Public flood risk mitigation and the homeowner's insurance demand response

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Abstract

This paper investigates the influence of public risk mitigating activities on individuals' decisions to privately mitigate their disaster risks through changes in their risk perceptions. We exploit heterogeneity in measures under the U.S. Community Rating System to empirically demonstrate that public investment in flood risk communication activities crowds-in individuals' flood insurance demand while activities that lower the flood hazard residents face crowd-out individuals' flood insurance demand. This paper contributes to the discussion of the efficacy of disaster risk mitigation strategies and who ultimately bears the costs of natural disasters.

Keywords: Community Rating System (CRS), flood insurance, behavioral response, risk perception, risk mitigation

JEL: D12; D83; G52; Q54

I. Introduction

As the costs associated with natural disasters grow, so does the debate surrounding who should foot the bill (Stein and Van Dam 2019). While governments have the objective to protect their residents against harm, individuals often generate the adverse impacts of natural disasters by living in harm's way (Brody et al 2007). In the case that government activities act as complements or substitutes for individual's risk mitigating behavior, the debate becomes even more complicated.

This paper investigates the influence of public disaster risk mitigating activities on risk perceptions and subsequently individuals' decisions to privately mitigate their risks. We hypothesize that public actions, depending on the type, will elicit behavioral responses that either crowd-in or crowd-out private risk mitigation. Our research question highlights a challenge that policymakers often face in natural disaster planning: while some public risk mitigating activities perform as expected, others have unintended consequences that increase society's total disaster cost burden (Raschky and Weck-Hannemann, 2007).

The setting for this paper is the U.S. Federal Emergency Management Agency's (FEMA) Community Rating System (CRS). The CRS program is tasked with incentivizing communities to lower their citizens' flood risks by engaging in CRS-prescribed activities (FEMA 2017). In exchange, communities receive points that allow them to improve within the CRS class system and earn their residents discounts on flood insurance policies. In 2017, approximately 1,500 U.S. communities participated in the CRS program. While only 8 percent of total flood risky communities, the CRS communities represented 72 percent of insurance policies and 59 percent of insurance claims.

CRS activities are varied in how they intend to lower communities' flood risk. For example, activity 340, “hazard disclosure” has the intended consequence of promoting risk awareness. On the other hand, activity 620, “levee safety”, intends to reduce the flood hazard that residents face. Using a two-way fixed effects regression, we estimate the causal impact of activity type on communities' flood insurance demand. We hypothesize that not only would activities with the intention of communicating risk induce insurance purchases from an increase in perceived risk, but also that activities, which reduce residents' exposure to flood hazards, would have the consequence of discouraging insurance purchases from a decrease in perceived risk. Our results demonstrate that this is indeed the case.

One of FEMA's primary goals for the CRS program is to “strengthen and support insurance aspects of the National Flood Insurance Program (NFIP)” (FEMA 2017).[i] That means, in addition to answering a broader question about behavioral responses, this paper also pointedly evaluates if and how the CRS program reaches its goal of increasing insurance demand. We show that, when evaluating the influence of communities' CRS engagement on their insurance penetration rates, not all CRS points should be treated equally: while all points contribute to reductions in the price of insurance, points stemming from risk communication activities amplify the effects of the insurance premium discounts while hazard mitigation points dilute them.

One focus of this paper is the efficacy of activities that advise residents about flood hazards and flood insurance. By doing so, we are contributing to a strand of literature addressing the role of public risk communication in encouraging private risk mitigation. Generally speaking, research has demonstrated that the provision of risk information is effective in helping people avoid or adapt to environmental hazards. In terms of flood risk, Ferris and Newburn (2017) show that wireless alert messages for flash flood warnings reduce short-term exposure to the hazard. In a randomized control trial of Thai households, Allaire (2016) estimates that a flood risk information intervention led to a 5 percent increase in insurance purchases. To our best knowledge, this paper is the first to examine the relationship between risk communication from authorities and the purchase of natural disaster insurance outside of an experimental setting.

A second focus of this paper is on activities like stormwater (450) and drainage system (540) management that seek to reduce residents' exposure to flood hazards. In this respect, we are contributing to a body of literature studying how public expenditures on risk mitigation can crowd out private measures. Davlasheridze and Miao (2019) and Kousky et al (2018b) demonstrate that reducing individuals' exposure to flood damages via federal relief funds discourage insurance purchases in the United States. In a survey of French flood-prone residents, Richert et al (2019) show that dike protection reduces the probability of taking individual adaptation measures. This paper builds on the extant literature by combining the two aforementioned approaches, essentially applying a large administrative dataset to the question of whether public investment in hazard mitigation crowds out insurance demand.

We see this work as timely because in 2017 a panel of experts determined that a “stronger body of evidence on the effectiveness of CRS” was needed (Cunniff 2018). Heeding the panel's message, this paper contributes to a group of studies evaluating the effectiveness of the CRS program in reaching its goals. Generally speaking, participation in the CRS program is associated with greater insurance penetration rates, fewer flood damages and better disaster recovery outcomes (Burton 2015; Highfield and Brody 2017; Frimpong et al 2019). A 2006 RAND report provided evidence that insurance penetration rates are higher amongst CRS communities only because of lower insurance prices and not because of the CRS activities themselves (Dixon et al 2006). The report's authors hypothesized that CRS activities that reduce exposure to flood hazards also reduce perceived risk, effectively voiding education efforts aimed at increasing residents' awareness of flood risks. This paper extends upon the RAND report by formally and empirically testing its hypothesis. We also contribute to the larger body of CRS research by examining the influence of specific activity types on insurance penetration rates. This study is also the first to evaluate the CRS program for all states at once, covering all flood risk and homeowner types.

To preview our results, we show that, risk communication activities encourage insurance purchases through an increase in perceived risk. As this is the intention of these activities, we conclude that they are effective in their intentions. Hazard mitigation activities, on the other hand, discourage insurance purchases through a decrease in perceived risk. We view this as an additional cost that should be taken into account by community floodplain managers. Our findings also demonstrate that flood managers can influence insurance demand by providing discounts on insurance premiums. Finally, we show heterogeneous effects in behavioral responses associated with income, education and history with flooding. Taken together, our findings give evidence that governments have the ability to influence perceived flood risk and private flood risk mitigation decisions, and through that, who bears the costs of flooding.

The paper proceeds as follows. The next section describes the background of the study and the data used in the analysis. Section 3 discusses the conceptual framework motivating the paper's hypotheses. Section 4 details our empirical strategy to test our hypotheses. Section 5 provides estimation results and discusses them. Section 6 concludes.

II. Background and Data

The Community Rating System

Created in 1990, the Community Rating System was designed to incentivize community-level flood management activities beyond the minimum required by FEMA's National Flood Insurance Program (FEMA 2017). The CRS program specifies three goals: (1) to reduce flood damage to insurable property, (2) to strengthen and support the insurance aspects of the NFIP and (3) to encourage a comprehensive approach to floodplain management at the community-level. By undertaking CRS-prescribed activities, communities accumulate points and residents within the communities receive discounts on their flood insurance premiums.

FEMA divides CRS activities into four series: (1) 300: public information, (2) 400: mapping and regulation, (3) 500: flood damage reduction and (4) 600: flood preparedness. Each series contains three to six activity elements from which communities may earn credit points (Table 1). The maximum amount of points for each activity type reflects the effort level of the community to implement it. As communities accumulate points, they move down the class system and earn increasingly larger flood insurance premium discounts for their residents (Table 2). For example, a class 9 CRS community, which is the introductory class, earns a 5 percent discount on flood insurance premiums for residents inside the riskiest floodplain designation. A class 5 community earns a 25 percent discount and a class 1 community earns a 45 percent discount.[ii] Table 2, which summarizes CRS class data in our sample, demonstrates that, in 2017, the overwhelming majority of communities in our sample were between class 9 and class 5, earning a 5 to 25 percent discount on their insurance premiums.

To join the CRS program, a community must apply to FEMA with documentation proving engagement in CRS-prescribed activities. After the application review concludes, a CRS specialist completes a verification visit and the community joins the CRS program, usually with a class 9 certification. On average, 40 communities joined the CRS program in each year during this paper's study period, which is 2008 to 2017.

