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PRESENTED BY **Mili-Ann Maguigad Tamayao**

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Chris T. Hendrickson	September 25, 2014
ADVISOR, MAJOR PROFESSOR	DATE
Jeremy J. Michalek	September 25, 2014
ADVISOR, MAJOR PROFESSOR	DATE
Douglas Sicker	September 30, 2014
DEPARTMENT HEAD	DATE

APPROVED BY THE COLLEGE COUNCIL

Vijayakumar Bhagavatula	October 2, 2014
DEAN	DATE

Urbanization and Vehicle Electrification in the United States: Life Cycle CO_2 Emissions Estimation and Climate Policy Implications

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Mili-Ann Maguigad Tamayao

B.S., Industrial Engineering, University of the Philippines

M.S., Industrial Engineering, University of the Philippines

Carnegie Mellon University

Pittsburgh, PA

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Abstract

Recent sustainability research has focused on urban systems given their high share of environmental impacts and potential for centralized impact mitigation. Most previous works rely on descriptive statistics obtained from place-based case studies representing major cities, metropolitan areas, and counties using emissions inventories that may have inconsistent and/or limited scope (e.g., transportation and residential emissions only). This limits the potential for general insights and decision support related to the role of urbanization in CO_2 emissions reduction.

Here, I implement generalized linear and multiple linear regression analyses to obtain robust insights on the relationship between urbanization and CO_2 emissions in the U.S. I used consistently derived county-level scope 1 & 2 CO_2 inventories for my response variable while predictor variables included dummy-coded variables for county geographic type (central, outlying, and non-metropolitan), median household income, population density, and climate indices (heating degree days (HDD) and cooling degree days (CDD)). There is statistically significant difference in per capita emissions by sector for different county types, with transportation and residential emissions highest in nonmetropolitan (rural) counties, transportation emissions lowest in central (most urbanized) counties, and commercial sector emissions highest in central counties. More importantly, contrary to most previous findings, there is not enough statistical evidence indicating that per capita scope 1 & 2 emissions differ by geographic type, ceteris paribus. These results are robust for different assumed electricity emissions factors. Given that emissions production rate in more urban counties are not significantly different from that of less urban ones and population is concentrated in urban counties, significant national emissions reduction could be achieved if efforts are focused on central counties.

There are various climate mitigation techniques – both from the supply and demand side. Given the large contribution of transportation in total county emissions and the fact that this technology bridges the transportation and electricity sector which is currently the biggest contributor to CO_2 emissions, I investigated the emission reduction benefits from driving electric instead of gasoline vehicles. Vehicle electrification has also received sustained support from the local to the supranational level and is seeing an optimistic market trend. I characterize and assess the uncertainty in CO_2 emissions per mile travelled for vehicles in the U.S. given regional variation and uncertainty in electricity emissions factor (marginal *vs* average, generation- *vs* consumption-based, different regional boundaries), driving pattern, and daily vehicle miles traveled (DVMT). I also investigate vehicle emissions estimates under convenience (vehicle starts charging when it arrives at home) and delayed (vehicle starts charging at 12am) charging. Using marginal emissions factors results in electric vehicle emissions estimate that are higher than average emissions estimates in the northeastern and north central U.S., and lower emissions in the south central U.S. In other regions, using marginal emissions versus average emissions factors may lead to differences in emissions estimates by as much as 28%. Delayed charging leads to higher emissions, given that off-peak electricity demand is supplied by fossil generators in most regions (e.g., coal). Using marginal emissions estimates, the Nissan Leaf electric vehicle has lower operation emissions compared to the Toyota Prius (the most efficient US gasoline vehicle) in western U.S., and the Leaf has higher operation emissions in the north central, regardless of assumed charging scheme and estimation method. In other regions the comparison is uncertain because of regional variation and uncertainty in emission factor estimates. Consumption- and generation-based marginal emissions also significantly (5 % - 28%), enough to result unclear comparison results. Average vehicle emissions estimates under different regional boundary definitions also differ significantly (e.g., state-based estimates deviate from National Electricity Reliability Commission (NERC) region-based estimates by as much as 122%).

Other factors such as driving pattern and daily vehicle miles traveled also influence vehicle emissions. I conduct a locational comparison of electric and gasoline vehicle life cycle emissions in the U.S. taking into consideration the regional variation in the joint effect of consumption-based marginal electricity emission factors, driving pattern (city, highway or combined), and daily vehicle miles traveled (DVMT) distribution. I find that electricity generation emissions rate, determined by grid mix and charging scheme, has the largest influence on electric vehicle emission levels and the emissions differences of gasoline and electric vehicles. Secondary to this is urbanization level, especially for PHEVs, as it influences driving pattern and daily vehicle miles traveled. Highest CO_2 emission reductions from electric vehicles can be attained in metropolitan counties in CA, TX, FL, NY, and New England states. Policies for wider adoption of electric vehicles such as incentives and other adoption facilitating mechanisms including investments in public charging infrastructure are encouraged in metropolitan counties, especially the denser ones. On the other hand, these policies are discouraged in north central states where electric vehicles would only increase emissions because of a relatively carbon-intensive grid. These findings reflect the pivotal role of the electricity and transportation sectors nexus in achieving national goals of CO_2 emission reductions. Unless the U.S. decarbonizes its electricity system further, electric vehicles will only be beneficial in climate mitigation efforts in certain locations in the country.

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1 Introduction

According to the most recent Intergovernmental Panel for Climate Change report (IPCC 2013), the certainty of climate change due to anthropogenic activities has increased, from 90% in 2007 to 95% in 2013. The U.S., which contributes about 36% of global greenhouse gas (GHG) emissions, has a significant opportunity in mitigating climate change.

The U.S. population has grown by about 10% in the past decade and most of the growth occurred in already populous areas (US Census Bureau 2011). As of 2010, over 4/5 of the U.S. population live in metropolitan areas. Geographic distribution of population data between 2000-2010 shows that population has grown more rapidly in most metropolitan areas than the national average, implying increased concentration of people in metropolitan areas. However, this population increase has become more spatially dispersed within the metropolitan areas since population growth occurred mostly in areas outside the metropolitan core areas.

In Chapter 1, I investigate how urbanization level is related to aggregate and sectorial scope 1 and scope 2 GHG emissions at the county level in the U.S. through regression analysis. Scope 1 emissions include emissions produced form activities done within the physical boundary of the system under study. Scope 2 emissions correspond to emissions relating to electricity consumed by the system, whether or not the electricity was produced within the physical boundary of the system.

Meanwhile, mass electrification of vehicles has been seen as a promising solution to the problems of reducing greenhouse gas (GHG) emissions, air pollution, and energy security concerns in the U.S.. Hybrid electric vehicles (HEV), compared to conventional internal combustion (IC) vehicles, offer the benefit of increased fuel efficiency, therefore lower emissions from petroleum combustion. Plug-in hybrid electric vehicles (PHEV) also offer the increased fuel efficiency as well as the reduction of tail-pipe emissions corresponding to miles traveled using grid electricity. However, studies comparing emissions related to these different vehicle types show different results.

In the succeeding chapters, I investigate the life cycle emissions of electric vehicles throughout the U.S. to verify the claim that electric vehicles reduce transportation CO_2 emissions, especially in urban areas. Ultimately, with the locational life cycle assessment results, I aim to determine where in the U.S. can electric vehicles contribute to bigger CO2 emissions reductions.

In Chapter 3, I provide a background on existing policies on electric vehicle development and adoption in the U.S.. In Chapter 4, I estimate life cycle EV emissions given uncertainty and regional variation in electricity emission estimates and compare these with gasoline vehicle emissions estimates. In Chapter 5, I factor in in urbanization level into my model for estimating and comparing EV and gasoline vehicle emissions by differentiating emissions in different driving patterns and daily vehicle miles traveled. In Chapter 6, I summarize the major conclusions of this work and provide congruent policy recommendations.

2 Urbanization and Local Emissions in the U.S.: Do U.S. Metropolitan Core Counties Have Lower Scope 1 & 2 CO2 Emissions Than Less Urbanized Counties?[1]

2.1 Introduction

At the confluence of both a changing climate and increased urbanization, cities have become a focal point for measuring and mitigating greenhouse gas (GHG) emissions [ICLEI 2012; UN 2012]. However, there exists considerable uncertainty about the link between geographic variation and GHG emissions. These uncertainties confound a richer understanding of the relationships between GHG emissions, emissions mitigation, and geographic change.

Early research on energy use and urban systems focused mainly on the transportation sector, where studies suggest reduced transportation energy requirements are associated with increased density, access to non-vehicle modes, and mixed land use planning [for examples see Newman and Kenworthy 1989; Cervero and Kockelman 1997; Frank and Pivo 1997; Pushkarev and Zupan 1977].

With increasing empirical information on local GHG emissions, researchers started to include in-city ("territorial") emissions from additional end-uses in the late 2000's. Comparing residential plus personal transportation emissions from 66 major U.S. metropolitan area, Glaeser and Kahn (2010) suggest that a household would produce lower GHG if it was in an urban area of higher population density, near city centers, in a location with moderate climate (i.e., warmer winter and cooler summer), and is serviced by cleaner electric utilities (i.e., less coal used for power production). Brown et al. (2008) similarly found that the average metropolitan resident has lower per capita residential plus personal transportation emissions (2.24 tons/yr) than the average American (2.60 tons/yr), which the authors attribute to less car

[1] Accepted for publication in Environmental Research Letters (August 2014), co-authored with M F Blackhurst and H S Matthews.

travel and electricity use. Expanding the scope of in-city emissions to include all buildings, on- and off-road transportation, and fugitive emissions from industry and waste management, Kennedy et al (2009) contrasted emissions for ten global cities, finding a five-fold difference in emissions per capita that was attributed to a combination of geophysical (climate and access to resources), socio-economic (population density and per capita income) and infrastructure factors (power generation and urban design). Meanwhile, several studies have been performed regarding the relationship between transportation emissions and population density [Newman and Kenworthy (1988), Manville and Shoup (2005), and Chatman (2013)]. In their original work where they did not correct for income, fuel prices, or transportation costs in determining the relationship between energy use for travel per inhabitant and urban density, Newman and Kenworthy (1988) found a native relationship. After updating their work, they found density to be less significant. Meanwhile, Chatman (2013) argues that higher urban density is often related with lower per capita travel energy needs because not so much because of higher availability of public transit but due to lower auto ownership. Manville and Shoup (2005) also point out the influence of automobile ownership, availability of roadways, and parking spaces in major U.S. cities; they find that cities generally have lower ratio of street per person contributing to lower travel per person but higher congestion.

More recent research has emphasized the challenge of isolating the effect of urbanization on local GHG emissions. Analyzing in-city emissions for 62 European cities, Baur et al. 2014 challenged established correlations between emissions and population density, finding such correlations were highly sensitive to the geographic scale of the analysis as well as household occupancy and income. York et al. (2003) apply simple linear regression to an expanded, log-log format of the IPAT identity (Impact = Population x Affluence x Technology) for 138 countries, showing emissions increase both with increasing urban populations and gross domestic product, with a possible Kuznets relationship between urbanization and emissions.

The impact of wealth creation and re-spending on urban emissions has recently been emphasized by researchers aiming to include emissions embodied in goods and services imported and exported across city boundaries. As summarized in Table 1, emissions embodied in imports and exports are classified as scope 3, which differ from emissions that occur directly within a city boundary (scope 1 or "territorial" emissions) and those directly associated with city energy demands but emitted outside the city boundary (scope 2). The allocation of scope 3 emissions to cities is estimated to increase their global emissions share to as much as 80% [Satterthwaite 2008]; though other researchers caution that attributing such allocations purely to urbanization is likely misleading [Dodman 2009; Hoornweg et al. 2011].

Table 1. Source Fuels, Energy End-uses, and Estimation Methods Per Emissions Scope

Emissions Scope	Definition	Typical Source Fuels of Emissions	Typical energy end-uses
1	Emissions from direct combustion of fuels within a geographic boundary ("territorial" emissions)	Natural gas, gasoline, diesel, jet fuel	Home heating, cooking, on- and off-road transportation
2	Emissions from energy consumed within a geographic boundary generator elsewhere	Varies across the electrical grid	Lighting, air conditioning, appliances
3	Emissions embodied in imported goods and services and exported wastes	Varies within the supply chain of imported goods and services	N/A (energy embodied in the supply chain of imported good or service)

The inclusion of scope 3 emissions in local inventories has precipitated "trans-boundary" and "consumption-based " accounting schemes. Trans-boundary schemes include emissions estimates associated with imports of energy (scope 2) and select basic provisions such as example food, water, and building materials (Ramaswami et al. 2011, Chavez & Ramaswami 2011, and Hillman & Ramaswami 2010). Consumption-based inventories attempt to include emissions embodied in all imports and exports that cross geographic boundaries (Larsen and Hertwich 2009; Minx et al. 2009).

Trans-boundary and consumption-based accounts use environmental life cycle assessment techniques to estimate scope 3 emissions attributed to imports and exports. Most studies emphasize case studies that include summary statistics of local GHG's by emissions scope. In a more comprehensive consumptive-based study, Minx et al. (2013) utilize a multi-regional input-output model to estimate consumption-based emissions for all 434 municipalities in the United Kingdom (UK). They identify correlations between per capita footprints and occupancy, car ownership, and education. Minx et al. find that scope 3 emissions are generally higher than territorial emissions (scopes 1 and 2) for most municipalities in the UK, independent of urban or rural geography and emphasize that consumption-based accounting has the effect of geographically homogenizing point emissions sources, namely industrial plants.

While the literature generally treats all emissions scopes equally, we emphasize a few important distinctions in the context of measurement and mitigation. First, policy actors – particularly local governments – have much less jurisdiction over scope 3 emissions than scopes 1 and 2. Second, emissions scopes 2 and 3 are scope 1 for producers located upstream in the supply-chain. The implications for this are twofold. It means no emissions can be reduced if all actors in the supply chain focus exclusively on scope 3 emissions. Perhaps more importantly, it means that any and all features of scope 1 emissions – such as uncertainty and variation – are represented in emissions scopes 2 and 3, which is currently not yet reflected in mitigation planning (Blackhurst et al. 2011).

In addition to uncertainty and variation in scopes 1 and 2 (see Blackhurst et al. 2011, Weber et al. 2010, Siler-Evans et al. 2012), scope 3 emissions also include uncertainty and variation introduced by incomplete empirical data describing supply chains (Bullard 1977; Basket et al 1997); factors used to allocate final demand in space and time and by productive sector (Wilting 2012); an incomplete representation of international trade (Andrew et al. 2009; Lenzen et al. 2010; Weber 2008); representing production technologies and factor inputs as national and sector averages (Blair and Miller 2009; Weber et al. 2010; Siler-Evans et al. 2012); static supply chains (Bullard 1977; Wood 2011); and price and currency conversions (Weber 2008). Since only several of these assumptions have been discretely tested in the literature, the uncertainty and variation in currently reported scope 3 estimates is likely underreported, complicating a clear understanding of the relationship between urbanization and scope 3 emissions and confounding efforts to measure baseline scope 3 emissions, plan mitigation targets, and measure progress.

Finally, Kennedy and Corfee-Morlot (2013) indicate that additional capital expenditures in low-carbon infrastructure – which increases scope 3 emissions – has led to an observed decrease in emissions scopes 1 and 2. Such trade-offs have been established for many sources of discrete technical change in LCA (for examples see Keoleian et al. 2000; Pacca et al. 2007; Chester and Horvath 2009; Blackhurst et al. 2010). However, these connections have not yet been integrated into city-scale GHG measurement and respective decision-making, further challenging the approach of treating emissions scopes equally with respect to mitigation planning.

Further confounding insights into the connection between geographic variation and GHG emissions are differing and changing definitions of "urban" and variation in the dynamics contributing to urbanization (Morrill et al. 1999; Schneider and Woodcock 2008; Anderson et al. 1996) as well as a lack of clarity in how metropolitan scale dynamics – such as regional land use planning and commuting – should be reflected in territorial emissions and respective mitigation planning.

As a result of the above uncertainties, differing definitions, and empirical limitations, the connection between geographic change and GHG emissions remains unclear. With this in mind, my objective is to identify any statistically significant variation in scope 1 and 2 emissions that can be explained by county-level geographic variation, using consistent geographic descriptors, controlling for previously identified sources of variation in emissions. This method is intended to serve as additional technical support behind future efforts with robust consideration of uncertainty for scope 1, 2, or 3 boundaries.

2.2 Methods

2.2.1 Geographic Definitions

The U.S. Census Bureau classifies counties as central, outlying, and nonmetropolitan (US Census Bureau 2011). Central counties are the most urbanized core in a Metropolitan Statistical Area (MSA). A central county is defined as having at least 50% of its population in urban areas with population of at least 10,000 or containing at least 5,000 residents in a single urban area with population of at least 10,000. Meanwhile, Outlying counties are located in an MSA if they meet certain requirements of social and economic integration with one or more of the central counties in the MSA, such as regional commuting to central counties. Counties not included in an MSA are classified as nonmetropolitan counties (generally rural areas). Detailed definitions for these designations are available from the US Census Bureau (2011). A map of the U.S. showing the different MSA types is provided in Appendix I.

2.2.2 County Level CO_2 Data

The emissions inventories used here include direct emissions (scope 1) and indirect emissions from electricity consumption (scope 2). Scope 1 GHG emissions estimates for the 3,141 counties in the US for 2002 were obtained from Project Vulcan, a database that provides a county-level resolution of production-based emissions from fossil fuel combustion by aggregating publically available data from EPA, DOE, etc. Gurney et al (2009) provides a discussion of the methodology in deriving this database, which has predominantly been used for much finer resolution modeling of individual facilities. Scope 1 emissions are reported by sector: *residential, industrial, commercial, and onroad, nonroad, and air transportation.* Emissions from agriculture and waste management were not included in this analysis.

Scope 2 emissions were computed as the product of county-level electricity consumption and electricity emissions factors. We used multiple regression model to estimate electricity consumption, c_i, for each county i with general form shown in (1). Predictor variables included population (Pop), population density (Pop_Density), economic indicators (Econ_Ind) (e.g., total payroll, household aggregated income, number of employees, number of establishments, total sales), climate indices (Climate_Ind) (e.g., heating degree days (HDD) and cooling degree days (CDD)), and the interaction between population climate indices (Pop_Clim). The model that resulted in the most accurate prediction of electricity consumption is shown in (1), where i is the country identifier, c_i, is the electricity consumption, Pop is population, Pop*HDD is the interaction between Population and HDD). County level electricity consumption data used for modeling include publicly available data constituting all California counties (2006-2009), all Vermont counties (2006-2009), five Illinois counties (2005), and King County, Washington (2005-2009). The main criterion for final model selection is accuracy of electricity consumption prediction. A more detailed discussion of the modeling method is found in Appendix II.

$$Elec\_Cons_i = \beta_0 + \beta_{Pop}Pop_i + \beta_{Econ\_Ind}Econ\_Ind_i + \beta_{Clim\_Ind}Clim\_Ind_i + \beta_{Pop\_Clim}Pop\_Clim_i + e_i \quad (1)$$

The electricity emissions factor is a function of the fuels used to generate electricity consumed at the county scale. It is non-trivial (some authors suggest not possible) to associate a given county's electricity consumption with specific generation assets to derive an emissions factor (Weber et al. 2008). Electricity generally flows freely within operating regions defined by the North American Electric Reliability Corporation, often referred to as the "NERC regions," but little electricity generally crosses these regions (Marriott and Matthews 2008). In this chapter, it is reasonable to use average emissions factors for NERC regions as my base case since dealing with aggregate county electricity emissions. I perform a sensitivity analysis using average emissions factors defined for eGRID subregions (eGRID 2004) and U.S. states (eGRID

2004) to show differences in these different regional boundaries. In Chapter 3, I provide a more detailed discussion electricity emission factors.

A total of 618 counties, about 6% of the U.S. population, (Outlying = 6, Nonmetropolitan = 612) were omitted as outliers during model diagnostics and selection for electricity consumption prediction.

2.2.3 Regressing Emissions vs. Urbanization Level

The most general form of the model describing predictors of county GHG is shown in Equation 2. Regressions were performed for both total and capita emissions using Equation 2

$$GHG_{i,j}^{Total\ or\ Per\ Capita} = \beta_0 + \beta_{Geo1}Geo1_i + \beta_{Geo2}Geo2_i + \beta_{GDP}HH\_GDP_i + \beta_{\rho}Pop\_DENSITY_i + \beta_{HDD}HDD_i + \beta_{CDD}CDD_i + e_i \qquad (2)$$

where $GHG_{i,j}^{Total\ or\ Per\ Capita}$ is total or per capita scope 1 and 2 emissions for county i for either all sectors or by sector $j \in$ residential, commercial, industrial, onroad, nonroad, and air transportation, and electricity consumption, HH_GDP_i is the median household income,$Pop\_DENSITY_i$ is the population density, HDD_i is the heating degree days, CDD_i is the cooling degree days, and $Geo1_i$ and $Geo2_i$ are the dummy codes for county geographic types - central, outlying, and nonmetropolitan. I controlled for other variables (i.e., HDD/CDD, population density, and income), which have been shown in previous works to have a significant relationship with energy consumption [e.g., Quayle and Diaz 1980, Eto 1988, Sailor & Munoz 1997, Zhang 2004, and Carson et al. 1997 to name a few]. By varying the reference geographic type, I used this model to determine whether there is significant difference between mean emissions (i.e., coefficients are significant) stemming from geographic variation. For example, with type "central" as the reference, Geo1 = outlying and Geo2 = rural, and regression results for $\beta_{Outlying}$ and β_{Rural} indicate differences between emissions levels associated with outlying and rural counties relative to central counties, all else equal. The coefficients were evaluated at 5% significance level.

Model screening indicated the assumptions for ordinary least squares (OLS) do not hold. I did not transform variables to enable an intuitive interpretation of the relationship between geographic type and local emissions. Best models were found using both linear regression model (using robust regression) and generalized linear model (GLM) techniques, using the Inverse Gaussian family.

Due to observed correlations between independent variables, some were dropped from Equation 1. I found weak correlations between geographic type and both median household income and population density. This is likely because the MSA classification I used, as defined by the U.S. Census Bureau (2011), is partly based on population density. Previous works suggest a positive relationship between urbanization and income [Jones and Kone 1996, Bloom et al 2008, Glaeser 2011]. But Bloom et al (2008) provides the caveat that nascent stages of urbanization are not correlated with income growth, which may explain the weak correlation I found. I also found weak correlation between median HH income and population density, indicating a relationship between urbanization, income, and population density. Meanwhile, moderate negative correlation between HDD and CDD was observed. In model selection, I dropped some of these variables to avoid multicollinearity. I retained variables based on maximizing goodness-of-fit (Adjusted R^2 and Akaike Information Criterion (AIC)). I provide additional information on data used in Appendix III and further discussion on model fitting, diagnostics, and selection are presented in Appendix IV.

2.3 Results and Discussion

Regression results for per capita scope 1&2 emissions for all sectors are summarized in Table 2. The intercept is interpreted as the average per capita emissions in central counties while the coefficients for the other geographic types indicate differences from central counties (e.g., avg. nonmetropolitan per capita scope 1&2 emissions (last column) is central county avg. per capita scope 1&2 emissions (22.81) plus nonmetropolitan coefficient (0.11) which is equal to 22.92 tons CO_2/persons –year). Regression results presented here correspond to a reduced (less predictor variables, outliers and influential variables excluded) model, which I deem is most appropriate to use in this analysis, as in the case of Minx, et al. (2013).

In the residential and transportation (onroad, nonroad, and air) sectors, per capita emissions in nonmetropolitan counties are the highest. Mean per capita direct residential emissions are about 4% ((1.67 tons CO_2 per capita – 1.6 tons CO_2 per capita/1.67 tons CO_2 per capita) higher in central counties than outlying counties, ceteris paribus. The opposite is true in the onroad and nonroad transportation sectors, where outlying counties have higher per capita emissions by about 45% and 33%, respectively. Potential reasons for this observation are varying land use patterns, density, and access to transit and non-motorized modes (Newman and Kenworthy 1989; Cervero and Kockelman 1997; Frank and Pivo 1997; Pushkarev and Zupan 1977).

In the commercial sector, outlying counties were found to have the lowest average per capita emissions, ceteris paribus – about 36% and 43% lower than central and nonmetropolitan counties, respectively. Central counties were found to have the highest commercial sector emissions, although at only 2% higher than nonmetropolitan counties, ceteris paribus. This could be due to the role of central counties serving as regional centers of commerce, with neighboring outlying counties as likely beneficiaries.

I did not find enough statistical evidence to say that industrial emissions differ by urbanization level. For scope 2, I find per capita emissions in central counties to be similar to outlying counties but 40% higher in non-metropolitan counties. That is, I find metropolitan residents to have more emissions from electricity consumption than rural residents. For electricity, these results are robust with parametric variation in emissions factors assuming different electricity grid regions (states, NERC regions, or eGRID regions).

Importantly, contrary to previous findings, I find no statistically significant relationship between geographic variation and total scopes 1 plus 2 per capita emissions. These results are robust across parametric variation in the emissions factor and regression methods. Even if I relax the need for statistical significance to 10%, the predicted values indicate a maximum of 3% difference by geographic type.

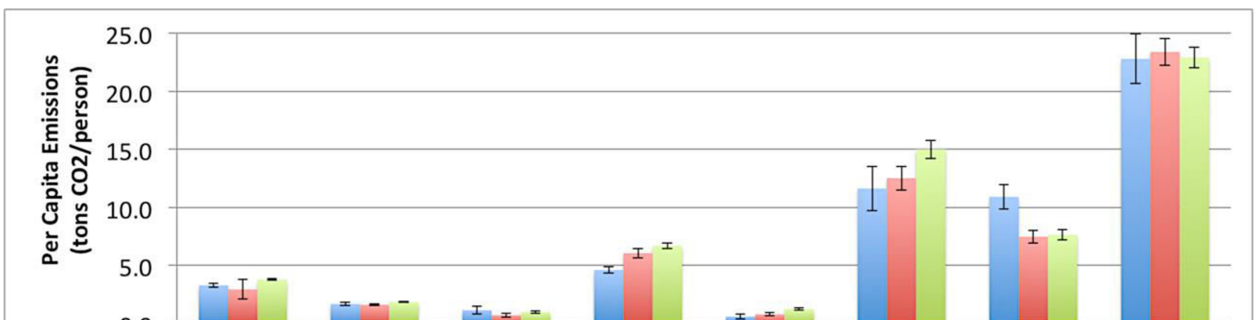
Table 2. Sector Per Capita Emissions Regression Analyses Results (Y2002)

Variable	Industrial	Residential	Commercial	Transportation Onroad	Transportation Nonroad	Transportation Air	Scope 1	Scope 2 NERC	Scope 1+ 2 NERC
Intercept	3.28*** (0.08)	1.67*** (0.07)	1.13*** (0.16)	4.62*** (0.14)	0.32*** (0.06)	0.13* (0.06)	11.62*** (0.95)	10.91*** (0.52)	22.81*** (1.06)
Nonmetro	0.49 (0.03)	0.17*** (0.03)	-0.16* (0.06)	2.09*** (0.12)	0.64*** (0.03)	0.06 . (0.03)	3.38*** (0.39)	-3.27*** (0.22)	0.11 (0.44)
Outlying	-0.35 (0.41)	-0.07 . (0.04)	-0.43*** (0.08)	1.45*** (0.20)	0.15*** (0.03)	-0.07 . (0.04)	0.89 . (0.51)	-0.34 (0.28)	0.59 (0.57)
Med. HH Inc.	-2.02e-05 (1.40e-05)	8.57e-06*** (1.23e-06)	6.26e-06* (2.84e-06)		6.55e-06* (1.21e-06)	3.94e-06** (1.23e-06)	-7.80e-06 (1.73e-05)	-3.53e-06 (9.47e-06)	-1.60e-05 (1.92e-05)
Pop. Dens.				-1.80e-04*** (1.32e-05)					
CDD	4.32e-04 (1.59e-04)	-5.22e-04*** (1.39e-05)	-3.20e-04*** (3.22e-05)	3.70e-04*** (7.95e-05)	-2.06e-04*** (1.23e-05)		-1.09e-04 (1.96e-04)	-1.44e-04 (1.07e-04)	-3.27e-04 (2.16e-04)
HDD						-1.56e-05** (5.77e-06)			
AIC	15523	3465.1	7632.9	11178	2946.8	3740.9	16567	13586	16444
Adj. or Pseudo R^2	0.01	0.44	0.06	0.09	0.13	0.01	0.04	0.13	0.05
Model	LRM	LRM	LRM	GLM	LRM	LRM	GLM	LRM	GLM

*Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'*

As shown in Table 2, I controlled for income instead of dropping it entirely, noting that I found very weak correlation between urbanization and income; also, previous works suggest caution in emphasizing this relationship (Bloom et al. 2008). But to further check the robustness of my conclusions, I looked at the results when income is dropped from the equation. The coefficients for the geographical types changed (i.e., estimates for per capita emissions by MSA level changed) but I still did not find enough statistical evidence to suggest relationship between urbanization and total scope 1&2 emissions.

Figure 1 summarizes predicted per capita emissions by sector using models specified in Table 2. As shown, the mean total scope 1&2 in central counties, 22.8 tons CO2/year, is slightly lower than that of outlying and nonmetropolitan counties – 23.4 and 22.9 tons CO2/year, respectively – but the spread of central county emissions values is much wider. Table 3 summarizes ratios of estimated per capita emissions by both sector and geographic type.



	Ind.	Res.	Comm.	Onroad	Nonroad	Scope 1	Scope 2	S1+2 NERC
Central	3.3	1.7	1.1	4.6	0.6	11.6	10.9	22.8
Outlying	2.9	1.6	0.7	6.1	0.8	12.5	7.5	23.4
Nonmetro	3.8	1.8	1.0	6.7	1.2	15.0	7.6	22.9

Figure 1. Total Scope 1+2 and Sector Per Capita Emissions by Urbanization Level in the U.S. (Y2002). Bars show mean per capita emissions while error bars show 95% confidence interval values obtained using reduced GLM (GLM 2). [Central (*N* = *488*), Outlying (*N* = *300*), Nonmetropolitan (*N* = *1686*)]. Per capita air transportation emissions were omitted due their very low values (< 0.2 for all county types).

Table 3. Comparison of Per Capita Emissions by Urbanization Level [Cell Values = ratio (row/column) of average county type emissions; Red: Row > Col, Green: Row < Col; Grey: NS difference]

RATIOS FOR AVERAGE *PER CAPITA* EMISSIONS		
INDUSTRIAL		
	Outlying	Nonmetro
Central	NS	NS
Outlying		NS
RESIDENTIAL		
	Outlying	Nonmetro
Central	1.0	0.9
Outlying		0.9
COMMERCIAL		
	Outlying	Nonmetro
Central	1.6	1
Outlying		0.7
ONROAD		
	Outlying	Nonmetro
Central	0.8	0.7
Outlying		0.9
NONROAD		
	Outlying	Nonmetro
Central	0.8	0.5
Outlying		0.6
AIRPORT		
	Outlying	Nonmetro
Central	2.2	0.7
Outlying		0.3
ELECTRICITY		
	Outlying	Nonmetro
Central	NS	1.4
Outlying		1.4
SCOPE 1+2		
	Outlying	Nonmetro
Central	NS	NS
Outlying		NS

RATIOS FOR AVERAGE *TOTAL* EMISSIONS		
INDUSTRIAL		
	Outlying	Nonmetro
Central	NS	6
Outlying		2
RESIDENTIAL		
	Outlying	Nonmetro
Central	NS	NS
Outlying		1
COMMERCIAL		
	Outlying	Nonmetro
Central	9	NS
Outlying		1
ONROAD		
	Outlying	Nonmetro
Central	4	7
Outlying		2
NONROAD		
	Outlying	Nonmetro
Central	4	6
Outlying		2
AIRPORT		
	Outlying	Nonmetro
Central	NS	NS
Outlying		NS
ELECTRICITY		
	Outlying	Nonmetro
Central	12	5
Outlying		2
SCOPE 1+2		
	Outlying	Nonmetro
Central	4	9
Outlying		2

At the aggregate level, more urban counties have significantly higher emissions for all sectors with the biggest difference between urbanization levels in electricity consumption, commercial, and transportation. Electricity consumption (36% to 50%) and onroad transportation (22% to 29%) constitute over half of total scope 1&2 emissions. Per capita emissions exhibit a different profile for the different geographic type as discussed above, with central county per capita onroad transportation emissions about 0.7 – 0.8 that of less urban counties while electricity consumption in metropolitan counties (central and outlying) have electricity consumption per capita emissions about 1.4 times that of rural counties.

