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

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Caroline A. Hopkins *

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Abstract

Federal and local government policies are often interdependent, and therefore changes in one can have significant implications for the other. I study this interdependency in the context of flood hazard mitigation. I first consider the local government's decision to invest in hazard mitigation. To this end, I estimate a homeowner's marginal willingness to pay for the local government's flood hazard mitigation actions and flood insurance 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 alternative federal policies. The counterfactuals suggest that either increasing the proportion of homes in federally designated high risk zones or raising the federally set flood insurance rates increase investment in flood hazard mitigation, and implementing a cost subsidy rather than the insurance discount incentive currently used by the federal government may increase investment in municipalities with low property values.

*Department of Economics, Tepper School of Business, Carnegie Mellon University.
Mail: Caroline A. Hopkins, 4765 Forbes Avenue, Pittsburgh, PA 15213.
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1 Introduction

Environmental policy in the United States is often 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 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.

To estimate the model in this setting I utilize datasets from several sources. 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 might change 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 (2020)). Given the estimated low return from insurance discounts when housing values are low, low income 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 muncipalities may be under-investing in hazard mitigaiton. 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 5 and 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)).

[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.

This paper proceeds as follows. The remainder of Section 1 discusses related literature. Section 2 includes the details of the empirical setting, the data, and descriptive statistics. Section 3 presents the model. Sections 4 and 5 contain the estimation and the results. Section 6 provides the counterfactual analyses. Section 7 discusses the policy implications of this research and concludes.

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 underinvesting 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 (2013), Bakkensen and Barrage (2017), Keenan et al. (2018), Bernstein et al. (2019), and Eichholtz et al. (2019), Hopkins and Muller (2019)), 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 (2020)). 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.

2 Empirical Setting

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. 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

[2] These standards include permits for new development in high risk areas, no new development in floodways, 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.

[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).

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 New 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 municipalities may effect 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

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

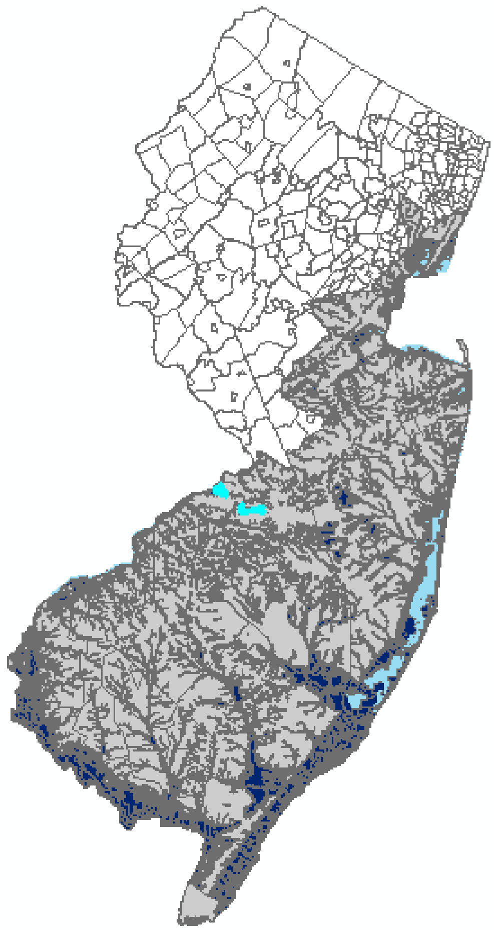
have brought significant rain and flooding to the area. However, it was the most significant in recent years. New Jersey is expected to see increases in flooding due to sea level rise on the coast. Additionally, the region is expected to have more frequent intense rain storms that can cause flooding due to climate change.

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 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 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.

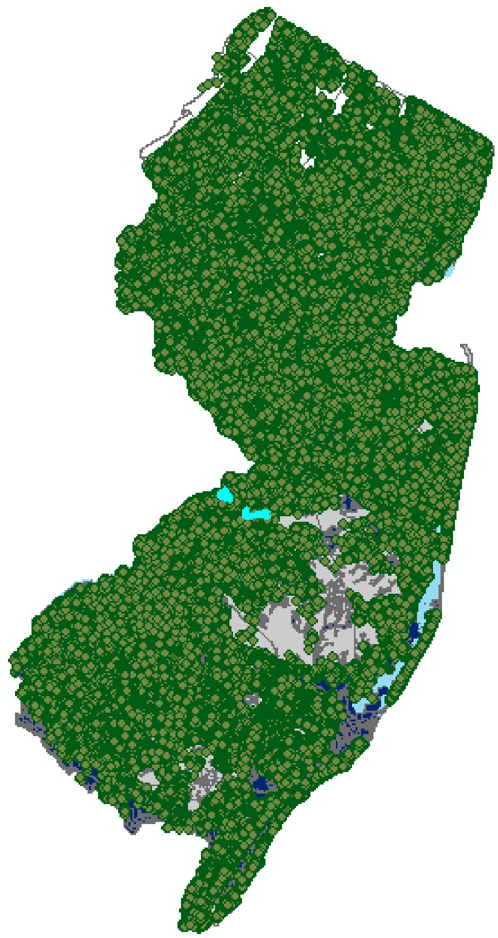
The sales and assessments ZTRAX database provides the parcel level data.[6] This database includes information on the location of the parcel, the sale price, the seller, the buyer, the age of building, the square footage, the assessed value for land, and the assessed value for the building