Cycle verifications are conducted every five years from the original application date for communities with class 9 to class 5 designations. Communities classified as 4 and below must undergo a cycle verification every three years.[iii] In addition to cycle verifications, communities are obligated to re-certify their classification each year through a self-assessment procedure. A community may modify its CRS classification at any time by applying for credit for new or revised activities. Just under 50 percent of communities changed CRS classes between 2008 and 2017. Of those that changed classes, 75 percent of communities changed once, 23 percent changed twice and 2 percent changed three times.

We collected information on each participating community's class standing and their fulfillment of CRS-prescribed activities within each series, for each year from 2008 to 2017.[iv] Approximately 1,100 communities participated in the CRS program in 2008 and 1,450 communities participated in 2017. Due to our empirical model setup as laid out in Section 4, we dropped 292 communities that resulted as singelton groups from our multiple fixed effect structure. The final, unbalanced sample contains 1,232 communities observed at least twice between 2008 and 2017, resulting in 10,355 total observations.[v] Figure 1 presents the locations of the CRS communities in our final sample. Nearly every U.S. state, and all types of flood risks are represented in the sample. Flood risks include coastal storm surges in the south and east, riverine flooding from the Mississippi river and flash flooding from mountain streams in the Rockies.

We identified each CRS activity as either communicating risk ("risk communication" or "RC") or reducing the flood exposure residents face ("hazard mitigation" or "HM").[vi] Under the former category, communities work to make the consequences of flooding known so that the residents themselves can take defensive actions, like purchasing flood insurance, to lower their flood risk. Activities include hazard disclosure by real estate agents (340) and outreach projects (330) as well as supportive actions like the mapping of floodplains (410). The latter category contains activities that reduce flood exposure, thereby reducing the possibility of flood damage. Residents' flood risk is lowered by avoiding the flood, rather than insuring against damages. Activities include open space preservation (420), acquisition and relocation (520) and levee maintenance (620). Each activity's classification is presented in Table 1.

After each activity was characterized into one of the two categories, we generated our two primary variables of interest. They are the number of points stemming from risk communication activities and the number of points stemming from hazard mitigation activities for each community-year observation.[vii] The average community in 2017 had one-third of their total earned CRS points coming from risk communication activities and two-thirds coming from hazard mitigation activities. Figure 3 in the Appendix illustrates within-community variation over time for the two point types, which each line in the figure representing a single community. Between 2008 and 2017, the average community earned 32 additional points from risk communication and 161 additional points from hazard mitigation, though some communities increased their risk communication and hazard mitigation points by as much as 665 and 1,735 points, respectively.

The National Flood Insurance Program

Nearly every flood insurance policy in the U.S. originates from FEMA's National Flood Insurance Program.[viii] The NFIP exists to reduce the socioeconomic impact of flooding by offering financial relief to those directly affected by flooding (Congressional Research Service 2021). Flood insurance has been shown to provide disaster victims with better and faster recoveries than simply relying on post-disaster aid (Kousky 2019).

The program is a voluntary partnership between the federal government and communities. Communities must agree to regulate development in floodplains to be allowed to purchase flood insurance. For a single-family residence, the NFIP provides insurance up to a maximum limit of 250,000 dollars for building coverage and 100,000 dollars for contents coverage. Insurance premium prices increase with flood risk and structure vulnerability.

Communities and FEMA work together to partition the landscape according to flood risk levels. In the riskiest floodplain designation, the Special Flood Hazard Area (SFHA), insurance is mandated on all properties with a federally-backed mortgage. Despite insurance requirements, the average community in the U.S. has an approximately 30 percent flood insurance penetration rate in the SFHA (Kousky et al 2018a). The CRS program is touted as one solution to people's reluctance to purchase flood insurance and resulting high levels of post-disaster aid paid by taxpayers (FEMA 2017).

Our main outcome variable is the number of residential flood insurance policies-in-force on the day that communities' CRS points are made public by being published in the CRS Coordinator's Manual.[ix] For example, on October 1st 2017, the median community in our sample of CRS communities had 297 insurance policies-in-force. With a single policyholder, the City of Southgate, Kentucky had the smallest insured population. The City of Houston in Texas had the largest insured population at 104,424 policyholders. Figure 2 demonstrates that communities with the largest number of policies-in-force tend to be located in densely-populated areas in the southeastern United States, where there is significant risk of hurricane-related flooding.

Other influences on insurance demand

Communities' demand for flood insurance is likely shaped not only by risk mitigation activities, but also recent flood experience, wealth levels, home values, the price of insurance and the number of households mandated to purchase flood insurance. In the case that these variables are also correlated with investment in CRS activities, their exclusion would confound identifying the impact of risk mitigation activities on insurance demand. We employ county-level data because community-level information is not available for the listed potential confounders. In doing so, identification rests on the assumption that, within each county, communities follow common temporal movements in these measured variables.

Flood experience

While recent experience with flooding increases insurance demand, receiving federal disaster aid after floods reduces it (Raschky et al 2013; Gallagher 2014; Kousky 2017; Andor et al 2020). Our estimates on the CRS point variables would be biased in the case that recent flood and aid experience is correlated with investment in a specific activity type. For example, if dikes are heightened after floods. Because we cannot rule out this possibility, we account for potential bias with flood experience information from FEMA.[x]

As recent flood information is not available at the community level, we turn to county-level information and make the assumption that all communities within a given county would be similarly affected by, and react similarly to, a given flood event.[xi] For post-flood aid, we record if and when a county received public and/or individual disaster assistance dollars through the Presidential Disaster Declaration (PDD) system. This accounts for the insurance crowding-out effect of post-flood disaster aid. We control for the existence and severity of all flooding events by recording the average size of all insurance claims in each county and year. The average county contains two CRS communities.

In 2008, 12 percent of the communities in our sample were located in counties with a PDD flood declaration. That figure reached a low in 2009 with 3 percent of communities experiencing a PDD flood and a high in 2017 with 40 percent of communities experiencing a PDD flood.

The median county received an average insurance claim equal to 2,888 dollars in 2017. In the same year, 75 percent of CRS communities in our sample were located in counties where insurance claims were made. Just 42 communities were located in counties where zero insurance claims were made between 2008 and 2017. Frequent losses are indicative of the fact that particularly flood-exposed communities are also those that tend to join the CRS program (Landry and Li 2011; Sadiq and Noonan 2015).

Median incomes

The American Community Survey reports yearly estimates for each county's median household income. The estimates are based on five-year survey results.[xii] The American Community Survey provides median income estimates for all U.S. counties between 2009 and 2017. For 2008, they provide median income estimates for only half of U.S. counties. We linearly extrapolated 2008 estimates for counties that did not have the 2008 American Community Survey estimates. The average county in our sample had a median household income of 51,469 dollars in 2008, increasing to 56,754 dollars in 2017.

Home values

Home values account for changes in capital-at-risk. Yearly home value estimates for each county come from Zillow.[xiii] Called the Zillow Home Value Index, the estimates are a smoothed and seasonally-adjusted measure of the typical single-family home value. Zillow reports home values for approximately 50 percent of U.S. counties. Each remaining county was assigned the yearly home value of the county closest to it by centroid distance. The median county in our sample had a single-family home value of 182,701 dollars in 2008 and 186,328 dollars in 2017.

Biggert-Waters/Homeowner Flood Insurance Affordability Act (BW/HFIAA)

Between 2008 and 2017, the average CRS community lost 422 NFIP insurance policies, or seventeen percent of its 2008 policies. The decrease in policies for CRS communities is not specific to the program, but instead reflective of an overall trend in the United States: the average non-CRS community lost 25 percent of its policies during the same time period.

