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Raise the Seawalls: Local Governments & Flood Protection

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Raise the Seawalls: Local Governments & Flood Protection

Abstract

Rising seas and more frequent and severe storms are increasing the risks and costs of flooding. Using 2009-2018 data for the U.S. state of Florida from FEMA's Community Rating System program (CRS), which scores participating local governments on their flood risk mitigation activities: I study (1) whether increasing flood risks have led to increases in program participation and score among Florida towns and cities; (2) what risk, fiscal, and demographic factors are driving local governments to invest in CRS-recognized flood risk mitigation measures; and (3) the association between CRS measures and home values.

Keywords

flood risk, public economics, climate change, real estate economics

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1. Introduction

Flood events are the costliest natural disasters in the United States, causing significant annual losses to individuals, business, properties, and infrastructure. According to the National Weather Service's (NWS) Annual Flood Loss Summary Reports, floods accounted for 1,130 fatalities and over $104 billion in damages from 2007 to 2018 (NWS, 2007-2018). Furthermore, due to more intensive floodplain development and the effects of climate change, the annual costs of flooding are increasing – Federal Emergency Management Agency (FEMA) data on "significant flood events" (events resulting in 1,500 or more insurance-paid losses) indicates that floods between 2006 and 2016 resulted in $20.6 billion in insurance-paid losses, compared to $7.3 billion from 1994 to 2004 (FEMA, 2019).

Along the coasts, the already considerable risks and costs posed by floods and storms will be multiplied in coming decades, as rising seas threaten communities and infrastructure. According to the United Nations' Intergovernmental Panel on Climate Change's (IPCC) Special Report on the Ocean and Cryosphere in a Changing Climate, global mean sea levels are projected to rise 1.4 to 2.8 feet relative to 1985-2005 levels by 2100, depending on the emissions scenario (IPCC, 2019). Localized rates of sea level rise will vary widely. Along the Eastern Seaboard of the United States, a slowing Gulf Stream, shifts in weather patterns, and effects from El Niño climate cycles are contributing to faster rates of sea level rise, with some communities reporting annual rises from 2011 to 2015 more than three times higher than the global mean rate (Morrison, 2018; Valle-Levinson et al., 2017).

Rising seas are already affecting daily life in these communities, with "sunny day flooding" – high tides pushing seawater into low-lying areas – posing a growing problem for local governments and residents. Miami, FL has seen a more than 400% increase in such flood events since 2006; Boston recorded 19 high tide flooding days in 2018 (Wdowinski et al., 2016; Page, 2019). In addition to tidal flooding, the frequency and severity of storms and hurricanes is increasing, with a "100-year" storm surge event projected to become a "10-year" event by 2050 (a 1% annual probability increasing to a 10% probability) and average and extreme rainfall totals increasing (Tebaldi et al., 2012; Patricola & Wehner, 2018).

The growing frequency of sunny day flooding and the growing risks from more frequent and severe storms are contributing to lower home values and disruptions to economic activity. According to an analysis by McAlpine and Porter (2018), the Miami-Dade, FL metropolitan area lost over $465 million in real-estate value between 2005 and 2016, as tidal flooding and sea level rise contributed to slower appreciation in home prices in at-risk areas. Per Hino et al. (2019), businesses in downtown Annapolis, MD lost as much as $172,000 in revenue in 2017, as repeat tidal flooding events contributed to lower visits and dollars spent.

Looking forward, according to a report by the Union of Concerned Scientists (2018), more than 300,000 homes, with a collective valuation of $117.5 billion, are at risk of regular flooding by 2045, and properties worth more than $1 trillion could be at risk by 2100.

In the face of these numbers, some local governments are acting, investing hundreds of millions of dollars in engineering solutions to safeguard property and infrastructure, implementing stricter building codes, and increasing public awareness of flood risks. The city of Miami Beach, Florida, home to an estimated $5.7 billion in residential property at risk of regular flooding by 2050 (Climate Central), is investing $650 million in improving drainage systems, elevating roads and public seawalls, installing pumps to replace gravity-based stormwater pipes, and re-nourishing beaches. Additionally, the city has made policy and regulatory changes, such as requiring all new buildings and seawalls to meet increased elevation requirements. Funding for these resiliency investments, spread over a 15-year interval, comes from a combination of special bond measures secured through a tripling of local stormwater fees, a general obligation bond secured through property tax increases, and tax increment financing (Plastrik, 2019).

Charleston, South Carolina, where local sea level has risen 1.07 feet over the past century, is also a leader in flood and sea level rise resiliency planning and investment. The city's 2019 "Flooding and Sea Level Rise Strategy" requires all new and substantially improved structures to be elevated 2 feet above the "100-year" flood stage, and the plan calls for the city to acquire and demolish repeatedly flooded structures. Major infrastructure investments in the plan, totaling $512 million, include drainage improvements, stormwater pumps, and higher seawalls. Funding comes from local stormwater fees and hospitality taxes, with the city tapping FEMA Hazard Mitigation Assistance funds for property acquisitions. Similarly, Hoboken, New Jersey's "Resist, Delay, Store, Discharge" plan includes a $230 million investment in pumps and coastal flood hazard mitigation projects, including a new park along the Hudson River that doubles as a system of storm surge levees. Funding comes from federal Hurricane Sandy recovery dollars, infrastructure and park grants from the state, local bonds, and partnerships with real estate developers (Plastrik, 2019).

A few common themes emerge from these examples of local government efforts to adapt to climate change and rising flood risks: the political impetus for investment and planning generally comes from local political leaders and activists, and funding sources are usually local. Federal funding for such projects is limited, as there are few nationwide frameworks for boosting flood resiliency proactively or for addressing climate change (Morrison, 2019).[1] The two examples of federal

[1] FEMA launched the Building Resilient Infrastructure and Communities (BRIC) program in August 2020 (after the submission of this thesis), which makes $500 million available to states

funds discussed above – Charleston's use of FEMA Hazard Mitigation grants and Hoboken's tapping of federal Hurricane Sandy recovery funds – were only made possible after the two cities experienced hurricane impacts (in Charleston's case, Hurricane Joaquin in 2015 and Hurricane Matthew in 2016).

Are the examples of Miami Beach, Charleston, and Hoboken reflective of a larger trend whereby cities and towns across the country are responding to rising climate risks by investing in flood risk mitigation measures? Relatedly, since most such investment is made (and funded) locally, what are the characteristics of the towns and cities that are taking these proactive (and expensive) measures? Pumps, new drainage systems, and higher streets and seawalls all carry hefty price tags, which means that smaller and poorer towns may not have the resources to afford these measures. Finally, in communities that are making these investments, are home prices rising, much in the same way they do in response to higher quality schools or lower crime, and do those changes differ by flood risk or income level?

In this thesis, I review prior literature on flood prevention, present an economic framework explaining how flood prevention investments may relate to home values, and then examine these questions using data for the state of Florida from 2009 to 2018. I compile a panel data set combining information from FEMA's Community Rating System (CRS), which scores participating local governments on their flood risk mitigation activities, with datasets on city-level characteristics, fiscal capacity, tax rates, and spending on other public goods. Using regression analysis, I find that investments in public flood risk mitigation are increasing over time, with an 11.8% increase in CRS program participation and a 19.8% increase in average "active" CRS scores among Florida municipalities from 2009-2018. This increase in active scores suggests that local governments in Florida are investing more in stormwater systems and flood protection infrastructure, setting stricter building codes, and acquiring and demolishing at-risk properties. As may be expected, CRS program participation is significantly related to flood risk, higher population density, higher median income, and more owner-occupied homes. Active CRS scores are also highest in the cities with more land area in flood zones and higher populations. However, in contrast to standard economic theories, cities with higher scores are also those with greater inequality, lower population densities, lower median incomes, and less financial capacity. Meanwhile, the cities with the greatest increases in score from 2009-2018 have less land area in flood zones, higher debt loads, and lower inequality. Using panel estimation with city-level fixed effects, I find that participation in the CRS program is positively but not statistically significant related to median home values, with a point estimate of an increase of $3,580 to $5,680. Active CRS scores are negatively related to home values, with every 100-point increase associated with a $6,250 decrease in values

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and local governments for mitigation activities. This program is the first example of a large-scale pre-disaster mitigation fund from the federal government.

in an average community. I find evidence for less negative (or positive) effects in communities with more land area in flood zones and higher median incomes.

These results suggest program participation may be driven by factors different from those influencing higher "active" CRS scores. While the CRS program is adequately incentivizing some higher flood risk communities to invest in active CRS mitigation measures, even if they have fewer financial resources, the program does not appear to be adequately targeting and incentivizing denser communities with potentially higher mitigation costs to invest in these measures. Finally, housing markets do not appear to value these flood risk mitigation measures, suggesting that the costs to local communities may exceed the (perceived) benefits or that these measures are themselves indicators of flood risk.

2. Background

This research builds on the broader literatures on the determinants of public expenditure decisions, governmental adoption and implementation of risk mitigation measures, housing market responses to public goods provision, and the economic costs of climate change by examining FEMA's Community Rating System (CRS). The CRS is a voluntary incentive program for local governments that encourages and rates community flood management activities that exceed those required for participation in the National Flood Insurance Program (FEMA, 2017).

2.1. The National Flood Insurance Program

The National Flood Insurance Program (NFIP), enacted by the U.S. Congress in 1968, is the primary tool used by the federal government to promote flood risk management and flood recovery. Congress established the program with multiple objectives in mind:

- Ensure the affordability of flood insurance premiums
- Increase flood risk awareness through risk-based premiums
- Secure widespread participation in the program by communities and property owners
- Earn premium income that would – over time – cover all program expenses
- Stem the rising cost of taxpayer-funded flood disaster relief (National Research Council, 2015)

As currently structured, the NFIP is a joint venture between the federal government, state and local governments, and private insurers. In addition to setting flood-insurance premiums, issuing policies, and paying policy claims, the federal government is responsible for producing detailed flood risk maps for premium-

setting and risk communication purposes. FEMA, which oversees the NFIP, also offers grant programs in support of pre-disaster risk mitigation and post-disaster recovery efforts (National Research Council, 2015). State governments exercise regulatory authority over insurance contracts within their borders, and local governments can only opt into the federal insurance program if they adopt adequate minimum floodplain management regulations. Private insurers market and sell policies and adjust flood claims on behalf of the federal government, but all risk is fully underwritten by the federal government (Li and Landry, 2018).

The structure of the NFIP has led to shortcomings, including low rates of insurance take-up among homeowners, a large and growing structural deficit, and outdated flood maps that do not reflect the growing risks from climate change. The number of policies in force has declined from a peak of 5.7 million in 2009 to 5 million in 2017. Earned premiums in 2016 and 2017 totaled $3.33 and $3.57 billion, while flood claim payments totaled $3.7 and $8.7 billion (Insurance Information Institute, 2019). In 2017, the NFIP reached its authorized borrowing limit of $30.425 billion; the U.S. Congress subsequently cancelled $16 billion worth of debt to allow the program to pay off claims following Hurricanes Harvey, Irma, and Maria. As of 2019, the program's outstanding debt stands at $20.525 billion (Horn, 2019). This legacy of debt has led to renewed attempts to study (and improve) the program.

