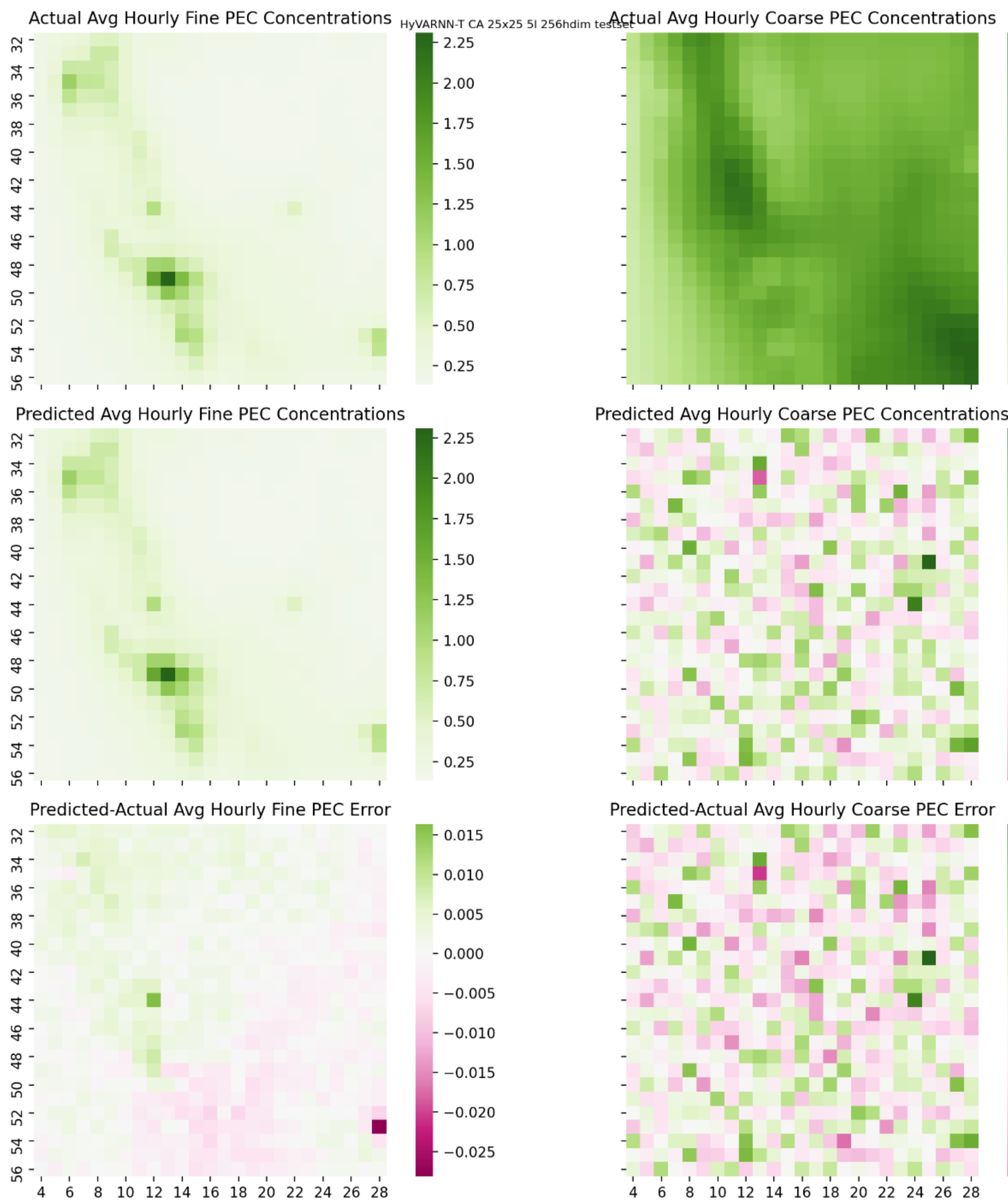

Fig. 99. Test set average hourly measurements for the 25x25 grid region in California state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

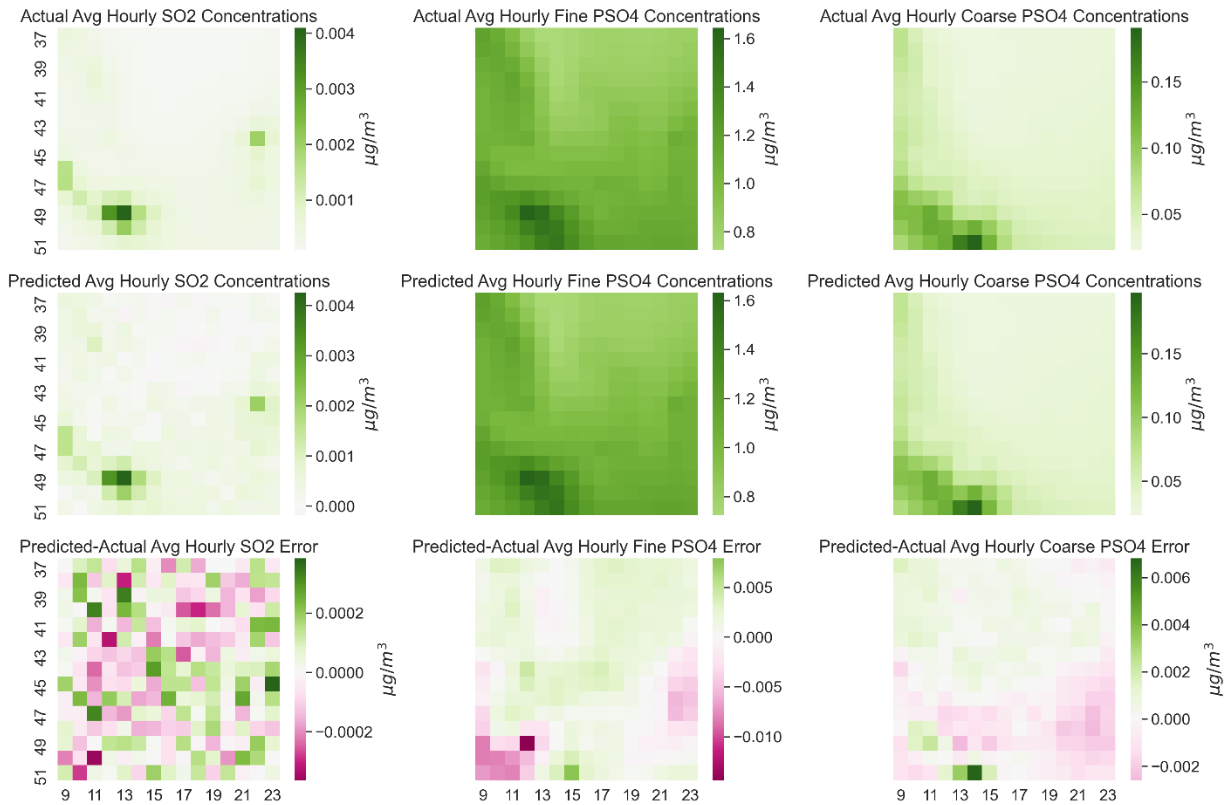

Fig. 100. Test set average hourly measurements for the 15x15 grid region in California state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

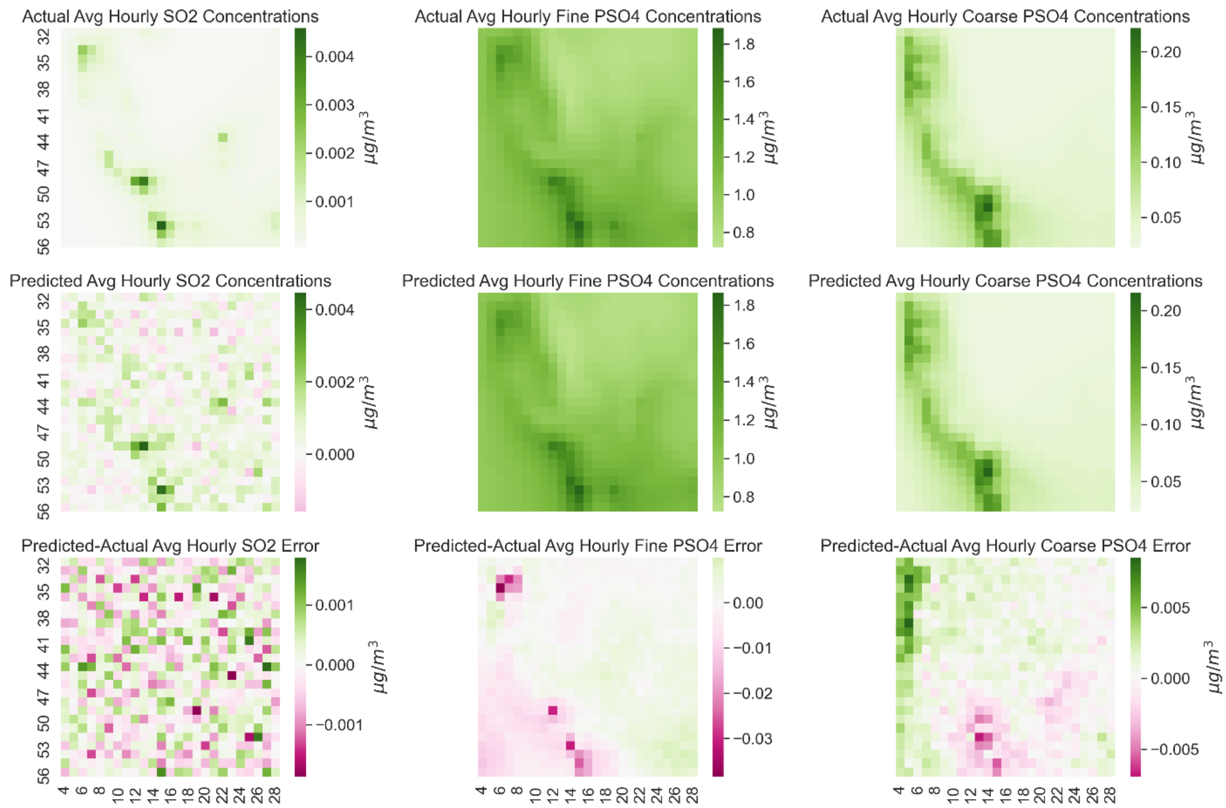

Fig. 101. Test set average hourly measurements for the 25x25 grid region in California state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

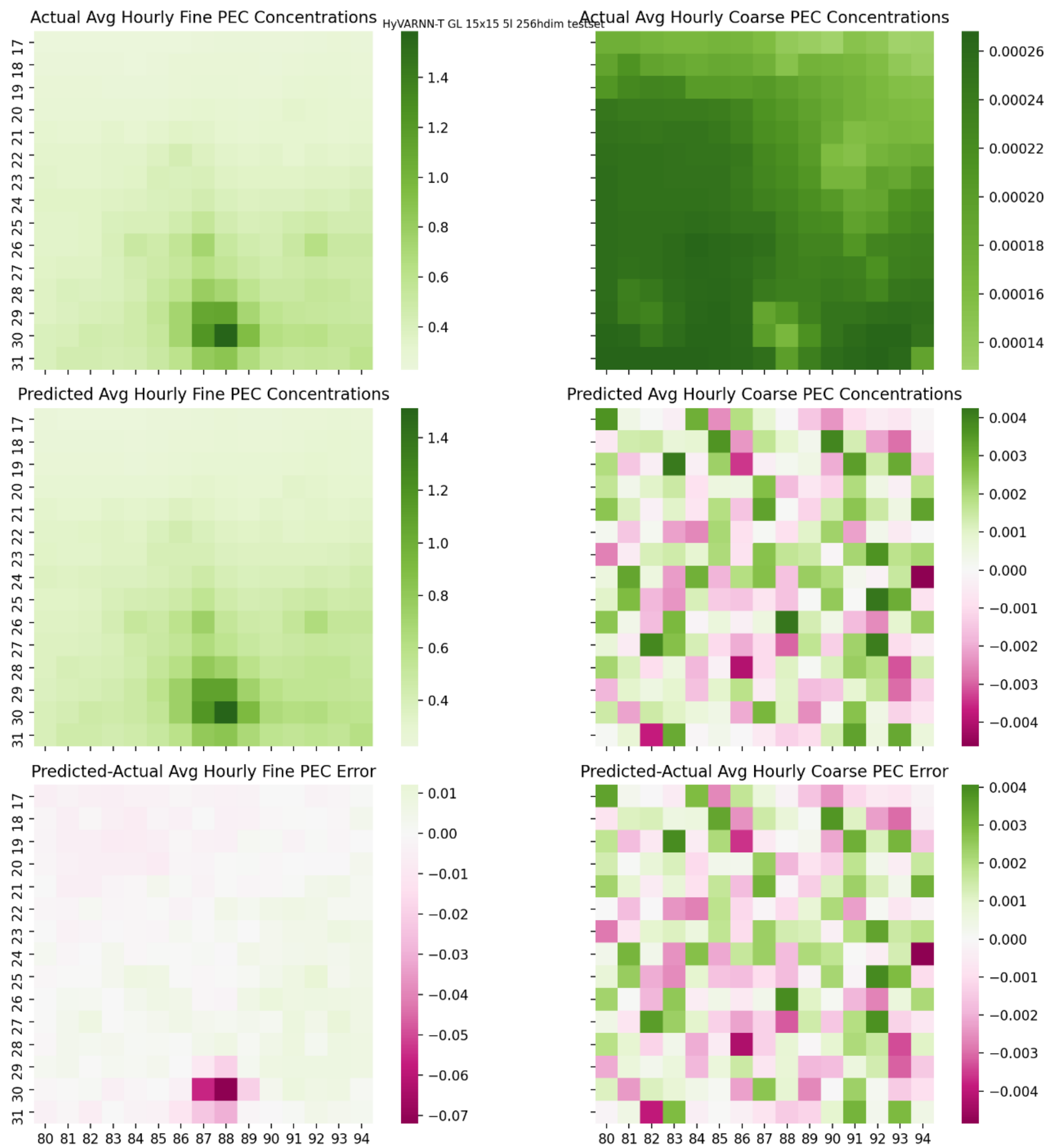

Fig. 102. Test set average hourly measurements for the 15x15 grid near the Great Lakes region. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

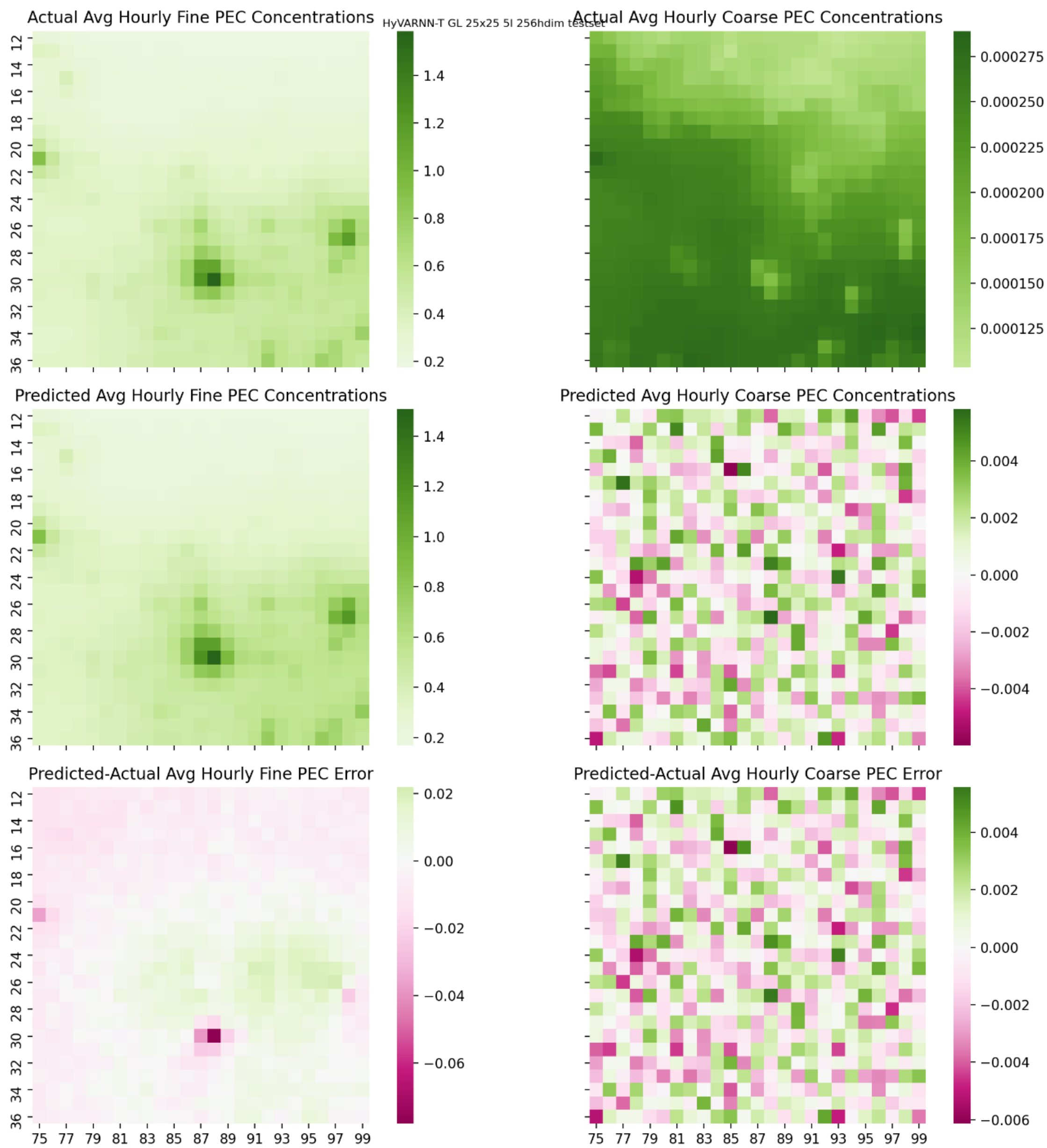

Fig. 103. Test set average hourly measurements for the 25x25 grid near the Great Lakes region. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

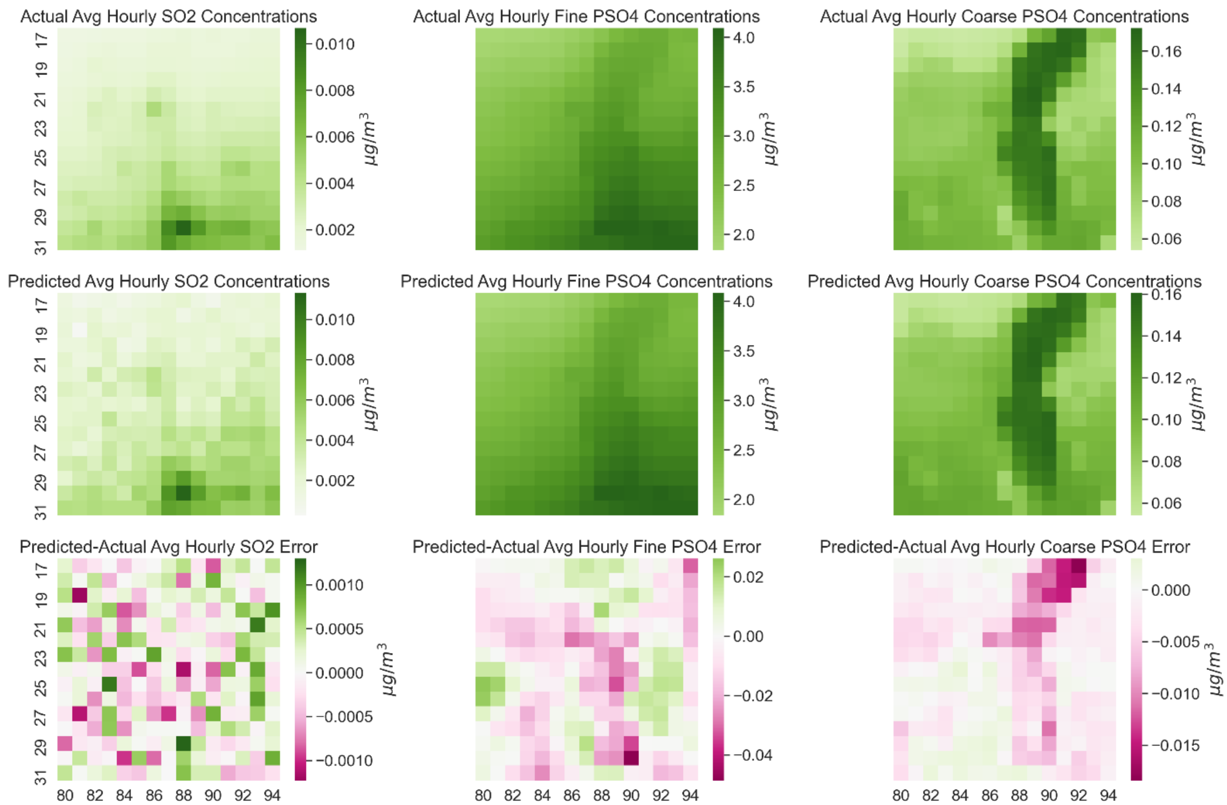

Fig. 104. Test set average hourly measurements for the 15x15 grid near the Great Lakes region. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