Recent research suggests that decreases in the (NFIP) insured population is, in part, the result of increases in insurance prices for previously subsidized policies (Kousky et al 2018). Beginning in 2013, the Biggert Waters Act, and its reformer, the Homeowner Flood Insurance Affordability Act, ordered insurance price increases on properties built before the first community floodplain maps were drawn. Prior to the legislation, FEMA subsidized these properties' insurance premiums, reasoning that home builders did not have the sufficient knowledge to make informed decisions about flood risk without floodplain maps that depicted the risk. Calls to make flood insurance actuarially fair led to the recent legislation, increasing insurance premiums on the previously subsidized properties by 5 to 25 percent per year. Twenty percent of total flood insurance policy holders were affected by the rate increase.[xiv]

We accounted for changes in the price of insurance stemming from BW/HFIAA with a variable equal to the yearly premium price per dollar of net coverage on subsidized properties. It was calculated by summing all premiums on all previously subsidized properties within each county, then dividing by the policies' coverage, minus their deductibles. In 2008, the median county's premium price on previously subsidized policies was 40 dollars per 10,000 dollars of coverage. In 2017, that figure was 60 dollars per 10,000 dollars of coverage.

Number of mortgage holders

Though poorly enforced, flood insurance is mandatory on properties that carry a federally-backed mortgage and are located in the riskiest floodplain (Michel-Kerjan 2010). To account for temporal changes in the number of properties required to carry flood insurance, we generated a variable equal to the number of residential mortgage holders in each county and year. We assume that temporal movements in the number of mortgage holders is the same inside the flood risky areas as it is for the whole county.

Mortgage information also comes from the American Community Survey and is based on five-year survey results.[xv] The American Community Survey provides mortgage holder estimates for all U.S. counties between 2009 and 2017. For 2008, they provide mortgage holder estimates for only half of U.S. counties. We linearly extrapolated 2008 estimates for counties that did not have the 2008 American Community Survey estimates. In 2008, the median county in our sample contained 21,464 residential mortgage holders. In 2017, the median county in our sample contained mortgaged 19,770 residential mortgage holders.

III. Conceptual framework

Our decision-maker is a potential flood insurance policy holder. Her decision to purchase insurance is influenced by her wealth level (+/-), the size of her expected loss (+), what she anticipates in terms of disaster aid (-), the price of insurance (-), her risk aversion parameter (+) and, notably, her perceived risk of being flooded (Browne and Hoyt 2000; Rees and Wambach 2008; Kousky et al 2018b).[xvi]

The decision maker's perceived risk is composed of two parts: background risk and contextual risk (Viscusi 1995). Her background risk can also be described as her real risk. It is the objective flood risk that would be assigned to her location by technical experts. Her contextual risk is subjective, formed by her experiences with flooding and other sorts of risk information personal to her. An increase in either part would also lead to an increase in her perceived risk.

An increase in the decision maker's perceived risk, holding all other factors that influence insurance demand constant, increases her likelihood of purchasing flood insurance. That means, as her contextual risk increases from, for example, being informed she is located in a place with a high risk of flooding, she will be more likely to become insured. Correspondingly, if her background risk decreases from, for example, a heightening of her neighborhood's dikes, she may be incentivized to discontinue her insurance coverage.

The influence of risk communication on perceived risk and risk mitigation measures is well documented. For example, teenagers in Kenya are less likely to engage in unprotected sex after receiving information about their relative risk of HIV infection (Dupas 2011). Smog alerts reduce attendance at outdoor activities and FDA advisories reduce the demand for risky food products (Shimshack et al 2007; Neidell 2009). In the context of natural disaster risk, property values fall in areas newly mapped as risky (Donovan et al 2007; Shr and Zipp 2019).

Government investments in risk mitigation that crowd out private precautionary measures can be divided into two groups: (1) measures that reduce residents' loss exposure and (2) measures that reduce residents' hazard exposure. The former category, often called the charity hazard, describes the case in which anticipation of post-disaster spending crowds out private disaster insurance demand. Essentially, people view government aid as a substitute for their own investments in resilience. Kousky et al (2018b) and Davlasheridze and Miao (2019) give evidence of the charity hazard, showing that government spending on individual and community post-disaster aid reduces flood insurance demand in the United States.

We are concerned with the second group: measures that decrease residents' hazard exposure. For example, government investments in better drainage systems would have the intended consequence of reducing how often residents' homes are flooded. In the case that residents recognize these changes as reductions in their background risk, their insurance demand would decrease. Evidence of reduced hazard exposure on private disaster mitigation has, to our best knowledge, been limited to laboratory experiments and surveys (Richert et al 2019). For example, Prante et al (2011) showed that wildfire fuel reductions on public land crowd-out wildfire fuel reductions on private land. Their conclusions are supported by numerical simulations (Crowley et al 2009).

This paper tests the hypothesis that government investment in risk communication activities caused growth in contextual risk and has the intended consequence of increasing insurance demand. To be precise, the effect of risk communication activities on insurance demand is ambiguous because some people may overestimate their perceived flood risk prior to the dissemination of risk information. However, given that fewer than 60% of homeowners in areas at risk of flooding are currently insured, likely reflecting an underestimation of flood risk, we hypothesize that the risk communication measures will have a positive impact on insurance demand. Concurrent to examining the effects of risk communication, we test the hypothesis that residents recognize decreases in their background risk from government investment in hazard mitigation and reduce their insurance demand.

Identifying the effects of government action on perceived risk requires that we account for all other variables that are correlated with governments' investment in risk mitigation activities and residents' insurance demand. Notably, within the context of the CRS program, greater investment in risk mitigation activities leads to cheaper insurance as communities move down through the CRS class system and earn increasingly larger discounts on their insurance premiums. Assuming a downward-sloping demand curve for flood insurance, failure to account for the price changes would lead to an overestimation of the risk communication effect and an underestimation of the hazard mitigation effect. We account for the price change confounder with yearly information about communities' CRS class designations and subsequent insurance premium discounts.

IV. Empirical implementation

Let y_{it} be the number of insurance policies-in-force for community i in year t. In order to assure non-negativity of the mean, we assume that the expected number of insurance policies-in-force for a community, conditional on individual characteristics of the community, is specified as

$$E(y_{it}|x_{it}) = \mu_{it} = \exp(x'_{it}\beta), \qquad [1]$$

where x_{it} is a k-dimensional vector of explanatory variables and β_{it} is a k-dimensional vector of parameters. The conditional mean specification of equation 1 implicitly defines a regression model as follows

$$y_{it} = \exp(\alpha + \beta_1 RC_{it} + \beta_2 HM_{it} + \sum_{j=1}^{7} \beta_{3j} Class_{jit} + \sum_{t=0}^{-3} \beta_4 PDD_{ct} + \sum_{t=0}^{-3} \beta_5 Claim_{ct} + \beta_6 X_{ct} + \lambda_i + \theta_{mt}) + \epsilon_{it} \qquad [2]$$

where y_{it} is a strictly positive integer number of insurance policies-in-force for community i in year t, and ε_it is an additive error term, reflecting unobserved heterogeneity between communities. We estimate equation 2 using a Poisson pseudo maximum likelihood estimator as proposed by Silva and Tenreyro (2006). The advantage of the Poisson pseudo maximum likelihood estimator is that it is more flexibly applicable as it does not rely on the data to be

Poisson distributed (Gourieroux et al 1984), it is consistent in the presence of fixed effects, it is invariant to the scale of the dependent variable and it allows for both - over- and under-dispersion.

We control for flood and aid experience with PDD_{ct} and $Claim_{ct}$. PDD_{ct} is a vector of indicator variables that record if county c, which contains community i, experienced a PDD flood in year t. $Claim_{ct}$ is a vector of continuous variables that records the average insurance claim in county c, which contains community i, in year t. For both flood experience variables, we account for delayed effects by doing the same for each of the three years preceding year t.

X_{ct} is a vector of county-level characteristics that influence insurance demand. All are logged. Median income controls for temporal changes in wealth common to all communities within county c. Home values account for changes in capital-at-risk. Insurance prices for subsidized properties control for recent legislation raising premium rates. The number of households with mortgages accounts for changes in the number of people obligated to purchase flood insurance.