Figure 2 shows variation in per capita emissions given population density. Similar to the empirical findings, these trends generally show a decrease in per capita transportation emissions with increasing density; however, emissions per capita for buildings trend upward with increasing density. Marginal changes for the transportation and buildings sectors decrease significantly around 300 persons/sq. mi. (log(300) ~ 2.5) and 100 persons/sq. mi. (log(100) = 2). I did the same for scope 1&2 per-capita emissions versus population density and found that decrease in marginal emissions become marginal at about 600 persons/sq. mi. While the uncertainty and variation in these data are large, these trends indicate there could be diminishing marginal changes to emissions with increasing population density and such changes vary by end-use sector. Fragkias et al. (2013) recently reached similar conclusions with respect to total MSA size, where total emissions and population were found to scale proportionally for a cross-sectional analysis of MSA emissions from 1999-2008. This evidence calls for further investigation and more work on figuring out the extent and form of urbanization that is sustainable.

These results highlight the importance of considering metropolitan dynamics in the context of local climate action planning. Central counties often serve as regional centers of commerce (higher commercial sector emissions), which induces regional transportation demands from trips originating in outlying and non-metropolitan counties. Regional land use planners may be interested in shifting commerce to outlying and non-metropolitan counties with the intent of reducing transportation demands in these counties. However, this may increase commercial sector emissions in outlying counties with unclear implications for transportation and commercial emissions in central counties. The data I used are limited to cross-sectional analyses for a single year; thus the temporal dynamics of such land use change remain unclear. Significantly more empirical data would be required for a time-series (panel) regression.

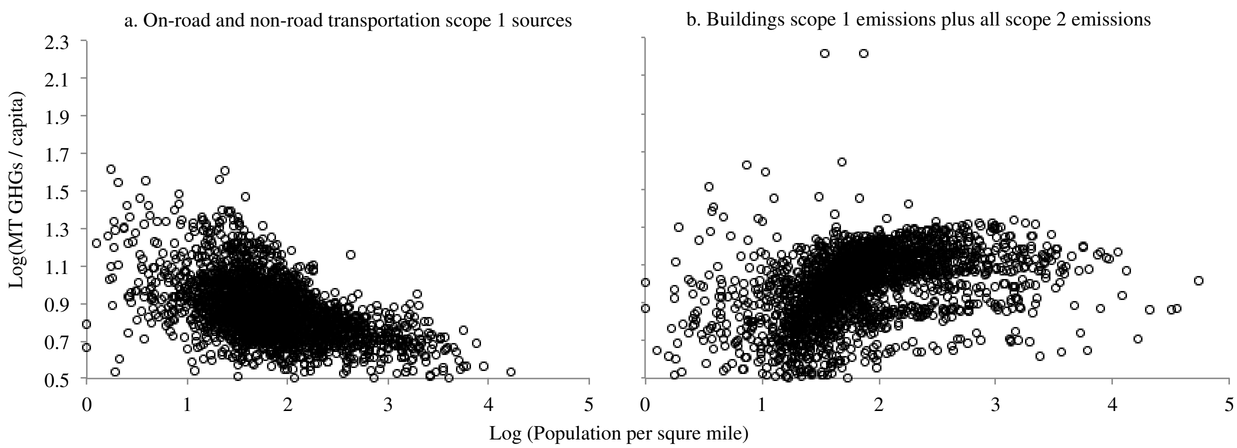


Figure 2. Population Density versus a. transportation sector scope 1 emissions and b. emissions from the buildings sectors plus all scope 2 emissions (excluded Wilcox County, AL because of outlier per capita emissions value > 2, 000 tons/year)

I also emphasize the importance of uncertainty in local emissions estimates ("GHG inventories") for planning emissions reductions. Assigning the various reported emissions factors at the county level, I found an average change from the base case (using NERC emissions factors) of about 13 to 15%. Thus, similar to other studies, I find using inappropriate emissions factors may be misleading when measuring and planning emissions reductions at the local scale (Ackerman and Sundquist 2008, Weber, et al 2010, and Marriott and Matthews 2008; Blackhurst, et al 2010). This partial accounting of uncertainty in total emissions is well within the range of planned GHG reduction targets (ICLEI 2012), thus complicating planners' ability to set representative baseline emissions and to benchmark changes to emissions. Thus, planning methods that do not reflect inherent uncertainty in baseline or expected emissions factors may be misleading.

Future work could include estimates of Scope 3 emissions to provide a more comprehensive estimate of the GHG implications of urbanization; however, estimates of scope 3 emissions of similar empirical quality or missing and unlikely to be available soon. Nevertheless, one would expect total scope 3 emissions to be higher for urban systems given the more intensive material requirements for urban infrastructure (Minx, et al. 2013). My regression results show that per capita scope 1&2 emissions do not differ by urbanization level; it is likely that when scope 3 emissions are included, per capita emissions in more urbanized counties could actually be much higher, on average, compared to less urban counties.

Given that scope 1&2 emissions production rate in more urban counties are not significantly different from that of less urban ones and population is concentrated in urban counties, significant national emissions reduction could be achieved if efforts are focused on the 500 U.S. central counties.

There are several ways to reduce CO2 emissions – both from the supply and demand side. I choose to focus on estimating CO2 emissions of electric vehicles further for the following reasons. About 22% of emissions come from transportation. However, the electric vehicles link the transportation emissions to electric consumption emissions, with the latter currently making up about 50% of central county emissions, on average. Electric vehicle use moves transportation emissions from scope 1 to scope 2. So I want to investigate whether switching form gasoline to electric vehicles will help reduce transportation CO_2 emissions. Moreover, electric vehicle development and wider adoption have received sustained policy support from the local to the supranational level as well as substantial investment from the private sector (e.g., automobile manufacturers, battery manufacturers). Because of this support, electric vehicle sales have been increasing consistently since introduction in 2010. It is one of the major alternative fuel vehicles that are in widest use today along with E85, propane, and compressed natural gas.

In the following chapters, I investigate the locational life cycle emissions of electric vehicles throughout the U.S. to verify the claim that electric vehicles reduce transportation CO_2 emissions, especially in urban areas. With the locational life cycle assessment results, I aim to determine where in the U.S. can electric vehicles contribute to bigger CO_2 emissions reductions.

3 Policy and Market Background on Electric Vehicles in the U.S.

Policies relevant to vehicle electrification in the U.S. include those that facilitate research and development of electric vehicle technology, battery research and development (particularly to reduce cost), promote infrastructure readiness for electric vehicle adoption, and reduce cost of purchase or ownership of EVs. A highly intertwined policy area is the decarbonization of the U.S. electricity grid. In this section, I provide a general discussion of the state of policy support for vehicle electrification in the U.S., historical background and future vehicle electrification related policies. I also present electric vehicle sales data from December 2010 to July 2014 and forecast trajectory of electric vehicle adoption until 2020.

3.1 Major Policies

About four decades ago, the U.S. Congress passed a law to expedite wider use of electric and hybrid vehicle technology, called the "Electric and Hybrid Vehicle Research, Development, and Demonstration Act of 1976" mainly in the interest of national security, stability in foreign policy, and economic well-being of the country (U.S. Government Printing Office 2014). The Congress further justified this Act by citing additional advantages of the electric and hybrid vehicle technology such as reduced air and noise pollution from cars, use of existing electric generating capacity if vehicles are charged during off-peak hours, and concentrated source of pollution (i.e., electric plants), making pollution more tractable and easier to control.

In the same decade, the Clean Air Act (CAA) of 1970/1977, amended in 1990, conferred power and responsibility to the Environmental Protection Agency to reduce air emissions form stationary (includes power plants) and mobile sources (U.S. Government Printing Office 2014). While electricity production and transportation made up about

32% and 28% of U.S. 2012 emissions, respectively, emissions level from these two sources have decreased sharply since the implementation of the CAA (EPA 2014). The EPA recently proposed the Clean Power Plan which provides guidelines at the state level for reducing CO_2 emissions from fossil-fueled power plants with the goal of reducing power sector CO_2 emissions by 30% as well as smog levels by over 25% by 2030 from 2005 levels (EPA 2014).

Policies such as the Clean Air Act, which is designed to control emissions from both stationary and mobile sources, have been instrumental in reducing emissions from new power plants and prove the ease of control through regulation of emissions related to electricity consumption. On the other hand, the Corporate Average Fuel Economy (CAFÉ) has also achieved success in reducing tailpipe emissions by inducing the increase in U.S. average fleet energy efficiency. This policy is also expected to induce the production of electric vehicles to meet vehicle efficiency targets.

3.2 Federal, state, and local policies on electric vehicles

Subsidies and programs to promote increased use of electric vehicles are in place at the federal, state , and local levels. At the federal level, a tax credit is provided for new qualified plug-in electric drive motor vehicle that draws propulsion using a traction battery that has at least five kilowatt hours (kWh) of capacity, uses an external source of energy to recharge the battery, has a gross vehicle weight rating of up to 14, 00 pounds, and meets specified emission standards. The minimum credit amount is $ 2, 500 and the credit may be up to $ 7, 500, based on each vehicle’s traction battery capacity and the gross vehicle weight rating. The credit will begin to be phased out for each manufacturer In the second quarter following the quarter in which a minimum of 200, 000 qualified plug-in electric drive vehicles have been sold by that manufacturer for use in the United States. The tax credit applies to vehicles acquired after December 31, 2009, through the

American Taxpayer Relief Act 2012, (U.S. GPO 2014).

A map of subsidies for electric vehicle ownership by state is shown in Figure 3. State subsidies range from $ 389 (Iowa) to $ 7, 500 (West Virginia). Federal and local government partnership is shown through the Clean Cities Project of the Department of Energy received over $ 8.5 M of funding to help communities in planning for wider adoption of plug-in hybrid electric vehicles (PHEV). The Clean Cities Program aims to facilitate access to PHEV charging infrastructure. Participating states are shown in Figure 4.

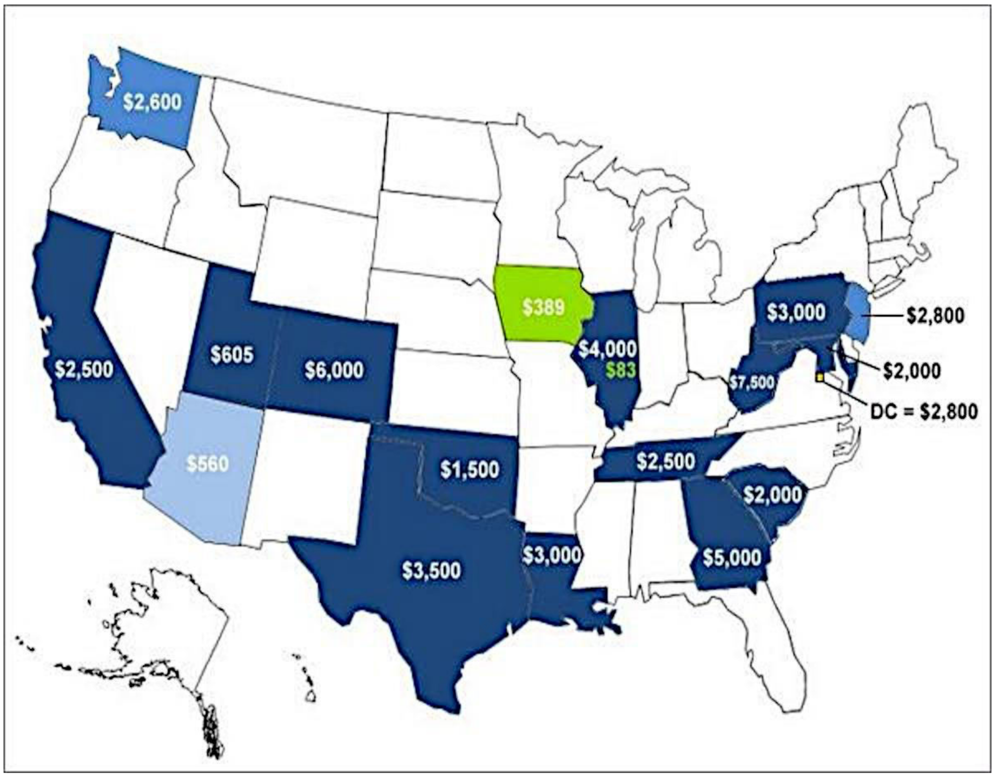


Figure 3. State Incentives for Electric Vehicles (Source: DOE Alternative Fuels Data Center (AFDC) 2014)

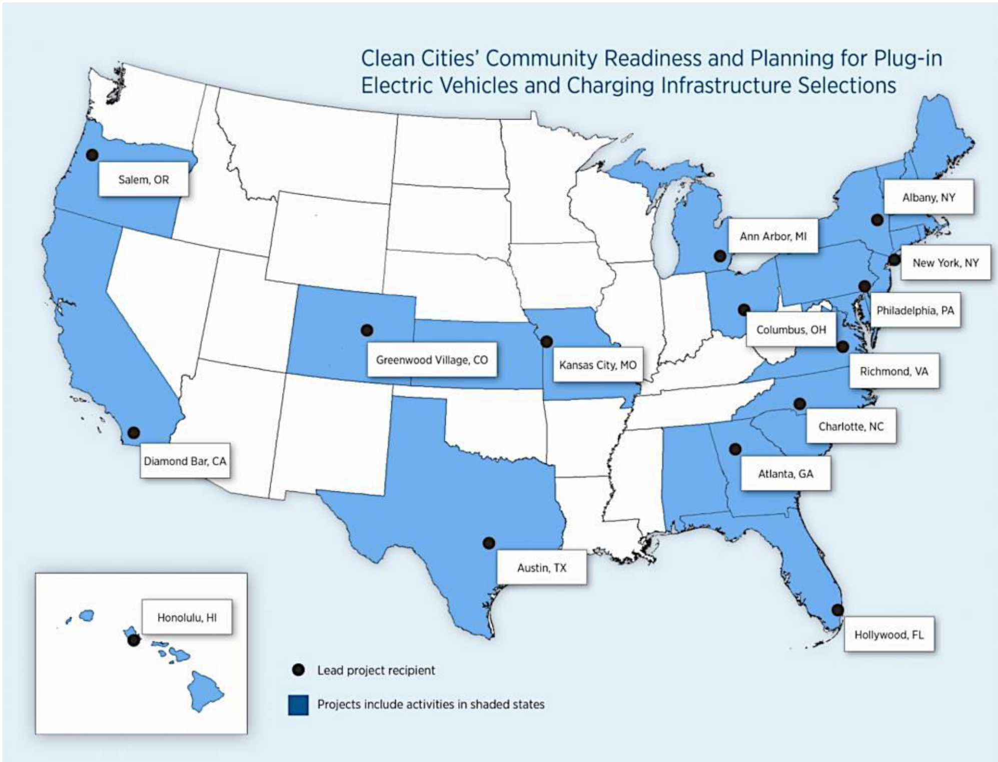


Figure 4. Clean Cities Project Fund Recipient for PHEV Adoption (Source: DOE 2011)

A complete list for both federal and state laws and regulation, programs, and subsidies that support vehicle electrification can be accessed in DOE AFDC 2014.

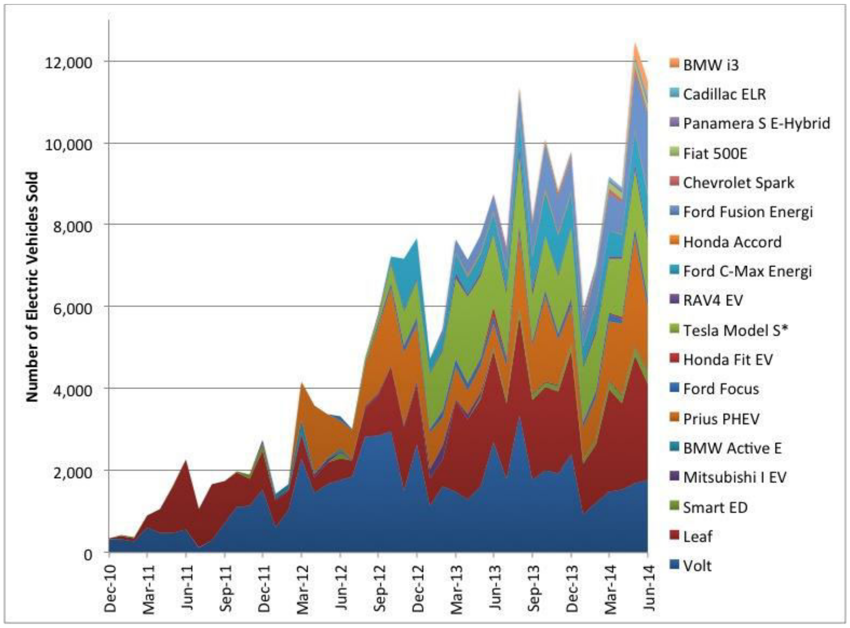
This list shows that CA and other states in the above maps have the most aggressive vehicle electrification policies ranging from incentives, increased charging infrastructure, access to HOV lanes, to parking permits.

3.3 Market Background

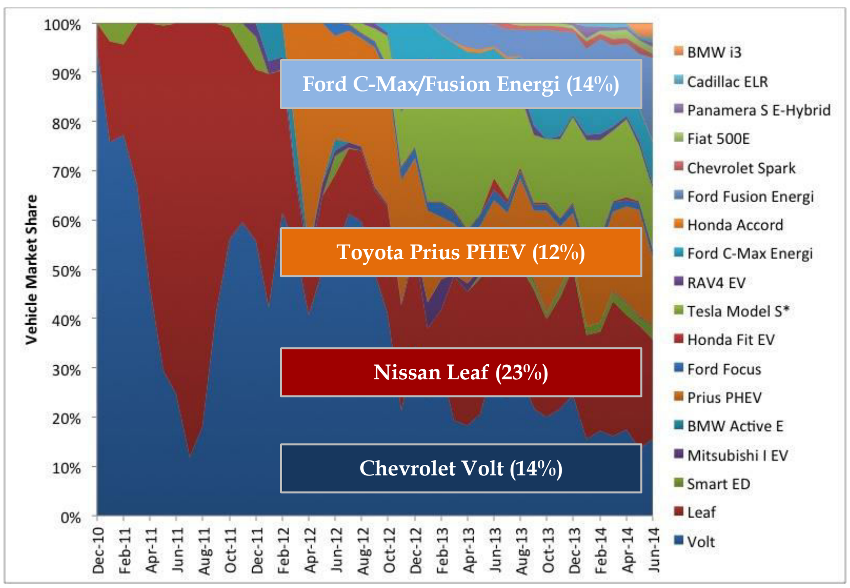
Plug-in hybrid electric vehicle (PHEV) and battery electric hybrid (BEV) sales data start in December 2010 with the Nissan . The Argonne National Laboratory (2014) reported rapid increase in electric vehicle sales from December 2010 through April 2014 (see Figure 5). The Chevrolet Volt, Toyota Prius PHEV, Nissan Leaf, Tesla Model S, and Ford Fusion Energy (in order of percentage sales) constitute over 95% of all sales as of

2014[2]. Current electric vehicle owners indicate high level of satisfaction with high inclination for purchasing another electric vehicle at a level higher than other vehicle types (JD Power 2012). Although electric vehicles only constitute about 1.3% (3.4% with HEVs) of total car sales as of date (ANL 2014), data point to an optimistic outlook for mass electrification of vehicles.

[2] Complete electric vehicle sales data can be requested from ANL (ANL 2014).



(a) Electric Vehicle Sales



(b) Electric Vehicle Market Share

Figure 5. a) Electric Vehicle Sales from December 2010 - April 2014 (Source: ANL 2014 with labels revised for legibility) b) Market share by electric vehicle from December 2010 – April 2014 (Data Source: ANL 2014)

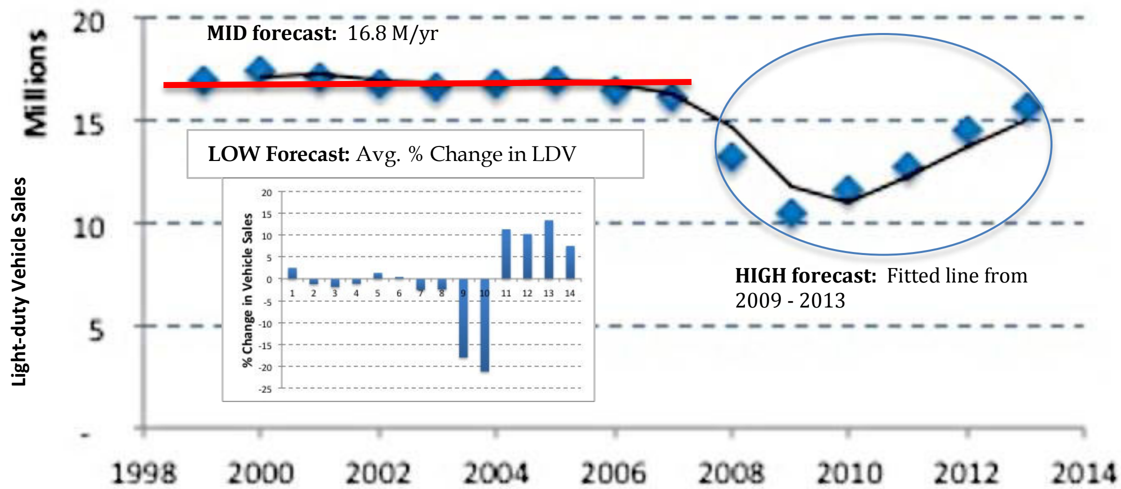


Figure 6. Light duty vehicle sales data (1999 - 2013) and forecast methods (Data source: ANL 2014)

Meanwhile, Figure 6 shows historical data (1999 – 2013) and forecasting methods (2014 – 2020) on light-duty vehicle sales. I estimated light-duty vehicle (LDV) sales for three cases – low, mid, and high. In the mid case, I assume that LDV sales will replicate the stable annual sales exhibited before the U.S. financial crisis of 2007 – 2009, which hovered around 17 M units per year. For a high sales scenario, I assume that the growth from 2010 – 2013 will continue until 2020 and for this, I use a fitted line for data from 2009 – 2013. For the low case, I assumed that the average percentage change in LDV sales (i.e., ~ 8%) from 1970 - 2013 will hold true from 2014 – 2020.

Based on car sales data from ANL 2014, car sales, has been, on average, 50% of total LDV sales from 1999 to 2013. Moreover, car and LDV sales as of first half of 2014 is higher than it was the same period in 2013. Unless a sudden market disturbance happens, 2014 car sales is likely to hit an 8M mark (i.e., LDV sales will likely be close to 16M). Data for the past 5 years exhibit a pattern different to sales pattern from 1990 to 2013 where there seems to be a seven-year parabolic trend in car sales with 7-year average decreasing since 1990 by an average of 8%. If we were to project this pattern from 2014 to 2020, sales at the end of 2014 should be lower than 2013, with car sales down to 6.5M and LDV sales to about 13M by 2020. However, given the optimistic trend from recent years, policy support, and lower deliquency rates in loan payments, and new developments in the car industry, I think that in the next seven years, the mid case of levelling off at ~ 17 M and the high case of continued car sales increase are more likely, with the latter having a higher likelihood. The resulting LDV sales forecasts are shown in Figure 7.

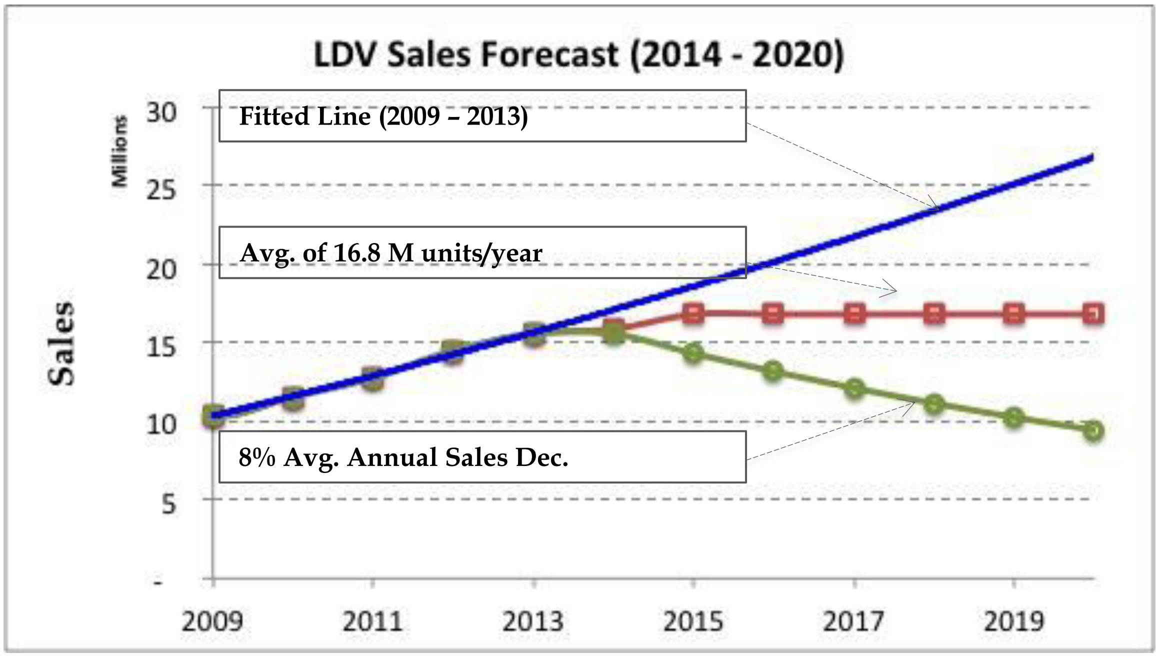


Figure 7. LDV sales forecast (2014 - 2020)

To forecast electric vehicle sales, I assume three levels of average electric vehicle annual sales as a percentage of LDV sales for the period of 2014 - 2020 – High: 4% per year (Deutsche Bank 2008); Mid: 2% per year (Boston Consulting Group 2010); and Low: 0.6% per year (JD Power 2009). Cumulative electric vehicle sales for these three cases and the three LDV sales forecasts are illustrated in Figure 8. Based on these estimates, electric vehicle sales in the high case will hit close to the 1M unit goal declared by President Obama in his 2011 State of the Nation Address in 2016, a year later than the 2015 target. These sales are subject to many factors such as a potential car bubble that may burst soon because of the low interest rates that autodealers have been giving out to buyers. This may result in future EV sales that are even lower than my low scenario. On the flip side, the economy has been growing and sustained incentives and increased policy support for facilitating EV adoption such as charging infrastructure investments, parking and HOV lane privileges may boost EV sales even higher than my high case. The growth in EV use is currently not as fast as was desired but evidence points to a more optimistic market trajectory.

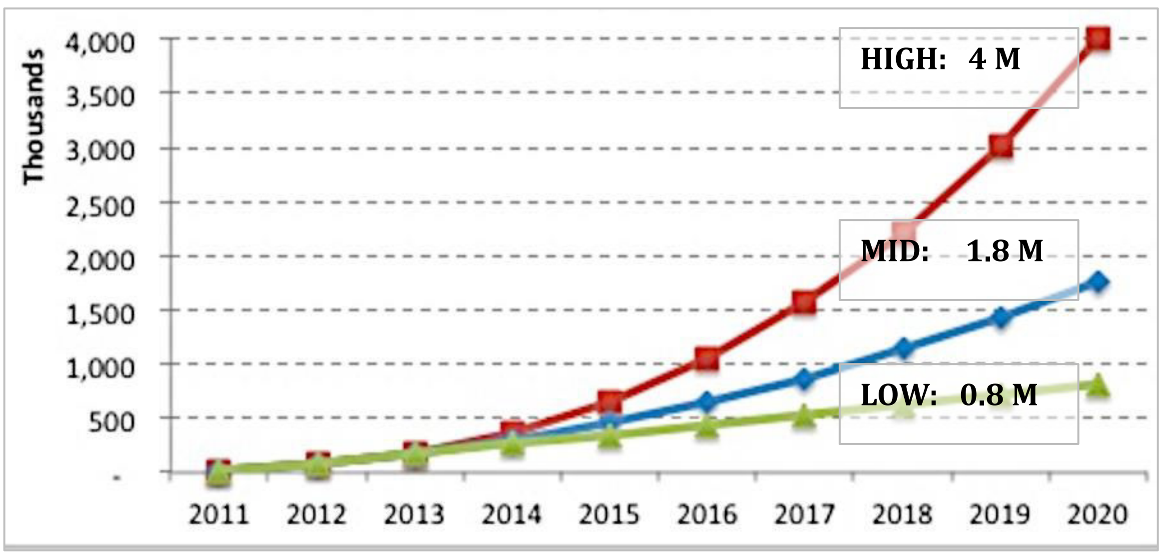


Figure 8. Cumulative electric vehicles sales (2014 - 2020) - High: high LDV sales and 4% annual increase in electric vehicle sales; Mid: mid LDV sales (i.e., level off at 17M) and 2% annual electric vehicle sales increase; and Low: low LDV sales and 0.6% annual electric vehicle sales increase.

4 A Characterization of Regional Variation in CO_2 Emissions Across the United States: *Where should we have electric vehicles?*[3]

4.1 Introduction

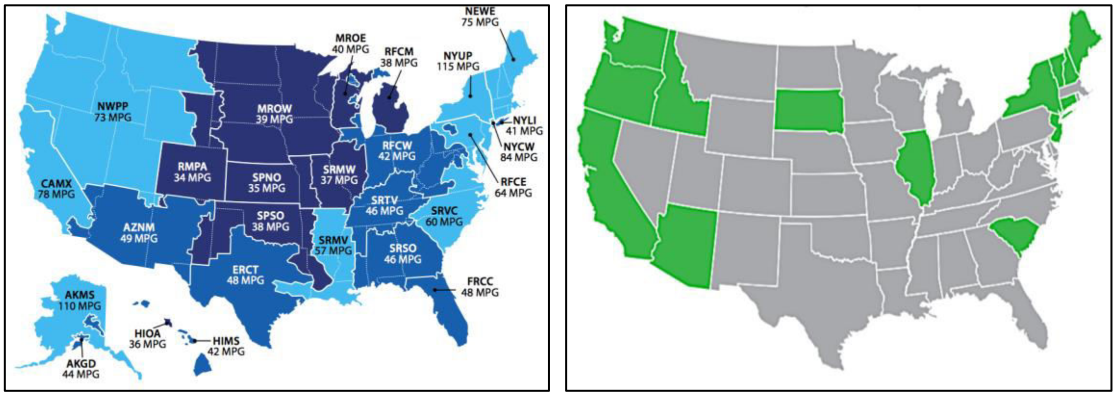
Much attention has been provided to comparisons between electric vehicle (EV) and gasoline vehicles greenhouse gas (GHG) emissions e.g.: [Zivin et al (2014), Faria, R. et al (2013), Marshall, B. M. et al (2013), Sharma, R. et al (2013), Yawitz *et al.* (2013), Anair & Mahmassani (2012), Hawkins *et al.* (2012), Ma et al (2012), Kelly, J. et al (2012), Raykin, L. (2012), Michalek *et al.* (2011), Axsen et al (2011), Peterson et al (2011), Huo, H. (2010), Siosanshi & Denholm (2009), Elgowainy *et al.* (2009), Samaras & Meisterling (2008), EPRI (2007), Parks *et al.* (2007), Stephan and Sullivan (2007) and Matsuhasi *et al.* (2000)]. Most of these works suggest that a significant factor when comparing plug-in electric vehicles and gasoline vehicles is the magnitude of emissions associated with electricity production.

Most of the literature relies on a single electricity production emissions factor, or conducts sensitivity analyses to grid emissions factor over a range of power plant types [Michalek *et al.* (2011) and Samaras & Meisterling (2008), EPRI (2007)]. EVs may have higher or lower emissions than gasoline vehicles depending on what type of power plants respond to the increased demand, which varies by charging location and time of day.