2.2. The Community Rating System

In order to strengthen the NFIP, incentivize household flood insurance take-up, and promote community-level flood hazard mitigation, FEMA created the Community Rating System (CRS) in 1990. The CRS is a voluntary incentive program for local governments that "encourages community floodplain management activities that exceed the minimum NFIP requirements." Homeowners' flood insurance premium rates are discounted according to the degree of community participation in efforts to meet the three primary goals of the CRS:

- Reduce flood damage to insurable property
- Strengthen and support the insurance aspects of the NFIP
- Foster comprehensive floodplain management (FEMA, 2017)

Local governments that opt into the CRS program are awarded points based on their commitment to and adoption of specific floodplain management activities organized under 4 categories: (1) Public information, (2) Flood mapping and regulation, (3) Flood damage reduction, and (4) Flood preparedness. The maximum possible point total is 12,654, and point totals translate into a CRS

classification, ranging from 10 (the "entry-level" score: less than 500 points) to 1 (the highest score: more than 4500 points).[2] Based on this classification, community flood insurance premium discounts range from 5% to 45% (FEMA, 2017).

2.3. Investing in Flood Risk Mitigation

The benefits to local governments of participating in the CRS are clear: community involvement secures immediate flood insurance premium discounts for property owners. In 2019, Miami Beach, FL improved its CRS rating from Class 6 to Class 5, securing an additional $2 million in annual insurance premium savings for city residents and businesses. The city's Class 5 rating provides all policyholders with a 25% flood insurance discount, which translates into $8.4 million in total annual savings (Miami Beach Rising Above, 2019).

Further, empirical studies have demonstrated that CRS participation reduces flood damages and increases flood insurance take up. Using data from 1998 to 2014 for all NFIP communities in Alabama and Mississippi, Frimpong et. al. (2019) find that Class 5 CRS ratings are associated with a 5.8% reduction in the magnitude of damage claims in the aftermath of a flood event (versus not participating in the CRS). They find negative – but less significant – effects for Class 7 and Class 6 communities. Similarly, looking at data from Florida for the years 2000-2005, Michel-Kerjan and Kousky (2010) find a 7% to 9% reduction in flood claim amounts among Class 5 communities, with negative (but insignificant) effects for communities with Class 6 through 9 ratings. Brody et. al. (2007), looking at data from Florida coastal counties from 1997 to 2001, find a much larger effect from CRS participation, reporting that every increase in CRS rating reduces average flood damages by $303,525. Given a reported $2.6 million mean flood event total loss value, a Class 5 community would see a 58% reduction in flood damages.

Additionally, CRS participation is associated with an increased rate of flood insurance take up among homeowners. Per Frimpong et al. (2019), CRS participating communities see significantly higher rates of insurance take up than non-participating communities, with increasing participation as community CRS rating improves. According to their model, NFIP participation in Class 5 CRS communities is 142% higher compared to non-CRS communities and 30% higher than other CRS-participating communities. Meanwhile, higher rates of NFIP participation create positive externalities, since federal flood insurance provides

[2] Zahran and Brody (2010) find that communities are "gaming" the non-linear, tiered classification structure, with a clustering of point totals just above each classification's point requirement. This precludes a "regression discontinuity" approach to this thesis.

funds faster and in greater amounts than federal disaster aid alone. This speeds community rebuilding and recovery in the wake of a disaster (Kousky, 2017).

However, CRS participation is costly. Per Li and Landry (2018), flood hazard identification, assessment, and management are resource intensive, requiring skilled personnel and capital investments. Aside from any immediate insurance premium discounts offered by the CRS, the benefits of investing in hazard mitigation come only in the aftermath of flood events and are difficult to quantify. More immediate concerns, such as crime or economic development, may crowd out concerns relating to the uncertain risks of future flood and disaster events. Further, flood-prone areas are often prime real estate – effective floodplain management policies may require restricting development or adding regulations that make building more costly, thus reducing property tax revenues and attracting opposition from developers and property owners. The authors find that communities with more fiscal resources do in fact engage in more flood hazard mitigation activities, with the effect particularly significant for more costly (and effective) mitigation activities relating to flood protection and property acquisition. Conversely, higher rates of crime and unemployment are associated with fewer mitigation activities, suggesting that a crowding out effect does exist. Brody et al. (2009) find that the most significant driving factor for CRS participation is the premium discounts offered by the program – increases in population density and insured property value lead to higher potential per capita gains from participation, which in turn incentivizes community flood risk mitigation activities.

In addition to socio-economic factors, flood history and the salience of past flood events influence community mitigation decisions. Li and Landry (2018) find that an increase in the number of flood events in the past year drives a small (but significant) increase in mitigation activities, whereas more distant flood events have no significant impact. Brody et al. (2009) find that an increase in the frequency (but not intensity) of flood events over the preceding 10 years induces modest policy change. Given that community flood mitigation policy decisions are a function of the political process, these results reflect individual actions in the wake of disaster events. Specifically, Beracha and Prati (2008) find little long-term effects on home prices in zip codes impacted by hurricanes, suggesting that disaster events may lead to transitory changes in risk salience but few long-term effects.

The factors that influence why certain communities engage in flood risk mitigation are a central focus of the empirical literature, with certain patterns emerging in predictable ways – wealthier and denser communities with a longer history of flooding invest more in mitigation, while poorer communities tend to underinvest in beneficial mitigation activities.

2.4. Valuing Flood Risk Mitigation

A less studied area within the literature is the value that individuals and homeowners place on flood risk, flood risk mitigation, and community CRS participation. Bin et al. (2008), employing a GIS-based measure of view in order to isolate risk factors from amenity factors that are often highly correlated (e.g. flood risk and water views), find a significant 11% discount for properties in flood hazard zones. Meanwhile, Husby et al. (2018), tying an assumption that spatial differences in flood risk and flood protection are priced in by housing markets, construct a residential sorting model to illustrate that lower home prices in riskier locations will induce lower-income households to migrate to those areas. This follows the literature on Tiebout-sorting, which suggests that supply and quality of public goods drives household migration decisions.

Returning to the CRS literature, Fan and Davlasheridze (2016) analyze households' flood risk perceptions and willingness to pay (WTP) for community CRS mitigation activities, finding that wealthier and more educated households have a higher WTP for CRS activities. Their paper employs a residential sorting model to examine location choices under changes in flood risk and local mitigation policies across U.S. Metropolitan Statistical Areas, finding heterogeneity in risk perception and WTP based on age, ethnicity and race, educational attainment, and prior risk exposure. Their results follow the convention that wealthier households tend to value (and be able to pay for) higher quality public services, and they find that the value households place on CRS activities exceeds the insurance discounts on offer through the program, suggesting a preference for community safety and mitigated flood risks beyond the immediate benefits that come from lower insurance premiums.

2.5. Pricing in Climate Change

A related body of literature focuses on the general question of whether market dynamics and prices are reflecting the growing flood and storm risks posed by climate change. Keenan et al. (2018) find evidence of "climate gentrification" in Miami-Dade County, whereby the rates of price appreciation for single-family homes at lower elevations have not kept pace with the rates of appreciation for homes at higher elevations. Similarly, looking at coastal home valuations across the country, Bernstein, Gustafson, and Lewis (2018) find that homes exposed to sea level rise risk are trading at a 7% discount versus otherwise observably equivalent properties, with heterogeneity in climate risk capitalization across sophisticated and less-sophisticated market segments (non-owner occupied vs. owner-occupied homes). Walsh et al. (2019) examine the impact of both sea level rise and risk mitigating measures on coastal home values in Anne Arundel County, Maryland. Employing a hedonic model to examine the price effects of private flood protection measures, they find that certain structures (bulkheads and ripraps) have a positive

effect on home prices, with the effects strongest for homes most exposed to sea level rise risk.

2.6. Summary

There is a large body of literature on the determinants and benefits of community flood risk mitigation investments, housing market responses to spatial differences in flood and sea level rise risk, households' willingness to pay for mitigation, and the CRS program. My thesis seeks to build on these studies of the CRS program by adding two new dimensions – a more recent study period (2009-2018)[3] and an analysis of whether home prices respond to program participation. Specifically: I examine whether increasing flood risks during this time period have led to increases in program participation and increases in score among participants; I look at the socio-economic characteristics of the communities that are participating and the participating communities that are increasing their scores, along the lines of Brody et al. (2009) and Li and Landry (2018); and I study the relationship between CRS program participation and home values and active CRS scores and home values.

3. Theory

In analyzing local governments' CRS-credit earning flood risk mitigation investments and any associated home value changes, I first turn to the seminal study of Oates (1969), who showed that property values are positively associated with public goods provision and negatively associated with property tax rates. This "capitalization effect" demonstrates that consumers value public goods, and this is manifested in higher home values in communities that provide higher quality public goods (e.g. low crime and good schools). Brueckner (1982) extends this result to show that the use of a property values capitalization approach "provides a way for local governments to set public-good levels in a socially optimal manner" (Brueckner, 2011). Referencing these two studies, and drawing upon Brueckner (2011), I first demonstrate the relationship between public good levels and property values, and then I build a (stylized) bid-rent model for my context of public flood protection.

3.1. Capitalization

[3] Other studies of CRS program participation examine periods prior to 2013, when CRS program scoring criteria changed. This presents an empirical challenge; I deal with this change in **Appendix A**.

Consider the rental housing market. Suppose that the utility of a renter household in any town depends on non-housing consumption *C*, housing consumption *H*, and consumption of a standard public good *G* (e.g. fire protection). Consumption of *G* is determined by location choice – where a household rents determines which bundle of municipal public goods it consumes. Each household faces a budget constraint, spending some percentage of income on *H* (in the form of rent *R*) and the remainder on *C*. Formally, each household maximizes utility subject to its budget constraint:

$$max\ u(C,H,G)$$
$$\text{s.t. } Y = C + R$$

In equilibrium, all households with a given income must obtain the same utility regardless of location choice. That is, if living in Town A supplies a household with higher *G* (e.g. faster fire department response times), while living in Town B supplies a household with lower *G* (slower response times), households in A must necessarily pay a higher rent than in B (for an otherwise identical housing unit). This allows households in Town B to enjoy a higher level of consumption of the non-housing good, ensuring that the two households achieve the same overall utility level. Otherwise, households would sort between the two towns, bidding up (or down) rental prices until utility was equalized. Housing rents are thus a function of the level of public goods supplied by the local government:

$$R = R(G)$$

Housing values, meanwhile, are directly linked to rents: the value of a rental property is equal to the present discounted value of the lifetime income (rent) that flows to the owner, minus any operating costs. Continuing in the Brueckner (2011) framework, a major operating cost for property owners is the annual property tax *T*. Allowing δ to be the discount rate, the value *V* of an individual home is equal to the present discounted value of the annual rental price it commands minus the annual property tax liability over *N* years:

$$V = \sum_{t=1}^{N} \frac{R_t - T_t}{(1+\delta)^t}$$

Property values are thus positively associated with rents (themselves positively associated with the level of public goods) and negatively associated with taxes.