Community fixed effects, λ_i, absorb community characteristics that were largely unchanged during our study period, and are correlated with insurance demand and investment in CRS activities. These include, for example, the size of the area at risk of flooding and the type of flood risk, e.g. coastal or riverine (Sadiq and Noonan 2015b; Frimpong et al 2019). Metropolitan Statistical Area(MSA)-by-year fixed effects, θ_{mt}, account for any remaining, confounding factors that vary over time and are common to all communities within an MSA, e.g. local economic conditions (Gallagher 2014).[xvii] The average MSA contains 3.3 communities. Inclusion of the fixed effects means that coefficient estimates on our variables-of-interest are being driven by within community variation in policies-in-force, tempered by general insurance demand movements specific to each MSA. Finally, the error term, ε_{it}, contains unobserved community-level demand and risk characteristics. ε_{it} is assumed to be i.i.d. and is clustered at the MSA-level to account for common unobserved shocks in insurance demand.

$Class_{jit}$ is a vector of indicator variables equal to 1 if community i has reached CRS class j in year t. The reference group is Class 9, the lowest class achievable. Inclusion of the CRS class variables accounts for changes in premium discounts.

Finally, our key variables-of-interest are RC_{it} and HM_{it}. RC_{it} is the number of risk communication points earned in year t by community i. Similarly, HM_{it} is the number of hazard mitigation points earned in year t by community i.[xviii] Following our discussion in Section 3, changes in perceived flood risk resulting from changes in these two activity types should manifest in a statistically significant estimate of β_1 and β_2. A nonzero coefficient estimate implies that a community's level of flood insurance uptake is determined by the intensity of risk communication and hazard mitigation measures implemented under the CRS program. Notably, every community in our sample invested in both activity types in each year, alleviating some concerns surrounding strategic behavior by floodplain managers and self-selection into particular activity types. We are not, however, able to completely rule out strategic behavior by floodplain managers as there still may be unobserved, time-varying local factors that influence investment decisions.[xix] We also do not observe systematic changes in community demographics that are associated with investment in risk communication or hazard mitigation, giving us confidence that our sample is unaffected by non-random attrition.[xx]

In line with our discussion in Section 3, we expect β_1 to be positive, meaning that an increase in the level of flood risk awareness encourages insurance purchases. We expect β_2 to be negative because of crowding-out effects. The ideal experiment for estimating β_1 and β_2 would involve randomly shocking a single community with risk communication and hazard mitigation activities, while leaving potential confounders unchanged. We argue that, through the fixed effect structure and with the inclusion of the specified control variables, we are able to disentangle the impact of the two CRS activity types on insurance demand from time-varying and time-invariant confounding factors, providing an acceptable substitute for the ideal experiment.

In our empirical setting the main identification concern is reverse causality: should current policies-in-force influence current decisions about whether and which CRS activities to invest in, we cannot claim that equation 2 is causal. We do not believe reverse causality is an issue because of the time lag between decision and implementation of CRS activities.[xxi] CRS communities only earn points after activities have been fully implemented. As most activities take years to implement it is very unlikely that current policies-in-force influence past decisions on flood risk mitigation measures. In the case that managers systematically make strategic CRS investment decisions based on expected (and realized) insurance demand trends, reverse causality would be an issue. However, as we do not have strong priors about their systematic decision making, e.g., if managers expect insurance demand to fall would they invest in risk communication or hazard mitigation, we are confident equation 2 can be interpreted causally.

A second concern is possible measurement error in the CRS points variables. The database recording CRS activities and earned points is not updated every year, but rather every time a community changes classes or has a verification visit. Verification visits occur every five years from the original CRS application date for class 5-9 communities; visits are every three years for class 1-4 communities. A class change, which can occur in any year, happens when communities earn enough points to reach the next point threshold. We believe our conclusions hold in spite of the possible measurement error for two reasons. First, the measurement error would come from only small, likely positive, deviations in points. Communities must undergo a re-certification process each year to verify that they are continuing to implement the activities for which they have earned credit. As such, any unobserved changes in activities would be those that add to the community's activity portfolio but are not large enough to push the community to the next class. Second, in most cases, the measurement error would cause the coefficient on risk communication to be downward biased and the coefficient on hazard mitigation to be upward biased, making our coefficients a conservative estimate of the true effect.[xxii]

V. Results and discussion

CRS points and classes

Following the existing literature, we begin our analysis by estimating the relationship between CRS points and insurance policies-in-force. Zahran et al (2009) estimate a positive effect of CRS points on insurance demand. We expand their analysis to the entire U.S. and demonstrate the same phenomenon, though imprecisely estimated. As shown in Table 3 column (1), a 100 point increase in total CRS points is associated with a 0.4 percent increase in insurance policies-in-force.[xxiii] That is, stronger participation in the CRS program, as defined by earned CRS points, is associated with greater insurance penetration.

The CRS point effect estimated in column (1) is the composition of three sub-effects. The first sub-effect is the premium discount effect. As communities earn points, they improve their standing within the CRS class system. Each class improvement earns communities additional discounts on their insurance premiums. For example, class 9 communities earn 5 percent discounts on their insurance premiums while class 8 communities earn 10 percent discounts. In the case that insurance abides by the law of demand, a decrease in the insurance's price will increase its demand (Browne and Hoyt 2000).

We test for the existence of the premium discount effect by including dummy variables for each CRS class in the regression. The reference category is class 9, the entrance class into the program. Table 3 column (2) shows that people are indeed responsive to price changes in their insurance premiums. Demand increases as communities improve their class standing and earn additional discounts on their premiums. Between class 9 and class 5 and below, each additional discount is associated with an average 5 percent increase in the number of insurance policies-in-force. It should be noted that specification 2, with the inclusion of the BW/HFIAA variable, accounts for changes in insurance prices for previously-subsidized policies. The estimated effects on the CRS class dummy variables, therefore, represent changes in insurance demand by the 80 percent of policy holders not affected by BW/HFIAA.[xxiv]

Risk communication, hazard mitigation and price discounts

Table 3 column (2) demonstrates that, after controlling for insurance premium discounts, the magnitude of the CRS point effect shrinks. Within classes, additional points, coming from additional activities, do not yield additional policies-in-force. Dixon et al (2006) theorized that this is the result of the two remaining, and competing, sub-effects not yet accounted for: crowding-in from risk communication activities and crowding-out from hazard mitigation activities. We test Dixon et al's theory by estimating specification 2, as presented in Table 3 column (3). Compared to column (2), the total earned points variable is replaced with its decomposition into risk communication points and hazard mitigation points.

Consistent with our hypotheses established in Section 3, we find that investment in risk communication activities leads to increases in insurance demand. Conversely, investment in hazard mitigation activities brings about decreases in insurance demand. In the case of risk communication, a 100 point increase results in a 0.8 percent increase in insurance policies-in-force. In the case of hazard mitigation, a 100 point increase results in a 0.7 percent decrease in insurance policies-in-force.[xxv] Because the average effects of risk communication and hazard mitigation activities are approximately equal, but also have opposing signs, they cancel each other out. In short, as Dixon et al predicted, we find that insurance gains coming from investment in risk communication are reversed by crowding-out effects coming from investment in hazard mitigation.

To put our estimates into context, consider the CRS community Miami Beach, Florida. Located on Florida's Atlantic Coast, Miami Beach has a low elevation, near sea level, that causes flooding issues from heavy rainfall, high tides and storm surges. In 2017, Miami Beach, with

2,060 CRS points, was a class 6 community containing 4,660 flood insurance policies. Suppose Miami Beach's floodplain manager aims to move the community to a class 5 rating. A class 5 rating requires that the city invest in enough activities to meet the rating's 2,500 point threshold. Assuming that the city meets the threshold solely through risk communication activities, they would see an uptick of approximately 393 insurance policies: 233 from the additional premium discount and 160 from the risk communication activities' effect on perceived risk. In the case that the city meets the threshold solely through hazard mitigation, they would see a net increase of only 93 insurance policies, including the 140 policy dropout coming from the hazard mitigation activities' effect on perceived risk.

In all three columns of Table 3, and generally speaking, point estimates on our control variables are signed as expected. For example, after controlling for the severity of flooding, recent disaster aid significantly crowds out insurance purchases. Within-county percentage growth in income is significantly, positively correlated with percentage increases in insurance demand, suggesting that insurance is a normal good. House values, the number of mortgage holders and insurance prices for properties impacted by BW/HFIAA are all also positively correlated with increases in insurance purchases, though imprecisely estimated.