These studies covered varying life cycle scopes. Yawitz et al 2013 covered vehicle and battery manufacturing as well as vehicle use while Anair & Mahmassani 2012 and EPRI 2007 only covered vehicle operation energy use. Different assumptions were made

[3] Submitted to Transportation Research Board (TRB) for presentation, co-authored with J Michalek, C Hendrickson, and I Azevedo

on plug-in hybrid electric vehicles (PHEV) utility factors, or the average portion of distance traveled on electricity.



(a) (b)

Figure 9. (a) EV Ratings comparing Nissan Leaf to gasoline vehicle using 2009 eGRID subregion avg. emission factors [**Violet** = EV is comparable to gasoline vehicle with 31-40 mpg); **Blue** = EV is comparable to gasoline vehicles with 41-50 mpg; and **Light Blue** = EV is comparable to gasoline vehicles with >51 mpg)] (Anair & Mahmassani (2012)); (b) Leaf *vs* Toyota Prius HEV using 2010 State Average Emissions Factor (Green: Leaf is lower emitting), Source: Yawitz, et al. (2013))

Table 4 summarizes published reports that have focused on a regional comparative analysis of electric and gasoline vehicle emissions in the U.S., and Figure 6 shows maps highlighting how different the implications are from different analyses. These studies covered varying life cycle scopes. Yawitz et al 2013 covered vehicle and battery manufacturing as well as vehicle use while Anair & Mahmassani 2012 and EPRI 2007 only covered vehicle operation energy use. Different assumptions were made on plug-in hybrid electric vehicles (PHEV) utility factors, or the portion of distance traveled on electricity on average.

Table 4. Summary of Studies Comparing the GHG Emissions of EVs and Gasoline Vehicles in U.S. Regions

	Zivin et al (2014)	**Yawtiz *et al.* (2013)**	**Anair & Mahmassani (2012)**	**EPRI (2007)**
Regional definition used:	NERC Regions	50 States	26 eGRID subregions	13 NERC regions
Electricity emissions factor:	Marginal regional consumption	Average regional generation	Average regional generation covering transmission and upstream loss (286 - 983 g CO2e/kWh)	Regional bottom-up model (573 g CO2e/kWh in 2010; 97 – 412 g CO2e/kWh in 2050)
Electric vehicles considered:	2012 Nissan Leaf (0.34 kWh/mi) and 2012 Chevrolet Volt (0.36 kWh/mi)	2013 Nissan Leaf (0.29 kWh/mi); other EVs in the market (EPA 2013)	2012 Nissan Leaf (0.34 kWh/mi); Mitsubishi "i" (0.3 kWh/mi); Chevrolet Volt (0.36 kWh/mi, 37 mpg)	2010 PHEV (10, 20, 40): (0.312 kWh/mi, 37.9 mpg)
Electric vehicles utility factor:	Not stated	PHEV: 0.5	Chevrolet Volt: 0.64	PHEV10: 0.12 PHEV20: 0.49 PHEV40: 0.66
Gasoline emissions factor	8.9 kg CO_2/mi	11.8 kg CO2e/gal	11.2 kg CO2e/gal	11.1 CO2e/gal
Gasoline or hybrid vehicles considered:	Avg. gasoline (21.7 mpg); Avg. comparable economy car (31 mpg); 2012 Toyota Prius Hybrid (50 mpg)	Toyota Prius Hybrid (50 mpg); Ave. new gasoline cars (25 mpg); other gasoline cars in market (EPA 2013)	Toyota Prius Hybrid (50 mpg); Ave. new gasoline vehicle (27 mpg); other gasoline cars in market (combined city/highway fuel economy from EPA 2012)	Ave. 2010 ICEV: 24.6 mpg Ave. 2010 HEV: 37.9 mpg
VMT:	35 mi/day	50,000 and 100,000 mile/vehicle	166, 000 mi/vehicle	12, 000 mi/yr
Scope of emissions covered:	Gasoline combustion; production of electricity	WTW for gasoline; upstream and production for electricity; and Life Cycle	Well-to-Wheels (WTW) for gasoline; upstream and production for electricity	WTW for gasoline; upstream and production for electricity
Year of emissions estimates:	2007-2009	2010, 2012	2009	2010-2050
Data sources:	CEMS, EPA	EIA, GREET	2009 eGRID, GREET	NEMS, MOBILE6
Findings:	PEV is lower emitting only in WECC and Texas and higher emitting than the Toyota Prius in MRO. PEVs have higher emissions when charged from midnight – 5 am.	The HEV (Prius) has lower emissions than the BEV (Honda Fit) in 39 states over the first 50, 000 miles. Over 100, 000 miles, the BEV is better in ID, OR, VT, and WA.	The EV (Leaf) is lower emitting than the average gasoline vehicle throughout U.S.. The EV is better than the Prius in about half of populated America.	In low to high GHG grid mix and market penetration levels, PHEVs have lower emissions than both hybrid (by 7%-46%) and conventional gasoline vehicle (by 40%-605%).

The key issues in assessing regional variation are (a) regional boundaries of analysis, (b) whether generation or consumption based emissions factors are used, and (c) whether marginal emissions factors for electricity (MEFs) or average emissions factors (AEFs) are used. Here, I describe the concerns associated with each of these issues. The electricity emissions factors assumed for analyses will depend heavily on the regional boundaries assumed. For example, Weber *et al.* (2009) emphasize that studies assessing regional emissions should assess robustness of findings to different regional definitions. However, there is yet no good way to track exactly the emissions associated with generation at different regional scales. Regional studies tend to model emissions associated with electricity using data on average regional generation, since data are readily available on generation and emissions and because of the policy jurisdiction of decision makers, e.g.: [Yawitz *et al* 2013, Anair & Mahmassani 2012]. However, given the electricity trades across regions, consumption of electricity in a location may lead to an increase in emissions in a different location. Zivin *et al.* (2014) compared electricity generation and demand per NERC region and showed that the MRO, NPCC, FRCC, WECC, and TRE consume more than they produce while SERC, RFC, and SPP are net exporters. Most existing studies use average emissions factors for electricity, with the exception of EPRI (2007) and Zivin et al. (2014).

To assess the emissions implications of adding new electric vehicle (EV) charging load in a particular region of the US electricity grid at a particular time, one would estimate marginal emissions associated with increased generation at the power plants that respond to meet the new demand. This is difficult to do in practice because the electricity grid is a complex network, moving supply from geographically diverse generators to geographically diverse demand locations within and between regions dynamically while responding to economic signals and technical factors such as ramp rates, downtime, frequency regulation, and transmission constraints. It is generally impossible to know in practice which power plant(s) will ramp up production in response to a new load at a given time.

Given this difficulty, several studies of regional EV emissions employ readily available estimates of average regional generation mix instead (see Table 5): Anair and Mahmassani (2012) use average generation emissions within each NERC subregion, and Yawitz *et al.* (2013) use average generation emissions within each state. But average emissions rates in a region vary substantially from the change in emissions that a new load will create for two reasons: (1) many baseload plants and non-dispatchable renewable generators, which make up a substantial portion of average generation, will not change output in response to new load, and (2) electricity is traded across regional boundaries, so the profile of emissions produced in a region is not necessarily a good measure of the emissions produced to satisfy demand in that region.

Figure 7 illustrates both of these issues for a snapshot in time. This simplified example includes two regions, each with generators that produce enough supply to satisfy the baseload demand. In region 1 the nuclear generator is fully utilized and the coal generator is partly utilized to satisfy baseload demand. If new EV load were added in this region, the coal generator would increase production to satisfy the new load. While average generation in this region is a mix of nuclear and coal power sources, the marginal generation associated with supplying new EV load is 100% coal.

Region 2 has only a nuclear generator that is fully utilized in supplying the baseload demand, so any new EV load would need to be satisfied by importing electricity from a neighboring region. While region 2's average generation emissions factor would be near zero, marginal emissions associated with supplying new EV load in the region are those associated with coal generation from the neighboring region. These examples show why emissions associated with marginal consumption in a region may differ substantially from emissions associated with average generation in that region per additional unit of electricity demand.

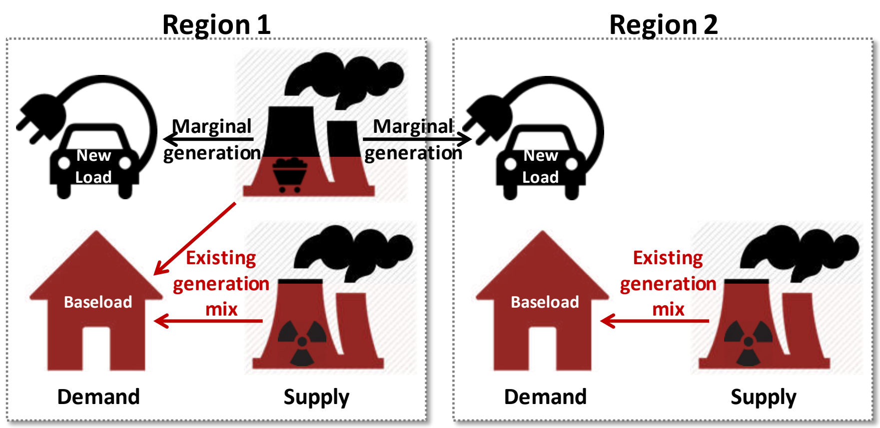


Figure 10: Illustration of the differences between emissions associated with average generation, marginal generation, and marginal consumption

Table 5: Studies assessing regional variation in electric vehicle charging emissions in the US (Siler-Evans *et al.* (2012) study added for comparison)

		Emissions associated with		
		Marginal consumption	Marginal generation	Average generation
Within region	NERC Regions	Zivin et al. (2014)	Siler-Evans et al. (2012)	
	NERC Subregions			Anair and Mahmassani (2012)
	States			Yawitz et al. (2013)

There are two broad approaches to assessing marginal consumption emissions factors: bottom up and top down. A bottom up approach models power plant operations and computes how generators should behave in response to a load profile in order to best respond to economic signals (e.g.: minimize cost). Such studies include simple dispatch supply curves or complex optimization models [Axsen et al (2011), Peterson et al (2011), Siosanshi & Denholm (2009), Hadley & Tsvetkova (2008), Dallinger *et al* (2013), Foley *et al* (2013), and Weis *et al* (2014)] to model generator response to load profiles.

However, it is difficult to correctly model all of the factors that determine plant behavior in practice (e.g.: transmission constraints, ramping constraints, unscheduled maintenance, weather, regulation, etc.) for a region large enough to capture all relevant factors in such an interconnected system, and there is generally a gap between model predictions and plant operation in practice

The top down approach applies regression models to assess how generation has changed historically in response to changing load. Zivin *et al.* (2014) regresses generation in each interconnect (Eastern Interconnect, Western Interconnect, and ERCOT) as a function of load in each NERC region for each hour of the day. This approach has the advantages of avoiding error in estimating the portion of power generated by each plant that is not sold (e.g.: used on site) as well as regional variation in transmission losses. However, it also captures all changes in generation that co-occur with changes in load, including some non-dispatchable renewable units (wind and solar generators), which generally produce the same output regardless of demand, and some buffered renewable units (hydroelectric generators), which can make limited shifts of generation timing in response to changes in load but generally produce the same total output regardless of marginal changes in load. These factors may introduce bias to the marginal consumption emission factor estimates by attributing marginal generation to units that would not in practice change generation in response to new load.

Siler-Evans *et al.* (2012) avoid this issue by considering only fossil fuel generators as marginal generators. They regress change in emissions as a function of change in CEMS fossil generation for each hour and season in each NERC region. However, the focus on marginal generation rather than marginal consumption misses the effect of trade between regions and the different transmission losses associated with marginal load in each region, and the use of CEMS ignores generation from fossil generators smaller than 25 MW.

In summary, to properly assess the emissions implications of adding new EV charging demand in a particular region, one should estimate marginal consumption emission factors. Zivin *et al.* (2014) attempt to do this directly for each interconnect, with some potential for bias due to the effects of renewable generators, and Siler-Evans *et al.* (2012) avoid renewable generators but focus on marginal generation rather than marginal consumption, ignoring interregional trade and regional variation in transmission losses. Both estimates have potential sources of error, and we apply both to assess robustness of findings and compare to implications of prior studies using average generation emission factors.

In this chapter, I assess the regional variation in electric and conventional vehicles CO_2 emissions under a range of assumptions for regional boundaries, electricity emissions factors, and charging patterns. Other factors that may influence vehicle emissions estimates are investigated in the next chapter.

4.2 Data and Methods

In this section, I explain the assumptions and data sources for daily vehicle miles travelled, vehicles considered and relevant parameters, charging time, and electricity emission factor. Since I am performing a comparative life cycle assessment of the vehicles, I only included parts of the vehicle life cycle that differ for the vehicle types. These include vehicle upstream, parts assembly, and manufacturing; lithium-ion battery upstream and manufacturing[4]; gasoline upstream and combustion; and electricity

[4] Lead acid battery is used in all vehicle types; thus, we excluded lead-acid battery manufacture and disposal from our analysis.

upstream, generation, transmission, and distribution. I discuss here my method for estimating vehicle emissions per mile with focus on vehicle operation emissions. For other life cycle stages, I obtained emissions rate data from veritable data sources such as published works, EPA, and GREET. I summarize these data sources in Appendix V.

4.2.1 Vehicles considered and key vehicle parameters

For EVs, we focused on the Nissan Leaf (BEV) and Chevrolet Volt (PHEV) because they are the highest selling in their categories as of 2013 constituting 23% and 12% of all 2013 EV sales, respectively and they have been in the market the longest (Argonne National Laboratory 2014). Nissan Leaf also has the highest energy efficiency, at 0.29 kWh/mi, among EVs in the market (U.S. DOE 2014). I compare these with the Toyota Prius HEV, the most efficient gasoline vehicle (at 50 mpg) and highest selling HEV (~44% of 2013 HEV sales) (ANL 2014). I also compared the EVs to the sales weighted average car with fuel economy of 24.6 mpg (University of Michigan Transportation Institute 2013). Relevant vehicle parameters such as all electric range (AER) and energy use as well as battery charge acceptance rate and capacity are summarized in Appendix VI.

I assumed life cycle mileage to range from 100k to 150k miles with best estimate of 125k miles used for the base case analysis after considering estimates on battery and vehicle lifetime[5]. I used a functional unit of distance traveled (mi).

[5] Vehicle and battery lifetime depend on several factors such as use intensity, operating temperature conditions, and charging frequency [Axsen, J. et al (2008), Zhang et al (2006)].

4.2.2 Distance traveled

Daily vehicles miles travelled (DVMT) were obtained from the National Household Travel Survey (NHTS) 2009 data set (NHTS 2009). These data were obtained through a sample of 26,000 households throughout the U.S. who were surveyed between March 2008 and May 2009. I extracted the DVMTs for over 76,800 automobile entries[6]. We show an empirical cumulative probability distribution (ECDF) of this Figure 8 and the AERs of the electric vehicles considered. The NHTS DVMT data set has an average of 34.5 mi with a 5th and 95th percentile of 2.6 mi and 104 mi, respectively. As shown, about 93% of the data have DVMT less than or equal to the Nissan Leaf AER (~ 84 mi).

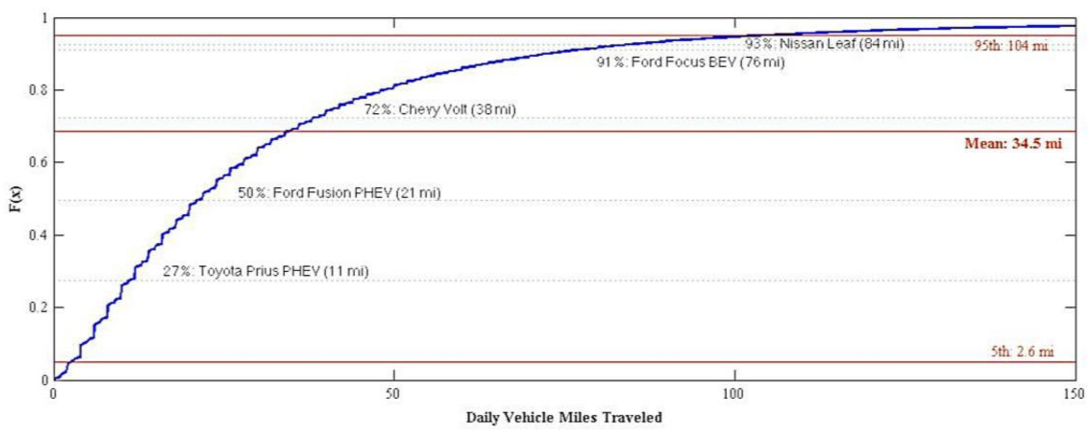


Figure 11. Empirical cumulative distribution function of DVMT by US automobiles

4.2.3 Vehicle emissions per mile

The average use-phase CO_2 emissions per vehicle mile traveled, $E[\Upsilon_{jrv}]$, (g CO_2 per mile) of vehicle type v using emissions factors set j in region r is computed as:

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[6] Part of NHTS 2009 used in this study was initially processed by Traut et al (2013) using data from U.S. Department of Transportation (2011).

$$E\left[\widehat{\Upsilon}_{jrv}\right] = \frac{\sum_i \left[d_{iv}^{\mathrm{ELEC}} \widehat{\Phi}_{ijrv}^{\mathrm{ELEC}} q_v^{\mathrm{ELEC}} + \left(d_i - d_{iv}^{\mathrm{ELEC}}\right) \frac{\widehat{\Phi}^{\mathrm{GAS}}}{q_v^{\mathrm{GAS}}}\right]}{\sum_i d_i}$$

$\widehat{\Phi}_{ijrv}^{\mathrm{ELEC}}$ is the hourly weighted electricity emissions factor for vehicle entry i under vehicle type v using an electricity emissions factor j in region r, $\widehat{\Phi}^{\mathrm{GAS}}$ is the emissions factor for gasoline, d_i is the distance traveled by vehicle entry i, d_{iv}^{ELEC} is the distance that vehicle entry i under vehicle type v travels using electric power, q_v^{ELEC} is the energy use of vehicle v when driving on electricity (kWh/mi), q_v^{GAS} is the fuel economy of vehicle v when driving on gasoline (miles per gallon), and d_i^{REC} is the reciprocal of d_i. For gasoline vehicles, $d_{iv}^{\mathrm{ELEC}} = 0 \; \forall \; v$.

Miles traveled on electricity, d_{iv}^{ELEC}, for vehicle entry i of vehicle type v, are given by the following equations:

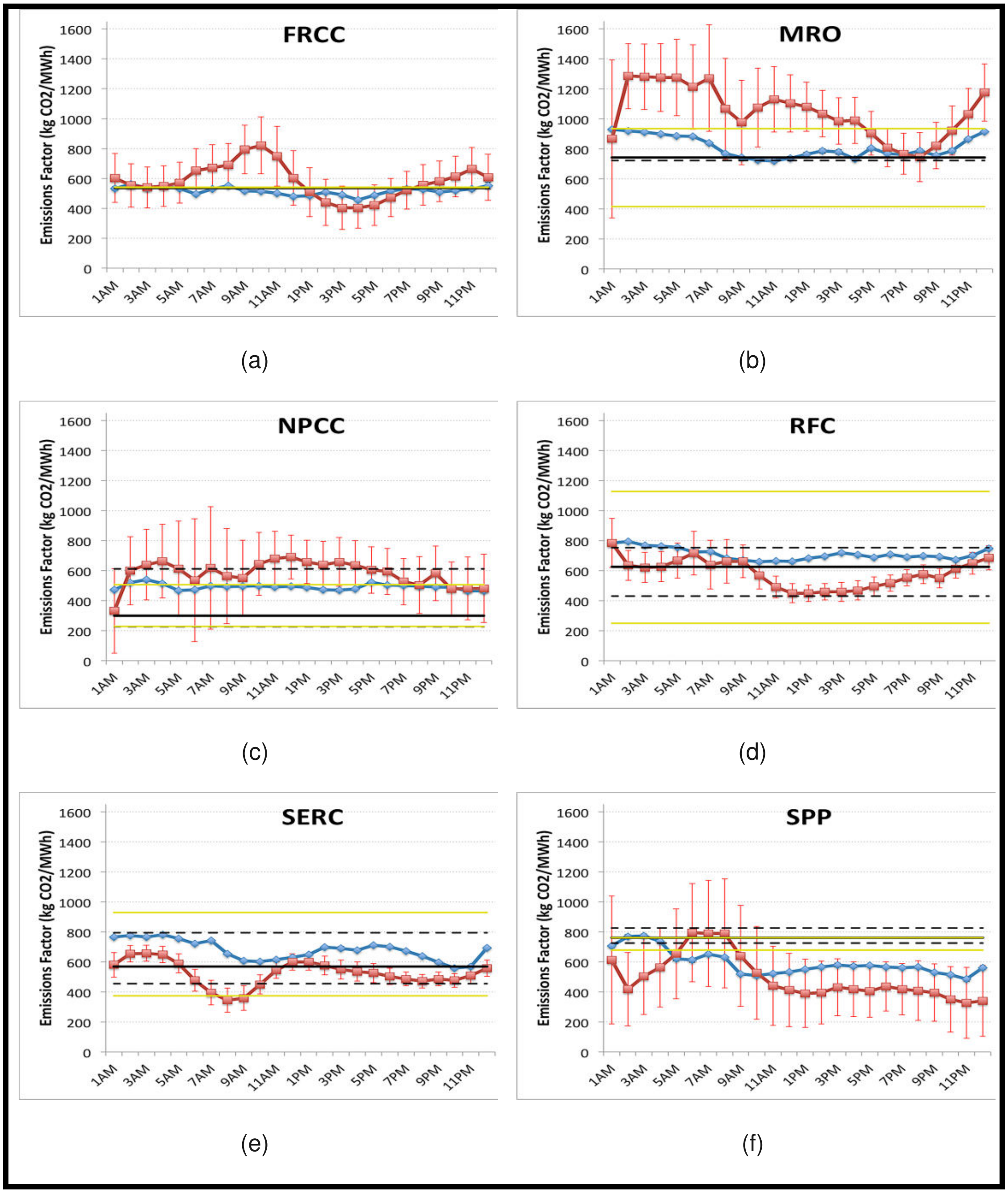
$$d_{iv}^{\mathrm{ELEC}} = \begin{cases} d_i \geq d_v^{\mathrm{AER}} & d_v^{\mathrm{AER}} \\ d_i < d_v^{\mathrm{AER}} & d_i \end{cases}$$

$\mathrm{d_v^{AER}}$ is the AER for vehicle type v and $\mathrm{d_i}$ is the DVMT for vehicle entry i.

4.2.4 Electricity emission factors

I use several of emissions factors for electricity, and discuss how these assumptions affect our results. These are: 1) hourly consumption-based MEFs from Zivin, *et al.* (2014); 2) hourly generation-based marginal emissions factors (MEF) from Siler-Evans, *et al.* (2012); 3) 2009 NERC regional average emissions factors (AEF); 4) 2009 eGRID sub-region average emissions factors; and 5) 2009 state average emissions factors. All AEFs were obtained from eGRID (2011), and aggregated at the needed regional boundary levels.

A comparison of the electricity emission factors by time of day and for each NERC region is shown in Appendix VII. Table 2 highlights key differences in the different emissions factors used.



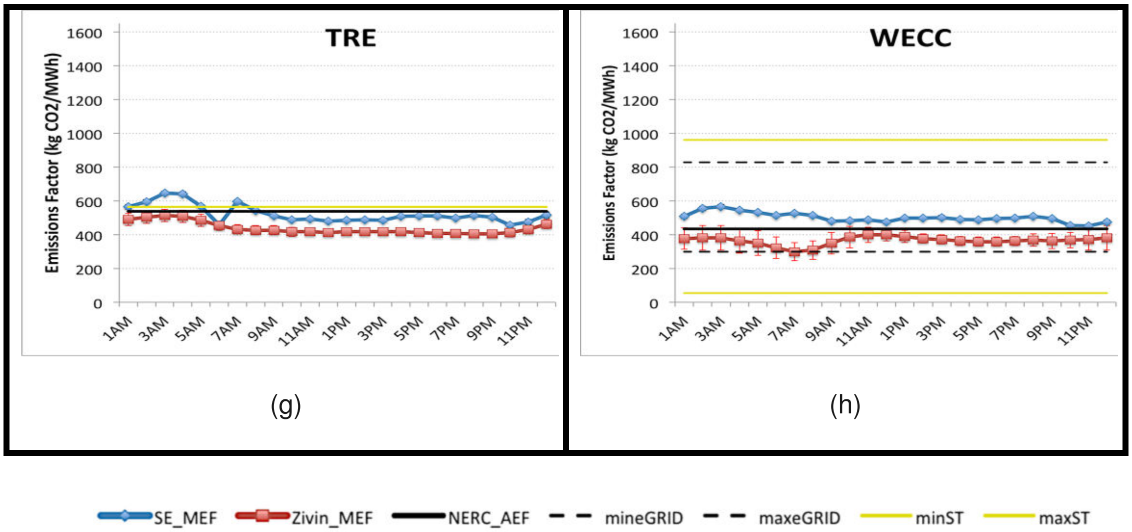


Figure 12. Hourly Consumption-based (Zivin_MEF) and generation-based (SE_MEF) marginal emission factors by NERC region. Lines show minimum and maximum eGRID subregion and state average emission factors (mineGRID, minST, maxeGRID, and maxST) in each NERC region as indicated by chart headings (e.g., Western Electricity Coordinating Council (WECC)). Error bars shw 95% confidence intervals of hourly MEFs.

Table 6. Electricity emission factors considered in the analysis

	MEF from Zivin, et al. (2014)	**MEF from Siler-Evans, et al. (2012)**	**2009 AEF (NERC)**	**2009 AEF (eGRID Subregion)**	**2009 AEF (State)**
Region:	NERC regions	NERC regions	NERC regions	eGRID Subregions	State
Consumption/ generation based emissions:	Consumption	Generation	Generation	Generation	Generation
Marginal or average emissions factors for electricity:	Marginal	Marginal	Average	Average	Average

In most cases, MEFs are lower than AEFs during peak load times, where natural gas is often the fuel used at the margin (Siler-Evans *et al.* (2012)). Also, hourly estimates for the consumption-based MEFs (Zivin, et al. 2014) vary more by hour and have wider uncertainty ranges, especially for the regions within the eastern interconnect, than the generation-based MEFs (Siler-Evans *et al.* 2012). This is presumably due to flow between regions but could also be biased by operation of renewable plants.

Discrepancies between generation- and consumption-based MEF values are least in the WECC and TRE regions where trading with other regions is limited. It is contentious that MRO consumption-based values are much higher than generation-based values (by up to 66%) when MRO is a net importer from regions that are less carbon-intensive. A potential explanation is that majority of the energy that MRO imports is supplied by coal power plants in neighboring regions (Zivin *et al* 2014).

Using the MEFs, I computed the hourly weighted MEFs (WEF) for both convenience and delayed charging. The WEF takes into account the time of the day and the duration that an EV is charged. To determine the WEFs, $\Phi_{ijrv}^{\mathrm{ELEC}}$, we performed a Monte Carlo simulation (N=10,000) using the following formula and the marginal emission factor distribution summarized in Appendix VII,

$$\hat{\Phi}_{ijrv}^{\mathrm{ELEC}} = \frac{\sum_t h_{tiv}^{\mathrm{CONVENIENCE}} \hat{\Phi}_{tjr}^{\mathrm{ELEC}}}{t_{iv}}$$

where $h_{tiv}^{\mathrm{CONVENIENCE}}$ is the fraction of hour t that vehicle entry i of vehicle type v charges; $\hat{\Phi}_{tjr}^{\mathrm{ELEC}}$ is the MEF for hour t, region r, using MEF set j; and t_{iv} is the total charge time for vehicle entry i under vehicle type v.

Both sets of MEFs only included emissions during power plant operation. To compute upstream emissions, I extrapolated hourly marginal grid mix from Siler-Evans 2012 and used emissions rate from GREET 2013 and NETL (2013). Note that marginal grid mix was not available for consumption-based MEFs; thus, I estimate upstream emissions using generation-based marginal grid mix. Details of this computation are provided in Appendix VIII.

4.2.5 Charging schemes and charge times

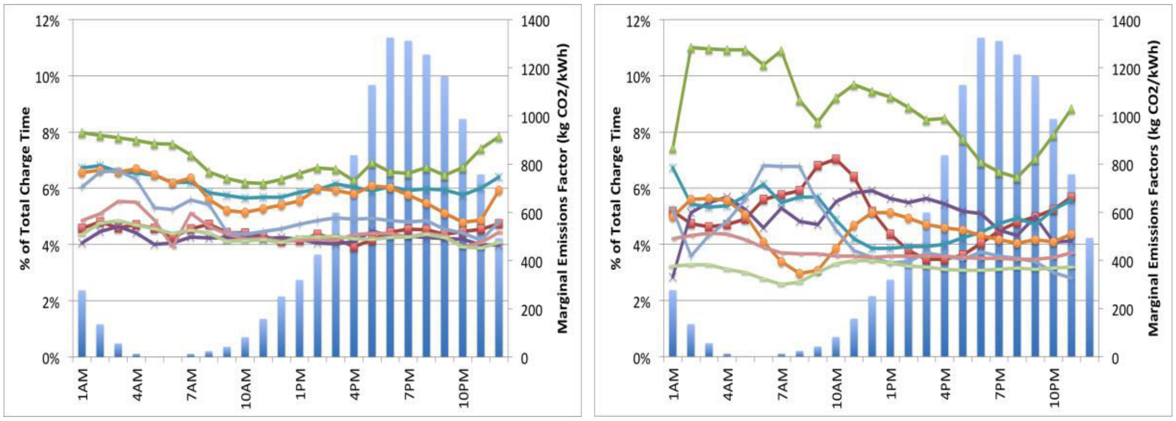
I consider two charging schemes - convenience and delayed charging. Under convenience charging scheme, we assume that vehicles start to be charged upon arrival to the home. I obtained data on arrival time for each vehicle entry from NHTS (2009). For the delayed charging scenario, I assume that the vehicles start charging at 12am.

The vehicle charge time, t_{iv}, for vehicle type v if it were to travel the same miles as vehicle entry i, is given by:

$$t_{iv} = \begin{cases} d_i \geq d_v^{\text{AER}} & t_v^{\text{CHARGE}} \\ d_i < d_v^{\text{AER}} & \dfrac{d_i}{d_v^{\text{AER}}} * t_v^{\text{CHARGE}} \end{cases}$$

t_v^{CHARGE} is the time it takes to fully re-charge vehicle type v, assuming combined (45% city, 55% highway) vehicle fuel efficiency (DOE 2014).

The national distribution of charging times under the convenience charging scheme assumption and the corresponding hourly MEFs are shown in Figure 10. The left y-axis shows the percentage of charge time that occurs within each hour, as indicated on the x-axis. The right y-axis shows the MEFs in kg CO_2/kWh. Under the convenience charging scenario, most of the charging (~80%) would occur within the period of 4:00PM to 11:00PM.



5a) Siler-Evans et al. (2012)

5b) Zivin et al. (2014)

Figure 13. Charge Time Distributions and Hourly Marginal Emissions Factors. Lines correspond to NERC regions while blue bar shows % of total charge time per hour.

4.2.6 Monte carlo simulation and statistical analyses on vehicle emissions estimates

I ran a monte carlo simulation (N=10,000) to estimate the vehicle emissions under different MEF estimation methodologies, charging scheme, marginal *vs* average, and regional boundary definitions. I summarize these scenarios in Table 7.

Table 7. Summary of scenarios considered.

	MEF versus **AEF** for electricity	**Consumption *versus* Generation**	**Region**	**Charging Scheme**
1	MEF	Consumption	NERC	Convenience
2	MEF	Consumption	NERC	Delayed
3	MEF	Generation	NERC	Convenience
4	MEF	Generation	NERC	Delayed
5	AEF	Generation	NERC	NA
6	AEF	Generation	eGRID	NA
7	AEF	Generation	State	NA

After estimating the vehicle emissions under the seven scenarios described above, I performed statistical comparisons of the vehicle emissions estimates to test whether the results are significantly different at 5% significance levels. I summarize the hypotheses and the corresponding tests in Table 8.