[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 refect the position of the Zillow Group.

along with other variables. This database also contains latitude and longitude information of each parcel, which I use to merge in the flood risk data from the FEMA flood maps.[7] Figure 2 displays the housing data (denoted by a green point for each parcel) over top Figure 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.

[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.

Figure 2: New Jersey Housing Data



Characteristics about the municipalities is sourced from the Rutgers New Jersey Databook. The 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 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 1: Descriptive Statistics

Variable	(1) Mean	(2) SD	(3) Min	(4) Max
Average Insurance Premium ($)	770.67	394.20	51.00	5825.00
Total CRS Points	239.50	602.10	0.00	3613.00
CRS Class	0.42	1.06	0.00	5.00
Log Population	8.81	1.21	5.40	11.78
Mayor Council	0.52	0.50	0.00	1.00
Number of Houses	3927.58	4852.75	40.00	38500.00
Out of State Non-Residents ($)	0.09	0.13	0.01	0.72
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.

Table 2: Descriptive Statistics: Participate in CRS

Variable	(1) Mean	(2) SD	(3) Min	(4) Max
Average Insurance Premium ($)	934.54	403.76	167.00	3372.88
Total CRS Points	940.66	874.40	0.00	3613.00
CRS Class	1.64	1.56	0.00	5.00
Log Population	8.78	1.37	5.40	11.48
Mayor Council	0.55	0.50	0.00	1.00
Number of Houses	5231.20	6166.94	214.00	38500.00
Out of State Non-Residents ($)	0.20	0.20	0.01	0.72
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.

I also present figures to demonstrate how CRS participation and Insurance Premiums change over time. Figure 3 demonstrates that CRS participation is increasing over time and that there is a sharp increase after Hurricane Sandy. Figure 4 demonstrates that average premiums are increasing overall, but not every year.

Figure 3: Average CRS Class Participation

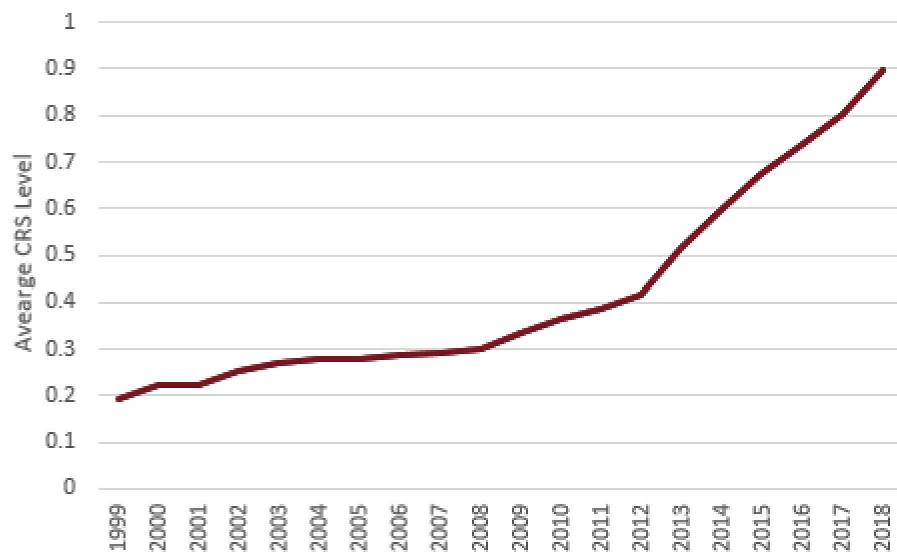
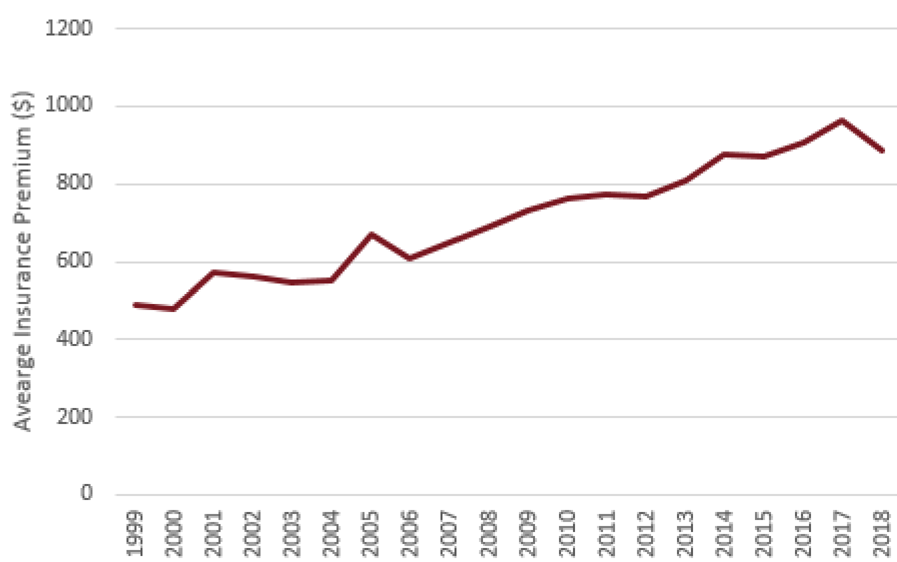


