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Essays on the Economics of Flood Risk

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Abstract

Climate change yields heightened flood risk due to both sea level rise and an increased frequency of significant storms. While prior literature has estimated flood damages, it is difficult to measure how agents will respond to an increase in flood risk. Furthermore, it is important to understand how policymakers can minimize these risks by investing in flood hazard protections. My dissertation studies the problem of valuing the cost of flood risk and the role of policymakers in response to flood risk. In the first part, I explore the relationship between flood risk and the housing market. This allows me to measure the cost of increased flood risk on housing markets using revealed preference methods. In the second part of my dissertation, Chapters 2 and 3, I study why policymakers invest in flood hazard reduction and how flood hazard mitigation is valued by homeowners. My findings on what factors influence policymakers to invest in flood hazard protection at the local level and how these investments are valued provide important insights for the federal government as it redesigns the National Flood Insurance Program (NFIP).

My first chapter (joint with Nicholas Z. Muller) provides evidence that well-informed homeowners of coastal real estate respond to flood risk. Our innovations in this paper are two-fold. First, we parse homeowners according to the quality of information they possess about their flood risk, and second, we disentangle flood risk from property damage. Prior literature has found evidence that homeowners respond to flood shocks, however these papers focus mostly on local flood shocks. As such, it is difficult to separate the cost of damages from the effect of information about risk. Our paper circumvents this identification issue by testing whether non-local flooding events affect housing prices in coastal markets. Utilizing a difference-in-differences methodology, we test whether homeowners in high flood risk areas along the coast of New Jersey respond to non-local flooding. We use several well-publicized hurricanes and tropical storms that did not strike the Atlantic seaboard as non-local shocks. We find that prices of homes in areas of high flood risk do not decrease after a storm, but rather increase. The literature has shown current and prospective homeowners do not always know their flood risk, so we further test if informed homeowners respond differently. We use participation in Community Rating System (CRS) public awareness activities as a measurement of homeowner's information. We find that homes in high flood risk zones situated in towns that participate in public flood awareness activities incur a 7 to 16 percent decrease in price after the non-local shock. Further, we show that firms are more responsive to risk information than individuals and that markets exposed to such information are less adversely affected by future disasters.

For my second chapter I study the decision to participate in CRS, which is a federally run program that incentivizes local jurisdictions to undertake activities related to flood hazard mitigation in exchange for flood insurance discounts for their constituents. In this chapter I study the decisions

of the government to participate in CRS from a static perspective. First, I build a model of the local government's decision to provide a public good that mitigates hazard risk. Second, I use participation in CRS in New Jersey to empirically test the hypotheses generated by the theoretical model in the context of flood hazard mitigation. Consistent with the model predictions, the empirical results show that an array of factors affect participation: income, population, housing values, risk, value of amenity access, information, and whether the local jurisdiction type is mayor-council. This paper further contributes to the literature on optimal public good provision by showing that incomplete information, weak government accountability, and lobbying can lead to inefficient levels of hazard mitigation.

My third chapter further explores the decision of local governments to invest in flood hazard mitigation and builds on my second chapter by using a dynamic structural model of the local government's decision, which accounts for the value of flood hazard mitigation to homeowners. Thus, I am able to consider the interdependency between changes in federal policy and the decisions of the local government. To this end, I estimate a homeowner's marginal willingness to pay for flood insurance and for the local government's flood hazard mitigation actions based on housing sales in New Jersey from 1998 to 2018. I then use a dynamic discrete choice model of the local government's investment decision to estimate their costs. I find that the spillover effects from mitigation are positive, insurance discounts are valued more than the actual savings, and that large initial perceived costs may prevent investments in hazard mitigation. Finally, I perform counterfactual analyses to consider the local government response to alternative federal policies. The counterfactuals suggest that either increasing the proportion of homes in federally designated high risk zones to account for climate change or raising the federally set flood insurance rates increase investment in flood hazard mitigation, and that implementing a cost subsidy rather than the current insurance discount policy may increase investment in municipalities with low property values.

Contents

Chapter 1

The Role of Information in the Market Response to Flood Risk: Hurricane Katrina and the New Jersey Coast

1.1 Introduction

Coastal real estate markets comprise large stocks of highly valued capital. Assets in these markets possess a high degree of exposure to natural disaster risk including floods, erosion, and wind. Natural disaster risks are changing due to anthropogenic climate change perhaps especially so in coastal environments. In this dynamic context, markets may not yield efficient outcomes. The concern is a form of hysteresis. As risks from sea level rise, storm frequency, and intensity, change, inaccurate beliefs about emergent risks may yield inefficient investment decisions and asset bubbles. Ultimately, the welfare consequences of large-scale mispricing of these assets is likely to be publicly shared due to government insurance programs and negative pecuniary externalities in both housing and mortgage markets (Ouazad and Kahn 2019). Further, given financial derivatives collateralized with residential real estate, the effects of this form of hysteresis may be far reaching. These market failures suggest a role for risk information policies.

In coastal communities, information pertaining to flood risk derives from accumulated experience. In the United States, public policy also plays a crucial role in conveying risk information to market participants. Risk designations are provided by the National Flood Insurance Program (NFIP)[1], which is administered by the Federal Emergency Management Agency (FEMA). To the extent that risk distributions are changing, the importance of NFIP rises as accumulated knowledge becomes less relevant. In recognition of this dynamic risk environment, the NFIP offers additional

[1]Communities choose whether to participate in NFIP. Once a community joins the NFIP, Flood Insurance Rate Maps (FIRMs) are drawn to demonstrate flood risk levels.

information on flood risk through the Community Rating System (CRS). The CRS is a voluntary component of the NFIP that encourages communities to increase floodplain management above the minimum federal standards. Among the actions comprising CRS, most enrolled communities pursue low-cost measures such as raising flood risk awareness (Michel-Kerjan, et al., 2016). As such, we posit that communities enrolled in CRS have better information about flood risk.

Centrally, this paper analyses the effect of information embodied in CRS enrollment on the manner in which coastal real estate markets respond to flood risk. Our identification strategy relies on the following consideration: observed housing market responses to a flooding event conflate the effect of risk perception among buyers and sellers with actual property damage. To separate these two effects, this paper examines whether prices for properties at risk of coastal flooding events adjust when environmental hazards manifest in geographically distant markets. This design decouples risk discounts from property damage. To implement this strategy, we use hedonic property models and a difference-in-differences (DID) specification. Our empirical setting is the New Jersey coastal real estate market.[2] This is a large, and economically significant context spanning 130 miles of coastline. The value of land and property along the coast grew from less than $1 billion in 1960 to greater than $170 billion today.[3] We assign homes in high-risk areas, as designated by FEMA's FIRMs, to the treatment group. The occurrence of a non-local hurricane or tropical storm identifies the time of treatment. Though we explore numerous hurricanes that did not strike New Jersey, our main specification uses Hurricane Katrina. We augment this specification in a triple difference design using CRS enrollment as an information treatment.

For our identification strategy to be viable, participants in New Jersey's coastal real estate markets must be "exposed" to the geographically-distant shock. We contend that it is quite likely homeowners in New Jersey were aware of highly publicized storms like Hurricane Katrina. This storm (and its subsequent destruction) was extensively covered by national media throughout the United States. Utilizing Google Trends provides support for this claim. Figure 1 shows that New Jersey residents searched for information related to the storm immediately after Hurricane Katrina made landfall in August, 2005. Interestingly, the New Jersey residents searched again for information regarding Hurricane Katrina, when Hurricane Irene made landfall in New Jersey in 2011 and Hurricane Sandy made landfall in New Jersey in 2012. This demonstrates the connection between local flooding events and distant disasters. Figures 2 and 3 demonstrate similar results using the search terms "Disaster" and "Flood Insurance" in Google Trends. Local media in New Jersey consistently made the connection between flooding from Hurricane Katrina and flooding in New Jersey. For example, the Asbury Park Press published an article on September 11th, 2005 titled

[2]We define the New Jersey coastal real estate market as homes located in Cape May, Atlantic, Ocean, and Monmouth counties.

[3]"How Rising Seas and Coastal Storms Drowned the U.S. Flood Insurance Program" Yale Environment 360. Accessed 6/9/2017

"Less than a Katrina would cause devastation in N.J". After Hurricane Katrina, readers of the Asbury Park Press expressed concern about New Jersey's vulnerability to flooding and the need for emergency preparedness.[4]

Figure 1.1: Google Trends in New Jersey for Hurricane Katrina Search Term

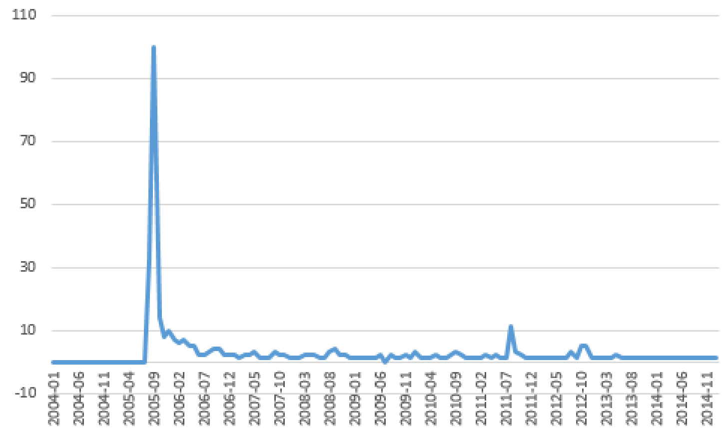
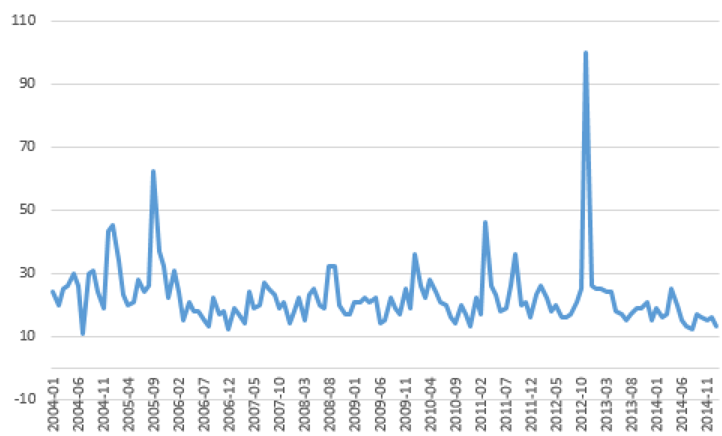
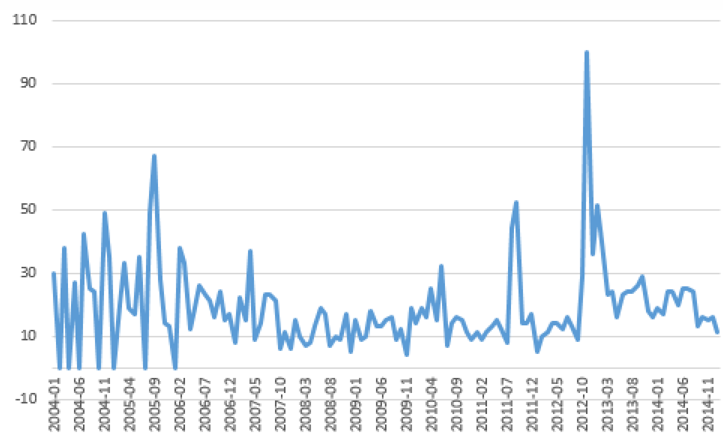


Figure 1.2: Google Trends in New Jersey for Disaster Search Term



[4]See "Readers take a look ahead in Katrina's aftermath", Aspbury Park Press, September 14th, 2005

Figure 1.3: Google Trends in New Jersey for Flood Insurance Search Term



Our main empirical results are summarized as follows. In the standard DID, we do not detect a drop in the price of properties in high risk locations following Hurricane Katrina or other named storms that struck other regions. However, in the triple difference, we find a significant drop in price of properties in high risk locations and in CRS towns after a storm.[5] For Hurricane Katrina, inclusive of all sales, we find significant risk discounts of 7% on sales beginning four months after the storm. This effect endures for sales up to one year after the storm. The discount peaks roughly 10 months following Katrina. Employing a repeat-sales model (Mendelsohn, et al., 1992) with parcel fixed effects, the effect increases. We report a drop of 11% for sales occurring within six months of the storm. This risk discount increases to 15.7% for sales within one year of the storm. We interpret this differential effect in CRS communities as an indication that information on flood risk is important to how markets respond to risk signals as embodied in the geographically-distant storms.

The paper then limits the sample to transactions involving firms (on either side of the transaction). We isolate firms based on the hypothesis that such investors are likely to treat real estate as assets (in contrast to consumers who may have varying degrees of emotional attachment to their homes). Thus, firms may process and internalize risk information differently than individuals. We detect much larger responses to flood risk information when firms are involved in transactions. For Hurricane Katrina, inclusive of all sales, we find significant risk discounts of between 25% and 50% on sales from two to 12 months after the storm. In the repeat-sales setting, the effect estimates are of similar magnitude but only statistically significant at 12 months after the storm. We note that the limited sample size in this context limits the power of these tests.

We then test whether the differential risk discounts in CRS versus untreated towns affects price

[5]Note our indicator for participation in CRS is defined as participating in public awareness activities and public map information activities. See Table A1 for more details.

responses to Hurricane Sandy, which struck coastal New Jersey in 2012, well after Katrina and the other storms considered in the preceding analysis. That is, did the information intervention mitigate hysteresis? With all transactions occurring after Sandy (including individuals and firms) we find no systematic effect of risk information. However, when we limit the sample to only firms, properties in CRS participating markets were sold at a premium of between 20 percent and 50 percent, relative to high risk properties not in CRS towns. One interpretation of this result is that flood risk information had already been incorporated into asset values. Thus, Sandy presented less of an information update to investors in information treated towns.

We explore numerous additional specifications in order to test possible threats to our identification strategy. First, we confirm no violation of the parallel trends assumption central to a causal interpretation in the DID models. Second we consider possible endogeneity of CRS enrollment. Recall that the indicator of "high risk" status stems from the NFIP flood maps. So, one concern is that some unobservable aspect of flood risk is higher in CRS towns, relative to other high risk towns that did not enroll in CRS and that this unobservable factor drives selection into CRS. To test this, we compare flood insurance claims in CRS and non-CRS communities. We find no evidence that average flood insurance claims are higher in CRS communities.

Another concern is that distant storms eventually result in flooding in New Jersey and that our models simply pick up this local effect. We test this by controlling for local flooding events. Our central results are unaffected.

Finally, we exploit the rich nature of our data to test whether the composition of buyers and sellers drives our findings. The coastal real estate market in New Jersey is comprised of numerous investors for whom properties in New Jersey are not their primary residence. These market participants may impart greater liquidity on the market and be more likely to sell following a storm. Econometrically, this phenomenon would be problematic if non-residents own a large share of properties in CRS towns. We do find evidence that non-residents are more likely to sell after non-local hurricanes, however the effect is very small. Additionally, non-resident buyers may lack full information about flood risks and, hence, it may be the case that sales following non-local storms exploit this information asymmetry. We find no evidence that non-resident buyers are more likely to make purchases after the hurricanes of interest.

1.1.1 Relevant Literature

Relative to the literature (Hallstrom and Smith, 2005; Bin, Kruse, and Landry, 2008; Pryce and Chen, 2011; Bin and Landry, 2013; Bernstein, Gustafson, Lewis, 2018), the present study offers three key innovations. First, we credibly identify the market response to flood risk distinctly from manifest damage due to realized flooding. Second, we demonstrate the importance of information, and a role for public policy in providing information, about flood risk in triggering market responses. Third, we show that markets exposed to such information are less adversely affected by future disasters that occur locally.

The first contribution stems from our identification strategy, which isolates the change in perceived flood risk on housing markets. Hallstrom and Smith (2005) attempt to separate out the information about flood risk from flooding damage by using an instance where a hurricane is predicted to hit an area, but instead the hurricane hits a neighboring county. The authors, using a difference in difference methodology, find that homes in high risk flood areas see a 19% decrease in property values relative to those in low risk areas in the county that the hurricane missed. The proximity between the physically affected county and county in which price effects are detected generates some concerns regarding identification of a pure risk effect. Additionally, the timing of the study may confound the information effect of Hurricane Andrew in 1992 with the 1994 legal change that made flood insurance premiums mandatory in high risk areas, therefore making it more expensive to own a high risk home.[6]

Tinsley, Dillon, and Cronin (2012) explore behavior related to near miss storms. The authors distinguish two interpretations of such events; one that emphasizes resilience and once focusing on vulnerability. Resilience leads to more risky behavior whereas vulnerability induces less risky behavior. In this framework, our results indicate that, in CRS enrolled towns, the vulnerability interpretation dominates the resilience interpretation.

In other related work, Bin and Landry (2013) find that home prices decrease after a flooding incident, but that such discounts manifest only after a local flood. Hence, the price decrease cannot be parsed into a risk effect and that due to property damages. Keenan, Hill, and Gumber (2018) find differential trends in property values in Miami-Dade County, Florida. Specifically, they report that lower elevation homes have appreciated less rapidly than those situated at higher elevations. Importantly, they too cannot disentangle the effects of flood risk perception and property damage in driving the differential trends. Bernstein, Gustafson, and Lewis (2018) report that properties at risk of sea level rise sell at a 7% discount, relative to comparable properties. Further, they argue that this effect is due to perception of future risk, rather than property damage, by showing that rental rates do not evince such a discount. While Bernstein, Gustafson, and Lewis (2018), demonstrate that property markets capitalize flooding risk, their focus is on long run cash flows whereas we zero in on acute, short run responses to current flooding events. Climate science indicates that anthropogenic climate change is currently affecting sea level and coastal flooding (IPCC, 2013). Our focus on capitalization of current risk speaks to this near-term dimension of climate change

[6] It is also difficult to separate out flood risk information due to zone designations from the cost of insurance premiums. Several studies have shown that flood zone identification does lead to lower housing prices, but this may be due to the cost of the insurance premiums. See for example Bin et al., 2009

and flood risk. Thus, the present paper is complementary to that of Bernstein, Gustafson, and Lewis (2018).

This paper's second contribution centers on the role of risk-relevant information in market responses to natural disasters. Our design assesses whether non-local flooding events differentially impact market outcomes in towns that enrolled in the CRS relative to communities not enrolled. In contrast to prior papers that demonstrate a response to flooding based (partially) on risk perception (Bernstein, Gustafson, and Lewis, 2018; Bin and Landry, 2013; Keenan, Hill, and Gumber, 2018) we illustrate whether and how information interventions affect market responses to natural disasters. While this is not a test a CRS' effectiveness, it is a novel test of the role that publicly provided information plays in the natural disaster risk setting. This paper is not the first to consider the how information or beliefs about flood risk effect the response of housing markets to changes in flood risk. Both Bakkensen and Barrage (2017) and Giglio, Maggiori, Rao, Stroebel, and Weber (2018) research how beliefs about climate change measured from survey data effect housing market evaluation of flood risk from inundation due to sea level rise. Baldauf, Garlappi, and Yannelis (2019) account for heterogeneity in information about climate change using textual analysis of housing listings. All three papers find similar results to ours; beliefs or information about the flood risk are associated with lower prices. Our work is complementary to these three papers as we focus on a response to short term changes in risk, rather than the long term risk of sea level rise.

We argue that this test has potentially fundamental implications. Prior literature contends that asset bubbles arise, in part, from information frictions (Brunnermeier and Oehmke, 2018). The CRS infuses risk-relevant information into the market. Corrections to asset values operating through purely informational channels may be welfare improving if they diminish either the likelihood or the severity of future bubbles. This is especially important for asset bubbles in large markets (such as residential real estate) that can have adverse and far-reaching consequences. Our third contribution investigates the ramifications of information treatments on subsequent market responses to local flooding events. At issue is whether the information interventions correct inefficient hysteresis or distort asset values. To do this, we explore whether firms respond to risk information interventions differently than individuals. Our hypothesis is that firms may be more likely to incorporate risk information into investment decisions than individuals as the latter may exhibit emotional attachments to properties as homes or residences. We then test how responses to risk information affect asset prices in a major subsequent local natural disaster: Hurricane Sandy.

Eichholtz, Steiner, and Yönder (2019) study commercial real estate markets in New York, Boston, and Chicago and find that commercial real estate exposed to flood risk in New York and Boston experience slower appreciation after Hurricane Sandy than similar unexposed properties. The authors utilize Chicago as a placebo test and find no difference in Chicago. Eichholtz, Steiner, and Yönder (2019) also argue that the slower appreciation rates are not just due to damages from the storm, but also from the risk salience from Hurricane Sandy experienced in both New York and Boston, but not Chicago. However, their results may also be capturing the expected change in insurance premiums due to the Biggert-Waters Act of 2012, which was passed just before Hurricane Sandy and required insurance premiums to increase for business properties in October of 2017. This is consistent with their finding that the price effect is due to changes in capitalization rates faced by exposed properties.

The remainder of the paper proceeds as follows. Section 1.2 presents the data and empirical methodology, Section 1.3 discusses econometric identification issues, Section 1.4 reports the results, and in Section 1.5 we conclude.

1.2 Data and Empirical Analysis

1.2.1 Data

This paper uses hedonic property models to test whether investors respond to non-local flooding events as a means to plausibly identify the value attributed to flood risk rather than physical property damage. The empirical analysis relies on several sources of data. The New Jersey Treasury provides housing parcel data (New Jersey Treasury). This database contains an array of information including the address, type of property, price, size of the property, year built, and information about the owner and the buyer. Since precise location data is needed to assess flood risk, we geo-locate all properties in the database to identify the longitude and latitude coordinates.[7]

All residential properties in New Jersey are included in the data which span the years from 2000 to 2015. We consider both the entire set of properties transacted and a subset of these properties owned by firms. We designate firm transacted properties as those where the seller or the buyer is listed as a firm. As Hurricane Sandy hit New Jersey in October of 2012, the main empirical models in the analysis are fit to transactions prior to Hurricane Sandy. To test whether CRS interventions subsequently affect responses to local flooding events, we then utilize the sales before and after Hurricane Sandy to test whether the non-local shock mitigated hysteresis.

The analysis relies on risk designations provided by the NFIP, which was created through the National Flood Insurance Act. The NFIP provides flood insurance policies to homeowners in flood-prone communities. Once a community joins the NFIP, FIRMs are created to demonstrate the level of flood risk. The analysis uses flood risk information from the FIRMS created by FEMA's NFIP.[8] In Figure A1 we present a map of risk zones for the counties in our analyses. Figure A2 overlays Figure A1 with a map of homes that sold from 2000-2012. Each parcel is assigned to a

[7]For this work we used BING maps API along with additional internet tools like google maps.

[8]We utilized the preliminary firms as opposed to the original firms as those had not been updated since the 80s. We argue the preliminary firms are a better assessment of current risk.

risk zone, which, in turn, affects the insurance premium. In the New Jersey coastal market, many of the homes are designated in Zones AE, AO, or V. Zones AE and AO indicate the home is in the 100-year floodplain, while Zone V indicates that the home is in a coastal area and subject to velocity hazard (wave action).[9] We classify high risk parcels as those located within the Special Flood Hazard Area (SFHA), which are areas that have a 1 percent annual chance of flooding.

The database delineating participation rates in CRS covers all municipalities from 2000 to 2015.[10] FEMA defines the level of participation based on the total number of points a town received for their prior CRS activities. The database reports the participation level for each town annually and it provides detailed information on the type of activities undertaken and the associated point values. The present analysis focuses on CRS participation in public awareness activities.

We focus on this dimension of the CRS for two reasons. First, we are interested in exploring the role of information with respect to risk valuations. Second, prior research in this area has shown that people do not always know or understand their risk (Bakkensen and Barrage 2017). Ascertaining individual market participants' endowment of information is not possible. As such, we use town-level CRS participation in public awareness activities as a proxy for market participants' information since one of the most common actions CRS towns take are public awareness campaigns (Michel-Kerjan, et al., 2016).[11]

Because housing markets respond to local environmental quality (Bajari et al., 2012), and because such attributes are likely correlated with proximity to coastal amenities, we use the monthly average level of fine particulate matter (PM2.5) from EPA's Air Quality System (AQS) dataset to control for air pollution. Further, we employ data on the number and value of new builds from the Census Building Permit Survey to control for changing market conditions. Finally, to identify the storms that comprise the non-local shocks, we selected storms that did not affect the New Jersey coast in years without a large flood shock to New Jersey.[12] This resulted in the following list of named storms: Hurricanes Allison, Charley, Katrina, Erin, and Dean, along with multiple storms that struck during September of 2002.

The estimation dataset is summarized for all residential sales is summarized in Table 1.1 Panel A. The average home in the database was built in 1974 and has approximately 1,378 square feet. The average sales price was almost $\$327,000$. The distribution of sales prices exhibits strong right-skewness. Approximately 16% of the houses are in municipalities that meet our definition

[9] There are some homes designated as Zone A in the four relevant counties. However, homes designated only as A, and not AE or AO, are along rivers and not along the coast. Thus they are not included in our analyses.

[10] The database was provided from FEMA upon request.

[11] We identify towns that participate in at least 1 of the 300 level activities, and either 410 or 440. The description of these activity codes is shown in Table A1.

[12] Some remnants of these storms did eventually pass over New Jersey, however these storms did not induce local flooding.

of CRS participation.[13] Further, 11% of homes are located both in high risk zones and in CRS municipalities. Table 1 also conveys information on CRS participation. The majority of the points are achieved through activities coded in the 300s and 400s. These categories contain public information activities.

Table 1.1: Descriptive Statistics

Panel A: Summary of All Residential Sales

Variable	Mean	SD	Min	Max
Total CRS Points	333.09	595.35	0	2288
CRS Class	9.43	1.05	6	10
CRS Pub Maps Par	0.16	0.37	0	1
Total CRS 300s Points	106.30	181.14	0	571
Total CRS 400s Points	108.99	220.11	0	1121
Total CRS 500s Points	71.96	149.03	0	554
Total CRS 600s Points	32.68	62.66	0	272
Zone High	0.27	0.44	0	1
CRS X Zone	0.11	0.31	0	1
Year Built	1974.22	25.15	1606	2012
Living Space (sq footage)	1378.41	1053.92	0	200400
Verified Sales Price ($)	326980.47	353859.31	400	44000000
Number of Monthly Sales	50.29	44.64	1	245
Total New Builds (Number of Units)	12.73	18.93	0	305
Total Value New Builds ($)	1535743.50	2085704.75	0	23094524
PM 2.5 Pollution (µg/m3)	11.48	4.45	2.95	38.07
Total Residents	15707.17	11143.02	150	42203
Primary Residents	10469.14	9097.26	67	32186
Secondary Residents	5238.03	3941.44	34	14546
Percent Non-Resident	0.37	0.23	0.07	0.89

Panel B: Summary of Firm Residential Sales

Variable	Mean	SD	Min	Max
Total CRS Points	459.67	673.44	0	2288
CRS Class	9.22	1.19	6	10
CRS Pub Maps Par	0.23	0.42	0	1
Total CRS 300s Points	146.07	205.27	0	571
Total CRS 400s Points	148.08	243.82	0	1121
Total CRS 500s Points	104.65	172.48	0	554
Total CRS 600s Points	45.10	71.57	0	272
Zone High	0.36	0.48	0	1
CRS X Zone	0.17	0.37	0	1
Year Built	1975.51	29.01	1638	2012
Living Space (sq footage)	1178.21	1184.21	0	49000
Verified Sales Price ($)	402351.28	649274.25	1000	44000000
Number of Monthly Sales	4.93	4.45	1	30
Total New Builds (Number of Units)	12.01	19.02	0	305
Total Value New Builds ($)	1506760.13	2157837.50	0	21281624
PM 2.5 Pollution (µg/m3)	11.23	4.23	2.95	38.07
Total Residents	13479.12	10517.84	150	42203
Primary Residents	8342.61	8542.99	69	32186
Secondary Residents	5136.52	3936.28	34	14546
Percent Non-Resident	0.44	0.25	0.07	0.89

Table 1.1 Panel B provides the same information for the residential sales transacted by firms. The two panels show that the limited sample is relatively similar to the entire dataset. For example the average home in transactions involving firms was built in 1975 and is approximately 1,178

[13] As defined in Table A1. Unless otherwise noted our use of CRS or CRS participation throughout the paper relies on this definition.

square feet in size. The distribution of prices for transactions involving firms is also right-skewed and the average price is approximately $\$400,000$. In addition, this restricted sample has a larger relative proportion of homes in high risk locations and CRS municipalities than the full dataset.

Table1.2 Panel A summarizes CRS enrollment status by flood risk level. Roughly 27 percent of parcels occur in high risk zones. Within this category, 42 percent of parcels are in CRS-enrolled towns. Table 2 Panel B reports that properties in high flood risk zones tend to sell for higher prices. This is expected because flood risk is effectively bundled with coastal amenities (views and proximity). Table 1.2 Panel B also demonstrates that CRS participation (and its interaction with the high flood risk indicator) is also positively correlated with prices. While this positive correlation is suggestive, the regression analyses that follow test whether this relationship changes both after a storm and conditional on controlling for other important factors that may also effect sale prices.

Table 1.2: Cross Tabulation and Correlations across Types of Homes

Panel A: Summary Cross Tabulation of Houses

	CRS	Non-CRS	Total
Zone High Risk	30,384	42,361	72,745
Zone Low Risk	12,977	186,860	199,837
Total	43,361	229,221	272,582

Panel B: Correlation Between Price and CRS, High Risk

	Zone High Risk	CRS	CRS x Zone
Log Price	0.1328	0.2211	0.2326

Note: Non-CRS refers to any municipality that does not meet our definition of CRS participation.

1.2.2 Empirical Analysis

The empirical analysis builds on the hedonic literature that describes the prices of a durable good (in this case, housing) as a function of its attributes (Ridker and Henning, 1967). Further, in order to identify the causal effect of flooding risk and information on price, we invoke a differences-in-differences specification (DD). Our treatment group consists of properties in the SFHA, the high risk zone ($zone_i$), as designated by FEMA's flood insurance risk maps. We denote homes outside of the SFHA as the control group. The treatment period is a flexibly defined period of time after the storm ($post_{ym}$). (Without a clearly defined post-storm period, we explore this semi-parametrically, considering a range of post-storm periods of 2 to 12 months.) The time windows are lagged by 1 month as many sales are negotiated at least 30 days prior to the actual sale date.

The empirics begin with the simplest model in Equation 1.1 where (i) denotes parcel, (t) reflects town, and (y) and (m) are year and month, respectively. In this model we are not controlling for any of the amenities (time invariant or not) associated with the home other than the flood shock.

This model does not control for any factors associated with parcels or market conditions other than the remote flood shock.

$$log(p_{iym}) = \alpha_0 + \alpha_1 Zone_i + \alpha_2 Post_{ym} + \alpha_3(Zone_i * Post_{ym}) + \epsilon_{iym} \tag{1.1}$$

The model in Equation 1.2 expands on Equation 1.1, by including year, month, county-year, and town (municipality) fixed effects (FE).[14] Equation 1.2 also includes time-variant controls: an indicator of CRS public awareness participation (CRS_{ty}), the number of monthly sales, the ratio monthly sales to average monthly sales in this municipality, the number of new building units, the log total value of new building units, the current and monthly lag average level of PM 2.5 pollution, and the age and size of the home. The $char_i$ and $char_{tym}$ terms index variables that are characteristics of house and town by year and month, respectively.

$$\begin{aligned} log(p_{iym}) =& \alpha_0 + \alpha_1 CRS_{ty} + \alpha_2 Zone_i + \alpha_3(CRS_{ty} * Zone_i) + \alpha_4 Post_{ym} + \alpha_5(Zone_i * Post_{ym}) \\ &+ \alpha_6 char_{iym} + \alpha_7 char_{tym} + FE_y + FE_m + FE_t + FE_c y + \epsilon_{iym} \end{aligned} \tag{1.2}$$

The model in (1.3) is a repeat sales model featuring parcel fixed effects. This diminishes the concern of omitted variable bias, as we cannot capture every feature of a home (Mendelsohn et al., 1992).

$$\begin{aligned} log(p_{iym}) =& \alpha_0 + \alpha_1 CRS_{ty} + \alpha_2(CRS_{ty} * Zone_i) + \alpha_3 Post_{ym} + \alpha_4(Zone_i * Post_{ym}) \\ &+ \alpha_5 char_{iym} + \alpha_6 char_{tym} + FE_y + FE_m + FE_i + FE_c y + \epsilon_{iym} \end{aligned} \tag{1.3}$$

Given the panel structure of the model, Post indicates that a sale occurs during the post-storm period and the parcel was previously sold prior to the storm. Hence, the repeated sales must straddle the storm to be included in this dataset. The fixed effects in (1.3) encompass year, month, county-year, and parcel (i). Further, note that model (1.3) retains the controls for time-variant characteristics of the home, such as living space and the age of the home and environmental and market conditions including: PM2.5 pollution, the number of monthly sales, the ratio monthly sales to average monthly sales in municipality (t), and new builds. The models in (1.1), (1.2), and (1.3) are applied to each of the storms listed above. The main empirical results section focuses on Hurricane Katrina.

[14] We use the monthly fixed effects to control for seasonality and the year fixed effects to control for changes to the real estate market for the state of New Jersey over time. We use the town fixed effects to control for specific attributes of the municipality that our other variables do not capture. Finally, the county-year fixed effects are included to control for anything that is changing over time in a specific county.

The following specifications invoke a triple-difference approach to test whether information provided through CRS on flood risk affects market responses to distant storms. Expression (1.4) replicates (1.2) in the triple difference setting, while (1.5) replicates (1.3). In the triple difference, the term of interest is the interaction between CRS enrollment, post-storm, and the high risk indicators. This interaction term enables a test of how owners of high risk parcels respond after a storm and how information (proxied by CRS participation) affects their response. This specification applied to all sales in shown in (1.4).

$$
\begin{aligned}
log(p_{iym}) =&\alpha_0 + \alpha_1 CRS_{ty} + \alpha_2 Zone_i + \alpha_3(CRS_{ty} * Zone_i) + \alpha_4 Post_{ym} + \alpha_5(Zone_i * Post_{ym}) \\
&+ \alpha_6(CRS_{ty} * Post_{ym}) + \alpha_7(CRS_{ty} * Zone_i * Post_{ym}) + \alpha_8 char_{iym} + \alpha_9 char_{tym} \\
&+ FE_y + FE_m + FE_t + FE_c y
\end{aligned}
\tag{1.4}
$$

The triple difference is also applied in the panel data context as shown in (1.5).

$$
\begin{aligned}
log(p_{iym}) =&\alpha_0 + \alpha_1 CRS_{ty} + \alpha_2(CRS_{ty} * Zone_i) + \alpha_3 Post_{ym} + \alpha_4(Zone_i * Post_{ym})) \\
&+ \alpha_5(CRS_{ty} * Post_{ym}) + \alpha_6(CRS_{ty} * Zone_i * Post_{ym}) + \alpha_7 char_{iym} + \alpha_8 char_{tym} \\
&+ FE_y + FE_m + FE_i + FE_c y
\end{aligned}
\tag{1.5}
$$

We estimate each of the models above with all buyer and seller combinations and separately for those only involving at least one firm. We define firm based on the name listed in the transaction. We consider whether the firm is the buyer or the seller or both in this subset of the data as a firm may only accept a lower price or be willing to sell at a lower price. The analysis also explores several robustness checks in an effort to dismiss various threats to our identification strategy. The particular specifications employed are shown and discussed in section 1.4.3 below.

1.3 Identification

Prior to presenting the main empirical results, we test the key assumption that dictates whether the DD models credibly identify a causal relationship between treatment and the outcomes of interest. The fundamental assumption undergirding causal inference, and hence, internal validity, in a DD specification is parallel trends in outcomes between the treatment and control groups, prior to treatment. We first document a simple graph of price trends before and after treatment. We then present results from an event study to further test the crucial assumption regarding trends in housing prices.

1.3.1 Parallel Trends

Figure A3 shows parallel price trends between the high risk treatment group (the middle price line) and the control group (the bottom price line). The vertical lines correspond to the storm dates. The second vertical line from the right denotes Katrina. Between 2000 and when the storm struck in late August, 2005, the price trends are roughly parallel.

The right-most vertical line corresponds to the month during which Hurricanes Dean and Erin struck. There is clearly a violation of the pre-trends assumption in this case as the control group parcel prices are rising more rapidly than the high risk group. The third line from the right denotes Hurricane Charley. Here, the parallel trend assumption appears to hold. For the cluster of storms that struck during 2002, again, the parallel trends assumption holds. Finally, the parallel trend assumption does not hold for Hurricane Allison (left-hand most vertical line), especially when comparing the high risk parcel prices with those for the control group.

The primary focus of the paper is on Hurricane Katrina. In Figure A4, we replicate Figure A3, narrowed down to one year before and after Katrina to more clearly explore the pre-post price trends. The first vertical line represents when Hurricane Katrina hit at the end of August 2005. Note, in the regression models we use a one month lag to define the post-storm indicator sales due to the negotiation period immediately prior to close. The vertical line representing this is denoted post. Figure A4 demonstrates strong support for the parallel trends assumption.

1.3.2 Event Studies

To further probe the important issue of pre-trends, we conduct several event studies. First we consider our difference-in-differences specification. For this event study we follow the methodology in Currie et. al., (2015) and fit the following regression:

$$\begin{aligned} log(p_{iym}) =& \beta_0 + \beta_1 CRS_{ty} + \beta_2(CRS_{ty} * Zone_i) + \beta_3 FE_{ym} + \beta_4(Zone_i * FE_{ym}) \\ &+ \beta_5 char_{iym} + \beta_6 char_{tym} + FE_t + \epsilon_{iym} \end{aligned} \tag{1.6}$$

This specification differs from (1.2) in that (1.6) includes year-month fixed effects (denoted FEym), whereas (2) employs the post-storm indicator and year fixed effects. Also in (1.2) the high-risk indicator is interacted with the post storm control. In (1.6), the high risk indicator is interacted with the year-month fixed effects. This yields monthly estimates of the effect of being in the high-risk flood zone on prices, controlling for year-month and town fixed effects as well as time-varying town, parcel, and house characteristics. For the event study figures, we then normalize the resulting coefficients such that our storm month coefficient is equal to zero. As Hurricane Katrina occurred at the end of August, 2005, September, 2005 is the event month. Recall, that the post-storm indicator includes a one month lag after the designated storm month, thus we will normalize our monthly periods to October, 2005.

Next, we consider the triple differences specification. For this event study we also follow the methodology outlined in Currie et. al., (2015). The coefficients of interest are in the vector β_6 in (1.7). As in (1.6), these are normalized such that the coefficient on the event month is equivalent to zero.

$$\begin{aligned} log(p_{iym}) =& \beta_0 + \beta_1 CRS_{ty} + \beta_2(CRS_{ty} * Zone_i) + \beta_3 FE_{ym} + \beta_4(Zone_i * FE_{ym}) \\ &+ \beta_5(CRS_{ty} * FE_{ym}) + \beta_6(CRS_{ty} * Zone_i * FE_{ym}) \\ &+ \beta_7 char_{iym} + \beta_8 char_{tym} + FE_t + \epsilon_{iym} \end{aligned} \tag{1.7}$$

We also present the coefficient vector β_4. We then perform the event studies using parcel fixed effects and we conduct an event study limiting the data to transactions involving firms.

In each event study figure the coefficient on year-month fixed effects interacted with the variable of interest is normalized to 0 when the storm hits. This is labelled as period -1, with the post month designated as period 0 as our time of interest. Each figure presents the normalized coefficients as the solid line and presents the 95% confidence intervals of the normalized coefficients as the dashed lines.

In Figure A5, we present the normalized β_4 coefficients from equation (1.6). The β_4 vector is noisy but without trend prior to the storm month. After the storm, β_4 remains noisy, but there is a clear level shift upwards. Hence, Figure A5 corroborates the assumption of no significant pre-trend in prices that would confound our interpretation of the model from equation (1.1). In Figure A6, we present the normalized β_6 coefficients from equation (1.7). This figure shows a weak upward trend in β_6 prior to the storm. However, at the storm month there is a clear break in trend; after the storm month β_6 is lower than before. In Figure A7 we present the normalized β_4 coefficients from equation (1.7). Figure A7 is consistent with Figure A5's lack of pre-trend and clear post trend and provides further support for our triple difference methodology. Hence, Figures A6 and A7 corroborate the assumption of no significant pre-trend in prices that would confound our interpretation of the model based on equation (1.4).

In Figures A8 through A13, we present the results the remaining event studies that explore the same models, but with house fixed effects instead of municipality fixed effects or limit the transactions to sales involving firms.

1.4 Results

The empirical results section here focuses on Hurricane Katrina and the coefficients of central importance to our hypothesis tests. The empirics begin with the standard DD model shown in (1.1), the fixed effects model with controls (1.2), and the repeat sales models (1.3), before moving on to the triple difference specifications shown in (1.4) and (1.5). In the discussion of our triple difference specifications we present the results that consider the subset of properties transacted by firms. We present these both for Hurricane Katrina and for Hurricane Sandy. We conclude the results section by discussing our various robustness checks which include running the specifications for other storms and exploring alternative mechanisms that could pose a threat to credible identification of the causal effect of CRS enrollment on housing prices.

1.4.1 Diff-in-Diff Model: High Risk Zone as Treatment

Table A2 presents the results from fitting (1.1). Each column represents post storm windows of a particular length and the table includes specifications for post storm periods of 2 to 12 months. The coefficients on the post storm variable and the interactions between the post storm and high-risk zone controls are reported for each post-storm period in each column.[15] For example the coefficient on the Post Storm Months variable in column 1 reveals the effect on sales prices when the post-storm period is defined as two months after Katrina. Table A2 reveals a premium on parcels sold in high risk zones of about 18.5% in all specifications. This premium likely stems from the frontage, view, and proximity services associated with parcels in high-risk zones. The coefficient on high risk interacted with post-storm is also robustly positive and significant. These results suggest that properties in high-risk zones sold for a premium after Katrina of between 9 and 15 percent.

Table 1.3 reports the estimates from model (1.2), which adds controls and a battery of fixed effects to (1.1). Adding controls and fixed effects accentuates the premium for parcels in high risk zones from 18.5% to 23%. Participation in CRS is associated with a small premium (less than 5%) though this effect is imprecisely estimated. The coefficient on the CRS-by-high risk zone term is negative and significant, implying a discount relative to high risk parcels not in CRS towns of about 13%. Consistent with Table A2, we find no evidence of a risk discount for parcels sold in high risk zones after Hurricane Katrina. The coefficient on the interaction between high risk and post storm is significant and ranges from 7 to 11 percent. Many of the other controls in model (2) behave as intuition would suggest (such as square footage and structure age) bolstering the credibility of the model.[16]

[15]This is the setup we use in all the tables that rely on these 6 post storm periods. See Table A2 for more information on the variables in each model.

[16]The results of the various controls are available upon request.