Table 8. Statistical comparison of vehicle emissions estimates

	Null Hypothesis	Alternative Hypothesis	Test
1a	Convenience - Delayed = 0 (Consumption-based marginal emissions estimates)	Convenience – Delayed < 0; Convenience – Delayed > 0	Paired one-tailed t-test
1b	Convenience – Delayed = 0 (Generation-based marginal emissions estimates)	Convenience – Delayed < 0; Convenience – Delayed > 0	Paired one-tailed t-test
2a	Consumption-based Generation -based = 0 (Convenience charging)	Consumption-based - Generation-based ≠ 0	Paired two-tailed t-test
2b	Consumption-based – Generation -based = 0 (Delayed charging)	Consumption-based - Generation-based ≠ 0	Paired two-tailed t-test
3a-d	NERC Average Emissions Estimates = Marginal Emissions Estimates (Generation- and consumption-based for both delayed and convenience charging)	NERC Average ≠ Generation-based	One-sample two-tailed t-test
4a-d	eGRID Average Emissions Estimates = Marginal Emissions Estimates (Generation- and consumption-based for both delayed and convenience charging)	eGRID Average ≠ Generation-based	One-sample two-tailed t-test
5a-d	State Average Emissions Estimates = Marginal Emissions Estimates (Generation- and consumption-based for both delayed and convenience charging)	State Average ≠ Generation-based	One-sample two-tailed t-test

4.3 Results and Discussion

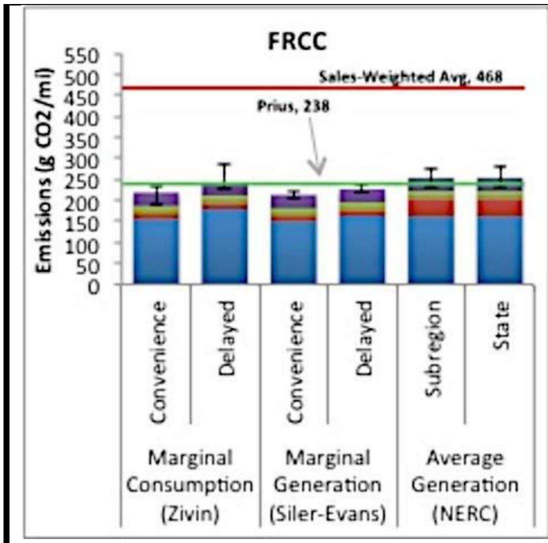
Marginal life cycle emissions estimates, as summarized in Table 9, indicate significant variation in EV emissions by region. For example, Nissan Leaf average life cycle emissions range from 171 – 213 g CO_2/mi in WECC to 298 – 400 g CO_2/mi in MRO.

Table 9. Summary of Nissan Leaf marginal life cycle emission estimate statistics (normally distributed with mean and standard deviation, N=10,000) by region and estimation method

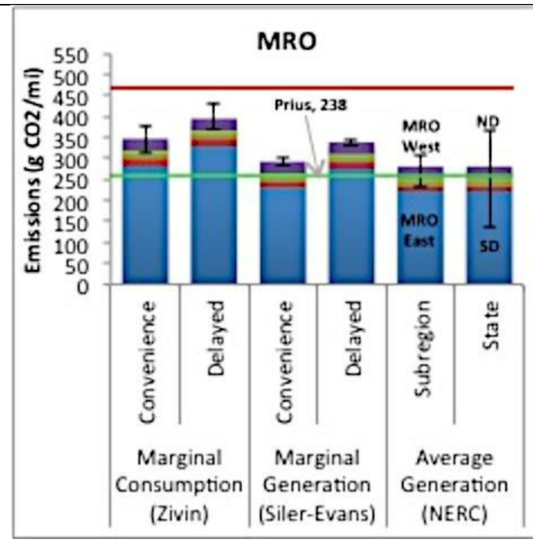
Region	Consumption, Convenience	Consumption, Delayed	Generation, Convenience	Generation, Delayed
FRCC	220 (42)	244 (24)	214 (16)	228 (13)
MRO	352 (45)	400 (49)	298 (18)	344 (13)
NPCC	245 (31)	200 (37)	210 (15)	206 (13)
RFC	219 (25)	278 (21)	274 (16)	297 (13)
SERC	218 (21)	238 (16)	264 (19)	285 (15)
SPP	188 (37)	196 (46)	230 (16)	257 (22)
TRE	185 (13)	205 (14)	212 (15)	228 (15)
WECC	171 (14)	174 (15)	210 (14)	213 (14)

Comparison results to the lowest emitting gasoline vehicle, Toyota Prius HEV, and sales-weighted average ICEV, thus, vary by region.

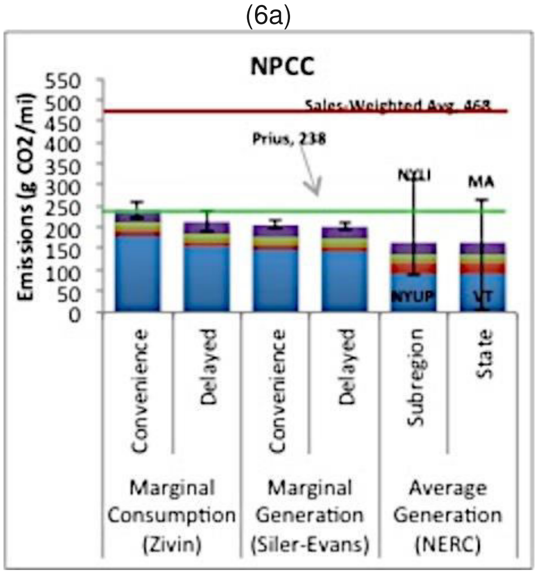
For each NERC region, Figures 6a to 6h show the life cycle emissions estimates for the Nissan Leaf CO_2 emissions per mile traveled, under different scenarios (colored bars) compared to that of Toyota Prius HEV (green line, 238 g CO_2/mi) and sales-weighted average ICEV (red line, 468 g CO_2/mi). The bars represent the mean Leaf life cycle emissions for different estimation methods and charging times. The marginal emission estimate error bars show the 25th and 75th percentiles reflecting the uncertainty in MEF values, battery emission rates, vehicle, and fuel upstream emissions. Average emission bars show average Leaf emissions by NERC region while error bars for subgerion and state correspond to lowest and highest eGRID subregion and state Leaf emissions estimate for each NERC region.


FRCC
Emissions (g CO2/mi)
550
500
450
400
350
300
250
200
150
100
50
0
Sales-Weighted Avg, 468
Prius, 238
Convenience
Delayed
Convenience
Delayed
Subregion
State
Marginal Consumption (Zivin)
Marginal Generation (Siler-Evans)
Average Generation (NERC)

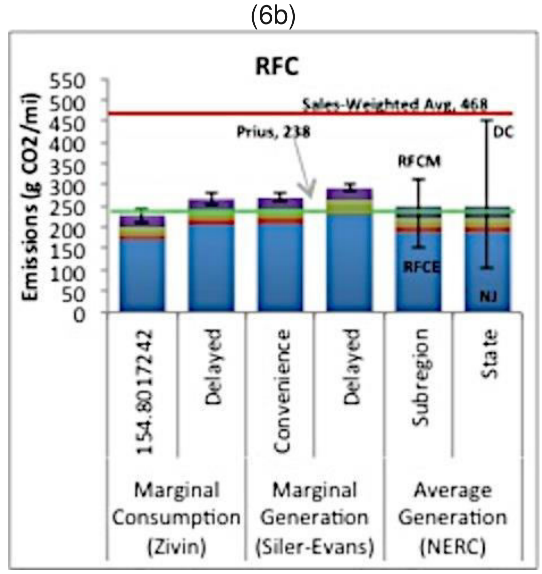
(6a)


MRO
Emissions (g CO2/mi)
550
500
450
400
350
300
250
200
150
100
50
0
Prius, 238
MRO West
ND
MRO East
SD
Convenience
Delayed
Convenience
Delayed
Subregion
State
Marginal Consumption (Zivin)
Marginal Generation (Siler-Evans)
Average Generation (NERC)

(6b)


NPCC
Emissions (g CO2/mi)
550
500
450
400
350
300
250
200
150
100
50
0
Sales-Weighted Avg, 468
Prius, 238
NYLI
MA
NYUP
VT
Convenience
Delayed
Convenience
Delayed
Subregion
State
Marginal Consumption (Zivin)
Marginal Generation (Siler-Evans)
Average Generation (NERC)

(6c)


RFC
Emissions (g CO2/mi)
550
500
450
400
350
300
250
200
150
100
50
0
Sales-Weighted Avg, 468
Prius, 238
RFCM
DC
RFCE
NJ
154.8017242
Delayed
Convenience
Delayed
Subregion
State
Marginal Consumption (Zivin)
Marginal Generation (Siler-Evans)
Average Generation (NERC)

(6d)

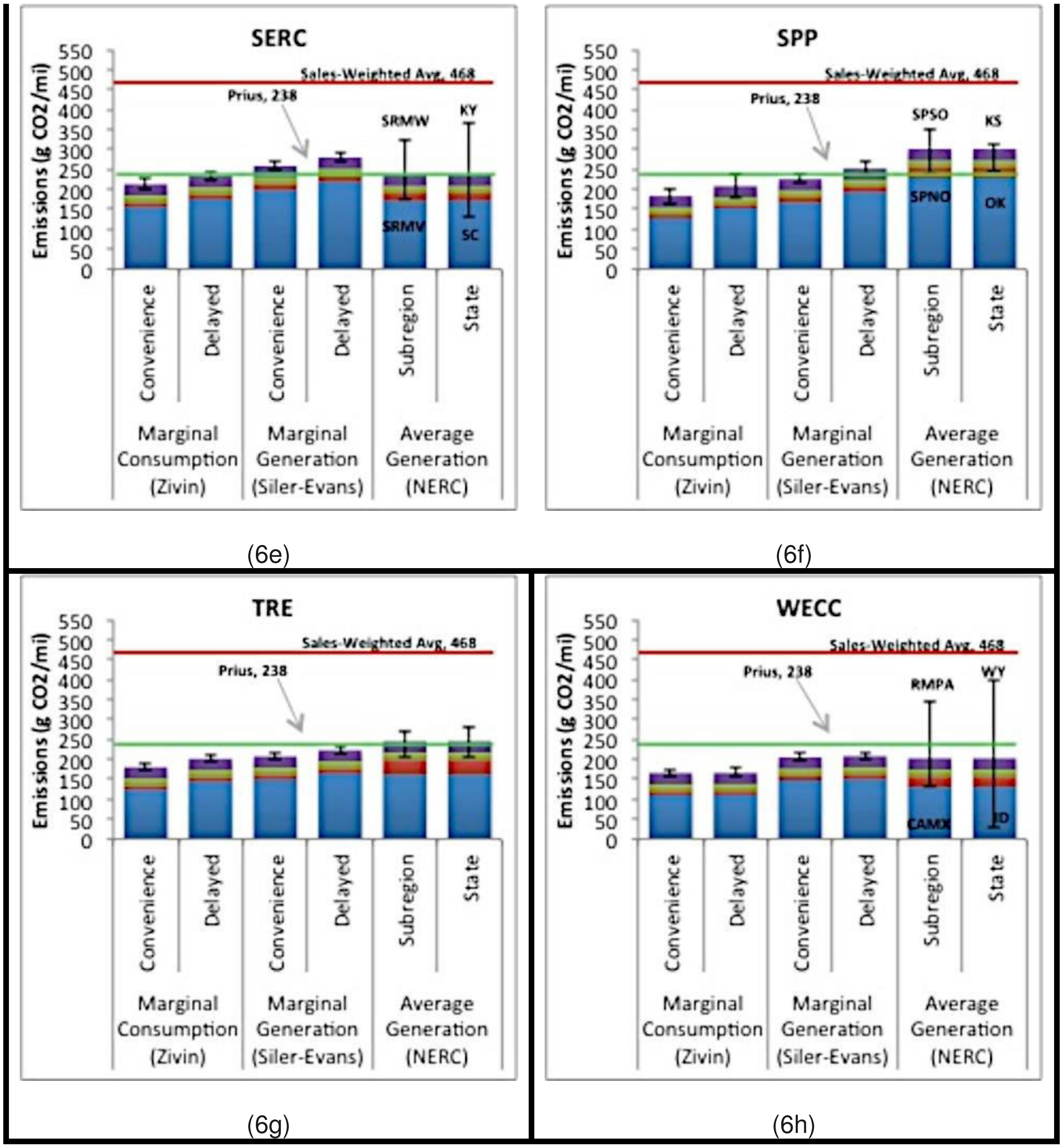


Figure 6. Nissan Leaf life cycle emissions (g CO_2/mile) using alternative grid emission factors. Life cycle stages covered include: Electricity production (blue); Electricity upstream (red); Vehicle assembly & mnfg. (green); and Battery upstream & production (violet). Error bars for marginal emissions show the 25th and 75th percentile values. Probability density plots for marginal emissions estimates are shown in Appendix IX. Average generation bar heights show NERC region average emissions estimates while subregion and state error bars show lowest and highest eGRID subregion and state emissions estimates for each NERC region. Green and red horizontal lines show average Toyota Prius Hybrid and Sales-weighted average emissions estimates. Combined driving pattern (45% city and 55% highway) energy use from EPA 2014 was used for all vehicles. Values used to generate these graphs are shown in Appendix X.

After performing t-tests to determine whether there is significant difference between electric and gasoline vehicles, I found that emissions estimates between vehicles are significantly different in all cases but results under different estimation methods lend comparisons inconclusive in some regions (i.e., FRCC under delayed charging, NPCC under convenience charging, RFC under convenience charging, SERC under both charging conditions, and SPP under delayed charging). I consider results to be inconclusive when consumption- and generation-based marginal emissions under the same charging scheme do not lead to the same conclusion. For example, in the FRCC region, consumption-based delayed charging emissions estimate indicate that Leaf is higher emitting than the Prius Hybrid by 3%, on average, but generation-based delayed charging emissions estimates indicate that the Leaf is lower emitting by 4%, on average. Table 10 summarizes the results for Nissan Leaf comparisons with the Toyota Prius Hybrid and the sales-weighted ICEV. Values indicate percentage differences in mean emissions estimates while colors indicate which vehicle was found to be lower emitting – green for Leaf and red for gasoline vehicle. Statistical results for both consumption-and generation-based emissions estimates indicate that the Nissan Leaf is lower emitting than both the Prius Hybrid and sales-weighted average ICEV in Texas (TRE, 4% – 22%) and western states (WECC, 10% - 28%). On the other hand, t-tests indicate that the Leaf is higher emitting than the Prius Hybrid under both convenience and delayed charging in northern central states (MRO, 25% - 68%), on average.

Table 10. Summary of average percentage emissions difference by region and estimation method computed as vehicle emissions difference divided by gasoline vehicle emissions. Green indicates that the Nissan Leaf is lower emitting while red means that the gasoline vehicle (Toyota Prius Hybrid or sales-weighted ICEV) is lower emitting. All comparisons are significant at 5% significance level.

NERC Region	Nissan Leaf vs. Toyota Prius Hybrid				Nissan Leaf vs. Avg. ICEV			
	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del
FRCC	8%	3%	10%	4%	53%	48%	54%	51%
MRO	48%	68%	25%	44%	25%	15%	36%	27%
NPCC	3%	16%	12%	13%	48%	57%	55%	56%
RFC	8%	17%	15%	25%	53%	41%	41%	37%

SERC	8%	0%	11%	20%	53%	49%	44%	39%
SPP	21%	18%	3%	8%	60%	58%	51%	45%
TRE	22%	14%	11%	4%	60%	56%	55%	51%
WECC	28%	27%	12%	10%	64%	63%	55%	55%

The t-tests summarized in Table 8 were performed to determine whether there is significant difference between results under different vehicle estimation methods. Test results for the Nissan Leaf are summarized in Appendix XI. Nissan Leaf comparisons were all found to be significantly different at 5% significance level, providing evidence for the following claims:

1) Delayed charging (12am until vehicle is fully recharged) results in higher electric vehicle emissions except in the northeast (NPCC region) where the opposite is true;
2) Generation- and consumption-based marginal emissions estimates are significantly different indicating the importance of considering electricity trading between regions in emissions factor emission estimates
3) Marginal and average emissions estimates result in significantly different vehicle emissions estimates indicating the importance of considering temporal and spatial variation in electricity emissions as influenced by fluctuations in electricity demand; and
4) Average emissions estimates differ significantly for different regional boundaries providing additional evidence for the importance of regional boundary definition even without considering temporal variation in electricity emissions.

Convenience vs Delayed Charging. Results show that conclusions may vary depending on the charging scheme. Under convenience charging, most charging occurs during peak system load times within which more expensive but cleaner energy sources are on the margin. With the exception of NPCC, delayed charging (starting 12am until vehicle is fully charged) results in higher emissions ranging from 6% - 15% for generation-based and 2% - 28% for consumption-based emissions. In the NPCC delayed charging results in lower emissions by up to 2% - 19%. In 2009, NPCC was composed of about 48% nuclear and hydro power (NPCC 2009, NPCC 2010). These sources have lower operating costs, thus, are used for base load. As a result, the more carbon-intensive energy sources is increased during peak hours, making convenience charging emissions higher in this region.

Consumption- vs Generation-Based MEFs. I found significant difference in the emissions estimates under consumption- and generation-based MEFs. Consumption-based MEFs yield higher Leaf emissions in the FRCC (3% -7 %) and MRO (14% - 16%) while lower in other regions with percentage difference ranging from 3% – 31% (consumption-based values were used as denominator). Estimates under two MEF sets are different enough to result in contradicting results as discussed above.

Marginal vs Average emissions. Marginal and average emissions estimates differ significantly. Marginal estimates are higher in the MRO (7-34%) and NPCC (39-46%) regions while always lower in SPP (11-87%). In other regions, marginal emissions may be as much as 24% higher (SERC) or 28% lower (TRE), depending on assumptions for charging scheme and marginal emission factor method estimation. These results provide evidence to the claim that the difference between marginal and average emissions is substantial and the magnitude and direction of difference vary across regions, but marginal emissions are also uncertain. EPRI (2007), which also used marginal emissions rates, found that PHEVs are lower emitting than the average HEV by 7-46% and the average ICEV by 40-65% depending on assumed market penetration and grid carbon intensity. EPRI 2007, however, did not provide a discussion of regional emissions variation. Anair & Mahmassani 2013 who estimated average Leaf emissions by eGRID subregion[7], suggest that the Leaf is lower emitting in NPCC and eGRID subregions in SERC whereas I find that results in these regions are uncertain at best.

Regional boundary definition. I also find that average emissions estimates are sensitive to regional boundary definitions, similar to Weber *et al* (2010). For example, state-based Leaf emissions in WECC vary from 16 to 288 kg CO_2/mi for Idaho and Wyoming, respectively, compared to NERC AEF estimates of 130 kg CO2/mi. Similarly, estimates using eGRID subregion AEFs vary significantly from NERC regional AEF estimates. Using the former, Leaf emissions range from 90 to 248 kg CO_2/mi in CAMX and RMPA, respectively. This is a key reason why conclusions from existing locational comparisons of EVs and CVs vary significantly. Yawitz et al 2014, using 2010 state EFs, conclude that the Leaf is better than the Prius in 14 states while Anair & Mahmassani 2013, which used eGRID subregion 2009 emissions rates, declared Prius to be lower emitting in more but sometimes different states. Yawitz et al 2014 indicate that the Leaf is lower emitting in SD while I find the opposite since SD is serviced by the MRO region.

I found the Chevrolet Volt is higher emitting in northern Midwest and FL and uncertain to reduce emissions in other regions. Compared to the sales-weighted average ICEV[8] the Volt can reduce emissions, on average by 27% (MRO) to 50% (WECC). This is comparable to estimates by Samaras & Meisterling (2008) of 38% - 41%. Results from Zivin et al 2014 indicate that the Volt is conclusively lower emitting than the average car and comparable economy car (at 31 mpg) in all regions except in MRO and only lower than the Prius Hybrid in the WECC region. These results do not include other life cycle

[7] eGRID subregions are subsets of NERC regions (EPA 2014). List of eGRID subregions under each region are provided in Appendix 4.
[8] We used fuel economy of 24.6 mpg for the sales-weighted average light duty vehicles which was computed including cars, SUVs, vans, and pickup trucks (University of Michigan Transportation Institute 2014).

stages that are shown in this work to be significant and only compare consumption-based marginal estimates to Toyota Prius Hybrid operation emissions point estimate. Further, I find that the Toyota Prius PHEV is lower emitting than the Prius Hybrid in FL, TX, and northeastern and western states. The Prius PHEV is higher emitting in northern Midwest and unclear to reduce emissions in the rest of the country. Summaries of the comparison results for the Chevrolet Volt and Toyota Prius PHEV versus the Prius Hybrid and sales-weighted average ICEV are provided in Appendix XI. All comparison results were significant at 1% significance level.

Vehicle operation constitutes the largest part of life cycle emissions for all vehicles as shown in Figure 14. Lithium-ion battery production emissions is significant for EVs, constituting 6% – 21% of total life cycle. Electricity upstream and vehicle assembly and manufacturing emissions have similar magnitudes. Electricity related emissions for electric vehicles, thus, constitutes at least 75% of EV emissions. These numbers are comparable to past estimates (Samaras & Meisterling 2008, Michalek et al 2011, Hawkins et al (2013)).

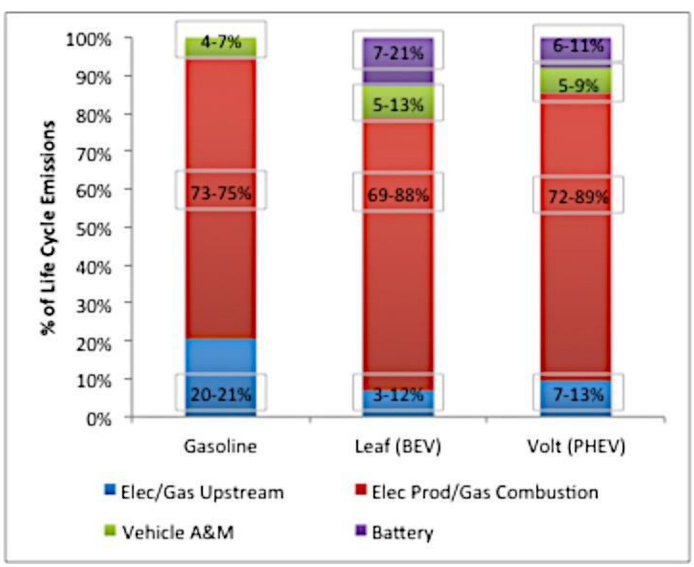


Figure 14. Life cycle emissions by vehicle type using marginal emission factors for Evs.

4.3.1 *Summary of Results: EV vs gasoline vehicle comparison under regional varied and uncertain electricity emission factors*

In summary, I found that the emissions reduction potential of EVs is location-dependent because of the regional differences in electricity emission rates due to grid mix variation. I also found that for the same geographic location, emissions estimates may vary under different EF assumptions – regional boundary, MEF estimation method, charging scheme. Consumption-based estimates are higher in the north-eastern and north-central U.S. and lower in the rest of the country. Emissions using delayed charging (starting midnight) are higher due to more carbon-intensive marginal grid mix during non-peak hours.

The uncertainty in emissions estimates can lend comparison of electric and gasoline vehicle inconclusive in some areas. Considering the life cycle emissions, statistical tests indicate that the Nissan Leaf is lower emitting than the Toyota Prius Hyrbid in TX, CA, and other western states within the WECC region while the opposite is true in northern Midwest states. In other regions, comparisons are inconclusive. Both the Chevrolet Volt and the Prius PHEV were also found to be significantly higher emitting than the Prius Hybrid in the northern Midwest. Results also indicate that the Prius PHEV is lower emitting than the Prius Hyrbid in most areas in the U.S..

5 Sensitivity of Electric Vehicle CO2 Reduction to Urbanization

5.1 Introduction

Studies mentioned in the previous chapter comparing emissions of electric and gasoline vehicles show different results as to the carbon reduction potential of electric vehicles. These studies have differing assumptions on important factors such as electricity grid mix, driving pattern, vehicle miles traveled, and charging time. In agreement with previous studies, I have showed in the previous chapter that the variation in emissions estimates due to differing electricity grid mix in the U.S. results in regionally different results and that uncertainty in electricity emission rates within in each region may lend unclear conclusions on the EV and gasoline vehicle comparison. I kept driving pattern and DVMT distribution uniform across the country. In reality, this is likely not the applicable.

In this chapter, I factor in locational variation in driving pattern and DVMT distribution across the U.S. to computation of both EV and gasoline vehicle emissions estimates and determine how this changes conclusions on vehicle comparisons. I relate the variation of these two parameters to geographic type (i.e., level of urbanization). In the next chapter, I will tie the results from this chapter to findings in chapter 1 as a basis for policy recommendations.

Emissions comparisons also differ depending on driving patterns, with PHEVs in urban driving conditions potentially reducing emissions by up to 60% relative to gasoline vehicles while resulting in marginal reductions in rural driving conditions [Karabasoglu and Michalek 2013]. However, most studies use data at the national scale and assume a uniform driving pattern and DVMT distribution. Elgowainy et al 2009 performed a analysis for both UDDS and HWFET[9] driving patterns while others conduct sensitivity analysis but usually on electricity intensity (e.g., low, average, and high carbon electricity) [Michalek et al. (2011), Samaras, et al. (2008)]. Using data at the national scale may mask important insights that could be obtained at finer geographic scales where there is enough policy control for further development and adoption of electric vehicles. A summary of important assumptions and data used in previous studies as well as the intended contribution of this chapter is provided in Table 8.

I perform a locational comparison of electric and gasoline vehicle life cycle emissions in the U.S. at the county level, taking into consideration the combined effect of locational variation of electricity emission factors, driving pattern (city, highway or combined), vehicle miles traveled (VMT), and charging time.

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[9] *UDDS = Urban Dynamometer Driving Schedule; and HWFET = Highway Fuel Economy Test; FUDS = Federal Urban Driving Schedule. The U.S. DOE 2013 defines City Driving as "…urban driving, in which a vehicle is started with the engine cold and driven in stop-and-go rush hour traffic." and Highway Driving as "… a mixture of rural and Interstate highway driving with a warmed-up engine, typical of longer trips in free-flowing traffic."*

Table 8. Literature Review Summary on Electric Vehicle Emissions Reduction Benefits

Work	Geographic Scale of Comparison	Electricity Emission Factors	VMT	Miles Traveled on Electricity	Driving Pattern	Life Cycle Scope
Yawitz et al 2013,	State	State Emissions Factors (Generation-based)	50, 000 miles and 100, 000 miles	50%	EPA 2013	Vehicle Manufacturing and Use
Michalek et al 2011,	National	U.S. Average weighted by power plant output and 5th, 50th, and 95th percentile by power plant damage intensity	National distribution based on NHTS 2001 Data	National Average computed from NHTS 2001	UDDS	**Vehicle and Battery Upstream, Manufacturing, and Use**
Siosanshi & Denholm 2009,	National	Input Emission Rates for Texas	Not specified	Not Specified	Not specified	Vehicle Use (WTW)
Elgowainy et al 2009,	Regional and U.S. Average	Generation per Region and U.S. Average	National distribution based on NHTS 2001 Data	Utility Factors based on NPTS 1999	**UDDS and HWFET**	Vehicle Use (WTW)
Samaras & Meisterling 2008,	National	3 Cases: U.S. Ave (670 g CO2e/kWh) Carbon-intensive (950 g CO2e/kWh) Low-carbon (200 g	National distribution based on NHTS 2001 Data	47% to 76% (based on NHTS 2001)	FUDS	Vehicle Upstream, Manufacturing, and Use

		CO2e/kWh)				
EPRI 2007,	**NERC regions**	**NERC Marginal Emission Factors**	12,000 mi/yr	Utility Factors based on NPTS 1999	FUDS	Vehicle Use (WTW)
Parks et al 2007,	Colorado	Generation in Colorado	St. Louis GPS-based data; ~ 38 mi/day and 13, 700 mi/yr on average	39% to 52% depending on charging scenario	GPS-based data	Vehicle Use (WTW)
Matsuhasi et al 2000	Tokyo	Not Specified	10, 000 km/yr	Not specified	10 Tokyo driving modes (different average velocities) and 1 at constant velocity (40 km/h)	Vehicle Upstream, Manufacturing, and Use
This Work	***County***	***Hourly-weighted consumption-based marginal emission factors by NERC regions under both convenience and delayed charging schemes***	***DVMT distribution by state and urbanization level extracted from NHTS 2009 data***	***Computed by state, urbanization level and EV type using NHTS 2009***	***One of three driving patterns – city, combined, and highway – related to county urbanization level***	***Vehicle Assembly and Manufacturing, Battery Upstream and Manufacturing, Gasoline upstream and combustion, Electricity Upstream and Production***

5.2 Materials and Methods

In the previous chapter, I focused on the Nissan Leaf and Chevrolet Volt. In this chapter, I include the Toyota Prius PHEV and Ford Fusion Energi, both of which are top-selling PHEVs as shown in Chapter 1, Figure 5. These vehicles are included to represent PHEVs with lower AERS. I compare these four EVs to gasoline vehicles in the market that have similar body, size, and aerodynamics. Vehicle buyers may not necessarily have vehicle choices that are comparable in the same way and the vehicle options may not be limited to light-duty vehicles. However, I think that the assumption that vehicle buyers first pick a vehicle type (e.g., light-duty) and then choose comparable vehicle models is reasonable. Consumer choice modeling is another research area on its own and is beyond the scope of this research. Moreover, I also compare the dominant EVs and Prius HEV, the most efficient gasoline vehicle and top-selling HEV in the market today.

Table 9. EV and gasoline vehicles compared

Electric Powered	Gasoline Powered
Toyota Prius (PHEV10)	Toyota Prius (HEV)
Ford Fusion Energi (PHEV20)	Ford Fusion FWD (HEV)
Chevy Volt (PHEV40)	Chevy Cruze Eco (CV)
Nissan Leaf (BEV73)	Nissan Versa (CV)

As in the previous chapter, I estimated life cycle emissions with a functional unit of g CO_2 per mile traveled. I included emissions from vehicle upstream, assembly and manufacturing (VAM), battery upstream and manufacturing, gasoline upstream and combustion, and electricity upstream and production. I excluded emissions related to lead acid battery since it is present in all vehicle types. I assumed a life cycle mileage to range from 100k to 150k mi with best estimate of 125k mi used for the base case analysis. These values are comparable to those assumed in existing studies mentioned above.

To compute the average life cycle GHG emissions per vehicle mile traveled, $\bar{\gamma}_{cv}$, of vehicle type v in county c, I used the following equation

$$\overline{\gamma_{cv}} = u_{cv}\hat{\phi}_{civ}^{\text{ELEC}} q_{cv}^{\text{ELEC}} + (1 - u_{cv})\frac{\hat{\phi}^{\text{GAS}}}{q_{cv}^{\text{GAS}}}$$

where u_{cv} is the utility factor for vehicle v in county c, $\hat{\phi}_{civ}^{\text{ELEC}}$ is the hourly-weighted electricity emissions factor for vehicle entry i of vehicle type v in county c, q_{cv}^{ELEC} is the electricity use (kWh/mi) of vehicle v when driving in county c, $\hat{\phi}^{\text{GAS}}$ is the emissions factor for gasoline, and q_{cv}^{GAS} is the fuel economy of vehicle v in county c. The utility factor u_{cv} is computed as $\frac{\sum_i d_{civ}^{\text{ELEC}}}{\sum_i d_{ci}}$, where d_{ci} is the daily vehicle miles traveled (DVMT) by vehicle entry i in county c and $d_{civ}^{\text{ELEC}} = min(d_{ci}, d_v^{AER})$ is the distance traveled on electricity. All electric range (AER) is the maximum miles an electric vehicle can drive on electricity. For gasoline vehicles, $d_{civ}^{\text{ELEC}} = 0\ \forall\ \text{c}, v$ (i.e., $u_{cv} = 0\ \forall\ \text{c}, v$). I interpret $\bar{\gamma}_{cv}$ as the average life cycle emissions of vehicle type v for each randomly selected mile in county c.