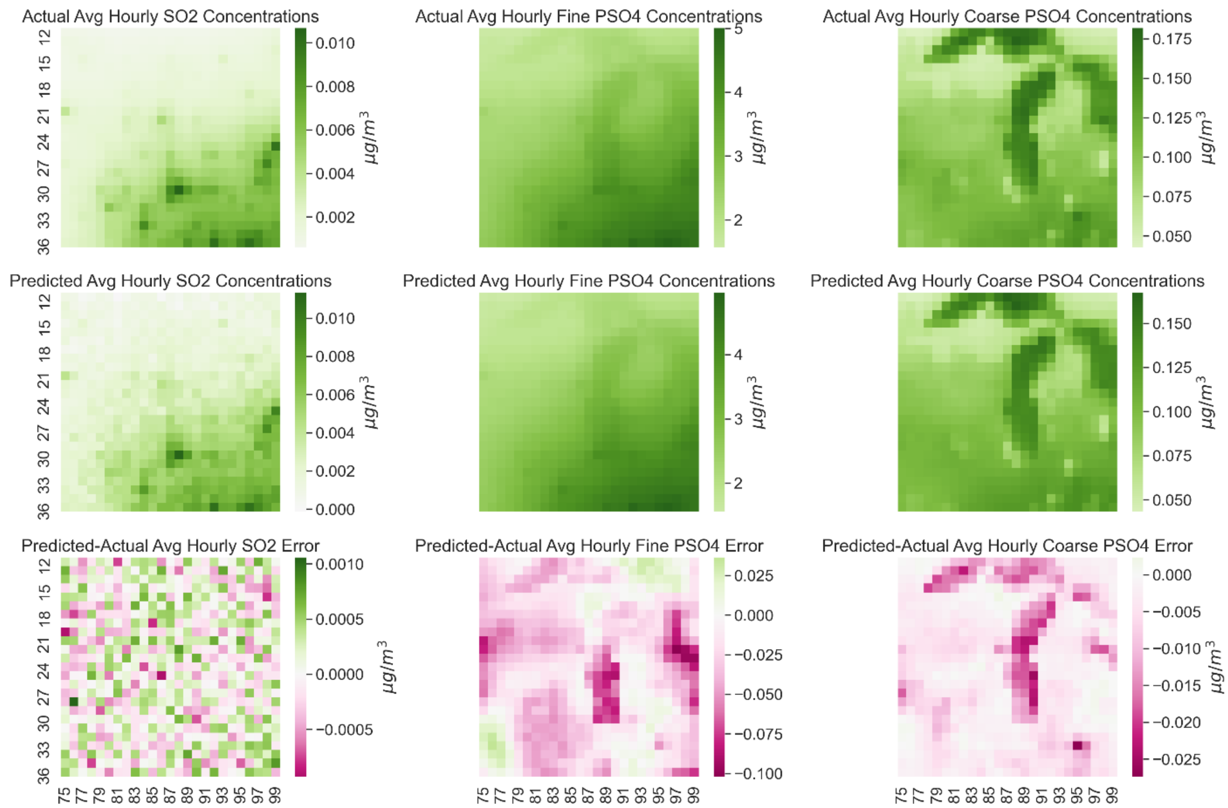

Fig. 105. Test set average hourly measurements for the 25x25 grid near the Great Lakes region. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

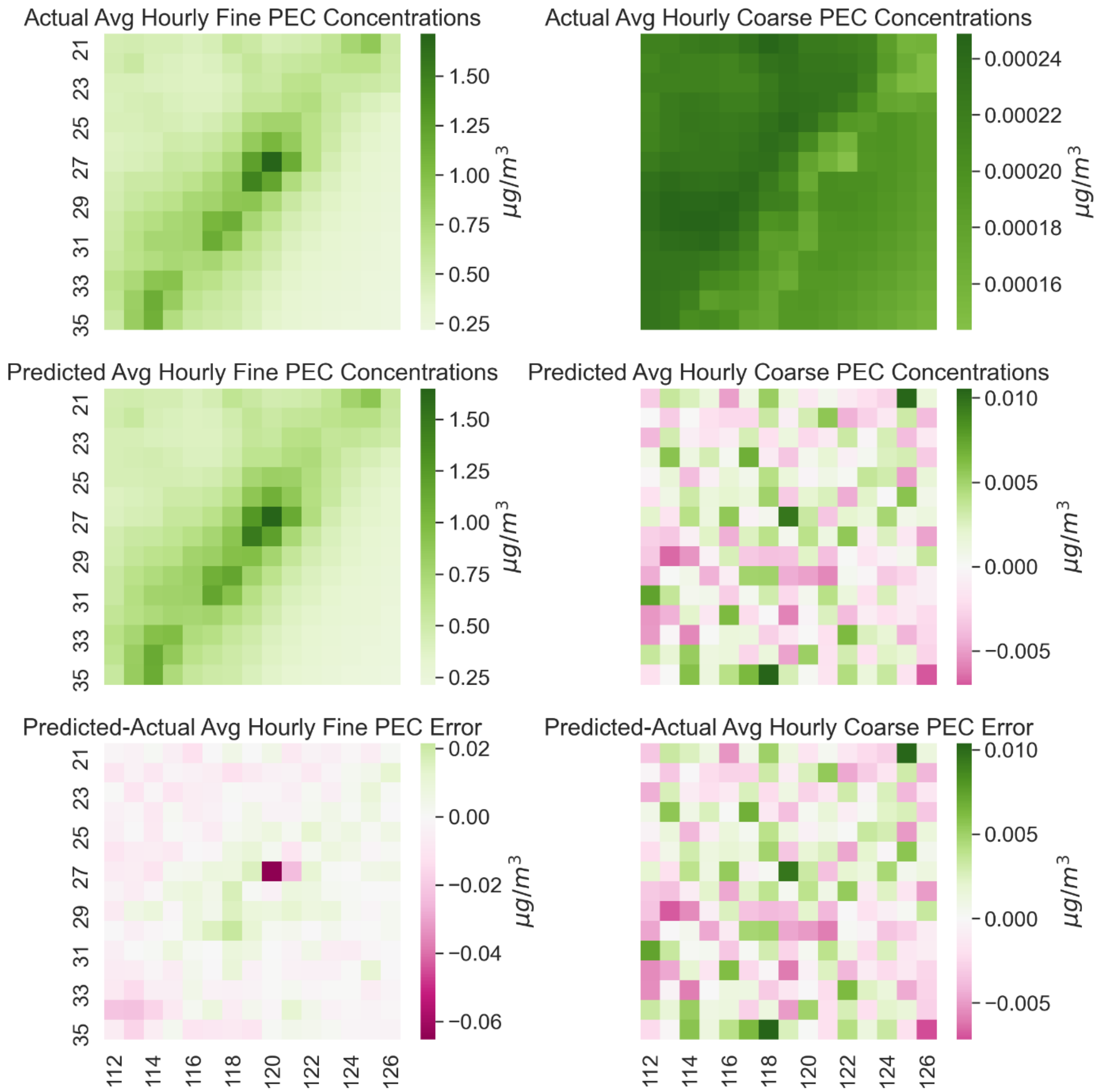

Fig. 106. Test set average hourly measurements for the 15x15 grid region in New York state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

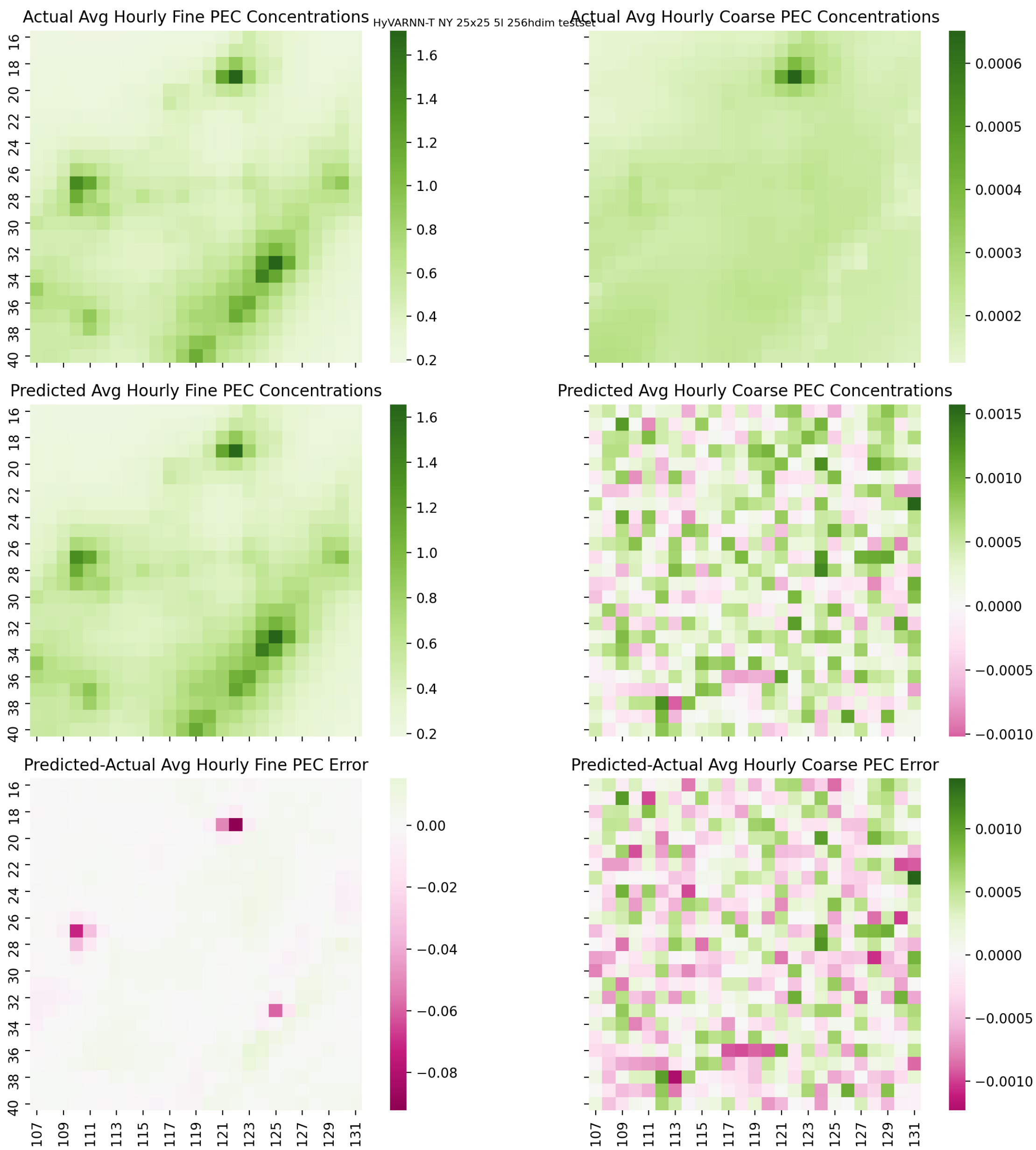

Fig. 107. Test set average hourly measurements for the 25x25 grid region in New York state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

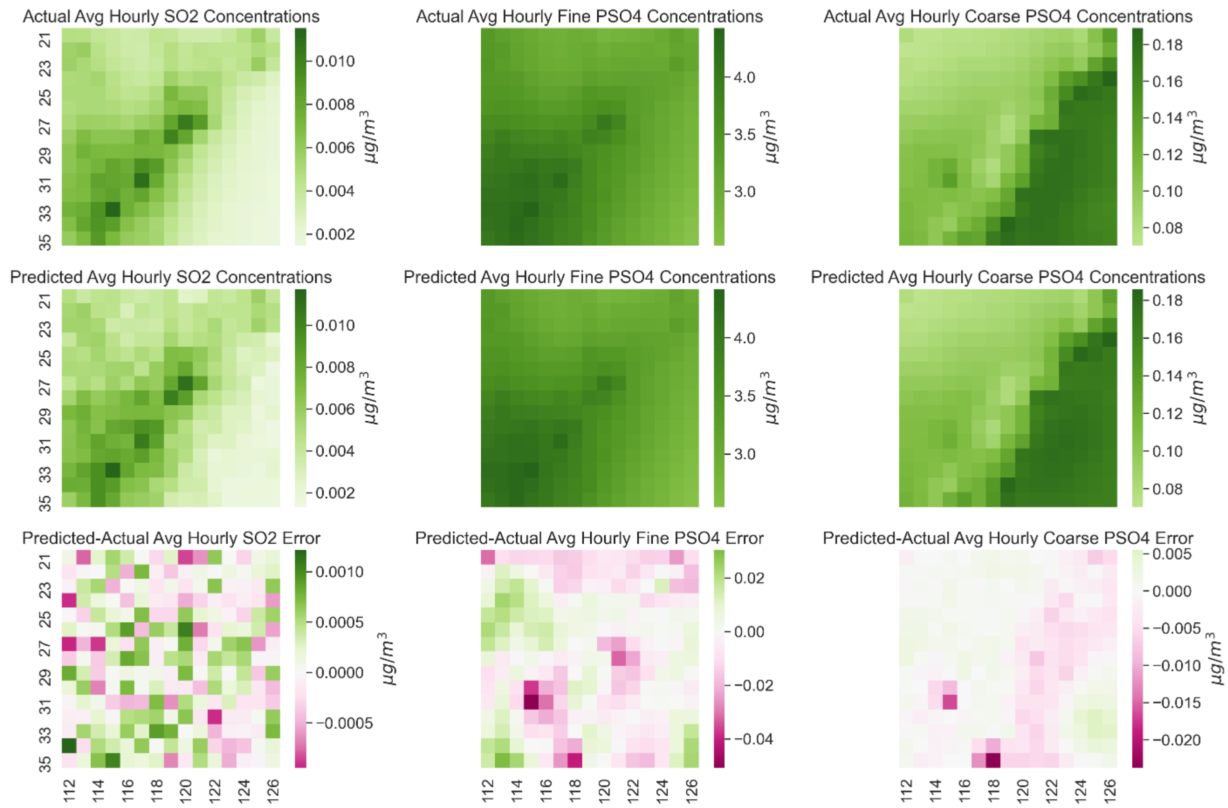

Fig. 108. Test set average hourly measurements for the 15x15 grid region in New York state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

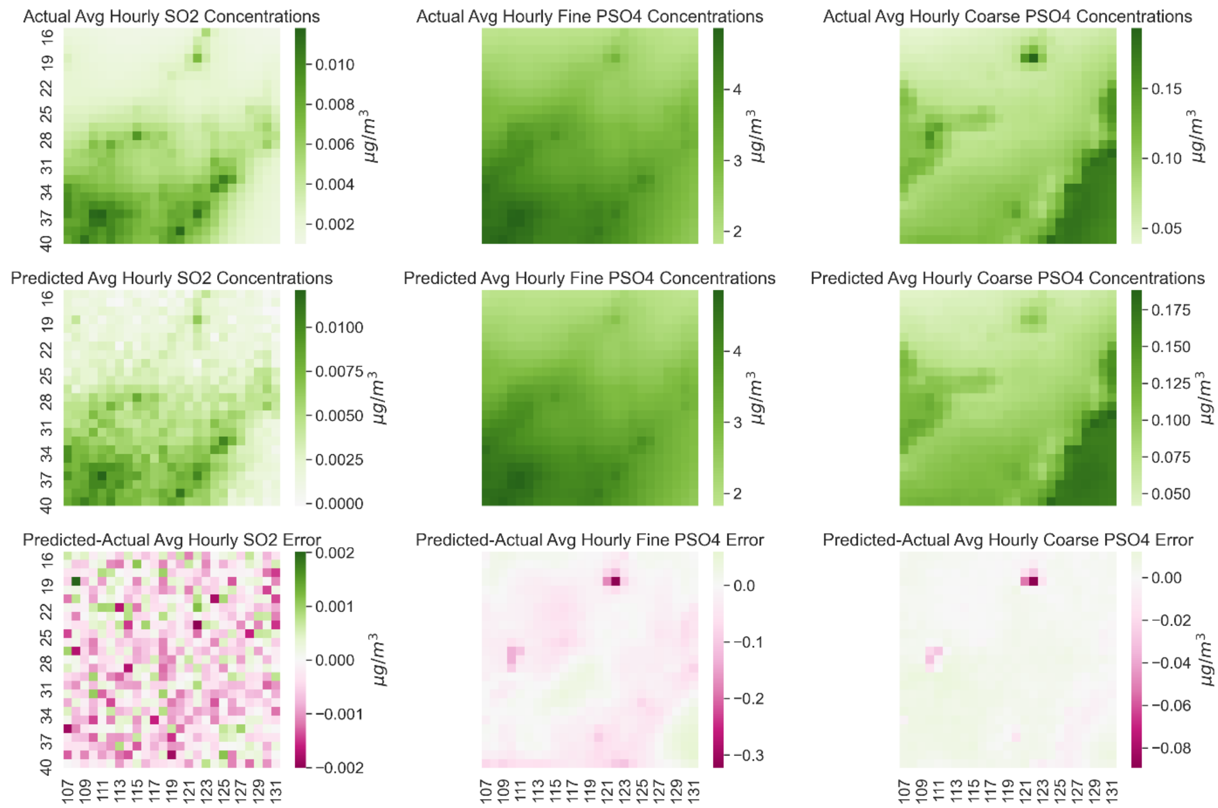

Fig. 109. Test set average hourly measurements for the 25x25 grid region in New York state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

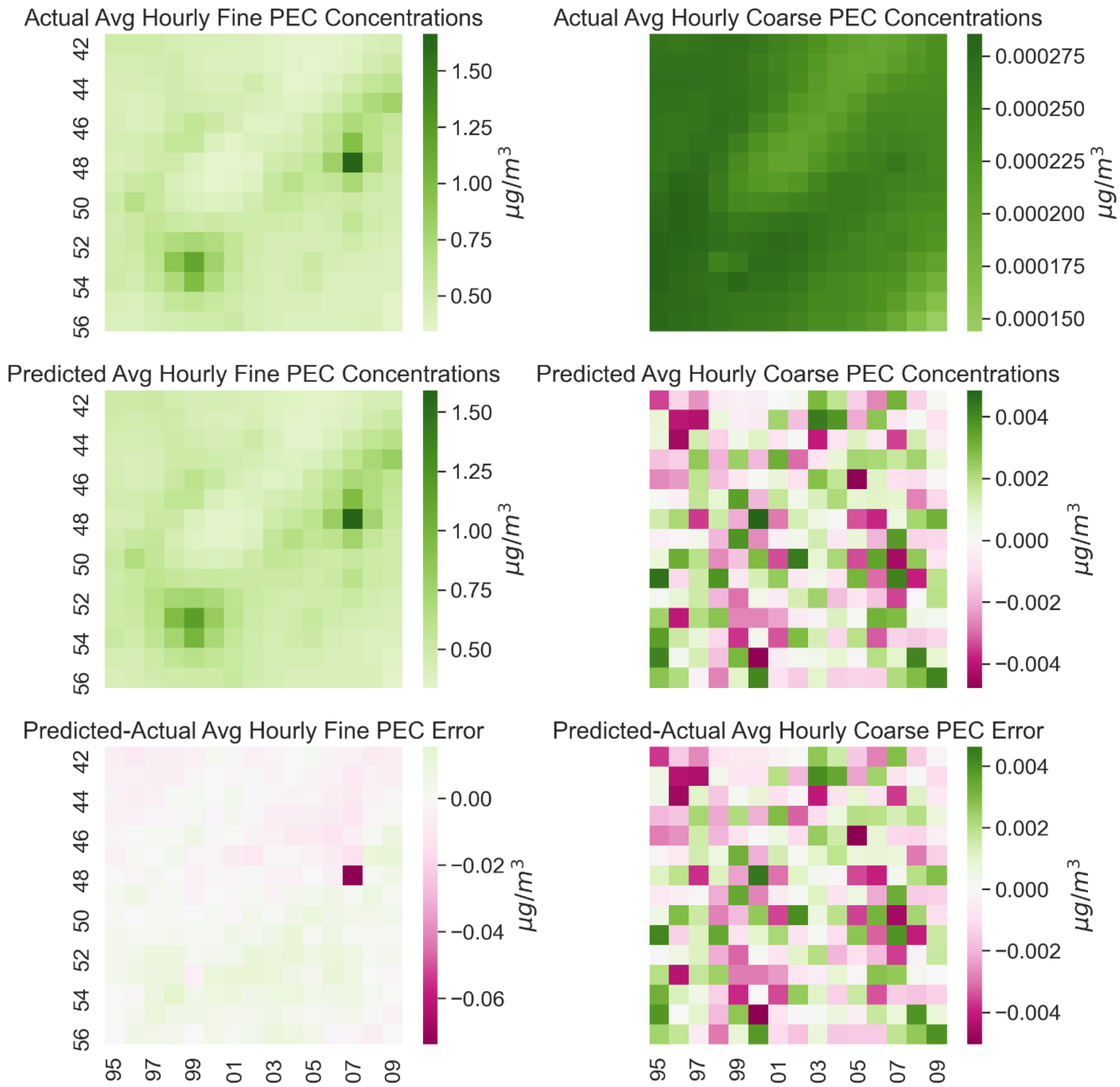

Fig. 110. Test set average hourly measurements for the 15x15 grid for the Southeast region. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