Table 1.3: DD Models for Hurricane Katrina Inclusive of all Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0511	0.0495	0.0439	0.0368	0.0338	0.0280
	(0.0243)	(0.0241)	(0.0237)	(0.0231)	(0.0227)	(0.0224)
Zone	0.234	0.232	0.231	0.231	0.230	0.229
	(0.00804)	(0.00788)	(0.00779)	(0.00757)	(0.00740)	(0.00724)
CRS x Zone	-0.129	-0.131	-0.131	-0.130	-0.131	-0.128
	(0.0127)	(0.0126)	(0.0124)	(0.0122)	(0.0120)	(0.0118)
Post Storm Months	-0.0188	-0.0144	-0.0105	-0.0100	-0.00751	-0.00726
	(0.00864)	(0.00714)	(0.00709)	(0.00708)	(0.00711)	(0.00710)
Zone X Post Storm Months	0.117	0.102	0.0876	0.0869	0.0791	0.0787
	(0.0194)	(0.0144)	(0.0123)	(0.0106)	(0.00965)	(0.00901)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	156,561	159,887	163,157	167,290	171,118	174,301
R-squared	0.630	0.632	0.632	0.634	0.636	0.638

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information. Zone is the high flood zone risk indicator.

Table 1.4 reports results from the repeat-sales model. This specification reduces the estimation sample from greater than 170,000 observations to about 60,000. The high risk zone control drops out with parcel fixed effects. CRS participation is associated with a premium of about 8 to 10%. The coefficient on the CRS-by-high risk zone interaction is no longer significant. The repeat sales model also suggests parcels sold during the post-Katrina periods did so at a small discount (less than 3%). However, the positive and significant coefficient on the high risk-by-post storm term obtains across all specifications. The effect estimate suggests a 10% premium on parcels in high-risk zones after Katrina.

Table 1.4: DD for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.106	0.102	0.0919	0.0880	0.0841	0.0813
	(0.0290)	(0.0286)	(0.0281)	(0.0267)	(0.0263)	(0.0259)
CRS x Zone	-0.0619	-0.0595	-0.0496	-0.0470	-0.0472	-0.0466
	(0.0315)	(0.0312)	(0.0306)	(0.0294)	(0.0290)	(0.0287)
Post Storm Months	-0.0305	-0.0289	-0.0280	-0.0249	-0.0232	-0.0208
	(0.0105)	(0.00899)	(0.00874)	(0.00859)	(0.00840)	(0.00828)
Zone X Post Storm Months	0.0909	0.0906	0.0967	0.0945	0.0994	0.0978
	(0.0222)	(0.0184)	(0.0150)	(0.0133)	(0.0118)	(0.0110)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information.

Across specifications in Tables A2, 1.3, and 1.4 we report evidence of a premium on sales in high risk zones after Katrina. What are possible explanations for this result? First, this premium may be due to an average increase in housing prices over time specific to high coastal amenity (and therefore high risk) homes. See Figure A14 which shows average sales price trends for high risk and low risk groups. Anecdotal evidence from newspaper reporting suggests that ocean front homes and those with ocean views (those typically categorized as high risk) saw an increase in prices relative to other homes in these coastal towns in 2005, 2006, and 2007. The reporting suggests that possible explanations for the price premium are 1.) financial gains from renting these homes, 2.) baby boomer generation looking to invest in real estate, and 3.) redevelopment.[17] Another explanation is that there was a substitution effect driving this result; homeowners considering whether to purchase coastal property were deterred from the Gulf Coast market by Hurricane Katrina. A viable (though imperfect) substitute market is in coastal New Jersey. Such an effect could increase prices differentially in high-risk zones.

1.4.2 Triple Difference Model: High Risk Zone, CRS Enrollment as Treatment

Bringing equation (1.4) to the data enables an exploration of the role that risk information plays in the coastal market. Table 1.5 presents the results from fitting equation (1.4) inclusive of all sales. Many of the results reported in Table 1.5 manifest in the triple difference context as well. These include the imprecisely estimated premium on CRS participation, the 23% premium associated with parcels in high risk zones and the 13% discount on parcels in high risk zones and CRS towns. In all of the specifications, the interaction between the high-risk zone and post-storm indicators remains positive and significant. The premium on such sales is remarkably robust, ranging between 10 and 12 percent.

[17] See "Many shore home buyers reap quick profits", Courier Post, 4/24/2005, "Homes Near the Shore For Older Buyers", The New York Times, 1/22/2006, "Housing boom reshapes look, feel of Jersey Shore", The Record, 02/02/2006, and "In New Jersey Summer Deals Amid a Downturn", The New York Times, 8/9/2009

Table 1.5: Triple Difference Models for Hurricane Katrina Inclusive of all Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0508	0.0472	0.0399	0.0316	0.0278	0.0219
	(0.0243)	(0.0240)	(0.0236)	(0.0231)	(0.0226)	(0.0223)
Zone High Risk	0.234	0.232	0.230	0.229	0.228	0.226
	(0.00798)	(0.00782)	(0.00771)	(0.00747)	(0.00731)	(0.00716)
CRS x Zone	-0.129	-0.128	-0.124	-0.120	-0.119	-0.116
	(0.0128)	(0.0127)	(0.0126)	(0.0125)	(0.0124)	(0.0123)
Post Storm Months	-0.0190	-0.0165	-0.0132	-0.0123	-0.00969	-0.00904
	(0.00862)	(0.00709)	(0.00704)	(0.00703)	(0.00705)	(0.00703)
Zone X Post Storm Months	0.123	0.117	0.108	0.113	0.105	0.103
	(0.0245)	(0.0177)	(0.0151)	(0.0132)	(0.0122)	(0.0113)
CRS X Post Storm Months	0.00514	0.0396	0.0464	0.0382	0.0382	0.0329
	(0.0458)	(0.0337)	(0.0273)	(0.0226)	(0.0204)	(0.0192)
CRS X Zone X Post Storm	-0.0221	-0.0776	-0.0970	-0.105	-0.106	-0.0986
	(0.0582)	(0.0425)	(0.0355)	(0.0299)	(0.0266)	(0.0248)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	156,561	159,887	163,157	167,290	171,118	174,301
R-squared	0.630	0.632	0.632	0.634	0.636	0.638

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information.

Of particular interest is the interaction term between CRS enrollment and the high-risk zone and post-storm indicators. Table 1.5 reports that this triple interaction term is negatively associated with price for all specifications. Beginning with the post-storm specifications at 6 months, the triple interaction is statistically significant at conventional levels. The effect estimate is also economically significant, implying a risk discount in CRS towns of about 10 percent. In contrast to the effect of being in the high risk zone, which attenuates with longer post-storm periods, the information treatment has a larger effect for longer post-storm periods.

This result indicates that high risk homes in CRS participating towns sold for a lower price after Katrina relative to parcels in non-CRS towns. Recall that the vast majority of towns enrolled in CRS pursue activities that provide community members with information about flood risk. One interpretation of this finding is that this information shock makes market participants more sensitive to a geographically distant, well-publicized coastal flooding event.

Table 1.6 reports the results from the repeat sales model. Several results from Table 5 are obtained here as well. Of particular interest, the coefficient on the interaction between the high-risk zone and post-storm controls is positive and significant. The magnitude is similar to that observed in prior specifications. Additionally, the triple interaction between CRS enrollment, high-risk zone, and post-storm is negative and significant for nearly all specifications. When significant, the effect estimate suggests that a high risk parcel in a CRS participating town sells for a discount ranging from approximately 11 to 16 percent following Hurricane Katrina.[18] We argue that the flood risk

[18] In our preferred specifications, we limit our analysis to compare sales before the storm to the post storm window. Recall that this post-storm period is flexibly defined from up to 2 months to one year after the storm. We choose to limit the post storm period to no more than one year because of the financial crisis. In an alternative specification, we

information provided to market participants via CRS activities is driving this discount.

Table 1.6: Triple Difference Models for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.106	0.101	0.0894	0.0826	0.0779	0.0734
	(0.0290)	(0.0288)	(0.0283)	(0.0271)	(0.0267)	(0.0264)
CRS x Zone	-0.0609	-0.0570	-0.0442	-0.0373	-0.0354	-0.0324
	(0.0315)	(0.0313)	(0.0307)	(0.0297)	(0.0293)	(0.0291)
Post Storm Months	-0.0288	-0.0310	-0.0306	-0.0280	-0.0263	-0.0243
	(0.0106)	(0.00914)	(0.00889)	(0.00873)	(0.00853)	(0.00840)
Zone X Post Storm Months	0.124	0.114	0.122	0.123	0.127	0.126
	(0.0299)	(0.0232)	(0.0184)	(0.0159)	(0.0139)	(0.0128)
CRS X Post Storm Months	-0.0376	0.0424	0.0517	0.0648	0.0697	0.0807
	(0.0416)	(0.0610)	(0.0472)	(0.0396)	(0.0347)	(0.0322)
CRS X Zone X Post Storm Months	-0.0575	-0.105	-0.116	-0.140	-0.146	-0.157
	(0.0560)	(0.0679)	(0.0533)	(0.0452)	(0.0397)	(0.0370)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information.

Table 1.7 reports the results from fitting equation (1.4) inclusive of all sales where a firm was on one side of the transaction (either a buyer or seller). Similar to the results in Table 1.5 and Table 1.6, the triple interaction between CRS enrollment, high-risk zone, and post-storm is negative and significant for all specifications. For the two month post-storm period, the estimated discount is 50%. This attenuates down to a 28% decrease. These results suggest that firms are more sensitive or responsive to the risk information interventions in CRS towns than individuals. Note that the discount on the triple interaction attenuates for the firms whereas it increases and then attenuates for all houses. One possible explanation is that non-firm homeowners receive additional information from the firm transactions.

include all sales after the storm. These results are presented in Table A4. The results are consistent with our main specifications. However, the coefficients are slightly smaller in absolute value terms and insignificant in two of the specifications.

Table 1.7: Triple Difference Models for Hurricane Katrina Limited to all Firm Transacted Residential Sales and with Control

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0863	0.0762	0.0605	0.0418	0.0357	0.0331
	(0.0647)	(0.0643)	(0.0637)	(0.0631)	(0.0625)	(0.0615)
Zone High Risk	0.254	0.246	0.238	0.235	0.233	0.231
	(0.0235)	(0.0234)	(0.0234)	(0.0233)	(0.0232)	(0.0230)
CRS x Zone	-0.295	-0.289	-0.277	-0.269	-0.267	-0.267
	(0.0472)	(0.0469)	(0.0466)	(0.0462)	(0.0460)	(0.0456)
Post Months	-0.0586	-0.0519	-0.0290	-0.0264	-0.0244	-0.0216
	(0.0459)	(0.0365)	(0.0355)	(0.0351)	(0.0346)	(0.0342)
Zone X Post Months	0.298	0.230	0.140	0.147	0.153	0.139
	(0.0874)	(0.0627)	(0.0571)	(0.0515)	(0.0477)	(0.0445)
CRS X Post Storm Months	0.212	0.304	0.244	0.190	0.136	0.168
	(0.105)	(0.112)	(0.0735)	(0.0631)	(0.0642)	(0.0616)
CRS X Zone X Post Storm Months	-0.504 (0.159)	-0.485 (0.144)	-0.311 (0.104)	-0.294 (0.0904)	-0.261 (0.0869)	-0.281 (0.0825)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	11,809	12,129	12,429	12,789	13,063	13,306
R-squared	0.622	0.623	0.623	0.623	0.623	0.623

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A5 reports the results of the repeat sales models after limiting our data to firm transactions. Similar to the results in Table 1.7, the triple interaction between CRS enrollment, high-risk zone, and post-storm is negative, but it is not significant for all post-storm periods except the 12 month post period. We emphasize the small number of observations in the panel context and the associated reduction in statistical power for this particular test.

Table 1.8 reports the results from fitting equation (1.4) inclusive of all sales with a firm on one side of the transaction (either a buyer or seller). However, in contrast to previous models, this regression explores outcomes before and after Hurricane Sandy. The motivation for this test is to ascertain whether risk information interventions in CRS towns resulted in different price responses to a local, large-scale flooding event. We find that high-risk properties owned by firms in CRS municipalities sell at a higher price after Hurricane Sandy relative to high-risk parcels not in CRS towns. The coefficient on the triple interaction is positive and marginally significant for the 2 to 6 month periods following the storm. For the post-storm periods of 8 months through 12 months, we find that, after Hurricane Sandy, such properties exhibit prices approximately 25 percent higher than high-risk parcels in non-CRS towns. This result, combined with the large risk discount affixed to high-risk properties in CRS towns reported in Table 1.7, provides evidence of the benefits to investors of the flood risk information intervention. Properties in vulnerable locations (with information-treated investors) held 25 percent more value than properties in equivalent risk designations without the information interventions. Thus, the risk discounts in Table 1.7 reflect a correction as evidenced by the resilience of high-risk assets in CRS participating towns in the face of Hurricane Sandy. Assets with equivalent flood risk profiles in non-CRS towns incurred corrections of up to 25 percent after Sandy struck. We are unable to determine whether CRS information treatments resulted in flood mitigation investments or if this effect is purely due to adjustments in the capitalization of risk by investors.

Table 1.8: Triple Difference Hedonic Regression Models for Hurricane Sandy Limited to Firm Transacted Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0758	0.0750	0.0738	0.0791	0.0796	0.0815
	(0.0352)	(0.0351)	(0.0347)	(0.0346)	(0.0345)	(0.0344)
Zone High Risk	0.220	0.220	0.219	0.219	0.218	0.219
	(0.0215)	(0.0214)	(0.0214)	(0.0213)	(0.0212)	(0.0212)
CRS x Zone	-0.210	-0.209	-0.209	-0.208	-0.209	-0.209
	(0.0319)	(0.0319)	(0.0318)	(0.0317)	(0.0317)	(0.0317)
Post Months	0.228	0.220	0.184	0.179	0.173	0.172
	(0.144)	(0.129)	(0.117)	(0.113)	(0.111)	(0.109)
Zone X Post Months	-0.227	-0.235	-0.183	-0.216	-0.223	-0.203
	(0.192)	(0.159)	(0.103)	(0.0754)	(0.0668)	(0.0658)
CRS X Post Storm Months	-0.349	-0.212	-0.118	-0.0983	-0.121	-0.106
	(0.210)	(0.138)	(0.0866)	(0.0774)	(0.0715)	(0.0682)
CRS X Zone X Post Storm	0.497	0.318	0.217	0.245	0.303	0.265
Months	(0.275)	(0.210)	(0.138)	(0.117)	(0.105)	(0.101)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	18,664	18,805	19,046	19,245	19,405	19,569
R-squared	0.617	0.616	0.617	0.616	0.617	0.616

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post Storm Months and variables interacted with Post Storm Months are consistent with these definitions of the post period. See Table A3 for more information.

In the appendix, we present the results of additional models applied to Hurricane Sandy. These include the repeat sales specification limited to firm transactions, all sales with all transactions, and repeat sales with all transactions in Tables A6, A7, and A8 respectively. The repeat sales specification with only firm transactions exhibits positive and significant coefficients on the triple difference only for 10 and 12 month periods. The model that includes all residential sales shows no robustly significant evidence of price differentials for assets in CRS towns in high-risk areas, after Hurricane Sandy. Hence, our ability to reject the null hypothesis of differential price effects by CRS participation status after Hurricane Sandy is limited to transactions involving firms.

1.4.3 Robustness Checks

This section proceeds by first examining the DD results from all storms. The intent is to ascertain whether the results presented above are unique to Katrina. Next, because of concerns that CRS enrollment is endogenous and that information is not driving our results, we run several robustness checks to determine if it is not the information from CRS, but some other variable causing our results. Our main concern is that CRS participation may be determined by unobserved factors that determine flooding risk and that it is this additional risk in CRS towns, not the information from CRS driving our results. To eliminate this concern we investigate alternative definitions of flood risk, and the sensitivity of our central results to local flooding events, and alternative degrees of CRS participation. We then consider whether systematic differences in the composition of market participants in CRS and non-CRS towns affects our conclusions. In particular, we examine whether participation by non-residents or second homeowners affects our results. We explore this mechanism as prior research has demonstrated that municipalities with a higher proportion of non-residents are more likely to participate in CRS (Hopkins 2020). We consider the potential influence of non-residents from both the supply and demand side.

The preceding results focus on Hurricane Katrina due to the immense damage, considerable loss of life, and highly publicized nature of the storm. Table A9 summarizes the results from regression analyses on the other storms. This table reports the number of specifications that yield negative and significant coefficients on the triple interaction term (CRS x high risk x post storm). For each storm, there are six specifications that encompass all sales and six repeat sales specifications. The number of specifications is dictated by the semi-parametric approach to measuring post-storm periods. Table A9 indicates that each storm, except for Hurricane Allison, adversely affected housing prices among high risk properties in towns that participated in CRS. Hurricane Allison made landfall in Texas in June of 2001. The lack of significant results associated with this storm is consistent with the fact that very few towns participated strongly in CRS at this time. For the multiple storms that struck in September of 2002, five out of twelve specifications yield negative, significant coefficients on the triple interaction of interest. For Hurricane Charley, ten out of twelve specifications produce negative, significant coefficients on the triple interactions of interest. And, similar results evince for Hurricanes Erin and Dean; seven out of twelve specifications produce negative, significant coefficients on the triple interactions of interest.

One possible threat to our identification strategy is that parcels in CRS towns are at higher risk (in ways that are unobservable to the econometrician) than parcels in the same FEMA risk zones, but not situated in CRS towns. This concern stems from the fact that municipalities select into CRS and that towns facing particularly high risk might select into CRS. Stated alternatively: do parcels within CRS towns in the high risk flood zones face more risk than parcels in non-CRS towns in those same zones? And, crucially, are they more likely to respond to a distant storm? To explore this alternative mechanism, we first examine whether the average flood insurance claim values are higher in CRS towns than in non-CRS towns. Our measure of average claims is defined as the total dollar amount of claims divided by the number of claims made in each town in each year. While we expect to find a positive relationship between CRS and claims (as CRS is positively correlated with FEMA's high risk zones and CRS provides information about flood insurance), a positive relationship between CRS towns with high levels of public awareness activities and average claims would provide evidence that the mechanism may be stemming from higher risk and not better information. We fit the following model:

$$AverageClaim_{tym} = \delta_0 + \delta_1 CRS_{ty} + FE_y + FE_m + FE_t + \epsilon_{tym} \tag{1.8}$$

Table A10 reports a negative relationship between CRS and average claims. Upon inclusion of municipality FE, the relationship becomes insignificant. While we cannot conclusively rule out this mechanism, Table A10 suggests that unobservable differences in risk within FEMA's risk zones across CRS participation is not driving our results.

We then consider whether local flood shocks might be driving our results. Local flooding shocks may effect a municipality's perceived risk and therefore their response to a non-local shock. Table A11 reports the results from the triple difference repeat sales model with a control for whether the sale occurred during a month in which a flood disaster had been declared in New Jersey.[19] Local flooding disasters do not appear to drive our results. The coefficient of interest on the local flood control (denoted "disaster declared" in Table A11) is negative, small in magnitude (less than 1 percent) and only marginally significant in one of the six specifications.

Assuming that flood risk in a particular town is highly correlated across time, limiting our data to municipalities that ever participate in CRS, and running the triple difference regressions separates the effect of risk from information. In this scenario, those who participate in CRS during Hurricane Katrina receive the information treatment, while those who participate in CRS later do not receive the information treatment, but have similar risk levels insofar as one suspects that CRS enrollment is actually a proxy for heightened flood risk. The results from these specifications are presented in Table A12 and are very similar to the results in Table 6.

We next use alternative measures of CRS enrollment. Tables A13 through A16 in the appendix report the results from models that employ alternate definitions of CRS participation. (These are all triple difference, repeat sales models.) Table A13 reclassifies CRS participation to include all municipalities that reached CRS level 8. The coefficient on the triple interaction is negative and significant in four of the six specifications, ranging between 11 and 14 percent. Table A14 reclassifies CRS participation to include towns that increase their level of participation with any of the activities coded as 300-level information-based actions. One of the six coefficients is significant and negative. However, the effect estimate is larger than in the main paper at 19.5 percent. In Table A15, we consider all activities that might affect flood risk information.[20] In this definition of

[19] We also considered municipality-month-year claims data as a control for other flood experiences and these data do not change our results.

[20] The relevant activities are presented in Table A17.

CRS participation, we include activities related to emergency response and warnings and limit our CRS treatment group to towns that participate in the top ten percent of these activities. Using this definition does not appreciably change the magnitude and significance of the triple interaction coefficient. In our last alternative definition we reclassify CRS participation as towns that participate in the program, but have not increased their information activities in the previous year. The results of this definition are presented in Table A16. Interestingly, the coefficients on the triple interaction are now positive and mostly insignificant. One interpretation of this set of results is that it is the information activities that are causing the price decrease following the distant hurricanes.

As a final test pertaining to the potential endogeneity of CRS participation with respect to flood risks, we investigate whether property owners in CRS communities perceive higher risk and that drives both the participation in CRS and the price drops after Hurricane Katrina. If so, we would expect transactions with buyers from outside of the CRS towns to have a significantly smaller price drop after Hurricane Katrina than transactions with buyers who are also from the CRS town. To run this test we limit the data to sales occurring in towns that participate in CRS and we fit the regression models in (1.9) and (1.10) for all sales in CRS towns and for repeat sales, respectively.

$$\begin{aligned} log(p_{iym}) = \alpha_0 &+ \alpha_1 OutsideBuyer_{iym} + \alpha_2 Zone_i + \alpha_3 (OutsideBuyer_{iym} * Zone_i) + \alpha_4 Post_{ym} \\ &+ \alpha_5 (Zone_i * Post_{ym}) + \alpha_6 (OutsideBuyer_{iym} * Zone_i * Post_{ym}) + \alpha_7 char_{iym} \\ &+ \alpha_8 char_{tym} + FE_y + FE_m + FE_t + FE_{cy} + \epsilon_{iym} \end{aligned} \tag{1.9}$$

$$\begin{aligned} log(p_{iym}) = \alpha_0 &+ \alpha_1 OutsideBuyer_{iym} + \alpha_2 Zone_i + \alpha_3 (OutsideBuyer_{iym} * Zone_i) + \alpha_4 Post_{ym} \\ &+ \alpha_5 (Zone_i * Post_{ym}) + \alpha_6 (OutsideBuyer_{iym} * Zone_i * Post_{ym}) + \alpha_7 char_{iym} \\ &+ \alpha_8 char_{tym} + FE_y + FE_m + FE_i + FE_{cy} + \epsilon_{iym} \end{aligned} \tag{1.10}$$

Tables A18 and A19 display that the coefficient on the interaction term between the non-resident buyer-by-high risk zone-by-post storm is insignificant across both specifications (repeated cross-sections and repeat sales) and all periods after Hurricane Katrina.

We next explore how the composition of market participants influences our central findings. We focus on the role of second homeowners and non-residents because prior research has shown that participation in CRS is correlated with higher non-resident populations (Hopkins 2020). On the supply-side, second homeowners may have more flexibility to sell than market participants selling their primary residence. Table A20 shows the breakdown of transactions according to residency status and CRS participation. The table reveals that second homeowners often possess property in towns with high CRS participation and in high risk zones. That the econometric models report parcels in CRS towns and high-risk zones sell at a discount following storms may reflect non-residents' greater liquidity. While this may still expose market participants' attitudes toward (or perceptions of) risk, it would obfuscate our ability to cleanly identify a causal effect of the CRS.

We use linear probability models to explore this mechanism. The first specification employs the entire population of properties (not just homes that sold) and is shown in (1.11).

$$\begin{aligned} S_{iym} = {} & \psi_0 + \psi_1 CRS_{ty} + \psi_2 Zone_i + \psi_3 (CRS_{ty} * Zone_i) + \psi_4 Post_{ym} \\ & + \psi_5 Nonresident_{iym} + \psi_6 (Nonresident_{iym} Post_{ym}) + \psi_7 char_{tym} \\ & + FE_y + FE_m + FE_t + FE_{cy} + \epsilon_{iym} \end{aligned} \tag{1.11}$$

where S_{iym} is an indicator of whether parcel (i) is sold in month-year (ym). The fixed effects, CRS, and Zone controls are defined as in the previous specifications. The index, $char_{tym}$, contains controls for the conditions in the town-month-year during which parcel (i) sold including: the average parcel price, average number of sales, if there are more sales than average in month (ym), the number of new units being built, the total new value being built, and the level of PM2.5 air pollution. Post indicates whether year-month (ym) is in the 12-month window after Hurricane Katrina. Nonresident is an indicator of whether the homeowner lists an address outside of the town containing parcel (i) as their primary residence. This is the covariate of interest. Table A21 reports the results from this regression. Parcels are more likely to be sold in a month during the post-Katrina period and if the parcel is in a CRS participating town. However, properties owned by non-residents are less likely to be sold after the storm. The second specification limits the data to parcels that sold and is shown in (1.12).

$$\begin{aligned} Nonresident_{iym} = {} & \psi_0 + \psi_1 CRS_{ty} + \psi_2 Zone_i + \psi_3 (CRS_{ty} * Zone_i) + \psi_4 Post_{ym} \\ & + \psi_5 char_{tym} + FE_y + FE_m + FE_t + FE_{cy} + \epsilon_{iym} \end{aligned} \tag{1.12}$$

The dependent variable is an indicator for non-resident sellers. The covariate of interest is the post storm indicator. As above, we approach this semi-parametrically, testing definitions of Post from two to twelve months following Hurricane Katrina. As above the models include controls for structure and market characteristics and year, month, county-year, and town fixed effects. Table A22 reports that sales occurring after Katrina are slightly more likely to involve non-residents. The effect is small (about 1.3 percent) and is marginally significant. However, Table A22 also demonstrates that sales are roughly 15 percent less likely to involve a non-resident if the parcel is in a CRS town and is located in a high flood risk zone. These results suggest that a supply-side role of non-residents is particularly unlikely to be driving the effect of CRS participation on high risk parcel prices.

Although Table A22 shows that non-residents are not selling significantly more after Katrina, it is possible non-residents are playing a role on the demand side of the market.[21] We test whether non-residents are more likely to buy properties after Hurricane Katrina by adopting the specifications used in the supply-side regressions (above) with the distinction that the dependent variable is an indicator for non-resident buyers. Table A23 shows that the coefficients for the post-Katrina periods are all negative and not statistically significant. Hence, we detect no evidence that non-resident buyers are disproportionately more likely to purchase parcels after Katrina and therefore induce the risk discount reported in Tables 5 and 6. Table A23 does suggest that parcels in high risk zones increases the likelihood that non-residents purchase the parcel. Conversely, parcels in CRS towns and high risk zones are between 5 and 7% less likely to be purchased by non-residents.

1.4.4 Monetary Impact of Flood Risk and Welfare Implications

The results from our triple difference specifications imply a large loss for the investors in CRS-participating municipalities after a flood shock. We calculate the approximate revenue lost to the investors that sold properties during the post storm periods and we calculate the potential value loss to all homes that are in CRS-treated towns and at high flood risk, but were not sold immediately following the storm. We use the fitted coefficients from the repeat sales models. We emphasize that this is an approximate calculation. Table 6 reports that the decrease in price during the 12 month window after the storm is 15.7%. There are 1,902 residential properties that are in municipalities that meet the definition of CRS public awareness activities, in a high risk zone, and that sold during this window. The average price of homes sold during the pre-Hurricane Katrina window that were in high risk zones and in CRS municipalities is about $460,000. Thus, in total sellers lost almost $140 million dollars (15.7% x 460,000 x 1,902). In addition, there are approximately 30,000 homes that are high risk and in CRS towns during the post Katrina window. As only a small subset of these homes sold during the window the loss of $140 million dollars represents only 7% of the total loss to all potential sellers.

It is possible that this adjustment to property values is welfare improving. As the financial crisis of 2008 made clear, real estate market corrections, and the resulting income effects, can affect the entire economy. The wide reaching effect of real estate market corrections is not unique

[21] The story for why non-resident's buying would drive a decrease in prices is not as straightforward as the non-resident's financial mobility selling mechanism. We propose an income effect of sorts. If non-resident second home owners are wealthier on average, it is possible that non-residents are more likely to have all cash offers than primary residents, which might be accepted by sellers at a lower price. With this mechanism an increase in non-residents (correlated with CRS) drives down prices, not information about risk.

to the financial crisis of 2008. The literature has shown that asset bubbles often lead to crashes, and that these crashes can spill over into other areas of the economy (Brunnermeier and Oehmke 2012). Further, information frictions can cause bubbles to arise, in turn contributing to future crashes (Brunnermeier and Oehmke 2012). The CRS program infuses risk-relevant information into the market. The price drop we detect after the distant storm, which provides investors with a visceral experience that appears to update their risk beliefs, may be a price correction in the market. This could be welfare improving if such a price adjustment prevents a future correction of greater magnitude with adverse effects on other real and financial markets. In fact, Sutter, Huber, and Kirchler (2012) exploit an experiment to show that markets with asymmetrically informed traders decrease the size of the bubble relative to uninformed traders.

There is empirical evidence that increasing the number of well-informed homeowners can be welfare improving in residential real estate markets. Bakkensen and Barrage (2017) find that increasing the number of realists (homeowners who know the true value of flood risk) minimizes the reduction in home price due to sea level rise. In the present paper, when the sample is limited to firm transactions, we show that investors incurring the price correction in CRS towns after the geographically-distant disaster fare much better after Hurricane Sandy. These investors were initially subject to the CRS information intervention. We argue that they are therefore well-informed about flood risks.

We also consider whether CRS improves insurance levels. The initial policy goal of the National Flood Insurance Program was to force investors to internalize risk through insurance. However, even though it was mandated for properties with federally backed mortgages, there has not been enforcement and take up has been slow (Michel-Kerjan, 2010).[22] One possible explanation is that people were uninformed about risk to properly insure (Chivers and Flores, 2012). While estimating the optimal level of insurance is beyond the scope of this paper, prior literature demonstrated that homes in high risk areas are still underinsured against their future risks (Michel-Kerjan, 2010). Thus, an increase in policy holders in municipalities with high risk areas should be welfare improving. Municipalities that participate in CRS have seen an increase in insurance policy holders. In Table A24 we present results from a regression of CRS public awareness participation on policy counts. We also include specifications with year, month fixed effects and year, month, municipality fixed effects. In all three of our specifications, participating in CRS, is positively and significantly related with the number of policy holders.

The results in table A10 further buttress the claim that the information provided by the CRS program may improve welfare in subsequent local flooding events. This table shows that participation in CRS is associated with a decrease in the average claim. Of course, while this is provocative

[22] While take up has increased over the years, prior research has shown at least half of the homes in high risk zones are uninsured. (Kriesel and Landry 2004). Michel-Kerjan, (2010) also discusses insurance penetration.

evidence that CRS may be effective in mitigating damages, further research is required to thoroughly explore this question.

1.5 Conclusion

The present study offers three key innovations over prior papers that examine how coastal real estate markets capitalize flood risks. First, we develop a novel identification strategy to isolate the market response to flood risk distinctly from damage due to realized flooding. Second, we demonstrate the importance of information specifically about flood risk in triggering market responses. Third, we show that for the case of transactions involving firms, markets exposed to such information are less adversely affected by future disasters. We interpret this as evidence that information interventions mitigate hysteresis rather than distorting asset prices.

These findings stand to inform policymakers in at least two ways. First, environmental regulators charged with conducting climate change related risk assessments now have compelling evidence that major coastal flooding events impact markets distant from the locus of the event. In the present case, direct property damage from Katrina is estimated at $125 billion (Knabb et al., 2005). Non-local risk discounts only in the coastal New Jersey CRS towns are estimated herein at $2 billion. Our findings argue strongly for further research in other coastal real estate markets to ascertain whether such effects evince there as well.

Second, analysts at FEMA may benefit from our findings. Specifically, we demonstrate a causal effect of CRS information campaigns on the sensitivity of participants to flood risk. Something about the CRS information treatment heightens risk awareness. In addition, the finding that firms are especially responsive to CRS programs and that this information appears to attenuate capital losses suffered in subsequent natural disasters may assist in targeting interventions to maximize impact.

Chapter 2

Why Local Governments Provide Hazard Mitigation: Evidence from The Community Rating System

2.1 Introduction

Given the rising risk of flooding due to climate change and growing populations, investment in flood hazard mitigation is becoming increasingly important to the function of local economies (Berman (2019)). Bakkensen and Mendelsohn (2016) show that the United States is more vulnerable to damages from storms due to the lack of adaptation in the United States relative to other countries. Further, Davlasheridze et al. (2016) find that ex ante mitigation is more effective than ex post adaptation. However, it is still not fully understood why some government invest in hazard mitigation more than others. Hazard mitigation can be both a private and public good. For example, investing in hazard resistant structures can happen at the individual private level. Whereas, at the public level, regulations can be passed to require new buildings to meet some level of building code, power lines can be buried, city-wide drainage systems can be built, emergency systems can be created, roads can be elevated, and/or sand can be dredged. Investment in these public goods is not driven by typical market forces and therefore must be provided by government organizations. Understanding why local governments invest in hazard mitigation is important for federal and state policymakers because local provision of public goods can have large effects on welfare (Ehrlich and Seidel (2018)).

This paper seeks to understand what municipality characteristics drive investment in hazard mitigation and whether current investment in hazard mitigation is sub-optimal. The theoretical part of this paper studies the issue of hazard mitigation broadly and yields conjectures on how some factors affect the investment in hazard mitigation and considers why the chosen level of hazard mitigation might be inefficient. The empirical analyses are then able to test these hypothesis in the context of flood hazard mitigation and demonstrate that the theoretical conjectures are consistent with the data.

In this paper, I start by building a model of government investment in hazard mitigation to understand what factors may increase investment in this good. The theoretical model is a representative agent model where the government's objective is to maximize the utility of the representative homeowner. The utility of the homeowner is a function of a composite good, the amenities in the municipality, and the probability that these amenities are damaged by some hazard. The model is similar to the model used by Boskin (1973), but does not allow for externalities across municipalities. In this way it is similar to the assumptions and logic set out by Tiebout (1956).[1]I rely on comparative statics of the model to examine how changes in various parameters change the optimal level of hazard mitigation. I then extend my model to consider the following cases: 1.) a change in the representative homeowner's preference for the amenities relative to the composite good, 2.) if the government or the homeowner has imperfect information about risk, and 3.) when the government's utility function differs from that of the homeowner's. These extensions provide several additional hypotheses, including that second homeowners will increase hazard mitigation, shocks will update individuals' information about risk and increase hazard mitigation, and special interest groups like real estate firms may decrease initial participation in hazard mitigation. Further, the extensions consider how accountability or a lack thereof may be deterring governments from investing in hazard mitigation.

The empirical analyses use participation in a federal flood hazard mitigation program, the Community Rating System (CRS), by New Jersey Municipalities to test the hypotheses generated by my model. Kousky and Michel-Kerjan (2017) show that participation in CRS decreases flood insurance claims, thus it is an effective form of hazard mitigation. Specifically, I use panel data for over 100 municipalities in four New Jersey coastal counties from 2002 to 2015 to test whether the various characteristics considered in my model are associated with an increase or decrease in the likelihood of participating in CRS. The dataset includes information on the municipalities' government, constituents, homes, and participation in CRS. Due to the heterogeneous characteristics of the governments across municipalities and over time, this paper is able to test the relationship between the parameters in the theoretical model and observed levels of investment in hazard mitigation.

[1]Tiebout (1956) argues that people vote with their feet. In other words, people will optimally sort into the local jurisdiction that provides the public good bundles and housing services that maximize their utility. These models typically focus on the location decision of the homeowner to solve for willingness to pay whereas my model focuses on the decision of the government choice and indirectly incorporates this sorting behavior by defining the objective function as the homeowners' utility.

The empirical analyses show that income, population, housing values, risk, value of amenity access, and a mayor-council structure of the local jurisdiction is all increase the likelihood that the municipality will participate in CRS. I argue that the accountability of an elected rather than appointed chief-executive is why a mayor-council governance structure is associated with an increase in the probability of participation. I support my argument by testing whether mayor-council governments invest more before versus after a flood shock. As an accountable government will be blamed if they are unprepared for the shock, they will be incentivized to invest prior to damages occurring. I use Hurricane Sandy as my local shock and show that after the hurricane, changes in CRS participation are homogeneous across the types of government. I also use Hurricane Sandy to show that overall participation increases after the storm due to an increase in information about the risk and/or costs of damages.

This paper offers several contributions. First, it builds a theoretical model that can be used to understand why local jurisdictions invest in hazard mitigation and how changing conditions might change the provision of hazard mitigation. This is helpful to federal and state policymakers who design policies to increase involvement at the local level. For example, the Federal Emergency Management Association (FEMA) has several programs designed to increase investment in hazard mitigation by states, counties, and local governments.[2] The setup of this model can be used to assess these other federal programs. Although the empirical analyses in this paper focus on flood risk, the model can be applied broadly to the mitigation of other hazards such as wind or fire and is further generalizable to the consideration of other public goods.

Second, this paper combines several different datasets on municipality participation in flood hazard mitigation, municipality characteristics, and homeowner characteristics to test the hypotheses produced by the model. Analyses of this data show that the conjectures of the model are consistent with the applicable empirical setting. Finally, the insights from both the model and the empirical analyses provide insight into how participation in federally designed programs may differ from expectations if the policy does not account for specific characteristics of the local governments and regions. The results of this study highlight the importance of municipality wealth, municipality size, and the value of the amenity for increasing investment in hazard mitigation. Further, they demonstrate that inefficiencies due to imperfect information, accountability, or special interest groups may create gaps between the optimal level of provision for the homeowners and the level of hazard mitigation the government actually offers. Thus, the model and empirical work provide both positive insights about what type of municipalities will invest in hazard mitigation and normative insights about whether municipalities may be under-investing in hazard mitigation relative to the optimum.

This paper contributes to prior research on optimal public good provision. In particular, the

[2] See discussion of the Stafford Act and Disaster Mitigation Act of 2000 FEMA

extensions of my theoretical model that allow for inefficiency due to imperfect information, accountability, and lobbying, and the empirical tests of these factors adds to the political agency literature. Note, that me model offers a simplified theoretical depiction relative to some of the political agency literature that focuses on fiscal policy across government forms Coate and Knight (2011). Coate and Knight (2011) examines how different forms of government (council-manager vs. mayor-council) in US Cities affect fiscal policy. The authors develop a theoretical model of expected public spending for either type of government and predict that spending will be lower under mayor-council. My model does not solve for specific budget expenditures, but instead focuses on the level of public good offered and finds that mayor-council governments increase initial investment in hazard mitigation. I contribute to the literature on public good provision with imperfect information, by utilizing an information shock to demonstrate how provision changes after the shock. As flooding in this region is a sufficiently rare event this new evidence contributes to the literature on inefficiencies in public good provision due to lack of information or incorrect beliefs. See Fox and Van Weelden (2015).

Accountability of the government is another important factor considered by the political agency model literature. The results from previous literature on what government structures are most accountable are mixed. Some work has shown that an elected chief executive is more accountable to its constituents and will provide more public goods. See Saha (2011). Others have shown no effect. See MacDonald (2008). Vlaicu (2008) finds that the effect of government form on spending on a policy depends on the policy's visibility. More recently, Vlaicu and Whalley (2016) found that mayor-council governments are more likely to pick popular policies. Consistent with Vlaicu (2008) and Vlaicu and Whalley (2016), I argue that mayor-council governments will invest more in flood hazard mitigation due to policy's visibility and the governments' increased accountability. My empirical tests are consistent with these predictions and contribute new evidence on how accountability may cause governments to be underinvested in a public good. I also find that voter turnout is associated with an increase in hazard mitigation in some of my specifications. I argue that high voter turnout may indicate that the government is held more accountable by its constituents. Further, by considering both the lobbying and accountability channel I am able to show that accountability has a stronger effect on participation than lobbying at the local level.

This paper also contributes to the prior literature that has studied the relationship between community factors and CRS participation. Thus far, the literature has shown that many factors affect CRS participation. Brody et al. (2009) analyzes changes in local flood mitigation policies from 1999-2005 in Florida and find that local jurisdictions learn from flood risk. Landry and Li (2018) examines what motivates participation in CRS in North Carolina from 1991-1996 and also find that flood experience matters. Landry and Li (2011) also find that tax revenue, low crime levels, and education increase CRS participation. Sadiq and Noonan (2015) find that local capacity, flood risk, socio-demographic characteristics, and political economy factors are all contributing factors for participation in CRS. Sadiq and Noonan (2015) use a national sample, but use only one year of CRS participation (2012). The findings of these studies are consistent with the results of this paper. This research improves on this prior literature by motivating the empirical work with a theoretical model, by introducing new specifications and variables, and by applying my empirical analysis to a different region and more recent and longer panel dataset.

The addition of a theoretical model is a significant contribution because it provides an explanation of the mechanisms that drive these relationships as well as policy insights into how investment can be incentivized or where investment may need to be incentivized. The panel dataset allows me to exploit variation at both the temporal and municipality level in participation in the CRS program. This is important as growing knowledge of climate change and recent flood shocks have changed homeowners' beliefs about flood risk. While this research is not the first to test the relationship between municipality characteristics and participation in CRS, it is the first to build a theoretical model to drive the empirical tests. It is also the first to study how the type of local government and lobbying affects the decision to invest in CRS. Finally, this paper uses a storm shock to understand how information about flooding and costs drives the decision to participate in flood hazard mitigation programs across government types.

The paper proceeds as follows: Section 2.2 provides additional background on the empirical setting, Section 2.3 depicts the theoretical model, Section 2.4 discuss the data, Section 2.5 presents the results of the empirical analyses, and Section 2.6 concludes.

2.2 Background

This section discusses several aspects of the empirical setting as the model will incorporate some of these key institutional details. Flood hazard mitigation is becoming increasingly important as climate change will cause sea levels to rise in turn increasing the risk of many coastal areas in the United States. Floods are a costly natural hazard due to the extensive property damage they cause. Hurricane Sandy caused over $70 billion in damage and a significant portion of that was due to flooding from both rain and coastal surges.[3] These growing future costs make local investment in flood hazard mitigation critically important.

The National Flood Insurance Program (NFIP) is the largest Federal program focused on mitigating and responding to flood risk. NFIP is also in significant debt. One key component of the NFIP in terms of local flood hazard mitigation is CRS. CRS started in 1990 with the purpose of encouraging communities to increase floodplain management above the minimum federal standards. Municipalities can join NFIP without joining CRS. Therefore, municipalities must choose to par-

[3] NOAA

ticipate in the CRS program. The program is made up of 10 class levels that communities attain by getting points from various actions related to floodplain management. The four categories of actions are:

- Public Information
- Mapping and regulation
- Flood damage reduction
- Warning and Response

Each activity is assigned a point value and the point values for all actions the communities pursue are totaled. The communities must undertake the activities and document their actions. The actions are then audited by FEMA and points are assigned. Each class level corresponds to a range of total points. If a community reaches 500 points they move from class 10 to class 9. To achieve a class 1 designation a community needs to reach 4,500 points. The main incentive to increase participation in the CRS is discounts on the flood insurance premiums purchased through the NFIP. CRS is designed so that communities receive a 5% discount off each homeowner's insurance premium for each increase in class.[4] Thus communities at level 4 get a 30% discount. Very few communities have reached the top levels of the CRS and many only pursue less costly actions.[5]

Participation in CRS was slow initially. Currently, levels of participation vary significantly across communities with some communities still not participating and very few reaching the highest class levels. Understanding why communities do or do not participate is pertinent to making CRS effective in managing future flood risk. If CRS can motivate local communities to mitigate flood hazards, then it might be an important factor in making the NFIP viable going forward. The literature on CRS demonstrates that people do value the program. In Fan and Davlasheridze (2016), the authors find that, people value activities that relate to repetitive flood loss reduction and public information about flood risk. Hopkins (2020a) uses a hedonic analysis and finds that CRS participation is associated with an increase in housing prices. Looking at a particular hazard mitigation activity, dredging, Dundas (2017) finds that protecting and increasing the beach width does increase the value of homes, but that this is attenuated by concerns about views and privacy.