In this chapter, I estimated vehicle emissions and performed statistical comparisons at the county level to investigate the aggregate effect of the locational differences in driving pattern, vehicle miles traveled, electricity grid mixes, and different charging times. This is the smallest geographic resolution for which I have data to differentiate driving patterns. I assigned an approximate driving pattern to each county based on its urbanization level following the geographic type classification I used in Chapter 1. I assumed that large central counties and nonmetropolitan counties would predominantly have city driving pattern and highway driving pattern, respectively. Outlying counties were assumed to have combined driving patterns (45% city, 55% highway) which is reasonable to assume because outlying counties have a high level of socio-economic integration with central counties, where city driving is expected to be predominant but this integration induces travel through road networks that is assumed to be predominantly entail highway driving patterns. I use estimates of vehicle energy use at different driving patterns form U.S. DOE (2014).

As for vehicle miles traveled, I extracted DVMT distribution by urbanization level and state from the NHTS (2009) data. I matched urban VMT distributions with metropolitan counties and rural VMT with nonmetropolitan counties. I provide a table of summary statistics for the DVMT distributions is provided in Appendix X. Average $DVMTs$ in rural areas are higher by over 45% except in Colorado, Mississippi, Oregon, and West Virginia. Table 10 summarizes the assigned driving pattern and DVMT distribution by geographic type.

Table 10. Driving pattern and DVMT distribution by geographic type

Code	Driving Pattern	VMT Distribution
Central Metropolitan Counties	City[10] driving	Urban
Outlying Metropolitan	Combined driving	Urban
Nonmetropolitan	Highway driving	Rural

In Chapter 4, I found that conclusion regarding which vehicle is lower emitting is highly influenced by assumptions made on electricity emission factors. The difference depends further in regional boundary definition, method for computing the marginal emission factor and charging scheme. In this chapter, I use consumption-based marginal emission factors (Zivin et al. 2014) for NERC regions under the convenience

[10] The U.S. Department of Energy provides three energy use rates: 1) City estimates represent "urban driving, in which a vehicle is started in the morning (after being parked all night) and driven in stop-and-go traffic"; 2) Highway estimates represent "a mixture of rural and interstate highway driving in a warmed-up vehicle, typical of longer trips in free-flowing traffic"; 3) Combined estimates represent a "combination of city driving (55%) and highway driving (45%)". These estimates were obtained form standardized laboratory tests. [U.S. DOE (2014)]

charging scheme for my base case. I matched each county with its corresponding NERC region and used the region's hourly marginal emission factor estimates from Zivin et al. (2014). I also extracted vehicle arrival time data (i.e., time vehicle gets home on the day survey was conducted) for each urbanization level and state from NHTS (2009), which is needed for computing hourly-weighted marginal emissions under the convenience charging scenario.

The emissions estimation model in Chapter 4 was modified slightly. To determine the hourly-weighted MEFs, $\hat{\phi}_{civ}^{\text{ELEC}}$, I used the following formula,

$$\hat{\phi}_{civ}^{\text{ELEC}} = \frac{\sum_t h_{citv}^{\text{CONVENIENCE}} \hat{\phi}_{ct}^{\text{ELEC}}}{t_{civ}}$$

where $h_{citv}^{\text{CONVENIENCE}}$ is the fraction of hour t that vehicle entry i under vehicle type v charges; $\hat{\phi}_{ct}^{\text{ELEC}}$ is the MEF for hour t in county c; and t_{civ} is the total charge time for vehicle entry i of vehicle type v. To compute charge time, t_{civ}, for vehicle type v if it were to travel the same miles as vehicle entry i, we used the following formula:

$$t_{iv}^{c} = \begin{cases} d_{ci} \geq d_v^{AER} AER_v & t_v^{\text{CHARGE}} \\ d_{ci} < d_v^{AER} & \dfrac{d_{ci}}{d_v^{AER}} * t_v^{\text{CHARGE}} \end{cases}$$

where t_v^{CHARGE} is the time it takes to fully re-charge vehicle type v [DOE 2014]. I illustrate the relationship between the different parameters I discussed in Figure 14.

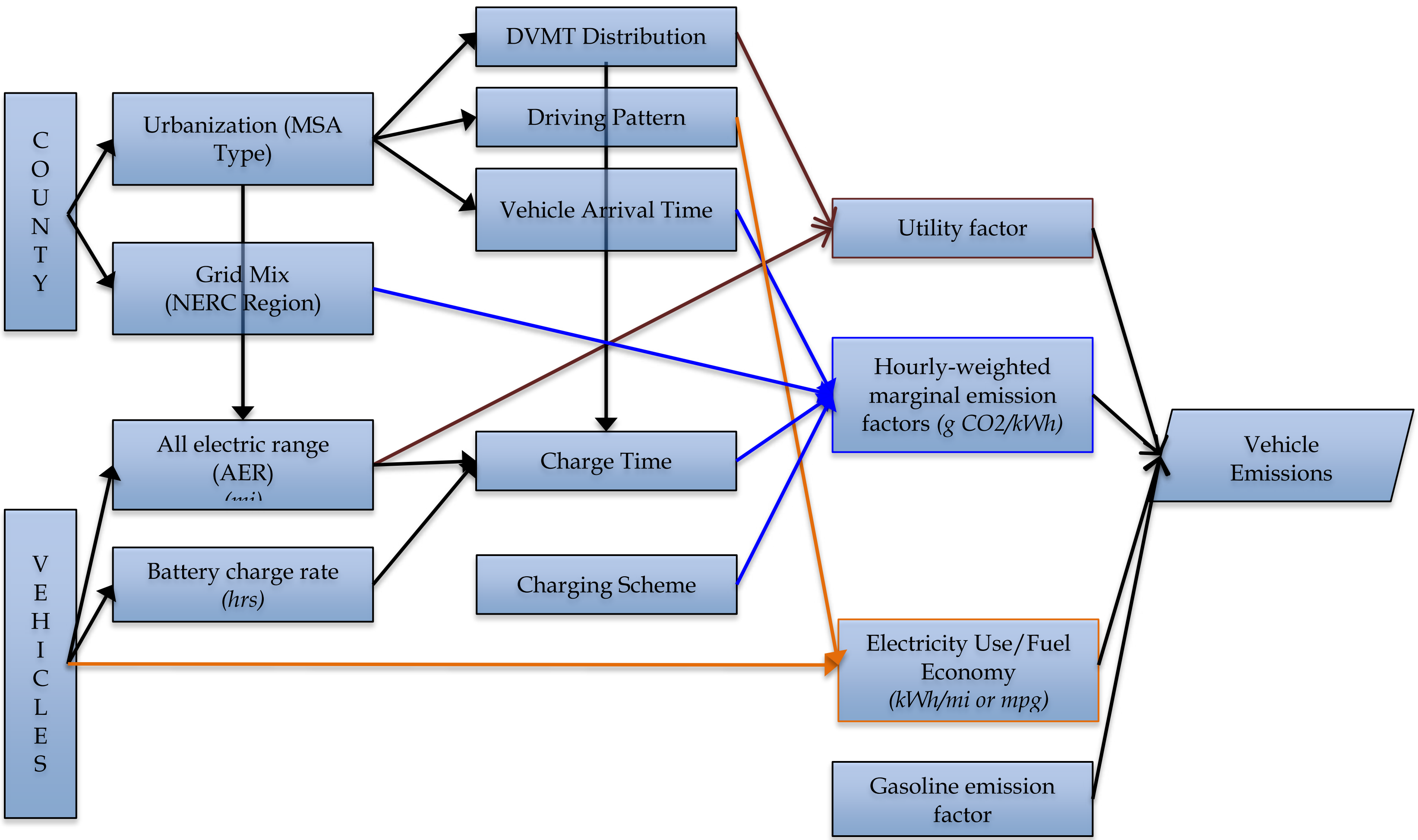


Figure 14. Vehicle emissions influence diagram

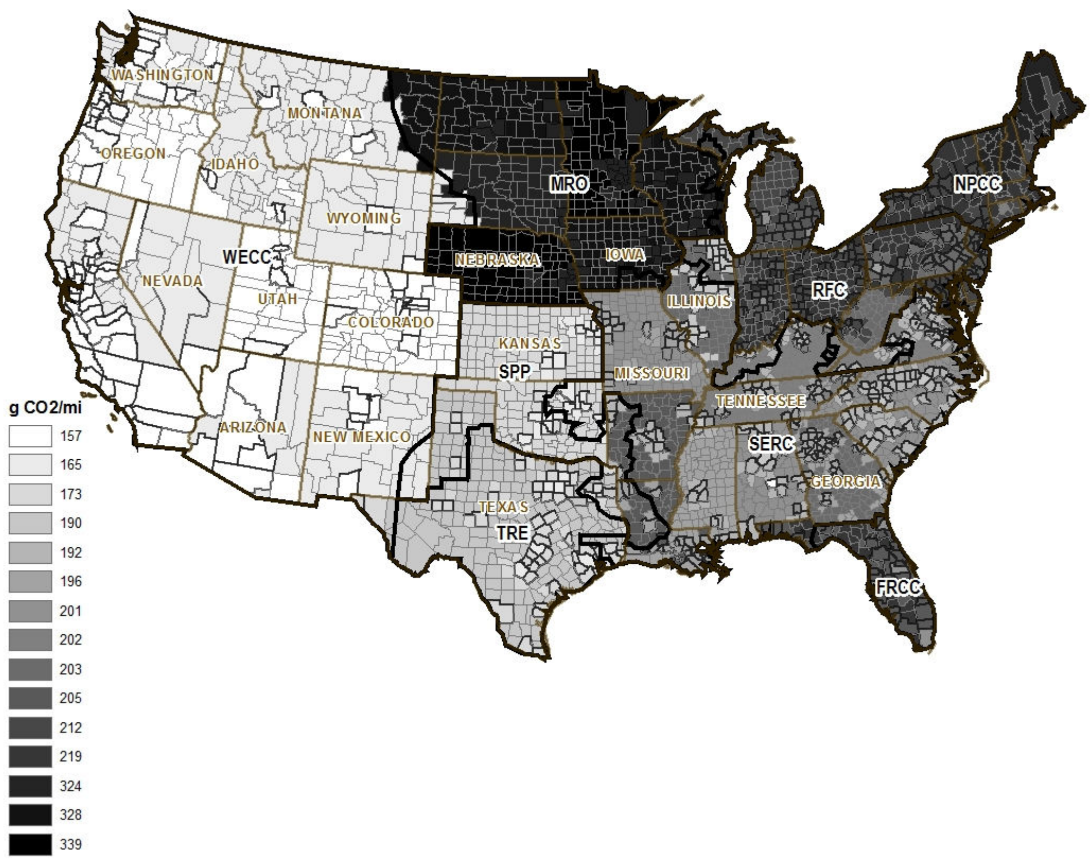
For other life cycle stages, I obtained emissions rate data from veritable sources such as published works, EPA, and GREET as in Chapter 4.

5.3 Results and Discussion

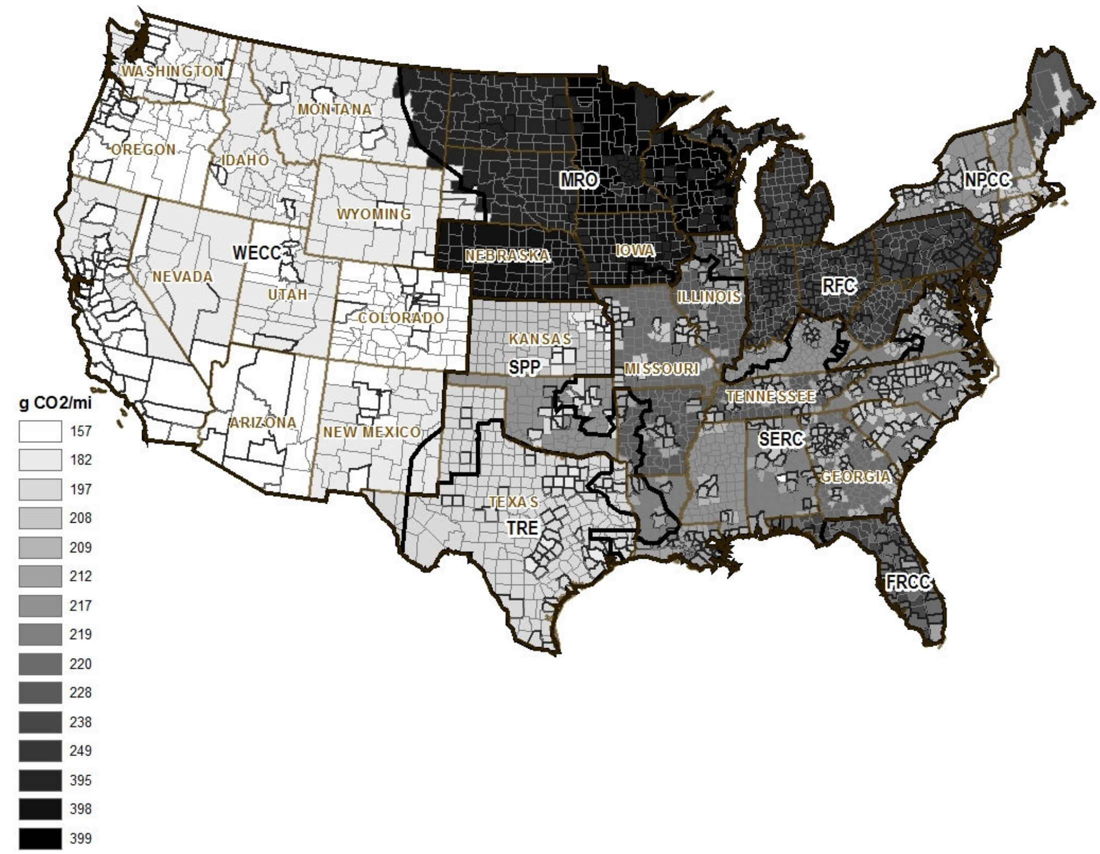
I first present the base case county emissions estimates and estimates under a delayed charging scheme. Next, I summarize conclusions considering uncertainty of MEFs by looking at comparisons under both consumption- and generation-based MEFs for convenience and delayed charging. And then I provide a sensitivity analysis of the emission estimates to changes in marginal emissions, charging scheme, driving scheme, and VMT distribution. In the succeeding chapter, I discuss these results along with results from previous chapters in the context of climate policies related to vehicle electrification presented in Chapter 3.

5.3.1 Base Case Emissions by County

I show in Figure 13-a the Nissan Leaf emissions estimates using base case assumptions – consumption-based marginal emissions factors, convenience charging scheme (i.e., vehicle is charged upon getting home), assigned driving pattern and DVMT distribution (see Table 11) - at the county level. Base case life cycle marginal emissions estimates for the Nissan Leaf range from 157 – 359 g CO_2/mi with lowest values in the WECC region and in most metropolitan counties in the rest of the country. The Leaf is most carbon intensive in the MRO region and rural areas in eastern states.



(13-a)



(13-b)

Figure 15. Nissan Leaf Emission Estimates by County. Counties colored red are where the Leaf is higher emitting than each gasoline vehicle as indicated in the legend. Emissions were computed considering differences in driving pattern, VMT distribution, electricity emission rates, and charging time. a) Base Case – consumption-based marginal emission factors, convenience charging scheme, assigned driving pattern and DVMT distribution (see Table 2); b) delayed charging scheme, other factors similar to Base Case. The Leaf is lower emitting than the lowest emitting gasoline vehicle (Toyota Prius HEV) in green-colored counties.

Figure 13-b shows Leaf estimates under delayed charging. As shown, emissions estimates are higher when the Leaf is charged during off-peak hours (e.g., 12 AM – 5 AM) except in the NPCC region. In the rest of the country, base load grid mix is more carbon-intensive due to higher level of reliance on coal power plants. Increase in

emissions relative to the base case convenience charging is more pronounced in the MRO and RFC region, which have the highest share of coal power plants.

5.3.2 Summary of Comparisons under Uncertainty

In this section, I summarize the paired t-test comparison results for consumption- and generation-based emissions estimates for both charging schemes. I first discuss results for comparable EV and gasoline and then compare the top-selling BEV, PHEV, and HEVs. Results for gasoline vehicles reflect assigned driving patterns and VMT distributions by county to provide a consistent comparison with EV emission estimates.

5.3.2.1 Top-selling BEV, PHEV, and HEV: Which is less emitting?

Looking at both consumption- and generation-based marginal emission estimates, I compare the Nissan Leaf, Chevrolet Volt, and Toyota Prius Hybrid. In each case, map color schemes denote: green – EV is lower emitting; red – gasoline vehicle is lower emitting; and yellow – results are inconclusive (i.e., consumption- and generation-based emissions have contradicting results). I found that the Leaf, compared to the Prius HEV, is lower emitting in western states, TX, Florida, and NPCC region (NY and New England states), regardless of MEF and charging scheme. The Leaf can be lower emitting in the south central as well, when charged as the vehicle gets home (i.e., convenience charging). The Prius HEV is lower emitting under both charging schemes in the MRO region; when charged at midnight until it is fully recharged, the Leaf becomes higher emitting in northeastern states as well. On the other hand, the Volt is higher emitting than the Prius HEV in except for metropolitan counties in western states, where results are inconclusive.

These results are different from what was found in Chapter 4, indicating that locational differentiation of driving pattern and DVMT distribution matters.

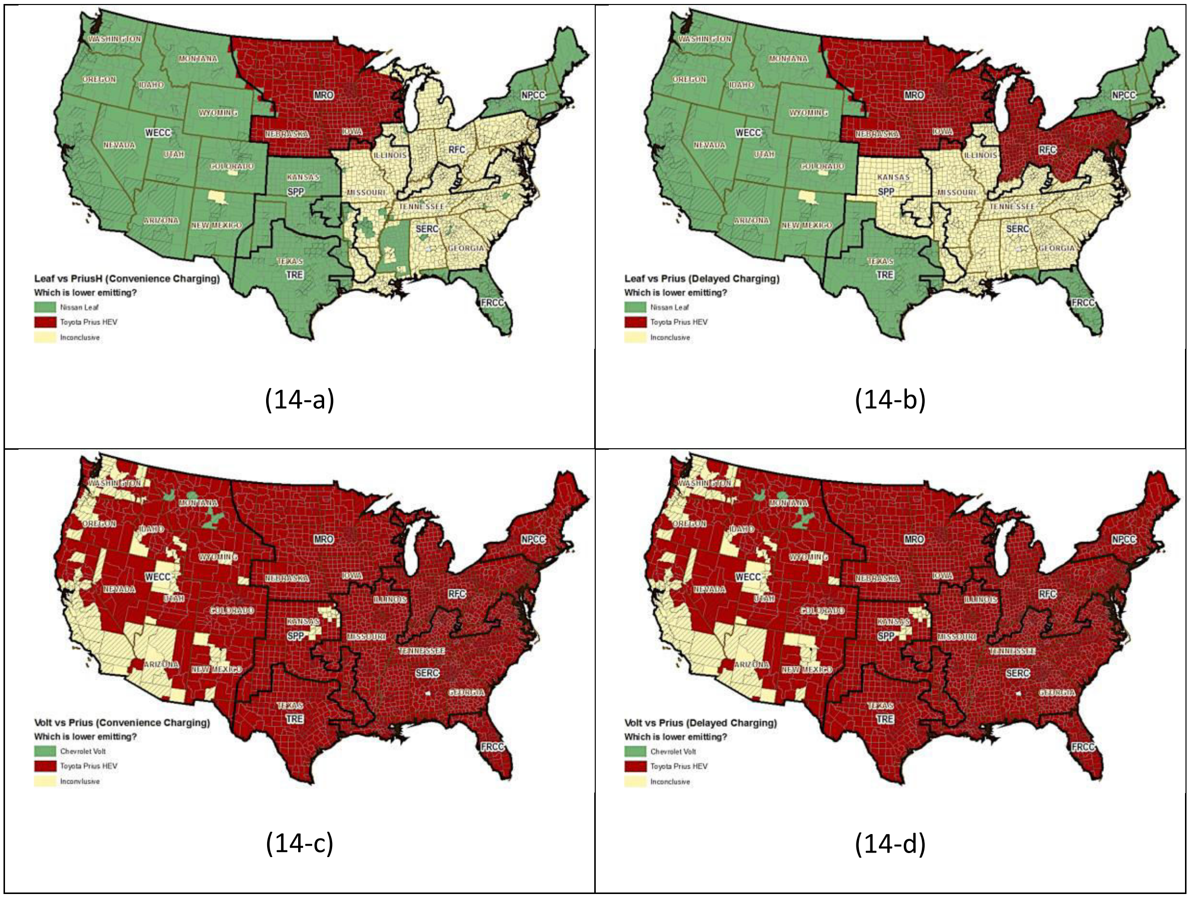
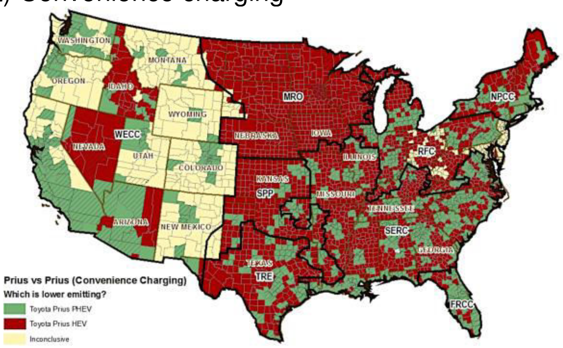


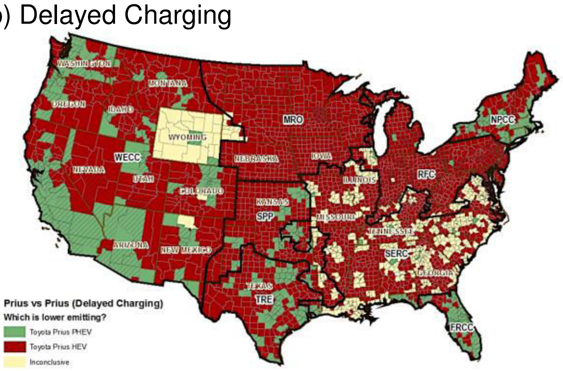
Figure 16. Base Case Marginal Emission Comparison for Toyota Prius HEV, Chevrolet Volt PHEV, and Nissan Leaf BEV. a) Leaf vs Prius (Convenience Charging); b) Leaf vs Prius (Delayed Charging); c) Volt vs Prius (Convenience Charging); and d) Volt vs Prius (Delayed Charging). Color schemes indicate comparison result between vehicles considering consumption- and generation-based emissions results: GREEN - EV is LOWER emitting under both MEFs; RED – EV is HIGHER emitting under both MEFs; and YELLOW – Inconclusive (i.e., MEFs results are contradictory).

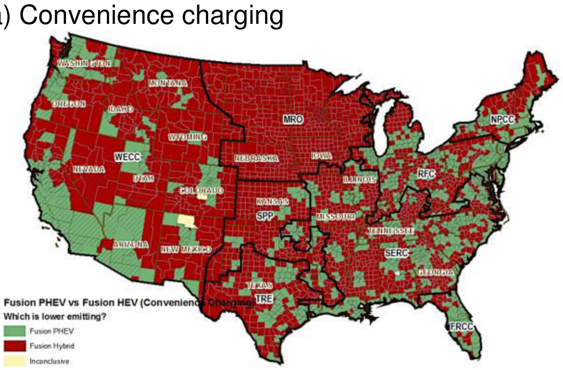
5.3.2.2 Comparable EV and gasoline vehicles: Which is less emitting?

Next, I look at comparable EV and gasoline vehicles and summarize the general conclusions in Table 11. Maps are also provided for each comparison to provide visual representations of the conclusions. Map color schemes are the same as in previous section. A prevailing pattern, except for the Nissan Leaf and Nissan Versa comparison, is that the electric vehicle is lower emitting in metropolitan counties (except in north central U.S.) and higher emitting in rural counties (except in some western states where results are inconclusive).

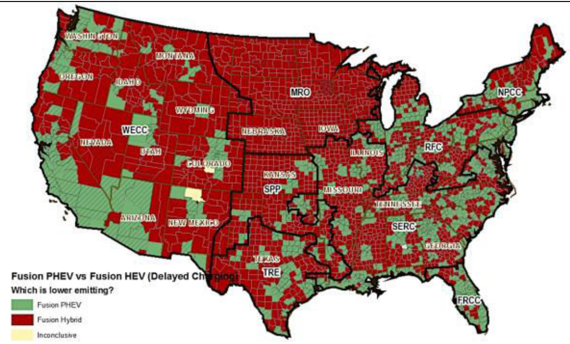
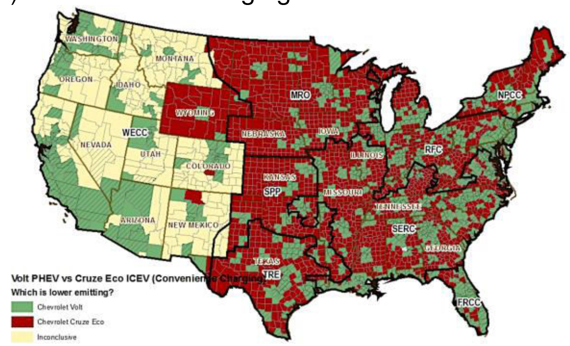
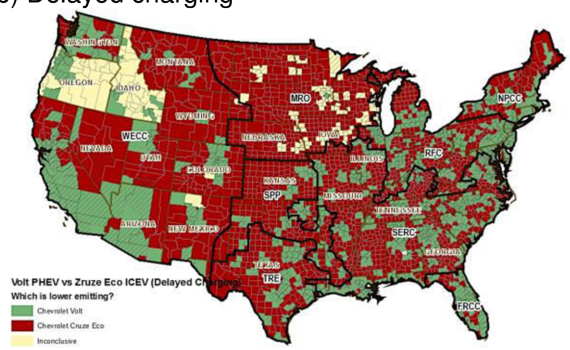
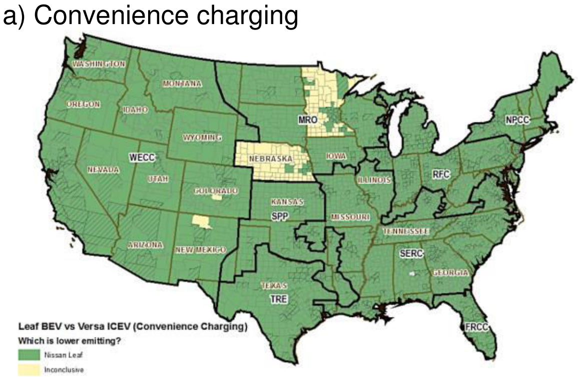
Table 11. Summary of results for comparable EV and gasoline vehicles under uncertain MEFs

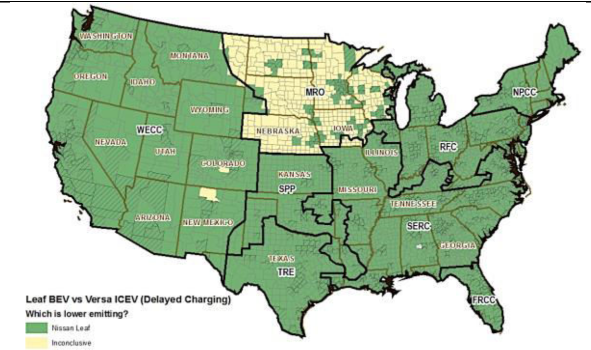
<table>
<tr><th>EV vs Gasoline Vehicle</th><th>Comparison Results</th></tr>
<tr><td>Toyota Prius PHEV vs Toyota Prius HEV
a) Convenience charging


b) Delayed Charging


</td><td>Under convenience charging, the Prius PHEV is lower emitting in metropolitan counties (central and outlying) and higher emitting in the MRO (both metro and nonmetropolitan counties) region regardless of MEFs and charging scheme assumptions. The Prius PHEV is higher emitting in nonmetropolitan counties except in most of the western states where results are inconclusive. This difference is mainly because of less carbon intensive WECC grid mix. Within the WECC, the Prius PHEV is higher emitting in nonmetropolitan counties of a few states (AZ, NV, and ID). This difference is due to variation in distribution of DVMT and arrival time, which affect weighted electricity emission factor.
Under delayed charging, the Prius PHEV become higher emitting in nonmetropolitan areas of the WECC region while the results become inconclusive in urban parts of the SERC region. Moreover, the Prius PHEV becomes higher emitting in the entire RFC region as well.</td></tr>
<tr><td>Ford Fusion Energi PHEV vs Ford Fusion HEV
a) Convenience charging


b) Delayed charging</td><td>Under both convenience and delayed charging, the Fusion PHEV is lower emitting in metropolitan areas and higher emitting in nonmetropolitan areas.</td></tr>
</table>

	
Chevrolet Volt PHEV vs Chevrolet Cruze Eco ICEV a) Convenience charging  b) Delayed charging 	Due to the significant difference in vehicle energy use for this pair, the Volt is lower emitting in metropolitan areas even in the MRO region. The Volt is still higher emitting in rural areas except in western states where conclusions are unclear. Under delayed charging, results become unclear in urban north central US and the Volt is higher emitting in rural western states.
Nissan Leaf BEV vs Nissan Versa ICEV a) Convenience charging  b) Delayed charging	Compared to ICEVs similar to the Versa, there is good amount of evidence to indicate that the Leaf is lower emitting than its gasoline vehicle counterpart in the U.S. under both charging schemes.



5.3.3 *Sensitivity of emission estimates MEFs, charging scheme, driving pattern, VMT distribution, and vehicle type*

In Chapter 4, I found that there is significant variation in EV emissions estimates depending on how electricity emission factors are derived. I found that even given the uncertainty of electricity emission factors, life cycle emission estimates indicate that the Leaf is higher emitting in MRO compared to the Prius hybrid. In other parts, comparisons are inconclusive (i.e., results under consumption- and generation-based marginal emissions factors do not lead to the same conclusion regarding which vehicle is lower emitting). In this chapter, I found that factoring in locational variation of driving pattern and DVMT distribution changes results. The next question to answer is how much do these factors affect emissions estimates?

I measured the change in emissions by vehicle with respect to a reference case, where I used consumption-based MEF, convenience charging, combined driving energy use, and national DVMT distribution. I summarize the change with respect to this reference case with the tornado diagrams in Figure 14. I found that life cycle vehicle emission estimates are most sensitive to regional grid mix variation and uncertainty. The Nissan Leaf, which fully relies on electricity, is expectedly the most sensitive to electricity emission changes, lowest being in the WECC region. Secondary to MEF uncertainty and regional variation, PHEV emissions are most sensitive to geographic type (i.e., urbanization level). PHEV emissions in rural counties can be over 30% higher than in metropolitan counties. The Leaf is much less sensitive to urbanization (~±5%). Urbanization has such effect because it influences the energy consumption of both electric and gasoline vehicles. Electric vehicles are more efficient in urban than highway driving while the opposite is true for gasoline vehicles. In addition to this, urbanization level also affects vehicle miles distribution, where rural DVMT is higher, on average. All vehicles are also mildly sensitive to assumed battery emission rate and lifetime mileage. Emissions are least sensitive to vehicle assembly and manufacture emission rates.