Robustness checks

To assure the robustness of our results against the assumptions our identification strategy depends on, we conducted a series of robustness exercises. Their results are presented in Table 4.

The 2013 manual

In 2013, communities began to see a re-structuring of CRS activity points. FEMA shifted points away from structural flood risk mitigation measures to non-structural measures as a way to encourage their implementation. Communities entered the new point system (here: Manual2013) in a staggered way, only implementing it when it was their turn for a cycle verification visit. For the purposes of this analysis, we made the two point systems comparable through a re-weighting procedure: essentially, the point structure from the new system was re-weighted to match the old system.

We test the robustness of our re-weighting procedure by introducing two additional variables to specification 2: risk communication and hazard mitigation points interacted with a dummy variable equal to 1 if community i in year t is using the new point system and 0 otherwise. The coefficient on the interaction term is interpreted as additional effects of activity type on insurance demand conditional on being part of the new point system. Table 4 column (1) shows that our re-weighting procedure was indeed satisfactory. The coefficients on the two interaction terms are close to zero and not statistically significant.

Balanced sample

Not every CRS community was in the CRS system every year between 2008 and 2017. For example, the City of Auburn in Alabama only entered the CRS program in 2014. Meanwhile, the City of Prestonsburg in Kentucky left the CRS program in 2009.

Our main estimating sample is unbalanced such that each community was not necessarily present in the CRS program every year. Our rationale is that communities entering or leaving the program during the study period are not systematically different in their insurance responses to risk communication and hazard mitigation activities.

We tested the validity of this assumption by estimating specification 2 on a balanced sample. Table 4 column (2) gives evidence that our conclusions are robust to the exclusion of the 467 "unbalanced" communities. The coefficients on the activity type variables are virtually unchanged.

Singletons

Due to our multiple fixed effects structure, 2,162 observations from our entire sample of CRS communities were identified as singleton observations, i.e., incidences with only one observation within the fixed effect group. In our case, this is the MSA-year level. Keeping singleton groups in such cases can lead to standard errors that are underestimated and statistical significance that is overstated. This is particularly problematic in the case that standard errors are cluster-robust and the standard errors are nested within clusters, as it is here.[xxvi] In our main model we iteratively drop all 292 singleton observations, which leads to our final sample in which each MSA is at minimum observed twice per year.

However, it is possible that these 292 communities are not distributed randomly but are systematically different in their behavioral responses to risk communication and hazard mitigation activities. For example, it could be that some rural communities are the only CRS community within their MSA. Given that these communities also tend to have a less dense housing stock, the costs to of implementing structural flood mitigation and coordination of flood risk information measures may also be more expensive and deter investment. This would lead to overestimation of the CRS point effect on insurance demand.

To test whether the exclusion of the singleton groups affects the parameter estimates in our main specification, we replaced the MSA-year fixed effects with MSA-period fixed effects, where each period covers two consecutive years in our sample. The usage of MSA-period fixed effects ensures that each community is at minimum observed twice in each MSA within a period. The strategy allows us to keep the entire sample. As shown in Table 4 column (3), including singletons leads to similar results. This implies that the exclusion of singletons does not systematically affect our parameter estimates of the impact of CRS on flood insurance uptake.

Sheldus disasters

Specification 2 controls for the size of recent flood events with a variable equal to the size of each county's average insurance claim in each year. While the quality of the claim data is very good, the variable does not account for per capita damages to uninsured residents. We test the robustness of our results by replacing average flood insurance claims with per capita property damage from the SHELDUS database.[xxvii] While the SHELDUS database is more comprehensive than the insurance claims data in the sense that it reports both insured and uninsured losses, it is also more vulnerable to measurement error because of the way it assigns losses to counties.

Table 4 column (4) presents results replacing insurance claim data with per capita damage information from the SHELDUS database. The point estimates on the risk communication and hazard mitigation variables are largely unchanged: risk communication induces insurance demand while hazard mitigation causes a crowding-out effect. Moreover, the coefficients on the flood experience variables are signed the same as the main results, though their magnitude is decreased.

Heterogeneous effects

We also considered heterogeneous effects. We postulate that communities are not identical in their responses to CRS activities, and that income, education, flooding frequency and flood hazard type may play a role in explaining response differences. In each case, we tested for heterogeneous effects with interaction terms, interacting the base RC, HM and class variables with an indicator variable designating a group with a particular characteristic. The coefficients on the interaction terms are interpreted as the marginal effects of being in the group designated by the indicator variable. The coefficients on the non-interacted terms are interpreted as the effects of being in the reference group. Summary statistics for income, education, flood experience and flood hazard type are provided in Table A2 in the Appendix.

Incomes

While all individuals may adjust their risk perceptions in response to risk communication efforts, we hypothesize that higher income individuals are more likely to have the means to act on their adjusted risk perceptions and purchase flood insurance. The indicator variable for the interaction term is equal to one if community i's median income in year t is greater than the median income level (52,951 USD) of all communities across all years; zero otherwise. Median income information comes from the U.S. Census Bureau, is defined at the county level and is based on five-year American Community Survey results.

Table 5, column (1) shows that the higher income group is associated with a stronger insurance demand response to risk communication activities, as indicated by the positive and statistically significant coefficient on the RC interaction term. In contrast, the lower income group is associated with a stronger crowding-out response to hazard mitigation activities, as indicated by the negative, statistically significant coefficient on the HM main effect variable, and positive, statistically significant coefficient on the HM interaction term. The estimated differential response supports the hypothesis that budget constraints matter: higher incomes may afford individuals the agency to purchase flood insurance in response to an increase in perceived risk. In the case that the perceived necessity of flood insurance decreases from hazard mitigation efforts, it appears that lower income individuals are the first to drop out of the market. The higher income group also appears to be less price elastic in their demand for flood insurance than the lower income group, as indicated by the negative, statistically significant coefficients on the class interaction terms.

Education

Holding incomes constant, we hypothesize that areas with higher education levels are more likely to adjust their risk perceptions and purchase flood insurance in response to risk communication efforts. Education is positively correlated with trust in institutions (in non-corrupt societies), which, we postulate, extends to trust in government-created and -distributed flood risk information materials (Hakhverdian and Mayne 2012). The indicator variable for the interaction term is equal to one if the percentage of community i's residents with at least a bachelor's degree in year t is greater than the median (27.6 percent) of all communities, across all years; zero otherwise. Like income, education information comes from the U.S. Census Bureau, is defined at the county level and is based on five-year American Community Survey results.[xxviii] Due to missing data, the 2008 and 2009 values were linearly extrapolated from the 2010 to 2017 values.

Table 5, column (2) gives the estimated heterogeneous effects for higher and lower education communities. The positive and statistically significant coefficient on the RC interaction term indicates that higher education communities are associated with a stronger insurance demand response to risk communication activities. The result lends support to the hypothesis that the higher education group is more likely to internalize risk communication products. For HM, the difference in responses from the two groups is not statistically different from zero, giving evidence that higher and lower education communities respond similarly to hazard mitigation efforts.

Flooding frequency

We hypothesize that behavioral responses to CRS activities are influenced by how frequently a community is flooded. It may be, for example, that individuals living in communities that are frequently flooded are more likely to update their perceived flood risk in response to risk communication efforts because they can put the new information into historical context. We also postulate that individuals living in communities that are only rarely flooded are more likely to drop their insurance policies in response to hazard mitigation efforts because they do not realize the benefits of flood insurance as regularly. To test the extent to which flood experiences influence response differences we generated an indicator variable equal to one if the number of flood events experienced by community i between 1990 and 2000 exceeds the 75th percentile of all communities in our sample; zero otherwise. Floods are defined as having occurred if there was a Presidential Disaster Declaration in the county the community is located in. Flood information comes from FEMA's open data portal.

Column (3) in Table 5 shows that flood frequency is associated with differential insurance demand responses. As indicated by the positive and statistically significant coefficient on the RC interaction term, communities that are more frequently flooded also react more strongly to risk communication efforts. The finding lends support to the hypothesis that experience with flooding makes individuals more amenable to updating their risk perceptions from risk communication. As indicated by the coefficient on the interaction term for HM, the difference between the two groups' responses to hazard mitigation activities is not statistically different from zero. The results do not support the hypothesis that communities that are less frequently flooded are less likely to drop out of the insurance market in response to hazard mitigation efforts.