Figure 4: Average Insurance Premium



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:

$$U(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it}) + \epsilon_{it}. \tag{1}$$

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:

$$b(S_{it}, d_{it}) = \sum_{n=1}^{N_i} log(P_n(S_{tni}, d_{it})) \tag{2}$$

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. Therefore the cost function can be defined as:

$$c(S_{it}, d_{it}) = F(d_{it}) + G(d_{it}, S_{ti}) \tag{3}$$

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

[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 (2020)

the government i as the sum of expected future payoffs:

$$V_t(S_{it}) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t}(b(S_{i\tau}, d_{i\tau}^*) - c(S_{i\tau}, d_{i\tau}^*) + \epsilon_{i\tau}\right] \tag{4}$$

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:

$$V_t(X_{it}, d_{it}) = \max_{d*} v_t(X_{it}, d_{it}) + \epsilon(d_{it}) \tag{5}$$

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

$$v_t(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it})) + \beta \sum_{S_{it+1}=s}^{S} V_{t+1}(S_{it+1}) f(S_{it+1}|S_{it}, d_{it}) \tag{6}$$

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:

$$v_t(S_{it}, d_{it}) = b(S_{it}, d_{it}) - c(S_{it}, d_{it})) + \beta \sum_{S_{it+1}=s}^{S} log\left[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j))\right] f(S_{it+1}|S_{it}, d_{it}) + \beta\gamma_e \tag{7}$$

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:

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) = b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) + \beta \sum_{S_{it+1}=s}^{S} log\Bigg[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) \\
- v_{t+1}(S_{it+1}, d_{it+1} = h))\Bigg] f(S_{it+1}|S_{it}, d_{it} = k) \\
+ \beta(v_{t+1}(S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k))
\end{aligned}
\tag{8}
$$

This can be rewritten further as:

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) = b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) + \beta \sum_{S_{it+1}=s}^{S} log\Bigg[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) \\
- v_{t+1}(S_{it+1}, d_{it+1} = h))\Bigg] f(S_{it+1}|S_{it}, d_{it} = k) \\
+ \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k) \\
+ \beta^2 \sum_{S_{it+1}} \sum_{S_{it+2}} log\Bigg[\sum_{j} exp(v_{t+2}(S_{it+2}, d_{it+2} = j) \\
- (v_{t+2}(S_{it+2}, d_{it+2} = z)\Bigg] f(S_{it+2}|S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k) \\
+ \beta^2 \sum_{S_{it+1}} \sum_{S_{it+2}} exp(v_{t+2}(S_{it+2}, d_{it+2} = j)) f(S_{it+2}|S_{it+1}, d_{it+1} = h) f(S_{it+1}|S_{it}, d_{it} = k)
\end{aligned}
\tag{9}
$$

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

$$
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) \tag{10}
$$

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

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) = {} & (b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) - (b(S_{it}, d_{it} = g) - c(S_{it}, d_{it} = g)) \\
& + \beta \sum_{S_{it+1}=s}^{S} log\Big[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\Big] f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta \sum_{S_{it+1}=s}^{S} log\Big[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\Big] f(S_{it+1}|S_{it}, d_{it} = g) \\
& + \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = g)
\end{aligned}
\tag{11}
$$