3.2. Property Value Maximization

Now suppose that each town is governed by a town manager, who is empowered to make tax and spend decisions for the town and who is assumed to act through a property-value-maximizing lens. The town manager has access to the jurisdiction's property value information, as well as the costs of providing each unit of the public good, which are fully borne by town residents through a property tax. The manager's decision problem involves weighing the marginal benefits of each additional unit of the public good versus the marginal cost – e.g. are the benefits from an additional firehouse (through faster response times for each household) greater than the cost? Recalling that home values are linked to rents (themselves a function of G) and taxes (which pay for G), the decision problem involves determining whether the increase in annual rents from an additional unit of the public good exceeds the increase in annual taxes. Formally, assuming just one time period and a discount rate of 0 for simplicity (N=1, δ=0), each town manager maximizes aggregate property values (equal to the sum of the values of all K homes in the town), whereby the sum of all annual taxes equals the annual cost $c(G)$ of providing the public good:

$$\sum_{k=1}^{K} V_k = \sum_{k=1}^{K} R_k - \sum_{k=1}^{K} T_k = \sum_{k=1}^{K} R_k - c(G)$$

If we assume that the marginal benefits from each additional unit of the public good are decreasing (the 2nd firehouse will provide fewer benefits than the first), there will come a point where the marginal costs exceed the marginal benefits of an additional unit of G: the current level of the public good is "socially optimal." This optimal level corresponds to the property-value-maximizing level – an additional unit of the public good would cause property values to decrease, since the marginal cost (paid for through higher property taxes) exceeds the marginal benefit. Meanwhile, the presence of other jurisdictions – and the threat of "voting-with-your-feet" – ensures that town managers have an incentive to achieve this optimal level of public goods provision. Otherwise, households would sort into another community that provide a more desirable bundle of home prices, public goods, and tax levels, and home values in the "non-optimizing" town would decrease.

3.3. The Optimal Level of Flood Protection

Consider the following example, which illustrates this process of property-value-maximizing in a context of fire and flood risk. Suppose first that a town has three renter households (K=3, for simplicity) living in identical homes, with each home commanding an annual rent of $10,000. The town manager has latitude to

determine both the level of fire protection provision G and the level of flood protection provision P, with G funded by a tax of T and P by a tax of T' levied on each home. The town currently supplies one "unit" of G (a firehouse) at an annual total cost of $150 divided equally between the three homes (T=$50). In any given year, there is some probability f of a fire destroying a home, with f a function of a home's fire risk and the town's level of G. Additionally, the town is subject to coastal flooding, and there is some annual probability q of a flood destroying a home, with q a function of the town's flood risk and the town's level of P. In the event of a flood or fire, the annual rent that a (now nonexistent) home commands is 0. In the presence of the firehouse (G=1), f is equal to 0.020. In the absence of any flood protection (P=0), q is equal to 0.10. The property value of home k is then equal to the rental income it commands multiplied by the probability that the home is not destroyed, net of all taxes. Formally, assuming 1 time period and a discount rate of 0 for simplicity (N=1, δ=0):

$$V_k = R_k * (1 - f - q) - (T + T')$$

Suppose that the local government now invests in one "unit" of flood protection (e.g. all seawalls are raised by one foot) at a total cost of $450, on top of the existing provision of G. The higher seawalls reduce the annual probability of a destructive flood to 0.060, as a flood event would have to be more severe for waters to crest the new (higher) seawalls. The value of each home goes up by $400 to reflect the (now lower) probability of destruction. However, the total cost of raising the seawalls is $450 (assessed through a new tax on each home of T'=$150), and this additional annual cost reduces the increase in each home's value to $250. Summing up the costs and benefits of this first unit of P, the aggregate property value of the town's 3 homes rises to $27,000. **Table 1** presents the numbers:

Table 1.

G	P	f	q	R * (1–f–q)	T	T'	V_k	$\sum_{k=1}^{K=3} V_k$	Marginal cost of *this unit* of P	Marginal benefit of *this unit* of P
1	0	0.020	0.10	8,800	50	0	8,750	26,250	0	0
1	1	0.020	0.060	9,200	50	150	9,000	27,000	450	1200
1	2	0.020	0.035	9,450	50	300	9,100	27,300	450	750
1	3	0.020	0.025	9,550	50	450	9,050	27,150	450	300

The table presents a scenario where every additional unit of P carries with it decreasing marginal benefits, a reasonable assumption given the example of seawalls (or other flood risk mitigation measures, e.g. more stringent building codes). As can be seen from the table, property values are maximized when P=2: the marginal costs of increasing P to 3 outweigh the marginal benefits. P=2 is thus

the "efficient" level of public flood protection provision for this town. At any point above P=2, home values would decrease.

Suppose that the above result – that of an "efficient" level of P=2 – holds for one time period. However, suppose that the probability of flood events is increasing due to climate change. In **Table 2**, the probability of flood events has increased – from 0.10 to 0.15 at baseline, and from 0.025 to 0.030 when P=3 – and the "efficient" level of P is now P=3:

Table 2.

G	P	f	q	$R * (1-f-q)$	T	T'	V_k	$\sum_{k=1}^{K=3} V_k$	Marginal cost of *this unit* of P	Marginal benefit of *this unit* of P
1	0	0.020	0.15	8,300	50	0	8,250	24,750	0	0
1	1	0.020	0.080	9,000	50	150	8,800	26,400	450	2100
1	2	0.020	0.050	9,300	50	300	8,950	26,850	450	900
1	3	0.020	0.030	9,500	50	450	9,000	27,000	450	600
1	4	0.020	0.020	9,600	50	600	8,950	26,850	450	300

This (stylized) model presents three assumptions: given increasing flood risks due to climate change, the "optimal" level of public flood protection provision is increasing, and we would expect increases in provision of this public good among towns. Meanwhile, given the reality of heterogeneity between towns – whether in flood risk, the marginal costs of flood protection provision (e.g. differences in population density or shoreline length would present different mitigation costs), or the marginal benefits of flood protection provision (e.g. a town with more valuable real estate would have a larger incentive to invest) – we would expect differences in flood protection provision across towns. Finally, if flood protection provision is viewed as a public good, we would expect housing markets to respond to its provision, much in the same way they do to the provision of fire protection or better public schools.

4. Methodology

These preceding three (testable) assumptions motivate my empirical questions: (1) are local governments increasing their investment in public flood protection provision as flood risks increase, as would be expected under their adjustment to the "social optimum?" Further, every town differs in its socioeconomic and demographic makeup, financial capacity, and political priorities, and each may choose to invest in a different level of flood mitigation – (2) what factors are associated with local governments that do invest in flood protection? Finally, (3) is there a relationship between flood provision and home values, and how might this vary by flood risk or residents' income levels?

4.1. Empirical Strategy

To answer these three questions, I build a dataset of 405 municipalities in the state of Florida,[4] combining data from FEMA, the U.S. Census Bureau, the Florida Department of Revenue, and the Florida Department of Financial Services. The FEMA data includes a dataset from the Community Rating System (CRS), which provides a detailed score breakdown for all Florida jurisdictions participating in the program from 2009-2018.[5] I first code each Florida jurisdiction based on whether it participates in the CRS program in each year: "1" for participating communities, "0" for non-participating communities. Following Sadiq and Noonan's (2015) classification of risk-reducing measures, I next break down participating community's CRS point totals into an "active" subtotal, defined as the sum of score totals for select series 400, 500, and 600 activities.[6] These "active" activities require large capital outlays (flood protection infrastructure), impose large costs on property owners (stronger regulatory standards), or result in large foregone tax revenues (open space preservation) and thus are more likely to influence property values. I employ *Active CRS score* as my proxy for a local government's investment in public flood protection provision. The maximum possible score total is 10,649 (FEMA, 2017), but the range of scores in my dataset tops out at just 1,889 points.[7] **Table 3** summarizes all variables I use in my analysis, and **Table 4** provides summary statistics:

Table 3.

Variable Name	Description	Years	Source
Participate	A categorical variable recording whether a municipality participates (1) or does not participate (0) in the FEMA CRS program.	2009-2018	Obtained from FEMA's Federal Insurance and Mitigation Administration (FIMA) on October 18, 2019 following an email request to Bill Lesser, FIMA's national CRS coordinator.
Active CRS Score	The sum of points awarded by FEMA each year to a local government for "active" flood plain management activities, which I define as *Class 420* (Open Space	2009-2018	Obtained from FEMA's Federal Insurance and Mitigation Administration (FIMA) on October 18, 2019 following an email request to

[4] My dataset includes all Florida cities, towns, and villages, except for those owned by the Walt Disney Co. (Bay Lake and Lake Buena Vista) and those with populations below 100 (removed after an outlier analysis).
[5] I received this data on October 18, 2019 following an email request to Bill Lesser, the national CRS coordinator at FEMA's Federal Insurance and Mitigation Administration.
[6] My dataset includes towns that switched between FEMA scoring regimes after 2013; my approach for dealing with this change is in **Appendix A**.
[7] In most of these "active" CRS subcategories, the maximum possible score is significantly higher than the maximum actual score achieved by any community in the United States.

	Preservation), *430* (Higher Regulatory Standards), *450* (Stormwater Management), *510* (Floodplain Management Planning), *520* (Acquisition and Relocation), *530* (Flood Protection), *540* (Drainage System Maintenance), *610* (Flood Warning and Response), *620* (Levees), and *630* (Dams) activities.		Bill Lesser, FIMA's national CRS coordinator.
Flood Zone Percentage	The proportion of a municipality's land area that is in a FEMA-designated "High Risk" flood area. FEMA periodically updates flood maps (roughly every 10 years for my study area).	As of Jan., 2020	Flood map overlays downloaded from the FEMA Flood Map Service Center at: msc.fema.gov/portal/home; ArcGIS used to calculate the flood zone percentage
1980-90 Flood Claims per cap	The number of flood insurance claims processed by the National Flood Insurance Program (NFIP) within a municipality's present-day boundaries from 1980-1990 divided by the municipality's population in 2009.	1980-1990	Accessed through the OpenFEMA "FIMA NFIP Redacted Claims Dataset", available online at: www.fema.gov/media-library/assets/documents/180374
Recent Flood Claims per cap	The number of flood insurance claims processed by the National Flood Insurance Program (NFIP) within a municipality's present-day boundaries within the preceding 3 years divided by the municipality's population in 2009.	2007-2017	Accessed through the OpenFEMA "FIMA NFIP Redacted Claims Dataset", available online at: www.fema.gov/media-library/assets/documents/180374
Millage Rate	The municipally set tax rate used to calculate local property taxes. The rate represents the amount of tax due each year per every $1,000 of assessed property value.	2009-2018	Accessed through the Florida Department of Revenue's annual "Municipal Report", published online at: floridarevenue.com/ property/Pages/DataPortal_DataBook.aspx
Taxable Property Value per cap	The total taxable property value in a municipality (after accounting for all property exemptions) divided by the municipality's population in 2009.	2008-2018	Accessed through the Florida Department of Revenue's annual "Municipal Report", published online at: floridarevenue.com/ property/Pages/DataPortal_DataBook.aspx
Debt per cap	The sum of long-term debt of a municipality government divided by the municipality's population in 2009.	2009-2018	Accessed through the Florida Department of Financial Service's annual "Total Revenues, Expenditures and Debt" report, published online at: apps.fldfs.com/LocalGov/Reports/
Police Spend per cap	A local government's spending on law enforcement each year from 2009-2018 divided by its 2009 population.	2009-2018	Accessed through the Florida Department of Financial Service's annual "Expenditure Details" report, published online at: apps.fldfs.com/LocalGov/Reports/
Road Spend per cap	A local government's spending on roads and streets each year from 2009-2018 divided by its 2009 population.	2009-2018	Accessed through the Florida Department of Financial Service's annual "Expenditure Details" report, published online at: apps.fldfs.com/LocalGov/Reports/