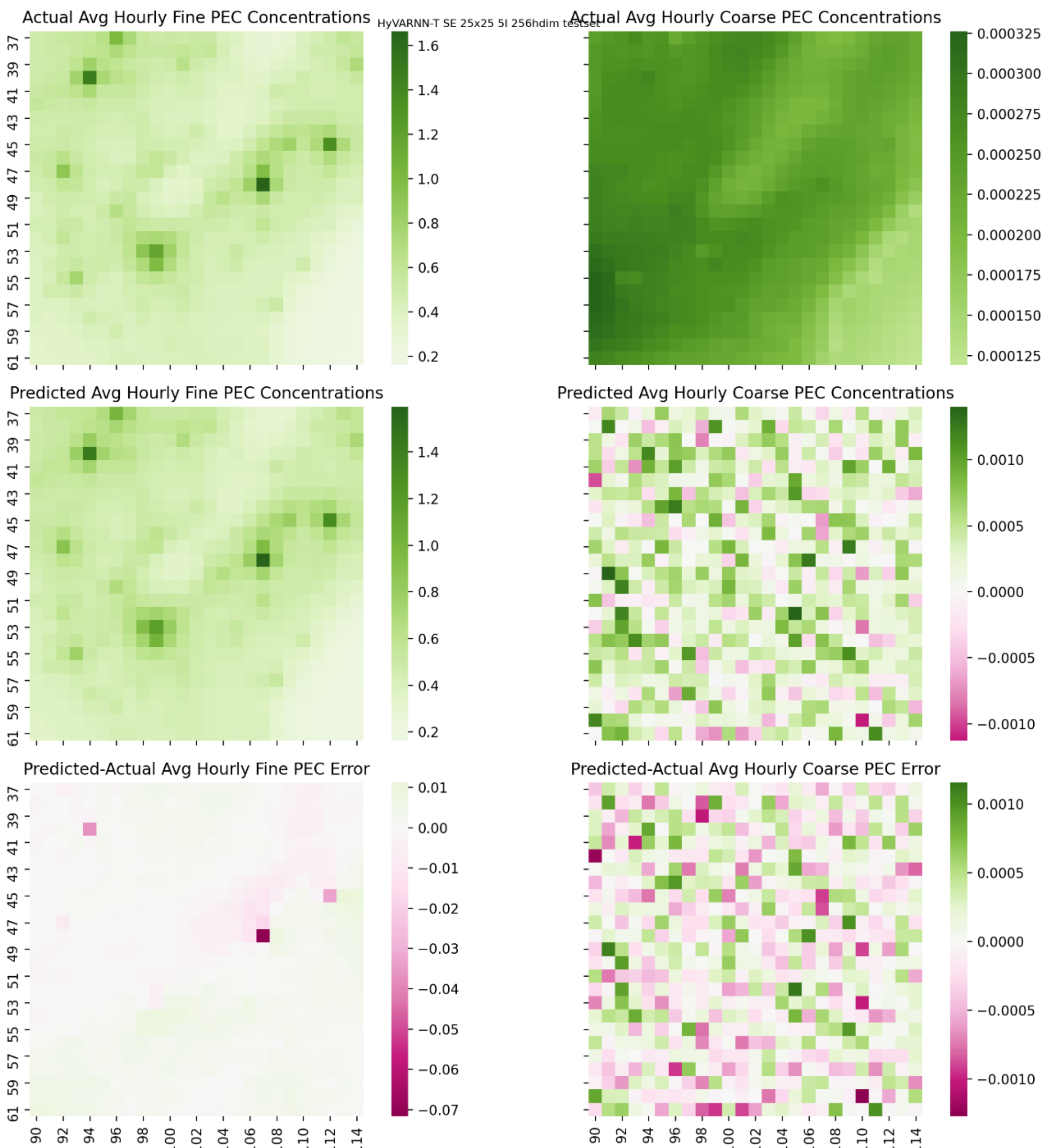

Fig. 111. Test set average hourly measurements for the 25x25 grid for the Southeast region. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

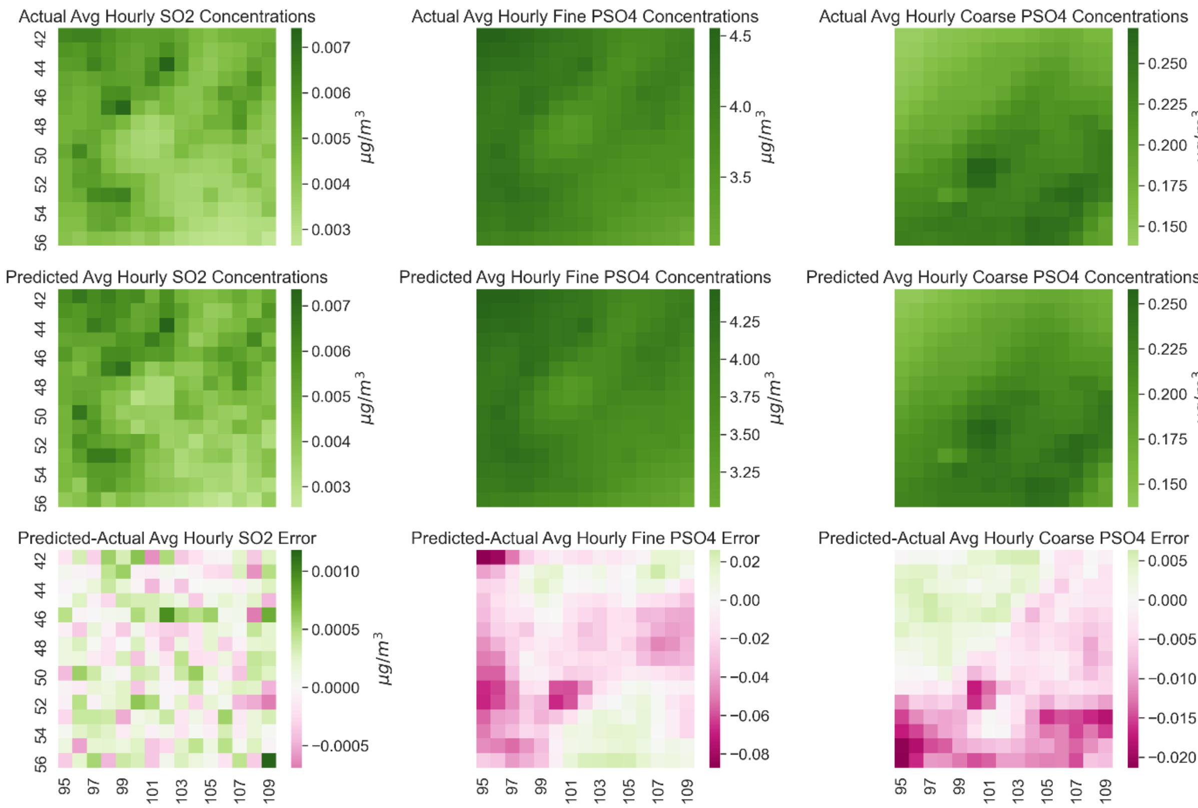

Fig. 112. Test set average hourly measurements for the 15x15 grid for the Southeast region. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

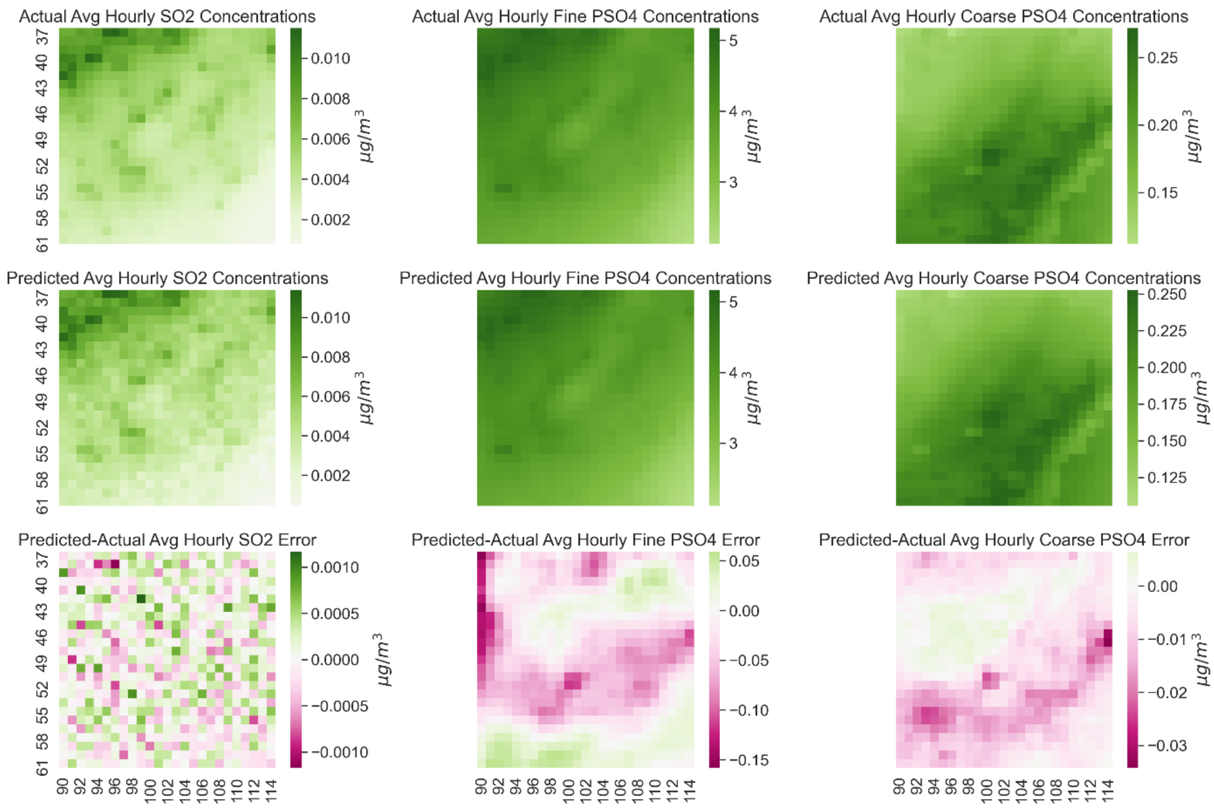

Fig. 113. Test set average hourly measurements for the 25x25 grid for the Southeast region. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

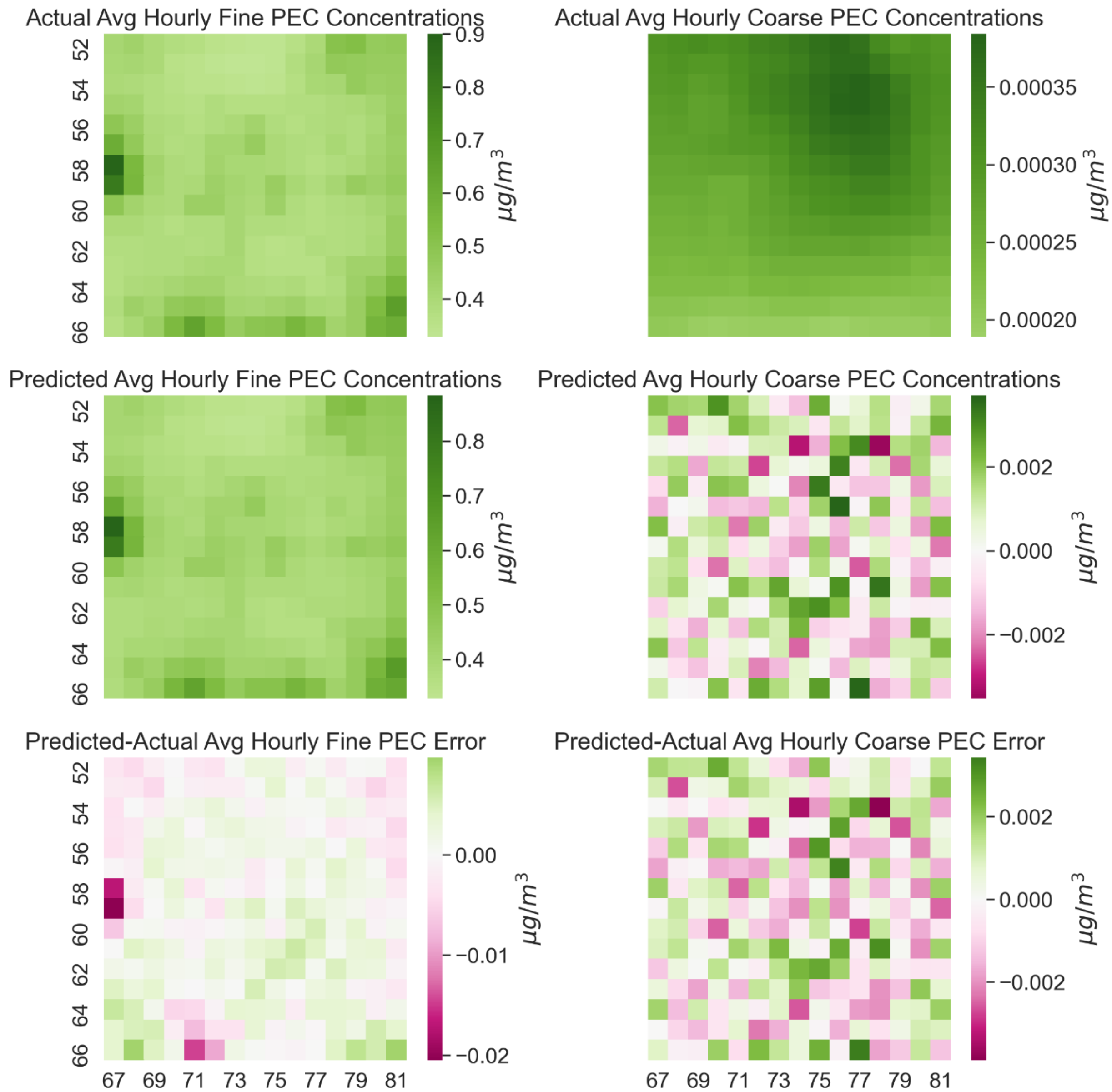

Fig. 114. Test set average hourly measurements for the 15x15 grid region in Texas state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

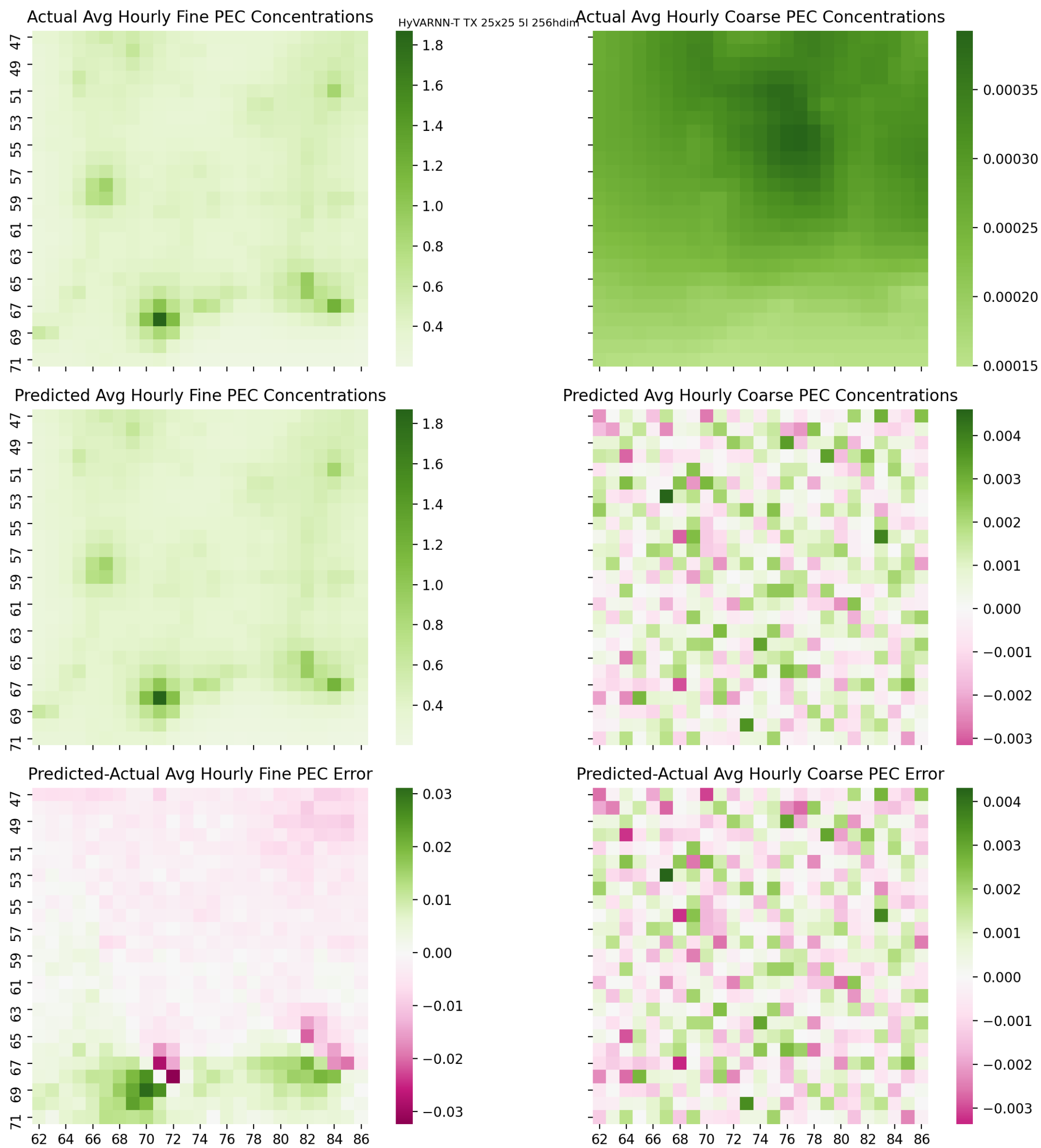

Fig. 115. Test set average hourly measurements for the 25x25 grid region in Texas state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

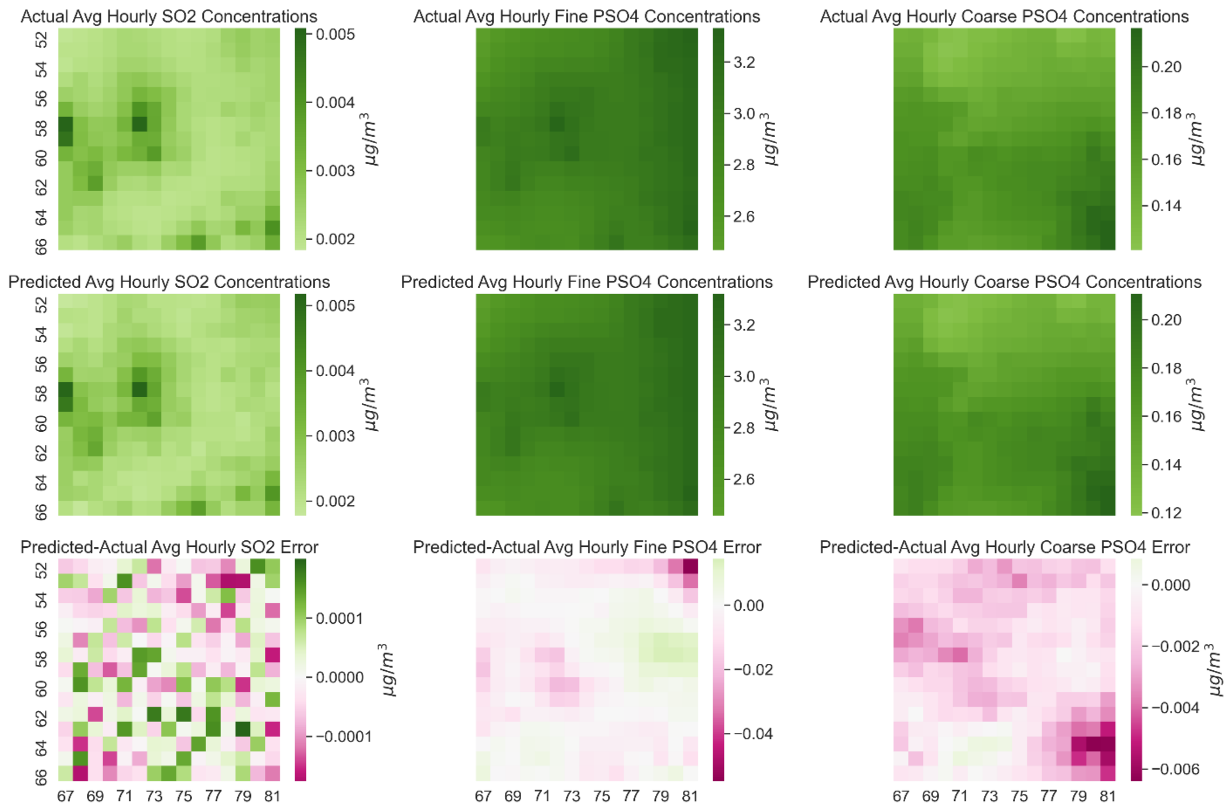

Fig. 116. Test set average hourly measurements for the 15x15 grid region in Texas state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