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

$$
-(Pr(d_{it} = h|s_{it}) = log\Big[\sum_{j=1}^{J} exp(v_{t+1}(S_{it+1}, d_{it+1} = j) - v_{t+1}(S_{it+1}, d_{it+1} = h))\Big] \tag{12}
$$

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

$$
\begin{aligned}
v_t(S_{it}, d_{it} = k) - v_t(S_{it}, d_{it} = g) = {} & (b(S_{it}, d_{it} = k) - c(S_{it}, d_{it} = k)) \\
& - (b(S_{it}, d_{it} = g) - c(S_{it}, d_{it} = g)) \\
& + \beta \sum_{S_{it+1}=s}^{S} -(Pr(d_{it} = h|s_{it})) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta \sum_{S_{it+1}=s}^{S} -(Pr(d_{it} = h|s_{it})) f(S_{it+1}|S_{it}, d_{it} = g) \\
& + \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = k) \\
& - \beta(b(S_{it+1}, d_{it+1} = h) - c(S_{it+1}, d_{it+1} = h)) f(S_{it+1}|S_{it}, d_{it} = g)
\end{aligned}
\tag{13}
$$

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.

4 Estimation

The model can be estimated using the data described in Section 2. Estimation follows directly from the Equation 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.

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:

$$\begin{aligned} d_{it} = \beta_0 + \beta_1\, ln(P_{nit'}) + \beta_2 d_{it'} + \beta_3 LogPremium_{it'} \\ + \beta_4 Spillover_{c_{-i}t'} + \beta_5 X_{nit'} + FE_{y(t')} + FE_{m(t')} + \mu_{nit} \end{aligned} \tag{14}$$

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.

$$\begin{aligned} logP_{nit} = \alpha_0 + \alpha_1 \hat{d_{it}} + \alpha_2 LogPr\hat{e}mium_{it} + \alpha_3 Spillover_{c_{-i}t} \\ + \alpha_4 X_{nt} + \alpha_5 ln(P_{nit'}) - \alpha_6 d_{it'} + \alpha_7 LogPremium_{it'} + FE_{y(t)} + FE_{m(t)} + \epsilon_{nit} \end{aligned} \tag{15}$$

Where $\hat{d_{it}}$ and $LogPr\hat{e}mium_{it}$ 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:

$$log(P_nit) = \alpha_0 + \alpha_1 d_{it} + \alpha_2 LogPremium_{it} + \alpha_3 spillover_{it} + \alpha_6 X_{it} + FE_{y(t)} + FE_{m(t)} + FE_n + \mu_{nit} \tag{16}$$

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.

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:

$$N_{it} = \alpha_0 + \lambda_1 N_{it-1} + FE_{ct} + \epsilon it \tag{17}$$

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.

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:

$$\hat{P}r(d_{it} = h|s_{it}) = \Lambda\bigg(\phi_{it} s_{it}\bigg) \tag{18}$$

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.

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:

$$c(S_{it}, d_{it}) = \gamma_{0_k} CRS_k(d_{it}) + \gamma_{1_k} CRS_k(d_{it}) \cdot M_{ti} \tag{19}$$

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_it 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:

$$l(\gamma) = \sum_{i=1}^{M}\sum_{t=1}^{T}\sum_{j=1}^{J} I[d_{it}=j] log(\frac{exp(v_j(S_{it}) - v_g(S_{it})}{\sum_{k=1}^{J} exp(v_k(S_{it}) - v_g(S_{it}))} \tag{20}$$

Where the definition of $(v_j(S_{it}) - v_g(S_{it})$ directly from Equation 13 of the model. Plugging in the estimates from the first stage into Equation 13 yields:

$$\begin{aligned} v_t(S_{it}, d_{it}=k) - v_t(S_{it}, d_{it}=g) = {} & (\hat{b}(S_{it}, d_{it}=k) - c(S_{it}, d_{it}=k)) \\ & - (\hat{b}(S_{it}, d_{it}=g) - c(S_{it}, d_{it}=g)) \\ & + \beta \sum_{S_{it+1}=s}^{S} -(\hat{P}r(d_{it}=h|s_{it}))\hat{f}(S_{it+1}|S_{it}, d_{it}=k) \\ & - \beta \sum_{S_{it+1}=s}^{S} -(\hat{P}r(d_{it}=h|s_{it}))\hat{f}(S_{it+1}|S_{it}, d_{it}=g) \\ & + \beta(\hat{b}(S_{it+1}, d_{it+1}=h) - c(S_{it+1}, d_{it+1}=h))\hat{f}(S_{it+1}|S_{it}, d_{it}=k) \\ & - \beta(\hat{b}(S_{it+1}, d_{it+1}=h) - c(S_{it+1}, d_{it+1}=h))\hat{f}(S_{it+1}|S_{it}, d_{it}=g) \end{aligned} \tag{21}$$

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

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

shares and the shares of municipalities that would participate based on the cost parameters.[10]

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.