[4] Homes in the highest risk zones get the additional 5% discount for each increase in class. Homes outside of the SFHA get a 5% discount for the first few levels and then a 10% discount for any of the higher levels. There are some restrictions on which homeowners qualify, but these are limited.

[5] Michel-Kerjan et al. (2016) ”find that virtually all the participating communities perform the “easier” or less resource-intensive activities, such as public information activities (series 300). Resource-intensive activities such as acquisition and relocation are done by only a handful of communities.”

This study is limited to coastal communities in New Jersey, which are colloquially known as the Jersey Shore. The focus is on the New Jersey Shore for several reasons: 1. New Jersey is one of the top five states that participates in the NFIP, 2. The coastal towns in New Jersey have seen changes in their CRS class over the relevant period, 3. There is variation in neighboring communities' class levels and variation in when these levels changed, 4. As Hurricane Sandy showed damages to New Jersey can be quite costly, and 5. Due to their proximity and similarities these towns can serve as substitutes for each other.

New Jersey has consistently been one of the top five states participating in the NFIP. In 2016 there were 231,956 policies in force in New Jersey. This number was only exceeded by Florida, Texas, Louisiana, and California. Many of the New Jersey homeowners who own NFIP policies reside along the Jersey Shore. The New Jersey Shore resides within 130 miles of coastline. A person can drive from Cape May, the southernmost beach, to Sandy Hook, the northern most beach, in approximately two hours on the Garden State Parkway. The beach communities are contained in Cape May, Atlantic, Ocean, and Monmouth counties.[6] The value of land and property along the coast has grown from less than $ 1 billion in 1960 to greater than $ 170 billion today Gaul.

Within the four coastal counties there are over 100 beach towns. The form of the government varies across these communities. There are 12 different types of municipality governments, but all the types can fall under three general categories: mayor-council, council-manager, and committee. These three types correspond to the following types of elected officials respectively: elected governing body and elected chief executive, elected governing body and appointed chief executive, or elected governing body-administrators Rutgers..

Many of these towns are located on barrier islands which have very high levels of flood risk. In fact many of the homes fall in the highest risk zones designated by FEMA.[7] The risk of flooding to the New Jersey shore from a severe weather event was evident when Hurricane Sandy hit the Jersey coast in 2012. Hurricane Sandy led to widespread flooding and damages along the coast. The flooding came from both storm surges and rain. The destruction was extremely damaging. In the Ortley Beach Community all but 60 of the 2,600 homes were destroyed Capuzzo (2017). In Mantoloking 119 of the 524 homes were significantly damaged and approximately half had first floor flooding Capuzzo (2017). Most of the coast and all of the barrier islands were flooded at varying levels. After Hurricane Sandy, New Jersey had the highest total claim payments from NFIP of all the states with almost $ 4 billion in 2013.

Storm damage and related flooding is not only being caused by hurricanes, more and more

[6] I do not include Middlesex county as a shore county, although it does contain the northern most part of the New Jersey coastline. This is due to the region's proximity to New York and that the characteristics of the area are different than those of the beach towns contained in the other four counties.

[7] The two highest zones are A and VE. Zone A designates that the home is in the Special Flood Hazard Area (SFHA) and Zone V designates that the home is subject to risk from waves.

Nor'easters are causing flooding on the Jersey Shore. The damages range from flooding in homes to eroding beach replenishment projects which are desperately needed to prevent worse flooding. For example on January 23rd, 2017 a Nor'easter hit the coast causing wide spread flooding and high winds gusting to 63 mph which led to road closures and dune erosion.[8]. In addition to storms, a report from NOAA found that areas along the shore could see a 10-20 percent increase in tidal flooding Kummer (2017). As sea levels rise it will no longer take a storm to flood the shore, the tides will do it. This makes it critical to understand why governments invest in flood hazard mitigation. Limiting my analysis to New Jersey does not limit the model to New Jersey as it can be applied both to other regions and expanded to other hazard mitigation policies. For example to other relevant areas to study are wild fire and wind hazard mitigation.

2.3 Model

This section proceeds as follows: the setup of the model is presented, the optimization problems of the homeowners and the government are detailed, and the initial model is derived. This section then derives some implications of the initial model, considers extensions to the homeowner's problem that allow for heterogeneity across and within municipalities, and finally, extensions that demonstrate potential inefficiencies in the government optimization problem are considered.

2.3.1 Model Setup

Consider a representative agent model for homeowners in each jurisdiction. Suppose the homeowners are homogeneous within each community, and therefore have the same income, houses, access to amenities, risk, and preferences. Hence, one homeowner can act as a representative agent for all other homeowners in the community. I allow for the representative homeowner to vary across communities. By maximizing the representative homeowner's utility, the government will maximize all of the homeowners' utilities. Suppose the local jurisdiction only collects taxes and provides hazard mitigation. The government acts as a social planner and chooses the tax rate and policy such that it maximizes the representative agent utility.[9]

The model will help to understand why some local jurisdictions participate in hazard mitigation and other nearby jurisdictions do not. The model is broad enough that it can be used in other hazard mitigation contexts and other policy questions as well. However, as my empirical setting analyzes

[8]Waves even pushed over the seawall in Atlantic City Lam (2017)

[9]I do implicitly assume that there are not spillover effects from other municipalities' investments in public goods. This is a notable assumption as Williams (1966) examines the spillover benefits of public goods across local jurisdictions to show that in even very simple settings it is not clear whether the amount of public goods will be under supplied or oversupplied generally.

flood hazard mitigation, I will use some institutional details from the Community Rating system in my model. These details have minor effects on the setup of the model and can easily be changed for different settings. Considering the potential wide array of changing hazards due to climate change, understanding how to motivate local governments to mitigate risk will be pertinent for policymakers at the state and federal levels.

2.3.2 Optimization Problems

Homeowners

Suppose the homeowners get utility from both the amenities in the town and commodities they can purchase. Let x be a composite of commodities a homeowner can buy and α capture the value of amenities a. The amount of value a homeowner gets from the amenities is dependent on if damage occurs and protection of the homeowner. Protection comes in the form of insurance and in the form of the public good provided by the government.[10] I define the function $\alpha(a, D, \psi(i, p))$ as:

$$\begin{cases} a & if\ D = 0 \\ a \times \psi(i, p)) & if\ D = 1 \end{cases}$$

Where D is an indicator for flood damage and $\psi(i, p))$ measures how well protected the amenities are. The components of ψ are an indicator for insurance, i, and the level of hazard mitigation public good i.e. CRS participation, p. Insurance ensures the homeowner can rebuild their home and still access the amenity if damage occurs and the protection from the public good investment minimizes damage to the house and the municipality more generally. As $\psi(i, p)$ measures how protected the amenity is, it serves as a weight that measures the proportion of how available the amenity is in the bad (damaged) state. Thus, I restrict $\psi(i, p)$ to be a value from 0 to 1.[11] Further, I assume $\psi(i, p)$ is well-behaved and concave in p. Specifically,

Assumption 1.

A1.1: $\psi(i, p) \in [0, 1)$

A1.2: $\frac{\partial \psi}{\partial p} > 0$

A1.3: $\frac{\partial \psi}{\partial i} > 0$

A1.4: $\frac{\partial^2 \psi}{\partial p \partial p} < 0$ *therefore* ψ *is concave in p.*

[10] In the paper's empirical setting, the public good is CRS participation.

[11] $\psi(i, p)$ cannot reach 1 because even with hazard mitigation some damage may occur and insurance does not allow for access to the amenity to be immediately fixed.

Let π measure the probability of damage from flood or other hazard. Let $u(\alpha(a, D, \psi(i, p)), x)$ measure the utility the representative homeowner gets from the amenities and the composite good x. Suppose:

Assumption 2. *u is quasiconcave in $\alpha(a, D, \psi(i, p))$ and x*

The expected utility of an agent is then:

$$U(\alpha(a, D, \psi(i, p)), x) = (1 - \pi) \times u(a, x) + \pi \times u(a \times \psi(i, p), x) \tag{2.1}$$

Let w denote the wealth of the representative homeowner.[12] Let $C_i(p)$ denote the cost of insurance to the homeowner. Consistent with the design of CRS, I define $C_i(p) = c_i \times (1 - (.05 \times p))$ where c_i is the initial cost of the insurance plan.[13] Let τ denote the tax rate for the homeowner and h denote the homeowner's housing value therefore $\tau \times h$ equals the taxes the homeowner pays. I normalize the cost of x, c_x to 1 therefore a homeowner can purchase $w - C_i(p) \times i - \tau \times h$ of x. . Combining, I rewrite the homeowner's expected utility as:

$$U(\alpha(a, D, \psi(1, p)), x) = (1 - \pi) \times u(a, w - C_i(p) - \tau \times h) + \pi \times u(a \times \psi(1, p), w - C_i(p) - \tau \times h) \tag{2.2}$$

Due to the NFIP requirement that all homeowners with federally backed mortgages must buy flood insurance in designated high risk flood zones, I assume that the representative agent will always purchase some level of flood insurance and set $i = 1$. This is a strong assumption as insurance take up rates have historically been low. However, it is not as strong of an assumption in my empirical setting of the coastal counties in New Jersey, where insurance take up rates are above the national average (Kousky and Michel-Kerjan (2012) and Kousky et al. (2017)). The reason for this simplification is that the focus of this research is on the government's choice to invest in hazard mitigation and not the optimal level of insurance for homeowners. As the rates are heavily subsidized the question of optimal insurance level is for future research.[14] Suppose I do not make this simplification and allow i to be a function of the level of protection and risk. If I assume that i is well behaved and concave with respect to both variables and that the cross partials are positive, then the initial implications of the model will still hold. Normally, one might be concerned that this assumption is not reasonable as increasing public hazard mitigation will crowd out private hazard mitigation, however research has found that CRS participation increases

[12] Wealth is limited to their income and savings which they can use for spending money. It does not contain their non-liquid assets.

[13] Insurance costs as a function of participation is consistent with other hazard mitigation policies as well. For example the state of Florida requires that insurers provide discounts on homeowner's insurance if certain wind mitigation standards are met.

[14] See Wagner (2019) for recent work on the optimal level of flood insurance.

policy take up. This increase in take up is most likely due to the incentives from the discounts on premiums (Kousky et al. (2018), Hopkins and Muller (2019) and Hennighausen and Borsky (2020)).

Local Government

The local government acts in the interest of the representative agent as a social planner. The government's role is to set the tax rates, collect taxes to pay for the public good, and choose the optimal level of the public good. Hence the government budget is defined as:

$$c_p \times p \leq T \tag{2.3}$$

Where c_p is the cost of protection, p denotes the level of protection, and T is the total taxes which is equal to $n \times \tau \times h$ where τ and h are defined as before and n is the number of property tax payers i.e. homeowners in the community. By Equation 2 and Equation 3, the government's optimization problem is:

$$\begin{aligned} \max_{t,p}\ & U(\cdot) = (1-\pi) \times u(a, w - C_i(p) - \tau \times h) + \pi \times u(a \times \psi(1,p), w - C_i(p) - \tau \times h) \\ & s.t. \\ & c_p \times p \leq n \times \tau \times h \end{aligned} \tag{2.4}$$

As the government works in the best interest of the representative agent, I argue that the budget constraint of the government will bind and $c_p \times p = T = n \times \tau \times h$. Define $W(p) = w - C_i(p) - \frac{c_p \times p}{n}$. I rewrite the optimization problem as:

$$\max_{p}\ U(\cdot) = (1-\pi)u(a, W(p)) + \pi \times u(a \times \psi(1,p), W(p)) \tag{2.5}$$

2.3.3 Optimal Public Good Provision

Consider the maximization problem in Equation 2.5. The first order condition with respect to hazard protection is:

$$
\begin{aligned}
\frac{\partial U(\cdot)}{\partial p} &= (1-\pi)\times\frac{\partial u(a,p)}{\partial W(p)}\times\frac{\partial W(p)}{\partial p} \\
&+\pi\times\Big[\frac{\partial u(a\times\psi(1,p),W(p))}{\partial\psi(1,p)}\times a\times\frac{\partial\psi(1,p)}{\partial p}+\frac{\partial u(a\times\psi(1,p),W(p))}{\partial W(p)}\times\frac{\partial W(p)}{\partial p}\Big] \\
&= 0
\end{aligned}
\tag{2.6}
$$

Taking the derivative of the FOC with respect to P yields the SOC:

$$
\begin{aligned}
\frac{\partial^2 U(\cdot)}{\partial^2 p} &= (1-\pi)\times\Big[\frac{\partial^2 u(a,p)}{\partial^2 W(p)}\times(\frac{\partial W(p)}{\partial p})^2+\frac{\partial u(a,p)}{\partial W(p)}\times\frac{\partial^2 W(p)}{\partial^2 p}\Big]+\pi \\
&\times\Big[\frac{\partial^2 u(a\times\psi(1,p),W(p))}{\partial^2\psi(1,p)}\times a^2\times(\frac{\partial\psi(1,p)}{\partial p})^2+\frac{\partial u(a\times\psi(1,p),W(p))}{\partial\psi(1,p)\partial W(p)}\times a\times\frac{\partial\psi(1,p)}{\partial p} \\
&\times\frac{\partial W(p)}{\partial p}+\frac{\partial u(a\times\psi(1,p),W(p))}{\partial\psi(1,p)}\times a\times\frac{\partial^2\psi(1,p)}{\partial^2 p}+\frac{\partial^2 u(a\times\psi(1,p),W(p))}{\partial^2 W(p)} \\
&\times(\frac{\partial W(p)}{\partial p})^2+\frac{\partial u(a\times\psi(1,p),W(p))}{\partial W(p)\partial\psi(1,p)}\times\frac{\partial W(p)}{\partial p}\times a \\
&\times\frac{\partial\psi(1,p)}{\partial p}+\frac{\partial u(a\times\psi(1,p),W(p))}{\partial W(p)}\times\frac{\partial^2 W(p)}{\partial^2 p}\Big] \\
&= 0
\end{aligned}
\tag{2.7}
$$

For the level of p that solves the FOC to be a maximum the SOC must be less than zero. By assumptions 1,2 and the definition of $W(p)$: $\frac{\partial\psi(1,p)}{\partial p} > 0$, $\frac{\partial^2\psi(1,p)}{\partial^2 p} < 0$, $\frac{\partial^2 u(a,p)}{\partial^2 W(p)} < 0$, $\frac{\partial^2 u(a\times\psi(1,p),W(p))}{\partial^2\psi(1,p)} < 0$ and, $\frac{\partial^2 W(p)}{\partial^2 p} = 0$ Thus a sufficient condition for the $SOC < 0$ is if the following holds: $\frac{\partial u(a\times\psi(1,p),W(p))}{\partial W(p)\partial\psi(i,p)} > 0$, $\frac{\partial u(a\times\psi(1,p),W(p))}{\partial\psi(i,p)\partial W(p)} > 0$, and $\frac{\partial W(p)}{\partial p} < 0$. Hence, for the the rest of the paper the model assumes:

Assumption 3.

A3.1: $\frac{\partial u(a\times\psi(1,p),W(p))}{\partial W(p)\partial\psi(i,p)} > 0$ *or that increasing consumption of the composite good enhances the value of amenities.*

A3.2: $\frac{\partial u(a\times\psi(1,p),W(p))}{\partial\psi(i,p)\partial W(p)} > 0$ *or that increasing the value of amenities increases the enjoyment of the composite good.*

Assumption 4. $\frac{\partial W(p)}{\partial p} < 0$

Assumption 3 is straight forward and can be understood intuitively. Suppose the composite good includes ice cream. Enjoying an ice cream cone on the beach also increases the value of the beach. In other words an increase in the composite good enhances the enjoyment of the coastal amenity. Similarly, suppose the beach increases in size i.e. consumption of the amenity increases, this will enhance the value of the ice cream. Assumption 4 implies that increasing hazard mitigation decreases W. First, increasing tax revenues to pay for p will decrease W. However, increasing p decreases the cost of insurance. Thus, assumption 4 holds if $.05c_i < \frac{c_p}{n}$ i.e. the five percent discount on insurance is less than the per person cost of the hazard mitigation public good. This is reasonable as one might expect that the insurance discount is sufficiently small relative to the cost of hazard mitigation.[15] Without making explicit assumptions about the functional form of $u(a \times \psi(i,p), W(p))$ and $\psi(i,p)$ I cannot solve for p explicitly. However, the next section shows that with these few assumptions the model yields several hypotheses.

2.3.4 Implications of the Model

Consider what happens to the level of hazard mitigation, p^*, when the following parameters of the model change: the probability of risk, the wealth of the representative homeowner, the housing value of the representative homeowner, and the population in the town. There are four direct hypotheses that come from the initial model. This section details these main conjectures of the mode. The proofs of these hypotheses predominantly rely on comparative statics and are included in the appendix.

Proposition 1. *Given assumptions 1-4 hold, then an increase in risk or increase in the probability of damages, π, will increase p.*

Proposition 2. *Given assumptions 1-4 hold, then an increase in wealth, w, will increase p.*

Proposition 3. *Holding tax rate, τ, constant, an increase in housing value, h, will increase p.*

Proposition 4. *Given assumptions 1-4 hold, an increase in n will increase p.*

Each of the propositions from the initial model are consistent with intuition. An increase in risk will increase public investment in hazard mitigation. This result is driven by the increased probability of the bad state, thus making mitigation or protection more valuable. An increase in wealth also increases public investment in hazard mitigation. Increasing housing values increases the government's budget and therefore will also increase public investment in hazard mitigation. Similarly, increasing the number of houses increases public investment in hazard mitigation. This

[15]Suppose the 5 percent discount is larger than the actual cost of hazard mitigation, all governments then would invest in CRS. However, we see low participation in CRS throughout the country.

finding is driven by the conditions in the model which yield that the per person benefit of hazard mitigation is greater than the cost of per person mitigation. While these four propositions are straight forward, they do provide insights into the potential for varying levels of participation in hazard mitigation across municipalities and highlight the concern that poorer regions might be falling behind in hazard mitigation relative to their wealthier counterparts of the same risk level.

2.3.5 Extension with Homeowner's Utility Function

Cobb-Douglas Utility Function

Previously, no functional form was placed on the homeowner's utility function. One model aspect to consider is how much a homeowner values the amenities relative to the composite good. Let θ capture homeowner's tastes in the homeowner's utility function, $u(\alpha(a, D, \psi(i, p), x)$ and allow it to vary across jurisdictions. θ is the homeowner's weight on the amenities and $1-\theta$ is the homeowner's weight for the composite good. For this example, assume the standard Cobb-Douglas utility for the representative homeowner and rewrite equation 2.1 as:[16]

$$U(\alpha(a, D, \psi(i, p)), x) = (1-\pi) \times a^{\theta} \times x^{(1-\theta)} + \pi \times (a \times \psi(i, p)))^{\theta} \times x^{(1-\theta)} \tag{2.8}$$

Given $u(\alpha(a, D, \psi(i, p), x)$ is Cobb-Douglas, as θ increases the amount of x needed for an agent to give up one unit of amenities and stay at the same utility increases. It can easily be seen that α increases when p increases given that damage occurs. Thus as long as $\pi > 0$, an increase in θ will increase the amount of CRS protection an agent wants. This also makes intuitive sense as any increase in relative preference for amenities should cause an increase in the value of hazard mitigation.

Consider what homeowners have a relatively higher preference for amenities. The Jersey Shore beach towns are broadly made up of two types of homeowners: 1.) primary home and 2.) secondary home.[17] I hypothesize second homeowners may value the amenities relatively more than the composite good as they purchased the home to take advantage of the amenities. As my model simplifies the government role to center around CRS, I assume other public goods like schools, libraries, and police are measured in the composite good. Primary homeowners might care more about those others goods. Thus another indication of the model is that communities with a higher ratio of non-residents to residents will be more likely to undertake hazard mitigation. Similarly, a homeowner can vary not just by resident status, but also by risk of flooding to their actual home.

[16]Other CES utility functions will work in this example. Cobb-Douglas is used for simplicity

[17]Primary homeowners are classified as residents and have voting rights, whereas second homeowners are non-residents and do not have any voting rights.

Thus if a municipality has a larger proportion of homes in high flood risk zones, the representative homeowner is more likely to face higher risk and will also have a higher θ. As this is a coastal region, higher flood risk is also an indicator for closer access to the coastal amenity. Therefore, homeowners that choose to buy in high risk areas, most likely pay a premium for that amenity access and have a higher θ.

Heterogeneous Wealth

The initial model requires homogeneous homeowners, which is not an entirely realistic restriction given the heterogeneous nature of homeowners. Suppose now wealth, w, varies across homeowners within a community. Each homeowner k now has wealth w_k and their expected utility becomes

$$\begin{aligned} U_k(\alpha(a, D, \psi(1, p)), x) = (1-\pi) \times u(a, w_k - C_i(p) - \tau \times h) \\ + \pi \times u(a \times \psi(1, p), w_k - C_i(p) - \tau \times h) \end{aligned} \tag{2.9}$$

The government's problem can be rewritten as:

$$\max_p \sum_{k=1}^{K} U_k(\cdot) = (1-\pi) \sum_{k=1}^{K} u(a, W_k(p)) + \pi \times \sum_{k=1}^{K} u(a \times \psi(1, p), W_k(p)) \tag{2.10}$$

Where $W_k(p) = w_k - C_i(p) - \frac{c_p \times p}{n}$. The solution to the problem that faces the government now is different than the solution to maximizing the representative agent's utility. However, I can solve for the solution to the government's problem. I have assumed thus far that homeowners have single peaked preferences or that there exists only one level of p that maximizes their utility. Thus as $|p^* - p_k|$ increases the utility of individual k decreases. Where p^* is the solution to the government's problem and p_k is the solution to the individual's maximization problem. Given the single peaked preferences and that the government is responsible for only one policy issue, I can apply Black's median-voter theorem. Black's theorem states that under these conditions, the median voter is the pivotal voter. Thus the solution to Equation 2.10 will be the level of publicly provided hazard mitigation that solves the median voter's individual problem. Let κ denote the median voter, then the government's problem can be simplified to:

The government's problem can be rewritten as:

$$\max_p U_\kappa(\cdot) = (1-\pi) u(a, W_\kappa(p)) + \pi \times u(a \times \psi(1, p), W_\kappa(p)) \tag{2.11}$$

But, this is the same problem as in Equation 2.5. Thus the results from the homogeneous case generalize to the case of heterogeneous wealth where all else is identical across agents within a community.

2.3.6 Extension with Government's Problem: Inefficient Case

In the model above I assumed the government acted as a social planner and thus maximized the utility of the representative agent subject to a binding budget constraint. Suppose instead the government does not act entirely in the interest of the representative agent. This may occur if the government does not have perfect information about the representative agent's utility function or if the government has a different utility function than the representative agent.

Imperfect Information

Consider the case where the representative agent does not have perfect information about the risk of damage from a flood or other hazard. Perhaps, due to lack of information about risk or optimistic beliefs, the representative agent believes damage will occur with probability $\hat{\pi}$ as opposed to π with $\hat{\pi} < \pi$. This is policy relevant as many of the flood maps that both residents and policy-makers rely on are static and outdated. The literature has also shown that incomplete or imperfect information is an issue when it comes to beliefs about flood risk (Gallagher (2014) and Bakkensen and Barrage (2017)). Then the government's problem will be:

$$\begin{aligned} \max_{t,p}\ U(\alpha(a,D,\psi(i,p)),x) = (1-\hat{\pi}) \times a^{\theta} \times (w - c_i(p) - \tau \times h)^{(1-\theta)} & \\ + \hat{\pi} \times (a \times \psi(i,p)))^{\theta} \times (w - c_i(p) - \tau \times h)^{(1-\theta)} & \\ s.t. & \\ c_p \times p \leq n \times \tau \times h & \end{aligned} \tag{2.12}$$

In this case the FOCs will proceed as before, however p^* will be dependent on $\hat{\pi}$ as opposed to π. If $\hat{\pi} < \pi$ then $p^*(\hat{\pi}) < p^*(\pi)$.[18] While this is consistent with intuition and may seem obvious, this result is important because it highlights how hazard mitigation may be under provided even in the case where the government's objective function is consistent with the social planners. If home-owners are uninformed about risk, then the resulting provision of public good is inefficiently low. Further this conjecture is testable, and as I show in the empirical section, we do see government increase participation in CRS after a flood information shock.

Government Utility Function Differs from Representative Agent

Now, consider the case where the government utility function differs from the representative agent. Suppose the chief-executive cares about being reelected and thus cares about more than just the

[18] This may explain why after flood shocks we see homeowners increase take up of insurance. See Gallagher (2014).

utility of the representative agent.[19] Let the government utility be a function of the utility of the representative agent, money from special interests groups, and an accountability signal. The accountability signal is important for hazard mitigation public goods because after disasters voters may award governments if the municipality is prepared for the disaster, or blame governments for lack of preparation. I define the value function of the government as:

$$V(U(\cdot),m(\cdot),f(\cdot)) = \omega_1 U(\alpha(a,D,\psi(1,p)),x) + \omega_2 m(\alpha(a,D,\psi(1,p)),x) - \omega_3 f(\lambda,\psi(1,p)) \tag{2.13}$$

Where ω_1, ω_2, and ω_3 are weights that measure the relative importance of the three components to the government. If ω_2 and $\omega_3 = 0$ and $\omega_1 = 1$ then the government's utility function matches the initial model. $U(\cdot)$ measures the utility of the representative agent as before, $m(\cdot)$ represents the money from special interests groups, and $f(\cdot)$ represents the disutility associated with the blame for not preparing the municipality for a disaster.[20]

Recall that $\psi(1,p))$ is a measure of protection and therefore demonstrates the level of preparation by the municipality. Let λ be the signal of accountability of the local government. $f(\cdot)$ is defined such that it measures how much blame should be assigned to the government if a shock occurs:

$$f(\alpha(a,D,\psi(1,p)),x,\lambda) = \lambda\pi(1-\psi(1,p)) \tag{2.14}$$

λ measures how accountable the representative agent will hold the government. π measures the probability of damage and thus measures how much the government should care about the potential blame. And, the third component represents the missing protection attributable to the government. The model can be used to show how the accountability of the government effects hazard mitigation i.e. the model can show how the government's investment in p changes given a change in λ.

Proposition 5. *By assumption 1 and given the definitions of f and V, an increase in λ will increase p.*

Proof. The government's problem is now:

$$\begin{aligned} &\max_{t,p} V(U(\alpha(a,D,\psi(1,p)),x),m(\alpha(a,D,\psi(1,p)),x),f(\lambda,\psi(1,p))) \\ &\quad s.t. \\ &\quad c_p \times p + m \leq n \times \tau \times h \end{aligned} \tag{2.15}$$

[19] I will use reelected to refer to either reelected or reappointed as some chief-executives are appointed by a committee that is elected.

[20] Examples of special interest groups could include specific businesses, industries, non-profits, etc. This research looks at the real-estate industry and construction services campaign contributions.

Following the comparative statics argument from before I know:

$$\frac{\partial p}{\partial \lambda} = -\frac{\frac{\partial V}{\partial p \partial \lambda}}{\frac{\partial^2 V}{\partial^2 p}} \tag{2.16}$$

The second order conditions of the maximization problem imply that $\frac{\partial^2 V}{\partial^2 p} < 0$ thus I just need to show that $\frac{\partial V}{\partial p \partial \lambda} > 0$, to prove that $\frac{\partial p}{\partial \lambda} > 0$.

Substituting in the budget constraint and taking the first order condition with respect to p yields:

$$\frac{\partial V}{\partial p} = \frac{\partial V}{\partial U} \times \frac{\partial U}{\partial p} + \frac{\partial V}{\partial m} \times \frac{\partial m}{\partial p} + \frac{\partial V}{\partial f} \times \frac{\partial f}{\partial p} = 0 \tag{2.17}$$

Solving for $\frac{\partial V}{\partial p \partial \lambda}$ yields:

$$\frac{\partial V}{\partial p \partial \lambda} = 0 + 0 + \frac{\partial V}{\partial f} \times \frac{\partial f}{\partial p \partial \lambda} \tag{2.18}$$

Well $\frac{\partial V}{\partial f} < 0$ by the definition of $V(\cdot)$. And, by the definition of $f(\cdot)$:

$$\frac{\partial f}{\partial p \partial \lambda} = -\pi(\frac{\partial \psi()}{\partial p}) \tag{2.19}$$

$\frac{\partial f}{\partial p \partial \lambda} < 0$ because π and $\frac{\partial \psi()}{\partial p}$ are both greater than 0. Hence, $\frac{\partial V}{\partial p \partial \lambda} > 0$ as desired. □

What is interesting is what type of government might have a higher λ. There are two main forms of government: mayor-council and council-manager.[21] The first type (mayor-council) is the only structure of government that elects the chief executive directly. It is not immediately clear whether an elected chief executive will have a higher λ. The results from prior literature are mixed, but an over-arching argument is that being elected can increase accountability for a visible or popular public good. See Saha (2011), MacDonald (2008), Vlaicu (2008), and Vlaicu and Whalley (2016). I argue that flood protection, which is a very visible public good, will yield higher signals for mayor-council governments. Thus I hypothesize that mayor-council governments will have a higher λ and therefore will have higher levels of flood protection.

Additionally, λ may not be static. Suppose there is a flood shock. How might λ change after this shock? A flood shock increases information about risk or probability of damages, but it may also effect the accountability of all governments. Local residents who were under informed about the potential risk, may not have held their government (of any type) accountable for the

[21] In New Jersey there are also a few municipalities with committee governments However, these governments are similar to council-manager governments in that there is no single elected chief executive.

potential hazard. Prior research has shown that homeowners may not reward governments for hazard mitigation. See Healy and Malhotra (2009) λ could be a function of both π and government structure. Thus, a flood shock might provide a large shock of accountability to all government types. This can be tested by considering how voter turnout effects participation before and after a shock.

Finally, I consider what type of special interest groups might affect the government's decision to invest in flood hazard mitigation. For example, consider real estate groups who might be concerned about the risk signal associated with flood hazard mitigation. While we expect that participating in flood hazard mitigation will have long term positive benefits on housing prices, a Realtor might be concerned that the initial shock of information from flood hazard mitigation and that potential disclosure laws will harm housing values. At higher levels of mitigation, the information shock is less important. Thus we might expect that the function $m(\alpha(a, D, \psi(1, p)), x)$ to be such that $\frac{\partial p}{\partial m} < 0$ and $\frac{\partial^2 p}{\partial^2 m} < 0$ i.e. the optimal level of p decreases from campaign contributions from real estate groups at a decreasing rate. If this is the case, I hypothesize that municipalities with high levels of campaign contributions from real estate groups will have lower levels of initial participation. Another, potentially relevant group is construction services. Federal hazard mitigation laws often require specific regulations for building. For example one aspect of CRS requires that new homes are built with higher base floor elevation. Thus construction services may have a negative relationship with p because regulations from p make their work more expensive, or a positive relationship with p because regulations from p increase their business.

2.4 Data

To apply the model empirically I need data on the CRS participation decision, form of government, socioeconomic characteristics of the constituents, tax, and election data for each municipality in New Jersey. I construct this dataset for the years 2002 to 2015. The data sources are detailed below.

2.4.1 Community Rating System

The CRS database is available from FEMA. The file contains the name of each community, the total points it has been awarded, and the number of points for each subsection. There is normally a file each year, but in some cases there is both a May and an October report. In these years I have taken the annual average of the point values. Using the point values given in the CRS database, I can map in the specific CRS level each town has reached. Approximately a third of the relevant communities are currently participating in a significant way (excludes communities at level 9 or

10). In 2008 the majority of these communities were at levels 7 and 8, but as of 2015 many of them have moved to levels 5 and 6.

2.4.2 Local Municipality Data

Rutgers New Jersey Data Book provides extensive information on municipalities in New Jersey.[22] The Data Book has numerous variables pertaining to the form of government including information on government type, election type, number of members, and election term. Approximately 60% of the governments are of the mayor-council form with the remaining 40% either council-manager or committee. These forms do not change over time. The size of the government (size of the elected municipal officials) ranges from 3 to 10 and the majority of the election terms are three or four years. The Data Book also has information on registered voters, total votes, and election results by municipality and by party for President, Governor, Senator, Congress, State Senator, and General Assembly. Using these results I am able to account for voter turnout which varies by election year and is calculated from general elections in each year. Other factors about the municipality including estimated population, poverty indicators, and taxable property are also included in the Rutgers databook and vary by municipality annually.

I supplement this data with data from FollowTheMoney.org. The data from FollowTheMoney.org contains campaign contributions at the district level to state legislators. The mapping from municipalities to district is not 1 to 1, but it is smaller than county level. There are 14 municipalities per district on average. The campaign contributions are denoted by industry type. The empirical section focuses on donations categorized by FollowTheMoney.org as from the Real Estate or Construction Services Industries. The donations at the district level are then mapped to municipalities. I assume that donations to the state legislators can be used as a proxy for donations to mayoral or council campaigns. Given that state legislators are from the same region, and the interconnection of local governments this is a reasonable assumption.

2.4.3 Descriptive Statistics

I present descriptive statistics of the relevant variables in my data in Table 3.1. This table relies on 14 years of data from 2002-2015 across 125 communities along the Jersey Shore. The 125 municipalities are contained in 4 separate counties. Participation in CRS on average is very low, however there are municipalities reaching higher levels of CRS over time. As Figure 2.1 shows, average total points increased over time, with a sharp increase after 2012. The highest class that has been reached during this time period in New Jersey is a Class 4. As noted previously CRS

[22] Source: New Jersey Data Book. Rutgers Center for Government Services, New Brunswick, NJ. njdatabook.rutgers.edu

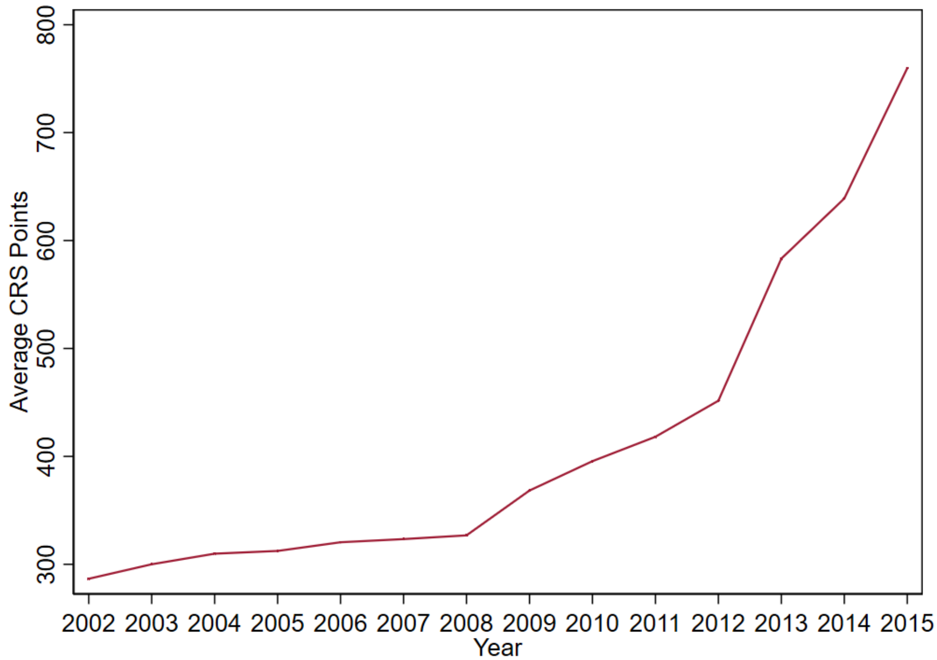
has ten levels, where class ten designates non-participation and is the lowest level. 58% of the municipalities have mayor-council governments where the chief executive is elected. Government size varies from 3 members to 10. Government size is correlated with type of chief executive, but there is heterogeneity in size within both types. In the empirical section an indicator for large government is used, defined as 8 members or more. Term length varies from 2 to 4 years, and the majority of the municipalities have 3 year terms.

The percentage of homes at high risk measures the percent of homes within a municipality that are designated in the 1 in 100 year flood zones. The average municipality has 30% of their homes in high risk flood zones. The proportion of non-resident homeowners in a municipality varies significantly, with an average of 40% non-residents. The municipalities in this region are majority republicans, but there are some municipalities with majority democrats. There is also significant variation in other characteristics of the municipality: population, property values, and wealth across municipalities. Campaign contributions from the two different industries of interest vary similarly.

Table 2.1: Descriptive Statistics

Variable	Mean	SD	Min	Max
CRS Points	413.94	730.44	0.00	3310.00
CRS Participation	0.28	0.45	0.00	1.00
CRS Class	9.28	1.31	4.00	10.00
Top CRS Levels	0.13	0.34	0.00	1.00
Mayor Council	0.58	0.49	0.00	1.00
Government Size	5.90	1.66	3.00	10.00
Term Length	3.28	0.47	2.00	4.00
Voter Turnout (%)	50.41	15.47	4.18	94.09
Homes at High Risk (%)	29.08	34.82	0.00	99.56
Non-Residents (%)	39.90	24.42	5.32	92.55
Democrats (%)	20.33	8.17	5.19	61.50
Log Population	8.65	1.34	5.23	11.51
Log Tax PC Property Values	12.22	1.28	4.14	17.27
Snap Beneficiaries (%)	5.07	6.56	0.00	45.63
Log Construction Services Contr.	9.41	1.19	5.99	11.31
Log Real Estate Contr.	9.91	0.94	7.13	11.64

Figure 2.1: CRS Participation Overtime



2.5 Empirical Results

In this section I utilize the data from New Jersey to test several implications of my model and extensions. I start by testing many of the predictions of my model utilizing my entire dataset. I then utilize Hurricane Sandy as a shock to people's beliefs and test if participation in CRS increases after beliefs are updated.[23] Finally, I consider how participation changes across government types before and after Hurricane Sandy. This allows me to test how governments behaved before and after a large local flood shock. By comparing the pre and post periods, I can better test the implication of my model that high accountability governments will invest in flood protection prior to the shock.

2.5.1 Initial Test of Model and Extensions

Using the initial model and extensions I examined how changes in flood risk, wealth, housing values, population, homeowner's relative weight for amenities over the composite good, government structure, and lobbying will change the optimal level of flood protection p. I start by using a linear

[23]Beliefs about flood risk may have been changing due to CRS participation or due to non-local hurricane shocks like Hurricane Katrina, but not with the same significant jump as after Hurricane Sandy.

model to test these implications. Consider the equation:

$$CRS_{tm} = \beta_0 + \beta_1 * H_{tm} + \beta_2 * G_{tm} + \beta_3 * X_{tm} + v_{ct} + \epsilon_{tb} \tag{2.20}$$

Where CRS is an indicator for level of CRS participation. Specifically, I utilize the total CRS points earned by a municipality in a year as the dependent variable in one specification and the CRS class level attained by a municipality in a given year as the dependent variable in another specification. H is vector of information on the homeowners including the proportion of second homeowners, G is a vector of information on the type of government, X is a vector of characteristics of each municipality m in year t. v_{ct} is defined as county-year fixed effects.[24] County-year fixed effects are included to control for other time-varying regional variation.

[24]Note that municipality fixed effects are not included as some of the characteristics of municipalities are not time varying.

Table 2.2: CRS Participation (Continuous Measures)

VARIABLES	(1) CRS Points	(2) CRS Class
Mayor-Council Indicator = 1	200.0***	0.353***
	(33.96)	(0.0619)
Percent Second Homeowners	8.810***	0.0158***
	(0.795)	(0.00145)
Log(Real Estate Contr.)	-36.63**	-0.0697**
	(18.15)	(0.0331)
Log(Construction Services Contr.)	66.34***	0.119***
	(16.46)	(0.0305)
Percentage Democrat Voters	-0.771	-0.00281
	(1.616)	(0.00293)
Percent Voter Turnout	2.852	0.00534
	(1.993)	(0.00359)
Term Length	35.01	0.0723
	(33.12)	(0.0615)
Indicator for Large Government = 1	73.32	0.102
	(47.05)	(0.0883)
Log(Est. Population)	92.59***	0.165***
	(11.81)	(0.0219)
Log(Per capita Tax from Property Value)	122.8***	0.219***
	(18.17)	(0.0335)
Percent on SNAP	-23.54***	-0.0437***
	(2.456)	(0.00440)
Indicator for Risk = 1	661.7***	1.150***
	(41.79)	(0.0752)
Constant	-3,001***	-15.32***
	(340.2)	(0.620)
Observations	1,598	1,598
R-squared	0.546	0.532

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

I now consider the implications of the model and whether they are consistent with the results from the data. First, consider whether increased risk increases CRS participation. The indicator for risk measures whether the number of highest risk homes, homes designated in zones V or A, is above average relative to all other municipalities on the New Jersey shore. As expected a community that is high risk is more likely to participate in CRS and participate at higher levels. Holding all else equal, going from a low risk municipality to a high risk municipality increases participation in CRS by 661.7 points or 1.15 classes. The appendix includes regressions with a continuous measure of risk, the percentage of homes in high risk zones, and the results are consistent.

The conclusions about wealth are also confirmed using a variable that measures the percentage of the population on SNAP benefits. An increase in the percentage of people using SNAP is associated with a slight decrease in total CRS points. This is consistent with the model which predicts an increase in wealth increases participation or a decrease in wealth (poorer municipalities) decreases participation.

Similarly, the conclusion that an increase in housing values will increase participation is confirmed by the variable that measures per capita taxable property values. Per capita taxable property values increase the likelihood of initial participation in CRS and high levels of participation. I take the log value of the per capita property value to transform the variable and reduce influence from outlier municipalities. A 1% increase in per capita property tax value yields an increase of 122.8 total points. Using the per capita measure also allows me to separately identify the effect of population on participation. Population has the expected positive relationship with CRS participation as well.

Now consider the θ parameter discussed in the Cobb-Douglas extension. Representative agents that are second homeowners may have a higher θ relative to primary homeowners. Percentage of non-residents (or second homeowners) is positively and significantly related with participation. A 25% increase in non-resident population (about a 1 standard deviation change) is associated with approximately a 220 point increase in CRS points.

Recall the accountability signal discussed in section 2.3.6; this testable extension examined how accountability might affect participation. First, I argue that elected chief executives will have a higher signal of accountability and thus will preemptively invest more. I use an indicator for mayor-council governments to test if a mayor-council government is more likely to have higher CRS participation and find that if a government is mayor-council, the total points are on average 200 points higher and the class level increases on average by a little over a third. This result shows that the accountability of the government does matter for flood protection policy. This finding is a significant and interesting result for two reasons. First it contributes to the open question of what type of government structure offers more public goods. And second, it might speak to why CRS participation has been so low. CRS may require actions that can take several years to implement. A chief executive who is accountable to the people's wishes and working to get reelected is more likely to push for CRS if it aligns with what the voters want. However, with infrequent flood shocks these executives will not reach the state where they are held fully accountable and so the size of the signal may be low even for mayor-council governments. See Fox and Van Weelden (2015) for a discussion of accountability and rare states. To further explore the accountability measure, I consider voter turnout as one might expect voter turnout increases accountability of the government. Table 2.2 shows that voter turnout is positively related with participation, but not statistically significant.