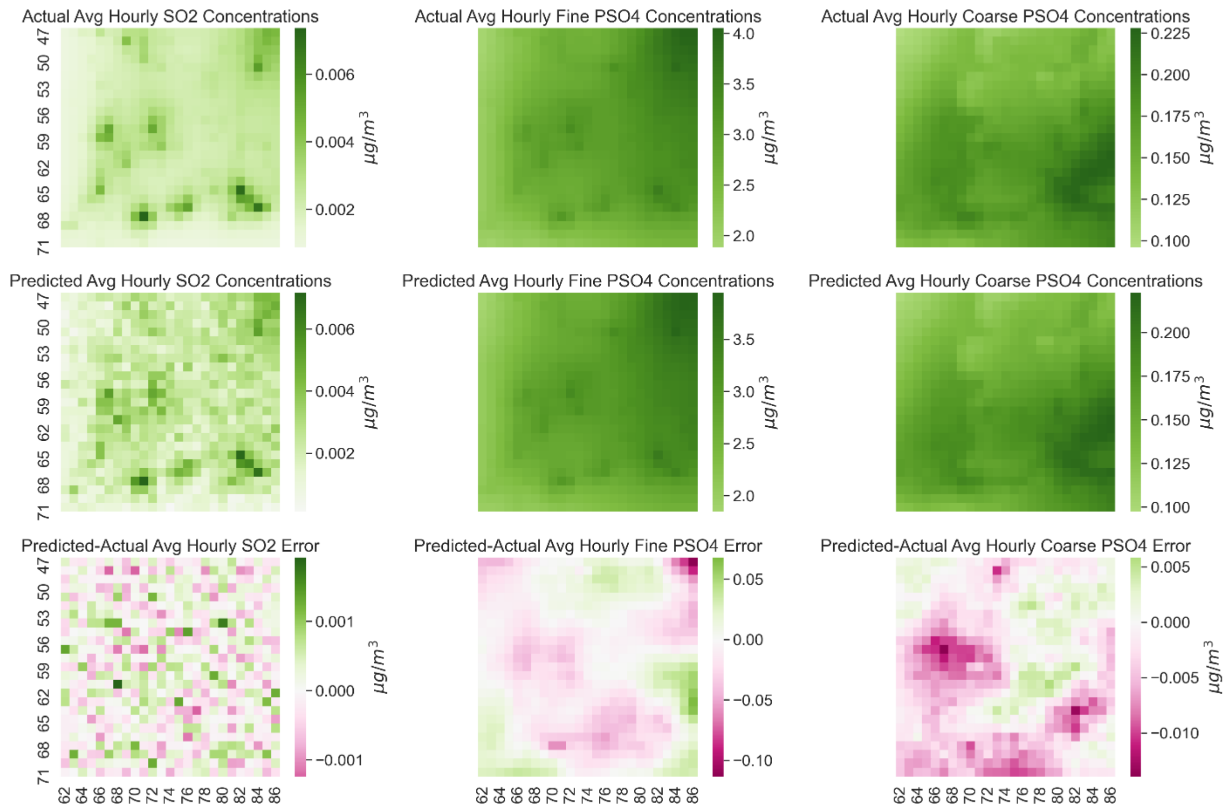

Fig. 117. Test set average hourly measurements for the 25x25 grid region in Texas state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

Fig. 118. Test set average hourly measurements for the 15x15 grid region in Washington state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

Fig. 119. Test set average hourly measurements for the 25x25 grid region in Washington state. $EC_{2.5}$ is on the left and EC_C is on right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

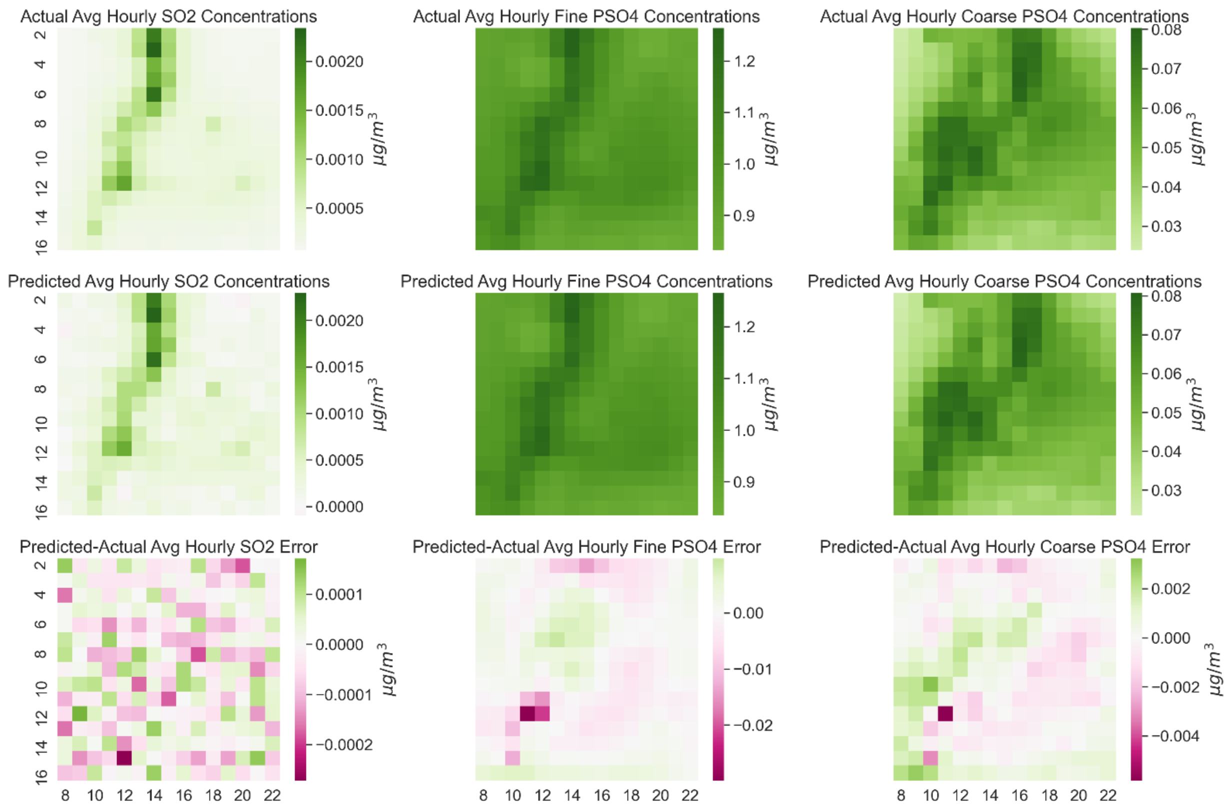

Fig. 120. Test set average hourly measurements for the 15x15 grid region in Washington state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

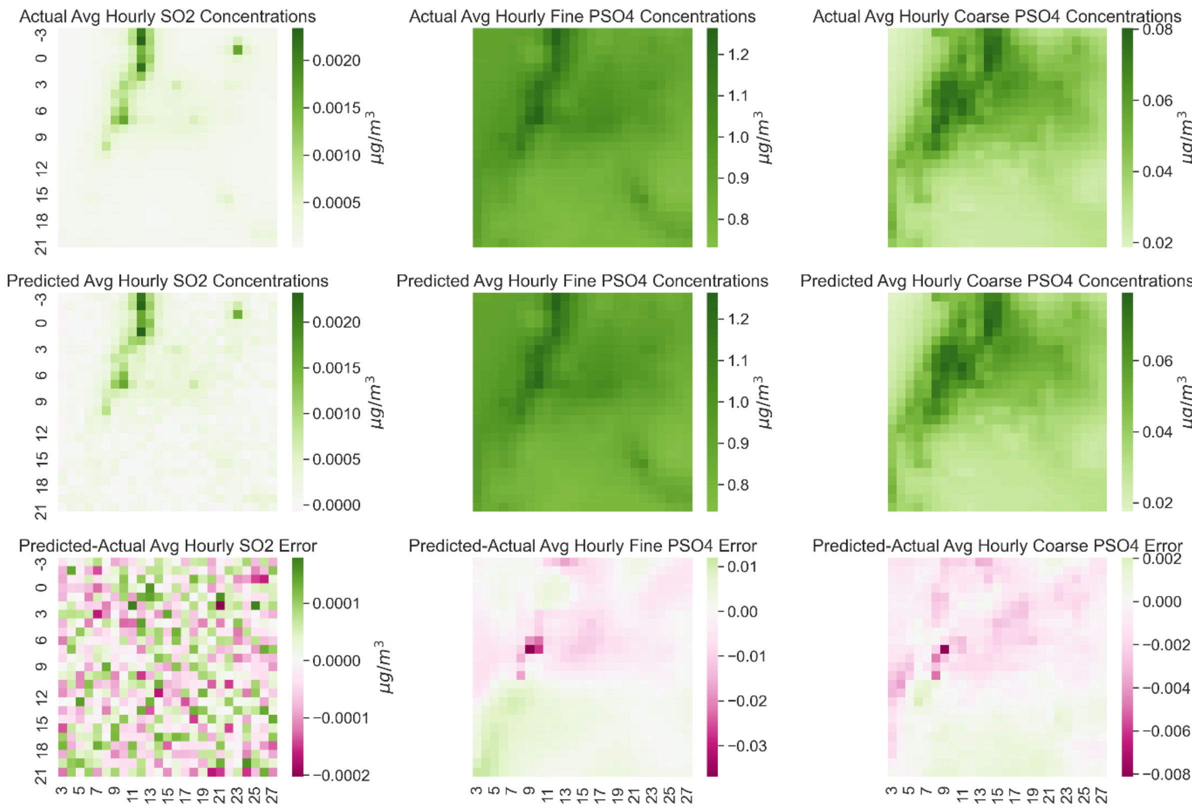

Fig. 121. Test set average hourly measurements for the 25x25 grid region in Washington state. SO_2 is on the left, $PSO_{4,2.5}$ is in the middle and $PSO_{4,C}$ is on the right. The top rows are the outputs of the CTM, the middle row is the prediction from HyVARNN-T and the bottom row contains the error (prediction – actual). For the error heatmap, green is an overprediction and pink is an underprediction.

Prediction vs. actual time series graphical results for HyVARNN-T model

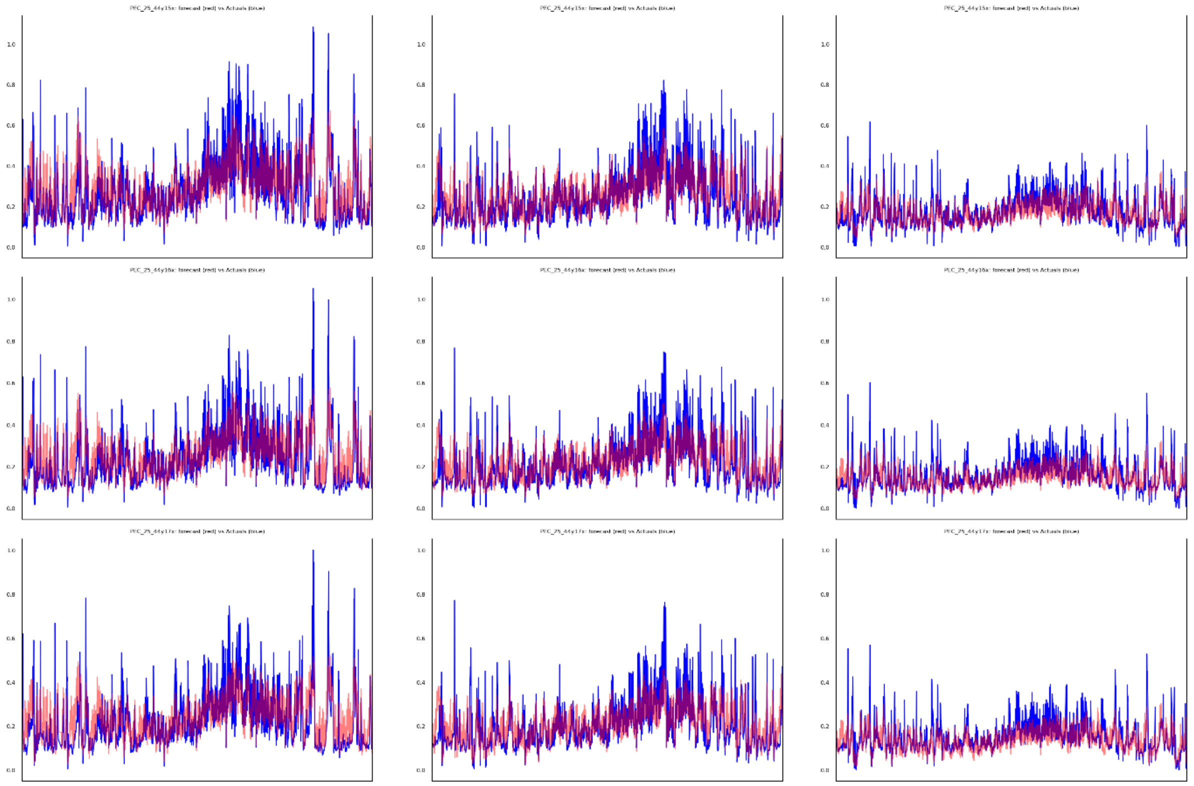

Fig. 122. Small California region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

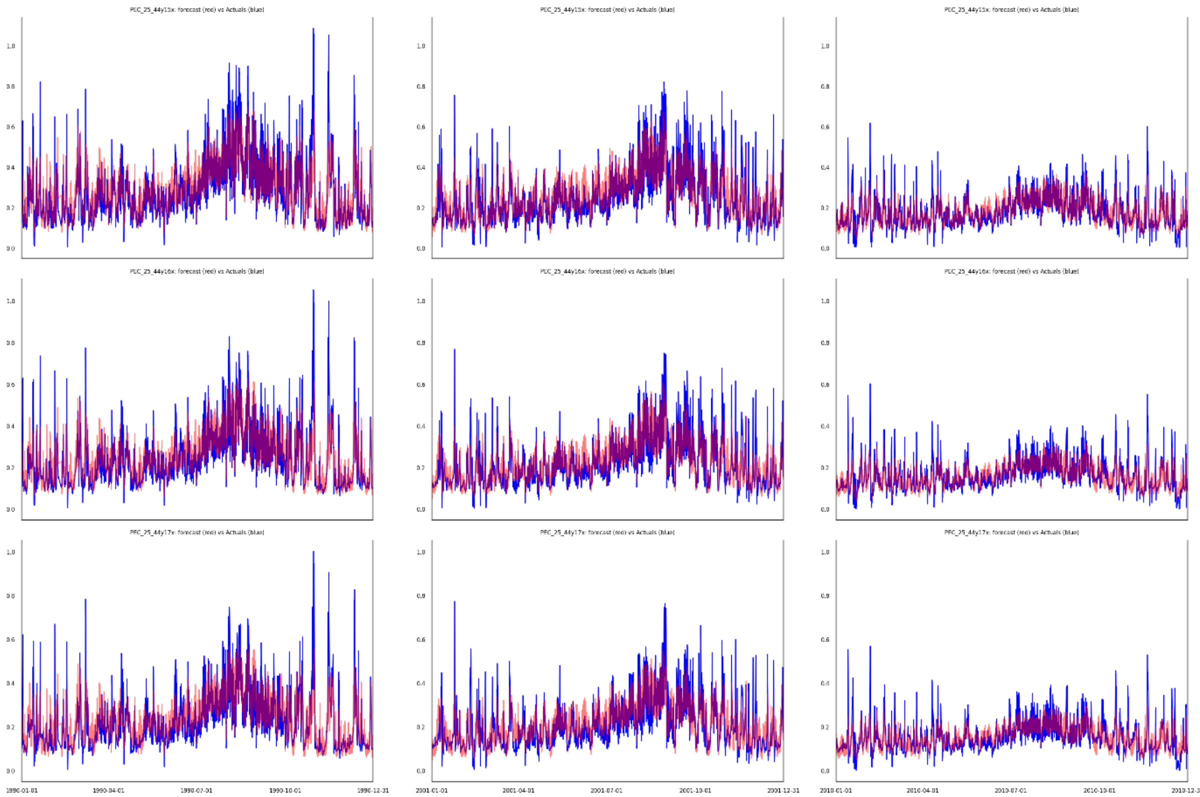

Fig. 123. Large California region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

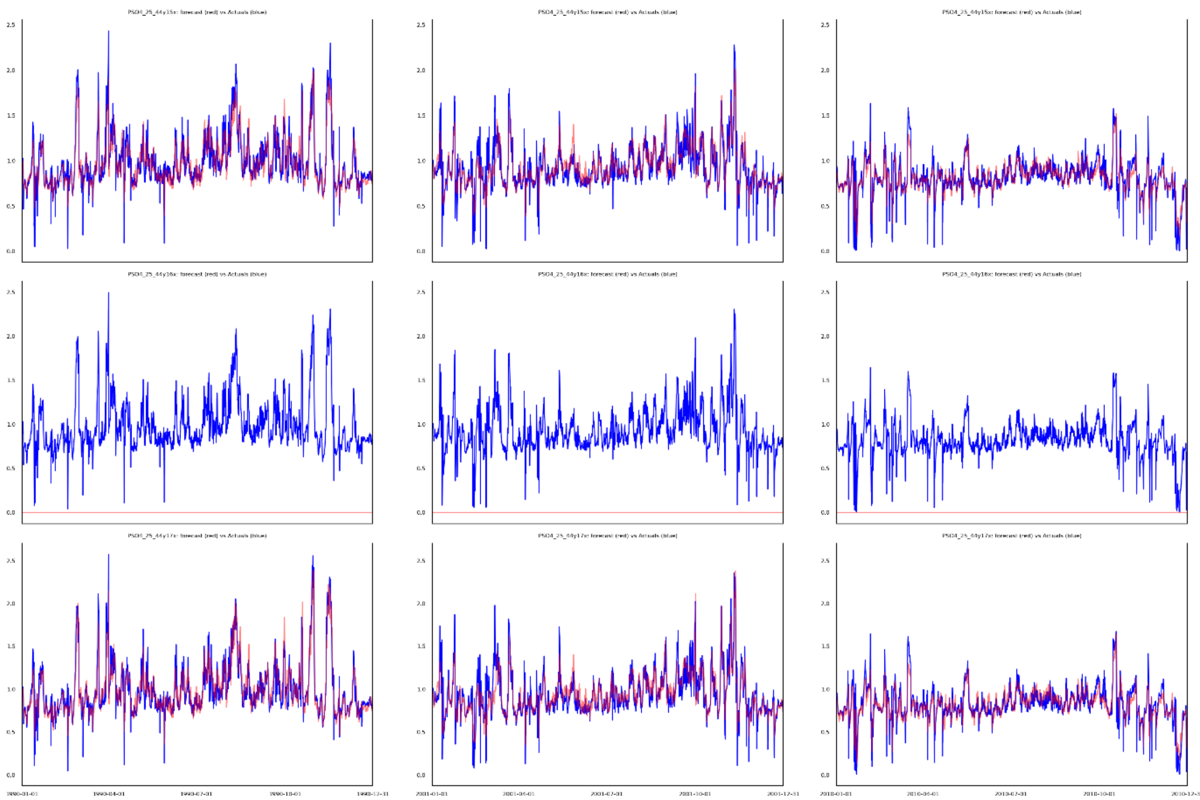

Fig. 124. Small California region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

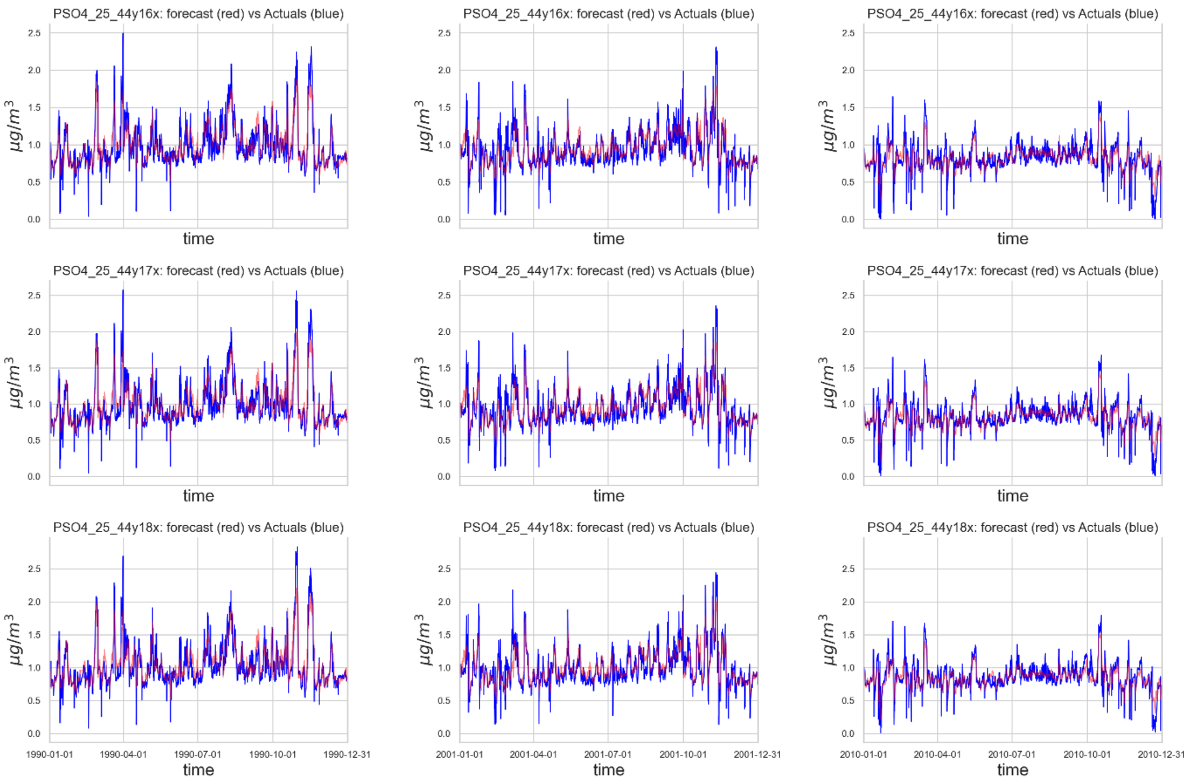

Fig. 125. Large California region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