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 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.[11]

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. 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

[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).

[11] 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 refect the position of the Zillow Group.

Table 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.

positive. This points to the importance in understanding the heterogeneity across regions.

I also present the results from the traditional hedonic analysis in Table 4.[12] There are two 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.

[12] 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 refect the position of the Zillow Group.

Table 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 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 fixed effects as opposed to repeat sales.

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 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.[13] 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 5: Estimates Of Perceived Costs (Million USD)

	Class 1	Class 2	Class 3	Class 4	Class 5
Base Cost	206.61	67.14	75.59	148.16	300.34
Higher Risk Muni	-10.03	-24.52	-24.84	-39.71	-49.97
Post Sandy	-0.00	-50.39	-75.29	-114.79	-199.32
Elected Chief Executive	-15.05	-15.02	-14.98	-10.00	-10.01
Greater than 20 % nonresident	-14.94	-15.03	-15.01	-10.02	-10.49

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.

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

5.3 Model Fit

The model fits the data relatively well. Table 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 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 8 and 9 demonstrate that the model fit is quite good both by year or class and by year and class.

Table 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 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 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 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.

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.

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 A1 presents the participation by class for each municipality in each year. Note, that nonparticipation (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 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 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 5: Increase Proportion of Homes at High Risk: Percentage Change in Participation by Class

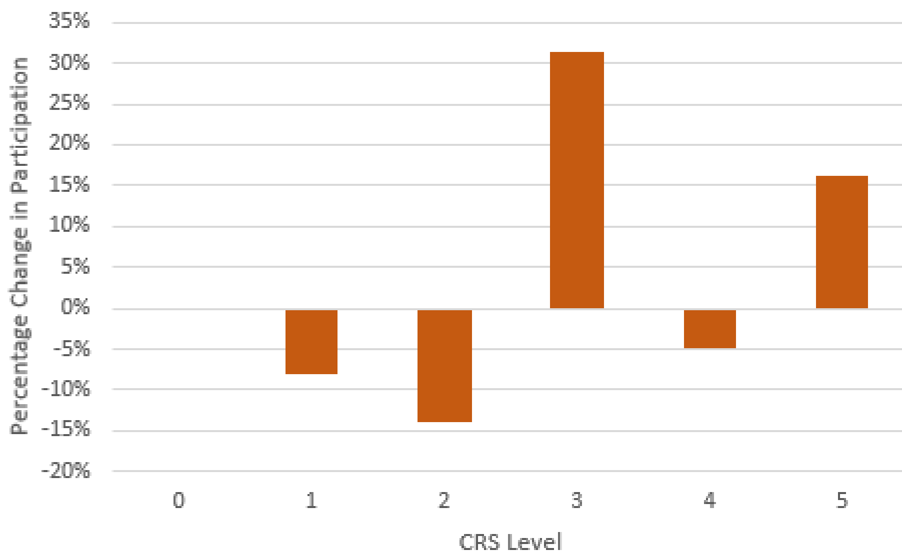
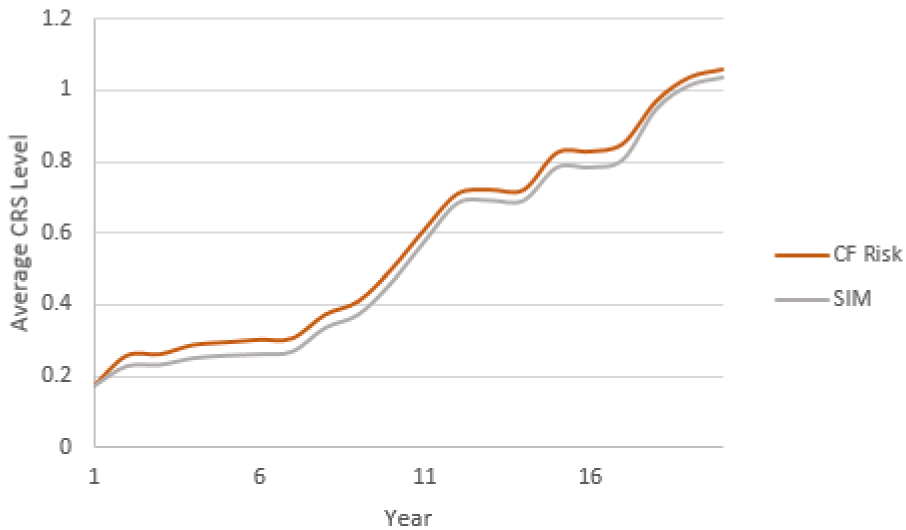