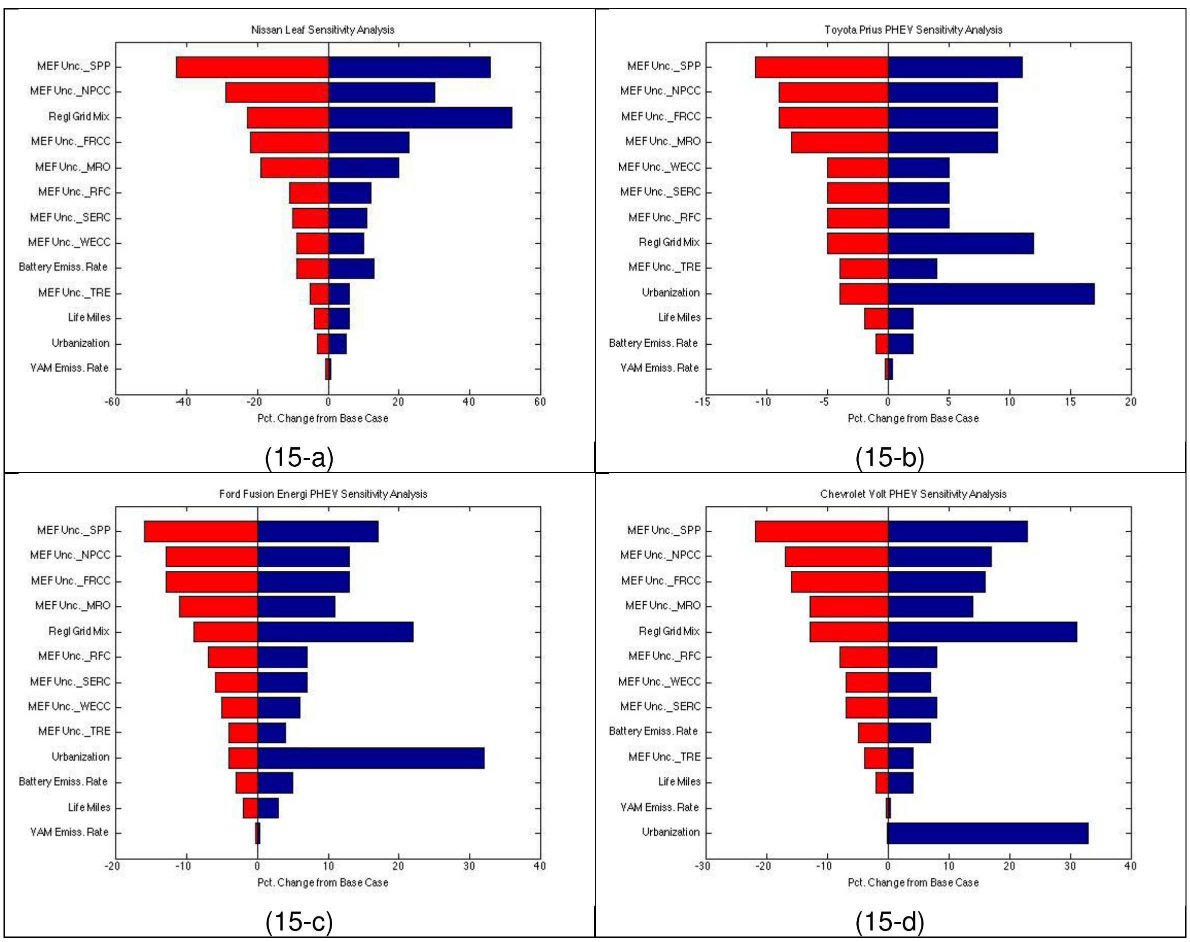


Figure 17. Vehicle emissions sensitivity analysis for a) Nissan Leaf, b) Toyota Prius PHEV, c) Ford Fusion Energi PHEV, and d) Chevrolet Volt PHEV. Percent change from the reference case (i.e., consumption-based MEF, convenience charging, combined driving pattern, national VMT distribution) is shown along the x-axis. Parameters that influence vehicle emissions are shown on the y-axis.

5.3.4 Summary of Results: Locational EV vs gasoline vehicle comparison

In summary, considering the combined effect of the locational variation of MEFs, driving pattern, and DVMT, highest CO_2 reduction from EVs can be gained in metropolitan WECC, TX, FL, NY, and New England states. Unless major changes are done to decarbonize the electricity system in the north central U.S., EV adoption in this area will not help in CO_2 reduction, although urban areas can be an exception. This is because the biggest factor influencing emissions levels and comparison results is electricity grid mix and MRO is highly reliant on coal power plants, making it highly carbon-intensive.

Urbanization level, which is related to driving pattern and VMT distribution, matters especially in making comparisons under delayed charging where EVs can sometimes become higher emitting in rural areas of states where EVs are lower emitting under convenience charging. These results indicate a need for locational differentiation of policies with respect to adoption of vehicle electrification facilitating mechanisms (e.g., incentives, charge station provision).

For future work, empirical data on energy use differences under different driving patterns as well as more localized data on miles traveled and driving pattern could improve the accuracy of locational analyses.

6 Conclusions and Policy Recommendations

6.1 Summary of Results

Contrary to previous findings, I find no statistically significant relationship between geographic variation and county scopes 1&2 per capita emissions. Per capita emissions are statistically different for residential, commercial, transportation, and electricity consumption, with central county per capita onroad transportation emissions about 0.7 – 0.8 that of less urban counties while per capita electricity consumption emissions in metropolitan counties (central and outlying) is about 1.4 times that of rural counties.

At the aggregate level, more urban counties have significantly higher emissions for all sectors with the biggest difference between urbanization levels in electricity consumption, transportation, and commercial. Electricity consumption (36% to 50%) and onroad transportation (22% to 29%) constitute over half of total scope 1&2 emissions.

These results along with the fact that over 75% of the U.S. population concentrated in metropolitan counties, support more focused effort on reducing per capita emissions related to U.S. metropolitan counties, especially larger ones.

I investigated vehicle electrification as a strategy for this, given other benefits that can be gained from the said technology and increasing public and private support. I found that the emissions reduction potential of EVs vary significantly under electricity emission factor assumptions, driving pattern, DVMT distribution, and charging scheme. I considered these four factors to estimate EV emissions at the county level in the U.S..

I found that CO_2 reduction benefits from EVs could be attained in urban counties in CA and other western states, TX, FL, NY, and New England states.

EV adoption in north central U.S., which is highly reliant on coal power plants, will only lead to higher transportation CO_2 emissions.

Marginal EV emissions using delayed charging (starting midnight) are higher due to more carbon-intensive marginal grid mix during non-peak hours, except for NPCC region.

6.2 Conclusions and Policy Recommendations

Federal as well as local climate policies and programs targeted on metropolitan areas should be further strengthened. In the U.S., over 235 cities and counties, representing 20% of the country's population, are participants of the Cities for Climate Protection Program (CCP) (Linstroth and Bell, 2007) and about 600 local governments are members of the International Council for Local Environmental Initiative (ICLEI) (ICLEI, 2009). Local governments also exhibit collaborative efforts manifested for instance by 500 mayors who signed the U.S. Conference of Mayors Climate Protection Agreement (CPA) (The US Conference of Mayors, 2007). Given the alignment of environmental, health, and energy security goals of targeting EV adoption in metropolitan U.S., this may be a strategy of focus in metropolitan counties.

However, EVs are best suited in certain areas in the U.S., given current the country's current electricity system and are discouraged in some. Policy pushing EV adoption in metropolitan counties, especially central ones, is encouraged in CA (and other western states), TX, FL, NY, and New England states. These states also happen to have the highest annual vehicle miles traveled as for the past thirty years. Thus, reduction in transportation emissions in these states would be significant at the national level (U.S. Department of Transportation 2013).

Further, based on comparisons made between the top-selling BEV (Nissan Leaf), PHEV (Chevrolet Volt), and HEV (Toyota Prius Hybrid), policies pushing for the adoption of BEVs comparable to the Nissan Leaf should be encouraged in the U.S. except in the MRO region. The Toyota Prius Hybrid is better encouraged over the Chevrolet Volt, in most parts of the country, especially in north central, central, and eastern states. It is not certain whether the Volt or the

Prius is lower emitting in western states. In more carbon-intensive regions such as the RFC and SERC, delayed charging should be discouraged for EVs.

The Toyota Prius PHEV, which has the same energy use rate as the Leaf under CD mode and a fuel economy equal to the most efficient gasoline vehicle in the market, Prius Hybrid, under CS-mode is the better option in eastern states. With increased provision of charging infrastructure in urban areas, the Prius PHEV, may be charged more frequently to allow the vehicle to operate on electricity for urban daily travel demands (with avg. DVMT of 30 mi), thereby avoiding tailpipe emissions while still reducing CO_2 emissions. Otherwise, it could run on CS-mode which compared to the more popular Chevrolet Volt, will still be lower emitting in terms of CO_2.

Unclear results in other parts of the country, mainly due to electricity grid CO2 intensity, provides another reason for further decarbonization of the U.S. electricity grid, especially in the north central and eastern U.S..

6.2.1 EV emissions estimates in the context existing policies promoting EV adoption

Figure 15 shows a map of incentives for EVs, the presence of Clean Cities PHEV Readiness Program, new vehicle registrations (2009-2012), and major city population by state.

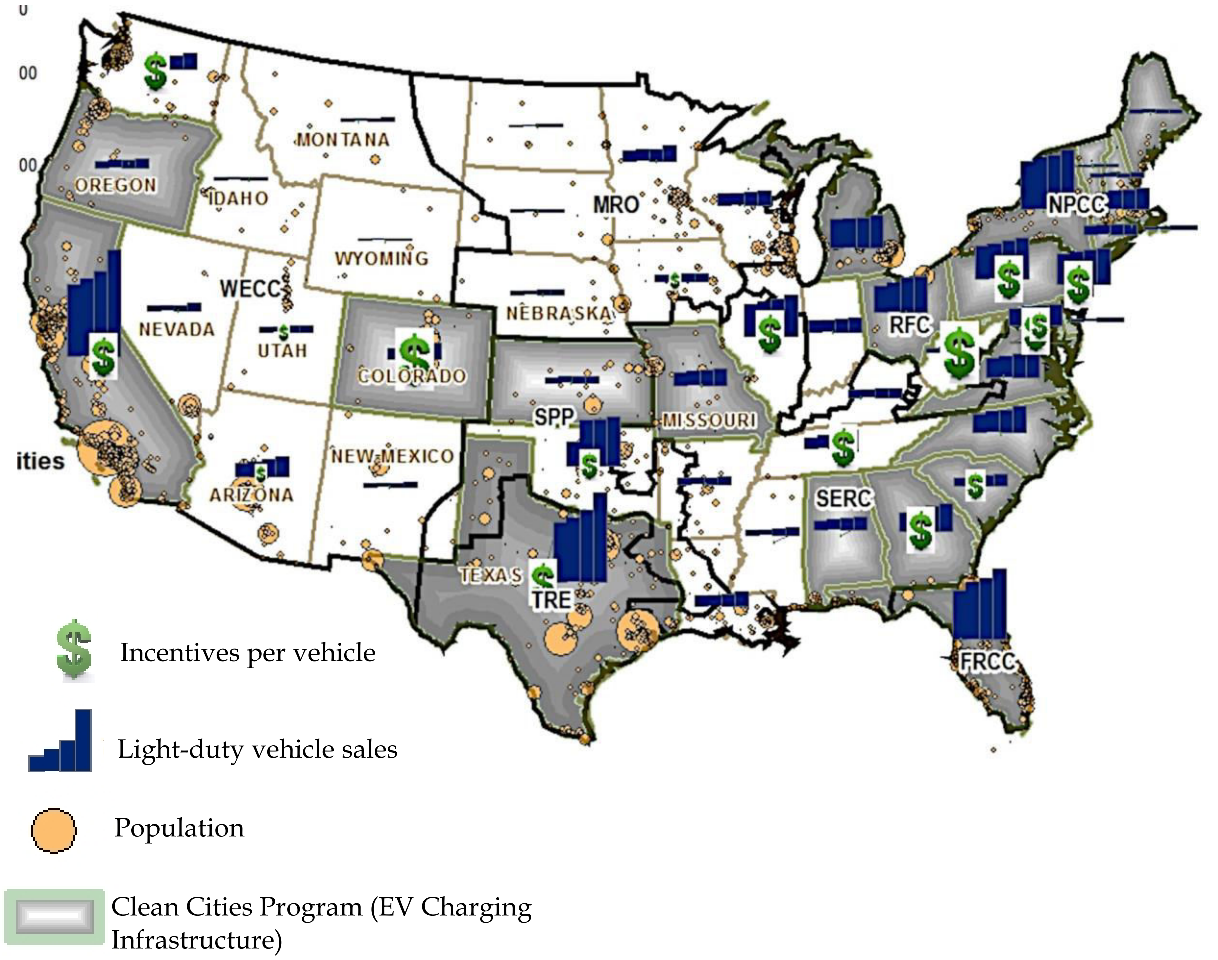


Figure 18. Incentives, Presence of Clean Cities PHEV Readiness Program, New Vehicle Registrations (2009-2012), and Major City Populations

This map shows that at present, the biggest incentives are given in eastern states with the highest in WV at \$ 7, 500. Most of these states also have the Clean Cities Program in place, which has the objective of increasing the accessibility of charging infrastructures to facilitate adoption of EVs. However, based on our results, CO_2 reduction from EVs in most of these states, especially in rural areas and the RFC region where WV is located, are the least. Based on our results, there is more evidence to say that the most efficient gasoline vehicle in the market, the Toyota Prius HEV, performs better in reducing CO_2 emissions in most of these states, especially in the RFC region where WV is located. These areas have a higher level of new car registrations compared to the rest of the country and so incentivizing adoption of EVs without increased effort in decarbonizing the electricity grid mix is likely to increase transportation emissions. Some of the most populated cities are located in these same areas and so reducing tailpipe emissions to reduce air pollution related health problems is a compelling reason to continue pushing for EV adoption in these areas. Indeed, environmental, health, and energy security objectives align in the adoption of EVs that are comparable to the Nissan Leaf and Toyota Prius PHEV in urban U.S.

6.2.2 Stakeholders in EV adoption

Several major players must work hand-in-hand to make vehicle electrification align with environmental, health, energy security, and economic objectives. In Table 12, I provide a summary of the parameters that influence EV emissions and the stakeholder that has control over each. As I have shown in Chapter 5, the biggest influencing factor in EV emissions is the variation and uncertainty of carbon intensity of the U.S. electricity system. I identify the major stakeholders that have primary control over this parameter to be the government (federal, state, and local) and the vehicle owners. Government policies that aid in decarbonizing the grid (e.g., Clean Air Act, proposed Clean Power Plan, Renewable Portfolio Standards, Carbon Cap and Trade) can further increase the environmental benefits of vehicle electrification and may lend EV environmentally beneficial in areas where EV CO_2 reduction potential are either uncertain (e.g. SERC region) or non-existent (e.g. north central U.S.). Electricity generators, meanwhile, have direct control over technological and operational changes that could decrease their operational carbon intensity. Vehicle owners also influence electricity emission rate through their charging pattern. As shown in previous sections, given current grid infrastructure and electricity market behavior, convenience charging generally results in lower weighted marginal electricity emissions compared to delayed charging. This is however in conflict with economic ends given that electricity prices are on average lower during off-peak hours (i.e., delayed charging), vehicle owners may opt, and are actually currently encouraged by some local policies such as the Plug-In Electric Vehicle (PEV) Charging Rate Reduction - Dakota Electric of MN (which is serviced by MRO region), to charge during these hours. This program is promoted based on the general claim that EVs reduce CO2 emissions (Dakota Electric Residential Services 2014). Our results prove this local program to be misguided.

Driving pattern and driving intensity, which are related with urbanization level, have also been shown to influence EV emissions level. I performed an analysis based on three standardized classifications of driving patterns – city, combined, and highway – and provided evidence that city driving combined with urban DVMT distribution is associated with lower EV emissions levels. Vehicle owners, of course, have direct control over their driving pattern and intensity but they are also constrained by the transportation networks available to them, which can be influenced by metropolitan planning authorities. Results from chapter 1 highlight the significance of taking metropolitan dynamics into account in the context of local climate action planning. Central counties that often serve as regional centers of commerce may induce regional transportation demands due to trips originating from outlying and non-metropolitan counties. Regional land use planners may explore shifting some commercial and other transportation inducing activities from central to outlying and non-metropolitan counties with the goal of decreasing aggregate transportation demands. However, it is uncertain how this may affect emissions in commercial and other sectors in outlying and nonmetropolitan counties.

Energy use, which is mainly dictated by vehicle design and is under the control of vehicle manufacturers, directly influences EV emissions. Vehicles have different energy use rates under different driving patterns. Thus, vehicle owners and metropolitan planning authorities also have indirect control over these parameters.

Table 12. Stakeholder control of EV emissions reduction

Positive Action	Stakeholder	Parameter: Electricity Emission Rate	Driving Pattern	Driving Intensity	Electricity Use rate	Gasoline use and emission rate
Policies on grid decarbonization, promoting vehicle energy use efficiency	Government	✓			✓	✓
Technologies/ Systems to lower operation carbon intensity	Generators	✓				
Charge during hours of lower electricity carbon intensity (i.e., midnight onwards); minimize driving distance	Vehicle Owners	✓	✓	✓	✓	✓
Design of more efficient vehicles	Manufacturers				✓	✓
Design transportation networks that lower driving intensity and city-like driving; promote metropolitan dynamics that decrease induced transportation from outlying and nonmetropolitan counties to central counties	Metropolitan Planning Authorities/Urban Planners		✓	✓	✓	✓

Lastly, vehicle assembly and manufacturing and battery production contribute a significant portion of life cycle emissions for EVs. Thus, automobile and battery manufacturers also have a pivotal role in helping EVs become a tool for CO_2 reduction.

Recall, however, that metropolitan counties already have significantly higher electricity consumption, both at the per capita and aggregate levels, constituting about 38% - 50% of total scope 1&2 emissions. With population concentration in metropolitan areas, this translates to concentrated electricity demand in metropolitan areas. Increasing electric vehicle adoption in urban areas would further increase this demand level; thus, electricity infrastructural feasibility as well as ways to curb transmission losses should be considered.

However, the U.S. PIRG reports that per capita travel in the U.S. from 2005 – 2009 has decreased significantly (U.S. PIRG 2013). Thus, if this trend continues, then the increase in electricity consumption due to EV use may not be that much (try to quantify). On the other hand, there are unclear implications of how switching to EV may have a rebound effect on driving distance. Policies that promote energy efficiency are suggested in conjunction with electric vehicle adoption to curb urban electricity demand.

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Appendix I. MSA Types and Aggregate Population

We show the U.S. Census Bureau classification of the 3,141 counties in the U.S. - central, outlying, and nonmetropolitan – in Figure 16.

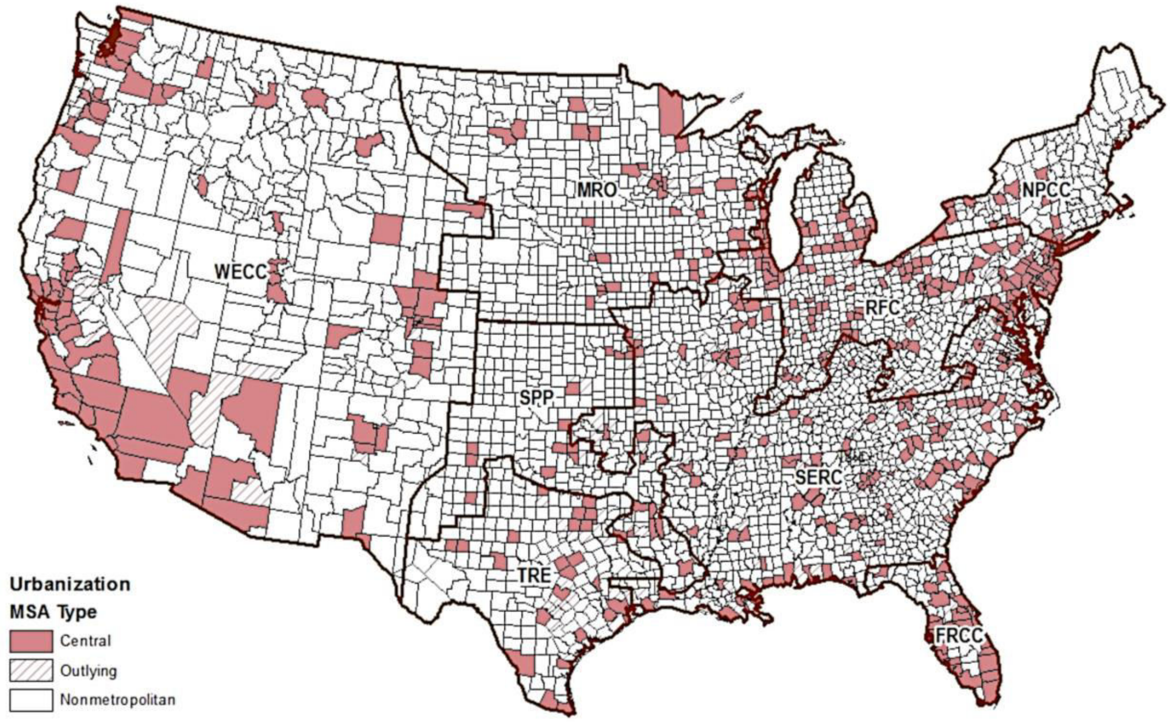


Figure 19. U.S. MSA Types - Central, Outlying, and Nonmetropolitan

A shown in Table 13, 500 were central, 317 were outlying, and 2, 324 were nonmetropolitan consisting of 67%, 7%, and 26% of the total U.S. population, respectively.

Table 13. Population by County Type

County Type	Count	Aggregate Population
Central	500	197, 570, 371 (67%)
Oultying	317	21, 956, 536 (7%)
Nonmetropolitan	2, 324	68, 270, 457 (26%)
Total	3141	287, 797, 364

Appendix II. Estimating Electricity Consumption

To estimate indirect emissions, county-level electricity consumption and the corresponding county electricity emissions factors were multiplied, as shown in the second term of the RHS of equation 1. Electricity consumption data at the county level is scarce; only California has a complete published database of county-level electricity consumption. Thus, a model was developed to estimate annual county-level electricity consumption from the data available.

Regression models employing the ordinary least squares method were investigated. The response variable for all these models is electricity consumption per county. County level electricity consumption data used for modeling include data from all California counties, all Vermont counties, five Illinois counties, and King County, Washington. The main goal was to obtain a model that was best at predicting annual electricity consumption. Several predictor variables and their combinations were used in different models. These set of predictor variables, **K**, include population, total payroll, household aggregated income, number of employees, number of establishments, total sales, heating degree days (HDD), cooling degree days (CDD), interaction between population and HDD, interaction between population and CDD, and metropolitan statistical area (MSA) code. The latter is a categorical variable while the rest are quantitative variables. The general form of the equation is shown in Equation 3.

$$c_i = \beta_{Central} + \beta_{outlying} Outlying + \beta_{nonmetro} Nonmetro + \sum_K \beta_k x_k + e_i \qquad (3)$$

Description and data sources for data used in modeling are summarized in Table 14.

Table 14. Electricity Consumption Modelling and Validation Data Sources

Parameter	No. of Observations	Unit	Year	Geographical Resolution	Temporal Resolution	Coverage	Source
Total Emissions	3, 141 (counties) x 8 (sectors)	tons C	2002	County	Annual	All 50 US states	Vulcan Project
Population by State	50 (states) x 9 (years)		2002-2010	State	Annual	All 50 US states	U.S. Census Bureau
Population by County	3, 141 (counties) x 9 (years)		2002-2010	County	Annual	All counties in 50 US states	U.S. Census Bureau
Heating Degree Days	360 (cities) x 2 (month) x 10		2001-2010	City	Monthly (December	AZ, CA, IL, MD, VT,	NOAA National

	(years)				and June)	WA	Weather Service
Cooling Degree Days	360 (cities) x 1 (month) x 10 (years)		2001-2010	City	Monthly (December)	AZ, CA, IL, MD, VT, WA	NOAA National Weather Service
Heating Degree Days	50 (states) x 2 (month) x 1 (year)		2002	State	Monthly (December and June)	All 50 US states	NOAA National Weather Service
Cooling Degree Days	50 (states) x 1 (month) x 1 (year)		2002	State	Monthly (December)	All 50 US states	NOAA National Weather Service
Aggregate HH Income	81 (counties) x 6 (years)	Dollars	2010 2006-2009 2002	County County County	5-year Annual 3-year	CA, IL, VT, WA	American Community Survey
Number of Housing Units	81 (counties) x 6 (years)		2010 2006-2009 2002				American Community Survey
Number of Employees	81 (counties) x 6 (year)		2010 2006-2009 2002				American Community Survey
Number of Establishments	81 (counties) x 2 (year)		2005 2007				County Business Patterns
Total Sales	81 (counties) x 2 (year)	Thousand dollars	2007				US Census Bureau
Total Payroll	81 (counties) x 6 (year)	Thousand dollars	2005 2007				County Business Patterns
Land Area (sq. mile) Source:	1, 3141 (counties)	sq. mile		County		All counties in 50 US states	US Census Bureau
State Electricity Consumption		GWh	2002,2004,2006 - 2009	State			eGRID
Electricity Consumption (CA)		GWh	2002,2004,2006 - 2010	County	Annual		ECDMS
Electricity Consumption (Vermont)	13 (counties) x 7 (years)	kWh	2004 - 2010	County			VEIC
Electricity Consumption (IL)	5 (counties) x 1 (year)	GWh	2005	County			
Electricity Consumption (WA)	1 (county) x 5 (years)	GWh	2005-2009	County			
Direct Emissions	1, 3141 (counties)	tons C	2002	County		US	Vulcan Project
2004 Emission Factors (eGRID, State, NERC)	1, 647	tons/MWh	2004	County	county		
MSA Type			2000	County		US	US Census Bureau

Equation 3 shows the general form of the regression models explored. The first two terms correspond to the dummy coded categorical variable corresponding to MSA type. The value of the coefficient βi stands for the difference between the mean values of electricity consumption for counties under MSA type i and the reference category j, ceteris paribus. The third term is the summation of the product between the values of the quantitative variables and their corresponding coefficients.

Over 20 regression models were investigated and those that were statistically significant in explaining the variation in electricity consumption at a significance level of 5% were further screened based on their adjusted R^2 and Akaike Information Criterion (AIC) goodness-of-fit values. Table 15 shows eight of the best models explored. A model with all explanatory variables was not considered for further analysis due to strong correlation between most of the economic variables.

Two models were considered for final use because they had the best combination of the lowest AIC goodness-of-fit values and highest adjusted R^2 (see Table 16). One (Model 3 - California) was derived using CA data only; thus, a reasonable adjustment factor was needed to calibrate the California model estimates to the rest of the US as it is known that California has the lowest per capita electricity consumption in the country. The adjustment factor was the ratio between per capita electricity consumption in each state and that of California. The second model (Model 8 – All Counties), on the other hand, has the advantage of making use of data from other states. It should however be noted that all Vermont counties are nonmetropolitan counties.

Table 15. Sample of Regression Models Explored for Electricity Consumption Estimation

Model	County Data Used	Explanatory Variables
Model 1	all 58 CA counties (2006 – 2009), 5* IL counties (2005), King County), WA (2005-2009)	Population, Population*HDD, Population*CDD
Model 2	30 central counties from CA (2006-2009), 5 IL counties (2005), King County**, WA (2005-2009)	
Model 3 (California)	all 58 CA counties (2006 - 2009) only	
Model 4	30 central counties from CA (2006-2009) only	

Model 5	all 58 CA (2006 - 2009) only	Aggregate HH Income, CDD, HDD, Population Density
Model 6		Household Units, CDD, HDD, Population Density
Model 7		Employees, CDD, HDD, Population Density
Model 8 (All Counties)	all 58 CA counties (2006 - 2009), 5* IL counties (2005), King County**, WA (2005-2009), VT*** (2006-2009)	Population, Populaiton*HDD, Population*CDD

Table 16. Electricity Consumption Regression Model Results

Explanatory Variable	**Model 1 (CA[1], IL[3], WA[4]; Population-based)**	**Model 2 (CA[2], IL[3], WA[4]; Population-based, Central Counties, Population>1M)**	Model 3 (CA[1]; Population-based)	**Model 4 (CA[1]; Population-based, Central Counties, Population>1M)**	**Model 5 (CA[1]; Agg HH Inc, Pop Dens, HDD, CDD)**	**Model 6 (CA[1]; HH Units, Pop Dens, HDD, CDD)**	**Model 7 (CA[1];Employees, Pop Dens, HDD, CDD)**	**Model 8 (CA[1], VT[2], IL[3], WA[4]; Population-based)**
Population (2006-2009)	0.00596*** (0.000202)	0.00606*** (0.000198)	**0.00548*** (0.000341)**	0.00534*** (0.000329)				0.00555*** (0.000331)
HDD (2006-2009)					1.522*** (0.335)	0.612** (0.261)	0.423* (0.217)	
CDD (2006-2009)					1.682*** (0.201)	0.513*** (0.181)	1.050*** (0.346)	
Population x HDD	8.63e-07*** (1.14 e-07)	8.50e-07*** (1.29e-07)	**1.19e-06*** (2.03e-07)**	1.30e-06*** (2.00e-07)				1.14e-06*** (1.97e-07)
Population x CDD	1.64e-07** (6.39e-08)	5.21e-08 (6.57e-08)	**2.30e-07*** (7.91e-08)**	2.56e-07*** (7.50e-08)				2.31e-07*** (8.03 e-08)
Aggregate HH Income (2006-2009)					2.90e-07*** (4.79e-09)			
Number of Housing Units (2006-2009)						0.0213*** (0.000248)		
No. of Establishments (2007)							0.285*** (0.00409)	
Population Density (2006-2009)					-0.183*** (0.0303)	-0.0898*** (0.0165)	-0.137*** (0.0335)	
Constant	62.06 (91.84)	34.36 (524.7)	**-87.40* (49.85)**	-238.79 (150.83)	-6, 068*** (1, 076)	-2, 078** (854.1)	-1, 836** (882.0)	-139.9051*** (40.36807)
Adj. R2	0.98	0.99	**0.98**	0.98	0.97	0.97	0.96	0.98
Number of Observations	245	43	**232**	124	160	160	58	302
AIC	17.56	17.97	**17.32**	17.97	18.17	17.99	18.29	17.07
BIC	6.15e+08	4.78e+08	**4.38e+08**	4.34e+08	6.82e+08	5.71e+08	2.51e+08	4.47e+08

[1] All CA Counties (2006-2009); [2] All VT Counties (2006-2009); [3]Cook County, DuPage County, Lake County, Will County, Kane County, Mc Henry County, and Kendall County (2005); [4] King County (2002, 2005-2009)

p-value: * < 0.1; ** <0.05; ***<0.001

To decide between Models 1 and 2, the percentage errors resulting from their use were analyzed in two ways - 1) comparing 2002 and 2004 California county estimates to reported county-level electricity consumption and 2) comparing state aggregated county estimates to published state-level electricity consumption. For the county comparison, Figure 17 was generated to show the estimation errors by urbanization level. Alpine and Sierra county, both of which are nonmetropolitan counties, resulted in outlier error (i.e., > |100%|). All other counties had error less than |100%| with an average of -7%.

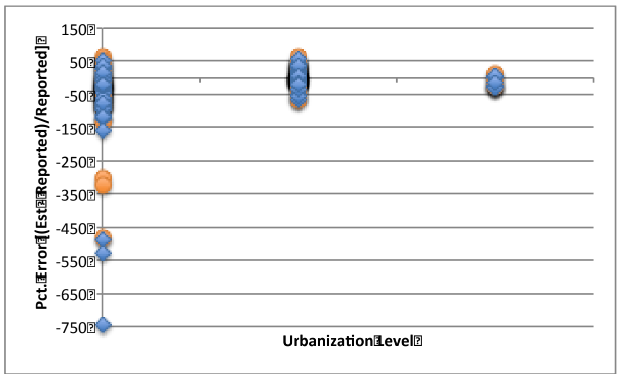


Figure 20. California Model Electricity Consumption Estimate Errors by Urbanization Level

For the state aggregate comparison, the state-level aggregates for all county electricity consumption estimates were compared with EIA state data for 2002 (n=50). Summary statistics for percentage errors are shown in Table 17. Similar to the trend for errors from allocation by population, the range of errors from the two models is narrower for metropolitan counties even with the introduction of climate index variables.

Table 17. Estimate Error Comparisons for California and All County Models (US, 2002)

	County Comparison		State Aggregate Comparison	
Model	Mean of % Error	Std. Dev. of % Error	Mean of % Error	Std. Dev. of % Error
California Model x Adj. Factor	- 7	33	- 11	32
All County Model	11	33	28	41

Outliers (i.e., errors > |100%|) were excluded from the calculation: 1) County Comparison: Alpine County and Sierra County for California Model, Alpine County, Sierra County, Mono County, and Modoc County for All County Model; 2) State Comparison: Alaska, Montana, Nebraska, North Dakota, and South Dakota.