Possible alternative arguments to why mayor-council towns are more likely to participate in CRS are that term length or government size matter. These arguments are important as government structure is correlated with term length and size. A longer term length might make it easier for a chief executive to take on these multi-year projects and therefore lead to higher investment in CRS. The results do not show a significant relationship between terms length and CRS participation. However, there is very little variation in term length in New Jersey. A larger government might make it easier for the government to manage investment in hazard mitigation or it might make it harder because too many administrative figures will not agree on paths forward. The findings in the literature on government size are mixed. Coate and Knight (2011) find that government spending increases with size. MacDonald (2008) shows that there is no significant relationship between city council size and expenditures. An indicator for large governments is included in the controls to test if this factor is driving the result instead of or in addition to mayor-council governments. In the main specification the coefficient on the government size indicator is insignificant. In the appendix I include indicators for each government size with the smallest size dropped. Table B2 shows that there may be a nonlinear relationship between government size and participation. In Table B2 the coefficients on the mayor-council indicator do not change significantly from the main specification.

I also consider the special interest group role in the government decision to invest in flood hazard mitigation. For this application, the most relevant special interest groups are the real estate and construction services industry because of the relationship between flood risk, flood hazard mitigation, and housing markets. I utilize data on campaign contributions to state legislators at the district level and find that a 1% increase in district Real Estate contributions decreases the associated municipality's participation in CRS by 36.63 points. Conversely, contributions from construction services increases participation in CRS by almost twice as much. This positive relationship may be due to the fact that new regulations can increase business for construction services. For example older homes are grandfathered in and are allowed to have base floor elevations below the federally required level in flood zones. However, if a homeowner wants to undertake renovations and the renovations were large enough, the homeowner will also have to elevate their base floor potentially increasing work for construction services. [25] Comparing, the coefficients on the

[25] I include a Table in the appendix that looks at individual activities that may be most relevant to each lobbying group to explore this mechanism further. The first two activities I look at are: 1.) 340 Hazard Disclosure, and 2.) 430 Higher Regulatory Standards. I expect the real estate industry contributions to have a negative relationship with the first and an insignificant relationship with the second. Conversely, I expect the construction contributions to have a positive relationship with 430 points, but the relationship with 340 points could be positive or negative. The results in the table are consistent with my expectations. One might expect that certain activities like 540 Drainage System Maintenance to have no relationship with real estate contributions, and that this could serve as a further test. However, reaching higher or costlier activities of CRS often is accompanied by preliminary steps that a real estate contribution may lobby against. This connection across CRS activities makes it difficult to separate out the relationship between lobbying and specific activities, thus I do not place significant emphasis on the results in this table. I include the results that use activity 540 as the dependent variable in the Table as well.

lobbying variables with the accountability variables demonstrates that accountability may be more important for optimizing hazard mitigation.

As a robustness test, I run a probit regression that tests the relationship between the same independent and control variables discussed above and indicator variables that measure any level and top levels of CRS participation. I present the marginal effects of running such a probit in Table 2.3 below. The results of these regressions are consistent with the discussion above and shown in Table 2.2. In the appendix, I include additional robustness tests using tobit and linear probability models with these new dependent variables. These robustness tests are presented in Tables B4 and B5 and they are consistent with the findings of my main specification.

Table 2.3: Probability of CRS Participation (Binary Measures): Marginal Effects

	(1)	(2)
VARIABLES	CRS	Top CRS Levels
Mayor-Council Indicator = 1	0.0450**	0.0500***
	(0.0195)	(0.0183)
Percent Second Homeowners	0.00499***	0.00411***
	(0.000506)	(0.000488)
Log(Real Estate Contr.)	-0.00294	-0.0189
	(0.0157)	(0.0149)
Log(Construction Services Contr.)	0.0563***	0.0317***
	(0.0129)	(0.0122)
Percentage Democrat Voters	0.00356***	-0.000783
	(0.00126)	(0.00124)
Percent Voter Turnout	0.000597	-0.000211
	(0.00107)	(0.00102)
Term Length	-0.0139	0.00603
	(0.0202)	(0.0183)
Indicator for Large Government = 1	0.109***	0.106***
	(0.0399)	(0.0389)
Log(Est. Population)	0.0550***	0.0462***
	(0.00814)	(0.00760)
Log(Per capita Tax from Property Value)	0.0534***	0.0285***
	(0.00902)	(0.00835)
Percent on SNAP	-0.0125***	-0.00988***
	(0.00158)	(0.00173)
Indicator for Risk = 1	0.436***	0.179***
	(0.0313)	(0.0254)
Observations	1,598	1,598

Notes: Dependent variable is defined as an indicator for participation in CRS in column 1 and as an indicator for participation at class 7 or higher in column 2. Includes County-Year fixed effects. Standard Errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).

Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

In column 1 the dependent variable is an indicator for community participation in CRS, whereas in column 2 the dependent variable is an indicator for communities in the top ten percent of CRS participation on the Jersey Shore from 2002-2015. Here the top ten percent of participation is reached if a community has reached level 7 or higher. By separating any level of participation from top levels of participation, this paper can test if the relationships between municipality characteristics and participation change as a municipality becomes more invested. This is important because if certain factors only effect initial investment levels, but not higher investment levels, then policies can target increasing initial participation. Table 2.3 demonstrates that the relationship does change for some factors. For example the positive relationship between risk and participation attenuates from a 43.6% increase in participation due to being high risk to an 17.9% increase at the top levels of participation. Similarly, the positive effect of construction services contributions and the positive effect of property values on CRS participation decrease at higher levels of CRS. Further, some variable are only significant for initial levels or for higher levels of participation and other variables, have consistent effects across both levels.

Note that with the binary measures of CRS participation voter turnout is no longer significant; however, percent of democrat voters is positive and significant for participation in CRS. Percent of democrats is included as democrats are typically more concerned about climate change and thus may value hazard mitigation or may believe they face higher levels of risk due to sea level rise. Given that this region is more heavily republican it is not surprising that these results are small and sometimes insignificant. Further, the coefficient on the Government Size indicator is also positive and now significant at the 5% level in both specifications.

2.5.2 Tests of the Role of Information

One of the extensions of my model considers the role of information in investment in flood hazard mitigation. Specifically, it relaxes the assumption that the representative homeowner can perfectly predict flood risk. The extension shows that if agents have values $\hat{\pi}$ less than the true value of π the local government will underinvest in flood hazard mitigation. Prior literature has shown that underestimating flood risk and heterogeneous beliefs about flood risk are an issue. See Bakkensen and Barrage (2017)

Hurricane Sandy directly hit the New Jersey Shore in October 2012. Residents and governments alike learned firsthand how costly flood damages can be and how prepared the municipality was for flood risk. Using Hurricane Sandy as a shock that provides information both on how at risk for flooding the municipality is and how costly damages can be, I test whether participation increases after the shock.[26] Gibson and Mullins (2020) use a differences in differences hedonic

[26]Table 2.6 above already provides some evidence that the relationship between CRS participation and Hurricane Sandy is positive.

study to demonstrate that Hurricane Sandy presented new information about flood risk to homebuyers in this region, thus Hurricane Sandy can serve as an exogenous shock of information. I start by considering the relationship between Sandy and participation in CRS consistent with my main specification. In my initial model, I cannot separately identify the role of information about risk and information about costs as they occur simultaneously. Other confounders are an issue here as well. For example the Biggert-Waters Flood Insurance Reform Act was passed in July of 2012, right before Sandy, and would have required increases in insurance rates by 2014. The insurance increases were delayed by another act passed in 2014. I cannot separate out the effect of the Biggert-Waters Flood Insurance Reform Act on participation from the effect of Sandy. However, Gibson and Mullins (2020) also examine potential confounders like the Biggert-Waters Flood Insurance Reform Act and still finds a significant effect from Hurricane Sandy.

Consider the equation:

$$CRS_{tm} = \alpha_0 + \alpha_1 * Post + \alpha_2 * H_{tm} + \alpha_3 * G_{tm} + \alpha_4 * X_{tm} + v_{ct} + \mu_{tb} \tag{2.21}$$

Where CRS, H, G, X, and v_{ct} are defined as in Equation 2.20. Post is a new variable that indicates if the year is before or after Hurricane Sandy. As Hurricane Sandy occurred in 2012, Post is 1 for years 2013 through 2015, and 0 otherwise.

Table 2.4: CRS Participation - Information Treatment

	(1)	(2)
VARIABLES	CRS Points	CRS Class
Mayor-Council Indicator = 1	200.0***	0.353***
	(33.96)	(0.0619)
Post Sandy	638.0***	1.189***
	(177.4)	(0.327)
Percent Second Homeowners	8.810***	0.0158***
	(0.795)	(0.00145)
Log(Real Estate Contr.)	-36.63**	-0.0697**
	(18.15)	(0.0331)
Log(Construction Services Contr.)	66.34***	0.119***
	(16.46)	(0.0305)
Percentage Democrat Voters	-0.771	-0.00281
	(1.616)	(0.00293)
Percent Voter Turnout	2.852	0.00534
	(1.993)	(0.00359)
Term Length	35.01	0.0723
	(33.12)	(0.0615)
Indicator for Large Government = 1	73.32	0.102
	(47.05)	(0.0883)
Log(Est. Population)	92.59***	0.165***
	(11.81)	(0.0219)
Log(Per capita Tax from Property Value)	122.8***	0.219***
	(18.17)	(0.0335)
Percent on SNAP	-23.54***	-0.0437***
	(2.456)	(0.00440)
Indicator for Risk = 1	661.7***	1.150***
	(41.79)	(0.0752)
Constant	-3,001***	-15.32***
	(340.2)	(0.620)
Observations	1,598	1,598
R-squared	0.546	0.532

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table 2.4 shows that post significantly and positively increases participation in CRS. The standard deviation of Total CRS points is 399.7 over the entire dataset and the years following Hurricane Sandy are associated with a 638 point increase in CRS points. Similarly, after Hurricane Sandy CRS Class increased by approximately 1 on average. This is a large jump in participation relative to prior years.

One can also see this by considering the probability a municipality increases their participation in a given year. Let INC_{crs} be defined as an indicator for whether or not the municipality increases participation. Let H, G, X, and v_{ct} be defined as in Equation 2.20. Let 2013 be defined as an indicator for if the year is 2013 or not. By focusing on whether or not participation increases right after Hurricane Sandy, I can isolate how immediate the response is to the shock.

$$INC_{CRS_{tm}} = \delta_0 + \delta_1 * 2013 + \delta_2 * H_{tm} + \delta_3 * G_{tm} + \delta_4 * X_{tm} + v_c + \delta_{tb} \tag{2.22}$$

In the first column of Table 2.5 the dependent variable is an indicator whether the municipality increased their total points after Hurricane Sandy and in the second column the dependent variable is an indicator whether the municipality increased their CRS class after Hurricane Sandy.

Table 2.5: Probability of Increased CRS Participation (Binary Measures) after Hurricane Sandy (Marginal Effects)

	(1)	(2)
VARIABLES	Increase Total Points	Increase CRS Class
Year = 2013 = 1	0.111***	0.109***
	(0.0315)	(0.0305)
Mayor-Council Indicator = 1	-0.00370	-0.00274
	(0.0150)	(0.0126)
Percent Second Homeowners	0.000935**	0.000561
	(0.000417)	(0.000355)
Log(Real Estate Contr.)	-0.00486	-0.00327
	(0.00845)	(0.00718)
Log(Construction Services Contr.)	0.0211***	0.0137**
	(0.00703)	(0.00611)
Percentage Democrat Voters	0.00111	0.000827
	(0.000877)	(0.000752)
Percent Voter Turnout	-0.00123***	-0.00117***
	(0.000441)	(0.000396)
Term Length	-0.0138	-0.0123
	(0.0149)	(0.0126)
Indicator for Large Government = 1	0.0350	0.00850
	(0.0304)	(0.0223)
Log(Est. Population)	0.0184***	0.0146***
	(0.00646)	(0.00555)
Log(Per capita Tax from Property Value)	0.0256***	0.0159**
	(0.00746)	(0.00636)
Percent on SNAP	-0.00359***	-0.00284**
	(0.00126)	(0.00111)
Indicator for Risk = 1	0.0727***	0.0497***
	(0.0189)	(0.0164)
Observations	1,598	1,598

Notes: Dependent variable is defined as an indicator for an increase in CRS points in column 1 and as an indicator for an increase in CRS class in column 2. Includes County fixed effects. Standard Errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS data from FEMA

For both specifications, I find a significant positive relationship between increased participation and the year immediately following Hurricane Sandy. Table 2.5 shows that after Hurricane Sandy, municipalities were 11.1% more likely to increase their total CRS points and 10% more likely to increase their CRS class. On average, municipalities increased their total points by 6.1% and their class level by 3.9% annually. Thus, this is a large increase in points and class (almost double or triple respectively) relative to the positive linear time trend.

Finally, one might be concerned that using Hurricane Sandy as a shock to all municipalities in the region who experienced varying levels of intensity, might not be properly accounting for the role of updated information. To correct for this problem I uses a differences in differences analysis that looks at what happens to participation before and after Hurricane Sandy in municipalities that were flooded by Hurricane Sandy relative to those that were not. There are two reasons why the response might be different between these two groups in the same region. The first reason is that experiencing actual and significant flood damages provides a different signal than being near flooding. See McCoy and Zhao (2018) and Gibson and Mullins (2020). The second reason is that federal aid for disaster relief may decrease adaptation, but federal subsidies for adaptation may increase mitigation. See Fried (2019). After, Hurricane Sandy additional FEMA led programs for hazard mitigation were introduced. Thus, one might expect that hazard mitigation increase more for those that were directly flooded by Sandy. The differences in differences specification that I use is: Consider the equation:

$$CRS_{tm} = \alpha_0 + \alpha_1 * Post + \alpha_2 * Flood + \alpha_3 * PostXFlood + \alpha_4 * H_{tm} + \alpha_5 * G_{tm} + \alpha_6 * X_{tm} + v_{ct} + \mu_{tb} \tag{2.23}$$

Where CRS, H, G, X, Post, and v_{ct} are defined as in Equation 2.23. Flood is a new variable that indicates if Hurricane Sandy flooded the municipality and Post X Flood is the interaction between Flood and Post. The results are included in the appendix and presented in Table B6. The results demonstrate that overall municipalities increase participation in CRS after Hurricane Sandy as Post Sandy still has a positive and significant coefficient. However, they also should that municipalities that were flooded invested at higher levels prior to Sandy. Potentially due to the fact that Sandy's damages were concentrated in coastal access municipalities with higher wealth, high risk, and higher proportion of non-residents. In addition, after Hurricane Sandy these flooded regions saw even more of an increase in participation than those who were not flooded.

2.5.3 Tests of Government Accountability Using Hurricane Sandy

The model conjectures that a higher accountability signal, whether homeowners will hold the government accountable for damages in reelection, yields an increase in CRS participation. I have shown this may be true using an indicator for form of government and by examining the effect of voter turnout on CRS participation. A further test is to look at what happens after a storm shock. As chief electives, i.e. mayor-council form, are incentivized by the accountability to invest in flood protection prior to the shock, it is likely that they will be awarded for this and do not need to invest more than manager council governments after the shock. To test this, I use Hurricane Sandy. First, I utilize the continuous measures of CRS participation and run the OLS regression describe in Equation 2.22 with an interaction between Post Sandy and Mayor Council indicators. If an accountability signal is driving the results I would expect the Mayor Council indicator to be significant prior to the storm i.e. they do not want to be blamed when flooding occurs and the coefficient on the interaction should be negative or insignificant.[27] As information about risk will increase investment in flood protection, I would still expect the coefficient on Post Sandy to be positive.

[27] Vlaicu and Whalley (2016) similarly find that after an information shock manager governments will pander to voters and reduce the investment differential across government type.

Table 2.6: CRS Participation and Government Accountability: Including Post Sandy Interaction

	(1)	(2)
VARIABLES	CRS Points	CRS Class
Mayor-Council Indicator = 1	229.4***	0.408***
	(32.46)	(0.0585)
Post Sandy	721.7***	1.345***
	(189.9)	(0.351)
Post Sandy x Mayor Council	-126.7	-0.236
	(83.52)	(0.156)
Percent Second Homeowners	8.829***	0.0158***
	(0.796)	(0.00145)
Log(Real Estate Contr.)	-37.28**	-0.0709**
	(18.21)	(0.0332)
Log(Construction Services Contr.)	67.31***	0.121***
	(16.47)	(0.0306)
Percentage Democrat Voters	-0.841	-0.00294
	(1.616)	(0.00293)
Percent Voter Turnout	2.887	0.00541
	(1.998)	(0.00360)
Term Length	34.90	0.0721
	(33.10)	(0.0614)
Indicator for Large Government = 1	74.51	0.104
	(47.00)	(0.0882)
Log(Est. Population)	92.54***	0.165***
	(11.84)	(0.0219)
Log(Per capita Tax from Property Value)	123.5***	0.220***
	(18.17)	(0.0335)
Percent on SNAP	-23.38***	-0.0434***
	(2.460)	(0.00440)
Indicator for Risk = 1	660.4***	1.148***
	(41.82)	(0.0753)
Constant	-3,028***	-15.37***
	(339.8)	(0.620)
Observations	1,598	1,598
R-squared	0.547	0.534

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table 2.6 shows that the interaction between Post and Mayor Council is negative and insignificant. As expected the coefficients on Mayor-Council and Post are both positive and significant. I run the same regressions, but with the binary dependent variables defined as in Table 2.3 and find consistent results. These results are included in the appendix.

I also extend the specifications in Table 2.6 to allow for Post to be interacted with all my variables of interest. These results are presented in Table 2.7. Interestingly, Post x Perc Voter Turnout has a positive and significant coefficient. The positive coefficient on the interaction between post and voter turnout variables demonstrates that after the information shock, homeowners may use voting to hold all government structures accountable or that due to the shock flood risk is now a salient voting issue. Further, the coefficient on Post X Indicator For Risk is significant at the ten percent level indicating that those who were thought to be high risk prior to the shock from Hurricane Sandy do update beliefs about their risk after the shock. Note that the coefficient on Post is actually negative and significant now. The interactions on Post and other municipality characteristics (Property Value, Population, SNAP, Risk) indicate that wealthier, larger, higher home value, and higher risk towns may be driving the response after Sandy.

Table 2.7: CRS Participation - Government Accountability

VARIABLES	(1) CRS Points	(2) CRS Class
Mayor-Council Indicator = 1	219.7***	0.383***
	(32.62)	(0.0584)
Post Sandy	-3,333***	-5.551***
	(921.3)	(1.738)
Post Sandy x Mayor Council	-112.2	-0.179
	(102.0)	(0.190)
Percent Second Homeowners	7.958***	0.0141***
	(0.777)	(0.00141)
Log(Real Estate Contr.)	-45.34**	-0.0848**
	(18.75)	(0.0340)
Log(Construction Services Contr.)	54.94***	0.103***
	(17.24)	(0.0317)
Percentage Democrat Voters	-0.922	-0.00248
	(1.548)	(0.00278)
Percent Voter Turnout	0.888	0.00234
	(1.978)	(0.00344)
Term Length	40.53	0.0878
	(30.57)	(0.0567)
Indicator for Large Government = 1	42.23	0.0664
	(46.53)	(0.0905)
Log(Est. Population)	67.64***	0.121***
	(11.30)	(0.0205)
Log(Per capita Tax from Property Value)	98.90***	0.175***
	(17.68)	(0.0322)
Percent on SNAP	-21.78***	-0.0394***
	(2.554)	(0.00444)
Indicator for Risk = 1	600.4***	1.033***
	(41.13)	(0.0730)
Post x Log(RE Contr.)	33.57	0.0481
	(64.54)	(0.120)
Post x Log(CS Contr.)	43.46	0.0652
	(43.39)	(0.0807)
Post x Perc Second Homeowners	3.191	0.00627
	(2.378)	(0.00435)
Post x Perc Democrats	1.105	-0.00161
	(5.685)	(0.0106)
Post x Term Length	-54.35	-0.114
	(104.2)	(0.193)
Post x Perc Voter Turnout	12.34**	0.0202*
	(6.178)	(0.0114)
Post x Large Govt	150.5	0.179
	(138.6)	(0.253)
Post x Log(Est. Pop)	140.9***	0.250***
	(37.12)	(0.0702)
Post x Log(PC Tax from Property Value)	133.6**	0.241**
	(52.72)	(0.101)
Post x Perc on SNAP	-1.997	-0.00557
	(5.913)	(0.0109)
Post x Risk	244.4*	0.468*
	(130.3)	(0.240)
Constant	-2,169***	-13.93***
	(335.8)	(0.606)
Observations	1,598	1,598
R-squared	0.566	0.553

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column

To further test this extension of the model, I run the same probit regression as in Table 2.3 for separate subsets of the data. I separate the regression into two sets: the first uses the years before Sandy (2002-2011) and the second uses the years after Sandy (2013-2015).[28] These results are presented in the appendix. As Table B8 shows the coefficient on mayor-council in relation to any participation in CRS is only significant before Sandy. Consistent with accountability signals of all governments potentially changing after a shock, percent voter turnout is only significant after Hurricane Sandy. Interestingly, the coefficients on term length are now significant at the 5% level for participation in the top CRS levels before Sandy and participation in all levels after Sandy. Prior to Hurricane Sandy, longer term lengths increased participation at the top levels, but after Sandy the opposite relationship holds. One possible explanation is that after Hurricane Sandy, governments facing shorter term limits try to quickly increase participation before their next election.

2.6 Conclusion

This research examines a local government's decision to invest in hazard mitigation and provides three main contributions: 1.) a model of the local government's decision to provide hazard mitigation which can be used in many settings and provides theoretical insights into why certain municipalities provide more hazard mitigation than others, 2.) an empirical application of the model, which demonstrates that the hypotheses from the model are consistent with the actual decisions to provide flood hazard mitigation, and 3.) evidence that government's may not be optimally investing in hazard mitigation due to poor information, accountability, or special interest groups.

This paper starts by building a theoretical model of the government's optimization problem and then extends the model in several ways. Both the model and its extensions yield several hypothesis about what factors will affect the level of the government's investment in hazard mitigation. Understanding why governments choose to participate in hazard mitigation is helpful in understanding how to motivate a government to invest in hazard mitigation. Local jurisdictions are often in the best position to respond to flooding or other hazard issues due to the local nature of these problems. Thus, it is critically important for both state and federal policymakers to understand what increases investment in this type of public good. If wealthier governments or those with second homeowners are investing more in hazard mitigation, federal and state governments may be concerned that high-risk poor regions are disadvantaged.

As my theoretical model yields several testable implications, I empirically test them using participation in flood hazard mitigation. I combine several datasets on CRS participation, municipality characteristics, and government structure for my analyses. Using a variety of specifications, I am

[28]Interaction terms cannot be interpreted with probit regressions, thus separating the data into subgroup is a better method.

able to show that wealth, risk, housing values, population, homeowner's preferences over amenities, and government structure are significantly and positively associated with the probability of participating in CRS. I also find that an increase in campaign contributions from real estate groups is associated with a decrease in CRS participation. Conversely, contributions from construction services is associated with an increase in participation. I also use Hurricane Sandy as a flood shock to test how a change in information can affect participation. Participation in CRS spikes after Hurricane Sandy, demonstrating that this information shock drove communities to increase their flood protection. These empirical findings are all consistent with the conclusions from my theoretical model.

One finding that merits further discussion and adds to the ongoing debate on government form and public good provision is that mayor-council governments are more likely to participate in CRS. I argue that what drives this finding is the perceived accountability of the elected chief executive. This argument is further supported by the results that utilize Hurricane Sandy, which show that higher signal governments, i.e. mayor-council, had higher levels of CRS prior to the shock. After the shock there is no discernible difference between the types of governments and participation. The accountability argument is also supported by the finding that voter turnout is associated with an increase in investment in hazard mitigation.

There are two main avenues for future work. The first area of potential research considers the political agency problem further. Future studies can allow for more heterogeneity in the homeowners within the municipality and can also consider how differences in information between the government and residents effect hazard mitigation. This avenue of research could also relax the assumption that there are no spillover effects across municipalities. The second area of research pertains to the empirical application. The literature on CRS and NFIP does not currently estimate the costs of investing in CRS, nor does it consider how the incentive system of CRS may preclude more vulnerable communities from investing in flood hazard mitigation. Both of these are open questions whose answers would benefit policy-makers.

This research contributes to both the theoretical and empirical public goods literature and this work builds on the growing literature that studies the NFIP and CRS. As climate change causes sea levels to rise and brings increasingly destructive storms, present investment in flood protection will be increasingly important for the economies of these municipalities. This paper shows that factors like wealth and housing values are associated with participation. These results indicate that poor and high risk areas might be especially vulnerable to future floods as they may not be able to invest in flood hazard mitigation. This study also demonstrates that the investment in hazard mitigation is inefficient due to lack of information, political accountability, or lobbying influence.

Chapter 3

Flood Hazard Mitigation and the Role of the Government: A Dynamic Model of Local Government Investment in a Public Good

3.1 Introduction

Environmental policy in the United States is frequently shaped by environmental federalism, which creates an interdependency between federal, state, and local governmental policies (Oates (2002), Dijkstra and Fredriksson (2010), Segerson (2020), and Shobe (2020)). In this vein, the Clean Air Act, Clean Water Act, and many other environmental policies in the United States consist of standards that are set by the federal government, but the decision on how to meet those standards is left to the state or local government. Accounting for this interaction between federal and local governments in research can provide important insights into the response of local governments to changes in federal policies. In this paper, I study this interaction in the context of flood hazard mitigation. The decision to invest in flood hazard mitigation is typically made by the local government, whereas the federal government sets the standards and provides guidance and funding.

Flood hazard mitigation is important because of the rising risk of floods and their costly damages. The risk of flooding is increasing due to sea level rise, intensifying frequency of rain, and slowing of hurricanes. In addition, growing population on the coasts increases the potential damages from flooding. By 2050, costs from flood damages in the United States may increase by $23 billion per year Schwartz (2018). Flood hazard mitigation is also cost effective as the savings after damages from floods exceeds the money spent on mitigation (Whitehead and Rose (2009) and Rose et al. (2007)). Despite the cost effectiveness of flood hazard mitigation, there are reasons to be concerned that governments may be under-investing in hazard mitigation. Policy makers may fail to prepare for sufficiently rare events (Fox and Van Weelden (2015)), and voters may reward politicians for disaster aid, but not for mitigation (Healy and Malhotra (2009)). In addition, voters may be ill-informed about future flood risk (Bakkensen and Barrage (2017) and Gallagher (2014)). Further, under-investment or over-investment in any public good may be due to spillover effects that are ignored by local governments (Boskin (1973)).

This paper studies the local government's decision to provide flood hazard mitigation and how federal policy affects that decision. Specifically, this research seeks to answer three questions. First, how do homeowners value flood hazard mitigation? Second, what are the perceived costs of flood hazard mitigation? And third, how can federal policy makers incentivize local governments to invest in flood hazard mitigation? To answer these questions I first use a hedonic analysis to estimate the marginal willingness to pay (MWTP) for both flood hazard mitigation and insurance premiums, I then build a dynamic discrete choice model of the local government's decision to invest in flood hazard mitigation to estimate the costs of their investments, and I run counterfactual analyses to understand how alternative federal policy design may incentivize investments in flood hazard mitigation.

My empirical setting considers participation of New Jersey municipalities in the Community Rating System (CRS). CRS is a component of the National Flood Insurance Program (NFIP) that encourages local governments to invest in flood hazard mitigation. CRS is made up of 10 levels; a local government can move up levels by investing in mitigation. The CRS program provides detailed guidelines about the various actions a local government may undertake to count towards their progress. For each new level a municipality reaches, the federal government offers an additional discount on their constituents' insurance premiums. The federal government is able to do this as they set the insurance rates through the NFIP. Thus, a local government will invest in CRS because its community benefits from flood hazard mitigation and/or because their community benefits from the lower insurance rates.

I utilize datasets from several sources in my empirical estimation. Insurance premiums, CRS participation, and flood risk information come from FEMA. Housing prices, housing characteristics, and transaction details are provided by a national database of sales and assessment data. Municipality and government characteristics are sourced from the Rutgers New Jersey Databook. Finally, tax rate data comes from the New Jersey Treasury.

After combining these datasets, I employ a hedonic analysis to estimate the MWTP for flood insurance discounts and CRS participation. I also estimate spillover effects from other municipalities in a given county participating in CRS. I exploit the variation in housing prices sales, CRS participation, and insurance premiums across municipalities and across time in my estimation. Importantly, insurance premiums are changing over time because of changes to federal rates and not only because of CRS discounts. I use repeat sales to control for house and municipality static unobservables. To correct for time-varying unobservables, I follow the methodology from Bajari et al. (2012).

The estimates of MWTP for hazard mitigation and insurance discounts enter directly into my dynamic discrete choice model as inputs to the local government's objective function. The local government's objective is to maximize the benefits net the costs of the investment. In the estimation I measure the benefits as the change in housing values due to the investment. This is consistent with the local government providing optimal levels of public goods by maximizing property values (Brueckner (1982), Brueckner (1983), Scotchmer (1994), Glaeser (1996)). This is also consistent with a government motivated by budget as local governments are dependent on tax revenues and the majority of tax revenue in New Jersey comes from property taxes. Costs of the investment are then estimated in the model based on these benefits and the actual decisions of the local governments. Estimation follows from Ma (2019) and Arcidiacono and Miller (2011).

With the estimated model, I run counterfactual analyses to consider how changes to federal policy effect investments in CRS. The first counterfactual increases the proportion of homes at high risk of flooding. This counterfactual is similar to the federal government updating their flood risk maps with additional high risk zones. The second counterfactual analyzes what happens if the federal government increases insurance premiums. The final counterfactual focuses on the incentive design of the program. Prior research has shown that poorer municipalities are less likely to participate in flood hazard mitigation (Landry and Li (2011), Sadiq and Noonan (2015), Landry and Li (2018), and Hopkins (2020a)). Given the estimated low return from insurance discounts when housing values are low, low property value municipalities may not generate enough revenue to invest in CRS. In this counterfactual, I allow for either a cost subsidy or an insurance discount.

This paper provides three central results. First, this research provides the first estimates in the literature of the MWTP for an increase in CRS participation accounting for changes in insurance premiums, which allows me to separate the MWTP for hazard mitigation from the insurance discounts. I estimate the MWTP across all risk levels for a one level increase in CRS to be $3,746 per homeowner and the MWTP across all risk levels for a 1 percent discount on their insurance premium to be $86. The large size of the MWTP for insurance discounts relative to the cost of insurance indicates that premiums are over-capitalized; perhaps due to an additional risk signal from changes in the premium. These results suggest that the insurance discounts are significant drivers of CRS participation. Further, I find that the insurance discounts and CRS participation are most important for high risk homes. Thus, as more homes become high risk due to sea level rise, the incentives to participate in CRS will strengthen.

The second main result is the measurement of positive spillover effects, which indicate that municipalities may be under-investing in hazard mitigation. I estimate the MWTP across all sales for a one level increase in the county wide average CRS participation exclusive of the municipality's own participation to be $\$3,069$. The positive spillover effect is driven by high MWTP from high risk homes. There are two possible reasons for this. First, high risk homes benefit from nearby municipalities investing in flood hazard mitigation. Second, high risk homes seem relatively less risky than other municipalities' high risk homes if the other municipalities are investing in hazard mitigation. Positive spillover effects indicate that there are positive externalities from participation at the local level and that a less decentralized provision of hazard mitigation will lead to a higher level of hazard mitigation that is closer to the optimal. A federal policy could account for these spillover effects to incentivize local governments to act optimally.[1]

The third central result includes the cost estimates from the dynamic discrete choice model and the resulting counterfactual analyses, which provide insights for policymakers. I address two interesting findings here and discuss the others in Sections 2.5 and 2.6. First, the estimates of perceived costs demonstrate that high levels of initial perceived costs prevent municipalities from joining CRS. Second, the counterfactual analysis that considers an increase in insurance premiums demonstrates how federal policies and local government decisions can interact. The federal government is currently planning to overhaul the insurance rates in the NFIP, as the program's rates are currently too low causing the NFIP to be in billions of dollars of debt. The counterfactual analysis finds that an increase in insurance premiums also increases participation in CRS. This leads to a feedback effect of lower revenue than expected for the NFIP.

In addition to these three central results, a contribution of this paper is the combination of reduced form and structural methods, which enables me to estimate the benefits and costs of a local government investment and account for federal policy. This methodology can be used to study the response of local governments to changes in federal incentives or standards for many environmental policies. This is an important contribution to the environmental federalism literature, which considers both the normative and positive implications of the division of environmental policy across the levels of government (Shobe and Burtraw (2012), Segerson (2020), and Shobe (2020)).

This paper proceeds as follows. The remainder of Section 3.1 discusses related literature. Section 3.2 includes the details of the empirical setting, the data, and descriptive statistics. Section 3.3 presents the model. Sections 3.4 and 3.5 contain the estimation and the results. Section 3.6 provides the counterfactual analyses. Section 3.7 discusses the policy implications of this research and concludes.

[1] For example, some states already participate in CRS at the county level, and given these positive spillover effects there are potential gains in requiring this type of participation. However, my research also finds that benefits are higher for riskier areas and heterogeneity affects perceived costs. Thus, this more centralized participation will be optimal when the municipalities within a county are homogeneous.

3.1.1 Related Literature

In addition to the Environmental Federalism literature, this work also relates to several other areas of literature. First, this paper relates to the structural econometrics literature that uses dynamic discrete choice methods. This literature is built upon the work of Rust (1987) and Hotz and Miller (1993). There are now many applications that utilize the empirical methodology of Arcidiacono and Miller (2011). Many of the relevant applications to this work consider homeowner's decisions to locate or the decision to build a new home (Bishop (2012), Ma (2019), and Murphy (2018)). I follow the literature in both my model and estimation, however my model considers a different decision maker: the local government. My application to the local government highlights an area of the literature that can benefit from dynamic discrete choice models.

Second, the methodology and the findings of this research relate to the broader optimal public goods literature. Much of the research in this area builds off the seminal work, Tiebout (1956), which theorizes that people vote with their feet and therefore local governments will provide the optimal public good level. Researchers following Tiebout (1956) often uses an equilibrium sorting model akin to Epple and Sieg (1999) or run empirical tests similar to Banzhaf and Walsh (2008). I take a different approach by focusing on the government's optimization problem through a dynamic discrete choice model. I assume that the benefits of the investment are measured by changes in property values following Brueckner (1982), Brueckner (1983), Scotchmer (1994), and Glaeser (1996). This assumption about the government's objective, the hedonic analyses, and the dynamic discrete choice methods allow me to simplify the estimation into two stages; a benefit of this approach. I further contribute to the empirical evidence in this literature by estimating spillover effects. I find positive spillover effects. Thus, local government optimization may lead to under-investing in hazard mitigation consistent with theory in Williams (1966), Pauly (1970), and Boskin (1973).

Third, this paper builds on the literature on environmental evaluation using hedonic methods. This literature allows for revealed preference valuations of environmental amenities and spans many areas including valuations of: shale gas development Muehlenbachs et al. (2015), hazardous waste Gamper-Rabindran and Timmins (2013), and traffic noise von Graevenitz (2018). The hedonic estimation of marginal willingness to pay for both CRS and insurance premiums allows this work to separate the value of discounts on insurance from CRS. These are new estimates in the environmental evaluation literature. Further, I follow the recommendations of best practices from Kuminoff et al. (2010) and Bishop et al. (2019). Specifically, I run several robustness checks using the methods in Bishop and Murphy (2011), Bajari et al. (2012), and Bishop and Murphy (2019).

Finally, this paper adds to the empirical research on CRS, NFIP, and hazard risk more generally through its estimation of the value of flood hazard mitigation and through the paper's dynamic model. While a wide array of research has studied the value of flood risk (Hallstrom and Smith

(2005), Bin and Landry (2012), Bakkensen and Barrage (2017), Keenan et al. (2018), Bernstein et al. (2019), Eichholtz et al. (2019a), Hopkins and Muller (2019), and Bakkensen and Ma (2020)), the value of flood hazard mitigation has not been as thoroughly considered. Dundas (2017) focuses on the value of mitigation through natural infrastructure only. Fan and Davlasheridze (2016) study CRS activities, but the paper is limited in that it uses data for only one year and measures values of CRS by comparing locations across the entire country. Given the relative local nature of flooding and the various factors that might affect location decisions, this paper builds on their work by focusing on a localized area (where substitution is likely) across time and by controlling for insurance premiums. Prior research has studied why local jurisdictions invest in hazard mitigation (Brody et al. (2009), Landry and Li (2011), Landry and Li (2018), Sadiq and Noonan (2015), Hopkins (2020a)). This paper builds on the prior work by allowing for the government's decision to be dynamic. Dynamics are important because increasing the level of hazard mitigation directly depends on the prior level of mitigation and current flood hazard mitigation affects the future value of homes.

3.2 Empirical Setting

3.2.1 Institutional Background

The National Flood Insurance Act was passed by congress in 1968 and created the NFIP. Congress was motivated by Hurricane Betsy, which devastated the gulf coast in 1965 and cost more than a billion dollars in damage. At the time (and still now) there was very little private flood insurance, so in response the government created NFIP to provide affordable flood insurance policies. Participation in NFIP is designated by community, and therefore a home owner can only purchase flood insurance through the program if the community their home is located in is in the program. Communities can volunteer to participate in the program and must maintain federal flood plain mitigation standards to participate.[2] Once a community joins the NFIP, Flood Insurance Rate Maps (FIRMs) are drawn up to demonstrate the level of flood risk.[3] The region with the highest level of risk is called a "Special Flood Hazard Area"; it is also known as a "100 Year Flood" as there is a 1% annual chance flood hazard. In addition to the FIRMs, each home is also assigned a zone.

[2]These standards include permits for new development in high risk areas, no new development in flood ways, and new or substantially improved construction must be elevated above a base elevation which varies by designation.

[3]Since these maps are not revised every year, property owners or communities may file for a change in the map. These changes to the zones or boundaries are detailed in Letters of Map Revisions (LOMRs). When a FIRM is established or updated varies by community and thus an out of date FIRM may not correctly calculate risk. This temporal variation may be relevant to my analysis.

The zone your home is assigned will affect the price of the premium.[4] One criticism of the rates set by the NFIP is that they are not actuarially correct and that many of the rates are subsidized leaving the federal government and therefore taxpayers on the hook when disaster strikes. Many of these subsidized rates come from discounts offered because homes are ”grandfathered” or from programs like CRS.

The Community Rating System is a voluntary component of the NFIP. CRS was introduced in 1990 and codifed in the 1994 National Flood Insurance Reform Act. To be eligible to participate in the program a community must be in the regular phase of the NFIP. The purpose of the program is to encourage communities to increase floodplain management and to go above the minimum federal standards. The program is made up of 10 class levels that communities attain by getting points from various actions related to floodplain management. There are four categories of actions and these categories are: Public Information, Mapping and Regulation Flood Damage Reduction, and Warning and Response.

Activities are assigned point values and the total point values a community receives helps determine the community's level of CRS participation. Once a community reaches 500 points they move from class 10 to class 9, where class 10 designates no or very low participation. The highest class a community can reach is class 1, which requires 4,500 points. The federal government incentivizes communities to increase participation in the CRS by providing discounts on the flood insurance premiums purchased through the NFIP to their constituents. For each increase in CRS class, each homeowner in the highest risk zones receives a 5% discount off each their insurance premiums. Those in lower risk zones receives 5% or 10% discounts depending on the CRS class.[5] Thus communities at level 4 get a 30% discount for homeowners in the high risk zones.

The region that I study empirically is New Jersey State. New Jersey has consistently been one of the top five states participating in the NFIP. Other states with high levels of participation in NFIP are Florida, Texas, Louisiana, and California. Many of the New Jersey homeowners who own NFIP policies reside either in the counties on the coast adjacent to the Atlantic Ocean or inland near the rivers. There are 21 counties in New Jersey and 565 municipalities. Of these municipalities only one community, Sea Isle City, has reached as high as a class 3 as of 2018.

These municipalities have different amenities and characteristics that are important to understanding the housing market and local government. For example some of these municipalities are on barrier islands which have very high levels of flood risk and high proportions of non-resident homeowners. Further, government form may differ across communities. The municipality government generally falls into two categories: an elected chief executive or not. These differences in

[4] Along the Jersey Shore many of the homes are designated in the Zones A or V. Zone A indicates the home is in the 100-year floodplain and Zone V indicates that the home is in a coastal area and subject to velocity hazard (wave action).

[5] There are some restrictions on which homeowners qualify, but these are limited

municipalities may affect both the benefits of investment in CRS and the costs of the program.

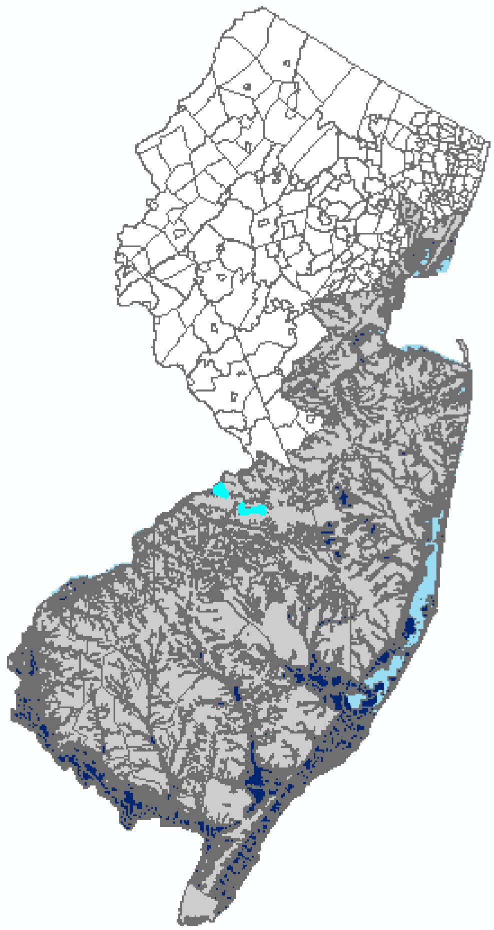
Hurricane Sandy hit the Jersey coast in 2012 and provided a recent shock on just how damaging and costly flooding can be. The storm led to widespread damages across the state due to both storm surges and rains. After Hurricane Sandy, New Jersey residents claimed approximately $ 4 billion in damages to NFIP, which was the highest total across all states in 2013. Hurricane Sandy, is not the only experience the state has had with flooding as other hurricanes and Nor'easter storms have brought significant rain and flooding to the area. However, it was the most significant in recent years. New Jersey is expected to see increases in flooding due to sea level rise on the coast. Additionally, the region is expected to have more frequent intense rain storms that can cause flooding due to climate change.