Figure 6: Increase Proportion of Homes at High Risk: Participation by Year



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 A2 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 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 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 7: Increase Insurance Premium: Percentage Change in Participation by Class

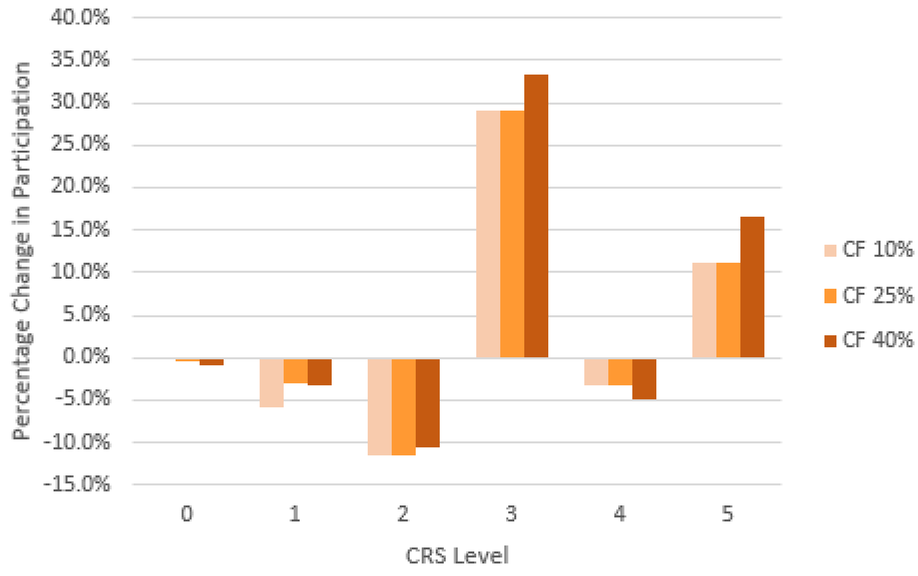
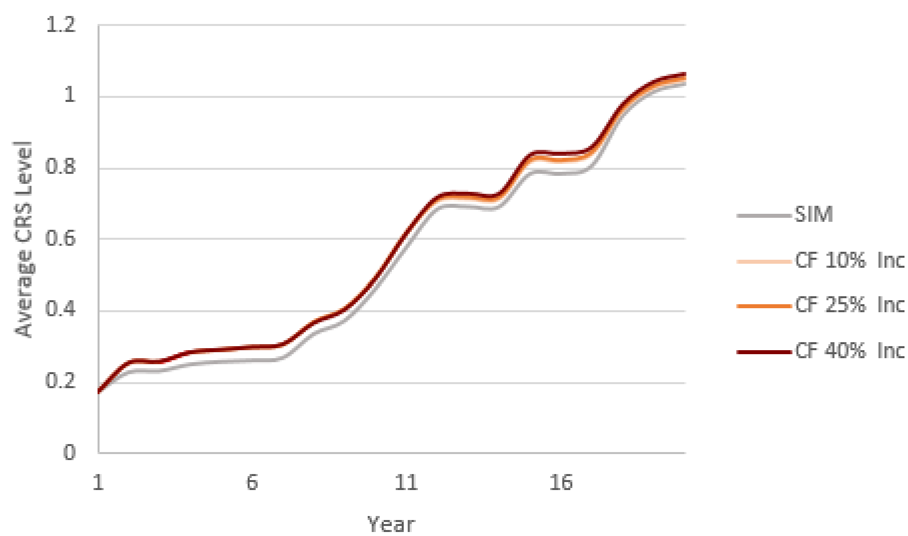


Figure 8: Increase Insurance Premium: Participation by Year



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 A3 and 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 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 9: Change Incentive Structure: Percentage Change in Participation by Class