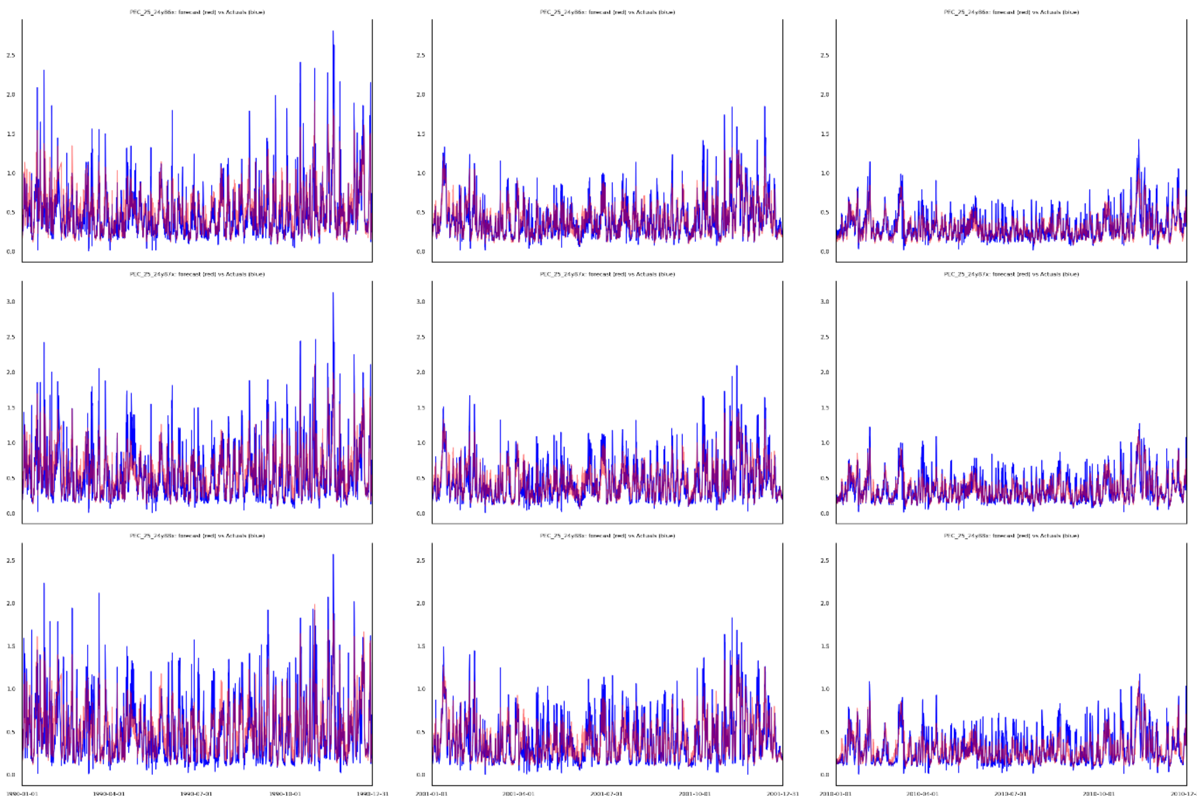

Fig. 126. Small Great Lakes region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

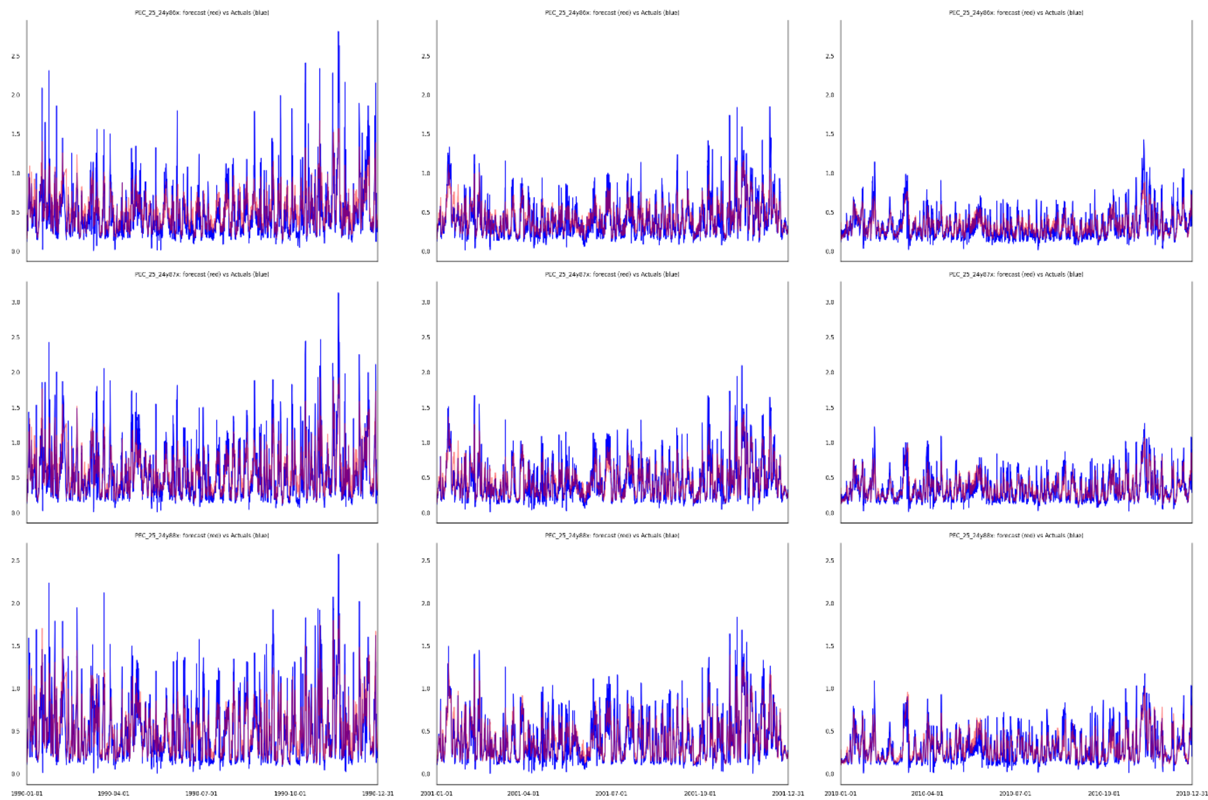

Fig. 127. Large Great Lakes region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

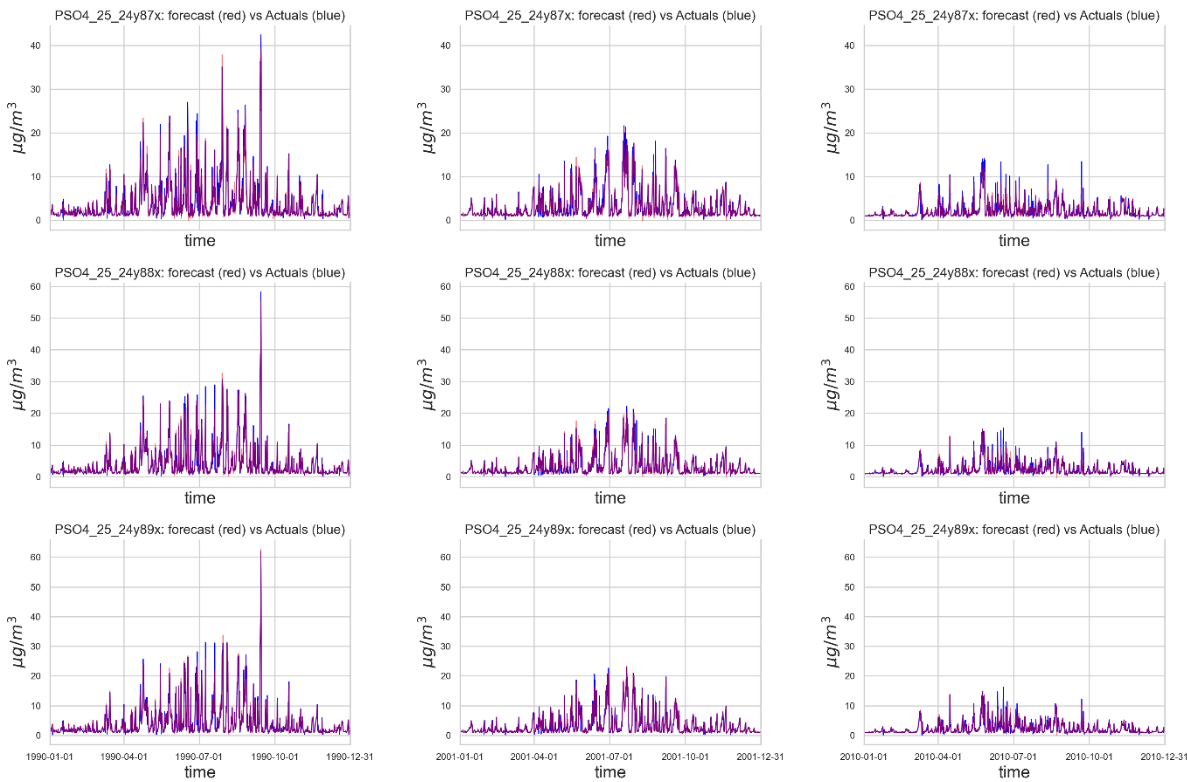

Fig. 128. Small Great Lakes region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

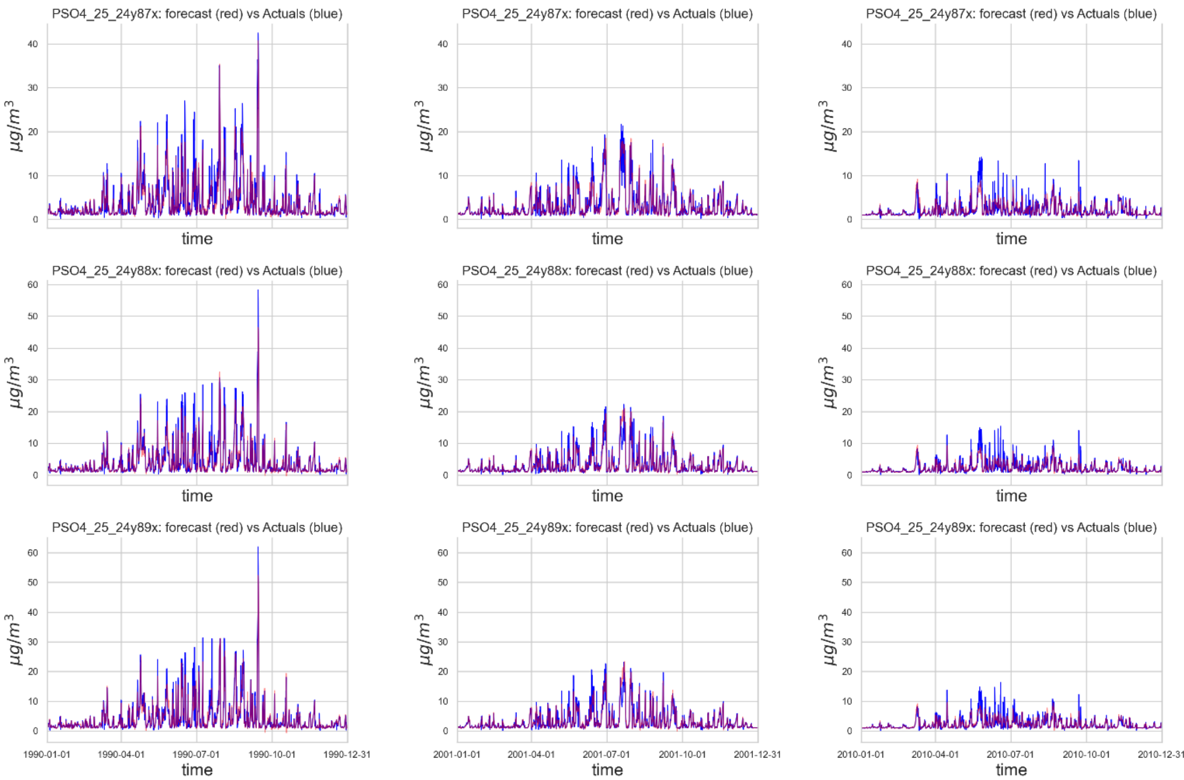

Fig. 129. Large Great Lakes region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

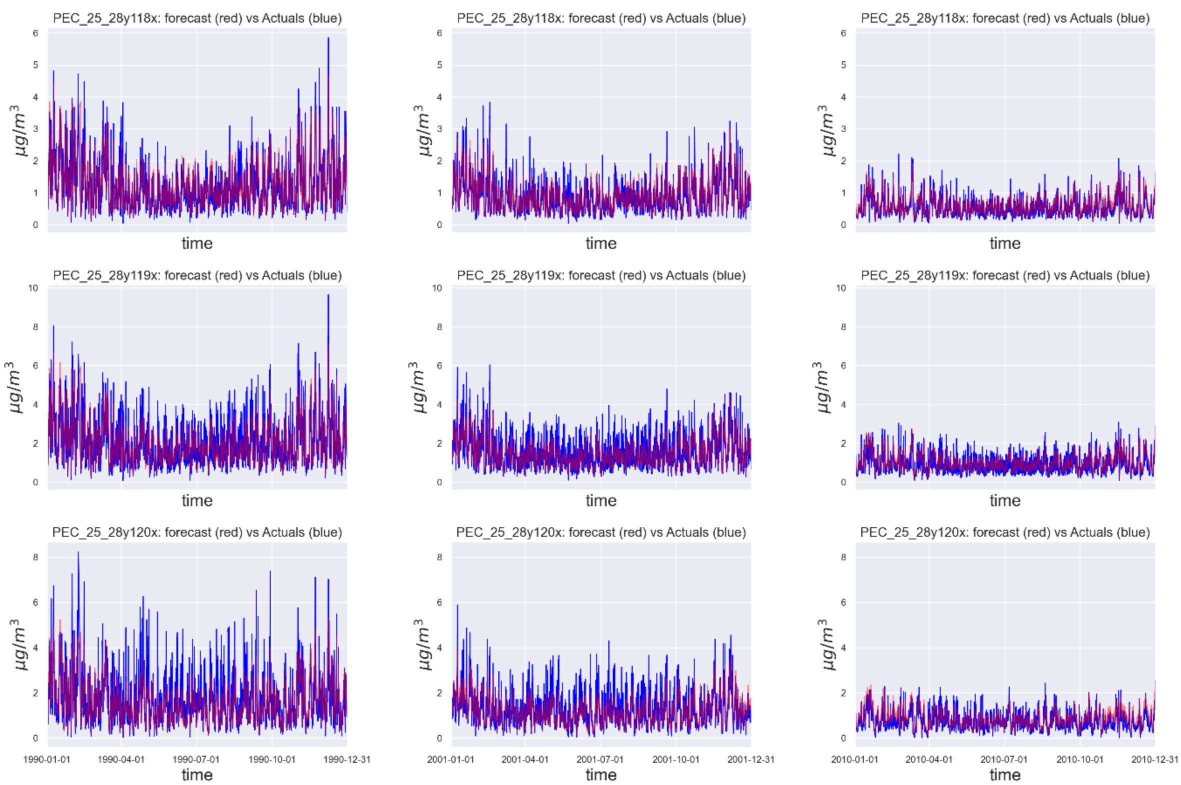

Fig. 130. Small New York region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

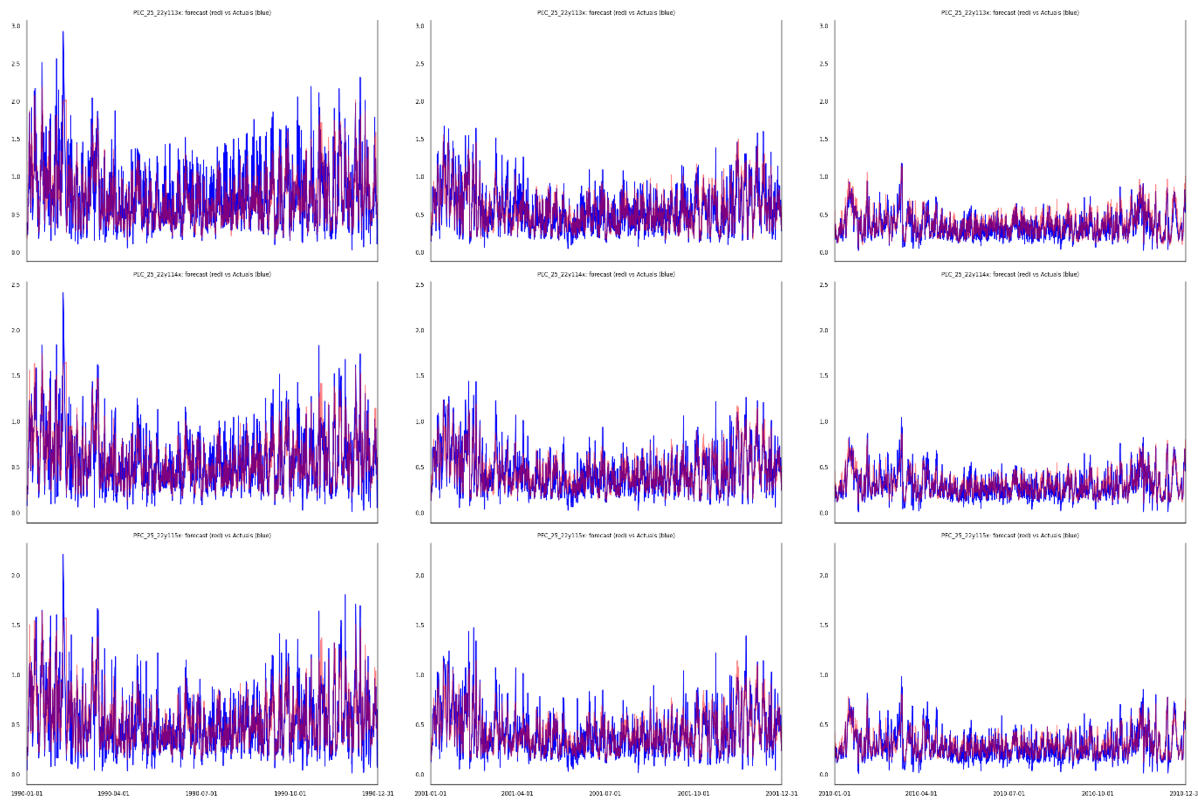

Fig. 131. Large New York region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

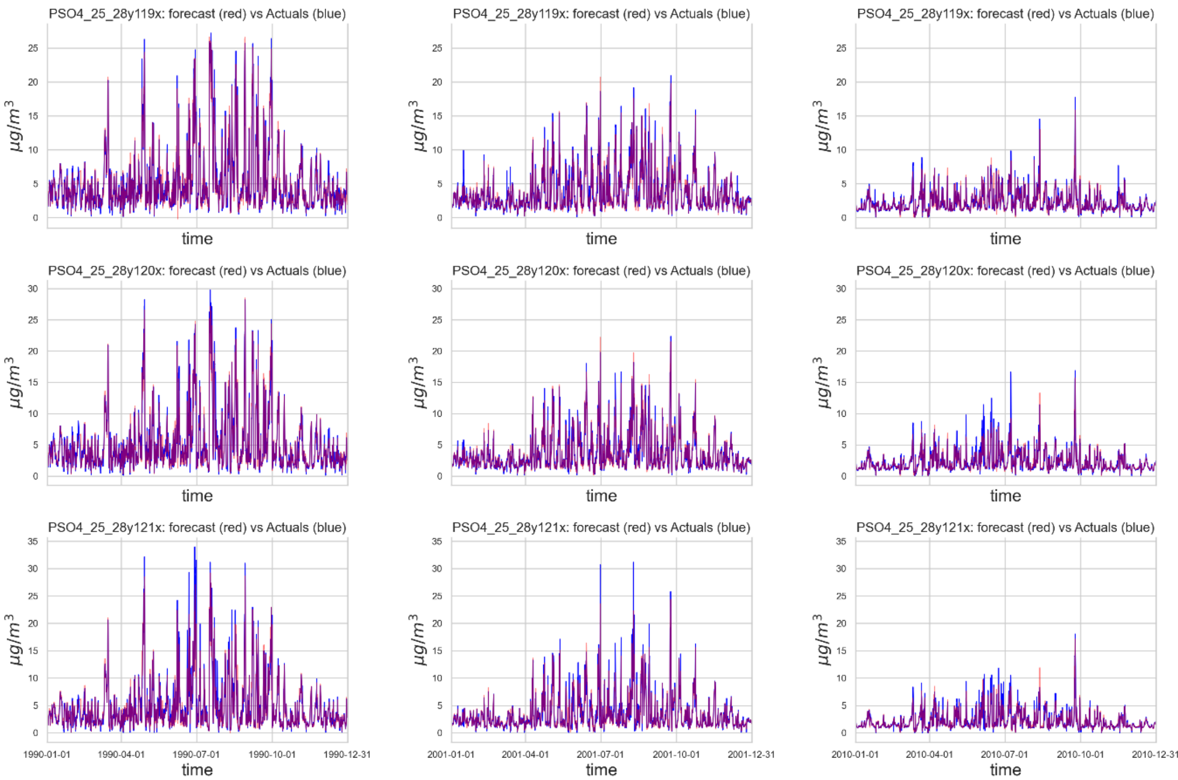

Fig. 132. Small New York region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