3.2.2 Data

I utilize datasets from several sources: 1) insurance premiums, CRS participation, and flood risk from FEMA, 2) housing prices, housing characteristics, and transaction details from a national database of sales and assessment data, 3) municipality and government characteristics from the Rutgers New Jersey Databook, and 4) tax rate data from New Jersey Treasury. The data spans 21 years from 1998 to 2018. 1998 is used as the first lag year, and estimation focuses on decisions made in 1999 to 2018.

The data on insurance premiums was made public by FEMA in July of 2019 and contains redacted insurance claim and policy information. The dataset includes information on the premium, the coverage amounts, the flood zone, whether or not it is a primary resident, or built prior to the FIRM was in place at the zip code level. This yields data on the average premium at the risk-resident-municipality-year level. I received data on the CRS participation from 1998 through 2018 through a Freedom of Information Act request to FEMA. The flood hazard mapping data is also from FEMA. Only digital flood maps for 13 of the 21 counties (330 of the 565 municipalities) are available to me and thus my analysis is first limited to just those 13 counties. The flood map includes information on risk at the sub municipality level. The data is a shape file with polynomials categorized by flood zone and I combine these maps with parcel level housing data. Figure 3.1 presents the overlap of the flood maps and the municipalities in New Jersey. The municipalities that are outlined and shaded white do not have available digitized flood maps. The darkest blue areas represent the regions that are most at risk for flooding. The light blue indicates open water. This map shows that the risk is centralized along the Atlantic coast and the inland waterways.

Figure 3.1: New Jersey Flood Maps



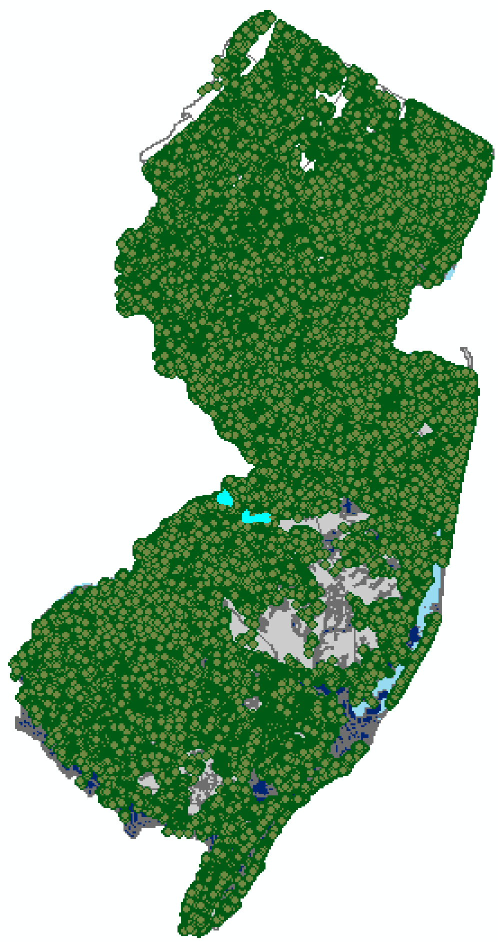
As the counties around New York City face a different set of substitutions and very different public and private good trade-offs, I further limit my model to the counties outside of the immediate New York City region. I drop Hudson, Union, Essex, and Middlesex counties from my data, leaving me with 9 counties and 271 municipalities.

The sales and assessments ZTRAX database provides the parcel level data.[6] This database includes information on the location of the parcel, the sale price, the seller, the buyer, the age of building, the square footage, the assessed value for land, and the assessed value for the building along with other variables. This database also contains latitude and longitude information of each

[6]Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of the Zillow Group.

parcel, which I use to merge in the flood risk data from the FEMA flood maps.[7] Figure 3.2 displays the housing data (denoted by a green point for each parcel) over top Figure 3.1. The housing data thoroughly covers the state except for regions where no houses were sold. For example the large region in the central part of Southern New Jersey with no green markets is where several large state forests reside.

Figure 3.2: New Jersey Housing Data



Characteristics about the municipalities is sourced from the Rutgers New Jersey Databook. The

[7]In some regions the ZTRAX dataset does not have complete longitude or latitude information or provides the longitude and latitude at the zip code centroid. To confirm that this is not an issue with the New Jersey data, I have both cross checked a sample of the longitude and latitude data points and checked that repeat latitude and longitude pairs is not an issue. If zip code centroid latitude longitude pairs were used instead of parcel level, then a concern would be that in a given municipality-year, the same latitude and longitude pair would be repeated several times or for most of the sales. I find that in 95 % of the observations the longitude and latitude pair is repeated at most once in a given municipality year.

Rutgers New Jersey Databook provides extensive information on municipalities in New Jersey. The databook has numerous variables pertaining to the form of government including information on government type, election type, number of members, and election term. Other factors about the municipality including estimated population, poverty indicators, taxable property, and voter turnout are also included in the Rutgers databook. (Rutgers.) I supplement this data with tax rate information at the municipality-year level for the entire time period from the New Jersey Treasury.

Table 3.1 presents descriptive statistics from my compiled dataset. As can be seen from the table the data varies significantly within my variables of interest. Note that CRS is designed such that the highest class is 1 and lowest class is 10. Given that in New Jersey the majority of participation is below a class 5, I have recast the variable such that a 0 is equivalent to class 10 and 5 is equivalent to class 5 and above.

Table 3.1: Descriptive Statistics

Variable	(1) Mean	(2) SD	(3) Min	(4) Max
Average Insurance Premium ($)	770.67	394.20	51.00	5825.00
Total CRS Points	239.50	602.10	0.00	3613.00
CRS Class	0.42	1.06	0.00	5.00
Log Population	8.81	1.21	5.40	11.78
Mayor Council	0.52	0.50	0.00	1.00
Number of Houses	3927.58	4852.75	40.00	38500.00
Out of State Non-Residents (%)	8.64	12.97	0.70	71.67
Tax Rate (%)	2.37	0.85	0.36	8.13
Average Sales Price ($)	266417.84	184179.86	20785.44	1258750.00
Homes at High Risk (%)	16.43	28.06	0.00	100.00

Notes: 5,420 Observations at the municipality-year level from 1999-2018.

It should be noted, that municipalities who participate in CRS and those who do not are different on average in the ways that one might expect: i.e. more risk, more non-residents, higher home values, high insurance premiums.

I also present figures to demonstrate how CRS participation and Insurance Premiums change over time. Figure 3.3 demonstrates that CRS participation is increasing over time and that there is a sharp increase after Hurricane Sandy. Figure 3.4 demonstrates that average premiums are increasing overall, but not every year.

Table 3.2: Descriptive Statistics: Participate in CRS

Variable	(1) Mean	(2) SD	(3) Min	(4) Max
Average Insurance Premium ($)	934.54	403.76	167.00	3372.88
Total CRS Points	940.66	874.40	0.00	3613.00
CRS Class	1.64	1.56	0.00	5.00
Log Population	8.78	1.37	5.40	11.48
Mayor Council	0.55	0.50	0.00	1.00
Number of Houses	5231.20	6166.94	214.00	38500.00
Out of State Non-Residents (%)	19.60	19.65	0.97	71.67
Tax Rate (%)	1.82	0.87	0.36	5.09
Average Sales Price ($)	366886.38	214350.94	38267.21	1258750.00
Homes at High Risk (%)	47.40	37.46	0.00	100.00

Notes: 1,380 Observations at the municipality-year level from 1999-2018. The data is limited to Municipalities who participate in CRS for at least one year.

Figure 3.3: Average CRS Class Participation

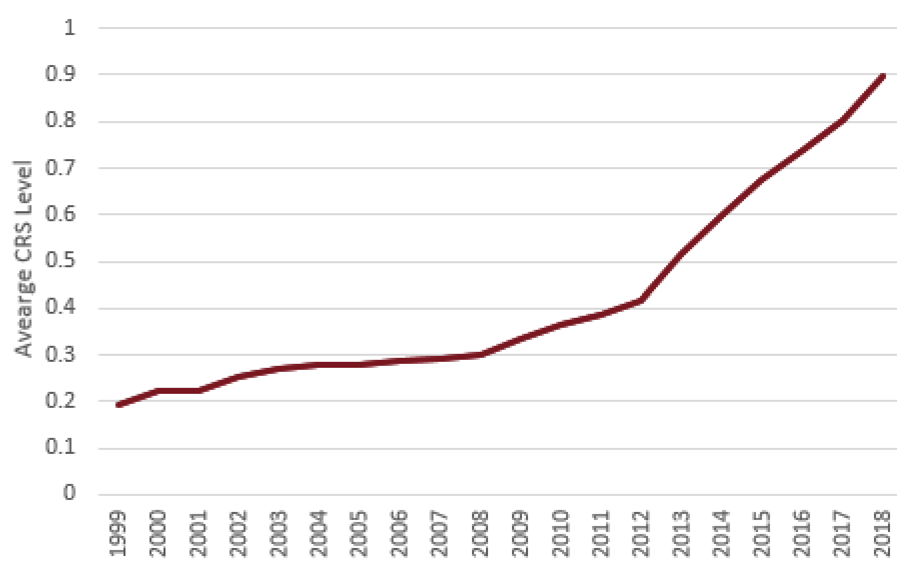
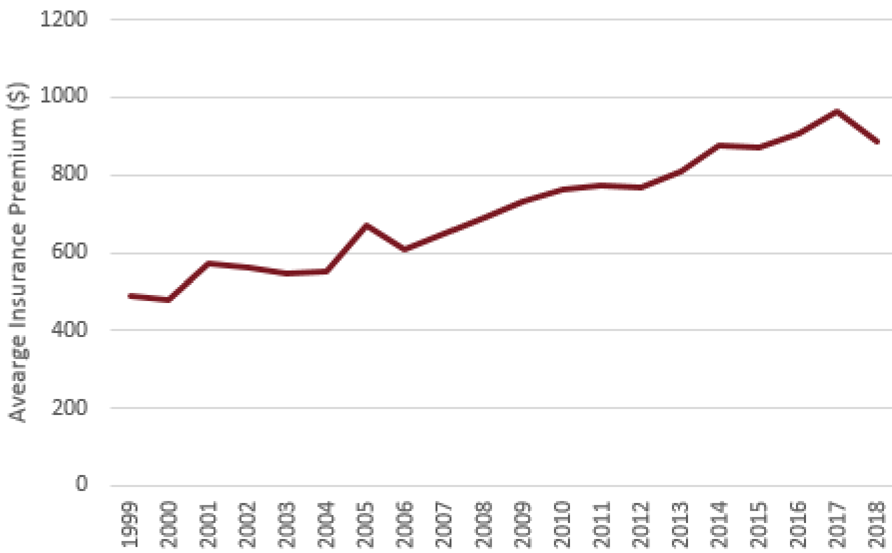


Figure 3.4: Average Insurance Premium



3.3 Model

I model local government investment decisions in a public good over time. The model is a dynamic discrete choice model with an infinite time horizon. I assume that time horizon is infinite to capture the accumulated value of flood hazard mitigation. This is also consistent with the view that public good investments effect future housing values and accrue future benefits. (Bayer et al. (2016)) In each period the local government chooses to invest to reach a specific level of the public good. The government will choose the level of public good that maximizes their expected lifetime utility. The expected lifetime utility of the government is generally defined as the expected benefits of investment in the public good net the perceived costs of the investment. The specifics of the model outlined below are consistent with the CRS, which pertains to local government's investing in flood hazard mitigation. However, this model can be generalized to consider other public good investments (e.g. education, crime prevention).

Let the decision municipality i makes in time t be denoted as $d_{i,t}$. In the application to CRS $d_{i,t} = k$ means that the local government invests such that they reach k class in the program. There are $j = [0, J]$ possible levels with $j = 0$ representing non-participation. The government will choose the k level that maximizes their expected utility. The utility of the government in municipality i is denoted as:

$$U(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it}) + \epsilon_{it}. \tag{3.1}$$

Where S_{it} denotes vector of state variables and ϵ_{it} is a random shock that is IID and type 1 extreme value. The benefits of the investment are captured by $b(\cdot)$ and the costs of the investment are measured by $c(\cdot)$. The benefits, costs, and random shock are assumed to be additively separable. The state variables include: the prior year CRS level, county CRS level (excluding the municipality), the number of homes, home prices, home characteristics including lot size and stories, and municipality characteristics including poverty, population, and tax rate.

In theory there are many ways to measure expected benefits for a local government. For example one might measure the benefits as the utility of the constituents, the utility of the government, or the probability of being reelected. In practice I will measure the expected benefits as the expected property values. The benefits function is defined as:

$$b(S_{it}, d_{it}) = \sum_{n=1}^{N_i} log(P_n(S_{tni}, d_{it})) \tag{3.2}$$

Where there are N_i homes in municipality i, and P_n is the price of house n given choice d_{it}. Note that S_{tni} is house specific state variables. This is a reasonable formation of the benefits function as prior literature has found maximizing property values can be consistent with the three potential benefits listed above. As the revealed preference method literature has shown, housing prices capture agents' willingness to pay for or utility from an aspect of their home. Based on the literature on 'voting with your feet' , housing values can demonstrate people's interest in moving to or away from a location thus capturing both the utility of the government and serving as a proxy for probability of reelection. Further, the property value literature has shown that maximizing property values can be optimal for local social planners. (Brueckner (1982)). Additionally, maximizing the property values will maximize tax revenues, taking the tax rate as given, as the majority of municipality revenues come from taxes on housing in my estimation region of New Jersey. This assumption is also consistent with capturing the utility of homeowners as homes are significant assets and often the most significant asset a person owns. However, it does not allow for inefficiencies in the government utility. For example, only measuring the benefits avoids measuring any influence from special interest groups.[8]

While the benefits function is limited to measuring property values, the measurement of costs is more flexible. The cost function is designed to capture the perceived costs to the municipality government. The perceived costs can capture both the government's beliefs about the accounting costs of implementing the public good investment and the opportunity costs associated with this investment. Therefore, governments may have different perceived costs because of the risk of their municipality, whether there was a flood shock, or any other variables that may affect their state.

[8]The author has other work that examines how lobbying from the real estate industry and construction groups can effect investment in hazard mitigation. (Hopkins (2020a))

Therefore the cost function can be defined as:

$$c(S_{it}, d_{it}) = F(d_{it}) + G(d_{it}, S_{ti}) \tag{3.3}$$

Where F is a function of the level of public good chosen and measured by $d_{it} = k$ and G is a function of choice $d_{it} = k$ and state variables, S_{it}. G allows the costs to vary by municipality or other characteristics.

The derivation of the conditional value function follows the dynamic discrete choice literature. (Rust (1987) and Arcidiacono and Ellickson (2011)). I start by solving for the value function of the government i as the sum of expected future payoffs:

$$V_t(S_{it}) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t}(b(S_{i\tau}, d^*_{i\tau}) - c(S_{i\tau}, d^*_{i\tau}) + \epsilon_{i\tau}\right] \tag{3.4}$$

Where d^* is the optimal decision, β is the discount rate, and the expectation is taken over the shocks and the transition probabilities. Following the assumptions on the error term and adding the assumption that the state transitions depend only on the prior period, I can write the government's problem as a Bellman equation. The government chooses d_{it} to solve:

$$V_t(X_{it}, d_{it}) = \max_{d*} v_t(X_{it}, d_{it}) + \epsilon(d_{it}) \tag{3.5}$$

Where $v_t(S_{it}, d_{it})$ is the conditional value function defined as:

$$v_t(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it})) + \beta \sum_{S_{it+1}=s}^{S} V_{t+1}(S_{it+1}) f(S_{it+1}|S_{it}, d_{it}) \tag{3.6}$$

Where $f(S_{it+1}|S_{it}, d_{it})$ denotes the CDF of the future state i.e. the state transition probabilities.

Given that I have one period ahead finite dependence, I can simplify this problem by using the methods introduced by Hotz and Miller (1993) and Arcidiacono and Miller (2011). This will allow me rewrite the problem in terms of the current period utility, the one period ahead conditional probabilities and the one period ahead state transition probabilities only. Versions of this derivation are also outlined in Bishop (2012), and Ma (2019). The first step is to note that with type 1 extreme value errors I can rewrite v_t using Euler's constant γ_e:

$$v_t(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it})) + \beta \sum_{S_{it+1}=s}^{S} log\left[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j))\right] f(S_{it+1}|S_{it}, d_{it}) + \beta\gamma_e \tag{3.7}$$

The second step is to note that I can expand v_t of choice k using an arbitrary choice h in the next period. The value function can then be rewritten as:

$$\begin{aligned}v_t(S_{it}, d_{it} = k) = b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) + \beta \sum_{S_{it+1}=s}^{S} log\Bigg[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j)\\ - v_{t+1}(S_{it+1}, d_{it+1} = h))\Bigg] f(S_{it+1}|S_{it}, d_{it} = k)\\ + \beta(v_{t+1}(S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k))\end{aligned} \tag{3.8}$$

This can be rewritten further as:

$$\begin{aligned}v_t(S_{it}, d_{it} = k) = b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) + \beta \sum_{S_{it+1}=s}^{S} log\Bigg[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j)\\ - v_{t+1}(S_{it+1}, d_{it+1} = h))\Bigg] f(S_{it+1}|S_{it}, d_{it} = k)\\ + \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k)\\ + \beta^2 \sum_{S_{it+1}} \sum_{S_{it+2}} log\Bigg[\sum_{j} exp(v_{t+2}(S_{it+2}, d_{it+2} = j)\\ - (v_{t+2}(S_{it+2}, d_{it+2} = z)\Bigg] f(S_{it+2}|S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k)\\ + \beta^2 \sum_{S_{it+1}} \sum_{S_{it+2}} exp(v_{t+2}(S_{it+2}, d_{it+2} = j)) f(S_{it+2}|S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k)\end{aligned} \tag{3.9}$$

Given that relative utilities are what matters when solving for the optimal choice under these assumptions. I can solve instead for:

$$v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) \tag{3.10}$$

With one period ahead finite dependence the β^2 terms will cancel out yielding the following equation:

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) = & (b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) - (b(S_{it}, d_{it} = g) - c(S_{it}, d_{it} = g)) \\
& + \beta \sum_{S_{it+1}=s}^{S} log\left[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\right] f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta \sum_{S_{it+1}=s}^{S} log\left[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\right] f(S_{it+1}|S_{it}, d_{it} = g) \\
& + \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = g)
\end{aligned} \tag{3.11}
$$

Additionally, the properties of the logit yield that the probability of a choice h is such that:

$$
-(Pr(d_{it} = h|s_{it}) = log\left[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\right] \tag{3.12}
$$

Therefore I can rewrite the v terms in the right hand side of the equation as conditional choice probabilities:

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) = & (b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) \\
& - (b(S_{it}, d_{it} = g) - c(S_{it}, d_{it} = g)) \\
& + \beta \sum_{S_{it+1}=s}^{S} -(Pr(d_{it} = h|s_{it})) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta \sum_{S_{it+1}=s}^{S} -(Pr(d_{it} = h|s_{it})) f(S_{it+1}|S_{it}, d_{it} = g) \\
& + \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = g)
\end{aligned} \tag{3.13}
$$

This derivation shows that with finite dependence the value function in period t will be a function of the government's utility in that period, their utility in the next period, the conditional choice probabilities, and state transition matrix. This equation greatly simplifies the optimization problem and leads to straightforward estimation. Further, it allows for non-stationarity across more than two periods. This is a benefit given that climate change and sea level rise may imply a non-stationary environment.

3.4 Estimation

The model can be estimated using the data described in Section 3.2. Estimation follows directly from the Equation 3.13 and from Arcidiacono and Miller (2011), Bishop (2012), and Ma (2019). There are two stages to the estimation. I start by estimating the parameters that are inputs to the dynamic model. These parameters include: the inputs to the benefits function, the state transition probabilities, and the conditional choice probabilities. In the second stage, I estimate the underlying primitives of the cost function using the first stage estimates, the decisions made by the local governments, and the dynamic discrete choice model. Thus, the empirical analysis assumes the local governments' decisions are optimal based on the beliefs of the local government and their constituents. Hence, I refer to the estimated costs as the perceived costs of the government decision maker.

3.4.1 First Stage: Benefits

First, I employ hedonic analysis to estimate marginal willingness to pay (MWTP). As both flood insurance premiums and CRS participation change across municipalities and over time, I am able to separately identify MWTP for both. The hedonic model provides a revealed preference methodology for measuring willingness to pay for attributes from customers purchase decisions and actual prices. The hedonic model is often used with property values to measure the value of housing or municipality attributes to homeowners. This type of model is utilized in a breadth of papers due to increasing data availability and the tractability and feasibility of the model. (Bishop et al. (2019)) Recent literature outlined best practices in hedonic models and raised concerns about what hedonic models we can trust. (Bishop et al. (2019) and Kuminoff et al. (2010)) I use the universe of actual housing transactions, detailed housing data, and a well-defined regional market to ensure that I follow these best practices. Further, I run a variety of hedonic specifications to understand how sensitive my estimates are to changes in the model. My preferred specification addresses the fact that CRS participation is not entirely exogenous as is the ideal hedonic setting. While CRS participation is exogenous to individual homes, the choice to participate in CRS is made by the local government, which might be influenced by other unobservables that relate to homeowners in their municipality.

To correct for the endogenous (to the government) CRS choice and potential omitted variable bias from changes in unobservables over time, I use the methodology from Bajari et al. (2012). The Bajari et al. (2012) method relies on 2SLS with lagged prices to control for unobserved variables. The instrument in this method is the prior period public goods. Thus I first estimate:

$$
\begin{aligned}
d_{it} = \beta_0 + \beta_1\, ln(P_{nit'}) + \beta_2 d_{it'} + \beta_3 LogPremium_{it'} \\
+ \beta_4 Spillover_{c_{-i}t'} + \beta_5 X_{nit'} + FE_{y(t')} + FE_{m(t')} + \mu_{nit}
\end{aligned} \tag{3.14}
$$

Where the d_{it} denotes the level of CRS participation in municipality i in year t and t denotes the time period of the previous sale, $LogPremium_{it}$ is the average insurance premium in municipality i and year t, $spillover_{it}$ is the county average CRS participation not including i, and x_{nit} are observed characteristics of the house and municipality. Year and month fixed effects are used to control for seasonal and annual trends in the housing markets. The instruments are lag price, lag CRS participation, lag insurance premium, lag spillover effects, and lag characteristics of house and municipality. Note that in estimation the variables of X are a subset of S. For example the average price in a municipality is not included. I use this same instrument specification for the insurance premium as well. This is due to the fact that the premium contains both the exogenous shock from the changes in insurance due to the federal government changes in rates and the discounts from CRS. In the second stage, I estimate the relationships between price and CRS, price and insurance premiums, and price and spillover effects.

$$
\begin{aligned}
logP_{nit} = \alpha_0 + \alpha_1 \hat{d_{it}} + \alpha_2 Log\hat{Premium}_{it} + \alpha_3 Spillover_{c_{-i}t} \\
+ \alpha_4 X_{nt} + \alpha_5 ln(P_{nit'}) - \alpha_6 d_{it'} - \alpha_7 LogPremium_{it'} + FE_{y(t)} + FE_{m(t)} + \epsilon_{nit}
\end{aligned} \tag{3.15}
$$

Where $\hat{d_{it}}$ and $Log\hat{Premium}_{it}$ are the predicted values based on the instrument in the first stage. I estimate this separately for homes that are in high risk zones (SFHA) and homes that are not.

This method requires the following assumptions: 1.) House price can be written as function of observed and unobserved attributes, 2.) Parameterization of the transition dynamics of the omitted variables, and 3.) Homeowners' predictions about the omitted characteristics are rational given their information. The first assumption is consistent with the more traditional hedonic models and highlights the intuition behind the Bajari et al. (2012) method: the residual of the hedonic regression contains information about the unobservables. The second assumption is relatively flexible and the third assumption can be tested. The results of these tests are included in the appendix and support this assumption.

As an additional robustness check I estimate the standard panel methods repeat sales hedonic regression:

$$
log(P_nit) = \alpha_0 + \alpha_1 d_{it} + \alpha_2 LogPremium_{it} + \alpha_3 spillover_{it} + \alpha_6 X_{it} + FE_{y(t)} + FE_{m(t)} + FE_n + \mu_{nit} \tag{3.16}
$$

This specification does not instrument for any of the variables of interests and includes house fixed effects so that the difference in prices controls for all time varying unobservables in the house and municipality. I run additional specifications of both the traditional and 2SLS methods. The results of these specifications are included in the appendix. To confirm that I do not need to correct for additional dynamics of the forward looking agents in my hedonic estimation I employ the empirical tests in Bishop and Murphy (2019). Bishop and Murphy (2019) demonstrate when the static hedonic methods generate biased coefficients and how to test for these conditions.

I use the hedonic estimates for CRS participation and insurance discounts in my dynamic model of the government's decision to invest in flood hazard mitigation. The dynamic model uses the coefficients from the hedonic estimation to capture MWTP. The MWTP estimates are used in the estimation of the benefits because the benefits are defined such that they capture the housing value change given the investment level. In other words the housing price function denoted in the benefits equation is a function of the coefficients estimated in this stage.

3.4.2 First Stage: Transition Probabilities

I then estimate transition probabilities,$f(S_{t+1}|S_t)$, for my state variables directly from the data. I do this by assuming either the variable does not change over time (e.g. physical size) or by assuming the variables follow an AR-1 process and using regression analysis with lagged variables. For example, consider the number of houses in the local municipality. To calculate this state transition I first run the following regression:

$$N_{it} = \alpha_0 + \lambda_1 N_{it-1} + FE_{ct} + \epsilon it \tag{3.17}$$

The regression analysis yields predicted future values based on the current state and allows for county-year fixed effects. To capture the transition probabilities, I use the residuals of the regression to define distributions for the transition probabilities. I use 1000 draws of the distribution to calculate the transition probabilities.

3.4.3 First Stage: Conditional Choice Probabilities

I estimate the conditional choice probabilities relying on the methods in Murphy (2018) and Ma (2019). I use a flexible logit to estimate the CCPs. The reduced form methods allows me to estimate the CCPs for every possible state of the world, which is not possible using the ideal bin estimator. Let Λ denote the logistic CDF. The CCPs are then calculated using the following logit:

$$\hat{P}r(d_{it} = h|s_{it}) = \Lambda\Bigg(\phi_{it} s_{it}\Bigg) \tag{3.18}$$

Note, that the probability a government invests at level $d_{it} = k$ is estimated based on the actual choices governments make and the states they are in when they make them.

3.4.4 Second Stage

Given that the benefits can be calculated directly from the hedonic estimates and the transition probabilities, the only primitives left to estimate at this point are the cost parameters. To estimate the cost parameters, I parameterize the cost function:

$$c(S_{it}, d_{it}) = \gamma_{0_k} CRS_k(d_{it}) + \gamma_{1_k} CRS_k(d_{it}) \cdot M_{ti} \tag{3.19}$$

Where γ will be a vector of parameters estimated by the model. Each γ represents a cost parameter: γ_0 is a k vector of parameters where each element measures the costs associated with each level of CRS. CRS_k is a function that is 1 if $d_{it} = k$ and $d_{it-1} \neq k$, and 0 otherwise. γ_1 is a an m by k matrix of parameters that measures the costs associated with each level of CRS interacted with municipality and time characteristics. These characteristics are a subset of the state variables, $S_i t$ and include risk level, flood shock, type of government, and proportion of nonresident homeowners.[9]

I estimate the γ parameters using this log likelihood function:

$$l(\gamma) = \sum_{i=1}^{M} \sum_{t=1}^{T} \sum_{j=1}^{J} I[d_{it} = j] log(\frac{exp(v_j(S_{it}) - v_g(S_{it})}{\sum_{k=1}^{J} exp(v_k(S_{it}) - v_g(S_{it}))} \tag{3.20}$$

Where the definition of $(v_j(S_{it}) - v_g(S_{it})$ directly from Equation 3.13 of the model. Plugging in the estimates from the first stage into Equation 3.13 yields:

[9] Currently, the model also allows for a type parameter designated by the econometrician. The model could instead allow for unobserved heterogeneity in type.

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) = &\ (\hat{b}(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) \\
&- (\hat{b}(S_{it}, d_{it} = g) - c(S_{it}, d_{it} = g)) \\
&+ \beta \sum_{S_{it+1}=s}^{S} -(\hat{Pr}(d_{it} = h|s_{it}))\hat{f}(S_{it+1}|S_{it}, d_{it} = k) \\
&- \beta \sum_{S_{it+1}=s}^{S} -(\hat{Pr}(d_{it} = h|s_{it}))\hat{f}(S_{it+1}|S_{it}, d_{it} = g) \\
&+ \beta(\hat{b}(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h))\hat{f}(S_{it+1}|S_{it}, d_{it} = k) \\
&- \beta(\hat{b}(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h))\hat{f}(S_{it+1}|S_{it}, d_{it} = g)
\end{aligned} \tag{3.21}
$$

In estimation I assume a discount rate of $\beta = .975$ and that the default choice, g, is the municipality's investment level in the prior period. With these assumptions and data on the other variables, the primitives (cost parameters) of the models can be identified. To estimate the remaining parameters in the log likelihood, I follow Ma (2019), Bayer et al. (2016). I start by estimating the difference in conditional values using the estimates from the first stage and a guess of the cost parameters. I then estimate the cost parameters by matching on the shares of the municipalities who participate in CRS classes. Specifically, I minimize the difference between the actual choice shares and the shares of municipalities that would participate based on the cost parameters.[10]

3.5 Results

This section starts by discussing the results of the hedonic analysis and then presents the results of the dynamic discrete choice model. The estimates of the regressions for the transition probability are included in the appendix. Following the discussion of results, this section presents an evaluation of the model and model fit.

3.5.1 Results of Hedonic Estimation

I start by presenting my preferred specification which utilizes the 2SLS method by Bajari et al. (2012). I find that the MWTP for a CRS level to be $\$4,026$ per high flood risk homeowner and the MWTP for a 1 percent discount on the insurance premium to be \$125. I find that the MWTP for a CRS level to be $\$2,631$ per low or no flood risk homeowner and the MWTP for a 1 percent

[10]This method is similar to Berry (1994) style contraction mapping and has also been used by Berry et al. (1995), Bayer et al. (2007), and Timmins and Murdock (2007).

discount on the insurance premium to be \$76. The spillover effects are positive for all homes, but are especially large for high risk homes. Note, that a 1 unit increase in average county participation in CRS is not likely in a given year. The MWTP are calculated using a mean house value for CRS participating municipalities of \$363,783 and are annualized based on a 30 year mortgage. These results are presented in Table 3.3.

Table 3.3: Estimates from Hedonic Regressions with 2SLS

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.332	$4,056.212
	(0.024)	
Log Premium	-1.027	$-125.579
	(0.225)	
Spillover	0.389	$4,760.126
	(0.024)	
Panel B: Zone Low		
CRS Class	0.217	$2,653.307
	(0.021)	
Log Premium	-0.623	$-76.178
	(0.199)	
Spillover	0.060	$731.055
	(0.021)	
Panel C: All Repeat Sales		
CRS Class	0.306	$3,746.006
	(0.016)	
Log Premium	-0.699	$-85.465
	(0.151)	
Spillover	0.251	$3,068.730
	(0.015)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Robust Standard Errors in parentheses.

Note that the hedonic analysis is limited to data on municipalities that participate in CRS ever and where homeowners participate in the NFIP. I further limited the data to the non-NYC counties given the difference in types of housing (tall condo buildings vs. single family homes) and relative difference in lifestyle and amenities. The results with all counties are presented in the appendix. The results using all counties are very similar to the results in Table 3.3. The main differences between these two sets of results are driven by low risk homes. In the case of all municipalities, (inclusive of the New York City counties), the spillover effects for low risk homes are no longer positive. This points to the importance in understanding the heterogeneity across regions.

I also present the results from the traditional hedonic analysis in Table 3.4.[11] There are two

[11] Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information

things to note from a comparison between these results and the results from my preferred specification. First, the spillover effects are much larger than the effects of own participation. This is possibly driven by the fact that time-varying unobservables drive county participation and municipality participation. Second, the insurance coefficient is much larger in absolute value terms from the 2SLS estimation. This may be due to the fact that insurance discounts are biased down in the static analyses. Using the tests from Bishop and Murphy (2019), I find that my hedonic estimates for CRS and Spillover effects will not be biased from the static estimation, but that my estimates of MWTP for insurance discounts will be biased down.

Table 3.4: Estimates from Hedonic Regressions

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.110	$1,347.854
	(0.016)	
Log Premium	-0.184	$-22.535
	(0.041)	
Spillover	0.765	$9,354.044
	(0.064)	
Panel B: Zone Low		
CRS Class	0.009	$104.761
	(0.011)	
Log Premium	-0.173	$-21.130
	(0.028)	
Spillover	0.234	$2,860.042
	(0.061)	
Panel C: All Repeat Sales		
CRS Class	0.046	$561.772
	(0.009)	
Log Premium	-0.155	$-18.945
	(0.022)	
Spillover	0.528	$6,453.688
	(0.044)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Robust Standard Errors in parentheses.

Given, my preference for the Bajari et al. (2012), I use the results for Table 3.3 in my dynamic discrete choice model. I do allow the MWTP to vary by risk, thus I use the results from those two columns. Additional robustness checks following Bishop et al. (2019) and Kuminoff et al. (2010) are discussed in the appendix. These robustness checks includes specifications using different subsets of data, the traditional hedonic method with additional controls, and all sales with municipality

on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of the Zillow Group.

fixed effects as opposed to repeat sales.

3.5.2 Results of Dynamic Discrete Choice Model

I estimate costs to be increasing with the change in CRS level and with maintaining higher levels of CRS. I also find that perceived costs are lower for higher risk municipalities and after Hurricane Sandy. One potential explanation for these changes in perceived costs is due to changes in opportunity costs. The opportunity costs of not investing increases for those with higher risk or the opportunity costs of investing decrease after a flood shock.

The costs are presented in Table 3.5. The first row of the table presents the base costs. The other rows present how costs change if the municipality was high risk, if the municipality invested after Hurricane Sandy, if the chief executive is elected, or if a large proportion of homeowners are nonresidents.[12] Further, the costs are such that they add up across columns if a municipality were to skip a level. In other words if I am a low risk municipality going from no participation to level 2, my perceived costs are the total in columns 1 and 2 of row 1.

Table 3.5: Estimates Of Perceived Costs (Million USD)

	Class 1	Class 2	Class 3	Class 4	Class 5
Base Cost	206.612	67.136	75.590	148.156	300.343
	(5.079)	(2.644)	(0.248)	(2.147)	(62.546)
Higher Risk Muni	-10.032	-24.524	-24.845	-39.708	-49.974
	(0.001)	(0.170)	(0.472)	(0.065)	(0.057)
Post Sandy	-0.000	-50.393	-75.290	-114.786	-199.318
	(0.000)	(0.286)	(0.158)	(0.110)	(7.783)
Elected Chief Executive	-15.053	-15.024	-14.983	-10.001	-10.012
	(0.030)	(0.004)	(0.005)	(0.004)	(0.002)
Greater than 20 % nonresident	-14.936	-15.031	-15.010	-10.025	-10.487
	(0.009)	(0.002)	(0.001)	(0.002)	(0.009)

Notes: Bootstrap Standard Errors in Parentheses. Costs are calculated based on moving up one level. To move from a Class 0 to Class 5 need to sum up entire row. The first row presents the base costs and the other rows present the changes to the base costs for some time or municipality specific factor.

[12] The 20% is chosen based on the average municipality who participates in CRS ever.

3.5.3 Model Fit

The model fits the data relatively well. Table 3.6 presents the percentage of municipality years at a particular CRS level (from 0 to 5) in the actual data and in the simulated data based on the estimated parameters. For the most part the model does well, although it under predicts classes 2 and 3 and over predicts class 1 and 5. Table 3.7 presents the average participation level across all municipalities within a given year. The model captures the increase in participation, but does not reach as high a level as the actual choices. Tables 3.8 and 3.9 demonstrate that the model fit is quite good both by year or class and by year and class.

Table 3.6: Moment Comparison by Class

CRS Class	Actual	Simulated
0	0.84	0.85
1	0.03	0.05
2	0.05	0.03
3	0.04	0.03
4	0.02	0.03
5	0.01	0.02

Notes: Percentage of municipality-years at each class level are calculated based on actual choices and simulated data from estimated cost parameters.

Table 3.7: Moment Comparison by Year

Year	Actual	Predicted
1999	0.19	0.17
2000	0.22	0.19
2001	0.22	0.19
2002	0.25	0.20
2003	0.27	0.20
2004	0.28	0.21
2005	0.28	0.21
2006	0.29	0.24
2007	0.29	0.27
2008	0.30	0.34
2009	0.34	0.41
2010	0.37	0.48
2011	0.39	0.48
2012	0.42	0.48
2013	0.52	0.58
2014	0.60	0.58
2015	0.68	0.60
2016	0.74	0.73
2017	0.80	0.77
2018	0.90	0.78

Notes: Average municipality participation for each year calculated based on actual decisions and simulated data.

Table 3.8: Overall Model Fit

Model Fit	MSE
By Year	0.0039
By Class	0.0002

Notes: Each MSE is calculated using participation by subcategories within group.

Table 3.9: Model Fit by Year and Class

Model Fit	MSE
1999	0.0001
2000	0.0001
2001	0.0001
2002	0.0001
2003	0.0002
2004	0.0002
2005	0.0002
2006	0.0005
2007	0.0004
2008	0.0004
2009	0.0003
2010	0.0004
2011	0.0003
2012	0.0003
2013	0.0004
2014	0.0003
2015	0.0004
2016	0.0014
2017	0.0018
2018	0.0025

Notes: Each MSE is calculated using participation by class and year.

3.6 Counterfactuals

Now that the model is estimated, I consider a few counterfactuals. Counterfactuals of interest are: 1.) Altering the risk of the municipality by increasing the proportion of high risk homes to beyond the 100 year flood plains, 2.) Increasing insurance rates to reflect size and cost to rebuild home, and 3.) Replacing the incentive structure. For all of the counterfactuals I simulate the data forward 20 years (including a flood shock similar to Sandy) and compare the counterfactual results to the newly simulated data.

3.6.1 Counterfactual 1

In this counterfactual I explicitly change the number of properties at risk of flooding. In the model I denote those at high risk of flooding as the homes in the designated SHFAs. This designation is based on FEMA's static and out of date maps that have not incorporated the future changes in flooding risk due to sea level rise and other factors. In this counterfactual I replace the designation of properties at high risk using recently released detailed flooding data from the First Street Foundation. (Foundation (2020)) On average, the First Street Foundation predicts that the properties at risk of substantial flooding in New Jersey will increase by 20%. Note that my counterfactual does not account for an individual homes increase in risk, but the overall municipalities increase in risk where risk is defined as greater than or equal to 1% chance of flooding annually.

An assumption I am making in running this counterfactual is that MWTP of people who own properties that were once classified as lower risk and are now classified as high risk is the same as those who own properties that were always classified as high risk. It is likely that these MWTP estimates are biased down as homeowners may have sorted into lower risk homes to avoid flooding risk. In this case, homeowners previously in lower risk homes may be willing to pay more and thus my estimates of changes in CRS participation are a lower bound.

Figure C1 presents the participation by class for each municipality in each year. Note, that non-participation (class 0) is not presented. The counterfactual increase in risk yields a decrease in the lower classes, and an increase in the higher class (except for class 4). However, it is difficult to tell from this graph whether there is an overall increase in participation and how large these changes are. Thus, in Figure 3.5 I present the percentage changes for each class (including nonparticipation). The percent change in nonparticipation is very small, but it is negative therefore there is an overall increase in participation in CRS. Moreover, this increase is happening at the higher levels of CRS. Participation in class 3 increases by over 30 percent. Participation in class 4 does decrease by about 5 percent, but this is outweighed by the approximately 15 percent increase in municipality-years at class 5. Figure 3.6 presents the average level of CRS participation across all municipalities in a year. The figure demonstrates that the increase in risk yields higher levels of

CRS throughout all years. Further, this counterfactual shows that updating the flood risk maps to account for changing present risk and/or future risk is important for municipalities to make optimal decisions about hazard mitigation.

Figure 3.5: Increase Proportion of Homes at High Risk: Percentage Change in Participation by Class

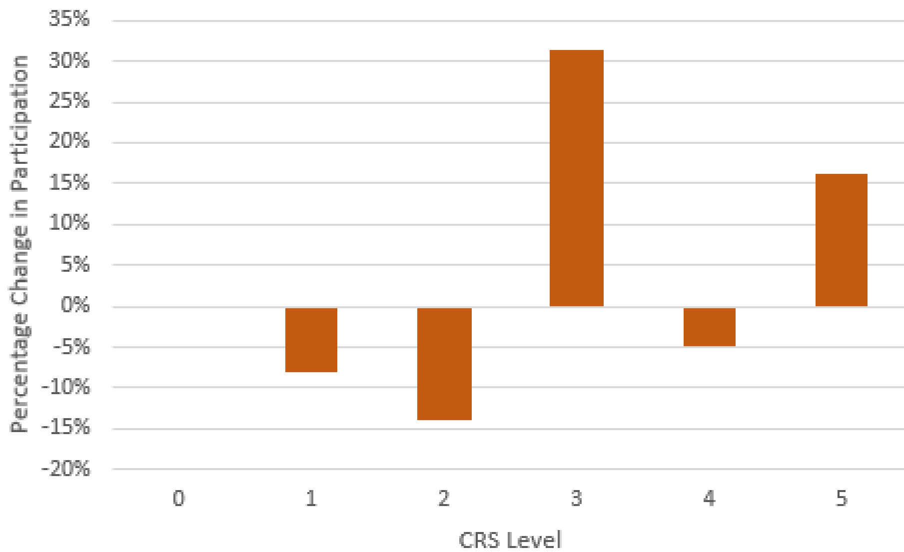
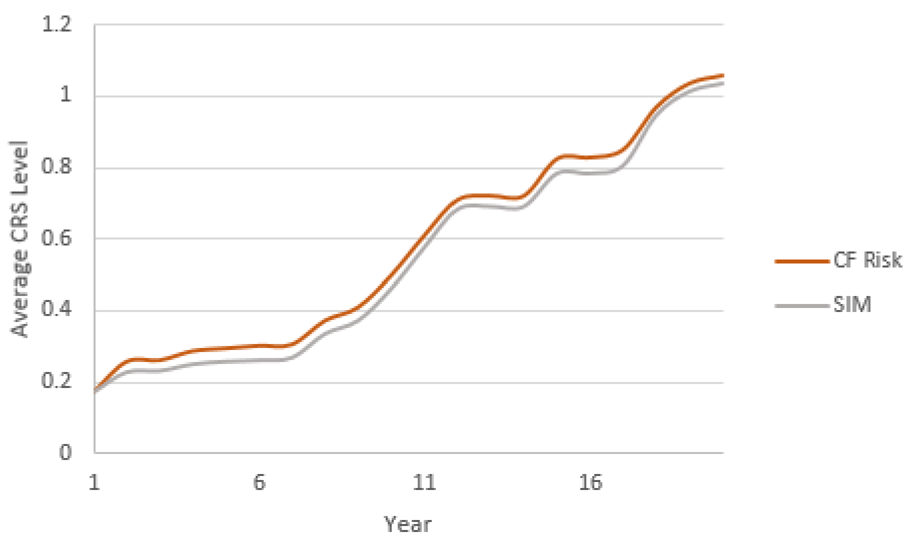


Figure 3.6: Increase Proportion of Homes at High Risk: Participation by Year



3.6.2 Counterfactual 2

This counterfactual considers the current White House proposal to increase insurance premiums to reflect size and cost to rebuild the home and to reflect more recent measures of risk. Why this counterfactual is particularly interesting in this context is because increasing insurance premiums, makes the discounts from CRS more valuable. If the CRS subsidies stay, could increasing the insurance rates drive up CRS participation? In turn how does this affect the expected revenue from increasing insurance premiums? In this counterfactual, I consider three different increases in the premiums: 10%, 25%, or 40%. These are chosen based on the Biggert-Waters Flood Insurance Reform Act of 2012 which instructed that heavily subsidized homes would have their premiums increased by 25% a year, the Homeowner Flood Insurance Affordability Act of 2014 which limited insurance premium increases to 5 to 15% a year, and FEMA which has states subsidized premiums represent 40 to 45% of the risk.