Hazard type

Finally, we explore if the type of flood hazard a community faces -- namely, riverine flooding and coastal flooding -- influences the community's insurance demand response to CRS measures.[xxix] The two flood hazard types have very different hazard profiles, with riverine flooding often being slow-moving, shallow and inundating an area for multiple days (like in the case of Mississippi River flooding) and coastal flooding tending to consist of storm surges compounded by wind effects from tropical storms. Here, the indicator variable is equal to one if community i faces coastal flood risk, zero if it faces riverine flood risk. Flood hazard types are designated at the community-level by FEMA.

Column (4) in Table 5 shows that communities facing coastal flood hazards and communities facing riverine flood hazards have similar responses to CRS risk mitigation activities. This is evidenced by the interaction terms that are not statistically significantly different from zero.

VI. Conclusion

Climate change and continued development in areas at risk of flooding means that the five costliest flood events in U.S. history occurred in the last fifteen years (Fountain 2019; Flavelle 2019b). Increasing flood costs have forced FEMA, for the first time, to borrow from the U.S. Department of Treasury in order to fund post-disaster recovery (GAO 2017). Typically, FEMA funds recovery with insurance premiums paid by insurance policy holders. Since Hurricane Katrina in 2006, however, FEMA has owed between 15 and 25 billion outstanding debt dollars to the Treasury Department. Simply put, collected insurance premiums are not covering recent flood costs.

FEMA's fiscal solvency problem has led to urgent calls for policy reform that reduces flood risk (GAO 2017). The calls have emphasized increasing communities' flood insurance penetration rates while also building defenses that reduce the flood hazards residents face. For example, the New York City government is currently weighing the decision of a 119 billion dollar sea wall while also, for the first time in three decades, updating flood risk maps across all five Burroughs (Chan 2018; Barnard 2019).

The paper gives evidence that governments, through their choice of public risk mitigation activity, can influence individuals' decisions to privately mitigate their flood risks. We show that risk communication activities, which heighten perceived risk, serve as complements to private risk mitigation and crowd-in insurance demand. Hazard mitigation activities, which depress perceived risk, serve as substitutes to private risk mitigation and have the consequence of crowding-out insurance demand. The intensity of the responses is associated with differences in community characteristics. For example, risk communication measures have been particularly effective in communities with higher income levels, higher education levels and a long history of flooding. Floodplain managers can use these differences to their advantage by strategically targeting their policies.

While both risk communication and hazard mitigation measures reduce residents' risk, they have differing implications for who actually bears the financial burden of flood risk. Risk communication activities shift the bulk of the costs to the individual property owners that live in harm's way as they fund their own post-flood recovery with their insurance premiums. Hazard mitigation activities, on the other hand, burden all taxpayers as they finance both the measures as well as post-disaster aid (in lieu of insurance payouts) in the event that hazard mitigation fails. For example, in the situation that a levee is overtopped.

Conditional on a government's objective function, and specifically who they believe should pay for flood risk costs, the results from this paper can provide policy guidance to community floodplain managers in forming their risk mitigation strategies. In the case that a community would like individual property owners living in risky areas to pay for flood costs, the community should invest in risk communication activities like hazard disclosure and improving the quality of flood risk data. In the case that they prefer the burden be carried by all taxpayers, investment in hazard mitigation, like building flood protection structures, is desirable.

In addition to answering a broader question about behavioral responses, this paper also evaluates how the CRS program reaches its goal of growing insurance demand. We give evidence that while all CRS points contribute to reductions in insurance prices, and consequent increases in insurance demand, points stemming from risk communication activities amplify the effect of premium discounts while hazard mitigation points dilute it. We are not able to comment on the CRS program's effectiveness of reaching its other two goals: (1) encouraging a comprehensive approach to floodplain management and (2) reducing flood damage to insurable property. See, for example, Frimpong et al (2019), Burton (2015) and Highfield and Brody (2017) for the positive impact CRS participation has on flood loss reduction and disaster recovery outcomes.

The CRS program is not necessarily welfare-improving. For example, in the case that the additional five percent premium discount achieved with an improved class is not reflected in the real risk households face, then premiums will no longer be actuarially fair. A possible outcome is an insurance program that takes in fewer premiums than it doles out in claims. The extent to which a society can tolerate this, particularly when the alternative to insurance is government aid, depends on a number of factors including preferences for who bears the cost of flooding: insurance holders or all taxpayers.

We see three limitations to this study. First, purchasing flood insurance is just one of numerous private risk mitigation activities available to residents. As we do not observe other risk mitigating behaviors, we cannot make definitive conclusions about the impact of CRS activities on people's overall flood risk levels. In the event that other private risk mitigating activities, like purchasing sandbags, serve as substitutes for insurance, then, in the absolute, risk communication's crowding-in effect, or hazard mitigation's crowding-out effect, would have had no effect on flood risk levels. Insurance would simply substitute for the other private protection measures. In the event that activities are complementary, then CRS activities' impact on flood risk levels would be amplified.

Of the few studies that have analyzed the relationship between the insurance purchasing decision and other private risk mitigating behaviors, most give evidence that the relationship is complementary. Hudson et al (2017), for example, show that homeowners in the U.S. and in Germany invest in more flood risk-mitigating behaviors if they are already insured against the risk. Botzen et al (2019) show the same phenomena with a survey of 1,000 homeowners in flood-prone areas of New York City, demonstrating that the behavior is largely driven by flood risk history as well as behavioral tendencies. Given these results, we conclude that from the potential complementary relationship between insurance purchasing and other risk mitigating behaviors, the overall impact of CRS activities on flood risk levels is likely to be amplified.

Second, this study focuses on one specific group of NFIP communities: those participating in the CRS program. CRS communities are not randomly pulled from the pool of total NFIP communities, but are different from non-CRS communities in several ways, as shown in Table A8 in the Appendix. For example, CRS communities tend to be at greater risk of flooding, resulting in higher flood insurance demand levels (Sadiq and Noonan 2015b). From a lack of data, we cannot directly test how residents in non-CRS communities would respond to risk communication and hazard mitigation measures.

A third limitation to this study is the potential for time-varying, unobserved confounders at the community-level. For example, if a community becomes more risk averse, it follows that insurance demand may increase independently of a change in CRS activity points, leading to bias in the estimated causal effect. We account for unmeasured confounders with the empirical specification's temporal fixed effects structure: MSA-by-year fixed effects eliminate unobserved shocks common to all communities within a Metropolitan Statistical Area (MSA). The strategy is sufficient in the case that temporal movements in the unmeasured confounders are correlated within an MSA. We cannot, however, fully rule out the existence of time-varying, unobserved confounders unique to communities.

Finally, we see two potential avenues for future research. The first is examining how other government interventions can be used to amplify or dampen the effects of CRS activities on perceived risk and insurance demand. For example, FEMA may seek to more strongly enforce insurance requirements to reduce the amount of crowding-out that occurs in response to hazard mitigation activities.

A second potential avenue for future research is investigating the economic efficiency with which risk communication and hazard mitigation activities reduce flood risk. This paper identifies behavioral responses to the CRS activities, which contribute to explaining efficiency outcomes. To fully understand the economic efficiency implications of the CRS activity types, information about activities' costs and effectiveness would also be needed. Knowing the economic efficiency of risk communication and hazard mitigation measures would be in the interest of policy makers who seek to minimize flood risk with limited budgets.