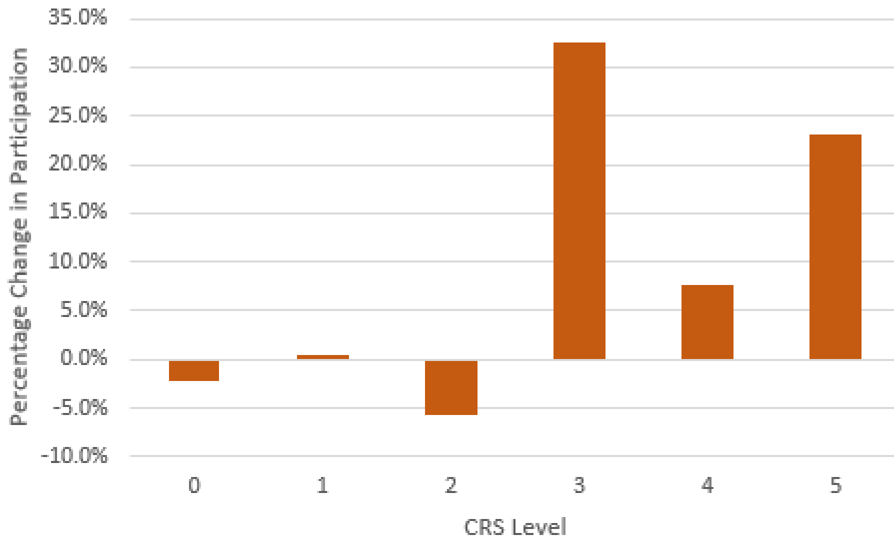
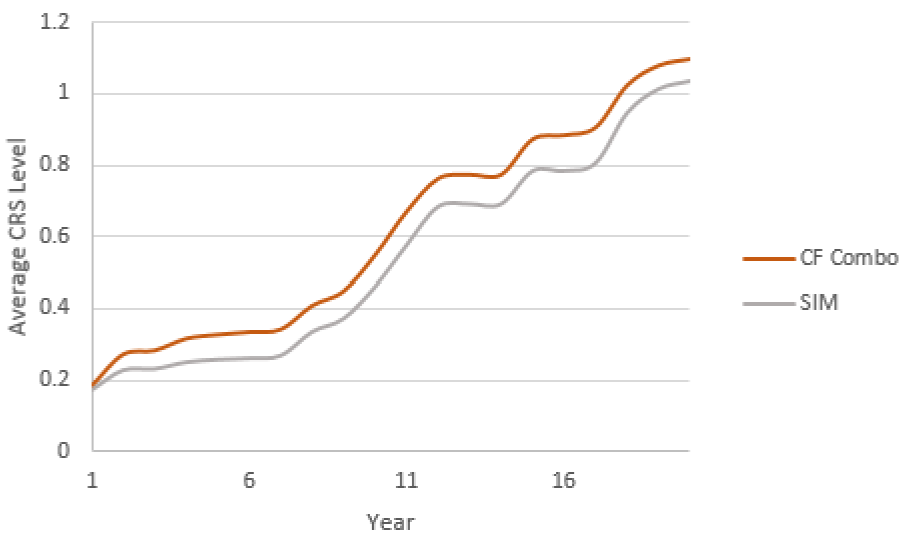


Figure 10: Change Incentive Structure: Participation by Year



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, to estimate the perceived costs of investment, and to consider how alternative policies can increase investment in hazard mitigation.

This paper uses 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. The positive spillover effects I find 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.

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. The federal government is also considering raising flood insurance premiums. Currently, rates are heavily subsidized relative to risk. My second counterfactual demonstrates that an increase in insurance premiums increases participation in CR; thus, the federal government may not recover their expected revenue from the rate increases. 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 lower housing value municipalities.

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 large 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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A 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.

A.1 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 A1: 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 backout 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:

$$\gamma_k = \frac{\sum_{t=1}^{T} \beta^{t-1} \rho_{1,k}^{t-1}}{\sum_{t=1}^{T} \beta^{t-1}} \tag{A1}$$

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 A2: 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.

A.2 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 A4 through **??**.

Table A3: 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 A4: 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 A5: 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 A6: 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 A7: 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 A8: 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.

B 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 4 and not Table 3

B.1 Results of Regressions for State Transition Matrix

Table A9 presents the results of Equation 17 for the Number of Houses, Average House Price, and the Municipality Tax Rate.

Table A9: 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.