For this counterfactual, I assume that the MWTP estimates will not change given these large increases in premiums. This is most likely true for the 10% increase as that is not significantly different from annual changes. However, the 25%, or 40% increase in insurance premiums might increase the MWTP estimates conditional on holding insurance and thus these predictions may be a lower bound on participation. Conversely, one might be concerned that insurance demand might actually fall. Currently, I am not accounting for insurance demand in my model. However, recent work by Wagner (2019) demonstrates that insurance should be enforced as mandatory in this high risk areas.

Figure C2 presents participation counts by class for each municipality-year and for each scenario: the model simulated data and the counterfactual data from a 10%, 25%, or 40% increase in premiums. Similar to the first counterfactual, the changes in class are relatively bi-modal with the increases in participation occurring in classes 3 and 5. The counterfactual with a 10% increase is very similar to the counterfactual with a 25% increase, however there are differences. The changes are most easily seen in Figure 3.7, which shows in overall increase in participate in all three scenarios. Notably, the largest increase in premiums leads to almost the same change in participate in classes 3 and 5 as the first counterfactual that increase the proportion of homes at high risk. Figure 3.8 demonstrates that on average the three insurance premium scenarios look fairly similar.

There are two reasons why this counterfactual is policy relevant. The first is because the federal government is considering raising insurance premiums due to their subsidized rates. The second reason is because NFIP is in a large amount of debt, and part of the goal of raising the insurance premiums is to increase their revenues. However, due to the incentives from the discounts associated with participating in CRS, the actual increases in revenue from increasing the premiums will be lower than expected if the government does not account for changes in CRS participation. I calculate a back of the hand estimate of the potential loss revenue from additional participation in

CRS assuming an average of 5000 homeowners per municipality with approximately half as high risk and half as low risk, an average premium of 1000 for low risk, and an average premium of 2000 for high risk. The total additional take up in discounts across all municipality years ranges from \$135 million for a 10% in premiums to \$455 million (approximately \$22.7 million per year) for a 40% increase.

Figure 3.7: Increase Insurance Premium: Percentage Change in Participation by Class

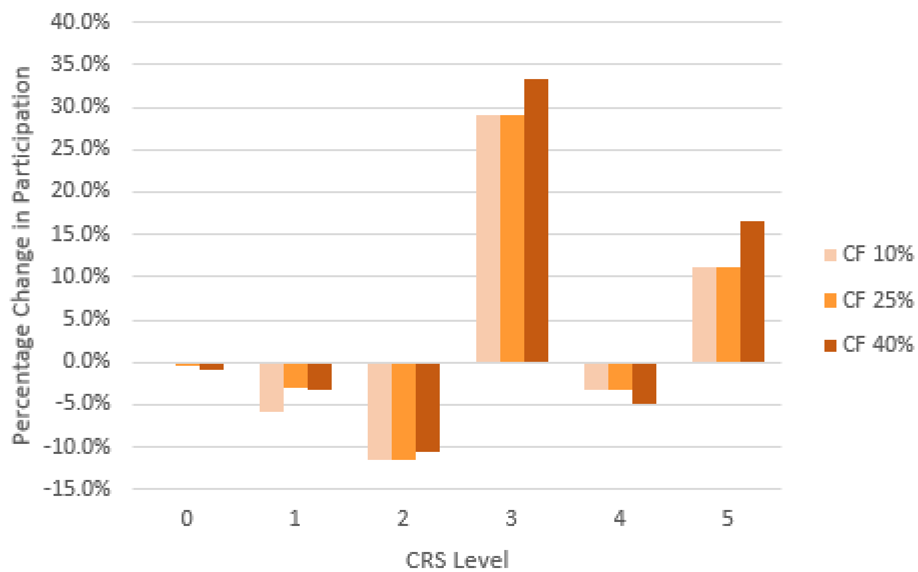
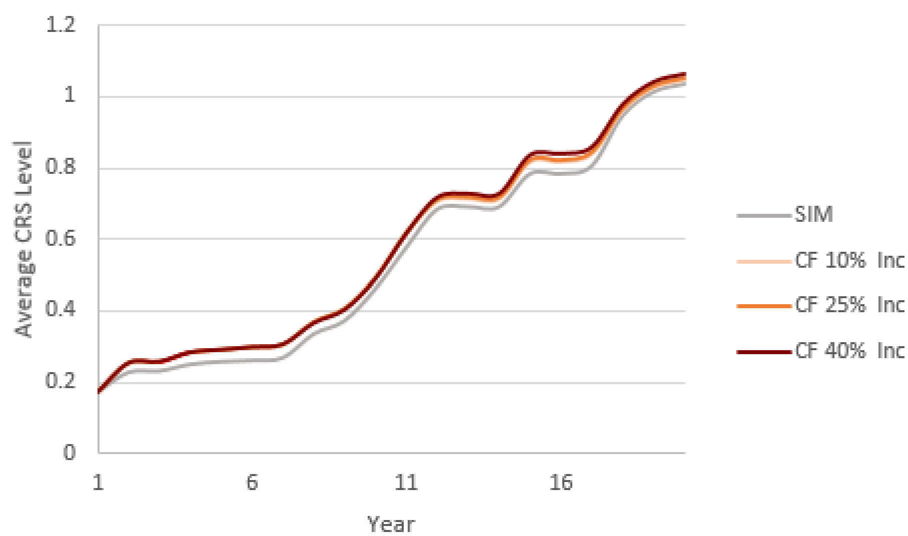


Figure 3.8: Increase Insurance Premium: Participation by Year



3.6.3 Counterfactual 3

The third counterfactual considers the incentive design of CRS. Currently, the incentives to participate are provided as insurance discounts for homeowners. This is an effective incentive for participation because, as the hedonic model has shown, insurance premiums are over capitalized i.e. a decrease in the insurance premium leads to a larger increase in the home than the actual reduction in payments. However, this over capitalization is true based on the average price of homes across participating municipalities. Prior work has shown that poorer regions participate in CRS at lower rates relative to wealthier areas. One explanation is that the incentive from insurance premium discounts is not sufficient in municipalities with lower housing values. To account for this problem, I run a counterfactual analyses that gives a lower housing value municipality a cost subsidy to enter the program equivalent to the cost of the insurance premium discounts to the federal government. The cost subsidy is only given once to municipalities when then enter the program (move from level 0 to level 1) and is calculated based on the number of homes, the number of years typically spent at class 1, the 5% discount to all houses, and the average insurance premium. The subsidy is approximate \$6.53 million dollars. I classify lower housing value municipalities as municipalities with average sale prices in the bottom 10% of home prices across all municipalities. This counterfactual assumes a municipality is indifferent between the direct cost reduction of a subsidy and the direct benefit of the insurance discount as long as the absolute value is equal.

Figures C3 and 3.9 show that overall participation goes up and in addition although the cost subsidy is only given to initial participators for those low housing value municipalities, participation is increasing in the highest levels of CRS. There are two reasons for this. The first explanation is what motivated the counterfactual: that the benefits from insurance premiums will be in absolute value terms smaller for municipalities with low housing values and therefore do not help them overcome the high perceived costs. The second explanation is that going from no participation to class 1 is costlier than going from class 1 to class 2. Hence, when non-participators become participators, they are able to continue investing in hazard mitigation past that initial level. Figure 3.10 demonstrates that average participation is higher every year with this counterfactual. Finally, this counterfactual presents evidence that cost subsidies may be more effective than insurance discounts for lower wealth areas to start investing in hazard mitigation.

Figure 3.9: Change Incentive Structure: Percentage Change in Participation by Class

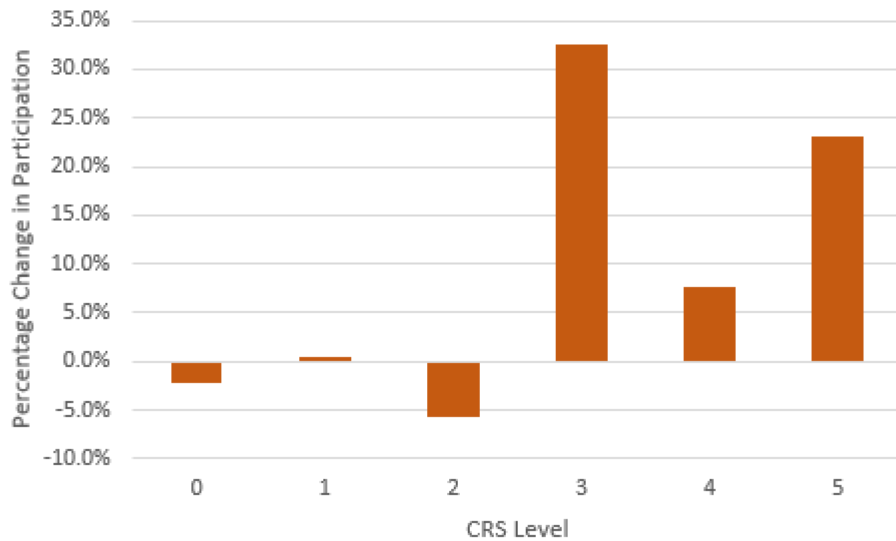
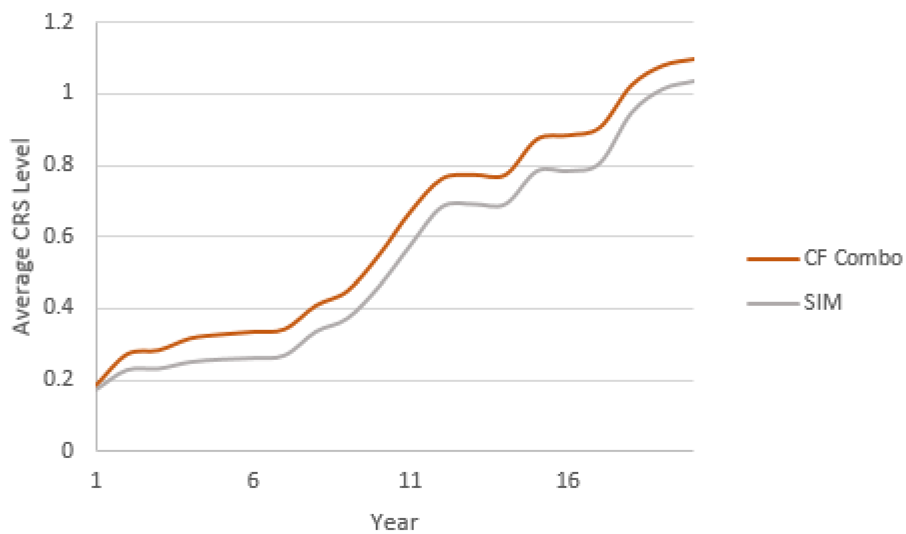


Figure 3.10: Change Incentive Structure: Participation by Year



3.7 Conclusion

With climate change and rising sea levels, flood hazard mitigation is becoming increasingly important. Understanding the dynamics of what motivates local governments to invest in hazard mitigation, as well as inefficiencies in the current policies, and how to improve them is critically important for solving this problem. This paper uses a unique combination of datasets, hedonic analyses, and a structural model to assess how much homeowners value flood hazard mitigation, estimate the perceived costs of investment, and consider how alternative policies can increase investment in hazard mitigation.

I use revealed preferences methods to estimate the value of additional hazard mitigation separately from its relationship with insurance discounts. The hedonic analysis shows that MWTP for hazard mitigation is positive, the MWTP to avoid an increase in the insurance premium is larger than the premium itself, and spillover effects across municipalities within the same county are positive. There was uncertainty whether these spillover effects could be negative or positive as hazard mitigation investment in another town could alert a neighboring town it its own risk or it could provide protection to these other towns through dredging or other mitigating investments. I find positive spillover effects which support the latter and highlight an inefficiency in current policy design. I then use the estimates from the hedonic analysis and local governments' actual mitigation decisions to measure the perceived costs of hazard mitigation. I find that the perceived cost of initial participation is high relative to other levels and the perceived costs are lower for municipalities with more high risk homes, or second homeowners, after a large risk shock, or with a chief executive that is elected rather than appointed.

Three additional insights come from the counterfactual analyses. Current federal policy uses the term 1 in 100 year floods to denote high risk zones. This terminology implies that there is a 1% chance of flooding each year or a 26% change of flooding during a 30-year mortgage in the highest risk areas. While both the size of the region that is at this high risk for flooding is increasing and the probability of flooding is increasing due to sea level rise, the first counterfactual only considers changes in the proportion of homes at risk. This counterfactual is consistent with FEMA updating their risk maps, which they are currently working on, to include additional areas designated as high risk. The analysis shows that increasing the region at risk yields a large increase in participation overall and at higher levels of mitigation. Thus, the static risk maps FEMA currently uses cause local governments to under invest in hazard mitigation.

The second counterfactual considers the insurance premium. The federal government is also considering raising flood insurance premiums because the current rates are heavily subsidized relative to risk. My second counterfactual demonstrates that an increase in insurance premiums increases participation in CRS. This results shows that the federal government will recover significantly less than their expected revenue from the rate increases if they do not account for the local government response to changes in policy. This is an important consideration for policymakers concerned about FEMA's significant debt. The third counterfactual demonstrates that a combination of cost subsidies and insurance discounts may increase investment in hazard mitigation for non-participating municipalities which are more likely to be poorer.

Future studies on hazard mitigation can build upon my work in several ways. From an empirical perspective applying this approach to a region with repeated flooding shocks in recent years, such as Texas or Florida, could provide new insights into how homeowners evaluate flood hazard mitigation as they learn about the damages from flood risk. While this paper incorporates risk and resident status heterogeneity into the estimation, additional research on heterogeneous valuations and response to hazard mitigation will be important for understanding how different regions may respond. The model can also be expanded to further consider the households decision. One possible method is to incorporate a sorting model that allows for households to sort based on the government's decision. This can potentially allow for additional heterogeneity in homeowners MWTP for hazard mitigation.

The structural model can also be expanded to further consider the trade-offs a local government faces when investing in public goods. The recent health and economic shock due to COVID19 has forced state and local governments to invest resources into public health goods. Anecdotal evidence shows that this shock may have shifted local government investment away from planned mitigation investments. (Flavelle (2020)) Incorporating these types of shocks into the model can provide additional understanding on how local governments behave when facing uncertain trade-offs.

In summary, the findings of this paper demonstrate the value of hazard mitigation, the inefficiencies of current policy design, and the methods policy-makers can employ to increase investment in flood hazard mitigation. Overall, the methods employed by this paper can be utilized to study many other applications. An obvious extension is other areas of hazard mitigation, for example wildfires, which are becoming increasingly prevalent due to climate change. Further, many environmental policies that are consistent with environmental federalism create interdependencies between different levels of government, and thus can be studied with this methodology. In addition, policy areas outside of the environment, including education, public health, and crime prevention are affected by both local government investment (either state, county, or municipality) and federal policy. Adapting this model to these domains is feasible and can provide new insights into the efficiencies or inefficiencies in decentralized policies.

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Appendices

A Appendix to Chapter 1

A.1 Appendix Tables

Table A1: Description of Public Awareness CRS Activities

Activity Number	Description
320	Map Information
330	Public Outreach Projects
340	Hazard Disclosure
350	Flood Protection Information
360	Flood Protection Assistance
410	Floodplain Mapping
440	Flood Data Maintenance

Table A2: DD Models for Hurricane Katrina Inclusive of all Residential Sales and with No Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
Zone High Risk	0.185	0.185	0.185	0.185	0.185	0.185
	(0.00429)	(0.00429)	(0.00429)	(0.00429)	(0.00429)	(0.00429)
Post Storm Months	0.441	0.436	0.423	0.432	0.443	0.442
	(0.0106)	(0.00789)	(0.00658)	(0.00559)	(0.00505)	(0.00471)
Zone x Post Storm Months	0.144	0.148	0.121	0.113	0.0914	0.0963
	(0.0269)	(0.0197)	(0.0166)	(0.0141)	(0.0126)	(0.0118)
Year FE	N	N	N	N	N	N
Month FE	N	N	N	N	N	N
County-Year FE	N	N	N	N	N	N
Municipality FE	N	N	N	N	N	N
House FE	N	N	N	N	N	N
Observations	178,844	182,491	186,126	190,609	194,668	198,060
R-squared	0.023	0.030	0.035	0.043	0.049	0.054

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A3: Table Setup for Post and Post Interaction Variables

Variables:	(1) Column Definition	(2) Column Definition	(3) Column Definition	(4) Column Definition	(5) Column Definition	(6) Column Definition
Post # Months	Post 2 Months	Post 4 Months	Post 6 Months	Post 8 Months	Post 10 Months	Post 12 Months
Zone X Post # Months	Zone X Post 2 Months	Zone X Post 4 Months	Zone X Post 6 Months	Zone X Post 8 Months	Zone X Post 10 Months	Zone X Post 12 Months
CRS X Post # Mos	CRS X Post 2 Months	CRS X Post 4 Months	CRS X Post 6 Months	CRS X Post 8 Months	CRS X Post 10 Months	CRS X Post 12 Months
CRS X Zone X Post # Mos	CRS X Zone X Post 2 Mos	CRS X Zone X Post 4 Mos	CRS X Zone X Post 6 Mos	CRS X Zone X Post 8 Mos	CRS X Zone X Post 10 Mos	CRS X Zone X Post 12 Mos
Secondary Res Buy X Post # Mo	Secondary Res Buy X Post 2 Mo	Secondary Res Buy X Post 4 Mo	Secondary Res Buy X Post 6 Mo	Secondary Res Buy X Post 8 Mo	Secondary Res Buy X Post 10 Mo	Secondary Res Buy X Post 12 Mo
OB X Post # Mos	OB X Post 2 Months	OB X Post 4 Months	OB X Post 6 Months	OB X Post 8 Months	OB X Post 10 Months	OB X Post 12 Months
OB X Zone X Post # Mo	OB X Zone X Post 2 Mo	OB X Zone X Post 4 Mo	OB X Zone X Post 6 Mo	OB X Zone X Post 8 Mo	OB X Zone X Post 10 Mo	OB X Zone X Post 12 Mo

Table A4: Triple Difference Models for Hurricane Katrina Limited to Repeated Residential Sales with Controls and Utilizes the Pre and After Post-Storm Period

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Maps Par.	-0.00929	-0.00963	-0.0106	-0.0115	-0.0119	-0.0121
	(0.00989)	(0.00990)	(0.00990)	(0.00991)	(0.00992)	(0.00992)
CRS x Zone	0.0635	0.0635	0.0643	0.0661	0.0665	0.0670
	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)
Age	-0.00399	-0.00399	-0.00399	-0.00400	-0.00400	-0.00399
	(0.000294)	(0.000294)	(0.000295)	(0.000295)	(0.000295)	(0.000295)
Living Space	4.52e-05	4.52e-05	4.53e-05	4.53e-05	4.53e-05	4.53e-05
	(2.14e-05)	(2.14e-05)	(2.14e-05)	(2.14e-05)	(2.14e-05)	(2.14e-05)
Mo Sales/Avg Mo Sales	-0.0100	-0.00972	-0.00989	-0.00987	-0.00893	-0.00838
	(0.00471)	(0.00471)	(0.00471)	(0.00470)	(0.00470)	(0.00470)
Mo Sales	0.000629	0.000633	0.000623	0.000614	0.000616	0.000622
	(6.70e-05)	(6.70e-05)	(6.69e-05)	(6.68e-05)	(6.68e-05)	(6.68e-05)
Lag Air Pollution	0.000905	0.000863	0.000857	0.000909	0.000950	0.000936
	(0.000293)	(0.000292)	(0.000292)	(0.000292)	(0.000292)	(0.000292)
Air Pollution	-0.000168	-0.000161	-0.000122	-0.000145	-5.26e-05	-6.36e-05
	(0.000289)	(0.000287)	(0.000287)	(0.000287)	(0.000287)	(0.000287)
Total New Builds	0.000144	0.000145	0.000140	0.000140	0.000142	0.000141
	(6.00e-05)	(6.00e-05)	(6.00e-05)	(6.00e-05)	(6.00e-05)	(6.00e-05)
Total Value New Builds	0.00370	0.00355	0.00346	0.00345	0.00340	0.00339
	(0.00107)	(0.00107)	(0.00107)	(0.00107)	(0.00107)	(0.00107)
Post # Months	-0.000420	0.0116	0.0134	0.0252	0.0286	0.0271
	(0.00789)	(0.00605)	(0.00507)	(0.00462)	(0.00462)	(0.00489)
Zone X Post # Months	0.0622	0.0539	0.0711	0.0744	0.0742	0.0721
	(0.0254)	(0.0180)	(0.0147)	(0.0130)	(0.0117)	(0.0109)
CRS X Post # Mos	-0.0432	0.0235	0.0439	0.0527	0.0536	0.0619
	(0.0305)	(0.0372)	(0.0293)	(0.0262)	(0.0238)	(0.0222)
CRS X Zone X Post # Mos	-0.0109	-0.0417	-0.0723	-0.0933	-0.0940	-0.105
	(0.0426)	(0.0435)	(0.0348)	(0.0311)	(0.0282)	(0.0263)
Constant	11.68	11.68	11.68	11.68	11.68	11.68
	(0.0306)	(0.0306)	(0.0306)	(0.0306)	(0.0306)	(0.0306)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	86,543	86,543	86,543	86,543	86,543	86,543
R-squared	0.969	0.969	0.969	0.969	0.969	0.969

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A5: Triple Difference Models for Hurricane Katrina Limited to Repeated Firm Transacted Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0822	0.0781	0.0721	0.0823	0.0843	0.119
	(0.163)	(0.161)	(0.167)	(0.168)	(0.167)	(0.163)
CRS x Zone	-0.0652	-0.0634	-0.0658	-0.0732	-0.0703	-0.0935
	(0.166)	(0.163)	(0.170)	(0.171)	(0.168)	(0.165)
Age	-0.00136	-0.00106	-0.000487	-0.000588	-0.000851	-0.00102
	(0.00111)	(0.00107)	(0.00121)	(0.00120)	(0.00110)	(0.00111)
Living Space	4.95e-05	7.15e-05	7.40e-05	7.84e-05	8.17e-05	8.32e-05
	(2.86e-05)	(2.79e-05)	(2.78e-05)	(2.85e-05)	(2.82e-05)	(2.83e-05)
Mo Sales/Avg Mo Sales	-0.0102	0.00338	-0.00163	-0.00516	-0.00159	-0.00600
	(0.0475)	(0.0450)	(0.0440)	(0.0441)	(0.0435)	(0.0439)
Mo Sales	0.00454	0.00276	0.00302	0.00305	0.00276	0.00404
	(0.00955)	(0.00905)	(0.00882)	(0.00876)	(0.00869)	(0.00875)
Lag Air Pollution	-0.00521	-0.00558	-0.00507	-0.00444	-0.00404	-0.00391
	(0.00290)	(0.00286)	(0.00280)	(0.00276)	(0.00267)	(0.00265)
Air Pollution	-0.00357	-0.00372	-0.00228	-0.00209	-0.00142	-0.00166
	(0.00276)	(0.00273)	(0.00275)	(0.00271)	(0.00269)	(0.00263)
Total New Builds	8.34e-06	0.000104	0.000129	0.000203	0.000253	0.000427
	(0.000710)	(0.000690)	(0.000672)	(0.000665)	(0.000652)	(0.000661)
Total Value New Builds	0.0189	0.0169	0.0143	0.0132	0.0115	0.0123
	(0.0116)	(0.0104)	(0.0101)	(0.0102)	(0.00971)	(0.00973)
Post # Months	-0.00903	-0.0299	-0.0364	-0.0370	-0.0331	-0.0266
	(0.0826)	(0.0734)	(0.0685)	(0.0647)	(0.0635)	(0.0625)
Zone X Post # Months	0.172	0.119	0.136	0.179	0.179	0.167
	(0.111)	(0.109)	(0.0961)	(0.0902)	(0.0852)	(0.0821)
CRS X Post # Mos	-0.142	0.336	0.333	0.293	0.305	0.337
	(0.107)	(0.296)	(0.271)	(0.244)	(0.225)	(0.202)
CRS X Zone X Post # Mos	-0.0395	-0.441	-0.405	-0.379	-0.377	-0.389
	(0.171)	(0.327)	(0.294)	(0.258)	(0.239)	(0.214)
Constant	11.46	11.37	11.38	11.43	11.46	11.46
	(0.183)	(0.194)	(0.174)	(0.169)	(0.161)	(0.159)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	2,215	2,260	2,288	2,326	2,365	2,390
R-squared	0.976	0.975	0.974	0.974	0.974	0.973

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A6: Triple Difference Hedonic Regression Models for Hurricane Sandy Limited to Repeated Firm Transacted Residential Sales and with Controls

Dep Var: Log Price	(1)	(2)	(3)	(4)	(5)	(6)
	2 Months	4 Months	6 Months	8 Months	10 Months	12 Months
CRS Public Info and Map Par.	-0.0615	-0.0503	-0.0705	-0.0670	-0.0681	-0.0712
	(0.112)	(0.110)	(0.104)	(0.104)	(0.0993)	(0.0978)
CRS x Zone	0.0946	0.0847	0.104	0.0990	0.0961	0.0894
	(0.125)	(0.123)	(0.118)	(0.117)	(0.113)	(0.111)
Age	-0.00362	-0.00368	-0.00395	-0.00397	-0.00399	-0.00395
	(0.000817)	(0.000811)	(0.000806)	(0.000773)	(0.000771)	(0.000753)
Living Space	0.000119	0.000120	0.000118	0.000119	0.000123	0.000125
	(1.98e-05)	(1.95e-05)	(1.93e-05)	(1.91e-05)	(1.93e-05)	(1.93e-05)
Mo Sales/Avg Mo Sales	0.0550	0.0580	0.0538	0.0498	0.0473	0.0524
	(0.0320)	(0.0319)	(0.0313)	(0.0312)	(0.0310)	(0.0307)
Mo Sales	-0.000408	-0.000471	-0.000339	-0.000350	-0.000312	-0.000320
	(0.000547)	(0.000544)	(0.000535)	(0.000528)	(0.000527)	(0.000523)
Lag Air Pollution	-0.00163	-0.00178	-0.00185	-0.00194	-0.00194	-0.00197
	(0.00225)	(0.00224)	(0.00223)	(0.00220)	(0.00219)	(0.00218)
Air Pollution	-0.00126	-0.00122	-0.00128	-0.00116	-0.00107	-0.00129
	(0.00233)	(0.00232)	(0.00230)	(0.00226)	(0.00226)	(0.00224)
Total New Builds	0.000629	0.000644	0.000628	0.000610	0.000615	0.000572
	(0.000535)	(0.000533)	(0.000529)	(0.000524)	(0.000523)	(0.000516)
Total Value New Builds	0.00879	0.00853	0.00886	0.00976	0.00850	0.0102
	(0.00771)	(0.00770)	(0.00766)	(0.00761)	(0.00757)	(0.00753)
Post # Months	0.326	0.258	0.278	0.257	0.254	0.243
	(0.151)	(0.139)	(0.127)	(0.124)	(0.117)	(0.114)
Zone X Post # Months	0.0537	-0.202	-0.188	-0.209	-0.630	-0.636
	(0.135)	(0.240)	(0.146)	(0.140)	(0.0915)	(0.0856)
CRS X Post # Mos	-0.559	-0.228	-0.268	-0.212	-0.271	-0.213
	(0.172)	(0.241)	(0.153)	(0.142)	(0.128)	(0.119)
CRS X Zone X Post # Mos					0.507	0.458
					(0.148)	(0.141)
Constant	11.61	11.71	11.67	11.69	11.65	11.64
	(0.162)	(0.162)	(0.134)	(0.128)	(0.127)	(0.125)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	3,638	3,654	3,676	3,697	3,713	3,734
R-squared	0.971	0.971	0.971	0.971	0.971	0.971

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A7: Triple Difference Hedonic Regression Models for Hurricane Sandy Inclusive of All Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0179	0.0190	0.0187	0.0192	0.0202	0.0194
	(0.00796)	(0.00788)	(0.00778)	(0.00770)	(0.00766)	(0.00760)
Zone High Risk	0.239	0.239	0.239	0.238	0.238	0.238
	(0.00531)	(0.00529)	(0.00527)	(0.00524)	(0.00521)	(0.00520)
CRS x Zone	-0.0817	-0.0816	-0.0816	-0.0808	-0.0803	-0.0801
	(0.00802)	(0.00799)	(0.00797)	(0.00795)	(0.00792)	(0.00790)
Age	-0.00203	-0.00204	-0.00206	-0.00206	-0.00207	-0.00207
	(5.55e-05)	(5.60e-05)	(5.62e-05)	(5.69e-05)	(5.76e-05)	(5.79e-05)
Living Space	0.000316	0.000317	0.000318	0.000319	0.000319	0.000320
	(3.24e-05)	(3.22e-05)	(3.19e-05)	(3.17e-05)	(3.15e-05)	(3.13e-05)
Mo Sales/Avg Mo Sales	-0.00438	-0.00465	-0.00540	-0.00579	-0.00662	-0.00732
	(0.00441)	(0.00441)	(0.00440)	(0.00437)	(0.00437)	(0.00433)
Mo Sales	0.000374	0.000380	0.000388	0.000398	0.000400	0.000411
	(6.58e-05)	(6.54e-05)	(6.47e-05)	(6.42e-05)	(6.39e-05)	(6.37e-05)
Lag Air Pollution	0.000132	0.000118	0.000146	0.000132	0.000148	0.000132
	(0.000328)	(0.000328)	(0.000328)	(0.000328)	(0.000326)	(0.000326)
Air Pollution	-0.000165	-0.000191	-0.000210	-0.000235	-0.000235	-0.000267
	(0.000301)	(0.000300)	(0.000300)	(0.000298)	(0.000297)	(0.000296)
Total New Builds	0.000399	0.000404	0.000399	0.000374	0.000369	0.000363
	(6.67e-05)	(6.67e-05)	(6.61e-05)	(6.46e-05)	(6.41e-05)	(6.39e-05)
Total Value New Builds	0.00426	0.00419	0.00412	0.00399	0.00394	0.00399
	(0.000988)	(0.000984)	(0.000979)	(0.000969)	(0.000961)	(0.000957)
Post Months	-0.0227	-0.0209	-0.0106	-0.0145	-0.0142	-0.0145
	(0.0220)	(0.0208)	(0.0199)	(0.0197)	(0.0195)	(0.0194)
Zone X Post Months	0.0753	0.0760	0.00128	0.0103	-0.00339	0.000294
	(0.0468)	(0.0352)	(0.0294)	(0.0254)	(0.0223)	(0.0203)
CRS X Post # Months	-0.0314	-0.0273	-0.0126	0.00668	0.00214	0.0123
	(0.0365)	(0.0234)	(0.0172)	(0.0148)	(0.0141)	(0.0132)
CRS X Zone X Post # Mos	-0.0386	-0.0544	-0.0353	-0.0627	-0.0375	-0.0583
	(0.0634)	(0.0455)	(0.0369)	(0.0321)	(0.0290)	(0.0267)
Constant	10.91	10.91	10.91	10.91	10.91	10.91
	(0.0530)	(0.0527)	(0.0523)	(0.0519)	(0.0517)	(0.0515)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	238,419	239,842	242,260	244,676	246,888	248,806
R-squared	0.653	0.653	0.653	0.653	0.654	0.654

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A8: Triple Difference Hedonic Regression Models for Hurricane Sandy Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	-0.00975	-0.00908	-0.0100	-0.0145	-0.0159	-0.0163
	(0.0101)	(0.0101)	(0.00989)	(0.00979)	(0.00965)	(0.00955)
CRS x Zone	0.0612	0.0611	0.0599	0.0630	0.0610	0.0594
	(0.0145)	(0.0145)	(0.0144)	(0.0143)	(0.0141)	(0.0139)
Age	-0.00344	-0.00349	-0.00355	-0.00357	-0.00359	-0.00362
	(0.000270)	(0.000269)	(0.000267)	(0.000265)	(0.000262)	(0.000259)
Living Space	4.53e-05	4.62e-05	4.72e-05	4.80e-05	4.88e-05	4.95e-05
	(2.22e-05)	(2.24e-05)	(2.26e-05)	(2.27e-05)	(2.28e-05)	(2.30e-05)
Mo Sales/Avg Mo Sales	-0.00789	-0.00853	-0.00765	-0.00788	-0.00839	-0.00809
	(0.00472)	(0.00470)	(0.00465)	(0.00460)	(0.00456)	(0.00453)
Mo Sales	0.000623	0.000633	0.000614	0.000594	0.000578	0.000569
	(7.00e-05)	(6.97e-05)	(6.94e-05)	(6.86e-05)	(6.77e-05)	(6.76e-05)
Lag Air Pollution	0.000928	0.000899	0.000914	0.000929	0.000983	0.000942
	(0.000307)	(0.000306)	(0.000305)	(0.000302)	(0.000300)	(0.000298)
Air Pollution	-0.000234	-0.000274	-0.000254	-0.000288	-0.000310	-0.000292
	(0.000300)	(0.000299)	(0.000297)	(0.000294)	(0.000292)	(0.000291)
Total New Builds	0.000137	0.000138	0.000148	0.000152	0.000145	0.000148
	(6.25e-05)	(6.23e-05)	(6.18e-05)	(6.08e-05)	(6.05e-05)	(6.03e-05)
Total Value New Builds	0.00442	0.00424	0.00422	0.00415	0.00421	0.00422
	(0.00112)	(0.00111)	(0.00110)	(0.00108)	(0.00106)	(0.00105)
Post # Months	-0.0832	-0.0835	-0.0775	-0.0840	-0.0819	-0.0822
	(0.0264)	(0.0242)	(0.0230)	(0.0223)	(0.0219)	(0.0216)
Zone X Post # Months	0.0348	0.0683	0.0392	0.0398	0.0256	0.0368
	(0.0706)	(0.0487)	(0.0431)	(0.0384)	(0.0319)	(0.0316)
CRS X Post # Mos	0.00844	0.00234	0.00565	0.0222	0.0229	0.0280
	(0.0441)	(0.0298)	(0.0214)	(0.0179)	(0.0159)	(0.0149)
CRS X Zone X Post Mos	-0.0467	-0.0717	-0.0638	-0.0577	-0.0407	-0.0599
	(0.0832)	(0.0593)	(0.0512)	(0.0454)	(0.0387)	(0.0373)
Constant	11.64	11.68	11.68	11.68	11.69	11.69
	(0.0367)	(0.0338)	(0.0325)	(0.0322)	(0.0319)	(0.0317)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	98,450	98,864	99,658	100,410	101,140	101,745
R-squared	0.971	0.971	0.970	0.970	0.970	0.970

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A9: Summary of Results from Analyses of All Non-Local Storms for Residential Sales

Storm	Description	All Sales	Repeated Sales
Allison	Tropical Storm Allison landed in Texas in June of 2001 and led to 30,000 homeless after storm flooding.	0	0
Multiple 2002	Several hurricanes and tropical storms that hit several regions of the US and the Caribbean in September 2002.	5	0
Charley	Hurricane Charley hit the US in August of 2004 and caused over 15 billion dollars in damages. Primarily in Florida.	6	4
Katrina	Hurricane Katrina hit the US in August of 2005. It was the costliest cyclone to ever hit the US and cost more than 100 billion in damages.	5	4
Multiple 2007	Hurricane Dean and Tropical storm Erin both occurred in August of 2007 and both caused wide spread damages. Hurricane Dean's destruction was felt primarily in the gulf coast and Mexico, where as Erin caused flooding in Texas and Oklahoma.	4	3

Notes: This table presents the number of negative and significant coefficients on the interaction term, CRS x Zone x Post # Months, across all six specifications for each storm and each dataset. In column "All Sales" we denote the number for the regressions that utilize all sales and in the column "Repeated Sales" we denote the number for the specifications that considered only repeated sales.

Table A10: Regression Results for Average Claims on CRS

Variables:	(1) Avg Claims	(2) Avg Claims	(3) Avg Claims	(4) Avg Claims
CRS Public Info and Maps Par	-2,712	-3,802	-3,498	-1,235
	(980.0)	(897.9)	(868.6)	(1,624)
Constant	11,003	6,782	5,892	20,232
	(600.5)	(1,769)	(2,297)	(6,553)
Year FE	N	Y	Y	Y
Month FE	N	N	Y	Y
Municipality FE	N	N	N	Y
Observations	2,200	2,200	2,200	2,200
R-squared	0.003	0.210	0.268	0.364

Robust standard errors in parentheses. Dependent variable is listed in the column header.