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Table 1: Classification of activities under the CRS program

activity	total possible points	average points earned (2008)	average earned points (2017)	designation
Public information (Series 300)				
310: Elevation certificates	162	69	57	RC
320: Map information service	140	130	113	RC
330: Outreach projects	380	86	85	RC
340: Hazard disclosure	81	11	12	RC
350: Flood protection information	102	29	36	RC
360: Flood protection assistance	71	27	18	RC
Mapping and regulation (Series 400)				
410: Additional flood data	1,346	35	46	RC
420: Open space preservation	900	156	185	HM
430: Higher regulatory standards	2,740	208	341	HM
440: Flood data maintenance	239	74	112	RC
450: Stormwater management	670	93	106	HM
Flood damage reduction (Series 500)				
510: Floodplain management planning	359	43	76	HM
520: Acquisition and relocation	3,200	35	51	HM
530: Flood protection	2,800	8	14	HM
540: Drainage system maintenance	330	172	102	HM
Flood preparedness (Series 600)				
610: Flood warning program	255	38	36	HM
620: Levee safety	900	0.1	1	HM
630: Dam safety	175	60	31	HM
Risk communication	2,521	460	479	RC
Hazard mitigation	12,329	813	943	HM
Total points	14,850	1,272	1,422	/

Notes: Points possible given for the CRS Coordinator Manual's 2007 version. Averaged earned points calculated for the communities in this paper's sample.

Table 2: CRS activities and premium discount per CRS class

CRS class	point threshold	insurance discount	number of communities	average earned RC points	average earned HM points
Class 9	500-999	5%	148	287	408
Class 8	1,000-1,499	10%	372	410	676
Class 7	1,500-1,999	15%	332	496	986
Class 6	2,000-2,499	20%	204	572	1293
Class 5	2,500-2,999	25%	110	681	1597
Class 4	3,000-3,499	30%	4	909	1848
Class 3	3,500-3,999	35%	2	1027	2078
Class 2	4,000-4,499	40%	6	1058	2053
Class 1	4,500+	45%	1	1157	3603

Notes: Community tally and earned points are for the year 2017. Insurance discount is listed for the riskiest floodplain, called the Special Flood Hazard Area (SFHA). Outside the SFHA, insurance discounts also increase with class standing, topping at 10 percent. Number of communities and average earned points calculated with this paper's sample.

Table 3: The impact of CRS on flood insurance penetration

	(1)		(2)		(3)	
	Coef.	SE	Coef.	SE	Coef.	SE
(ln) RC points (in 100)					0.008**	(0.004)
(ln) HM points (in 100)					-0.007**	(0.003)
(ln) total points (in 100)	0.004	(0.003)	-0.003	(0.002)		
Class 8			0.062**	(0.030)	0.054**	(0.027)
Class 7			0.058*	(0.031)	0.043	(0.030)
Class 6			0.124**	(0.060)	0.104*	(0.053)
Class 5 and below			0.183*	(0.101)	0.157*	(0.088)
PDD disaster declaration year (t)	-0.037*	(0.023)	-0.033*	(0.018)	-0.030**	(0.015)
t-1 PDD	-0.026	(0.023)	-0.023	(0.018)	-0.021	(0.016)
t-2 PDD	0.032	(0.045)	0.036	(0.047)	0.034	(0.046)
t-3 PDD	0.071*	(0.043)	0.067*	(0.035)	0.060*	(0.031)
mean flood damage claim year (t)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
t-1 flood	0.002*	(0.001)	0.002**	(0.001)	0.002**	(0.001)
t-2 flood	0.001*	(0.001)	0.001*	(0.001)	0.001*	(0.001)
t-3 flood	0.002**	(0.001)	0.002**	(0.001)	0.001**	(0.001)
ln (median income)	0.757**	(0.342)	0.739**	(0.331)	0.694**	(0.331)
ln (house value)	0.242	(0.167)	0.240	(0.161)	0.250	(0.163)
ln (BW/HFIAA)	0.206	(0.177)	0.230	(0.184)	0.221	(0.186)
ln (household mortgage)	0.150	(0.185)	0.152	(0.178)	0.113	(0.172)
Community FX	Yes		Yes		Yes	
MSA-year FX	Yes		Yes		Yes	
Observations	10,355		10,355		10,355	
pseudo R-squared	0.996		0.996		0.996	

Notes: Dependent variable is the number of insurance policies in force. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis, clustered at the metropolitan statistical area. Mean flood damage claim in 1,000 USD. Constant included but not reported.

Table 4: Robustness

	Manual 2013		Balanced Sample		Singletons		Sheldus Disasters	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
(ln) RC points (in 100)	0.011**	(0.004)	0.007*	(0.004)	0.009**	(0.004)	0.009*	(0.004)
(ln) HM points (in 100)	-0.007**	(0.003)	-0.008**	(0.004)	-0.006*	(0.003)	-0.008**	(0.003)
Class 8	0.052**	(0.028)	0.067**	(0.033)	0.056**	(0.028)	0.048*	(0.028)
Class 7	0.036	(0.043)	0.046	(0.030)	0.044	(0.029)	0.038	(0.033)
Class 6	0.096	(0.062)	0.119**	(0.058)	0.091*	(0.050)	0.099*	(0.054)
Class 5 and below	0.141*	(0.079)	0.186*	(0.095)	0.139*	(0.079)	0.161*	(0.090)
PDD disaster declaration year (t)	-0.029**	(0.012)	-0.032**	(0.016)	-0.020**	(0.010)	-0.021	(0.018)
t-1 PDD	-0.019	(0.014)	-0.024	(0.017)	-0.025***	(0.009)	-0.010	(0.024)
t-2 PDD	0.034	(0.047)	0.044	(0.050)	0.012	(0.011)	0.038	(0.044)
t-3 PDD	0.057**	(0.028)	0.073**	(0.032)	0.013	(0.010)	0.073**	(0.031)
mean flood damage claim year (t)	0.001*	(0.001)	0.001	(0.001)	0.000	(0.000)	0.001	(0.001)
t-1 flood	0.002**	(0.001)	0.002**	(0.001)	0.002***	(0.001)	0.011	(0.012)
t-2 flood	0.001*	(0.001)	0.001*	(0.001)	0.001**	(0.001)	-0.003	(0.002)
t-3 flood	0.002**	(0.001)	0.001*	(0.001)	0.001**	(0.001)	-0.001	(0.003)
(ln) RC points (in 100) * Manual2013	-0.004	(0.007)						
(ln) HM points (in 100) * Manual2013	0.006	(0.004)						
Manual 2013	-0.029	(0.056)						
Community FX	Yes		Yes		Yes		Yes	
MSA-year FX	Yes		Yes		No		Yes	
MSA-period FX	No		No		Yes		No	
Observations	10,355		8,220		12,404		10,355	
adj. R-squared	0.996		0.996		0.995		0.996	

Notes: Dependent variable is the number of insurance policies in force. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis, clustered at the metropolitan statistical area level. Mean flood damage claim in 1,000 USD. In the first column interaction terms with manuas2013 dummy are added. Parameter estimates in the second column are based on the balanced sample. In the third column MSA-period fixed effects are included instead of MSA-year fixed effects to avoid singletons. In the fourth column Sheldus disasters damage per capita in 1,000 USD are used as disaster risk proxy. (ln) median income, (ln) house value, (ln) BW/HFIAA, (ln) household mortgage and constant included but not reported.

Table 5: Heterogeneous Effects

	(1) Income		(2) Education		(3) Flooding freq.		(4) Hazard type	
	group = higher income		group = higher educ. level		group = higher flood freq.		group = coastal hazard	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
(ln) RC points (in 100)	-0.005	(0.007)	-0.001	(0.005)	0.002	(0.004)	0.014*	(0.0048
(ln) HM points (in 100)	-0.013***	(0.005)	-0.008	(0.005)	-0.005**	(0.003)	-0.008**	(0.0034
(ln) RC points (in 100)*group	0.019**	(0.010)	0.020**	(0.010)	0.009*	(0.005)	-0.009	(0.010)
(ln) HM points (in 100)*group	0.010**	(0.005)	0.002	(0.006)	-0.002	(0.005)	0.002	(0.006)
Class 8	0.109***	(0.040)	0.041**	(0.021)	0.069***	(0.021)	0.035	(0.043)
Class 7	0.156***	(0.051)	0.085**	(0.036)	0.110***	(0.026)	0.091**	(0.047)
Class 6	0.221**	(0.089)	0.147*	(0.080)	0.152***	(0.041)	0.129*	(0.070)
Class 5 and below	0.265**	(0.109)	0.192*	(0.108)	0.167***	(0.051)	0.170**	(0.085)
Class 8*group	-0.084***	(0.028)	0.047	(0.037)	-0.018	(0.045)	0.035	(0.043)
Class 7*group	-0.177***	(0.059)	-0.065	(0.072)	-0.093**	(0.035)	-0.057	(0.043)
Class 6*group	-0.153*	(0.082)	-0.062	(0.092)	-0.062	(0.064)	-0.021	(0.076)
Class 5 and below*group	-0.144**	(0.071)	-0.057	(0.081)	0.010	(0.109)	0.002	(0.135)
group dummy	-0.210**	(0.090)	0.001	(0.076)				
Controls	Yes		Yes		Yes		Yes	
Community FX	Yes		Yes		No		Yes	
MSA-year FX	No		No		Yes		No	