Park Spend per cap	A local government's spending on libraries, parks, and special events each year from 2009-2018 divided by its 2009 population.	2009-2018	Accessed through the Florida Department of Financial Service's annual "Expenditure Details" report, published online at: apps.fldfs.com/LocalGov/Reports/
Zillow Single-family Home Value Index	The Zillow Single-family Home Value Index each year from 2010-2019 for a municipality. The Zillow Single-family Home Value Index is a measure of a typical home's value as determined by overall local market conditions.	2008-2019	Accessed through Zillow Research's Housing Data portal, available online at: www.zillow.com/research/data/
2009 Population	The population of a municipality ("place"), as compiled by the American Community Survey's 2009 5-year estimates.	2009	Accessed through Social Explorer's American Community Survey tables, available at: www.socialexplorer.com/tables/ACS2009_5yr. ArcGIS used to calculate land area.
2009 Population Density	The population of a municipality ("place"), as compiled by the American Community Survey's 2009 5-year estimates, divided by its land area in square kilometers.	2009	Accessed through Social Explorer's American Community Survey tables, available at: www.socialexplorer.com/tables/ACS2009_5yr. ArcGIS used to calculate land area.
2009 Median Household Income	The median household income in 2009 inflation-adjusted dollars of a municipality ("place"), as compiled by the American Community Survey's 2009 5-year estimates.	2009	Accessed through Social Explorer's American Community Survey tables, available at: www.socialexplorer.com/tables/ACS2009_5yr
2009 Owner Occupied Homes per cap	The number of housing units in a municipality ("place") where the owner or co-owner lives in the unit, even if it is mortgaged or not fully paid for, divided by its 2009 population.	2009	Accessed through Social Explorer's American Community Survey tables, available at: www.socialexplorer.com/tables/ACS2009_5yr
2009 Gini Index	A summary measure of income inequality at the municipal ("place") level. The index ranges from 0 (perfect equality) to 1 (perfect inequality).	2009	Accessed through Social Explorer's American Community Survey tables, available at: www.socialexplorer.com/tables/ACS2009_5yr

Table 4.

Variable Name	**Mean**	**S.D.**	**Min**	**Max**	**# of Observations**
Participate 2009	0.421	0.494	0	1	404
Participate 2018	0.469	0.499	0	1	405
Active CRS Score	1025.825	283.644	231	1889	1742
2009-2018 Change in Active CRS Score	164.111	219.097	-748.693	914.904	190
Flood Zone Percentage	0.343	0.284	0	1	403
1980-90 Flood Claims per cap (#)	0.00861	0.0323	0	0.380	405
Recent Flood Claims per cap (#)	0.00256	0.0180	0	0.669	405
Millage Rate ($/$1000)	4.826	2.218	0.00148	10	3726
Taxable Property Value per cap ($)	143346.5	316090.4	5079.517	5117655	3737
Debt per cap ($)	2122.007	7006.848	0	116957.9	4005

Police Spend per cap ($)	388.217	406.310	0.00302	4172.149	3443
Road Spend per cap ($)	153.572	218.890	0.728	4384.267	3748
Park Spend per cap ($)	127.108	167.3214	0	1992.315	3457
ZHVI ($)	269561.8	421669	28678.33	5263528	3953
2009 Population	22990.32	57531.76	121	802843	404
2009 Pop Density (persons per km^2)	933.896	1072.69	8.155	8338.15	403
2009 Median Income	57205.13	28045.8	21998	265442	404
2009 Owner Occupied Homes per cap	0.284	0.0860	0.0776	0.605	404
2009 Gini Index	0.446	0.0657	0.255	0.636	404
# of Panel Observations	**2750**				

4.1.1. Participation and CRS scores over time

Beginning with question (1): an overview of my set of Florida municipalities indicates two observations – municipalities enter (and exit) the CRS program, and participating municipalities increase (or decrease) their active score totals over the study period. To see the degree to which program participation is increasing each year (as would be expected, if local governments are in fact responding to the growing risks from flooding due to climate change), I first run **Regression 1A:**

$$\textbf{(1A)}\ \Pr(\widehat{Participate_{it}} = 1|Time) = a_0 + a_1 Time_{it}$$

This linear probability model estimates the correlation between *participation* (equal to 1 in each year for CRS participating communities in that year and 0 otherwise) and *time* (from 2009 to 2018) for town *i* in year *t*. The town-level fixed effect is denoted by u_i. I elect to use a linear probability model for ease of interpretation, but I run a logistic regression (not shown) as a robustness check and find similar results. For this and all following panel regressions, I use robust standard errors and cluster at the town level.

Next, focusing on the municipalities that are participating in the program, I analyze whether these local governments are investing more in active CRS measures (e.g. flood protection measures) over the study period (2009-2018) by estimating the correlation between *time* and *active CRS score* for town *i* in year *t* in **Regression 1B**:

$$\textbf{(1B)}\ Active_CRS_{it} = a_0 + a_1 Time_{it} + u_i + \epsilon_{it}$$

I run specifications with and without city-level fixed effects for both regressions to determine how much variation can be explained by non-time varying town characteristics.

4.1.2. Determinants of CRS participation

Turning to question (2), I examine three different measures of government provision of flood protection: *CRS program participation* at the end of the study period (2018), *average active CRS score* from 2009-2018, and *change in active CRS score* from 2009-2018.

$$\textbf{(2A)}\quad \Pr(\widehat{Participate_{i,t=2018}} = 1|X) = b_0 + b_1 Millage_Rate_{i,t=2009} + b_2 Tax_Value_{i,t=2009} + b_3 Debt_{i,t=2009} + b_4 \sum_{t=1980}^{1990} Flood_Claims_i + b_5 Flood_Zone_i + b_6 Pop_Density_{i,t=2009} + b_7 Median_Income_{i,t=2009} + b_8 Owner_Occupied_{i,t=2009} + b_9 Gini_Index_{i,t=2009} + b_{10} Population_{i,t=2009}$$

I first run **Regression 2A** (a linear probability model) to examine the extent to which each of the following factors influence a municipality's *participation* in the CRS program at the end of my study period (2018): baseline financial capacity, historic flood history, flood risk, and a series of baseline demographic and socio-economic town characteristics. I employ *2009 millage rate*, *2009 taxable property value per capita*,[8] and *2009 debt per capita* as measures of baseline financial capacity, hypothesizing that lower millage rates, higher property values, and lower debt levels would promote flood protection investment. In the case of millage rates, a lower rate could provide a government with greater flexibility to raise rates in order to afford flood protection investments. I then include *per capita number of flood claims from 1980 to 1990*[9] as a measure of historic flood history and *flood zone percentage* as a proxy for flood risk, predicting that a higher number of historic flood claims and a greater percentage of land area in a flood zone would lead to greater investment. Finally, I include *2009 population density* as a city built environment control in order to test for whether density affects investment (I predict that more people and property at risk from flooding – and thus higher expected flood losses – would incentivize investment), *2009 median income* as a test for whether flood protection is a normal good, *2009 owner occupied homes per capita* as a proxy for resident engagement (I hypothesize that owner-occupants would be more engaged in matters pertaining to long-term investment decisions), *2009 Gini Index* as a test for whether population heterogeneity affects investment, and *2009 population* as an additional control (but with an uncertain impact – larger cities would likely have more resources to engage in flood risk mitigation, but these cities

[8] Taxable value includes residential and commercial properties.

[9] The FEMA CRS program was established in 1990. Floods prior to 1990 would have occurred in the absence of CRS-incentivized flood risk mitigation measures – this variable could thus be a candidate for an exogenous predictor of program participation and investment.

may also have more competing priorities). I run specifications with and without different variables due to concerns about collinearity.[10]

I next focus on participating communities and the factors that influence their degree of participation in the program:

$$\textbf{(2B)}\quad \overline{Active_CRS}_{i,2009-2018} = b_0 + b_1 Millage_Rate_{i,t=200} + b_2 Tax_Value_{i,t=2009} + b_3 Debt_{i,t=2009} + b_4 \sum_{t=1980}^{1990} Flood_Claims_i + b_5 Flood_Zone_i + b_6 Pop_Density_{i,t=2009} + b_7 Median_Income_{i,t=2009} + b_8 Owner_Occupied_{i,t=2009} + b_9 Gini_Index_{i,t=2009} + b_{10} Population_{i,t=2009} + \epsilon_{i,t}$$

In cross-section **Regression 2B**, I examine the *Average Active CRS Score* from 2009-2018 for town *i* as a function of the baseline indicators used in Regression 2A. This specification aims to explain who were "high-performing" cities during the study period, whether they began the study period with already-high CRS scores or increased scores during the period.

Finally, **Regression 2C** examines the *2009-2018 change in active CRS score* for town *i* as a function of baseline characteristics:

$$\textbf{(2C)}\quad \Delta Active_CRS_{i,t=2009-2018} = b_0 + b_1 Millage_Rate_{i,t=2009} + b_2 Tax_Value_{i,t=2009} + b_3 Debt_{i,t=2009} + b_4 \sum_{t=1980}^{1990} Flood_Claims_i + b_5 Flood_Zone_i + b_6 Pop_Density_{i,t=2009} + b_7 Median_Income_{i,t=2009} + b_8 Owner_Occupied_{i,t=2009} + b_9 Gini_Index_{i,t=2009} + b_{10} Population_{i,t=2009} + \epsilon_{i,t}$$

I use the same independent variables as in Regression 2A and 2B, with the objective of determining what 2009 town characteristics predict score changes over the next 10-year period. This specification differs from 2B in that it focuses on towns with large changes in the score over the study period; "high performing" towns that entered the period with high scores and maintained those scores would have a recorded change of "0". The differences between both specifications determine whether the characteristics of towns making CRS investments from 2009-2018 differ from those of towns that made investments prior to 2009.

4.1.3. Home values and investment in flood mitigation

Turning to question (3), I analyze the relationship between median home value (as measured by the community's *Zillow single-family Home Value Index*[11]) and local government investment in flood protection.