Table A11: Triple Difference Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and with Additional Control for Flooding

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Maps Par	0.106	0.101	0.0894	0.0826	0.0778	0.0734
	(0.0290)	(0.0288)	(0.0283)	(0.0271)	(0.0267)	(0.0264)
CRS x Zone	-0.0611	-0.0572	-0.0443	-0.0374	-0.0355	-0.0325
	(0.0315)	(0.0313)	(0.0308)	(0.0297)	(0.0293)	(0.0291)
Age	-0.00140	-0.00137	-0.00137	-0.00141	-0.00146	-0.00147
	(0.000383)	(0.000372)	(0.000366)	(0.000358)	(0.000350)	(0.000341)
Living Space	1.50e-05	1.63e-05	1.73e-05	1.80e-05	1.94e-05	2.05e-05
	(1.14e-05)	(1.22e-05)	(1.27e-05)	(1.29e-05)	(1.37e-05)	(1.43e-05)
Total Mo Sales/Avg Mo Sales	-0.00160	-0.00442	-0.00561	-0.00449	-0.00322	-0.00217
	(0.00828)	(0.00813)	(0.00783)	(0.00759)	(0.00730)	(0.00710)
Total Mo Sales	-0.000154	-7.19e-05	-2.16e-05	3.42e-06	6.22e-05	0.000134
	(0.000129)	(0.000125)	(0.000120)	(0.000116)	(0.000112)	(0.000108)
Lag Air Pollution	0.000345	0.000387	0.000480	0.000449	0.000541	0.000549
	(0.000405)	(0.000396)	(0.000385)	(0.000378)	(0.000365)	(0.000361)
Air Pollution	-0.000497	-0.000512	-0.000513	-0.000543	-0.000421	-0.000484
	(0.000401)	(0.000389)	(0.000383)	(0.000378)	(0.000372)	(0.000365)
Total New Builds	-7.70e-05	-8.53e-05	-0.000112	-0.000118	-9.88e-05	-0.000112
	(9.39e-05)	(9.22e-05)	(9.03e-05)	(8.84e-05)	(8.42e-05)	(8.32e-05)
Total Value New Builds	0.00424	0.00452	0.00554	0.00596	0.00591	0.00600
	(0.00201)	(0.00195)	(0.00190)	(0.00182)	(0.00169)	(0.00165)
Disaster Declared	-0.00668	-0.00578	-0.00612	-0.00446	-0.0111	-0.00425
	(0.00676)	(0.00669)	(0.00655)	(0.00637)	(0.00576)	(0.00560)
Post # Months	-0.0301	-0.0319	-0.0315	-0.0287	-0.0281	-0.0250
	(0.0108)	(0.00923)	(0.00898)	(0.00881)	(0.00860)	(0.00847)
Zone X Post # Months	0.124	0.114	0.122	0.123	0.127	0.126
	(0.0298)	(0.0232)	(0.0184)	(0.0159)	(0.0139)	(0.0128)
CRS X Post # Mos	-0.0379	0.0423	0.0517	0.0647	0.0695	0.0807
	(0.0416)	(0.0610)	(0.0472)	(0.0396)	(0.0347)	(0.0322)
CRS X Zone X Post # Mos	-0.0575	-0.105	-0.117	-0.140	-0.145	-0.157
	(0.0559)	(0.0679)	(0.0533)	(0.0452)	(0.0397)	(0.0370)
Constant	11.61	11.57	11.56	11.57	11.57	11.56
	(0.0319)	(0.0351)	(0.0320)	(0.0305)	(0.0293)	(0.0289)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A12: Triple Difference Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and CRS ever participating towns

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Info and Map Par.	0.0445	0.0437	0.0351	0.0319	0.0279	0.0252
	(0.0324)	(0.0322)	(0.0314)	(0.0304)	(0.0302)	(0.0299)
CRS x Zone	-0.0482	-0.0481	-0.0385	-0.0329	-0.0321	-0.0320
	(0.0315)	(0.0311)	(0.0303)	(0.0294)	(0.0291)	(0.0287)
Age	-0.00159	-0.00154	-0.00157	-0.00160	-0.00166	-0.00169
	(0.000437)	(0.000427)	(0.000415)	(0.000405)	(0.000386)	(0.000368)
Living Space	5.08e-05	5.75e-05	6.23e-05	6.67e-05	7.04e-05	7.41e-05
	(3.11e-05)	(3.33e-05)	(3.44e-05)	(3.55e-05)	(3.61e-05)	(3.71e-05)
Mo Sales/Avg Mo Sales	0.00350	0.000897	0.00171	0.00234	0.00186	0.00407
	(0.0123)	(0.0122)	(0.0117)	(0.0114)	(0.0110)	(0.0108)
Mo Sales	-0.000104	-4.51e-05	-3.77e-05	1.37e-05	9.21e-05	0.000144
	(0.000170)	(0.000166)	(0.000160)	(0.000156)	(0.000151)	(0.000146)
Lag Air Pollution	2.44e-05	9.32e-05	0.000261	0.000499	0.000647	0.000767
	(0.000697)	(0.000681)	(0.000663)	(0.000651)	(0.000633)	(0.000628)
Air Pollution	-0.000919	-0.000795	-0.000836	-0.000889	-0.000782	-0.000739
	(0.000701)	(0.000685)	(0.000680)	(0.000667)	(0.000660)	(0.000650)
Total New Builds	-0.000163	-0.000157	-0.000190	-0.000186	-0.000186	-0.000193
	(0.000173)	(0.000171)	(0.000167)	(0.000162)	(0.000157)	(0.000154)
Total Value New Builds	0.00885	0.00877	0.00966	0.0104	0.0105	0.0106
	(0.00334)	(0.00333)	(0.00326)	(0.00315)	(0.00315)	(0.00311)
Post # Months	-0.0535	-0.0533	-0.0543	-0.0504	-0.0457	-0.0408
	(0.0228)	(0.0191)	(0.0183)	(0.0176)	(0.0170)	(0.0166)
Zone X Post # Months	0.103	0.114	0.118	0.116	0.116	0.105
	(0.0381)	(0.0377)	(0.0299)	(0.0241)	(0.0213)	(0.0195)
CRS X Post # Mos	-0.0283	0.0510	0.0576	0.0687	0.0664	0.0745
	(0.0475)	(0.0581)	(0.0458)	(0.0392)	(0.0346)	(0.0320)
CRS X Zone X Post Mos	-0.0464	-0.125	-0.126	-0.142	-0.144	-0.147
	(0.0623)	(0.0671)	(0.0542)	(0.0461)	(0.0404)	(0.0374)
Constant	11.64	11.62	11.61	11.59	11.58	11.58
	(0.0615)	(0.0651)	(0.0629)	(0.0624)	(0.0629)	(0.0632)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	23,023	23,379	23,715	24,164	24,620	24,967
R-squared	0.982	0.981	0.980	0.979	0.978	0.978

Robust standard errors in parentheses. Dataset is limited to municipalities who participate in CRS at some point. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A13: Triple Difference Using CRS Class 8 or Above Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Class 8 or Above	0.194	0.189	0.192	0.189	0.190	0.189
	(0.0365)	(0.0366)	(0.0360)	(0.0346)	(0.0343)	(0.0340)
CRS x Zone	-0.0261	-0.0215	-0.0249	-0.0253	-0.0287	-0.0292
	(0.0398)	(0.0397)	(0.0389)	(0.0375)	(0.0371)	(0.0368)
Age	-0.00127	-0.00124	-0.00125	-0.00130	-0.00136	-0.00137
	(0.000371)	(0.000362)	(0.000358)	(0.000351)	(0.000344)	(0.000337)
Living Space	1.55e-05	1.68e-05	1.79e-05	1.86e-05	2.00e-05	2.11e-05
	(1.18e-05)	(1.26e-05)	(1.32e-05)	(1.34e-05)	(1.41e-05)	(1.47e-05)
Mo Sales/Avg Mo Sales	-0.00171	-0.00421	-0.00491	-0.00397	-0.00237	-0.00149
	(0.00821)	(0.00810)	(0.00782)	(0.00760)	(0.00732)	(0.00712)
Mo Sales	-8.87e-05	-1.45e-05	2.99e-05	5.18e-05	0.000115	0.000177
	(0.000128)	(0.000124)	(0.000119)	(0.000116)	(0.000112)	(0.000108)
Lag Air Pollution	0.000267	0.000309	0.000408	0.000393	0.000455	0.000499
	(0.000402)	(0.000393)	(0.000382)	(0.000375)	(0.000363)	(0.000359)
Air Pollution	-0.000511	-0.000530	-0.000532	-0.000562	-0.000428	-0.000505
	(0.000399)	(0.000387)	(0.000381)	(0.000376)	(0.000370)	(0.000363)
Total New Builds	-6.85e-05	-7.33e-05	-0.000102	-0.000111	-9.06e-05	-0.000105
	(9.37e-05)	(9.20e-05)	(9.02e-05)	(8.82e-05)	(8.42e-05)	(8.31e-05)
Total Value New Builds	0.00351	0.00382	0.00481	0.00533	0.00522	0.00542
	(0.00200)	(0.00193)	(0.00189)	(0.00181)	(0.00169)	(0.00164)
Post # Months	-0.0262	-0.0271	-0.0274	-0.0246	-0.0230	-0.0210
	(0.0106)	(0.00910)	(0.00883)	(0.00866)	(0.00847)	(0.00835)
Zone X Post # Months	0.121	0.115	0.121	0.121	0.124	0.122
	(0.0301)	(0.0235)	(0.0188)	(0.0167)	(0.0145)	(0.0134)
CRS X Post # Mos	-0.0730	0.00633	0.0430	0.0427	0.0531	0.0623
	(0.0348)	(0.0480)	(0.0418)	(0.0320)	(0.0300)	(0.0290)
CRS X Zone X Post # Mos	-0.0164	-0.0823	-0.115	-0.118	-0.126	-0.134
	(0.0509)	(0.0566)	(0.0482)	(0.0383)	(0.0354)	(0.0340)
Constant	11.60	11.56	11.55	11.56	11.56	11.55
	(0.0318)	(0.0349)	(0.0318)	(0.0304)	(0.0292)	(0.0289)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A14: Triple Difference Using Increase of CRS 300 Level Activities Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Inc Tot 300s	0.0217	0.0202	0.0210	0.0229	0.0242	0.0219
	(0.0137)	(0.0133)	(0.0131)	(0.0126)	(0.0122)	(0.0121)
CRS x Zone	0.0159	0.0153	0.0141	0.0136	0.0112	0.0125
	(0.0170)	(0.0165)	(0.0163)	(0.0158)	(0.0154)	(0.0153)
Age	-0.00125	-0.00123	-0.00123	-0.00126	-0.00132	-0.00132
	(0.000370)	(0.000362)	(0.000357)	(0.000349)	(0.000342)	(0.000334)
Living Space	1.51e-05	1.63e-05	1.74e-05	1.81e-05	1.95e-05	2.07e-05
	(1.15e-05)	(1.23e-05)	(1.28e-05)	(1.30e-05)	(1.38e-05)	(1.45e-05)
Mo Sales/Avg Mo Sales	-0.00317	-0.00555	-0.00614	-0.00469	-0.00285	-0.00158
	(0.00826)	(0.00814)	(0.00786)	(0.00761)	(0.00733)	(0.00713)
Mo Sales	-0.000134	-5.70e-05	-1.43e-05	2.59e-06	6.12e-05	0.000116
	(0.000128)	(0.000125)	(0.000120)	(0.000116)	(0.000112)	(0.000109)
Lag Air Pollution	0.000283	0.000335	0.000434	0.000420	0.000494	0.000542
	(0.000404)	(0.000395)	(0.000384)	(0.000376)	(0.000365)	(0.000361)
Air Pollution	-0.000439	-0.000476	-0.000484	-0.000511	-0.000380	-0.000468
	(0.000401)	(0.000389)	(0.000383)	(0.000378)	(0.000372)	(0.000365)
Total New Builds	-7.66e-05	-8.37e-05	-0.000110	-0.000116	-9.57e-05	-0.000112
	(9.41e-05)	(9.24e-05)	(9.04e-05)	(8.85e-05)	(8.43e-05)	(8.32e-05)
Total Value New Builds	0.00463	0.00497	0.00598	0.00640	0.00629	0.00649
	(0.00200)	(0.00194)	(0.00189)	(0.00182)	(0.00169)	(0.00164)
Post # Months	-0.0317	-0.0304	-0.0291	-0.0262	-0.0246	-0.0222
	(0.0105)	(0.00900)	(0.00875)	(0.00860)	(0.00841)	(0.00829)
Zone X Post # Months	0.0932	0.0955	0.102	0.101	0.106	0.105
	(0.0227)	(0.0186)	(0.0152)	(0.0134)	(0.0119)	(0.0111)
CRS X Post # Mos	0.0859	0.0892	-0.121	-0.0894	-0.0768	-0.0857
	(0.0424)	(0.0419)	(0.123)	(0.0988)	(0.0950)	(0.0856)
CRS X Zone X Post # Mos	-0.113	-0.197	0.0108	-0.0555	-0.0870	-0.0935
	(0.0884)	(0.0761)	(0.129)	(0.104)	(0.0998)	(0.0903)
Constant	11.60	11.57	11.56	11.57	11.56	11.56
	(0.0318)	(0.0350)	(0.0318)	(0.0304)	(0.0291)	(0.0287)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A15: Triple Difference Using Top Participation in All Public CRS Actions Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS Public Actions High	-0.123	-0.126	-0.123	-0.124	-0.124	-0.134
	(0.0425)	(0.0419)	(0.0418)	(0.0411)	(0.0407)	(0.0402)
CRS x Zone	0.0575	0.0597	0.0566	0.0586	0.0563	0.0638
	(0.0439)	(0.0432)	(0.0431)	(0.0423)	(0.0419)	(0.0414)
Age	-0.00115	-0.00113	-0.00113	-0.00117	-0.00124	-0.00125
	(0.000367)	(0.000358)	(0.000353)	(0.000347)	(0.000340)	(0.000333)
Living Space	1.55e-05	1.67e-05	1.78e-05	1.86e-05	1.99e-05	2.11e-05
	(1.18e-05)	(1.26e-05)	(1.32e-05)	(1.34e-05)	(1.42e-05)	(1.48e-05)
Mo Sales/Avg Mo Sales	-0.00288	-0.00564	-0.00666	-0.00541	-0.00379	-0.00289
	(0.00829)	(0.00817)	(0.00788)	(0.00763)	(0.00735)	(0.00715)
Mo Sales	-9.56e-05	-1.69e-05	3.08e-05	5.20e-05	0.000115	0.000181
	(0.000129)	(0.000126)	(0.000120)	(0.000117)	(0.000112)	(0.000109)
Lag Air Pollution	0.000268	0.000308	0.000405	0.000383	0.000444	0.000492
	(0.000403)	(0.000394)	(0.000383)	(0.000376)	(0.000364)	(0.000360)
Air Pollution	-0.000503	-0.000529	-0.000534	-0.000562	-0.000431	-0.000509
	(0.000400)	(0.000389)	(0.000383)	(0.000377)	(0.000371)	(0.000364)
Total New Builds	-8.67e-05	-9.26e-05	-0.000117	-0.000122	-9.94e-05	-0.000114
	(9.40e-05)	(9.23e-05)	(9.03e-05)	(8.84e-05)	(8.43e-05)	(8.32e-05)
Total Value New Builds	0.00499	0.00527	0.00619	0.00662	0.00642	0.00663
	(0.00201)	(0.00195)	(0.00190)	(0.00182)	(0.00169)	(0.00165)
Post # Months	-0.0285	-0.0295	-0.0287	-0.0253	-0.0236	-0.0213
	(0.0106)	(0.00912)	(0.00889)	(0.00870)	(0.00852)	(0.00840)
Zone X Post # Months	0.123	0.112	0.121	0.118	0.121	0.118
	(0.0284)	(0.0222)	(0.0174)	(0.0151)	(0.0132)	(0.0122)
CRS X Post # Mos	-0.0551	0.0332	0.0516	0.0630	0.0729	0.0798
	(0.0374)	(0.0524)	(0.0526)	(0.0439)	(0.0414)	(0.0399)
CRS X Zone X Post # Mos	-0.0375	-0.0972	-0.129	-0.150	-0.154	-0.160
	(0.0526)	(0.0606)	(0.0583)	(0.0490)	(0.0458)	(0.0440)
Constant	11.60	11.57	11.56	11.57	11.57	11.56
	(0.0320)	(0.0350)	(0.0320)	(0.0306)	(0.0292)	(0.0289)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,138	61,111	62,137	63,449	64,650	65,626
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A16: Triple Difference Hedonic Regression Models for Hurricane Katrina with using CRS Participation without Increases in Information and Limited to Repeated Residential Sales

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
CRS (No increase in Information)	-0.0217	-0.0211	-0.0201	-0.0226	-0.0257	-0.0240
	(0.0136)	(0.0133)	(0.0131)	(0.0126)	(0.0123)	(0.0122)
CRS x Zone	-0.0130	-0.0110	-0.00932	-0.00565	0.000505	0.00282
	(0.0169)	(0.0166)	(0.0162)	(0.0157)	(0.0153)	(0.0152)
Age	-0.00123	-0.00122	-0.00122	-0.00126	-0.00133	-0.00133
	(0.000369)	(0.000361)	(0.000356)	(0.000348)	(0.000342)	(0.000333)
Living Space	1.51e-05	1.63e-05	1.73e-05	1.80e-05	1.93e-05	2.04e-05
	(1.14e-05)	(1.22e-05)	(1.28e-05)	(1.29e-05)	(1.36e-05)	(1.43e-05)
Mo Sales/Avg Mo Sales	-0.00295	-0.00585	-0.00707	-0.00579	-0.00430	-0.00333
	(0.00824)	(0.00816)	(0.00787)	(0.00761)	(0.00732)	(0.00713)
Mo Sales	-0.000145	-5.20e-05	7.26e-06	3.85e-05	0.000113	0.000187
	(0.000128)	(0.000126)	(0.000121)	(0.000117)	(0.000113)	(0.000110)
Lag Air Pollution	0.000284	0.000331	0.000425	0.000401	0.000471	0.000513
	(0.000404)	(0.000395)	(0.000383)	(0.000376)	(0.000365)	(0.000361)
Air Pollution	-0.000446	-0.000477	-0.000481	-0.000517	-0.000390	-0.000486
	(0.000400)	(0.000389)	(0.000383)	(0.000377)	(0.000371)	(0.000364)
Total New Builds	-7.47e-05	-8.53e-05	-0.000111	-0.000115	-9.18e-05	-0.000105
	(9.39e-05)	(9.23e-05)	(9.04e-05)	(8.85e-05)	(8.45e-05)	(8.34e-05)
Total Value New Builds	0.00465	0.00497	0.00595	0.00634	0.00620	0.00633
	(0.00200)	(0.00194)	(0.00190)	(0.00182)	(0.00169)	(0.00165)
Post # Months	-0.0265	-0.0295	-0.0301	-0.0272	-0.0260	-0.0244
	(0.0109)	(0.00943)	(0.00910)	(0.00885)	(0.00861)	(0.00847)
Zone X Post # Months	0.104	0.0707	0.0840	0.0755	0.0780	0.0748
	(0.0398)	(0.0278)	(0.0221)	(0.0191)	(0.0171)	(0.0161)
CRS X Post # Mos	-0.0328	-0.00374	0.00524	0.00729	0.0112	0.0184
	(0.0260)	(0.0265)	(0.0213)	(0.0174)	(0.0150)	(0.0141)
CRS X Zone X Post Mos	0.00285	0.0367	0.0195	0.0289	0.0298	0.0268
	(0.0519)	(0.0453)	(0.0356)	(0.0303)	(0.0265)	(0.0248)
Constant	11.61	11.57	11.56	11.57	11.57	11.56
	(0.0319)	(0.0350)	(0.0320)	(0.0305)	(0.0292)	(0.0288)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	60,242	61,216	62,245	63,557	64,761	65,737
R-squared	0.980	0.979	0.978	0.977	0.977	0.976

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A2 for more information.

Table A17: Activities in Alternative Definition of CRS

Activity Number	Description
320	Map Information
330	Public Outreach Projects
340	Hazard Disclosure
350	Flood Protection Information
360	Flood Protection Assistance
410	Floodplain Mapping
440	Flood Data Maintenance
510	Floodplain Management Planning
610	Flood Warning and Response
620	Flood Warning and Response - Levees
630	Flood Warning and Response - Dams

Table A18: Triple Difference Using Buyer Type Hedonic Regression Models for Hurricane Katrina Inclusive of All Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
Outside Buyer (OB)	0.0558	0.0536	0.0531	0.0544	0.0541	0.0548
	(0.0145)	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)
Zone High Risk	0.152	0.148	0.147	0.150	0.150	0.151
	(0.0154)	(0.0153)	(0.0152)	(0.0152)	(0.0151)	(0.0151)
OB x Zone	-0.0352	-0.0333	-0.0325	-0.0341	-0.0341	-0.0351
	(0.0169)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Age	-0.00234	-0.00234	-0.00228	-0.00231	-0.00231	-0.00228
	(0.000156)	(0.000153)	(0.000152)	(0.000149)	(0.000147)	(0.000146)
Living Space	0.000452	0.000449	0.000450	0.000451	0.000451	0.000451
	(7.75e-06)	(7.60e-06)	(7.50e-06)	(7.37e-06)	(7.26e-06)	(7.16e-06)
Total Mo Sales/Avg Mo Sales	-0.0434	-0.0498	-0.0581	-0.0606	-0.0663	-0.0687
	(0.0162)	(0.0160)	(0.0159)	(0.0157)	(0.0153)	(0.0151)
Total Mo Sales	0.00184	0.00200	0.00230	0.00243	0.00264	0.00277
	(0.000396)	(0.000387)	(0.000391)	(0.000380)	(0.000369)	(0.000363)
Lag Air Pollution	-0.00246	-0.00255	-0.00234	-0.00229	-0.00227	-0.00239
	(0.00109)	(0.00109)	(0.00108)	(0.00107)	(0.00106)	(0.00106)
Air Pollution	-0.00150	-0.00171	-0.00167	-0.00173	-0.00157	-0.00184
	(0.00113)	(0.00112)	(0.00112)	(0.00111)	(0.00110)	(0.00110)
Total New Builds	-0.000480	-0.000421	-0.000275	-0.000133	-2.45e-05	-2.14e-05
	(0.000321)	(0.000319)	(0.000314)	(0.000311)	(0.000308)	(0.000307)
Total Value New Builds	0.0272	0.0268	0.0251	0.0246	0.0247	0.0230
	(0.00519)	(0.00516)	(0.00493)	(0.00492)	(0.00486)	(0.00482)
Post # Months	-0.0251	-0.0730	-0.0540	-0.0527	-0.0443	-0.0284
	(0.0527)	(0.0387)	(0.0342)	(0.0324)	(0.0303)	(0.0301)
Zone X Post # Months	0.0724	0.0489	0.0690	0.0407	0.0450	0.0328
	(0.0681)	(0.0501)	(0.0428)	(0.0382)	(0.0339)	(0.0317)
OB X Post # Mos	-0.0653	0.0511	0.0622	0.0587	0.0550	0.0233
	(0.0793)	(0.0600)	(0.0479)	(0.0406)	(0.0359)	(0.0342)
OB X Zone X Post # Mos	0.0808	0.00806	-0.0653	-0.0264	-0.0405	-0.0101
	(0.0959)	(0.0728)	(0.0604)	(0.0514)	(0.0456)	(0.0426)
Constant	10.82	10.83	10.85	10.85	10.85	10.87
	(0.0785)	(0.0779)	(0.0755)	(0.0751)	(0.0744)	(0.0737)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	20,982	21,411	21,866	22,392	22,838	23,221
R-squared	0.667	0.669	0.665	0.666	0.666	0.666

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A19: Triple Difference Using Buyer Type Hedonic Regression Models for Hurricane Katrina Limited to Repeated Residential Sales and with Controls

Dep Var: Log Price	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
Outside Buyer (OB)	-0.0218	-0.0260	-0.0290	-0.0292	-0.0371	-0.0405
	(0.0309)	(0.0297)	(0.0286)	(0.0278)	(0.0269)	(0.0262)
OB x Zone	0.0221	0.0267	0.0310	0.0342	0.0450	0.0498
	(0.0352)	(0.0338)	(0.0326)	(0.0317)	(0.0307)	(0.0300)
Age	-0.00141	-0.00934	-0.00885	-0.0139	-0.0135	-0.00988
	(0.0218)	(0.0224)	(0.0222)	(0.0218)	(0.0208)	(0.0202)
Living Space	0.000314	0.000463	0.000522	0.000783	0.000719	0.000767
	(0.000496)	(0.000497)	(0.000491)	(0.000478)	(0.000457)	(0.000432)
Total Mo Sales/Avg Mo Sales	-0.00334	-0.00337	-0.00348	-0.00357	-0.00359	-0.00360
	(0.000555)	(0.000542)	(0.000534)	(0.000521)	(0.000507)	(0.000491)
Total Mo Sales	0.000104	0.000115	0.000121	0.000131	0.000134	0.000139
	(2.45e-05)	(2.44e-05)	(2.31e-05)	(2.33e-05)	(2.26e-05)	(2.24e-05)
Lag Air Pollution	0.00154	0.00158	0.00181	0.00203	0.00207	0.00228
	(0.00155)	(0.00151)	(0.00148)	(0.00147)	(0.00144)	(0.00143)
Air Pollution	-0.000809	-0.000791	-0.000479	-0.000772	-0.000825	-0.00116
	(0.00156)	(0.00152)	(0.00150)	(0.00147)	(0.00145)	(0.00142)
Total New Builds	-0.000430	-0.000392	-0.000373	-0.000220	-0.000161	-0.000188
	(0.000412)	(0.000408)	(0.000398)	(0.000390)	(0.000381)	(0.000375)
Total Value New Builds	0.00799	0.00697	0.00699	0.00812	0.00765	0.00798
	(0.00653)	(0.00639)	(0.00617)	(0.00618)	(0.00609)	(0.00605)
Post Months	-0.0777	-0.0645	-0.0804	-0.0542	-0.0582	-0.0505
	(0.0885)	(0.0751)	(0.0661)	(0.0620)	(0.0575)	(0.0540)
Zone X Post # Months	0.0387	0.0328	0.0538	0.0150	0.0283	0.0181
	(0.117)	(0.103)	(0.0855)	(0.0734)	(0.0664)	(0.0609)
OB X Post # Months	-0.0329	0.0167	0.0306	0.0115	0.0174	0.0192
	(0.0969)	(0.118)	(0.0911)	(0.0835)	(0.0728)	(0.0668)
OB X Zone X Post # Mos	0.0286	-0.0466	-0.0601	-0.0336	-0.0506	-0.0487
	(0.128)	(0.128)	(0.105)	(0.0949)	(0.0827)	(0.0764)
Constant	11.82	11.79	11.79	11.76	11.76	11.75
	(0.102)	(0.108)	(0.0983)	(0.0977)	(0.0949)	(0.0934)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	N	N	N	N	N	N
House FE	Y	Y	Y	Y	Y	Y
Observations	7,814	7,929	8,044	8,177	8,283	8,372
R-squared	0.987	0.986	0.985	0.985	0.984	0.984

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A20: Cross Tabulation Across Resident Groups

		CRS	Non-CRS	Total
Primary Resident:				
	Zone High Risk	7,966	16,977	24,943
	Zone Low Risk	4,064	113,085	117,149
	Total	12,030	130,062	142,092
Non Resident:				
	Zone High Risk	22,418	25,384	47,802
	Zone Low Risk	8,913	73,775	82,688
	Total	31,331	99,159	130,490
All Residents				
	Zone High Risk	30,384	42,361	72,745
	Zone Low Risk	12,977	186,860	199,837
	Total	43,361	229,221	272,582

Note: Non-CRS refers to any municipality that does not meet our definition of CRS participation.

Table A21: Linear Probability Model of a Sale Before and After Hurricane Katrina

Variables:	(1) Sold
Post 12 Months	0.0126
	(0.000218)
Non-resident Sell	-0.986
	(0.000216)
Non-resident Sell x Post 12 Months	-0.0126
	(0.000216)
CRS Public Info and Maps Par.	0.000515
	(0.000107)
Zone High Risk	0.000259
	(2.28e-05)
CRS x Zone	-0.000551
	(6.32e-05)
Average Sales	0.0847
	(0.00129)
Number Sales Over Average	0.00184
	(2.78e-05)
Average Price	-0.000279
	(3.86e-05)
Average Lag Pollution	-2.29e-06
	(2.12e-06)
Average Pollution	2.67e-06
	(2.12e-06)
Total New Units	-3.34e-07
	(4.50e-07)
Total New Value	-6.67e-06
	(6.84e-06)
Constant	0.250
	(0.0112)
Year FE	Y
Month FE	Y
County-Year FE	Y
Municipality FE	Y
House FE	N
Observations	43,989,189
R-squared	0.542

Robust standard errors in parentheses. Dependent variable is listed in column header

Table A22: Linear Probability Model of a Non-Resident Sale Before and After Hurricane Katrina

Dep Var: Non-Resident Sale	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
Zone High Risk	0.0951	0.0937	0.0949	0.0959	0.0950	0.0952
	(0.00552)	(0.00544)	(0.00537)	(0.00527)	(0.00520)	(0.00514)
CRS Public Info and Maps Par.	0.0968	0.101	0.0853	0.0755	0.0602	0.0633
	(0.0362)	(0.0354)	(0.0340)	(0.0320)	(0.0304)	(0.0292)
CRS x Zone	-0.138	-0.136	-0.133	-0.134	-0.133	-0.133
	(0.0101)	(0.00992)	(0.00980)	(0.00963)	(0.00950)	(0.00938)
Age	1.01e-05	1.33e-05	8.96e-06	9.34e-06	1.66e-05	1.32e-05
	(6.38e-05)	(6.27e-05)	(6.18e-05)	(6.07e-05)	(5.98e-05)	(5.91e-05)
Living Space	-4.44e-05	-4.48e-05	-4.50e-05	-4.53e-05	-4.53e-05	-4.54e-05
	(1.07e-05)	(1.05e-05)	(1.03e-05)	(1.01e-05)	(9.78e-06)	(9.61e-06)
Average Price	-0.0587	-0.0609	-0.0586	-0.0596	-0.0608	-0.0679
	(0.0151)	(0.0148)	(0.0146)	(0.0142)	(0.0140)	(0.0137)
Average Month Sales	-0.00347	-0.00203	-0.00190	-0.000972	-7.16e-05	0.000801
	(0.00215)	(0.00207)	(0.00196)	(0.00185)	(0.00176)	(0.00170)
Total Mo Sales/Avg Mo Sales	-0.00293	-0.00146	-0.000970	0.000219	0.00260	0.00356
	(0.00486)	(0.00481)	(0.00477)	(0.00469)	(0.00460)	(0.00453)
Lag Air Pollution	-7.95e-05	-8.35e-05	-0.000151	-0.000198	-0.000150	-0.000231
	(0.000490)	(0.000489)	(0.000484)	(0.000478)	(0.000474)	(0.000470)
Air Pollution	-0.000120	-0.000129	-0.000132	-8.20e-05	-8.08e-05	-0.000125
	(0.000488)	(0.000481)	(0.000479)	(0.000477)	(0.000472)	(0.000467)
Total New Builds	-9.16e-05	-9.86e-05	-9.59e-05	-8.15e-05	-7.88e-05	-7.32e-05
	(9.67e-05)	(9.62e-05)	(9.55e-05)	(9.47e-05)	(9.37e-05)	(9.28e-05)
Total Value New Builds	0.000674	0.000781	0.00124	0.00106	0.000988	0.000517
	(0.00155)	(0.00153)	(0.00151)	(0.00148)	(0.00143)	(0.00141)
Percentage Homes Zone High	-0.315	-0.133	-0.0921	-0.0247	0.145	0.241
	(0.249)	(0.239)	(0.223)	(0.207)	(0.198)	(0.192)
Percentage Homes Non-resident	-0.109	-0.236	-0.246	-0.335	-0.522	-0.589
	(0.251)	(0.241)	(0.231)	(0.221)	(0.211)	(0.204)
Total Population	5.95e-06	1.25e-06	9.09e-07	-2.42e-06	-5.50e-06	-8.14e-06
	(7.77e-06)	(7.46e-06)	(7.09e-06)	(6.70e-06)	(6.34e-06)	(6.11e-06)
Post # Month	0.0121	0.0128	0.0129	0.0130	0.0131	0.0131
	(0.00881)	(0.00759)	(0.00759)	(0.00759)	(0.00759)	(0.00759)
Constant	1.263	1.301	1.262	1.295	1.340	1.434
	(0.182)	(0.178)	(0.174)	(0.170)	(0.166)	(0.162)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	110,624	113,950	117,220	121,353	125,181	128,364
R-squared	0.217	0.217	0.216	0.216	0.215	0.215

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A23: Linear Probability Model of Non-Resident Purchase Before and After Hurricane Katrina

Dep Var: Non-Resident Buy	(1) 2 Months	(2) 4 Months	(3) 6 Months	(4) 8 Months	(5) 10 Months	(6) 12 Months
Zone High Risk	0.0993	0.0985	0.0980	0.0985	0.0984	0.0979
	(0.00516)	(0.00508)	(0.00502)	(0.00494)	(0.00488)	(0.00481)
CRS Public Info and Maps Par.	0.0852	0.0851	0.0671	0.0353	0.0382	0.0362
	(0.0353)	(0.0342)	(0.0331)	(0.0316)	(0.0297)	(0.0284)
CRS x Zone	-0.0724	-0.0703	-0.0667	-0.0621	-0.0605	-0.0597
	(0.0101)	(0.00994)	(0.00982)	(0.00967)	(0.00954)	(0.00943)
Age	0.000147	0.000152	0.000151	0.000165	0.000175	0.000183
	(5.81e-05)	(5.71e-05)	(5.62e-05)	(5.53e-05)	(5.44e-05)	(5.37e-05)
Living Space	-3.51e-05	-3.53e-05	-3.55e-05	-3.59e-05	-3.56e-05	-3.53e-05
	(7.17e-06)	(7.04e-06)	(6.92e-06)	(6.81e-06)	(6.57e-06)	(6.38e-06)
Average Price	-0.0451	-0.0458	-0.0466	-0.0448	-0.0461	-0.0427
	(0.0127)	(0.0125)	(0.0122)	(0.0120)	(0.0117)	(0.0114)
Average Month Sales	0.00113	0.00229	0.00208	0.00300	0.00337	0.00317
	(0.00185)	(0.00178)	(0.00170)	(0.00160)	(0.00152)	(0.00147)
Total Mo Sales/Avg Mo Sales	-0.00199	-0.000327	0.000150	0.00113	0.00219	0.00319
	(0.00425)	(0.00421)	(0.00417)	(0.00411)	(0.00403)	(0.00398)
Lag Air Pollution	-0.00142	-0.00147	-0.00147	-0.00145	-0.00139	-0.00134
	(0.000435)	(0.000434)	(0.000429)	(0.000423)	(0.000420)	(0.000416)
Air Pollution	-0.000495	-0.000535	-0.000514	-0.000548	-0.000514	-0.000535
	(0.000431)	(0.000425)	(0.000424)	(0.000422)	(0.000417)	(0.000412)
Total New Builds	1.90e-05	-3.87e-06	-4.95e-06	-5.28e-06	-3.04e-05	-2.56e-05
	(8.09e-05)	(8.06e-05)	(7.99e-05)	(7.91e-05)	(7.84e-05)	(7.77e-05)
Total Value New Builds	-0.000607	-0.000505	-0.000332	0.000241	0.00118	0.000128
	(0.00142)	(0.00140)	(0.00137)	(0.00134)	(0.00129)	(0.00127)
Percentage Homes Zone High	-0.0789	0.104	0.215	0.392	0.532	0.573
	(0.217)	(0.208)	(0.195)	(0.182)	(0.174)	(0.171)
Percentage Homes Non-resident	0.285	0.0689	-0.0407	-0.268	-0.384	-0.366
	(0.242)	(0.233)	(0.224)	(0.214)	(0.203)	(0.199)
Total Population	-9.85e-06	-1.40e-05	-1.35e-05	-1.72e-05	-1.82e-05	-1.72e-05
	(6.65e-06)	(6.39e-06)	(6.10e-06)	(5.75e-06)	(5.44e-06)	(5.27e-06)
Post # Month	-0.00191	-0.00222	-0.00222	-0.00235	-0.00224	-0.00220
	(0.00789)	(0.00682)	(0.00682)	(0.00682)	(0.00681)	(0.00681)
Constant	0.647	0.695	0.724	0.737	0.757	0.720
	(0.157)	(0.154)	(0.150)	(0.147)	(0.143)	(0.140)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
House FE	N	N	N	N	N	N
Observations	110,624	113,950	117,220	121,353	125,181	128,364
R-squared	0.348	0.347	0.346	0.346	0.346	0.345

Robust standard errors in parentheses. Dependent variable is listed in the column header. Column 1 defines the post period as up to 2 months after the storm. Column 2 defines the post period as up to 4 months after the storm. Column 3 defines the post period as up to 6 months after the storm. Column 4 defines the post period as up to 8 months after the storm. Column 5 defines the post period as up to 10 months after the storm. Column 6 defines the post period as up to 12 months after the storm. Post # Months and variables interacted with Post # Months are consistent with these definitions of the post period. See Table A3 for more information.

Table A24: Regression Results for Policy Counts on CRS

Variables:	(1) Policy Count	(2) Policy Count	(3) Policy Count	(4) Policy Count
CRS Public Info and Maps Par	208.8	212.2	212.4	26.57
	(4.238)	(4.218)	(4.208)	(2.537)
Constant	60.95	61.34	48.96	-29.35
	(0.937)	(4.286)	(5.743)	(2.289)
Year FE	N	Y	Y	Y
Month FE	N	N	Y	Y
Municipality FE	N	N	N	Y
Observations	22,067	22,067	22,067	22,067
R-squared	0.196	0.199	0.203	0.936

Robust standard errors in parentheses. Dependent variable is listed in the column header.

A.2 Appendix Figures

Figure A1: Map of Flood Risk in New Jersey Counties

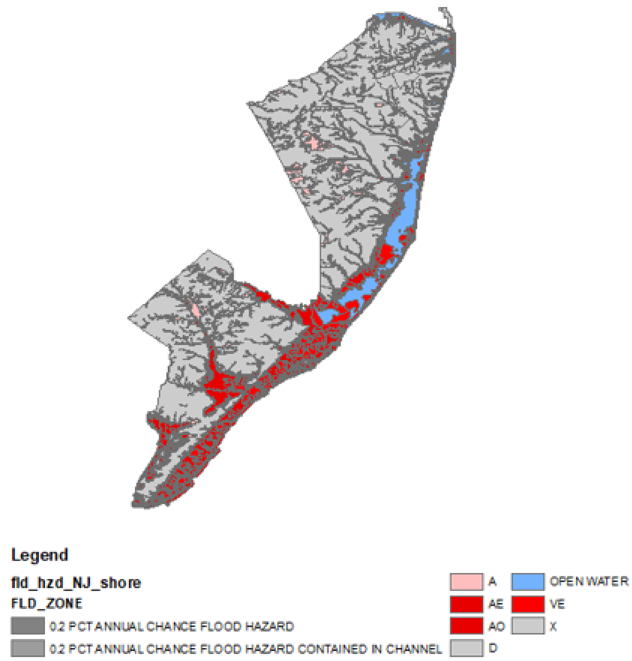


Figure A2: Map of Flood Risk in New Jersey Counties and Housing Sales

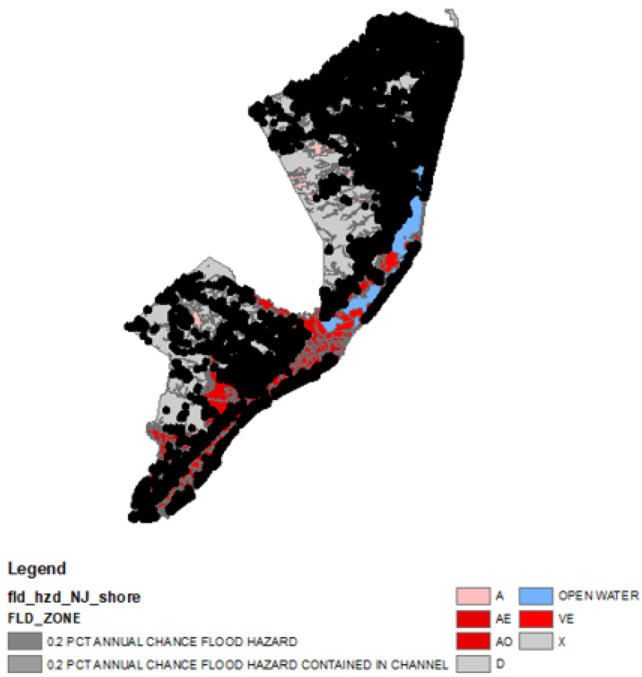


Figure A3: Trends Across All Storms

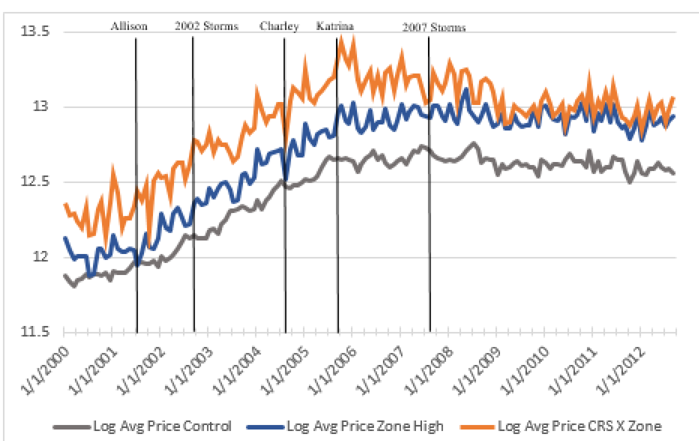


Figure A4: Trends Around Hurricane Katrina

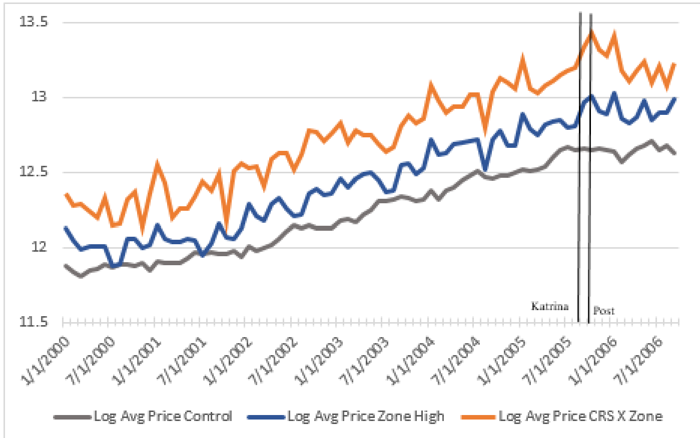
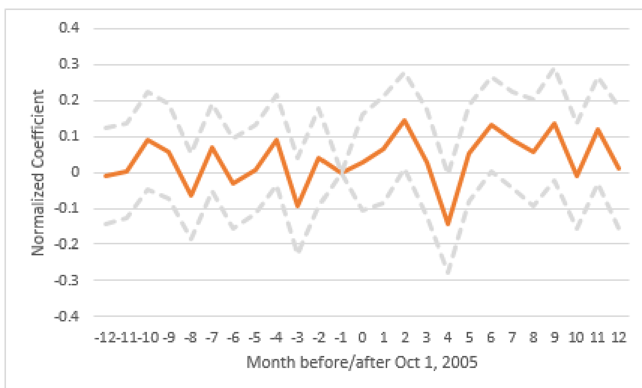
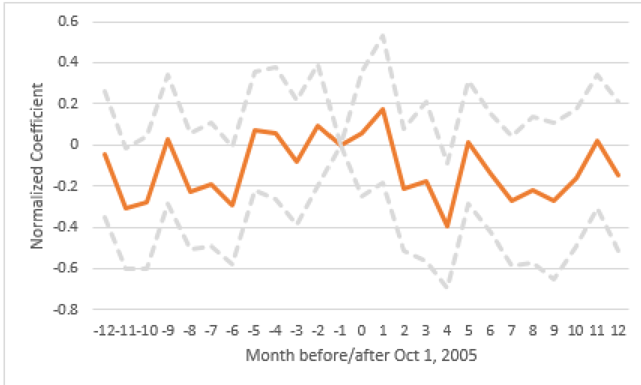


Figure A5: Event Study Coefficients on Zone x Month (All Sales, Municipality FE)



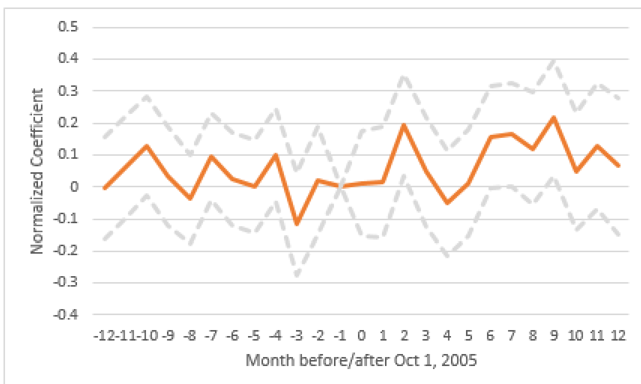
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A6: Event Study Coefficients on CRS x Zone x Month (All Sales, Municipality FE, Other Group Time Trends)



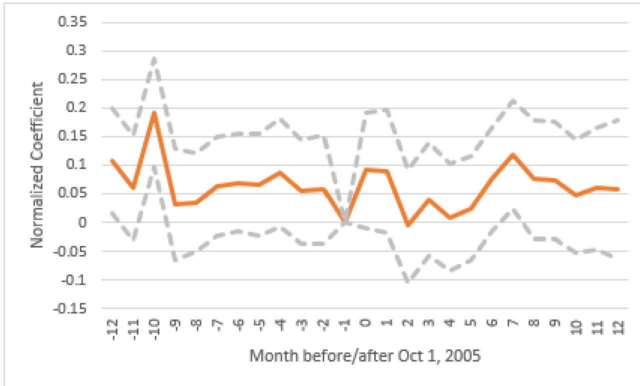
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A7: Event Study Coefficients on Zone x Month (All Sales, Municipality FE, Other Group Time Trends)



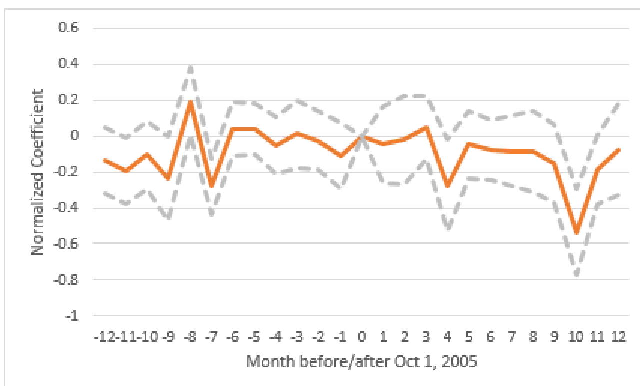
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A8: Event Study Coefficients on Zone x Month (All Sales, House FE)



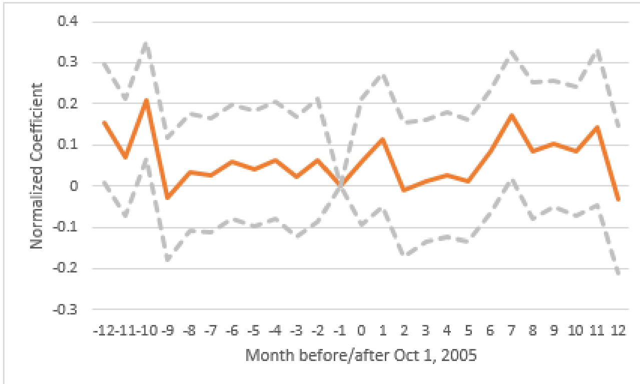
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A9: Event Study Coefficients on CRS x Zone x Month (All Sales, House FE, Other Group Time Trends)



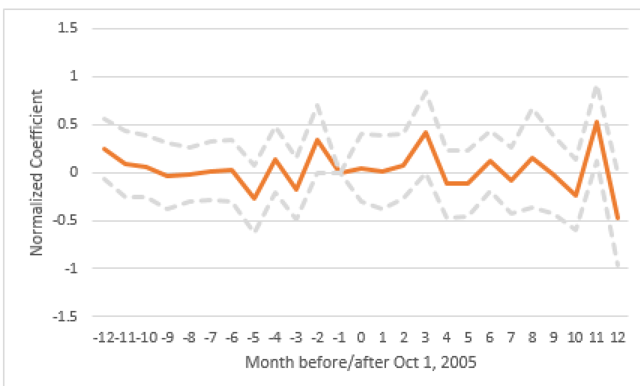
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A10: Event Study Coefficients on Zone x Month (All Sales, House FE, Other Group Time Trends)



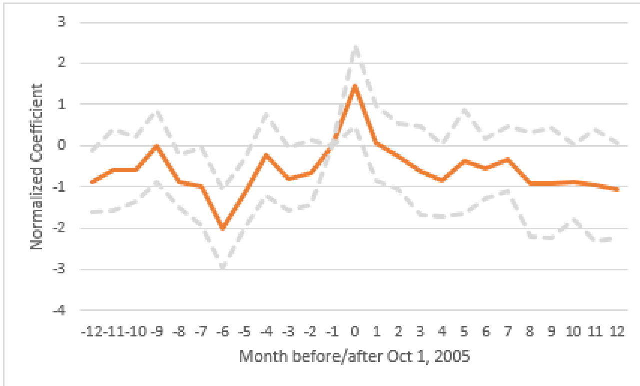
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A11: Event Study Coefficients on Zone x Month (Firm Sales, Municipality FE)



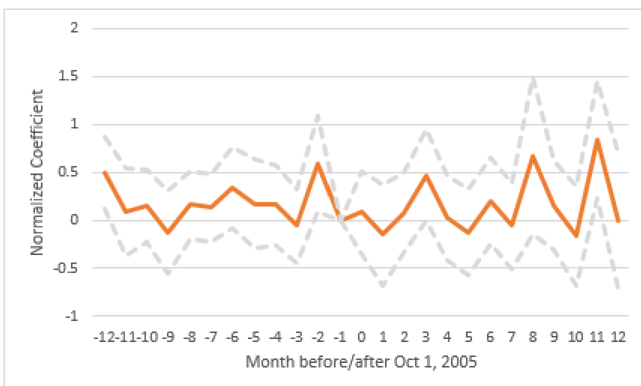
Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A12: Event Study Coefficients on CRS x Zone x Month (Firm Sales, Municipality FE, Other Group Time Trends



Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A13: Event Study Coefficients on Zone x Month (Firm Sales, Municipality FE, Other Group Time Trends)



Coefficients from an event study regression. Time is normalized to the month corresponding to our initial post period i.e. October 1, 2005 is set to 0. The coefficients are normalized such that the coefficient on September 1, 2005 (the month closest to Hurricane Katrina) is equal to zero. The dashed lines represent the 95% confidence interval.