B.2 Additional Counterfactual Figures

Figure A1: Increase Proportion of Homes at High Risk: Participation by Class

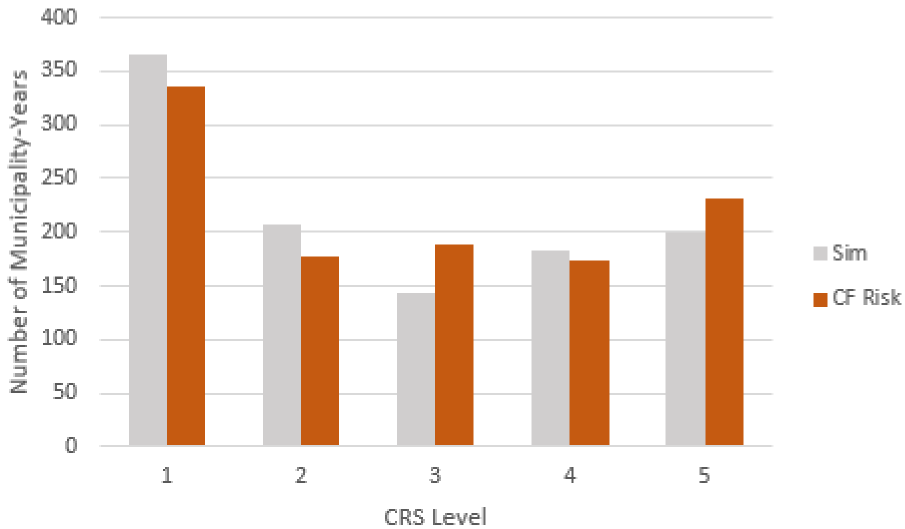


Figure A2: Increase Insurance Premium: Participation by Class

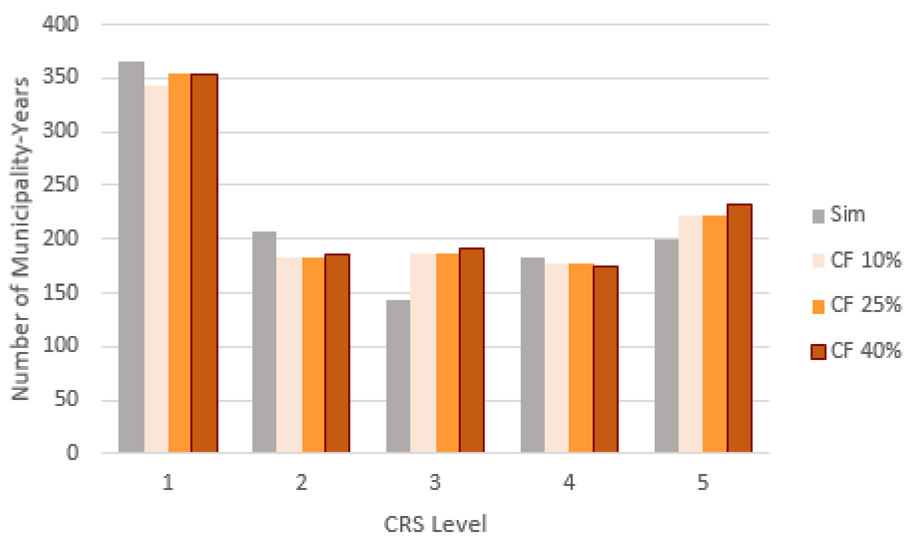
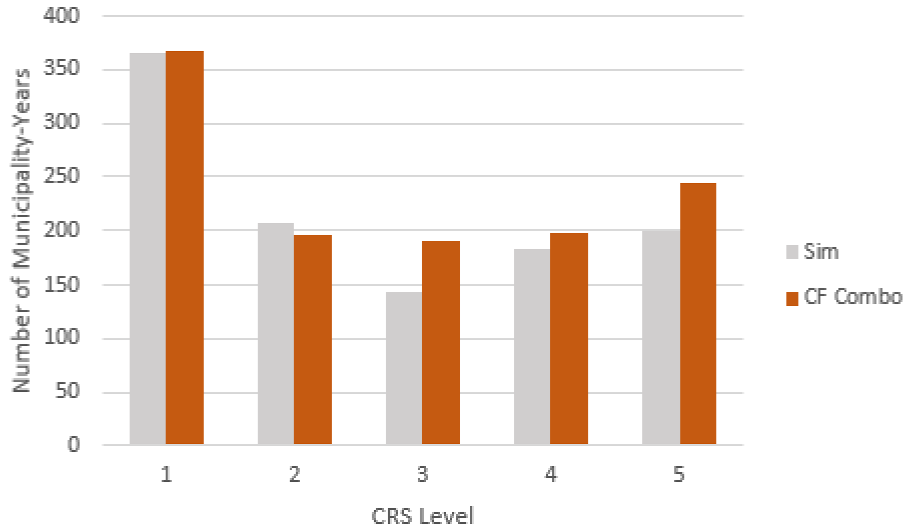


Figure A3: Change Incentive Structure: Participation by Class



B.3 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 A10: 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 A11: 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 A12: 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 A13: 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 A14: 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.