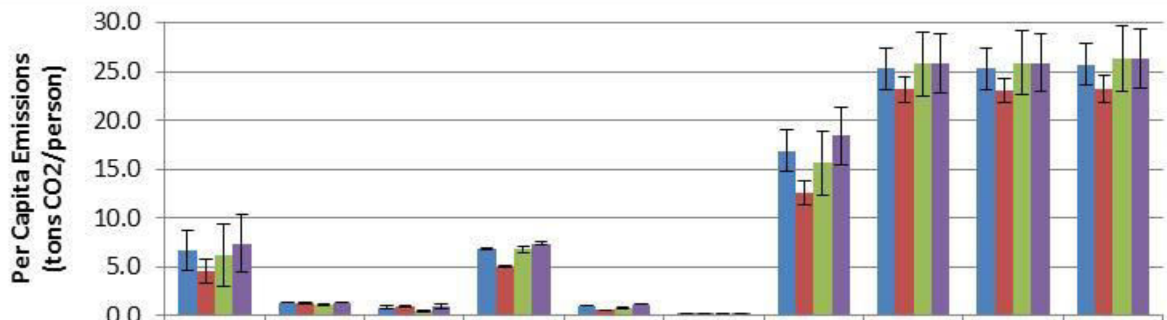
Since the California model results in average percentage error closer to zero with narrower error spread, it was chosen for computing electricity consumption. For the uncertainty analysis, the 5^{th} and 95^{th} percentile of the errors are -68% and 42%, respectively.

Negative electricity consumption estimates for year 2002 were excluded from further analysis (i.e., scope 2 emissions estimates). This resulted in over 2, 500 county electricity consumption and scope 2 emissions estimates. These counties represent over 94% of the total U.S. population in 2002.

Appendix III. Emissions Data

AIII.1 Descriptive Statistics

Descriptive statistics for the full data set are summarized in Figure 18. Looking only at these numbers would suggest that central counties may have lower scope 1&2 per capita emissions than both outlying and nonmetropolitan counties, which do not seem to differ.



	Ind.	Res.	Comm.	Onroad	Nonroad	Air	Scope 1	S1+2 NERC	S1+2 eGRID	S1+2 State
National	6.7	1.3	0.9	6.8	1.0	0.2	16.9	25.3	25.3	25.7
Central	4.6	1.3	0.9	5.1	0.6	0.2	12.6	23.1	23.0	23.2
Outlying	6.2	1.2	0.5	6.8	0.7	0.2	15.6	25.8	25.9	26.3
Nonmetro	7.4	1.3	0.9	7.4	1.2	0.3	18.4	25.8	25.9	26.3

Figure 21. Mean Per Capita Emissions (Full Data Set)

However, it is important to look at the distribution of the data to obtain a better understanding of per capita emissions differences by geographical type. To provide an idea of the distribution of per capita emissions per sector by geographical type, we generated the histograms as shown in Figure 5 a and b. Only the residential, onroad, and nonroad sectors seemed to demonstrate normal distribution. This was due to the inherent spread of the data and a few outliers.

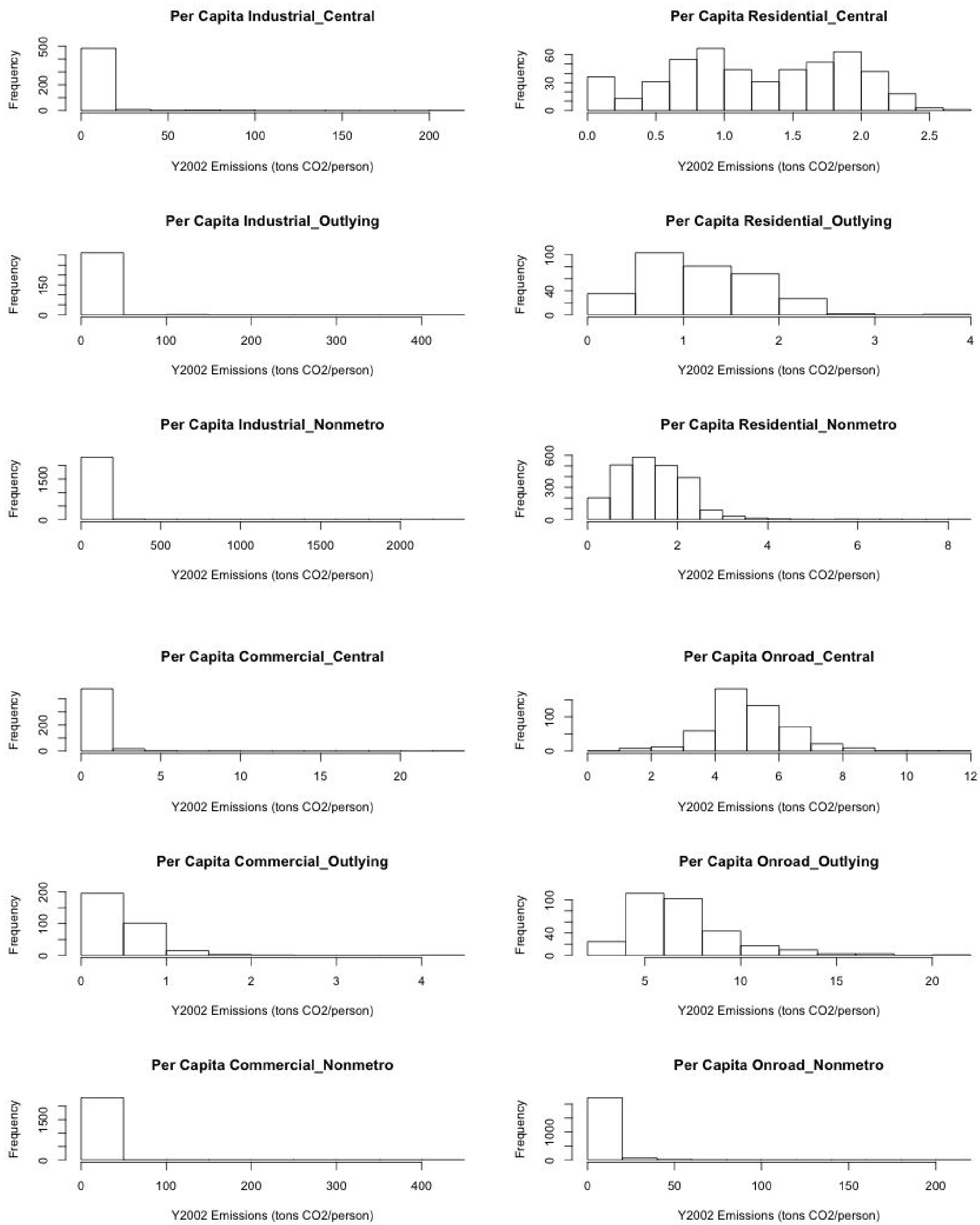


Figure 6a. Histograms by Sector and Geographical Type for Full Data Set – Industrial, Residential, Commercial, and Onroad

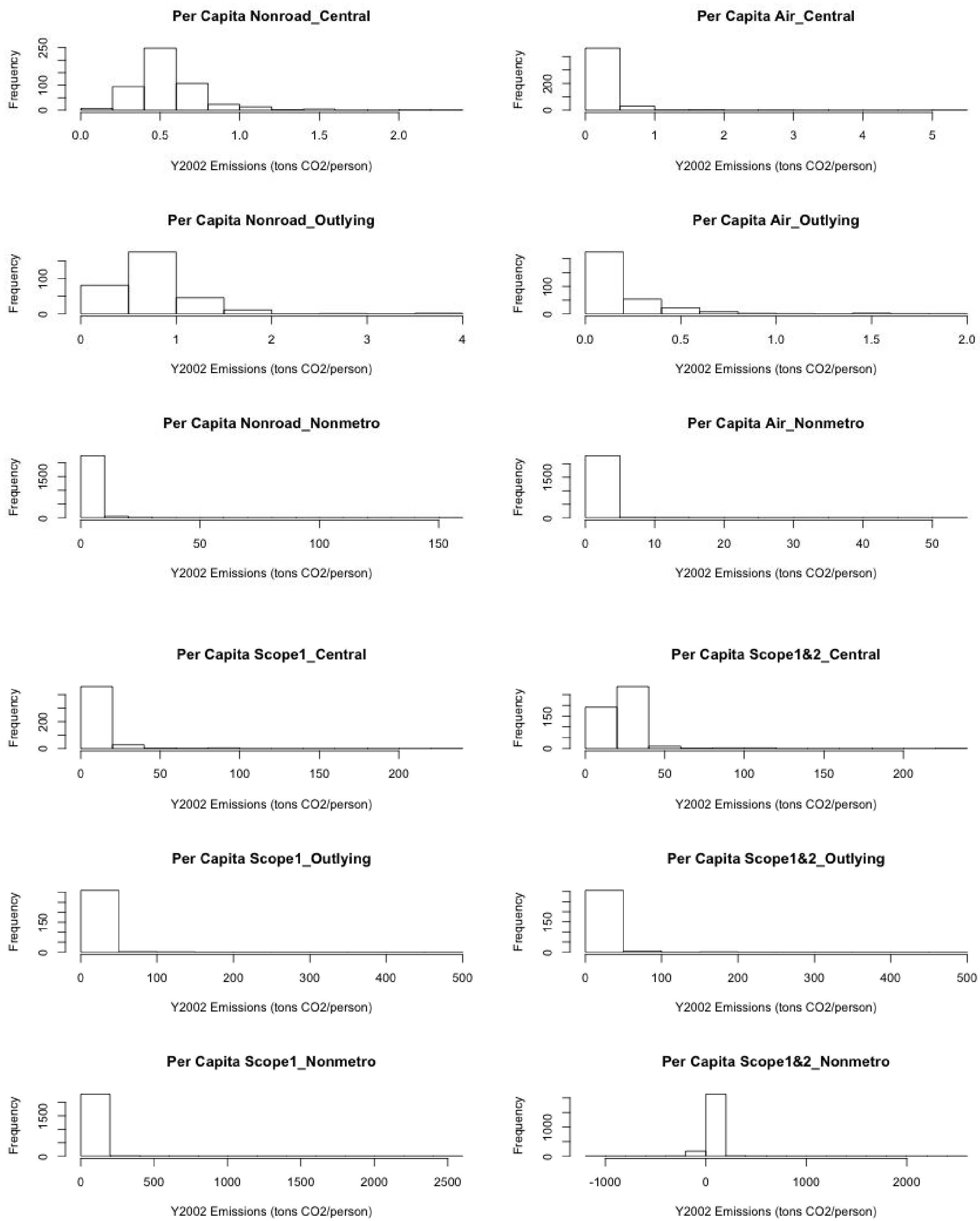


Figure 6b. Histograms by Sector and Geographical Type for Full Data Set – Nonroad, Air, Scope 1, and Scope 1&2

AIII.2 Predictor Variables – Distribution and Collinearity

A visualization of the distribution of the predictors and the correlation between the predictor variables is provided in Figure 6.

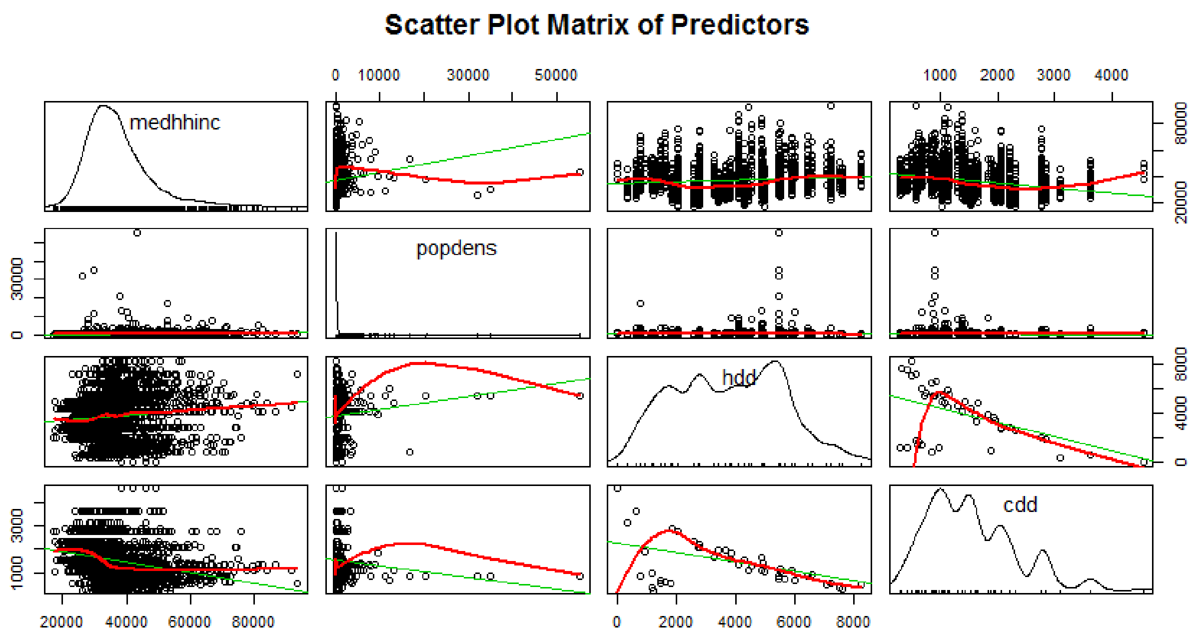


Figure 7. Scatterplot Matrix of Predictors

We investigated for collinearity of predictor variables to determine whether dropping some of the variables would be necessary. We found moderate correlation between the climate indices and weak correlation between median HH income and two variables - population density and CDD. Thus, in succeeding model selection, we opted to drop one of CDD and HDD as well as PopDens and MedHHinc to avoid multicolinearity.

Table 18. Predictor Variables Pearson Coefficients

	PopDens	MedHHInc	HDD	CDD	MSA
PopDens	1.00	0.11	0.05	-0.05	-0.19
MedHHInc	0.11	1.00	0.11	-0.29	-0.06
HDD	0.05	0.11	1.00	-0.48	0.05
CDD	-0.05	-0.29	-0.48	1.00	0.02
MSA	-0.19	-0.06	0.05	0.02	1.00

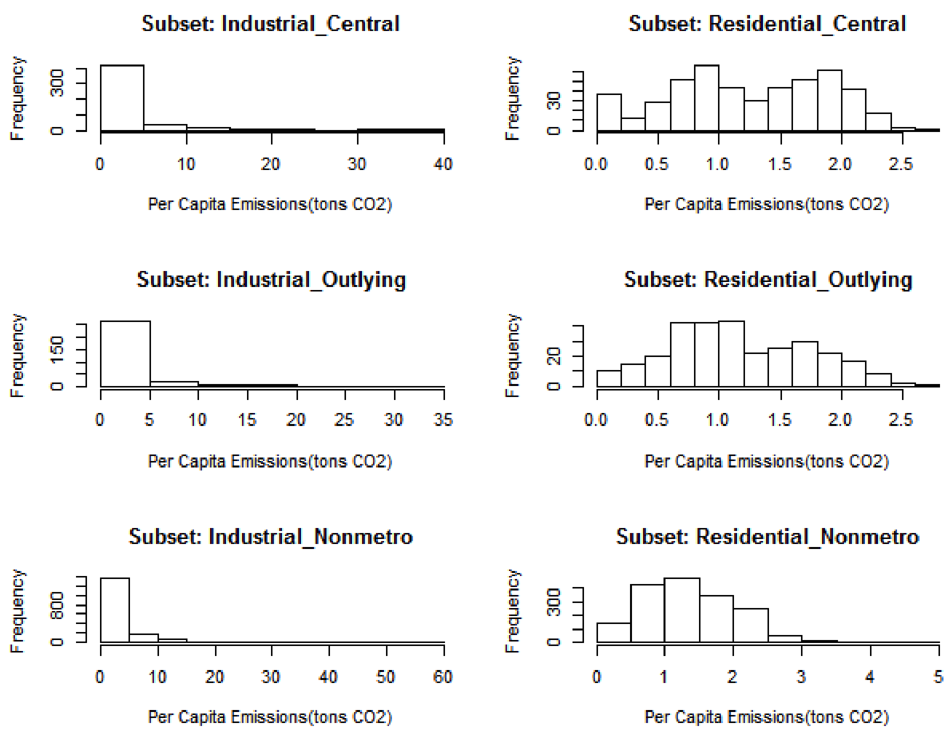
Appendix IV. Model Fitting, Diagnostics and Selection

Using R, we used the general LRM equation for model fitting. The results of the said analysis are summarized below. After model fitting using the general LRM presented in Section 2.3, we performed a series of model diagnostics mainly to determine whether the assumptions of OLS hold. Diagnostic graphs are shown after the regressions results summary.

We found that the OLS assumptions do not hold. In terms of normality of residuals, the residential, onroad, and nonroad sectors appear to be least problematic. Moreover, several outlier and influential data points were found. After removing outlier and influential data points, our final sample includes Central = 488, Outlying = 300, Nonmetropolitan = 1,686. Most of these counties have relatively very high industrial and commercial emissions. The final sample covers over 91% of the U.S. Population. All omitted counties had scope 1&2 per capita emissions higher than the national average, except for three – Bronx (9.2 tons CO_2/capita), Kings (8.6 tons CO_2/person), and New York (12.6 tons CO_2/person) – which are all central counties in NY state with population greater than 1M.

The most problematic data sets correspond to the industrial and commercial sectors because of the distribution of the data. In addition to omitting outliers and influential data points, we tried to fit GLM using Inverse Gaussian Family, which is usually used for response variables having only positive real values. Histograms of the final data set are shown in Figure 7. We went through several iterations of variable selection and chose the models that resulted in the lowest AIC or pseudo/Adj. R^2. In addition, we performed visual comparison of the fitted versus observed values to decide on models that have very close AIC or R^2 values. Except for the original (full data set and all predictors included) LRM, all models indicate no significant difference in scope 1&2 per capita emissions across different geographic type. Coefficients for the geographic types (i.e., mean emissions values for each geographic type), changed across different models but ratios of emissions values did not vary much. To provide a specific comparison, we summarize in Table 10 the regression results for the best models under LRM (robust regression).

The model diagnostic results for per capita scope 1&2 emissions – both original and final models – are shown in Figure 8. The same diagnostics were conducted for each sector. Although our models are statistically significant in explaining the variation in the values of per capita emissions, much can be done to improve the accuracy of the models in predicting emissions values. Nonetheless, we are confident of the model results in terms of determining whether there is statistically significant difference in emissions by geographical type, which is what we aimed to answer in this study.



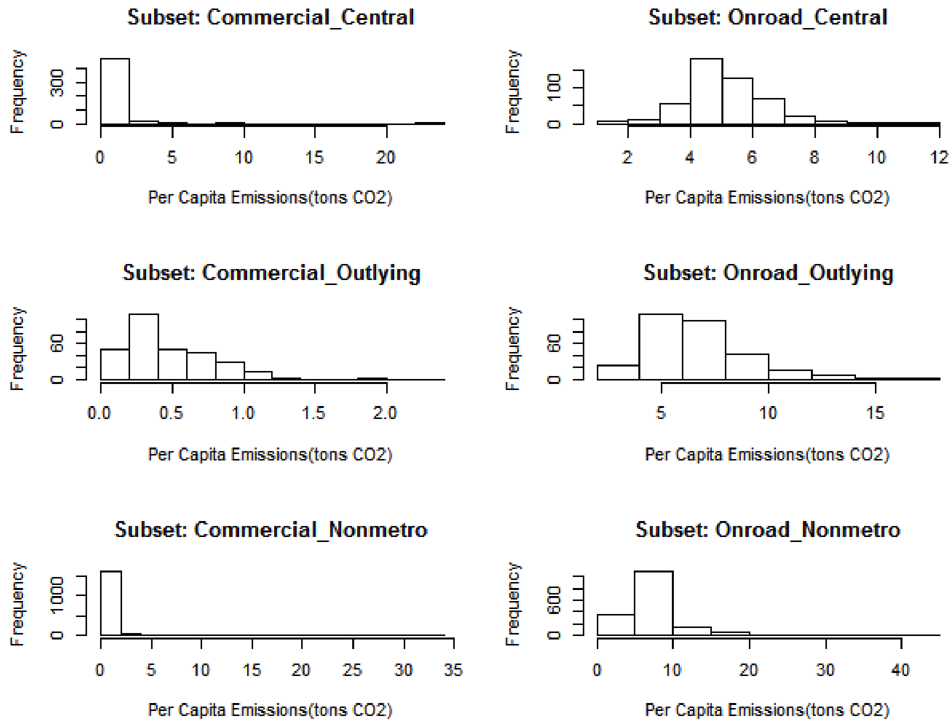
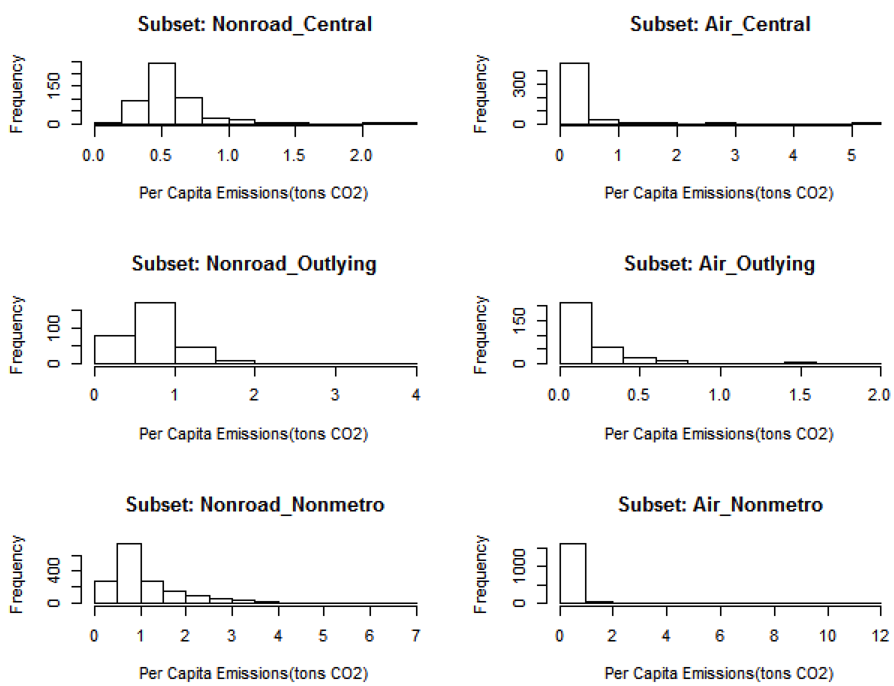


Figure 8a. Histograms by Sector and Geographical Type for Reduced Data Set – Industrial, Residential, Commercial, and Onroad



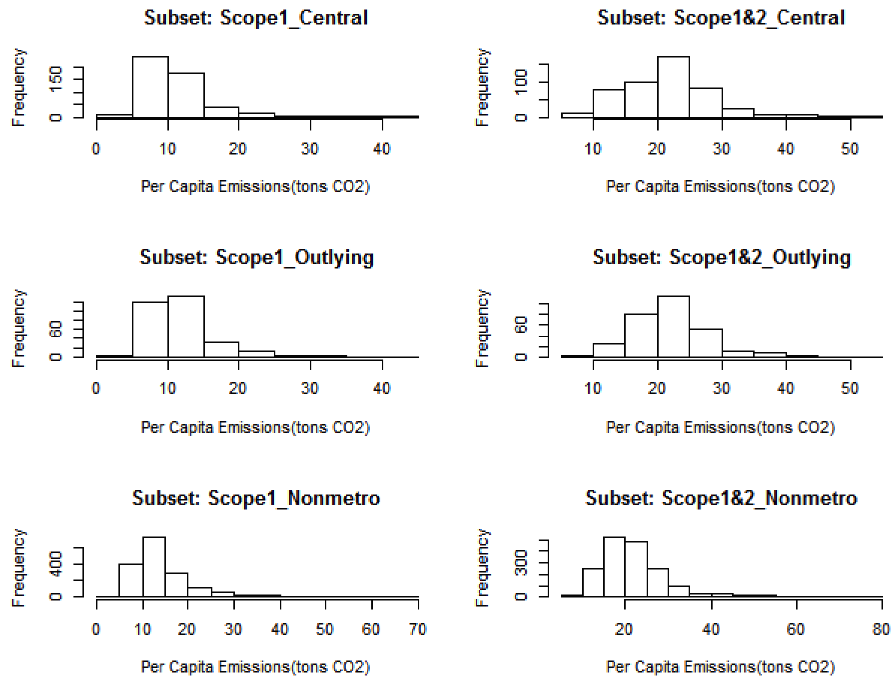


Figure 8b. Histograms by Sector and Geographical Type for Reduced Data Set – Nonroad, Air, Scope 1, and Scope 1&2

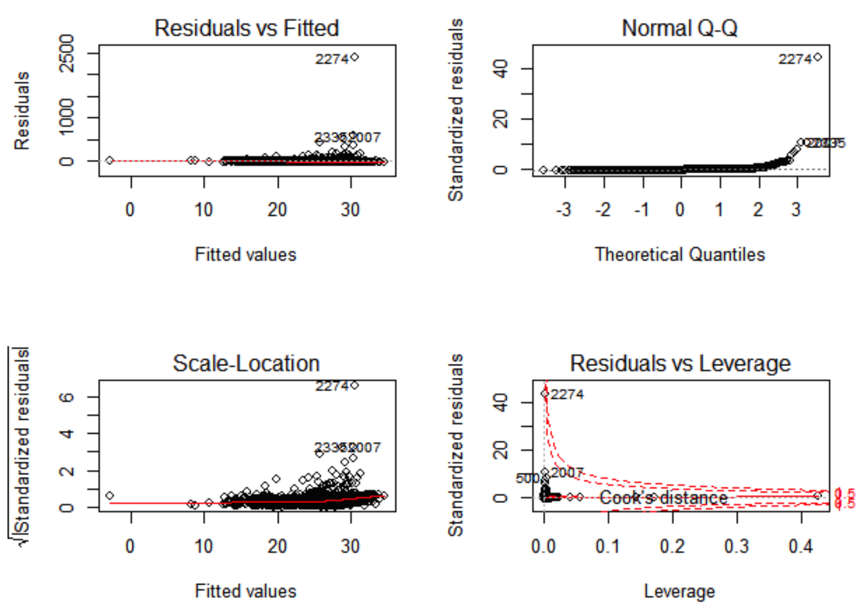


Figure 9a. Model Diagnostics for Per Capita Scope 1&2:LRM Using Full Data Set, All Predictor Variables

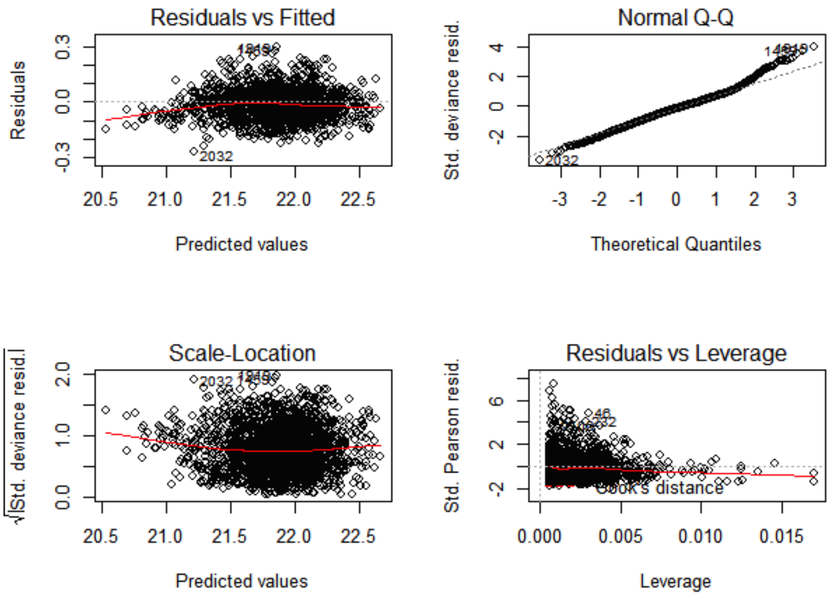


Figure 9b. Model Diagnostics for Per Capita Scope 1&2:GLM Using Reduced Data Set, Select Variables (MSA, MedHHInc, CDD)

Table 19. Summary of Best LRM Results

Variable	Industrial	Residential	Commercial	Onroad	Nonroad	Air	Scope 1	Scope 1+ 2 NERC
Intercept	2.016e+00*** (1.950e-01)	1.875e+00*** (7.435e-02)	8.255e-01*** (4.841e-02)	4.902e+00*** (1.049e-01)	3.536e-01*** (4.301e-02)	1.887e-01*** (1.808e-02)	1.095e+01*** (5.376e-01)	2.211e+01*** (8.665e-01)
Nonmetro	5.323e-02 (8.675e-02)	1.206e-01*** (2.786e-02)	-1.636e-01*** (2.022e-02)	1.126e+00*** (9.047e-02)	3.227e-01*** (1.916e-02)	-3.750e-02*** (9.133e-03)	2.359e+00*** (2.094e-01)	-6.270e-01 . (3.673e-01)
Outlying	-9.114e-02 (9.366e-02)	-8.906e-02** (2.968e-02)	-2.817e-01*** (2.177e-02)	1.052e+00*** (1.405e-01)	1.506e-01*** (1.809e-02)	-7.432e-02*** (1.059e-02)	9.772e-01*** (2.519e-01)	6.943e-01 (4.303e-01)
Pop. Density				-2.183e-04*** (6.519e-05)				
Med. HH Inc.	-1.007e-05** (3.371e-06)	6.373e-06*** (1.276e-06)	5.459e-06*** (9.083e-07)		5.567e-06*** (8.603e-07)	4.546e-07 (3.866e-07)	-6.596e-06 (-6.596e-06)	-1.282e-05 (1.498e-05)
HDD						-5.711e-06** (1.967e-06)		
CDD	8.292e-06 (4.242e-05)	-5.731e-04*** (1.397e-05)	-2.121e-04*** (8.266e-06)	2.408e-04*** (5.005e-05)	-4.011e-05*** (1.029e-05)		-3.611e-04** (1.202e-04)	-3.082e-04 (1.955e-04)
Adj. R^2	0.006796	0.5121	0.3365	0.1111	0.1322	0.02479	0.0669	0.00411

Appendix V. Data Sources and Values by Life Cycle Stage

Table 23 summarizes the data sources for emissions rate used to compute emissions for each life stage – Vehicle upstream, manufacture, and assembly; battery upstream and manufacturing (Lithium-ion); gasoline upstream and distribution; gasoline combustion; electricity upstream; and electricity production.

Table 23. Summary of data sources by life stage

Stage	Method/Source	Values
Vehicle Upstream, Manufacture and Assembly – ICEV Upstream: resource extraction and production of materials needed for vehicle assembly Mnfg. And Assembly: covers all material and energy needed during vehicle assembly	Avg.: GREET estimate for Generic 1532 kg (find sources for low and High)	Normal(Mean~2169, SE~230)
Vehicle A&M – HEV	GREET estimate for HEV 1683 kg	Normal(Mean~2002,SE~17)
Vehicle A&M – PHEV	GREET estimate for PHEV20 1746 kg; GREET estimate for PHEV40 1959 kg	PHEV20=1995 PHEV40=2165
Vehicle A&M – BEV	GREET estimate for BEV 2104 kg	2, 244
Battery Upstream and Manufacturing (Lithium-ion) – PHEV/BEV	Battery Capacity, Specific Energy, and EV AER: fueleconomy.gov Battery mnfg. And assembly emission rate: Hart et al. (2013), Zackrisson et al. (2010), Notter et al. (2010), and Majeau-Bettez et al. (2011)	Normal(Mean~15,SE~5)
Gasoline Upstream and Distribution: extraction, refining, and distribution from refineries to gasoline stations	Low: Venkatesh et al 2011 Avg.: Low and High Avg. High: GREET 2013	Normal(Mean~2.4,SE~0.01)
Gasoline Combustion	Low: EPA 2014 Avg.: Low and High Avg. High: Venkatesh et al 2011	Normal(Mean~87,SE~0.2)
Electricity Life Cycle:	See Appendix 6	

Upstream: fossil fuel extraction, production, and transportation to power plants Generation: fossil fuel combustion during generation (includes electricity consumed and onsite, transmission, and distribution	

Appendix VI. Vehicle and Battery Parameters

I summarize in Tables 6 and 7 the vehicle and battery parameters used in computations as described in the Methods section.

Table 21. Summary of vehicle all electric range (AER) and energy use

Vehicle Model	AER (mi)	*Combined Energy Use (kWh/mi)*	*Combined Fuel Economy (mpg)*
2014 Chevrolet Volt (PHEV)	38	0.35	37
2014 Nissan Leaf (BEV)	84	0.29	
2014 Toyota Prius HEV			50
Sales Weighted Ave. CV		24.6	

All Values are from fueleconomy.gov except for sales-weighted average light-duty vehicle, which was obtained from Eco-driving Index (University of Michigan Transportation Institute 2013). Gasoline fuel economy values correspond to combined driving. All vehicles are model year 2014.