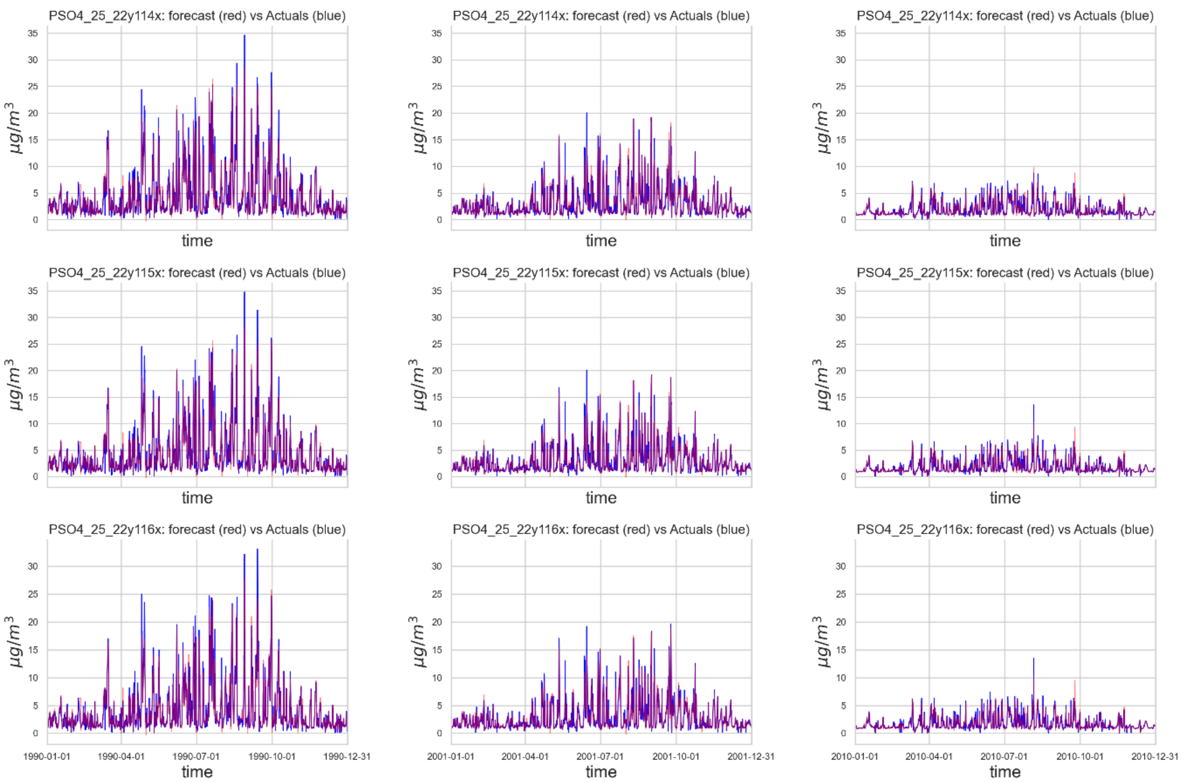

Fig. 133. Large New York region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

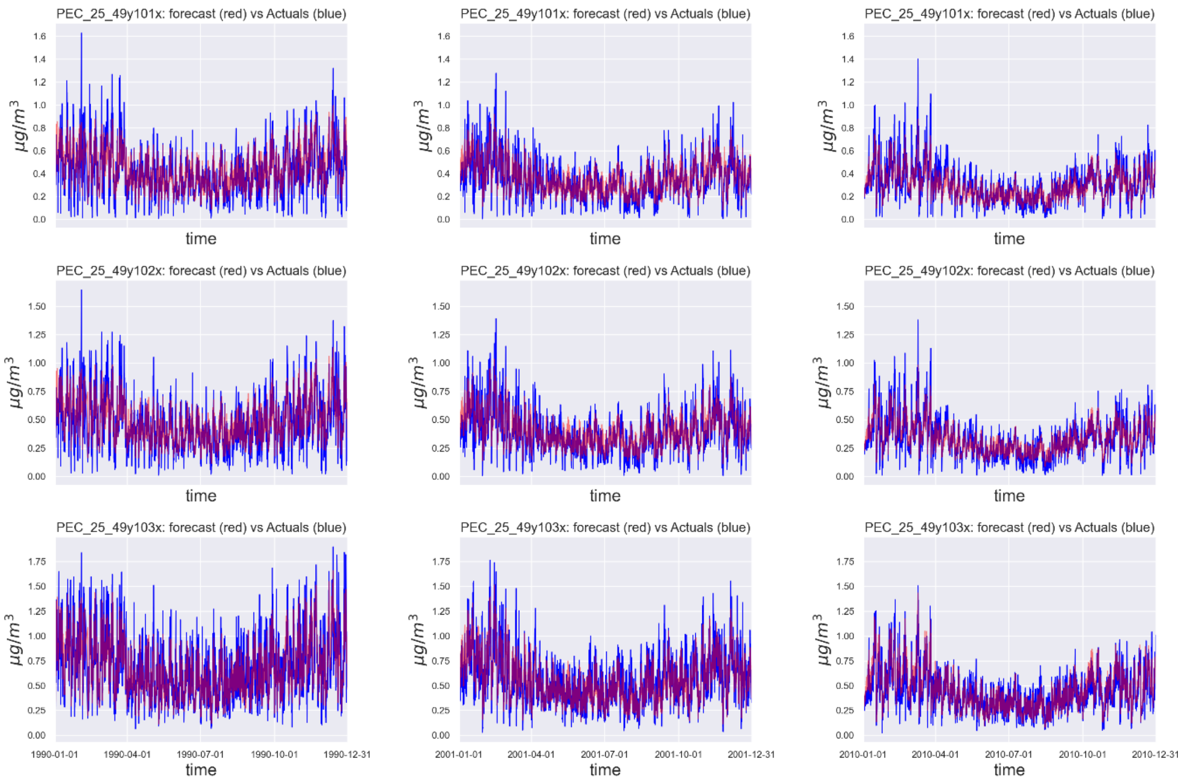

Fig. 134. Small Southeast region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

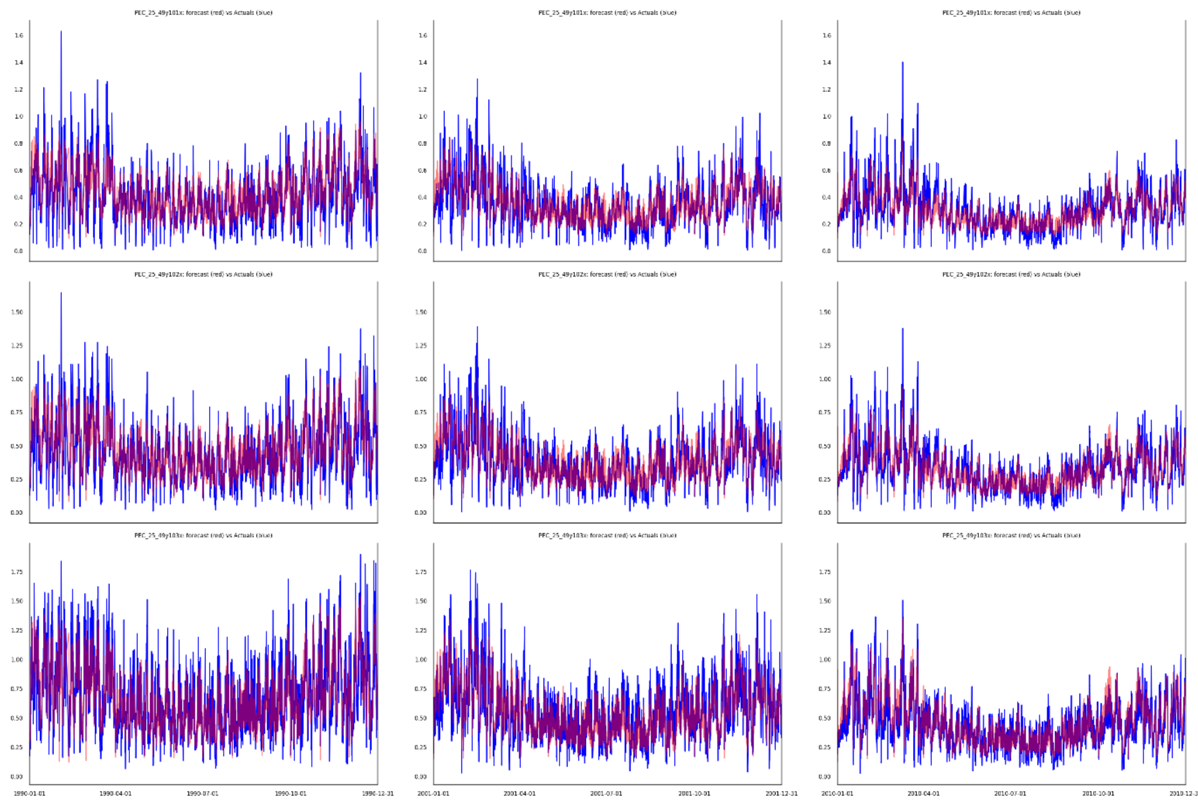

Fig. 135. Large Southeast region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

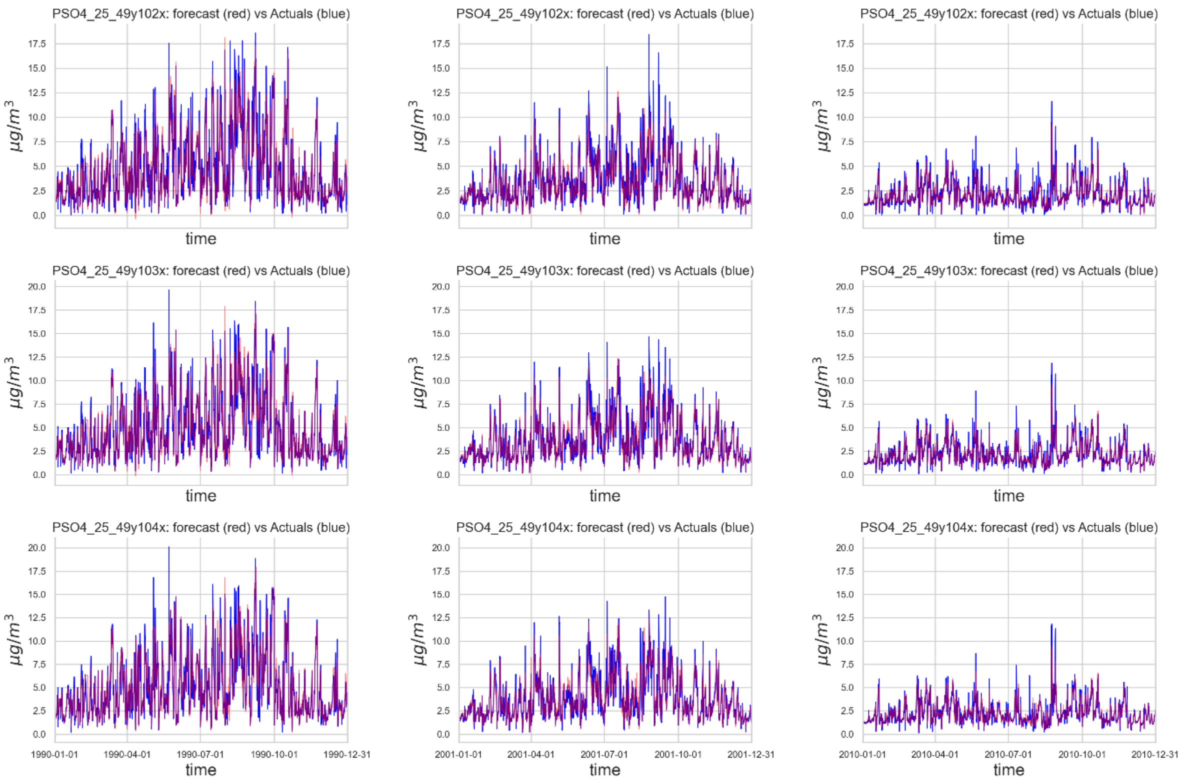

Fig. 136. Small Southeast region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

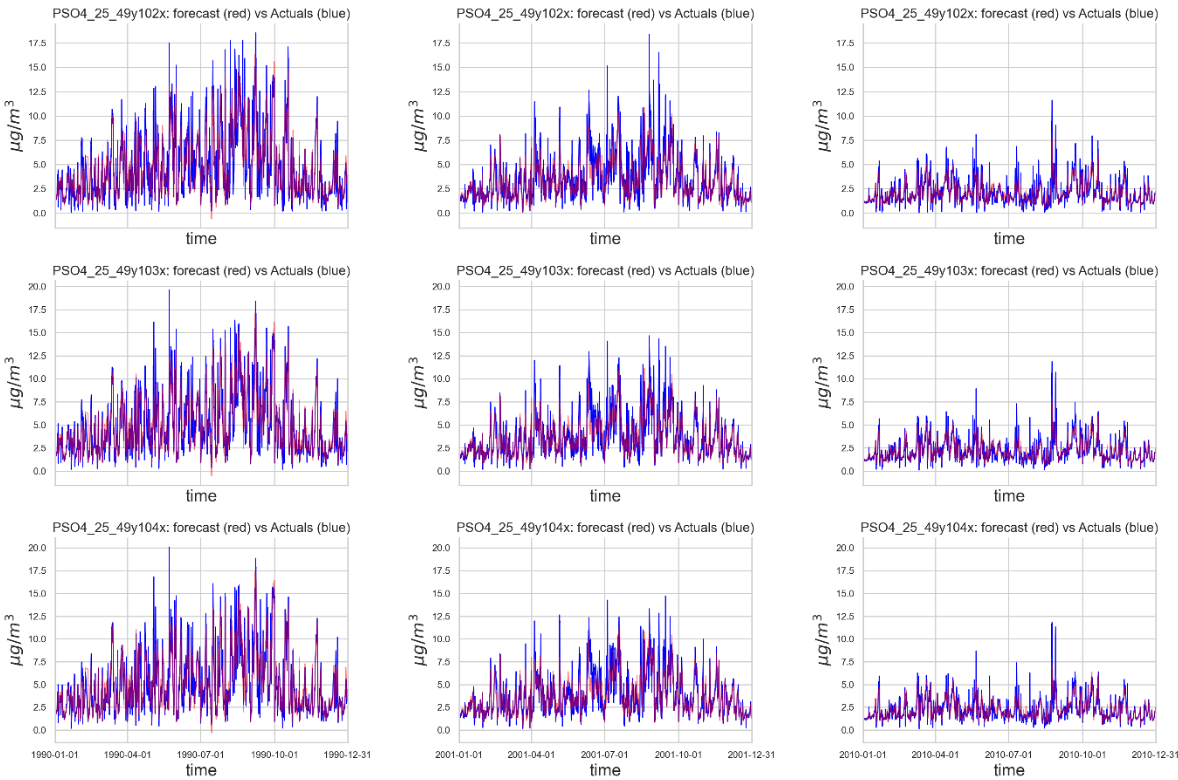

Fig. 137. Large Southeast region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

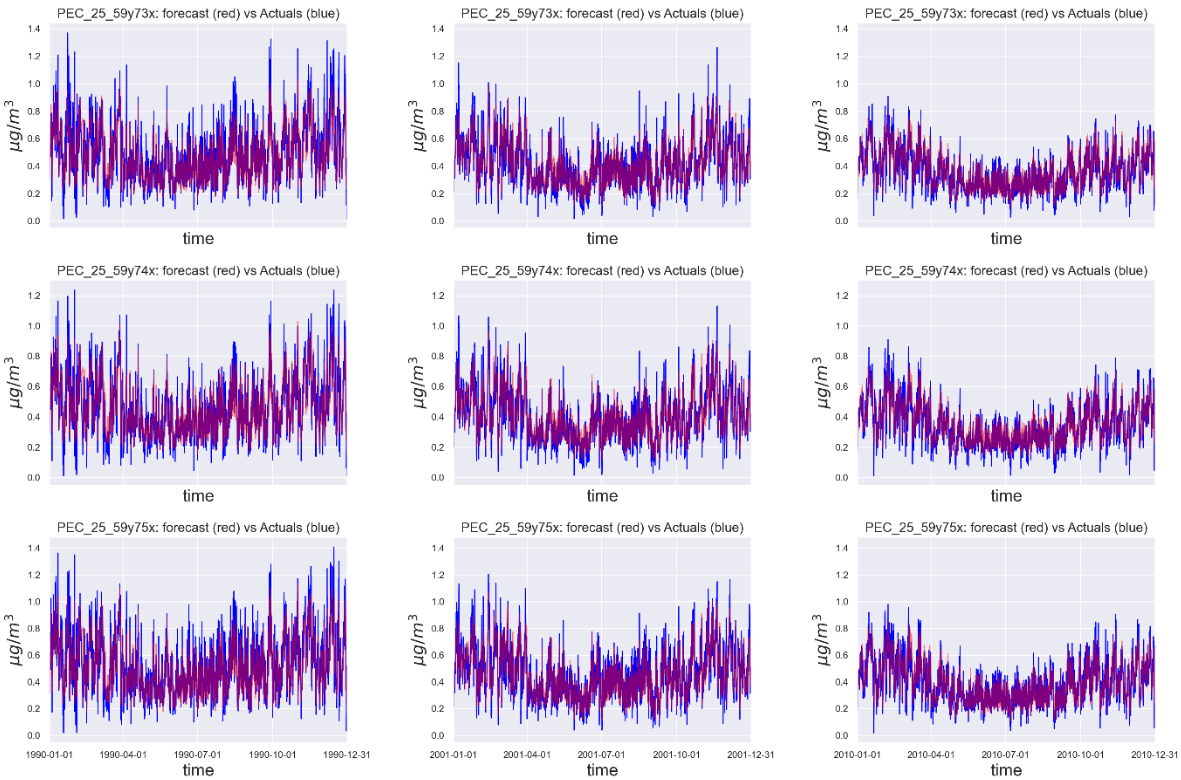

Fig. 138. Small Texas region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

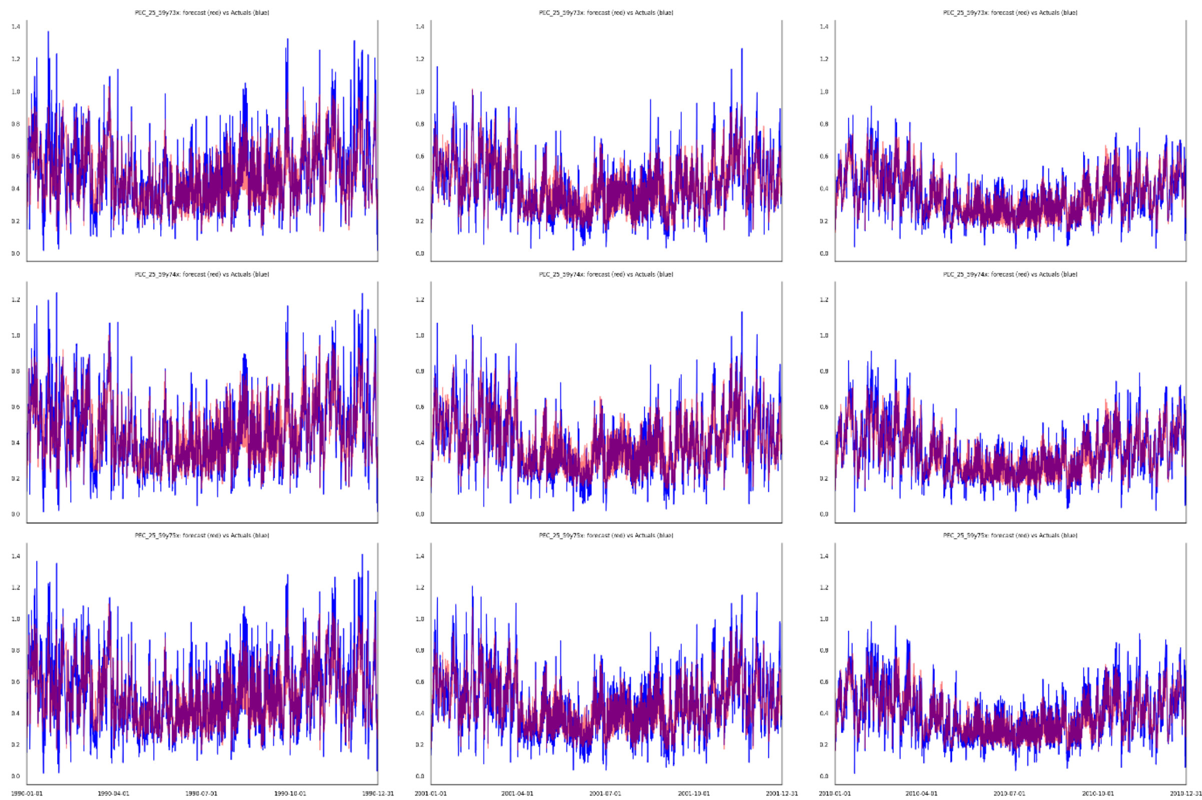

Fig. 139. Large Texas region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