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[10] Correlated variables (>0.40) include *median income* and *tax value* (0.51), *debt* and *tax value* (.67), *owner occupied homes* and *tax value* (0.41), *Gini index* and *tax value* (0.44), *owner occupied homes* and *median income* (0.43), and *flood zone %* and *1980-90 flood claims* (0.45).

[11] I focus solely on single-family homes in order to allow for a more precise comparison between home values across municipalities.

I first examine program *participation* in each year from 2009 to 2018 and home values in the following year in panel **Regression 3A**:

$$\textbf{(3A)}\quad Home_Value_Index_{i,t} = \beta_0 + \beta_1 Participate_{i,t-1} + \beta_2 Participate_{i,t-1} * Flood_Zone_i + \beta_3 Participate_{i,t-1} * Median_Income_{i,t=2009} + \beta_4 Millage_Rate_{i,t-1} + \beta_5 Police_{i,t-1} + \beta_6 Road_{i,t-1} + \beta_7 Park_{i,t-1} + \beta_8 \sum_{t-4}^{t-1} Flood_Claims_i + u_i + \theta_t + \epsilon_{i,t}$$

I incorporate an interaction term between *participate* and *flood zone percentage* in order to determine the additional effects of program participation in high flood zone percentage cities, as well as an interaction term with *2009 median income* to determine whether there is a differential effect on home values among different income CRS participating cities. I include a series of one-year lagged variables controlling for changing tax levels and provision of other local public goods: *millage rate*, *police spending per capita*, *road spending per capita*, and *park spending per capita*. In the state of Florida, schools are the purview of county governments, so these "other public goods" variables likely capture the most perceptible differences between municipalities. I predict that increases in park spending would be correlated with rising home values, while a rise in police spending could have opposing effects (either resulting in higher values due to increases in public safety, or lower values if higher spending is a response to rising crime). Higher road spending could likewise either raise home values (better infrastructure; less potholes) or lower home values (if spending is a response to higher traffic levels). Finally, I include a *recent flood claims* variable to control for any "shocks" to the housing market in the form of major hurricanes or other flood events. I further include city and time-fixed effects, in order to control for non-time varying city characteristics (baseline flood risk; natural amenities; distance to employment centers) and to control for fluctuations in home prices in each year.

In **Regression 3B**, I next turn to CRS participating cities, and I use the same specification as in 3A but with *active CRS score* in town *i* in year *t* as my independent variable of interest:

$$\textbf{(3B)}\quad Home_Value_Index_{i,t} = \beta_0 + \beta_1 Active_CRS_{i,t-1} + \beta_2 Active_CRS_{i,t-1} * Flood_Zone_i + \beta_3 Active_CRS_{i,t-1} * Median_Income_{i,t=2009} + \beta_4 Millage_Rate_{i,t-1} + \beta_5 Police_{i,t-1} + \beta_6 Road_{i,t-1} + \beta_7 Park_{i,t-1} + \beta_8 \sum_{t-4}^{t-1} Flood_Claims_i + u_i + \theta_t + \epsilon_{i,t}$$

5. Results

Figure 1.

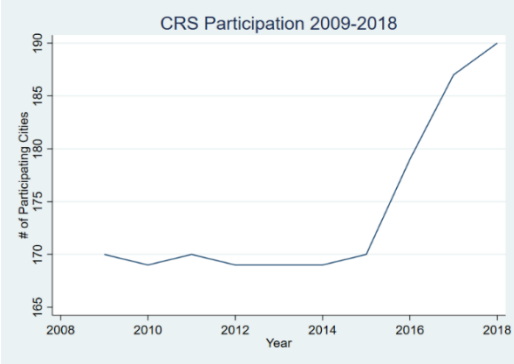

Figure 2.

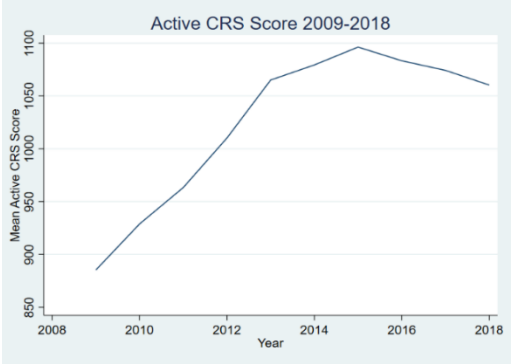

Table 5: (1A) CRS Participation 2009-2018

Dependent variable:	**CRS Participation**		**Active CRS Scores**	
	(1)	(2)	(3)	(4)
Time	0.00507***	0.00514***	20.57***	23.01***
	[0.002]	[0.002]	[2.403]	[2.259]
Constant	0.403***	0.403***	910.6***	896.9***
	[0.026]	[0.010]	[24.733]	[12.656]
City Fes	No	Yes	No	Yes
Observations	4,038	4,038	1,742	1,742
R-squared	0.001	0.930	0.044	0.837
Number of Cities	405	405	199	199

Notes: Observations in columns 1-2 are city-years for all cities (405), with *participation* = 1 for participating cities, 0 otherwise. Observations in columns 3-4 are city-years for all municipalities participating in the CRS program (199). Robust standard errors clustered by city in brackets: ***p<0.01, **p<0.05, *p<0.1

Turning first to question (1): is the level of public flood protection increasing, as measured by local governments' provision of this public good? Looking first at *CRS program participation*, the results in columns 1 and 2 suggest that time is statistically significant relative to program participation.[12] This confirms what is shown in **Figure 1**, whereby the number of cities participating increased after 2015. In 2009, 170 cities (out of 404) were participating; in 2018, 190 (out of 405[13]) were. Meanwhile, columns 3 and 4 analyze *active CRS scores*, and the results in column 4 indicate that there is a steady increase in score with each passing year, averaging 23 points (2.24% of the average annual score) within cities. The high R-squared value in the column 4 specification with fixed effects suggests that underlying town characteristics explain most of the variation in score changes.

[12] The magnitude and significance of the coefficient on *Time* are robust to a logistic specification (not shown).

[13] Estero, FL was incorporated in 2014; Westlake, FL was incorporated in 2016; Islandia, FL was unincorporated in 2012.

There is a slight decrease in average annual score after 2015 (**Figure 2**), perhaps coinciding with the growth in program participation (newly participating cities would likely enter the program with lower scores).

Table 6: (2A) Predicting CRS Program Participation in 2018

Dependent Variable:	**CRS Participation**				
	(1)	(2)	(3)	(4)	(5)
2009 Millage Rate	-0.0195		-0.0176	-0.0156	**-0.0230****
($/$1,000)	[0.012]		[0.013]	[0.013]	**[0.011]**
2009 Taxable Value per	**0.0159*****			-0.00912	0.000282
capita ($100,000s)	**[0.005]**			[0.015]	[0.012]
2009 Debt per capita		0.00120	0.00322	0.00354	0.000669
($1,000s)		[0.002]	[0.002]	[0.005]	[0.004]
1980-90 Flood Claims	**0.928***	**1.104****	0.724	**0.882***	**1.081****
per capita (#)	**[0.492]**	**[0.517]**	[0.467]	**[0.510]**	**[0.474]**
Flood Zone (% in	**0.256****	**0.246****	**0.275*****	**0.237****	**0.270*****
decimal)	**[0.101]**	**[0.108]**	**[0.100]**	**[0.109]**	**[0.100]**
2009 Population Density	**0.0140*****	**0.0128*****	**0.0139*****	**0.0133*****	**0.00876*****
(100s)	**[0.004]**	**[0.004]**	**[0.004]**	**[0.004]**	**[0.003]**
2009 Median Income		**0.0286****		**0.0273***	**0.0223***
($10,000s)		**[0.013]**		**[0.015]**	**[0.013]**
2009 Owner Occupied			**0.565***	0.253	**0.639****
Homes per capita (#)			**[0.341]**	[0.359]	**[0.321]**
2009 Gini Index (1-0)		0.438		0.476	0.140
		[0.404]		[0.421]	[0.369]
2009 Population					**0.0460*****
(10,000s)					**[0.010]**
Constant	0.316***	-0.0988	0.159	-0.103	-0.0806
	[0.071]	[0.172]	[0.126]	[0.229]	[0.201]
Observations	372	372	372	372	372
R-squared	0.184	0.201	0.187	0.207	0.348

Notes: Observations are cities with available data (372). Regressions predict CRS participation in 2018 (Participate = 1, 0 otherwise). Robust standard errors clustered by city in brackets:***p<0.01, **p<0.05, *p<0.1

Moving to question (2): What factors predict local government investment in flood risk protection? **Table 6** presents the results for *CRS program participation* in 2018.[14] Column 1 includes financial capacity and flood risk variables, apart from *debt*. Columns 2, 3, and 4 further incorporate socio-economic and demographic controls. Column 2 includes *median income* and *Gini index* but excludes *millage rate* and *tax value*. Column 3 includes *owner-occupied homes* but excludes *taxable value*, *median income*, and *Gini index*. Column 4 includes all variables, and column 5 includes *population* as an additional control.

Flood zone %, *population density*, and *median income* are significant positive predictors across all specifications, with a one standard deviation (SD)

[14] The relative magnitude and significance of the coefficients are robust to a logistic specification (not shown).

increase in *flood zone %* (0.28), *population density* (1,073), and *median income* (28,046) increasing the probability of participation by 6.6-7.7%, 9.4-15.0%, and 6.3-8.0%, respectively. *Flood claims per capita* is consistently significant and positive in all specifications except column 3, with a one SD increase (0.032) associated with a 2.8-3.5% increased probability. *Population* is also a positive predictor, with a one SD (57,000) increase associated with a 26.2% higher probability. *Taxable value per capita* has a significant and positive coefficient in column 1, but this significance disappears with additional controls (and interpretation is made difficult due to high correlations with *debt*, *median income*, and *Gini index*). *Owner occupied homes per capita* is significant and positive in columns 3 and 5, but this significance disappears in the absence of a *population* control in column 4. *Millage rate* is likewise significant (but negative) when controlling for *population*.

Overall, it appears that towns with higher flood zone percentages, more historic flood claims, higher population densities, higher median incomes, and larger populations tend to participate in the CRS program. Less certain but positive predictors of participation include the number of owner-occupied homes and taxable value, while higher millage rates are a negative predictor. These results suggest that the cities that are participating are those with higher expected flood losses (more land area in flood zones and greater densities of people and property), wealthier residents (program participation appears to be a "normal good"), and more owner-occupiers (and residents who may be more engaged with long-term issues).

Table 7 presents results for *average active CRS score*. Column 1 includes financial capacity and flood risk variables, except for *debt*. Column 2 includes *debt* and a *population* control but excludes *tax value*. Columns 3-5 incorporate socio-economic and demographic controls. Column 3 includes *median income* and *Gini index* but excludes *millage rate* and *tax value*. Column 4 includes all variables, while column 5 again incorporates *population*.