Table 22. Battery parameters (Lithium Ion)

Vehicle Model	Battery Capacity (kWh)	Battery Specific Capacity (kWh/kg)	Acceptance Rate (kW)	Charge Time (hrs)
Chevrolet Volt	16	0.080	3.3	4
Nissan Leaf	24	0.0873	3.3	8

Source: Barrett (2013)

Appendix VII. Summary of Electricity Emissions Factors

I show representative maps of the NERC and eGRID subregions in Figures 3 and 4. The tables that follow summarize the emission factors corresponding to each region and state.

Figure 23. Representational Map of U.S. NERC Regions (Source: eGRID 2012)

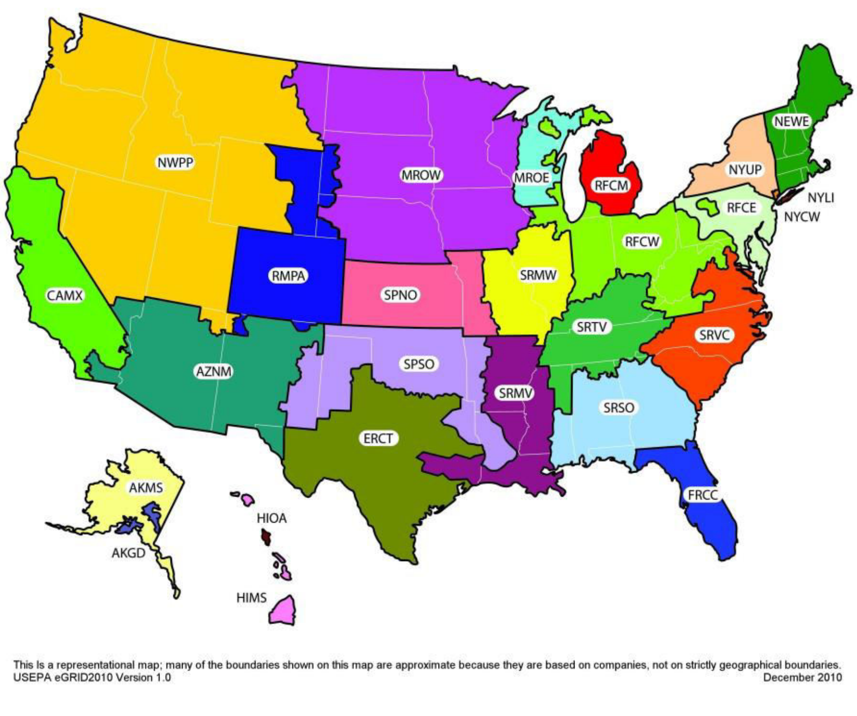


Figure 23. Representational Map of eGRID Subregions (Source: eGRID 2012)

Table 23. Regional Average Emission Factors (Source: eGRID 2012)

NERC region acronym associated with the eGRID subregion acronym	NERC region name	NERC Region annual CO_2 total output emission rate (kg/MWh)	eGRID subregion acronym	eGRID subregion name	eGRID subregion annual CO_2 total output emission rate (kg/MWh)
FRCC	Florida Reliability Coordinating Council	534	FRCC	FRCC All	534
MRO	Midwest Reliability Organization	736	MROE	MRO East	722
			MROW	MRO West	739
NPCC	Northeast Power Coordinating Council	297	NYLI	NPCC Long Island	611
			NEWE	NPCC New England	330
			NYCW	NPCC NYC/Westchester	277
			NYUP	NPCC Upstate NY	226
RFC	Reliability First Corporation	621	RFCE	RFC East	430
			RFCM	RFC Michigan	753
			RFCW	RFC West	690
SERC	SERC Reliability Corporation	566	SRMW	SERC Midwest	794
			SRMV	SERC Mississippi Valley	455
			SRSO	SERC South	601
			SRTV	SERC Tennessee Valley	616
			SRVC	SERC Virginia/Carolina	470
SPP	Southwest Power Pool	756	SPNO	SPP North	824
			SPSO	SPP South	725
TRE	Texas Regional Entity	536	ERCT	ERCOT All	536
WECC	Western Electricity Coordinating Council	432	CAMX	WECC California	299
			NWPP	WECC Northwest	372
			RMPA	WECC Rockies	828

	AZNM	WECC Southwest	540

Table 24. Hourly generation-based marginal emission factors, kg/ MWh (Source: Siler-Evans et al 2011).

Hour	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC
1AM	503	908	459	695	625	474	478	473
2AM	490	949	474	770	711	665	545	491
3AM	496	959	508	803	778	765	577	543
4AM	554	940	522	798	816	796	653	560
5AM	565	918	522	794	816	791	657	574
6AM	567	891	499	782	794	638	583	574
7AM	572	861	473	725	707	726	561	561
8AM	541	820	486	704	768	668	628	486
9AM	603	758	503	690	661	613	522	489
10AM	554	700	500	657	589	489	481	458
11AM	527	714	493	648	574	483	474	469
12PM	452	699	482	642	596	510	467	478
1PM	453	695	486	621	609	519	447	472
2PM	462	691	476	633	620	511	451	501
3PM	484	702	461	635	658	525	444	505
4PM	472	740	478	671	622	512	455	522
5PM	459	745	481	697	618	512	459	529
6PM	394	708	496	650	599	544	480	523
7PM	371	683	494	648	622	549	499	502
8PM	468	700	494	636	660	555	484	485
9PM	520	688	514	668	649	543	488	509
10PM	513	613	497	637	562	484	473	486
11PM	503	665	502	581	463	450	418	453
12AM	545	834	450	633	512	428	398	449

Table 25. Hourly consumption-based marginal emission factors, kg/MWh (Source: Zivin et al 2014).

Hour	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC
1AM	608	1175	481	685	558	340	463	381
2AM	603	866	331	785	581	612	490	376
3AM	553	1284	599	635	653	417	503	381
4AM	540	1279	640	621	658	503	513	381
5AM	549	1275	662	626	649	562	508	363
6AM	572	1275	612	667	590	653	485	349
7AM	653	1211	535	717	476	794	454	322

8AM	671	1270	617	640	395	789	431	299
9AM	689	1066	562	662	345	789	426	308
10AM	794	975	549	662	358	640	426	349
11AM	821	1075	644	567	449	526	417	386
12PM	748	1129	680	490	544	440	417	399
1PM	603	1102	689	449	599	413	413	399
2PM	508	1080	658	449	599	390	417	390
3PM	440	1034	640	458	576	395	417	376
4PM	404	984	658	458	549	431	417	372
5PM	404	989	635	467	535	417	417	363
6PM	422	903	603	494	526	404	413	358
7PM	472	807	594	517	503	435	408	358
8PM	522	767	526	553	485	417	408	363
9PM	558	744	503	576	472	408	404	367
10PM	581	821	581	549	485	395	404	363
11PM	612	921	476	612	476	349	413	367
12AM	662	1030	481	649	508	327	431	372

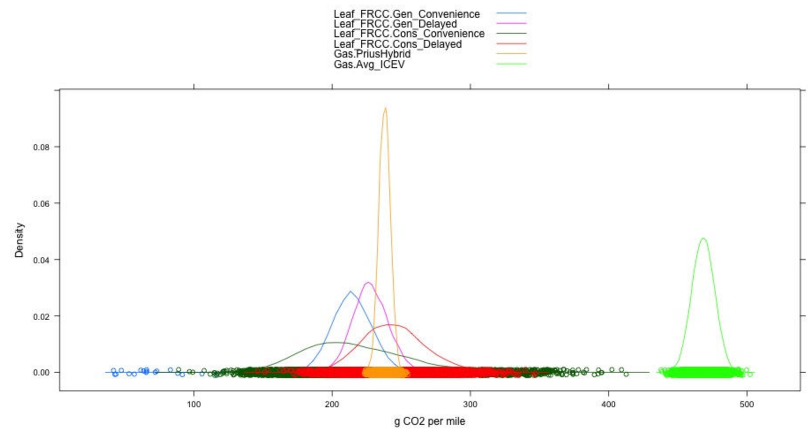
Table 26. 2009 State average emission factors (Source: eGRID 2012)

State	Average State EF (kg/MWh)
AL	472
AK	511
AZ	492
AR	505
CA	252
CO	788
CT	262
DE	814
DC	1127
FL	541
GA	583
HI	693
ID	54
IL	484
IN	922
IA	737
KS	759
KY	928
LA	512
ME	227
MD	559
MA	505
MI	691
MN	634

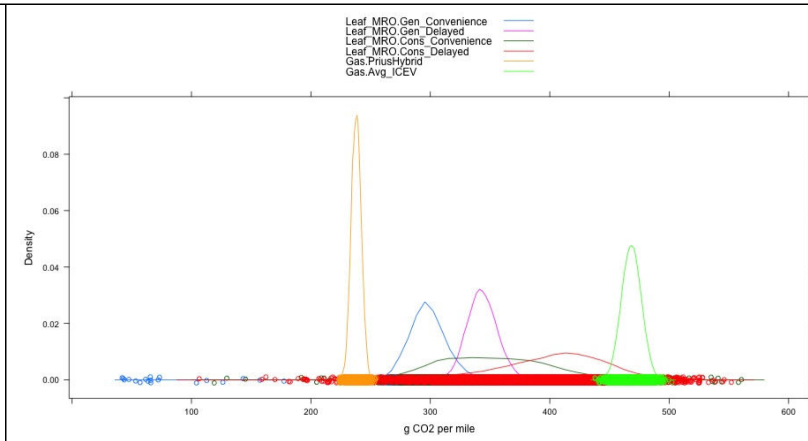
MS	500
MO	820
MT	653
NE	725
NV	481
NH	272
NJ	249
NM	826
NY	264
NC	525
ND	933
OH	808
OK	678
OR	165
PA	517
RI	406
SC	374
SD	414
TN	486
TX	564
UT	841
VT	1
VA	451
WA	130
WV	912
WI	687
WY	960

Appendix VIII. Vehicle emission estimates probability density plots

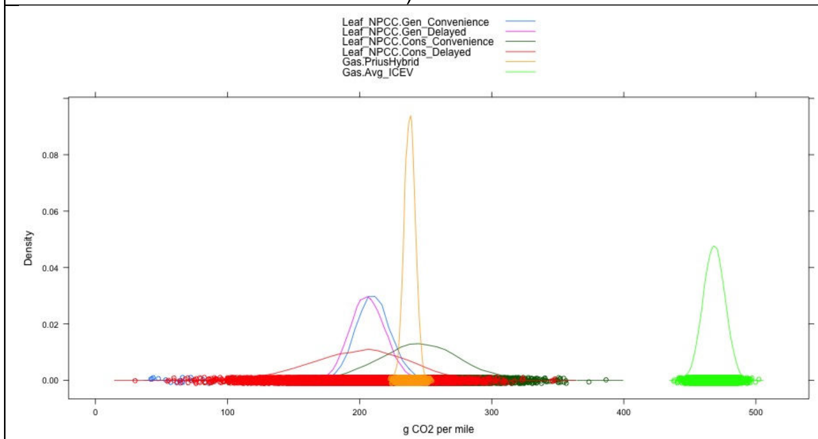
Table 30. Probability density plots of estimated Nissan Leaf marginal emissions, Toyota Prius Hybrid emissions, and sales-weighted average ICEV emissions



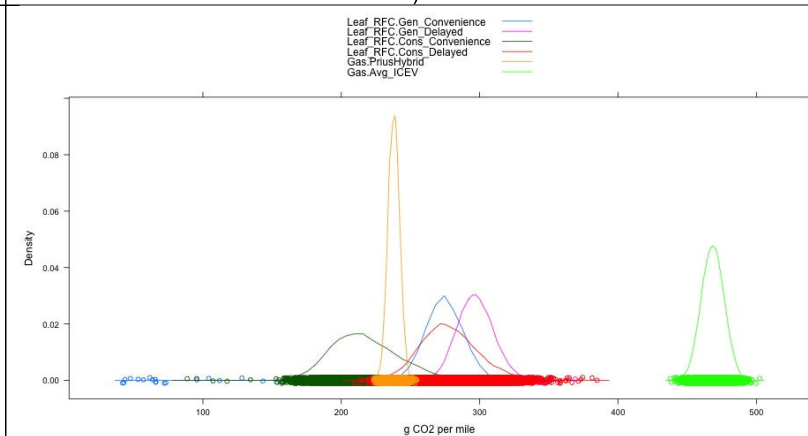
a) FRCC



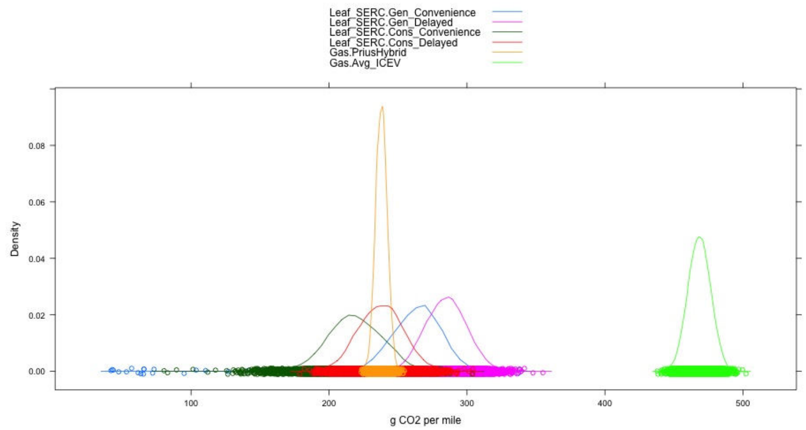
b) MRO



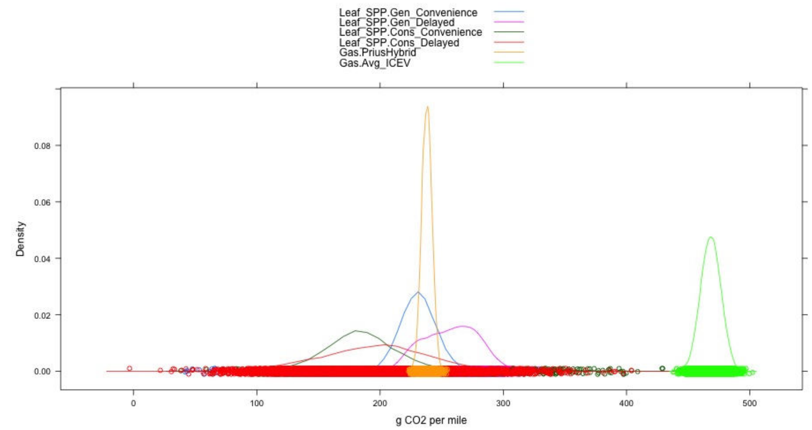
c) NPCC



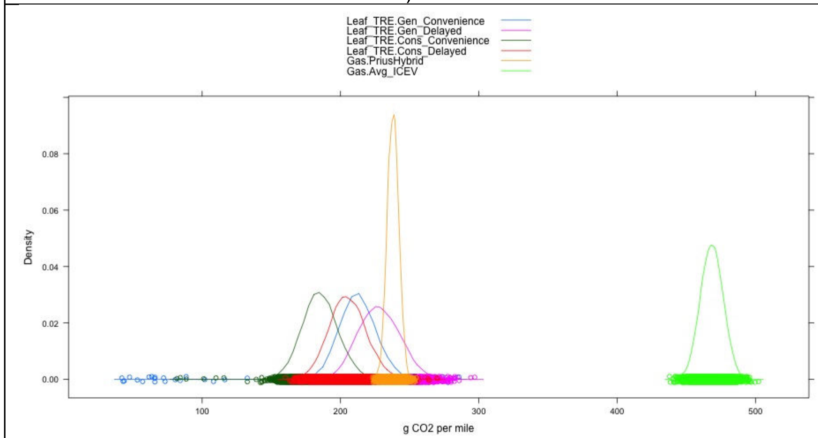
d) RFC



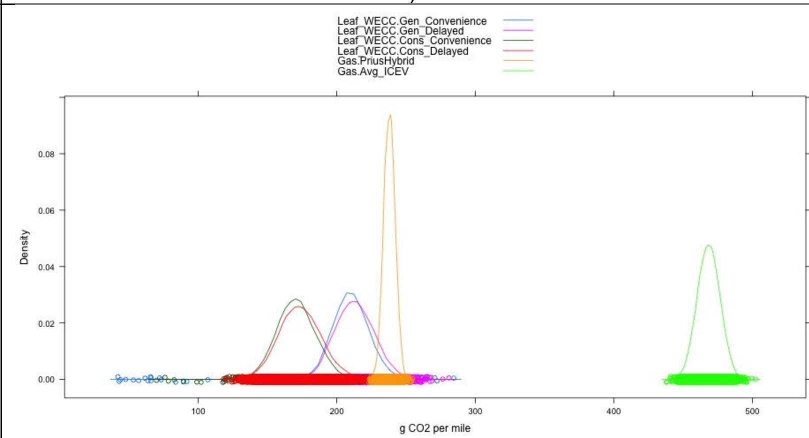
e) SERC



f) SPP



g) TRE



h) WECC

Appendix IX. Emission estimates by life cycle stage (kg CO2/mi)

The following tables summarize the emissions estimates in kg CO_2/mi for each life cycle stage. Electricity related emissions shown here correspond to the 2013 Nissan Leaf electricity use. Siler-Evans et al (2011) provide data on marginal grid mix – percentage of coal, gas, and oil – at 20 electricity load values. They also provide average load estimates for each hour of the day. To determine generation-based marginal grid mix by hour of the day, we extrapolated values from the load-grid mix data set and the hour-load data set using the following equation:

$$Mix_{itr} = \frac{U_{ir} * (x_{tr} - L_{ir}) + L_{ir} * (U_{ir} - x_{tr})}{U_{ir} - L_{ir}}$$

where Mix_{itr} is the percentage of fossil fuel type $i \in \{Coal, Gas, Oil\}$, for hour t in region $r \in \{FRCC, MRO, NPCC, RFC, SERC, SPP, TRE, WECC\}$, x_{tr} is the estimated load in region r at hour t form Siler-Evans et al (2011), and the range $[L_{ir}, U_{ir}]$ are values from the load-grid mix data set that include x_{tr}. To compute upstream electricity emissions by hour, $\widehat{\Phi}_{tjr}^{Upstream\_Elec}$ (j=generation-based from Siler-Evans et al 2011), I used the following formula, where I assumed distributions/values shown in Table 31.

$$\widehat{\Phi}_{tjr}^{Upstream\_Elec} = \sum_{i} Mix_{itr} * \widehat{\Phi}_{i}^{Upstream\_Fuel}$$

Table 31. Upstream fossil fuel emissions estimates (g CO_2/kWh)

Fossil Fuel	Upstream Fuel Emissions ($\widehat{\Phi}_{i}^{Upstream\_Fuel}$)

Coal	Normal(mean = 32, std. error = 13)
Gas	Normal(mean = 115, std. error = 44)
Oil	43

Zivin et al (2014) do not provide a grid mix or load data that can be used to estimate hourly marginal grid. As an approximation of hourly consumption-based upstream electricity emission, $\hat{\Phi}_{tjr}^{Upstream\_Elec}$ $(j = consumption - based)$, we used the following formula:

$$\hat{\Phi}_{itjr,j=consumption-based}^{Upstream\_Elec} = \frac{\hat{\Phi}_{tjr,j=generation-based}^{Upstream\_Elec}}{\Upsilon_{ijrv,j=generation-based}} * \Upsilon_{ijrv,j=consumption-based}$$

where Υ_{ijrv}^{Elec} is the vehicle operation electricity emissions estimate for vehicle sample i, vehicle type v, using emissions factors set j in region r in g CO2.

Table 32. Nissan Leaf electricity upstream and production emissions estimates (kg CO2/mi) by region (eGRID Subregion and state values correspond to minimum and maximum values within the NERC region)

Region	Emission Factor Type	Charging	Marginal Electricity Upstream Emissions (kg CO2/mi)			Marginal Electricity Production Emissions (kg CO2/mi)		
			5th	Mean	95th	5th	Mean	95th
FRCC	Marginal Consumption (Zivin)	Convenience	13	17	22	120	162	204
		Delayed	12	16	20	132	177	222
	Marginal Generation (Siler-Evans)	Convenience	16	16	17	151	154	158
		Delayed	11	14	18	158	163	167
	Average Generation (NERC)	Subregion	43	43	43	161	161	162
		State	43	43	43	160	161	161
MRO	Marginal Consumption (Zivin)	Convenience	7	9	11	226	280	334
		Delayed	5	7	9	262	348	434

	Marginal Generation (Siler-Evans)	Convenience	8	8	8	237	241	244
		Delayed	5	5	6	270	273	276
	Average Generation (NERC)	Subregion	11	13	13	217	222	222
		State	7	13	14	124	222	280
NPCC	Marginal Consumption (Zivin)	Convenience	13	147	26	108	164	220
		Delayed	9	147	28	76	155	234
	Marginal Generation (Siler-Evans)	Convenience	17	167	18	144	147	149
		Delayed	17	149	18	144	147	149
	Average Generation (NERC)	Subregion	0.1	90	58	68	90	183
		State	28	90	41	0.3	90	152
RFC	Marginal Consumption (Zivin)	Convenience	6	7	7	149	171	192
		Delayed	5	6	7	171	205	240
	Marginal Generation (Siler-Evans)	Convenience	8	8	8	209	211	214
		Delayed	7	7	7	227	229	231
	Average Generation (NERC)	Subregion	15	15	18	129	188	226
		State	15	15	43	75	188	338
SERC	Marginal Consumption (Zivin)	Convenience	7	8	9	140	156	173
		Delayed	6	6	7	157	176	195
	Marginal Generation (Siler-Evans)	Convenience	10	10	10	195	197	200
		Delayed	8	8	8	221	223	225
	Average Generation (NERC)	Subregion	35	20	13	136	171	238
		State	12	20	16	112	171	278
SPP	Marginal Consumption (Zivin)	Convenience	5	10	15	59	123	188
		Delayed	3	8	13	64	153	242
	Marginal Generation (Siler-Evans)	Convenience	14	14	14	168	170	173
		Delayed	11	11	11	197	201	204
	Average Generation (NERC)	Subregion	17	27	32	218	228	247
		State	38	27	15	203	228	228

TRE	Marginal Consumption (Zivin)	Convenience	14	15	16	121	127	134
		Delayed	12	13	14	135	145	155
	Marginal Generation (Siler-Evans)	Convenience	17	18	18	149	152	155
		Delayed	15	15	16	166	170	174
	Average Generation (NERC)	Subregion	38	38	38	161	161	161
		State	38	38	38	161	161	169
WECC	Marginal Consumption (Zivin)	Convenience	12	13	15	97	110	123
		Delayed	10	12	14	90	111	132
	Marginal Generation (Siler-Evans)	Convenience	18	18	18	145	147	149
		Delayed	16	17	17	152	155	159
	Average Generation (NERC)	Subregion	38	26	27	90	130	248
		State	9	26	38	16	130	288

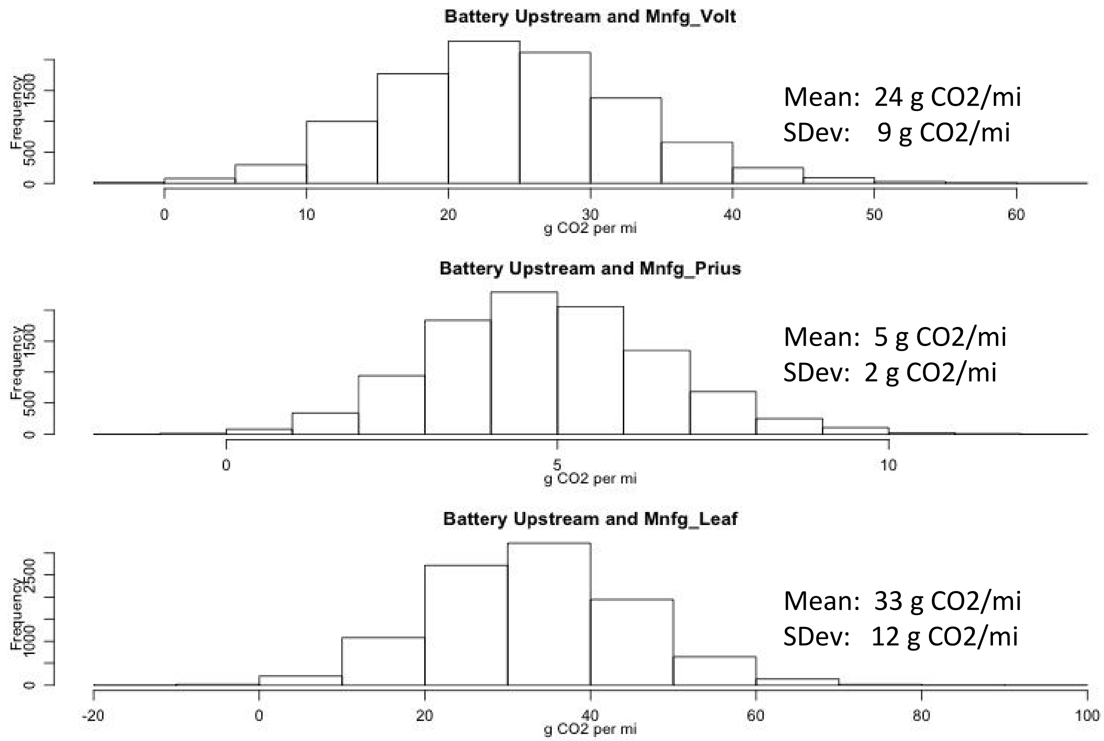


Figure 25. Lithium-ion Battery upstream and manufacturing emissions estimate for Chevrolet Volt, Toyota Prius PHEV, and Nissan Leaf

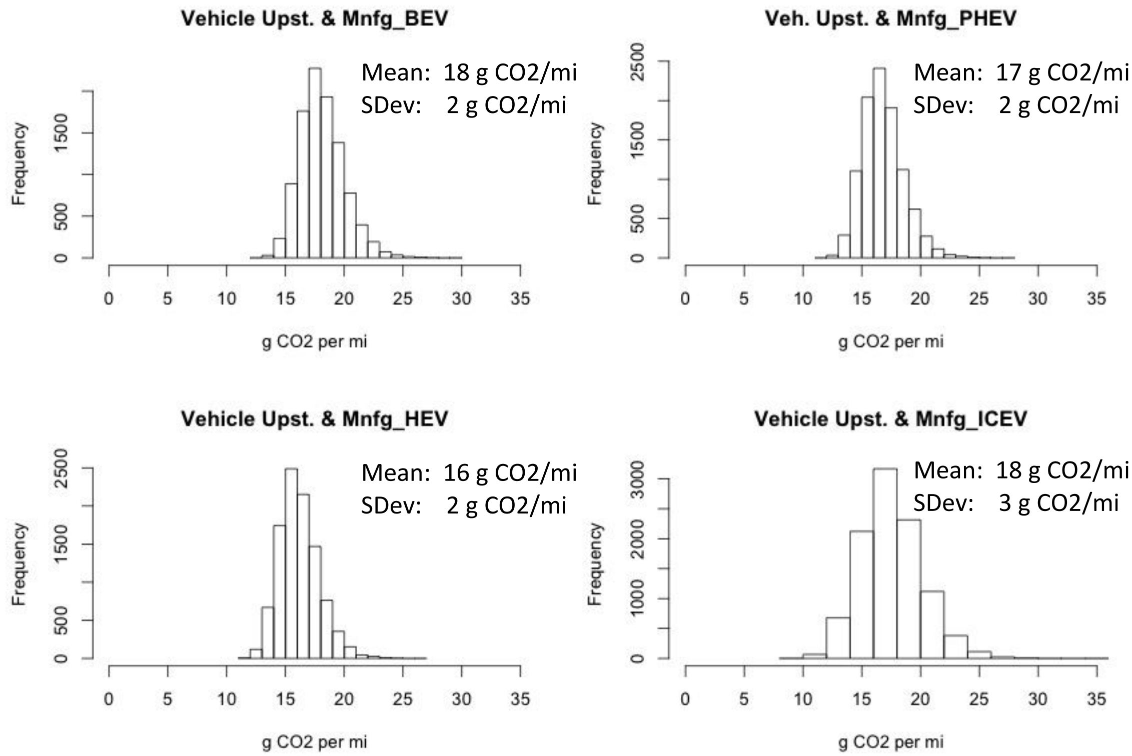


Figure 26. Vehicle upstream and manufacturing emissions estimates by vehicle t–pe - Battery electric vehicle (BEV), Plug-in hybrid electric vehicle (PHEV), Hybrid electric vehicle (HEV), and Internal combustion engine vehicle (ICEV).

Appendix X. Nissan Leaf t-test results for comparing results under different estimation methods

Table 33. T-test results for Nissan Leaf emissions estimates under different marginal emissions estimation methods

Region	Convenience Minus Delayed Charging				Consumption-based Minus Generation-based			
	Consumption-based		Generation-based		Convenience Charging		Delayed Charging	
	p-value	% Mean Diff.	p-value	% Mean Diff.	p-value	% Mean Diff.	p-value	% Mean Diff.
FRCC	< 1%	-11%	< 1%	-6%	< 1%	-3%	< 1%	-7%
MRO	< 1%	-13%	< 1%	-15%	< 1%	-16%	< 1%	-14%
NPCC	< 1%	19%	< 1%	2%	< 1%	14%	< 1%	3%
RFC	< 1%	-28%	< 1%	-8%	< 1%	26%	< 1%	7%
SERC	< 1%	-9%	< 1%	-8%	< 1%	21%	< 1%	20%
SPP	< 1%	-4%	< 1%	-11%	< 1%	23%	< 1%	31%
TRE	< 1%	-11%	< 1%	-7%	< 1%	15%	< 1%	11%
NPCC	< 1%	-2%	< 1%	-1%	< 1%	23%	< 1%	23%

Appendix XI. Comparison Results for Chevrolet Volt and Toyota Prius PHEV versus the Toyota Prius Hybrid and sales-weighted average ICEV

Table 34. Comparison results for the Chevrolet Volt versus the Toyota Prius Hybrid and sales-weighted average ICEV by region and marginal emissions estimation method. Values are mean percentage differences while cell colors indicate which vehicle is lower emitting – green: Chevrolet Volt and red: gasoline vehicle.

NERC Region	Chevrolet Volt vs Toyota Prius Hybrid				Chevrolet Volt vs. Avg. ICEV			
	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del
FRCC	5%	14%	2%	8%	47%	42%	48%	45%
MRO	62%	83%	39%	59%	18%	7%	30%	19%
NPCC	15%	3%	0%	1%	41%	51%	49%	50%
RFC	4%	30%	28%	39%	47%	34%	35%	29%
SERC	4%	13%	24%	34%	47%	42%	37%	32%
SPP	9%	4%	9%	23%	54%	51%	44%	37%
TRE	11%	1%	1%	9%	55%	50%	49%	45%
WECC	17%	16%	0%	3%	58%	57%	49%	48%

Table 35. Comparison results for the Toyota Prius PHEV versus the Toyota Prius Hybrid and sales-weighted average ICEV by region and marginal emissions estimation method. Values are mean percentage differences while cell colors indicate which vehicle is lower emitting – green: Chevrolet Volt and red: gasoline vehicle.

NERC Region	Toyota Prius PHEV vs Toyota Prius Hybrid				Toyota Prius PHEV vs Avg. ICEV			
	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del	Cons_ Conv	Cons_ Del	Gen_ Conv	Gen_ Del
FRCC	12%	5%	13%	10%	55%	52%	56%	54%
MRO	19%	28%	6%	17%	23%	10%	35%	25%
NPCC	5%	18%	14%	16%	52%	58%	56%	57%
RFC	13%	3%	1%	6%	56%	48%	49%	46%
SERC	12%	9%	1%	2%	54%	56%	53%	52%
SPP	19%	19%	9%	6%	59%	59%	54%	52%
TRE	20%	16%	14%	11%	59%	57%	56%	55%
WECC	23%	22%	14%	14%	61%	61%	56%	56%