Figure A14: Trends for High Risk and Low Risk Zones

B Appendix to Chapter 2

B.1 Model Proofs

Proposition 1. *Given assumptions 1-4 hold, then an increase in risk or increase in the probability of damages, π, will increase p.*

Proof of Proposition 1. Consider how the optimal p changes given a change in π. From the implicit function theorem yields the linear approximation:

$$\frac{\partial^2 U}{\partial^2 p} \times \partial p + \frac{\partial U}{\partial p \partial \pi} \times \partial \pi = 0 \tag{B1}$$

Rearranging yields:

$$\frac{\partial p}{\partial \pi} = -\frac{\frac{\partial U}{\partial p \partial \pi}}{\frac{\partial^2 U}{\partial^2 p}} \tag{B2}$$

The SOC yields $\frac{\partial^2 U}{\partial^2 p} < 0$. Therefore, proposition 1 holds if $\frac{\partial U}{\partial p \partial \pi} > 0$.

$$\begin{aligned}
\frac{\partial U}{\partial p \partial \pi} = (-1) \times \frac{\partial u(a, W(p))}{\partial W(p)} \times \frac{\partial W(p)}{\partial p} + \Big[\frac{\partial u(a \times \psi(1,p), W(p))}{\partial \psi(1,p)} \\
\times a \times \frac{\partial \psi(1,p)}{\partial p} + \frac{\partial u(a \times \psi(1,p), W(p))}{\partial W(p)} \times \frac{\partial W(p)}{\partial p}\Big] \\
= \frac{\partial u(a \times \psi(1,p), W(p))}{\partial \psi(1,p)} \times a \times \frac{\partial \psi(1,p)}{\partial p} \\
+ \frac{\partial W(p)}{\partial p} \times \Big[\frac{\partial u(a \times \psi(1,p), W(p))}{\partial W(p)} - \frac{\partial u(a, W(p))}{\partial W(p)}\Big]
\end{aligned} \tag{B3}$$

The first term is greater than zero by assumptions 1 and 2. The second term is greater than zero as $\frac{\partial W(p)}{\partial p} < 0$ by assumption 4 and $\frac{\partial u(a \times \psi(1,p), W(p))}{\partial W(p)} < \frac{\partial u(a, W(p))}{\partial W(p)}$ by assumption 3. Therefore, $\frac{\partial U}{\partial p \partial \pi} > 0$ and $\frac{\partial p}{\partial \pi} > 0$ as desired. □

Proposition 2. *Given assumptions 1-4 hold, then an increase in wealth, w, will increase p.*

Proof of Proposition 2. Following the same argument as the proof to proposition 1, I have:

$$\frac{\partial p}{\partial w} = -\frac{\frac{\partial U}{\partial p \partial w}}{\frac{\partial^2 U}{\partial^2 p}} \tag{B4}$$

As before, I need to show $\frac{\partial U}{\partial p \partial w}$

$$\frac{\partial U}{\partial p \partial w} = (1-\pi) \times \frac{\partial^2 u(a, W(p))}{\partial^2 W(p)} \times \frac{\partial W(p)}{\partial p} \times \frac{\partial W(p)}{\partial w} + \pi \times \Big[\frac{\partial u(a \times \psi(1,p), W(p))}{\partial \psi(1,p) \partial W(p)} \times a \times \frac{\partial \psi(1,p)}{\partial p} \times \frac{\partial W(p)}{\partial w} + \frac{\partial^2 u(a \times \psi(1,p), W(p))}{\partial^2 W(p)} \times \frac{\partial W(p)}{\partial p} \times \frac{\partial W(p)}{\partial w}\Big] \tag{B5}$$

By definition of W(p), assumption 2 and assumption 4, I know that the first term is greater than zero. By assumptions 1-3 and the definition of $W(p)$, the second term is greater than zero. By assumptions 2,4 and definition $W(p)$ the last term is also greater than zero. Combining, yields $\frac{\partial U}{\partial p \partial w} > 0$ as desired. □

Proposition 3. *Holding tax rate, τ, constant, an increase in housing value, h, will increase p.*

Proof of Proposition 3. The proof of this proposition is straightforward and does not rely on comparative statics. The government budget constraint binds at the optimum and therefore:

$$c_p \times p^* = n \times \tau \times h \tag{B6}$$

Suppose h is increased to $\overline{h}$ then:

$$c_p \times \overline{p}^* = n \times \tau \times \overline{h} \tag{B7}$$

Since I assumed τ is held constant then $\overline{p}^* = \frac{n \times \tau \times \overline{h}}{c_p} > p^* > \frac{n \times \tau \times h}{c_p}$ as desired. □

Proposition 4. *Given assumptions 1-4 hold, an increase in n will increase p.*

Proof of Proposition 4. Following the same argument as the proofs to proposition 1 and 2, I have:

$$\frac{\partial p}{\partial n} = -\frac{\frac{\partial U}{\partial p \partial n}}{\frac{\partial^2 U}{\partial^2 p}} \tag{B8}$$

As before, I need to solve for $\frac{\partial U}{\partial p \partial n}$

$$\frac{\partial U}{\partial p \partial n} = (1-\pi) \times \Big[\frac{\partial^2 u(a, W(p))}{\partial^2 W(p)} \times \frac{\partial W(p)}{\partial p} \times \frac{\partial W(p)}{\partial n} + \frac{\partial u(a,p)}{\partial W(p)} \times \frac{\partial W(p)}{\partial p \partial n}\Big] + \pi \times \Big[\frac{\partial u(a \times \psi(1,p), W(p))}{\partial \psi(1,p) \partial W(p)} \times a \times \frac{\partial \psi(1,p)}{\partial p} \times \frac{\partial W(p)}{\partial n} + \frac{\partial^2 u(a \times \psi(1,p), W(p))}{\partial^2 W(p)} \times \frac{\partial W(p)}{\partial p} \times \frac{\partial W(p)}{\partial n} + \frac{\partial u(a \times \psi(1,p), W(p))}{\partial W(p)} \times \frac{\partial W(p)}{\partial p \partial n}\Big] \tag{B9}$$

By definition of W(p), assumption 2 and assumption 4, I know that the first term and second term are greater than zero. By assumptions 1-3 and the definition of $W(p)$, the third term is greater than zero. By assumptions 2,4 and definition $W(p)$ the last two terms are also greater than zero. Combining, yields $\frac{\partial U}{\partial p \partial n} > 0$ as desired. □

B.2 Model Proofs: Relaxing Assumption on Full Insurance

Suppose I relax the assumption that insurance is equal to 1. If instead, I assume that i a function of risk π and protection p and i is well behaved and concave with respect to both variables and that the cross partials are positive, then the propositions 1-4 of the model will still hold.

Consider the maximization problem in Equation 2.5 and the relaxed assumption on i. The first order condition with respect to hazard protection is now:

$$\begin{aligned}\frac{\partial U(\cdot)}{\partial p} &= (1-\pi) \times \frac{\partial u(a,p)}{\partial W(p)} \times \frac{\partial W(p)}{\partial p} \\ &+ \pi \times \Big[\frac{\partial u(a \times \psi(i,p), W(p))}{\partial \psi(i,p)} \times a \times \Big(\frac{\partial \psi(i,p)}{\partial p} + \frac{\partial \psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p}\Big) \\ &+ \frac{\partial u(a \times \psi(i,p), W(p))}{\partial W(p)} \times \frac{\partial W(p)}{\partial p}\Big] \\ &= 0\end{aligned} \tag{B10}$$

Note that the difference between Equation B.2 and the original FOC is the additional term

$\frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p}$ Taking the derivative of the with respect to P yields the New SOC:

$$\begin{aligned}
\frac{\partial^2 U(\cdot)}{\partial^2 p} = (1-\pi) \times \Big[\frac{\partial^2 u(a,p)}{\partial^2 W(p)} \times (\frac{\partial W(p)}{\partial p})^2 + \frac{\partial u(a,p)}{\partial W(p)} \times \frac{\partial^2 W(p)}{\partial^2 p}\Big] + \pi \\
\times \Big[\frac{\partial^2 u(a \times \psi(1,p), W(p))}{\partial^2 \psi(i,p)} \times a^2 \times \Big(\frac{\partial\psi(i,p)}{\partial p} + \frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p}\Big)^2 \\
+ \frac{\partial u(a \times \psi(i,p), W(p))}{\partial\psi(i,p)\partial W(p)} \times a \times \Big(\frac{\partial\psi(i,p)}{\partial p} + \frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p}\Big) \times \frac{\partial W(p)}{\partial p} \\
+ \frac{\partial u(a \times \psi(i,p), W(p))}{\partial\psi(i,p)} \times a \times \frac{\partial^2\psi(i,p)}{\partial^2 p} + \frac{\partial u(a \times \psi(i,p), W(p))}{\partial\psi(i,p)} \times a \times \frac{\partial^2\psi(i,p)}{\partial^2 i} \\
\times \frac{\partial i}{\partial p}^2 + \frac{\partial u(a \times \psi(i,p), W(p))}{\partial\psi(i,p)} \times a \times \frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial^2 i}{\partial^2 p} \\
+ \frac{\partial^2 u(a \times \psi(i,p), W(p))}{\partial^2 W(p)} \times (\frac{\partial W(p)}{\partial p})^2 + \frac{\partial u(a \times \psi(i,p), W(p))}{\partial W(p)\partial\psi(i,p)} \times \frac{\partial W(p)}{\partial p} \times a \\
\times \Big(\frac{\partial\psi(i,p)}{\partial p} + \frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p}\Big) + \frac{\partial u(a \times \psi(i,p), W(p))}{\partial W(p)} \times \frac{\partial^2 W(p)}{\partial^2 p}\Big]
\end{aligned} \tag{B11}$$

Following the assumptions from the main text, Equation B11 is less than 0 if $\frac{\partial^2 i}{\partial^2 p} \leq 0$ and $\frac{\partial^2\psi(i,p)}{\partial^2 i} \leq 0$. Proposition 3 clearly still holds. And, Propositions 2 and 4 hold as the only additional terms in the cross partials ($\frac{\partial U}{\partial p \partial w}$ and $\frac{\partial U}{\partial p \partial n}$) are greater than zero. Thus, I will just show the proof for Proposition 1.

Proof of Proposition 1. To prove Proposition 1, I just need to show that $\frac{\partial U}{\partial p \partial \pi} > 0$.

$$\begin{aligned}
\frac{\partial U}{\partial p \partial \pi} = \frac{\partial u(a \times \psi(1,p), W(p))}{\partial\psi(1,p)} \times a \times \Big(\frac{\partial\psi(i,p)}{\partial p}\Big) \\
+ \frac{\partial W(p)}{\partial p} \times \Big[\frac{\partial u(a \times \psi(1,p), W(p))}{\partial W(p)} - \frac{\partial u(a, W(p))}{\partial W(p)}\Big] \\
+ \frac{\partial u(a \times \psi(i,p), W(p))}{\partial\psi(i,p)} \times a\Big[\frac{\partial\psi(i,p)}{\partial i} \times \frac{\partial i}{\partial p} \\
+ \pi \times \frac{\partial i}{\partial p} \times \frac{\partial^2\psi(i,p)}{\partial^2 i} + \pi \times \frac{\partial\psi(i,p)}{\partial i}^2 \times \frac{\partial i}{\partial p \partial \pi}\Big]
\end{aligned} \tag{B12}$$

The first and second lines of the simplified equation are still greater than zero because of assumptions 1-4. The last two lines of Equation B12 are greater than 0 as long as the absolute value of $\frac{\partial^2\psi(i,p)}{\partial^2 i}$ is sufficiently small. Therefore, $\frac{\partial U}{\partial p \partial \pi} > 0$ and $\frac{\partial p}{\partial \pi} > 0$ as desired. □

B.3 Empirical Results

In the empirical analysis I discuss additional specifications I run as robustness tests. I include those results here.

Table B1: CRS Participation with a Continuous Risk Measure

VARIABLES	(1) CRS Points	(2) CRS Class
Mayor-Council Indicator = 1	153.9***	0.273***
	(33.79)	(0.0621)
Percent Second Homeowners	7.441***	0.0134***
	(0.796)	(0.00145)
Log(Real Estate Contr.)	-35.71**	-0.0682**
	(17.47)	(0.0318)
Log(Construction Services Contr.)	47.11***	0.0854***
	(16.53)	(0.0308)
Percentage Democrat Voters	0.582	-0.000458
	(1.505)	(0.00276)
Percent Voter Turnout	3.462*	0.00640*
	(1.986)	(0.00360)
Term Length	2.453	0.0161
	(31.43)	(0.0584)
Indicator for Large Government = 1	51.88	0.0644
	(46.24)	(0.0853)
Log(Est. Population)	90.84***	0.162***
	(11.78)	(0.0219)
Log(Per capita Tax from Property Value)	95.35***	0.171***
	(17.60)	(0.0325)
Percent on SNAP	-25.27***	-0.0467***
	(2.612)	(0.00469)
Percentage of Homes at High Risk	10.47***	0.0182***
	(0.565)	(0.00102)
Constant	-2,462***	-14.39***
	(331.0)	(0.605)
Observations	1,598	1,598
R-squared	0.560	0.545

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B2: CRS Participation with Government Size Indicator Controls

VARIABLES	(1) CRS Points	(2) CRS Class
Mayor-Council Indicator = 1	193.2**	0.321**
	(77.78)	(0.144)
Percent Second Homeowners	9.106***	0.0164***
	(0.766)	(0.00139)
Log(Real Estate Contr.)	-31.31*	-0.0606*
	(18.27)	(0.0333)
Log(Construction Services Contr.)	64.58***	0.118***
	(16.36)	(0.0303)
Percentage Democrat Voters	-0.145	-0.000917
	(1.638)	(0.00293)
Percent Voter Turnout	3.128	0.00611*
	(1.960)	(0.00354)
Term Length	165.7***	0.304***
	(37.83)	(0.0711)
Government Size = 4	173.1*	0.321*
	(103.9)	(0.191)
Government Size = 5	153.1***	0.319***
	(51.13)	(0.0971)
Government Size = 6	-183.4	-0.247
	(120.3)	(0.222)
Government Size = 7	203.4**	0.400**
	(82.72)	(0.155)
Government Size = 8	170.2	0.350*
	(104.4)	(0.196)
Government Size = 10	275.6**	0.326
	(120.5)	(0.229)
Log(Est. Population)	90.14***	0.154***
	(14.85)	(0.0278)
Log(Per capita Tax from Property Value)	124.8***	0.222***
	(18.48)	(0.0341)
Percent on SNAP	-25.37***	-0.0454***
	(2.780)	(0.00495)
Indicator for Risk = 1	631.0***	1.105***
	(42.12)	(0.0758)
Constant	-3,612***	-16.42***
	(353.7)	(0.648)
Observations	1,598	1,598
R-squared	0.558	0.544

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B3: CRS Participation By Activity

VARIABLES	(1) C340 Points	(2) C430 Points	(3) C540 Points
Mayor-Council Indicator = 1	0.620**	15.47	20.62***
	(0.295)	(10.97)	(4.755)
Percent Second Homeowners	0.0395***	1.369***	0.616***
	(0.0101)	(0.236)	(0.116)
Log(Real Estate Contr.)	-0.535**	3.475	-7.274**
	(0.260)	(4.805)	(2.906)
Log(Construction Services Contr.)	0.303*	10.26**	8.654***
	(0.170)	(4.925)	(2.299)
Percentage Democrat Voters	0.0406	0.216	-0.719**
	(0.0303)	(0.435)	(0.287)
Percent Voter Turnout	0.0250	0.496	0.331
	(0.0203)	(0.599)	(0.293)
Term Length	0.320	-8.658	20.18***
	(0.321)	(11.62)	(4.567)
Indicator for Large Government = 1	-0.785***	18.02	-16.35**
	(0.283)	(15.91)	(7.109)
Log(Est. Population)	0.189	19.63***	4.263**
	(0.120)	(3.690)	(1.860)
Log(Per capita Tax from Property Value)	0.551***	28.46***	14.96***
	(0.126)	(5.094)	(2.340)
Percent on SNAP	-0.0296**	-5.584***	-2.749***
	(0.0143)	(0.818)	(0.351)
Indicator for Risk = 1	1.121***	96.39***	104.3***
	(0.191)	(11.15)	(6.688)
Constant	-8.777***	-699.1***	-282.4***
	(2.855)	(106.2)	(46.94)
Observations	1,598	1,598	1,598
R-squared	0.138	0.371	0.523

Notes: Dependent variable is defined as CRS total points for each activity. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).

Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B4: CRS Participation (Binary Measures) - Tobit

VARIABLES	(1) CRS	(2) Top CRS Levels
Mayor-Council Indicator = 1	0.0967***	0.0857***
	(0.0195)	(0.0176)
Percent Second Homeowners	0.00539***	0.00387***
	(0.000499)	(0.000451)
Log(Real Estate Contr.)	-0.00870	-0.0251*
	(0.0144)	(0.0131)
Log(Construction Services Contr.)	0.0560***	0.0290***
	(0.0121)	(0.0110)
Percentage Democrat Voters	0.00228*	-0.00209*
	(0.00118)	(0.00107)
Percent Voter Turnout	0.00261**	0.000956
	(0.00112)	(0.00101)
Term Length	0.00524	0.0190
	(0.0203)	(0.0183)
Indicator for Large Government = 1	0.0857***	0.0825***
	(0.0327)	(0.0296)
Log(Est. Population)	0.0565***	0.0431***
	(0.00776)	(0.00702)
Log(Per capita Tax from Property Value)	0.0623***	0.0389***
	(0.00881)	(0.00797)
Percent on SNAP	-0.0126***	-0.00969***
	(0.00145)	(0.00131)
Indicator for Risk = 1	0.456***	0.196***
	(0.0219)	(0.0198)
Observations	1,598	1,598

Notes: Dependent variable is defined as an indicator for participation CRS in column 1 and as an indicator for participation at class 7 or higher in column 2. Includes County-Year fixed effects. Standard errors are in parentheses. Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B5: CRS Participation (Binary Measures) - LPM

VARIABLES	(1) CRS	(2) Top CRS Levels
Mayor-Council Indicator = 1	0.0967***	0.0857***
	(0.0206)	(0.0171)
Percent Second Homeowners	0.00539***	0.00387***
	(0.000507)	(0.000446)
Log(Real Estate Contr.)	-0.00870	-0.0251**
	(0.0123)	(0.0105)
Log(Construction Services Contr.)	0.0560***	0.0290***
	(0.0110)	(0.00974)
Percentage Democrat Voters	0.00228**	-0.00209**
	(0.00105)	(0.000929)
Percent Voter Turnout	0.00261**	0.000956
	(0.00125)	(0.00102)
Term Length	0.00524	0.0190
	(0.0195)	(0.0187)
Indicator for Large Government = 1	0.0857***	0.0825**
	(0.0271)	(0.0323)
Log(Est. Population)	0.0565***	0.0431***
	(0.00714)	(0.00676)
Log(Per capita Tax from Property Value)	0.0623***	0.0389***
	(0.0108)	(0.00928)
Percent on SNAP	-0.0126***	-0.00969***
	(0.00151)	(0.00112)
Indicator for Risk = 1	0.456***	0.196***
	(0.0272)	(0.0219)
Constant	-1.973***	-1.082***
	(0.223)	(0.181)
Observations	1,598	1,598
R-squared	0.530	0.338

Notes: Dependent variable is defined as an indicator for participation CRS in column 1 and as an indicator for participation at class 7 or higher in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B6: CRS Participation - Information Treatment DID

VARIABLES	(1) CRS Points	(2) CRS Class
Mayor-Council Indicator = 1	221.4***	0.396***
	(32.34)	(0.0588)
Post Sandy	423.8**	0.789**
	(176.8)	(0.328)
Flood	100.9***	0.219***
	(29.89)	(0.0545)
Post Sandy X Flood	289.0***	0.515***
	(91.50)	(0.171)
Percent Second Homeowners	8.421***	0.0150***
	(0.770)	(0.00139)
Log(Real Estate Contr.)	-41.56**	-0.0792**
	(17.64)	(0.0320)
Log(Construction Services Contr.)	47.23***	0.0806***
	(16.49)	(0.0302)
Percentage Democrat Voters	-1.466	-0.00418
	(1.592)	(0.00290)
Percent Voter Turnout	1.781	0.00324
	(1.965)	(0.00353)
Term Length	-1.168	-0.000520
	(33.49)	(0.0619)
Indicator for Large Government = 1	60.00	0.0748
	(46.20)	(0.0867)
Log(Est. Population)	86.65***	0.153***
	(11.71)	(0.0217)
Log(Per capita Tax from Property Value)	113.5***	0.200***
	(17.50)	(0.0321)
Percent on SNAP	-23.60***	-0.0438***
	(2.372)	(0.00429)
Indicator for Risk = 1	658.1***	1.143***
	(42.66)	(0.0768)
Constant	-2,435***	-14.20***
	(351.9)	(0.636)
Observations	1,598	1,598
R-squared	0.562	0.550

Notes: Dependent variable is defined as CRS total points in column 1 and CRS Class in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).

Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B7: CRS Participation (Binary Measures) - Government Accountability

VARIABLES	(1) CRS	(2) Top CRS Levels
Mayor-Council Indicator = 1	0.105***	0.0964***
	(0.0218)	(0.0197)
Post Sandy	0.266***	0.310***
	(0.100)	(0.0906)
Post Sandy x Mayor Council	-0.0355	-0.0456
	(0.0385)	(0.0348)
Percent Second Homeowners	0.00540***	0.00388***
	(0.000509)	(0.000460)
Log(Real Estate Contr.)	-0.00889	-0.0253*
	(0.0147)	(0.0133)
Log(Construction Services Contr.)	0.0563***	0.0293***
	(0.0124)	(0.0112)
Percentage Democrat Voters	0.00226*	-0.00212*
	(0.00121)	(0.00109)
Percent Voter Turnout	0.00262**	0.000969
	(0.00114)	(0.00103)
Term Length	0.00521	0.0189
	(0.0207)	(0.0187)
Indicator for Large Government = 1	0.0860**	0.0829***
	(0.0334)	(0.0302)
Log(Est. Population)	0.0565***	0.0431***
	(0.00792)	(0.00716)
Log(Per capita Tax from Property Value)	0.0625***	0.0392***
	(0.00900)	(0.00813)
Percent on SNAP	-0.0126***	-0.00963***
	(0.00148)	(0.00134)
Indicator for Risk = 1	0.456***	0.195***
	(0.0224)	(0.0202)
Constant	-1.980***	-1.092***
	(0.215)	(0.195)
Observations	1,598	1,598
R-squared	0.530	0.339

Notes: Dependent variable is defined as an indicator for participation CRS in column 1 and as an indicator for participation at class 7 or higher in column 2. Includes County-Year fixed effects. Robust standard errors are in parentheses. Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

Table B8: Probability of CRS Participation (Binary Measures) Before and After Hurricane Sandy: Marginal Effects

	(1)	(2)	(3)	(4)
VARIABLES	CRS Before Sandy	Top CRS Levels Before Sandy	CRS After Sandy	Top CRS Levels After Sandy
Mayor-Council Indicator = 1	0.0679***	0.0754***	-0.0146	-0.0156
	(0.0228)	(0.0202)	(0.0445)	(0.0460)
Percent Second Homeowners	0.00472***	0.00397***	0.00622***	0.00472***
	(0.000572)	(0.000538)	(0.00120)	(0.00128)
Log(Real Estate Contr.)	-0.0151	-0.0183	0.0543	0.0299
	(0.0163)	(0.0140)	(0.0567)	(0.0579)
Log(Construction Services Contr.)	0.0488***	0.0328**	0.0623*	0.0290
	(0.0149)	(0.0135)	(0.0356)	(0.0384)
Percentage Democrat Voters	0.00290**	-0.00189	0.00690**	0.00569
	(0.00136)	(0.00131)	(0.00333)	(0.00376)
Percent Voter Turnout	-0.000475	-0.000559	0.00486*	0.00206
	(0.00116)	(0.00106)	(0.00265)	(0.00273)
Term Length	0.0141	0.0524**	-0.0911**	-0.118***
	(0.0237)	(0.0208)	(0.0459)	(0.0458)
Indicator for Large Government = 1	0.0797*	0.114**	0.236***	0.117
	(0.0428)	(0.0452)	(0.0909)	(0.0916)
Log(Est. Population)	0.0338***	0.0224***	0.109***	0.116***
	(0.00905)	(0.00785)	(0.0203)	(0.0209)
Log(Per capita Tax from Property Value)	0.0438***	0.00602	0.0672***	0.0931***
	(0.00969)	(0.00842)	(0.0222)	(0.0218)
Percent on SNAP	-0.0124***	-0.00829***	-0.0135***	-0.0152***
	(0.00212)	(0.00227)	(0.00290)	(0.00375)
Indicator for Risk = 1	0.413***	0.129***	0.484***	0.334***
	(0.0385)	(0.0253)	(0.0582)	(0.0618)
Observations	1,099	1,099	374	374

Notes: The first two columns limit the data to the years prior to Hurricane Sandy and the final two columns limit the data to the years after Hurricane Sandy. The dependent variable in the even columns is defined as an indicator for CRS participation. The dependent variable in the odd columns is an indicator for participating in CRS at class 7 or higher. Includes County-Year fixed effects. Standard errors are in parentheses. Asterisks indicate statistical significance at 10% (*), at 5% (**) and at 1% (***).
Sources: CRS and flood risk data from FEMA, contribution data from National Institute on Money In Politics, municipality characteristics from Rutgers New Jersey Data Book.

C Appendix to Chapter 3

C.1 Hedonic Analyses Appendix

In this section of the appendix I consider the robustness of the results of my hedonic analyses by running several empirical tests of the assumptions and by utilizing alternate specifications for the hedonic analysis. The first subsection considers and tests the assumptions of my empirical analyses and the second subsection presents the alternate specifications.

Tests of Assumptions

As my preferred specification follows Bajari et al. (2012), I start by testing the third and testable assumption of their method. This test is consistent with the test Bajari et al. (2012) present in their paper. This test relies on a regression of annual returns on average returns and the relevant housing attributes. A small R-squared indicates that their explanatory power is small and that the assumption is reasonable. I find that the R-squared is very small.

Table C1: Efficient Market Hypothesis: Test of Assumption 3

Variable	Annual Return
Average Return	0.011
	(0.008)
CRS Class	0.003
	(0.002)
Log Premium	0.041
	(0.004)
Spillover	0.019
	(0.005)
Zone High Indicator	-0.056
	(0.005)
Percent on Snap	0.000
	(0.000)
Number of Stories	-0.005
	(0.001)
Log Population	-0.009
	(0.002)
R-sqaured	0.001
N	202,355

Notes: Robust Standard Errors in parentheses.

I also consider the traditional hedonic model, which assumes that homeowners are myopic about future amenities and thus the coefficients are essentially static estimates. However, homeowners may consider the current housing attribute as a reflection of the future attribute in their purchasing decision. To check and correct for this problem, I employ the tests detailed in Bishop and Murphy (2019). These tests consider the relationship between prior level of housing attribute and the current level of attribute to back out whether the static estimates are biased or not. Specifically, a regression of the current variable is run on the lag variable and time trend. The bias estimate is then calculated from the regression result using this formula:

$$\gamma_k = \frac{\sum_{t=1}^{T} \beta^{t-1} \rho_{1,k}^{t-1}}{\sum_{t=1}^{T} \beta^{t-1}} \tag{C1}$$

Where β is the discount rate, $\rho_{1,k}$ the coefficient on the lag variable x_k from the regression, and T is the number of years into the future the adjustment accoutns for. As I have three hedonic estimates of interest (CRS, Premium, and Spillover), I employ the test for each variable. I find that the static hedonic estimates on CRS class and Spillover variables will be relatively unbiased with the CRS class static coefficient slightly biased up. Whereas, the hedonic coefficient on premium will be biased down.

Table C2: Estimate of Bias from Static Hedonic Analyses

	CRS Class	Log Premium	Spillover
Bias Estimate	1.08	0.23	1.00
Implied Bias (%)	7.31	-333.41	0.03

Accounting for this bias, changes the MWTP for an increase in premium to be much closer to the MWTP results from the preferred 2SLS method.

Alternate Specifications

The alternate specifications I consider use different subsets of data, the traditional hedonic method with additional controls, and all sales with municipality fixed effects as opposed to repeat sales. These are presented in Tables C4 through C8.

Table C3: Static and Forward Looking Hedonic Estimates

Variable	CRS Class	Log Premium	Spillover
Panel A: Zone High			
Static MWTP ($)	1347.854	-22.535	9354.044
Forward Looking MWTP ($)	1249.364	-97.6692	9351.456
Panel B: Zone Low			
Static MWTP ($)	104.761	-21.13	2860.042
Forward Looking MWTP ($)	97.10593	-91.57977	2859.251
Panel C: All Repeat Sales			
Static MWTP ($)	561.772	-18.945	6453.688
Forward Looking MWTP ($)	520.7224	-82.10974	6451.903

Notes: Static MWTP are from initial Hedonic analysis. The MWTP estimates are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Robust Standard Errors in parentheses.

Table C4: Estimates from Hedonic Regressions with 2SLS: All Municipalities

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.332	$4,059.101
	(0.024)	
Log Premium	-1.039	$-127.030
	(0.226)	
Spillover	0.389	$4,761.098
	(0.024)	
Panel B: Zone Low		
CRS Class	0.210	$2,569.314
	(0.020)	
Log Premium	-0.032	$-3.853
	(0.157)	
Spillover	-0.029	$-360.742
	(0.018)	
Panel C: All Repeat Sales		
CRS Class	0.288	$3,526.276
	(0.015)	
Log Premium	-0.067	$-8.184
	(0.133)	
Spillover	0.154	$1,885.479
	(0.013)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are included. Robust Standard Errors in parentheses.

Table C5: Estimates from Hedonic Regressions: All Municipalities

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.107	$1,311.618
	(0.016)	
Log Premium	-0.166	$-20.360
	(0.042)	
Spillover	0.756	$9,240.724
	(0.063)	
Panel B: Zone Low		
CRS Class	0.002	$28.218
	(0.010)	
Log Premium	-0.084	$-10.331
	(0.025)	
Spillover	0.016	$191.969
	(0.041)	
Panel C: All Repeat Sales		
CRS Class	0.035	$424.130
	(0.009)	
Log Premium	-0.088	$-10.729
	(0.021)	
Spillover	0.262	$3,209.164
	(0.034)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are included. Robust Standard Errors in parentheses.

Table C6: Estimates from Hedonic Regressions with 2SLS: Additional Controls

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.215	$2,633.174
	(0.033)	
Log Premium	-0.728	$-88.994
	(0.380)	
Spillover	0.262	$3,209.258
	(0.090)	
Panel B: Zone Low		
CRS Class	0.189	$2,307.577
	(0.027)	
Log Premium	-0.790	$-96.648
	(0.262)	
Spillover	0.256	$3,127.495
	(0.076)	
Panel C: All Repeat Sales		
CRS Class	0.219	$2,673.036
	(0.019)	
Log Premium	-0.797	$-97.495
	(0.209)	
Spillover	0.275	$3,358.902
	(0.052)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Additional Controls Included Robust Standard Errors in parentheses.

Table C7: Estimates from Hedonic Regressions: Additional Controls

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.067	$819.972
	(0.017)	
Log Premium	-0.170	$-20.790
	(0.041)	
Spillover	0.481	$5,881.199
	(0.066)	
Panel B: Zone Low		
CRS Class	0.021	$257.040
	(0.011)	
Log Premium	-0.070	$-8.557
	(0.027)	
Spillover	0.118	$1,443.958
	(0.061)	
Panel C: All Repeat Sales		
CRS Class	0.045	$552.503
	(0.009)	
Log Premium	-0.075	$-9.167
	(0.022)	
Spillover	0.326	$3,983.252
	(0.044)	

Notes: MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Additional Controls Included Robust Standard Errors in parentheses.

Table C8: Estimates from Hedonic Regressions: All Sales

Variable	Coefficient	MWTP
Panel A: Zone High		
CRS Class	0.093	$1,139.940
	(0.008)	
Log Premium	-0.085	$-10.418
	(0.017)	
Spillover	0.592	$7,237.324
	(0.030)	
Panel B: Zone Low		
CRS Class	0.009	$107.280
	(0.005)	
Log Premium	-0.106	$-13.014
	(0.011)	
Spillover	0.205	$2,506.137
	(0.027)	
Panel C: All Repeat Sales		
CRS Class	0.037	$456.895
	(0.004)	
Log Premium	-0.091	$-11.105
	(0.009)	
Spillover	0.412	$5,034.565
	(0.020)	

Notes: Hedonic regressions of price on characteristics using all sales and municipality fixed effects. MWTP are calculated at the mean house value of 366,886 USD and annualized for a 30 year mortgage. Counties around NYC are dropped. Additional Controls Included Robust Standard Errors in parentheses.

C.2 DDC Model Appendix

First, I present the results of the regressions estimating the state transitions. Note, many of the state transitions are not time-varying or are deterministic. Thus, I have included the results for the three variables that need their states predicted. Second, I present additional figures form the counterfactual analyses. Third, I present the results of the cost estimates if I utilized the Hedonic MWTP from Table 3.4 and not Table 3.3

C.3 Results of Regressions for State Transition Matrix

Table C9 presents the results of Equation 3.17 for the Number of Houses, Average House Price, and the Municipality Tax Rate.

Table C9: Transition Regressions

Variable	Number of Houses	Tax Rate	Price
Lag Number of Houses	1.008 (0.001)		
Lag Tax Rate		1.003 (0.003)	
Lag Price			0.961 (0.005)
Observations	5,420	5,420	5,420
R-squared	0.990	0.985	0.928

Notes: All regressions control for county-year fixed effects. Standard Errors in parentheses.

Additional Counterfactual Figures

Figure C1: Increase Proportion of Homes at High Risk: Participation by Class

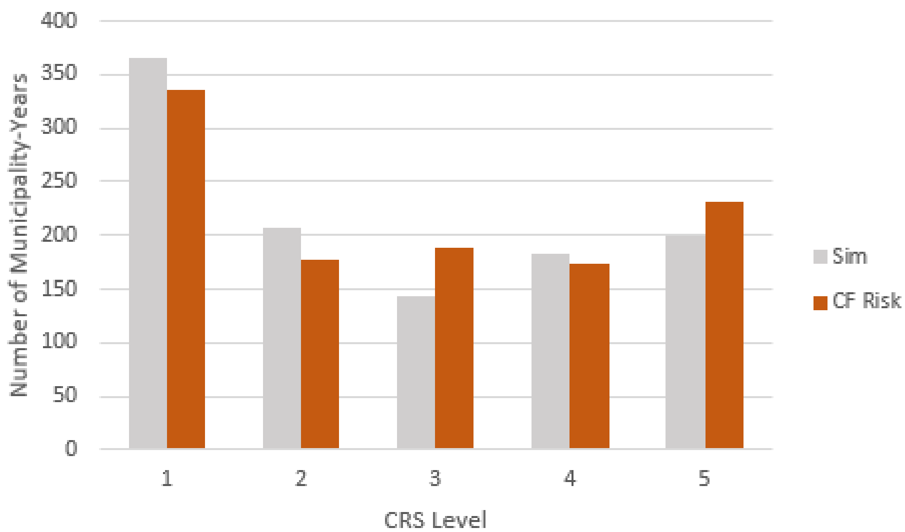


Figure C2: Increase Insurance Premium: Participation by Class

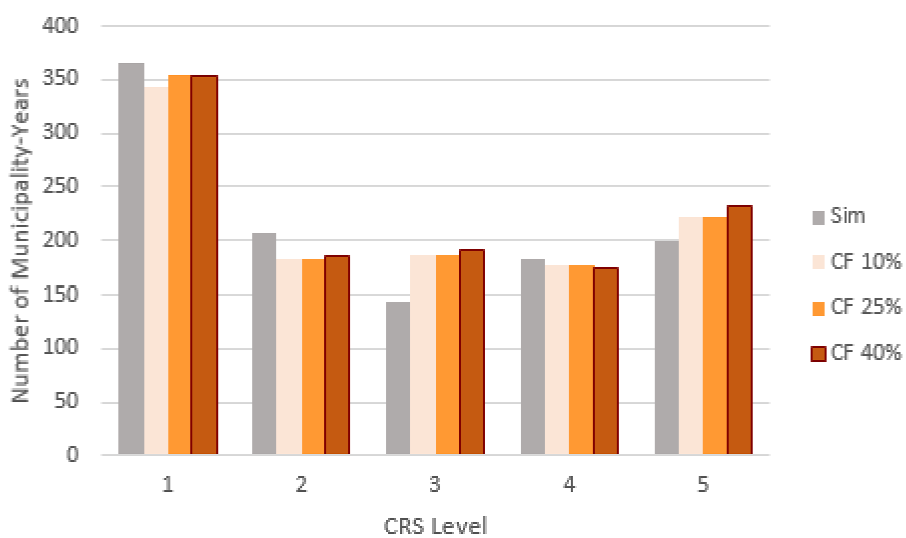
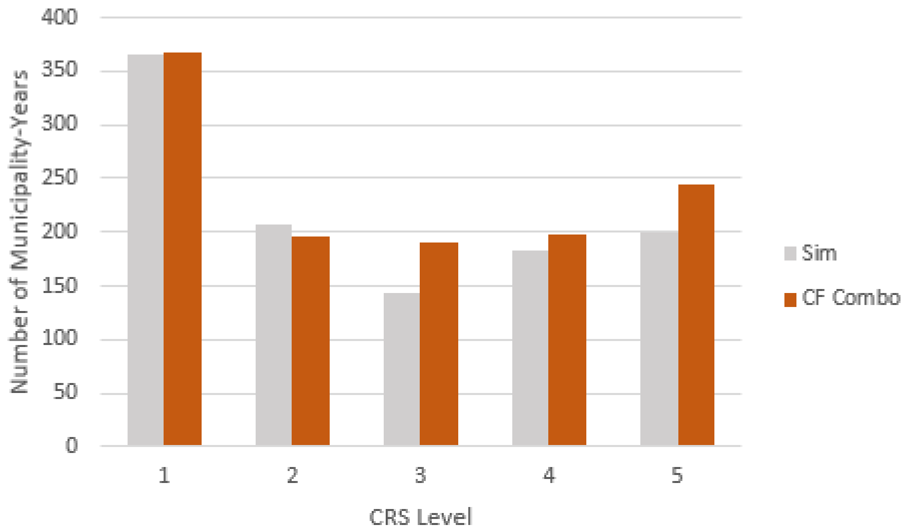


Figure C3: Change Incentive Structure: Participation by Class



Results using Traditional Hedonic MWTP Estimates

In this section I present the cost estimates and fit of the dynamic discrete choice model, if I used the estimates from the traditional hedonic model in the first stage instead.

Table C10: Estimates Of Perceived Costs (Million USD) - Using Traditional Hedonic Model in First Stage

	Class 1	Class 2	Class 3	Class 4	Class 5
Base Cost	193.43	51.21	62.82	133.02	220.69
Higher Risk Muni	-10.21	-29.61	-24.78	-48.92	-52.90
Post Sandy	-50.15	-75.58	-95.50	-115.35	-160.57
Elected Chief Executive	-14.65	-14.51	-15.08	-9.90	-9.86
Greater than 20 % nonresident	-14.71	-15.92	-20.10	-10.02	-10.36

Notes: Costs are calculated based on moving up one level. To move from a Class 0 to Class 5 need to sum up entire row. The first row presents the base costs and the other rows present the changes to the base costs for some time or municipality specific factor.

Table C11: Moment Comparison by Class - Using Traditional Hedonic Model in First Stage

CRS Class	Actual	Simulated
0	0.84	0.84
1	0.03	0.03
2	0.05	0.03
3	0.04	0.03
4	0.02	0.02
5	0.01	0.04

Notes: Percentage of municipality-years at each class level are calculated based on actual choices and simulated data from estimated cost parameters.

Table C12: Moment Comparison by Year - Using Traditional Hedonic Model in First Stage

Year	Actual	Predicted
1999	0.19	0.18
2000	0.22	0.27
2001	0.22	0.27
2002	0.25	0.28
2003	0.27	0.28
2004	0.28	0.29
2005	0.28	0.30
2006	0.29	0.32
2007	0.29	0.36
2008	0.30	0.44
2009	0.34	0.52
2010	0.37	0.58
2011	0.39	0.58
2012	0.42	0.58
2013	0.52	0.69
2014	0.60	0.70
2015	0.68	0.72
2016	0.74	0.81
2017	0.80	0.88
2018	0.90	0.91

Notes: Average municipality participation for each year calculated based on actual decisions and simulated data.

Table C13: Overall Model Fit - Using Traditional Hedonic Model in First Stage

Model Fit	MSE
By Year	0.0113
By Class	0.0002

Notes: Each MSE is calculated using participation by subcategories within group.

Table C14: Model Fit by Year and Class - Using Traditional Hedonic Model in First Stage

Model Fit	MSE
1999	0.0000
2000	0.0005
2001	0.0004
2002	0.0001
2003	0.0001
2004	0.0002
2005	0.0001
2006	0.0002
2007	0.0003
2008	0.0005
2009	0.0009
2010	0.0012
2011	0.0011
2012	0.0009
2013	0.0009
2014	0.0009
2015	0.0012
2016	0.0025
2017	0.0029
2018	0.0029

Notes: Each MSE is calculated using participation by class and year.