Population density and *median income* have significant negative coefficients across specifications, with a one SD increase in each (1,072 additional residents; a $28,045 increase in income) associated with a 53.1-73.7-point decrease (5.2-7.2% of the average score of 1,026) and 50.2-60.0-point (4.9-5.8%) decrease in score, respectively. Meanwhile, greater inequality (a higher *Gini index*) has a positive association with score, with a 1 SD (0.0657) increase associated with a 44.2-60.0-point increase in score. Columns 2 and 5 suggest that *population* is positive and significant, with every additional 57,000 residents associated with an additional 73.3-75.6 points. *Flood zone %* has a significant and positive coefficient in all specifications but column 4, with a 0.28 increase predicting a 36.7-45.3-point increase in score. *Millage* is a consistent negative predictor of average scores, with

the significant coefficients in columns 2 and 5 suggesting a 50-point decrease with every 2.22 mill increase in property tax rates. *Debt* is significant and negative in the absence of *tax value* (columns 2 and 3), while *taxable value* is significant and negative in 1 and 4. The high correlation between both variables (0.67) makes interpretation of their coefficients difficult, but the results suggest that higher taxable values, even when controlling for debt, are associated with lower scores, while the association between *debt* and *score* is less clear.

Table 7: (2B) Predicting Average Active CRS Score from 2009-2018

Dependent Variable:	**Average Active CRS Score**				
	(1)	(2)	(3)	(4)	(5)
2009 Millage Rate	-16.74	**-22.75****		-17.36	**-22.08****
($/$1,000)	[12.048]	**[11.200]**		[11.928]	**[11.140]**
2009 Taxable Value per	**-8.466****			**-19.31***	-14.90
capita ($100,000s)	**[3.759]**			**[10.714]**	[10.904]
2009 Debt per capita		**-2.326*****	**-2.628****	3.437	1.817
($1,000s)		**[0.884]**	**[1.018]**	[3.635]	[3.652]
1980-90 Flood Claims	-141.5	-41.51	-68.00	-252.0	-239.8
per capita (#)	[399.220]	[391.205]	[383.894]	[394.742]	[391.206]
Flood Zone (% in	**150.0***	**161.7****	**130.9***	124.5	**147.1***
decimal)	**[79.820]**	**[76.550]**	**[74.312]**	[86.405]	**[83.907]**
2009 Population Density	**-4.955*****	**-5.996*****	**-6.674*****	**-6.055*****	**-6.867*****
(100s)	**[1.808]**	**[1.794]**	**[1.663]**	**[1.733]**	**[1.728]**
2009 Median Income			**-17.91****	**-16.63***	**-16.28***
($10,000s)			**[8.061]**	**[9.091]**	**[8.877]**
2009 Owner Occupied				281.5	541.7
Homes per capita (#)				[322.995]	[330.974]
2009 Gini Index (1-0)			**816.6*****	**913.0*****	**672.3****
			[310.676]	**[327.426]**	**[323.197]**
2009 Population		**13.26*****			**12.83*****
(10,000s)		**[3.157]**			**[3.360]**
Constant	1,091***	1,061***	778.9***	736.3***	733.0***
	[68.513]	[66.894]	[137.130]	[191.162]	[185.406]
Observations	189	189	189	189	189
R-squared	0.083	0.146	0.111	0.139	0.198

Notes: Observations are cities participating in the CRS program and with available data (189). Regressions predict Average Active CRS score from 2009-2018. Robust standard errors clustered by city in brackets: ***p<0.01, **p<0.05, *p<0.1

Overall, it appears that towns with larger populations, greater inequality (as measured by a higher Gini index), lower population densities, and lower median incomes have higher average scores, with lower taxable values, lower millage rates, and higher flood zone percentages additional (but less certain) predictors of higher scores. These results suggest that the driving forces behind higher active CRS scores are different than those behind program participation: while population density, income, and taxable value are positive predictors of participation, these variables have negative associations with score. Additionally, historic flood claims

have a positive (and significant) association with participation but are insignificant with regards to score. Conversely, inequality (as measured by the Gini index) is not significant for participation but is significant with regards to score.

Table 8: (2C) Predicting Change in Active CRS Score 2009-2018

Dependent Variable:	**Change in Active CRS Score**					
	(1)	(2)	(3)	(4)	(5)	(6)
2009 Millage Rate	-3.072		-5.127	-4.314	-5.143	
($/$1,000)	[9.549]		[9.446]	[9.702]	[9.879]	
2009 Taxable Value per	-1.379			4.228	5.004	
capita ($100,000s)	[6.769]			[8.713]	[8.635]	
2009 Debt per capita	1.731	**1.271***	**1.932*****	0.604	0.320	
($1,000s)	[2.552]	**[0.700]**	**[0.594]**	[2.797]	[2.779]	
1980-90 Flood Claims per	225.8	240.7	221.7	219.6	221.7	
capita (#)	[318.683]	[319.919]	[311.553]	[313.746]	[314.160]	
Flood Zone (% in	**-113.5***	**-110.7****	**-98.74***	**-107.9***	-104.0	
decimal)	**[61.086]**	**[54.947]**	**[59.455]**	**[63.807]**	[64.302]	
2009 Population Density	-0.928	-1.037	-0.528	-0.484	-0.627	
(100s)	[1.486]	[1.466]	[1.516]	[1.511]	[1.549]	
2009 Median Income		-0.150		-1.260	-1.198	
($10,000s)		[7.085]		[9.432]	[9.399]	
2009 Owner Occupied				34.29	79.97	
Homes per capita (#)				[232.729]	[246.489]	
2009 Gini Index (1-0)			-376.7	**-441.5***	**-483.8***	
			[237.433]	**[262.375]**	**[268.228]**	
2009 Population					2.253	
(10,000s)					[2.395]	
2009 Active CRS Score						**-0.396*****
						[0.065]
Constant	228.5***	214.8***	396.5***	419.1***	418.5***	669.5***
	[57.423]	[54.472]	[121.372]	[147.392]	[147.806]	[144.994]
Observations	189	189	189	189	189	163
R-squared	0.027	0.027	0.037	0.039	0.041	0.257

Notes: Observations in columns 1-5 are cities participating in the CRS program and with available data (189). Column 6 is cities participating in the CRS program in 2009 (163). Regressions predict 2009-2018 change in active CRS points. Robust standard errors clustered by city in brackets: ***p<0.01, **p<0.05, *p<0.1

Table 8 presents results for *change in active CRS score from 2009-2018*. Column 1 includes all financial capacity and flood risk variables. Columns 2-5 incorporate socio-economic and demographic controls. Column 2 includes *median income* but excludes *tax value* and *millage rate*. Column 3 includes *median income* but excludes *tax value* and *median income*. Column 4 includes all variables, and column 5 adds *population* as a control. Finally, column 6 examines the association between *2009 active CRS score* and *change in score*.

In comparison to Table 7, the signs on *millage rate*, *population density*, *owner occupied homes*, and *population* are the same, although none of the variables are significant. Meanwhile, the signs on *flood claims*, *flood zone %*, *Gini index*,

tax value in columns 4-5 and *debt* in columns 2-3 are opposite between both tables, with *flood zone*, *Gini index*, and *debt* having significant signs in select specifications. A one SD increase in *flood zone*, *Gini index*, and *debt per capita* (0.28, .0657, and $7,007) is associated with a 27.6-31.8-point decrease in score (16.8-19.4% of the average change of 164.1 points), 29.0-31.8-point decrease, and 8.9-13.5-point increase (5.4-8.2%) across significant specifications, respectively.

Overall, it appears that the towns making the largest improvements in their scores during this time period are different from those that have the highest average scores. *2009 CRS score* has a negative 0.40 association with *change in score*, suggesting that participating cities with high scores in 2009 increased their scores by less when compared to 2009 participating cities with low scores and/or cities that entered the program during the study period. Higher *flood zone percentage* and more unequal cities appear to have been the "first movers" when it comes to *active CRS score*, while the "more recent movers" are at lower flood risk (when proxied by *flood zone percentage*), more equal, and appear to have higher debt loads (perhaps directly related to their flood prevention investments).

Turning to Question (3): is there a relationship between flood provision and home values, and does this vary by flood risk or income? **Table 9** examines *CRS program participation* and the effects on median home values. Column 1 examines whether there is a relationship between *participation* and *home value* according to the panel specification; column 2 adds an interaction term with *flood zone*; column 3 adds taxation and public goods provision controls; columns 4 and 5 add interaction terms, first with *flood zone* and then with *median income*; column 6 repeats the column 3 specification but with *recent flood claims per capita* as an additional control.

Focusing first on columns 1 and 3, the results suggest that there is a positive but not statistically significant association between program participation and median home values. The point estimate indicates that participation is associated with a $6,079 increase in home values (2.3% of the mean value of $269,562) in column 1. This drops to a $3,579 increase (1.3% of the mean) when controlling for tax levels and public goods, with the 95% confidence interval extending from -$16,718 to $23,876. The magnitude rises to $5,675 when controlling for *recent flood claims* in column 6. The interaction terms in columns 2 and 4 provide mixed evidence for whether there is a differential effect on home values in towns with large flood zones: participation in a city with 63% of its land area in a flood zone (one SD above the average 34%) is associated with an insignificant $13,847 increase in home values (3.3% of the mean value of $416,690, when using the predicted home value based on a regression of *ZHVI* on *flood zone %*) in column 2, but the magnitude drops to $3,209 (0.7% of the mean) in column 4 in the presence of control variables. Interacting with *median income* in column 5, the results do

provide evidence for a differential effect on home values in high income locales: the interaction term is significantly different from zero. The magnitudes suggest that participation for a city with a median income of $85,250 (1 SD above the mean) is associated with an insignificant $21,738 increase (4.1% of the mean value of $528,053, when using the predicted home value based on a regression of *ZHVI* on *median income*), with the confidence interval extending from -$5,195 to $48,671. However, for a city with a median income at the 25th percentile ($38,980), the magnitude drops to -$16,807 (-16.2% of the mean home value of $103,649). Meanwhile, *millage rate* and *park spending* are both significant across specifications, with results suggesting that housing markets do value park spending (though this correlation does not extend to police or road spending) and that higher taxes are capitalized in the form of lower home values.