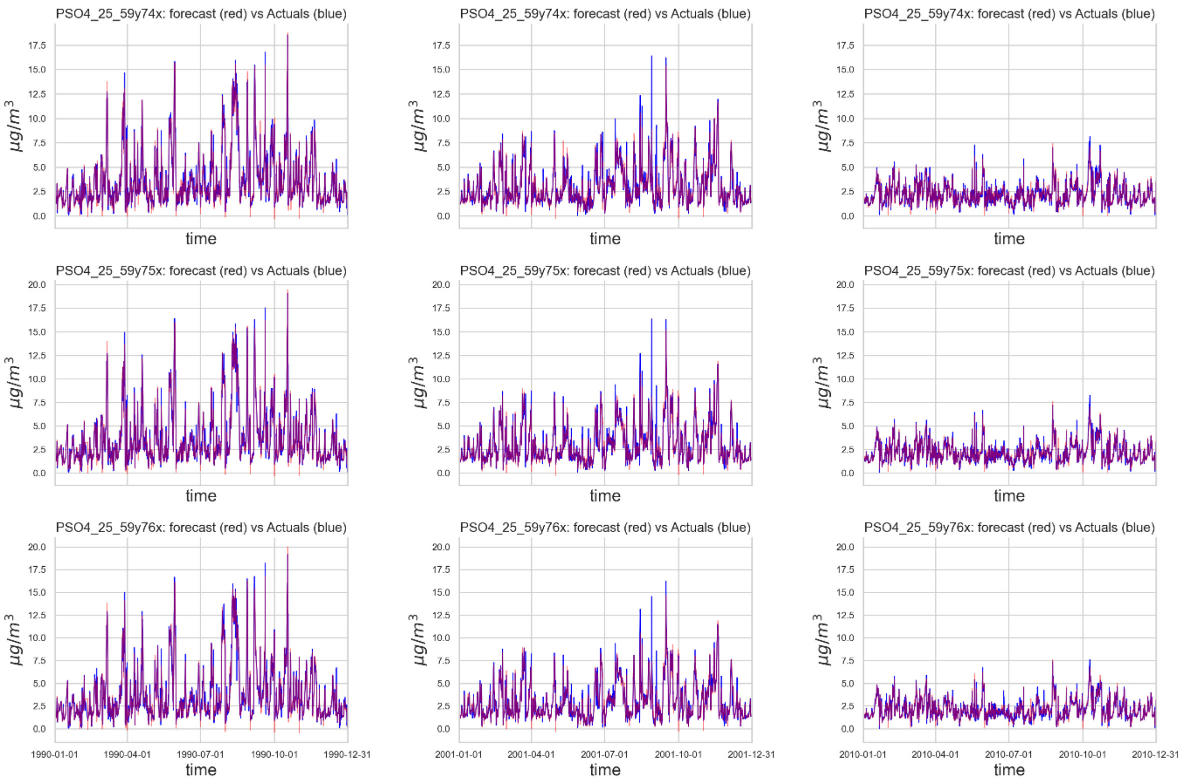

Fig. 140. Small Texas region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

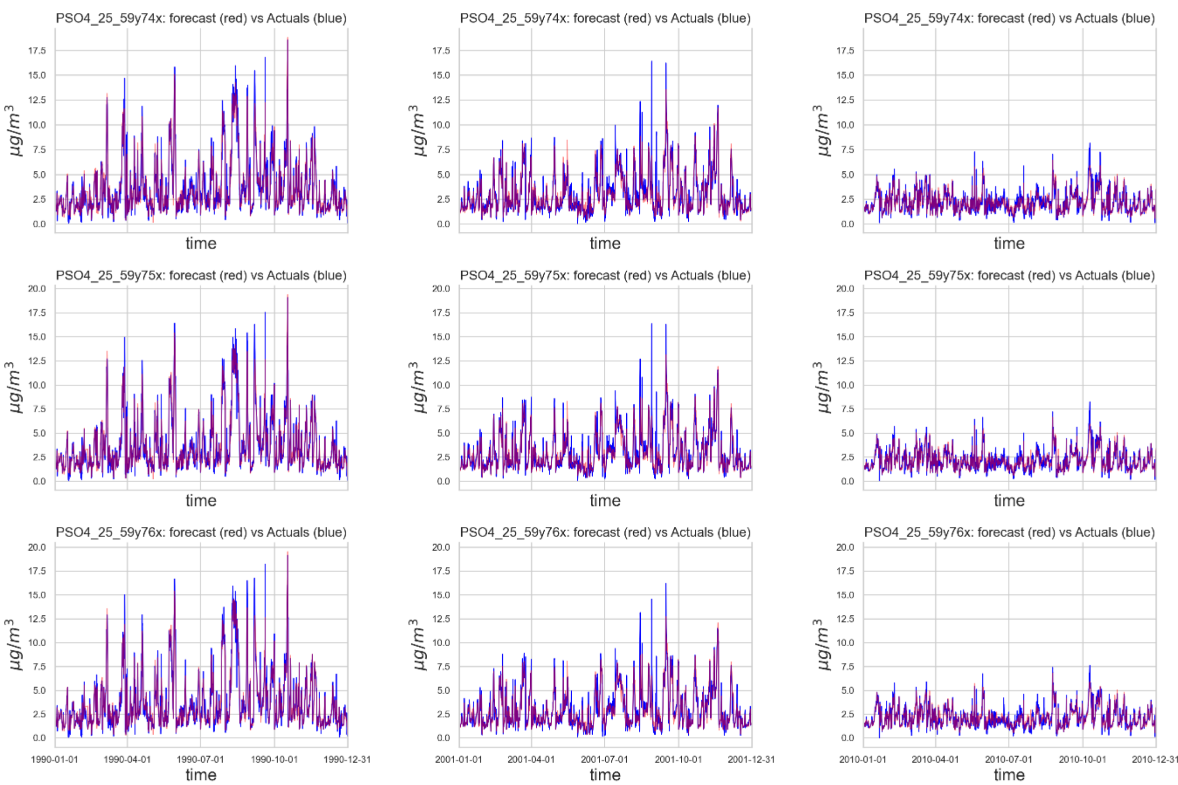

Fig. 141. Large Texas region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

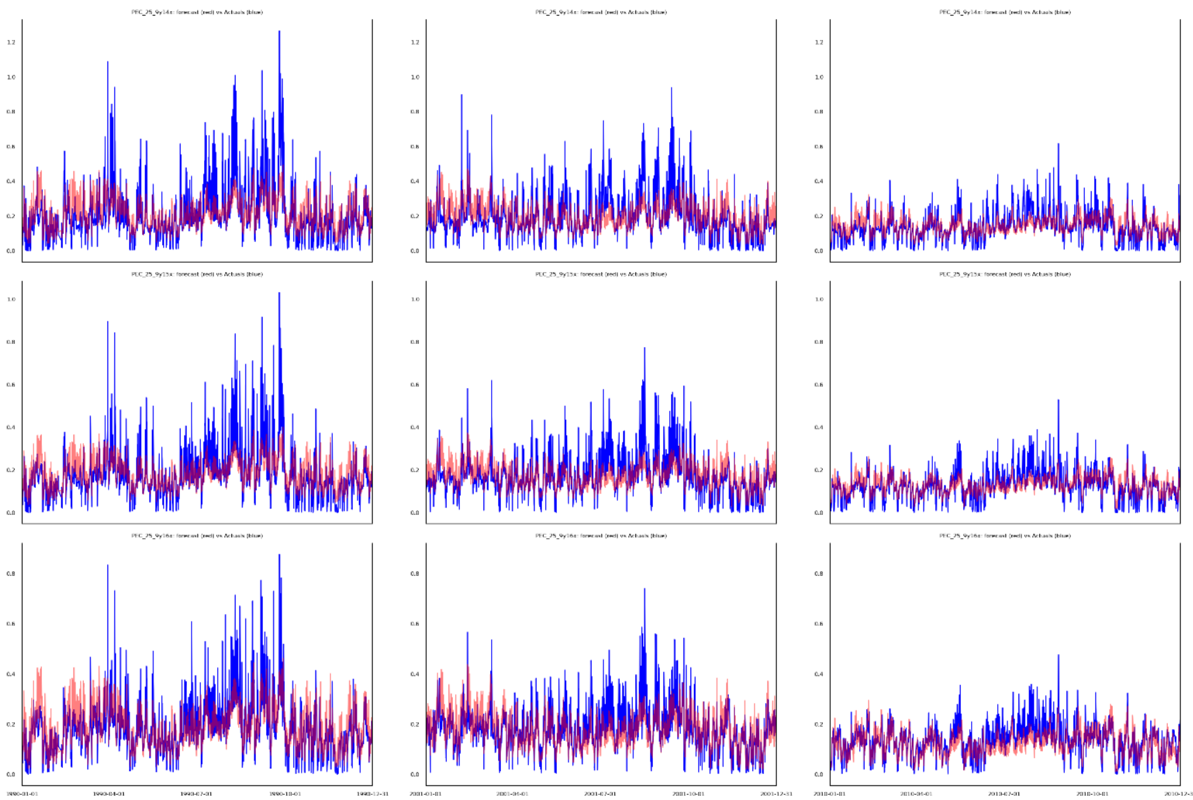

Fig. 142. Small Washington region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

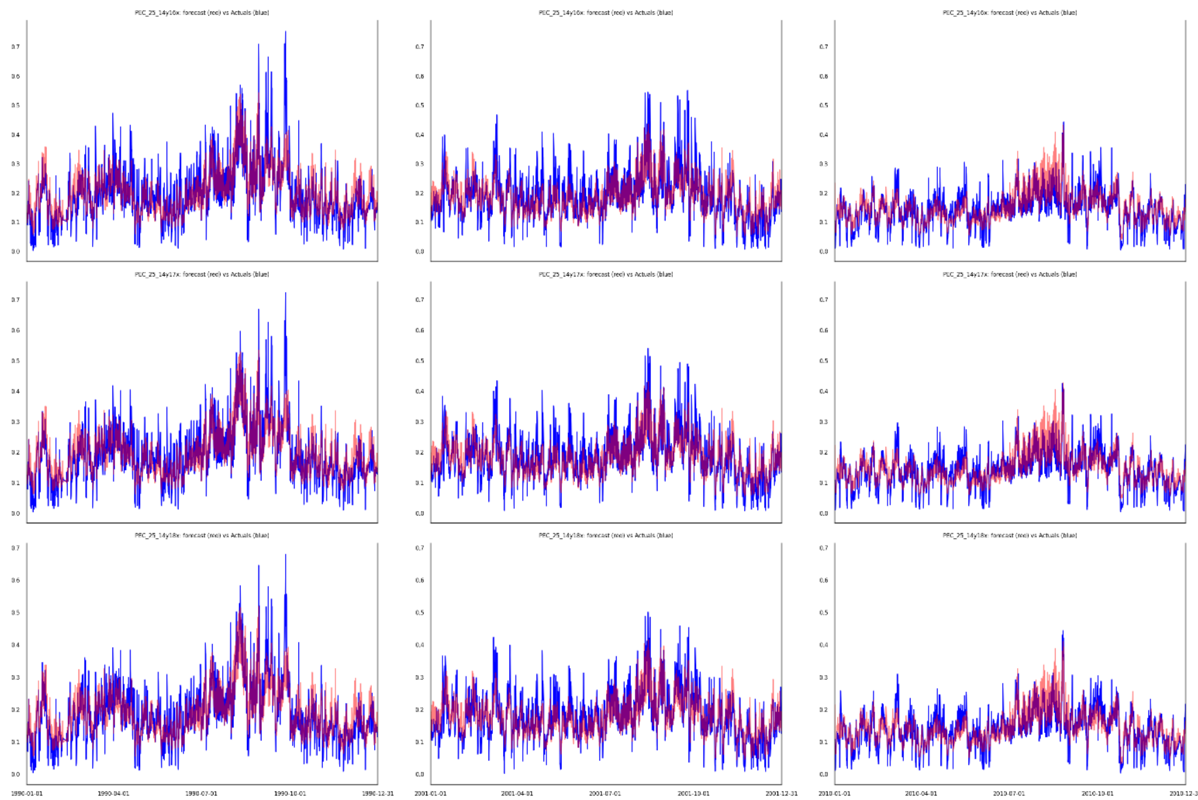

Fig. 143. Large Washington region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $EC_{2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

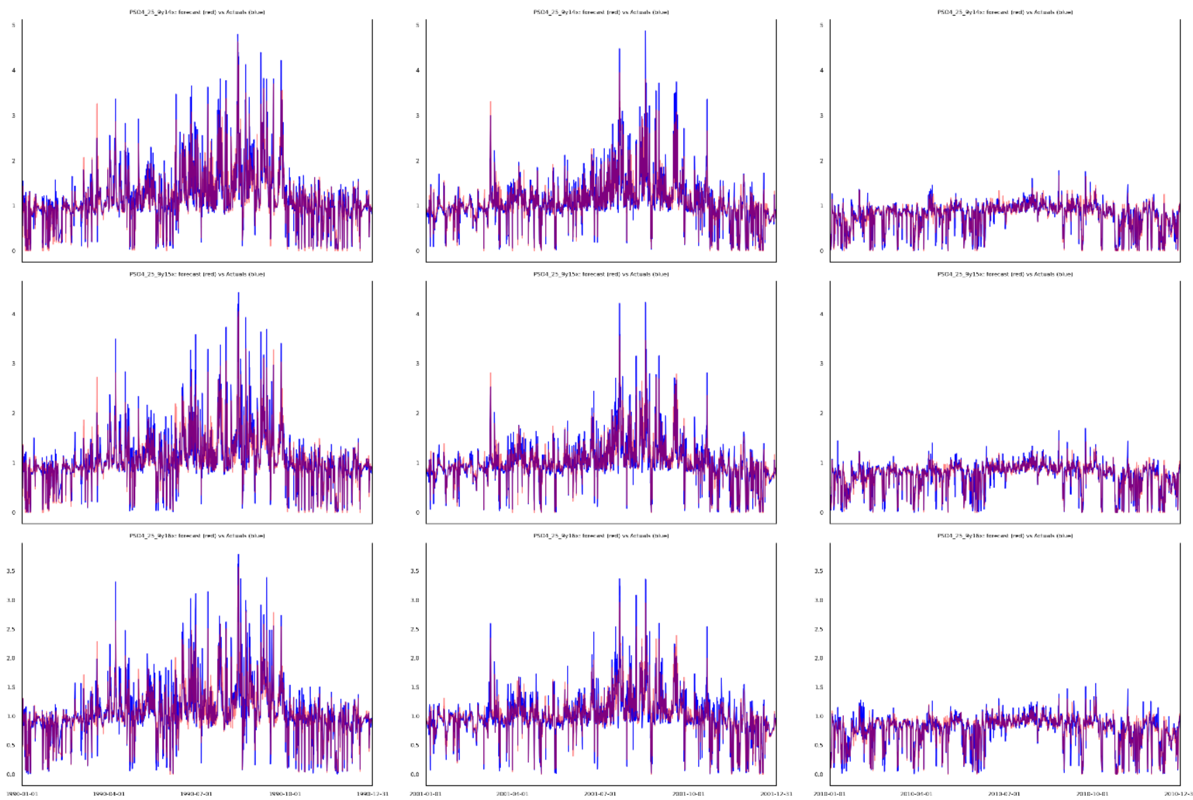

Fig. 144. Small Washington region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

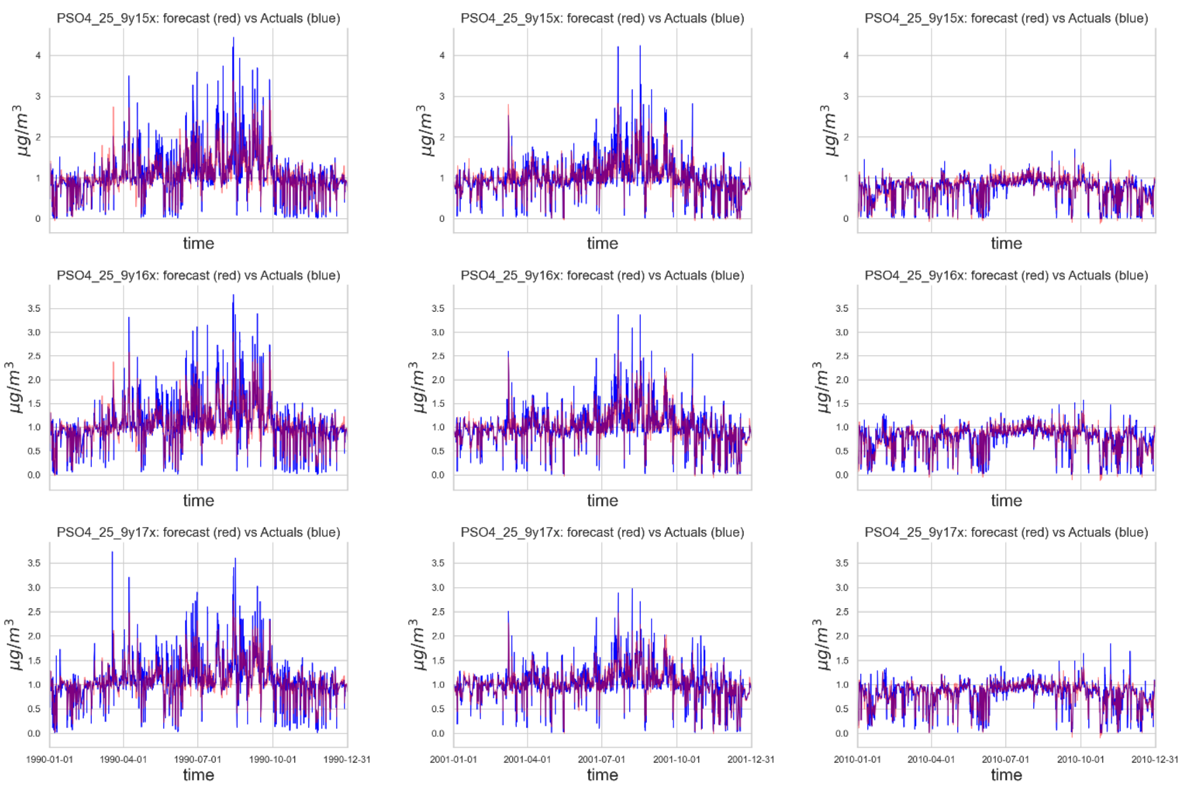

Fig. 145. Large Washington region prediction (red) vs actual (blue) in 1990 (left), 2001 (middle) and 2010 (right) for $PSO_{4,2.5}$ in three grid cells in the middle of the region. The red is transparent so any purple hues are where the prediction and actual match. Data points are hourly measurements in a single grid cell annotated by the x and y coordinates in the graph title.