Table 9: (3A) Homes Values and CRS Participation 2009-2018

Dependent Variable:	**Median Home Value**					
	(1)	(2)	(3)	(4)	(5)	(6)
CRS Participation (*t*-1)	6,079	-4,239	3,579	4,070	**-49,280****	5,675
	[10,184.49]	[14,232.32]	[10,314.72]	[13,187.48]	**[23,426.29]**	[10,667.67]
City Millage Rate (*t*-1) ($/$1,000)			-16,094**	-16,099**	-16,094**	-16,628**
			[7,654.752]	[7,667.230]	[7,651.596]	[8,270.012]
Police spending per capita (*t*-1) ($10s)			375.3	375.4	353.7	-72.22
			[1,686.712]	[1,687.996]	[1,689.669]	[1,838.419]
Road spending per capita (*t*-1) ($10s)			523.3	523.2	522.0	403.0
			[431.399]	[430.985]	[431.923]	[417.906]
Park spending per capita (*t*-1) ($10s)			1,739*	1,739*	1,735*	1,708*
			[948.717]	[952.379]	[949.949]	[945.356]
CRS Participation (*t*-1) x Flood Zone (% in decimal)		28,709		-1,366		
		[37,283.10]		[40,758.75]		
CRS Participation (*t*-1) x 2009 Median Income ($10,000s)					**8,330****	
					[3,740.937]	
Recent Flood Claims per capita (#)						-78,710
						[68,689.95]
Constant	209,445***	208,946***	241,066***	241,107***	242,456***	259,039***
	[6,949.431]	[7,063.580]	[83,518.84]	[83,343.85]	[83,735.28]	[90,642.46]
City & Year Fes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,773	2,773	2,773	2,773	2,773	2,498
R-squared	0.957	0.957	0.959	0.959	0.959	0.959

Notes: Observations are city-years for cities with available data (305), with one less year of data for column 6. Regressions predict the impact of 1-year lagged CRS program participation (Participate = 1, 0 otherwise) on the Zillow home value index from 2010-2019. Robust standard errors clustered by city in brackets:
***p<0.01, **p<0.05, *p<0.1

Overall, the results suggest that there is no statistically significant effect from *CRS participation* on home values. However, based on relative magnitudes

and confidence intervals, there is evidence that participation has higher magnitude and higher percentage effects on home values in towns with higher median incomes.

Table 10: (3B) Home Prices and Active CRS Score 2009-2018

Dependent Variable:	**Median Home Value**					
	(1)	(2)	(3)	(4)	(5)	(6)
Active CRS Score (*t*-1) (100s)	**-6,754****	**-17,082*****	**-6,250****	**-15,645*****	**-29,667***	**-6,948****
	[2,786.03]	**[6,020.46]**	**[2,577.885]**	**[5,809.670]**	**[15,979.31]**	**[2,747.685]**
City Millage Rate (*t*-1) (mills)			-44,452**	-42,953**	-43,167**	-44,463**
			[18,230.65]	[17,490.96]	[17,678.04]	[18,004.09]
Police spending per capita (*t*-1) ($10s)			-3,035	-2,967	-3,006	-3,578
			[2,767.037]	[2,781.782]	[2,771.663]	[2,851.469]
Road spending per capita (*t*-1) ($10s)			422.9	328.1	415.6	163.2
			[530.851]	[522.812]	[529.636]	[633.175]
Park spending per capita (*t*-1) ($10s)			2,212	2,273	2,145	2,514
			[1,576.564]	[1,566.146]	[1,530.411]	[1,811.750]
Active CRS Score (*t*-1) (100s) x Flood Zone % (dec)		**30,471****		**27,588****		
		[11,751.1]		**[13,071.66]**		
Active CRS Score (*t*-1) (100s) x 2009 Median Income ($10,000s)					3,853	
					[2,392.099]	
Recent Flood Claims per capita (#)						-69,796
						[43,332.24]
Constant	331,711***	311,228***	602,240***	575,288***	589,736***	629,661***
	[16,867.4]	[20,992.2]	[160,357.5]	[163,033.5]	[161,342.9]	[163,970.2]
City & Year Fes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,362	1,362	1,362	1,362	1,362	1,210
R-squared	0.958	0.959	0.962	0.962	0.962	0.962

Notes: Observations are city-years for cities participating in the CRS program and with available data (167), with one less year of data for column 6. Regressions predict the impact of 1-year lagged Active CRS scores on the Zillow Home Value Index from 2010-2019. Robust standard errors clustered by city in brackets:
***p<0.01, **p<0.05, *p<0.1

Table 10 presents results for *active CRS scores* for all program participating cities, with columns following the same pattern as in Table 9.

Beginning with column 3, the results suggest that on average, across towns, increases in *active CRS score* have a significant but negative effect on home values in the following year. Controlling for taxes and public goods, every 100-point increase (a roughly 10% improvement on the mean score of 1,026) is associated with a $6,250 decrease in home values (-2.3% of the mean of $269,562), with the 95% confidence interval extending from -$11,340 to -$1,160. The magnitude is slightly larger when also controlling for *recent flood claims* in column 6. The results for the interaction term in column 4 provide evidence for a differential effect on home values in towns with large flood zones, with a positive and statistically

significant interaction between active score and *flood zone %*. Evaluated at realistic values, however, the estimated change in home prices is not statistically significant: a 100-point increase in a city with 63% of its land in a flood zone is associated with a $1,735 increase in home values (2.3% of the mean value of $416,690), with the confidence interval extending from -$6,890 to $10,360. Interacting with *median income* in column 5, the results provide suggestive evidence for a differential effect on home values in high income cities, but the results are again not significant: a 100-point increase in a city with a median income of $85,250 is associated with a $3,178 increase in home values (0.6% of the mean value of $528,053), with the confidence interval extending from -$7,679 to $14,036. This association drops to a $14,649 decrease in home values (-14.1% of the mean value of $103,649) for a city with a $38,980 median income, with the confidence interval ranging from -$28,499 to -$799. Meanwhile, *millage rate* again has a significant and negative association with home values.[15]

Overall, it appears that *active CRS score* levels have a significant and negative association with home values in the average Florida municipality, but CRS scores in cities with more land area in flood zones and/or higher median incomes appear to have a less negative (or positive) effect on home values.

6. Discussion

Through the lens of the FEMA Community Rating System program, local governments in the state are responding to rising flood risks. From 2009-2018, there has been an 11.8% increase in CRS program participation among municipalities and a 19.8% increase in average "active" scores among CRS participating municipalities. This increase in active scores suggests that communities are investing more in stormwater systems and flood protection infrastructure, setting stricter building codes, acquiring and demolishing at-risk properties, and preserving open spaces.

The cities that are participating in the program are those most at risk (when flood risk is proxied by the percentage of a city's land area in a FEMA-designated high risk flood zone and the number of historic flood claims) and those with higher population densities, higher incomes, and more owner-occupiers, with some evidence for a positive association with taxable property values. These results align with Brody et al. (2009), whose study of local jurisdictions in Florida from 1999-2005 found that the primary driving force of CRS participation was the flood insurance premium discounts on offer by the program for communities – higher

[15] *Millage rate* has a significant and negative association with home values, with a one mill increase predicting a $42,953-44,463 decrease in home values. This (seemingly unrealistic, in terms of magnitude) result could perhaps be the result of millage rate having a significant correlation with other unobserved time-varying city characteristics.

population densities and taxable property values would suggest higher potential per capita flood insurance savings from participation and thus a greater incentive to participate. Meanwhile, the finding that CRS program participation is associated with higher median incomes follows Fan and Davlasheridze (2016), who find that the willingness to pay for CRS activities is higher among wealthier households. Higher citywide median incomes also suggest lower unemployment and crime rates, following a common negative association between crime and income in the empirical literature (e.g. Patterson, 1991) and my own findings of a -0.38 correlation (significant at the 1% level) between *median income* and *unemployment rate*.[16] Following Li and Landry (2018), lower rates of crime and unemployment are in turn associated with more mitigation activities, as communities face fewer "competing priorities" in the form of crime or economic development issues that may crowd out concerns related to the risks of future flood and disaster events.

Among program participating cities, the localities investing the most in "active" CRS measures are those with larger populations, more land area in flood zones, greater inequality, and lower population densities, taxable values, millage rates, and median incomes. The negative associations between density and score and tax value and score could be explained if "active" CRS activities (e.g. open space preservation, stricter building codes) become more expensive with more people and development, with the higher costs outweighing benefits from higher per capita flood insurance savings and lower expected flood losses. This aligns with Sadiq and Noonan (2015), who find that the communities likeliest to be responding to the incentive structure of the CRS program are those with lower densities and property values – these communities may have moderate flood risks that can be addressed through lower-cost mitigation measures, while the mitigation costs for denser communities may outweigh the immediate flood insurance discount incentives offered by the program. These results also suggest that communities are not hindered by less financial capacity (in the form of lower taxable values) in their ability to make CRS investments, but these communities' lower baseline millage rates also suggest that they may have more room to raise tax rates to fund investments. Meanwhile, the negative association with median income could be the result of property costs being lower in the highest flood risk cities. Along the lines of Husby et al. (2018), this flood risk discount would attract lower income households willing to make a tradeoff between lower property costs but higher flood risks. At the same time, these low property values may also attract high income households with the means to self-insure against flood losses or afford

[16] I exclude *unemployment rate* from my (2) series regressions due to this high correlation, selecting *median income* as my preferred indicator of community socio-economic wellbeing.

the high costs of building elevated, flood-proof homes,[17] providing a possible explanation for the positive association between inequality and score.[18] This follows Noonan and Sadiq (2018), who find that CRS-participating communities attract both poor and wealthy households. Finally, lower millage rates may also be reflective of cities having fewer competing priorities (e.g. in the form of high policing or economic development expenditures) and thus a greater capacity to invest in flood risk mitigation.

The characteristics of the cities that made the largest increases in score differ from those that simply had the highest scores from 2009-2018, with less land area in flood zones, lower inequality, and higher debt loads predicting large score changes. One explanation could be that lower flood risk cities (as proxied by *flood zone %*) are "catching-up" to higher risk cities that have already taken mitigation measures. The positive association with debt suggests that financial capacity again does not appear to be a limiting factor for cities making investments in CRS measures. Meanwhile, the results in this case for inequality align with a classic result in the public economics literature, whereby more homogenous cities devote more spending to "productive" public goods (e.g. Alesina et al., 1999).

Across both "active" score analyses, two further conclusions can be made: while both the number of owner-occupied homes per capita and the number of 1980-90 flood claims are significant predictors of program participation, neither is a driving force of higher scores, suggesting that historic flood claims are not strong predictors of flood risk mitigation today and that owner-occupiers are not necessarily more engaged in flood risk mitigation issues. Overall, the CRS program appears to be adequately targeting and incentivizing some higher flood risk communities to participate and invest in "active" mitigation measures, and financial constraints in the form of lower median incomes, lower taxable values, and higher debt loads do not appear to be a hindrance to investment. However, denser communities appear to be investing less in these measures, which suggests that cities with higher mitigation costs are not being adequately targeted and incentivized by the program.

Given the incentive structure of the CRS program, the effects from participation on a home's value (if any) would be expected to come through two routes: flood insurance savings and lower expected flood losses. Combining the average class ranking of "7" for cities in my dataset, an average nationwide NFIP flood insurance premium of $642 (Insurance Information Institute, 2019), and a 5-15% discount on flood insurance premiums (depending on a home's location) for

[17] Anecdotally, many Florida coastal communities are increasingly a "mishmash" between older, ground-level (and cheaper) bungalows and newer, elevated (and expensive) mansions, providing support for this "flood zone-driven inequality" hypothesis.

[18] There is a positive correlation of 0.29 between *Gini index* and *flood zone %* (significant at the 1% level), providing some further evidence for this "flood zone-driven inequality" hypothesis.

properties in CRS class 7 communities (FEMA, 2017), the discounted lifetime flood insurance savings (assuming a 2% interest rate and a 50 year home lifespan) would range from $1,009 to $3,026 for a city that enters the CRS program.

The real-world analysis of CRS participation on homes values appears less clear-cut, with statistically insignificant findings. Program participation is associated with a $3,579 increase in home values (1.3% of the median home value in the average city), with the 95% confidence interval extending from -$16,718 to $23,876. Although this $3,579 finding is insignificant, it does appear to be within the realm of possibility, given the above (conservative) approximation of an average flood-insurance-carrying-home's lifetime premium savings. There is evidence suggesting that housing markets in wealthier cities value the program more, with both higher magnitude and higher percentage effects on home prices in higher median income communities. This provides further evidence that CRS program participation is a normal good and aligns with Fan and Davlasheridze (2016), who find that the willingness to pay for CRS activities is higher among wealthier households.

Meanwhile, results for active CRS scores show a significant and negative association with home values in the average Florida municipality, with some evidence for less negative (or positive) effects on home values in higher flood risk and higher income communities. These counterintuitive results – at least when considered within this paper's theoretical framework – could be explained in two ways: either the marginal costs of mitigation, above and beyond any increases in millage rates (e.g. non-property tax fees, such as stormwater fees, or simply the inconvenience of construction), outweigh the marginal (perceived) benefits of flood risk mitigation measures, or active mitigation measures (such as new stormwater systems or higher seawalls) are a "risk signal", reminding residents and visitors of the risks of living in low-lying or coastal areas (and perhaps keeping away new homebuyers). This would align with Gibson et al. (2019), who find that belief updating in response to new risk signals (in the form of updated flood maps or flood events) drives down affected home prices. New flood protection infrastructure – and any associated town hall meetings and public debates – could play a role akin to new flood maps or flood events.

6.1. Limitations

This analysis misses one perhaps crucial aspect of the CRS program: cooperation between cities and within counties on issues pertaining to flood risk mitigation. Specifically, the part (2) regressions assume that individual governments act independently of one another. However, in the context of flood risk mitigation, it is probable that there do exist interjurisdictional spillovers – towns may share best practices and human capital, and one town's actions may

induce a neighboring town to follow in its stead. Furthermore, Florida county governments are powerful entities and are also able to participate in the CRS program. Some county risk mitigation measures (e.g. county-wide flood risk studies) could inform or directly impact city-level activities within the county. Both factors suggest that spatial autocorrelation could be a source of bias in my part (2) results.

7. Conclusion

Floods are the costliest natural disasters in the United States, and rising seas, more frequent and severe storms, and more intensive floodplain development will only increase the human and economic toll from flooding in coming decades (Tebaldi et al., 2012; Patricola & Wehner, 2018; Li & Landry, 2018). Given the uncertainties and complexities of climate and flood risks, planning for, mitigating, and adapting to these risks falls into the hands of local communities. Determining the extent to which local governments are wary of and responding to the risks of climate change, the factors that are driving some (and not others) to proactively invest in risk mitigation, and the degree to which housing markets are responding to these investments is critical for understanding the broader socioeconomic consequences of climate change. To what extent will the policy mechanisms in place serve to accentuate (or mitigate) the welfare costs of climate change?

In seeking to answer this question, I study flood risk mitigation investments among Florida cities and towns from 2009-2018 and their association with home values. Florida's unique vulnerability to rising sea levels and stronger and more severe hurricanes (U.S. EPA, 2016) makes the state a prime setting for a study on climate risks, and my study period – a decade that saw a large increase in flood events and media attention to climate change (FEMA, 2019; Guertin, 2019) – adds a new dimension to the existing literature on FEMA's Community Rating System (CRS). Using regression analysis, I find that investments in public flood risk mitigation are increasing over the study period, with an 11.8% increase in CRS program participation and a 19.8% increase in average "active" CRS scores. CRS program participation is associated with more owner-occupiers and higher flood risk, population densities, and median incomes. Active CRS scores are highest in cities with more land area in flood zones, higher populations, greater inequality, and lower population densities, median incomes, and financial capacity, while the cities with the greatest increases in score over the past decade tend to have less land area in flood zones and lower inequality. Using panel estimation with city-level fixed effects, I find that program participation is positively but not significantly related to median home values, with a point estimate of an increase of $3,580 to $5,680. Active CRS scores are negatively related: every 100-point increase is associated with a $6,250 decrease in values in the average community, with

evidence for less negative (or positive) effects in cities with more land area in flood zones and higher median incomes.

These results suggest that FEMA's CRS program is meeting one of its primary goals: fostering comprehensive floodplain management (FEMA, 2017). Florida cities and municipalities are, on average, responding to the program's incentives, investing more in flood risk mitigation measures, and the program is adequately targeting some higher flood risk communities, even if they have fewer financial resources. However, the program does not appear to be adequately targeting and incentivizing denser communities with potentially higher mitigation costs to invest in these measures. Finally, housing markets do not appear to value flood risk mitigation measures, suggesting that the costs of mitigation to local communities may exceed the (perceived) benefits or that these measures are themselves indicators of flood risk.

Programs such as the Community Rating System will continue to play a critical role in guiding and incentivizing local governments to plan for, mitigate, and adapt to rising flood and climate risks. Further study of the program's successes, failures, and impacts, as well as those of comparable programs and frameworks in nations around the world, is warranted. The changing climate will not wait.

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9. Appendix A

The Federal Emergency Management Agency's Community Rating System (CRS) revised its scoring system in 2013. The new system reweighed certain "active" CRS activities, with no "crosswalk" or equivalence formula. Communities gradually transitioned to the new system as they received verification visits after the changes were made effective in the Spring of 2013 (FEMA, 2017). My CRS scores dataset (extending from 2009-2018) thus includes scores for cities from both the old scoring system and the new system, with cities transitioning to the new system at various points in time after 2013 (as of 2018, there are still a few cities scored on the old system).

To "unify" scores from these two disparate scoring systems, I first construct a "Predicted Active CRS Score" to transition scores under the new system to the old scoring system based on a regression of "Old Active CRS Score" on "New Active CRS Score." The "Predicted Active CRS Score" is equal to 404.760 + 0.476*("New Active CRS Score"). Next, I construct a "Combined Active CRS Score", bringing together "Old Active CRS Scores" with the "Predicted Active CRS Scores." **Figure A.1** plots the "Old", "New", and "Combined" Active CRS Scores. **Figure A.2** plots the distribution of the "Old Active CRS Score"; **Figure A.3** the distribution of the "New Active CRS Score"; **Figure A.4** the distribution of the "Predicted Active CRS Score."

Figure A.1.

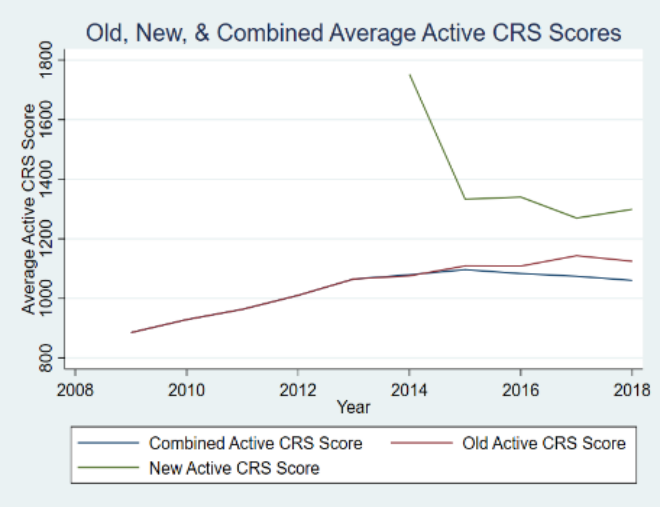


Figure A.2.

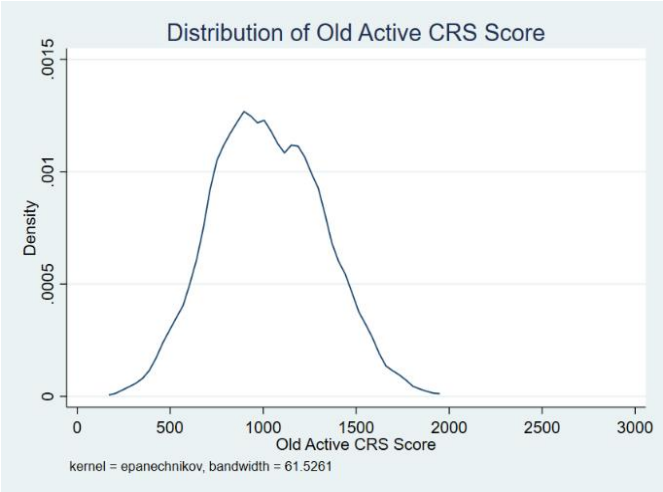


Figure A.3.

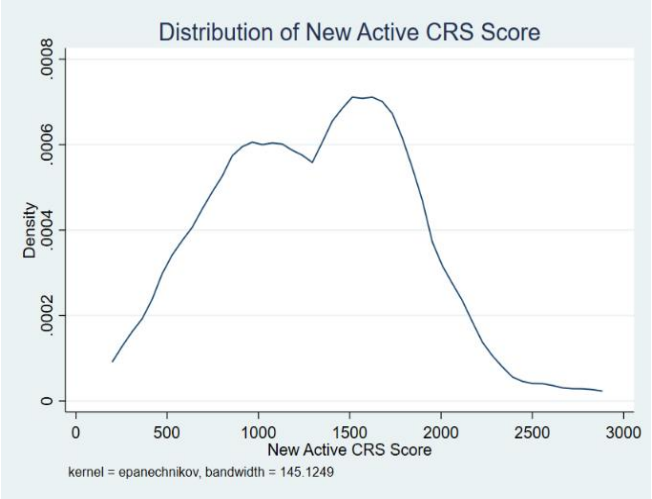
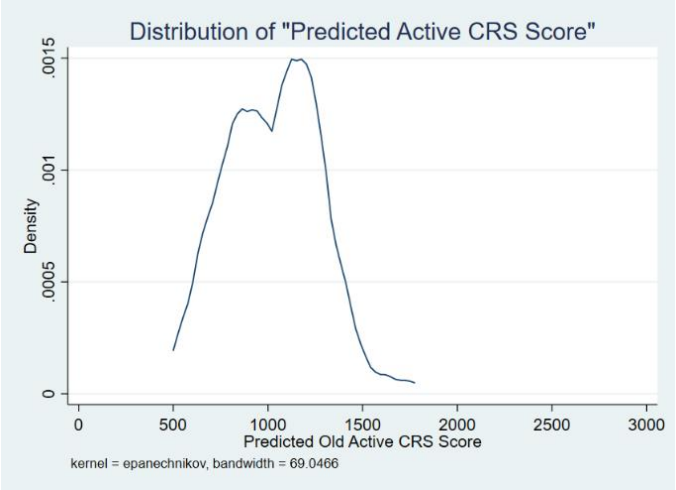


Figure A.4.


Distribution of "Predicted Active CRS Score"
Density
0
.0005
.001
.0015
0
500
1000
1500
2000
2500
3000
Predicted Old Active CRS Score
kernel = epanechnikov, bandwidth = 69.0466