Prediction vs. actual scatterplot graphical results for HyVARNN-T model

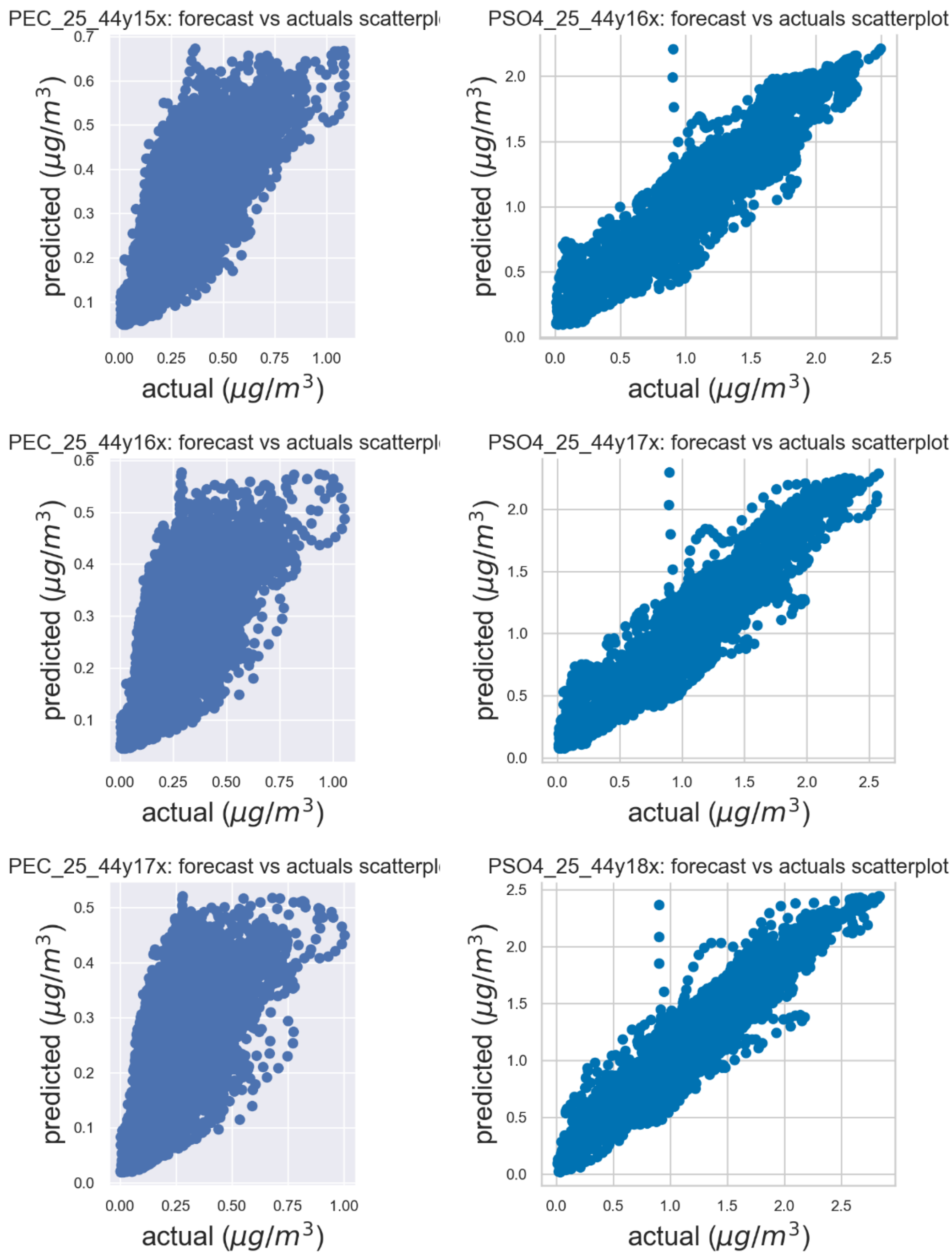

Fig. 146. Small California region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

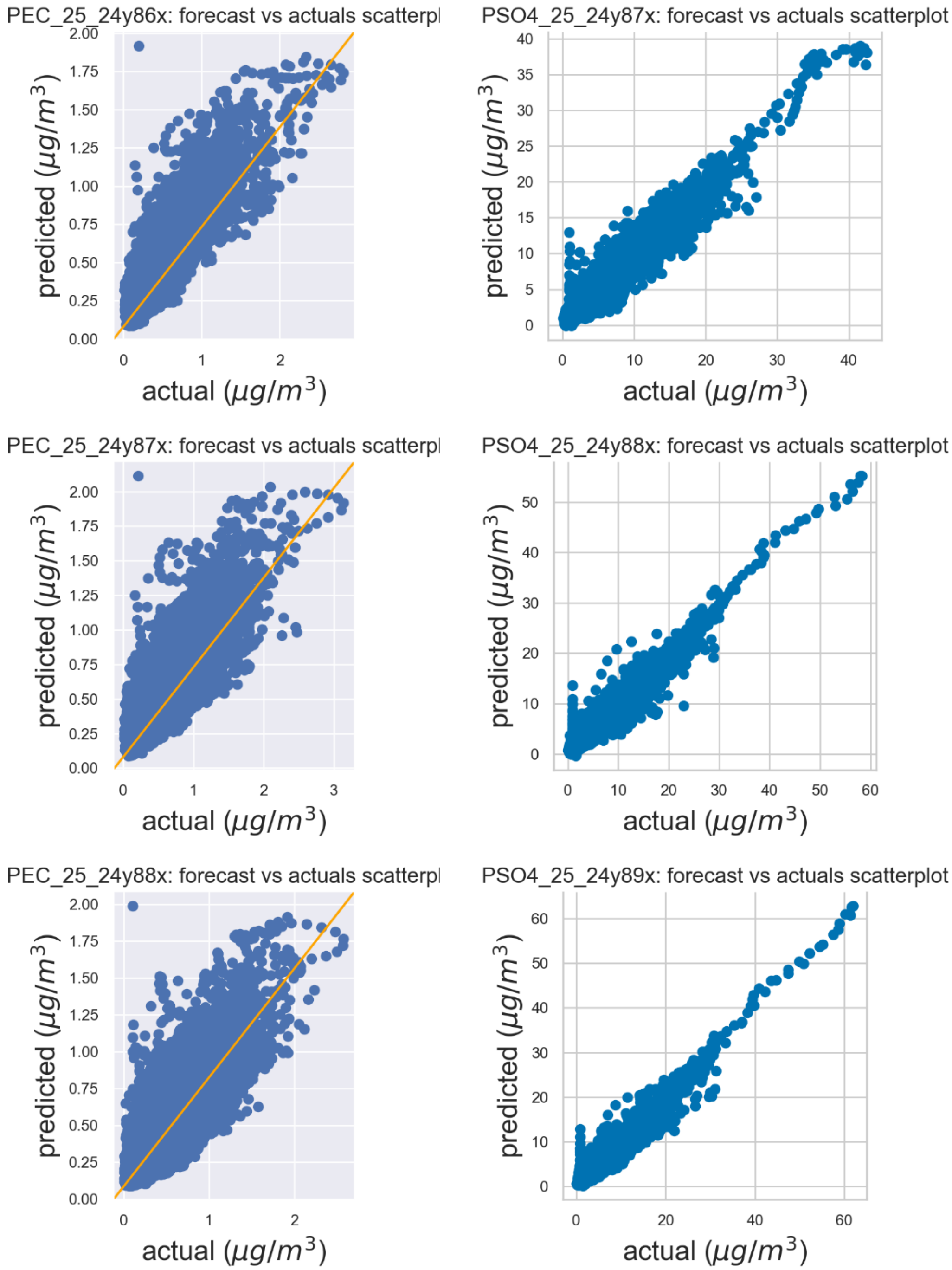

Fig. 147. Small Great Lakes region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

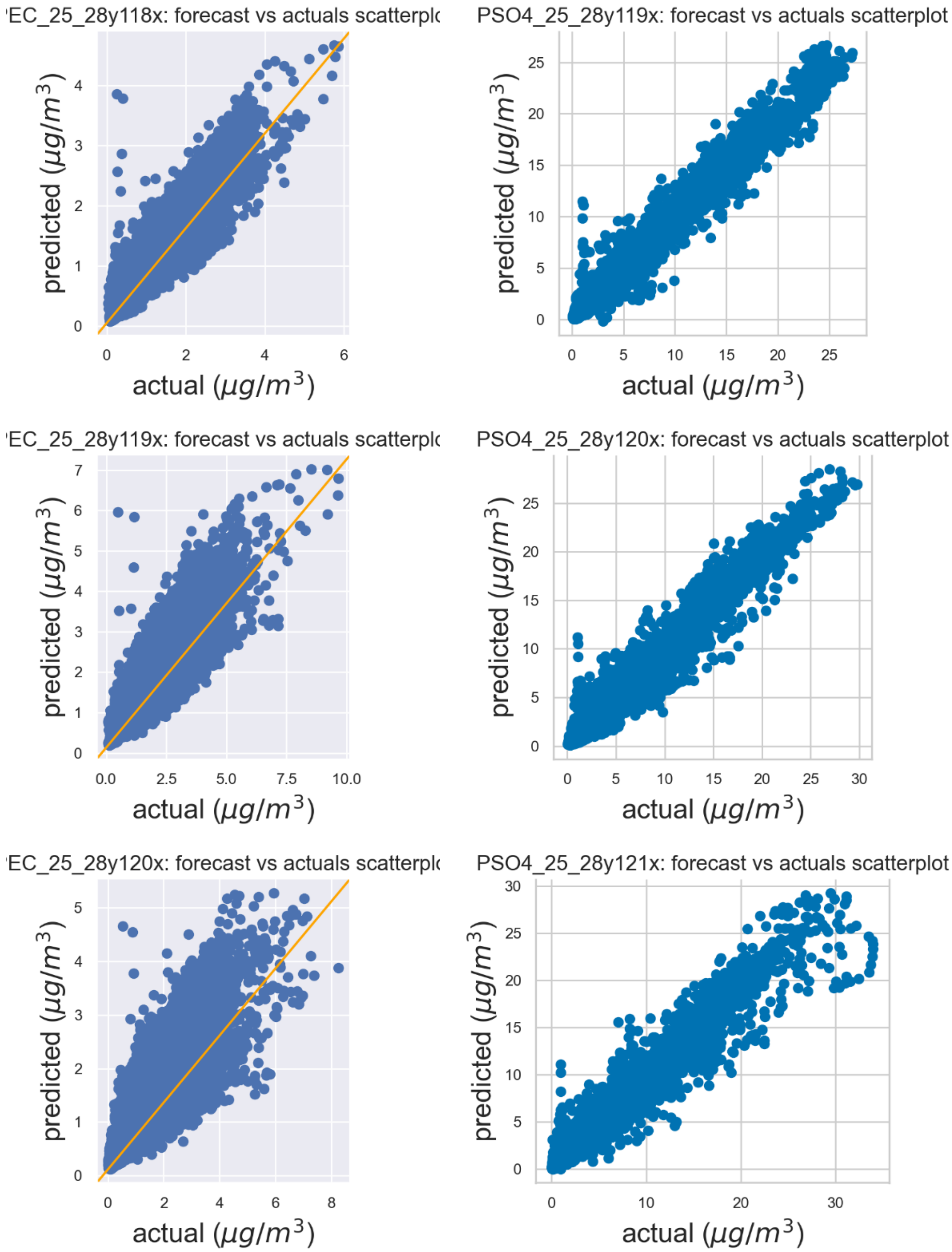

Fig. 148. Small New York region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

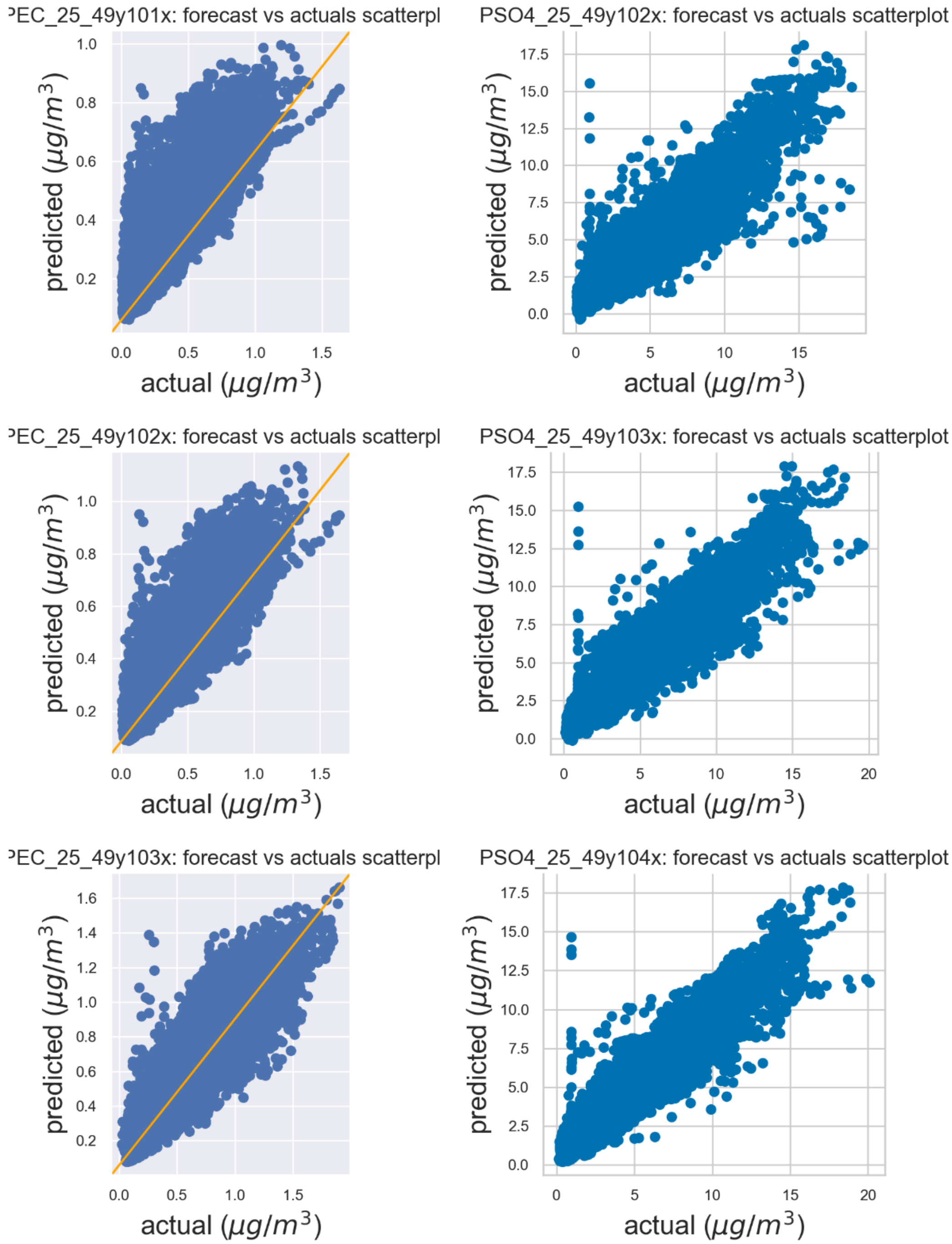

Fig. 149. Small Southeast region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

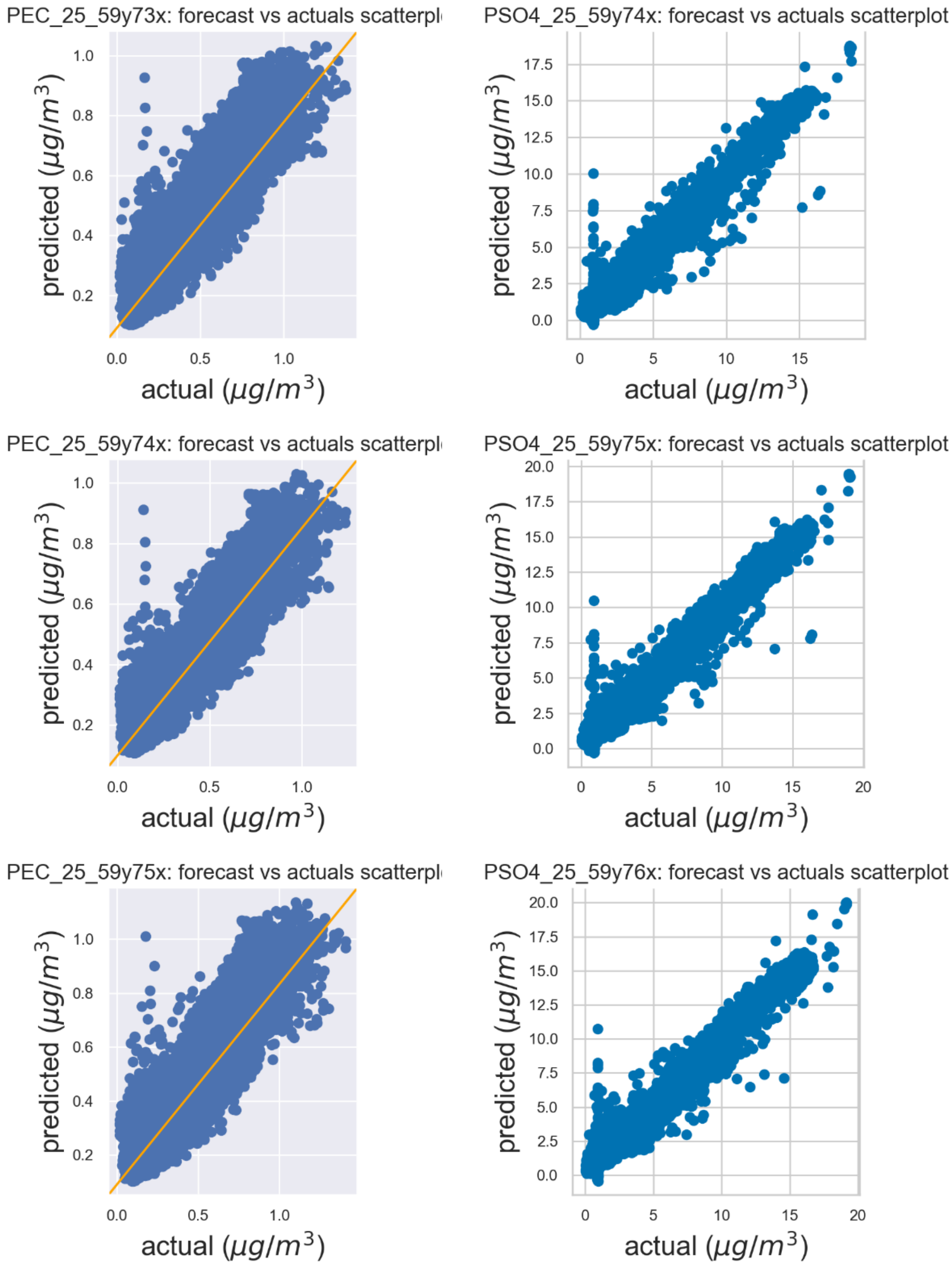

Fig. 150. Small Texas region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.

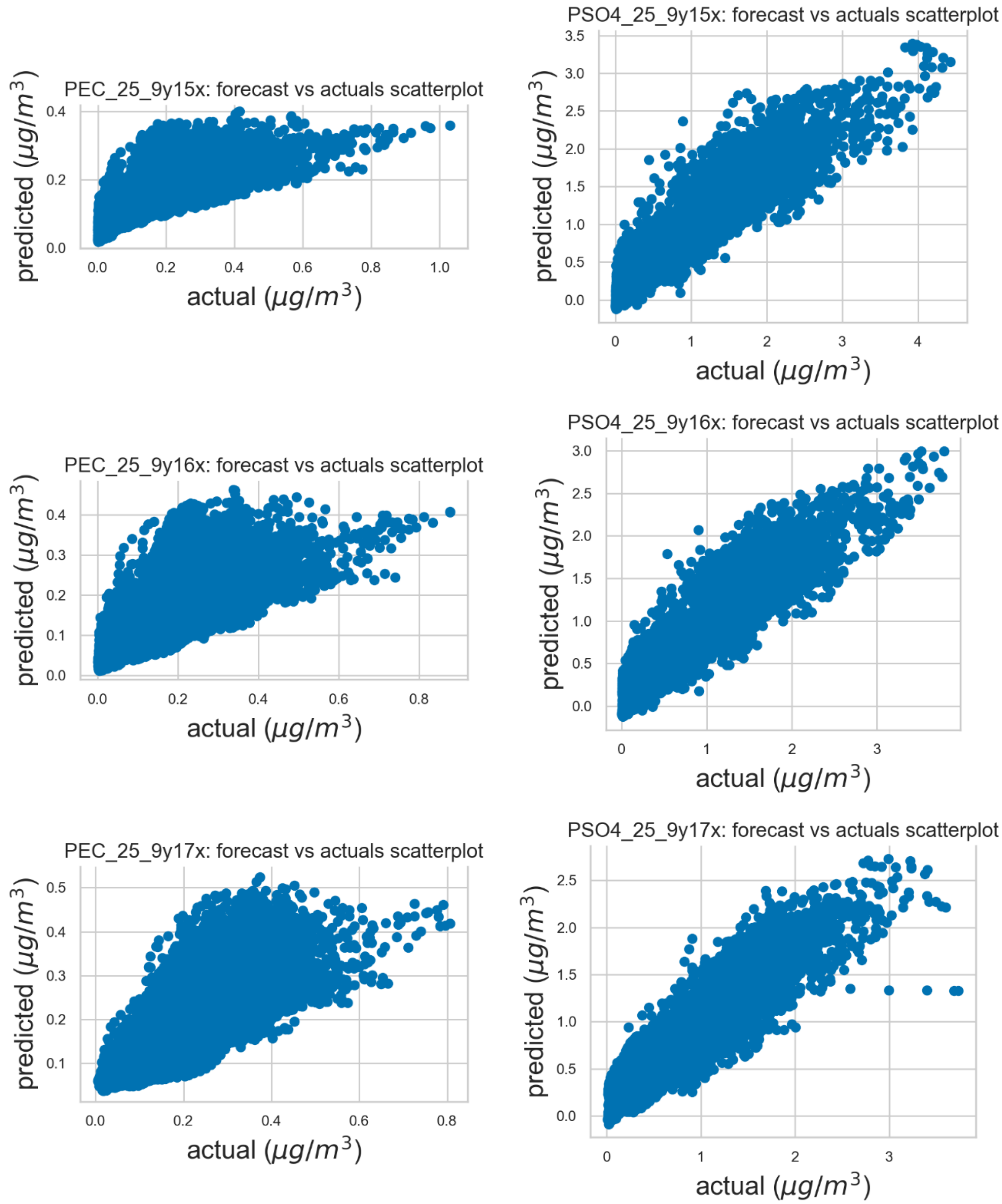

Fig. 151. Small Washington region scatterplots of predicted to actual values of $EC_{2.5}$ (left) and $PSO_{4,2.5}$ (right) for three grid cells in the middle of the region. The plot area has a consistent aspect ratio for x and y axes. A perfect plot would find all points on a 45° diagonal. Each point represents one hour, each graph is for a single grid cell annotated by the x and y coordinates in the graph title.