Notes: Dependent variable is the number of insurance policies-in-force. Number of observations is 10,355. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis, clustered at the metropolitan statistical area level. Mean flood damage claim in 1,000 USD. In model 1 grouping variable for interaction terms is 1 if a community is situated in a county with above median income; 0 otherwise. In model 2 grouping variable for interaction terms is 1 if a community is situated in a county with above median percentage of population 25+ years old with a bachelor's degree or higher; 0 otherwise. In model 3 grouping variable for interaction terms is 1 if a community is situated in a county with above the 75th percentile in the occurrence of floods between 1990 and 2015; 0 otherwise. In model 4 grouping variable for interaction terms is 1 If a community is a coastal community; 0 otherwise. Constant included but not reported.

Figure Titles

Figure 1: In- and out-of-sample CRS communities. *Notes*: The locations of CRS communities are provided on the map. CRS communities shaded in black are in the sample from which we estimate our model. CRS communities shaded in grey are dropped from the sample due to the main specification's fixed effect structure. The dropped communities are either the only community within an MSA or they only participated in the CRS program one year during the 2008 - 2017 timeframe.

Figure 2: Number of insurance policies-in-force for each CRS community, as recorded in October 2017.

[i] The CRS program's remaining two goals are to (1) “reduce and avoid flood damage to insurable property" and (2) “foster comprehensive floodplain management" (FEMA 2017).

[ii] Outside of the riskiest floodplain designation, discounts also increase with class improvement, though the maximum price discount is only 10 percent.

[iii] Verification visits can also occur outside the “normal pattern”. This happens when a neighboring community is up for verification, and FEMA decides to concurrently evaluate all CRS communities in close proximity. It follows that CRS communities do not necessarily follow their verification visit cycles based on initial application date, but can instead be verified in an earlier year.

[iv] CRS points are reported twice per year: May and October. Unfortunately, our CRS point data is incomplete in that for the years 2008 and 2009 we only have May information and for the years 2013 and 2015 we only have October information. For this analysis, we use point information for October of each year except for the years 2008 and 2009, where we use May information. As demonstrated in Table A5 in the Appendix, our conclusions are robust to using the May points in every year but 2013 and 2015, where we use the October information.

[v] Because of concerns surrounding selection bias, we checked the robustness of our results by dropping all communities that were not in the CRS program for the entirety of our study period. Conclusions remain the same.

[vi] Our activity categorization process was the following: (1) separately read the detailed descriptions of each activity in the 2013 CRS Coordinator's Manual (FEMA 2017); (2) separately categorize each activity into “risk communication” or “hazard mitigation”; (3) come together and compare results. After comparing results, we found that we had identically categorized the activity types. These are the activities' final categorizations used in this paper.

[vii] CRS point information was obtained via email correspondence with the 2018 CRS Program Manager and Federal Insurance and Mitigation Administration Directorate. Beginning in 2013, the maximum credit points available for each activity were changed to better reflect the new ideals and goals of FEMA and the CRS program. Activities that FEMA deemed more important, like flood protection information, were allotted more credit points than under the previous system. Activities that FEMA deemed less important or reflecting outdated ideals, like levee maintenance, were allotted fewer points than under the previous system. Implementation timing of the new scoring system has been staggered, with a community subject to the new system if it has had a cycle verification visit or changed classes after 2012. For example, in 2017, 59 percent of communities in our sample were using the new scoring system, up from 23 percent in 2015. To make the two scoring systems comparable, we re-weighted earned points under the new, 2013 scoring system, with the weights reflecting conversion from the new to the old scoring system. Table 4 contains results demonstrating the robustness of our re-weighting procedure.

[viii] The private residential flood insurance market is still small in the U.S. and accounted for roughly 3.5 to 4.5 percent of all primary residential flood policies in 2018 (Kousky et al 2018).

[ix] An alternative outcome variable would be the intensive margin of insurance coverage. We believe the extensive margin is a better indicator of changes in risk perceptions because policyholders are not usually flexible in adjusting their insurance coverage. Policy holders are either obligated to purchase the amount of insurance coverage that covers their mortgage or are given a very specific menu of insurance coverage options. We acquired community-by-year policy counts through a Freedom of Information Act request.

[x] Flood claims and Presidential disaster declaration information is available at OpenFEMA: https://www.fema.gov/openfema.

[xi] Communities that crossed multiple county boundaries were assigned to the county that contains the majority of the community's land area.

[xii] American Community Survey's median income information is available on the American FactFinder website: https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

[xiii] Zillow data is available at its website: https://www.zillow.com/research/data/.

[xiv] https://yourfloodrisk.com/assets/BW12-HFIAA.pdf

[xv] American Community Survey's mortgage holder information is available on the American FactFinder website: https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

[xvi] Expected directions of the individual variables' effects on insurance demand are in parentheses.

[xvii] As a robustness check, Table A3 in the Appendix contains estimates with state-by-year fixed effects.

[xviii] Communities' investment in risk communication and hazard mitigation is moderately positively correlated with a Pearson's product-moment correlation of $r(10{,}353) = .523$, $p < 0.0005$. Table A4 in the Appendix provides additional evidence that the two activity types are exogenous to each other by demonstrating the robustness of our main conclusions when excluding RC or HM from the analysis.

[xix] For example, if the only floodplain managers that invested in risk communication are those that believed their residents are particularly responsive to risk communication efforts, then our point estimate on the risk communication variable would be upward biased because communities who are not responsive to risk communication would left out of the treatment. Similarly, if the only floodplain managers that invested in hazard mitigation are those that believed their residents are not likely to drop out of the market - as this is seen as unfavorable - then our point estimate on the hazard mitigation variable would also be upward biased because communities who are most likely to drop out of the market in response to hazard mitigation would be left out of the treatment. Rather than strategically investing in activity types based on beliefs about behavioral responses, Brody et al (2009) give evidence that floodplain managers

instead strategically select into activities types based on cost, going for the “lowest-hanging fruit” first.

[xx] In the case that investment in either risk communication or hazard mitigation leads segments of the population with specific characteristics to move in or out of communities, and these specific characteristics are correlated with high or low insurance demand (for example, through risk preferences), point estimates on risk communication and hazard mitigation would be biased. To check for changes in the demographic composition of our sample population, we chose three different demographic measures known to have an influence on risk preferences and investigate the development of these variables over time for communities scoring either above or below the median for the two activity types (see Figures 4, 5 and 6). For all three demographic measures, we do not observe systematic differences in their temporal development. Moreover, as shown in Table A6, our results are robust when including the variables as additional controls. For all three demographic measures, we do not observe systematic differences in their temporal development.

[xxi] The time lag in the implementation of flood risk mitigation measures under the CRS program can be different. Activities like hazard disclosure by real estate agents and outreach projects could be implement quite quickly, whereas activities like levee maintenance and relocation take often multiple years to be finished. To account for this in a robustness exercise we re-estimate specification 2 using the CRS measures information one year lagged to give more time space between decision making and flood insurance demand. Our two CRS measures, as shown in Table A7 in the Appendix, stay robust in their direction of influence.

[xxii] The measurement error would cause overestimation of the activities' impacts in the case that the size of the insurance effect of a given activity builds up from the activity implementation date.

[xxiii] Note, the coefficient estimate in a Poisson model is interpreted as a semi-elasticity derived as $\Delta_j \hat{y} = \left(e^{\beta_j} - 1\right) * 100$

[xxiv] Excluding the BW/HFIAA variable from the specification leads to little change in the coefficient estimates on the CRS class dummy variables. Results for this robustness exercise are available upon request.

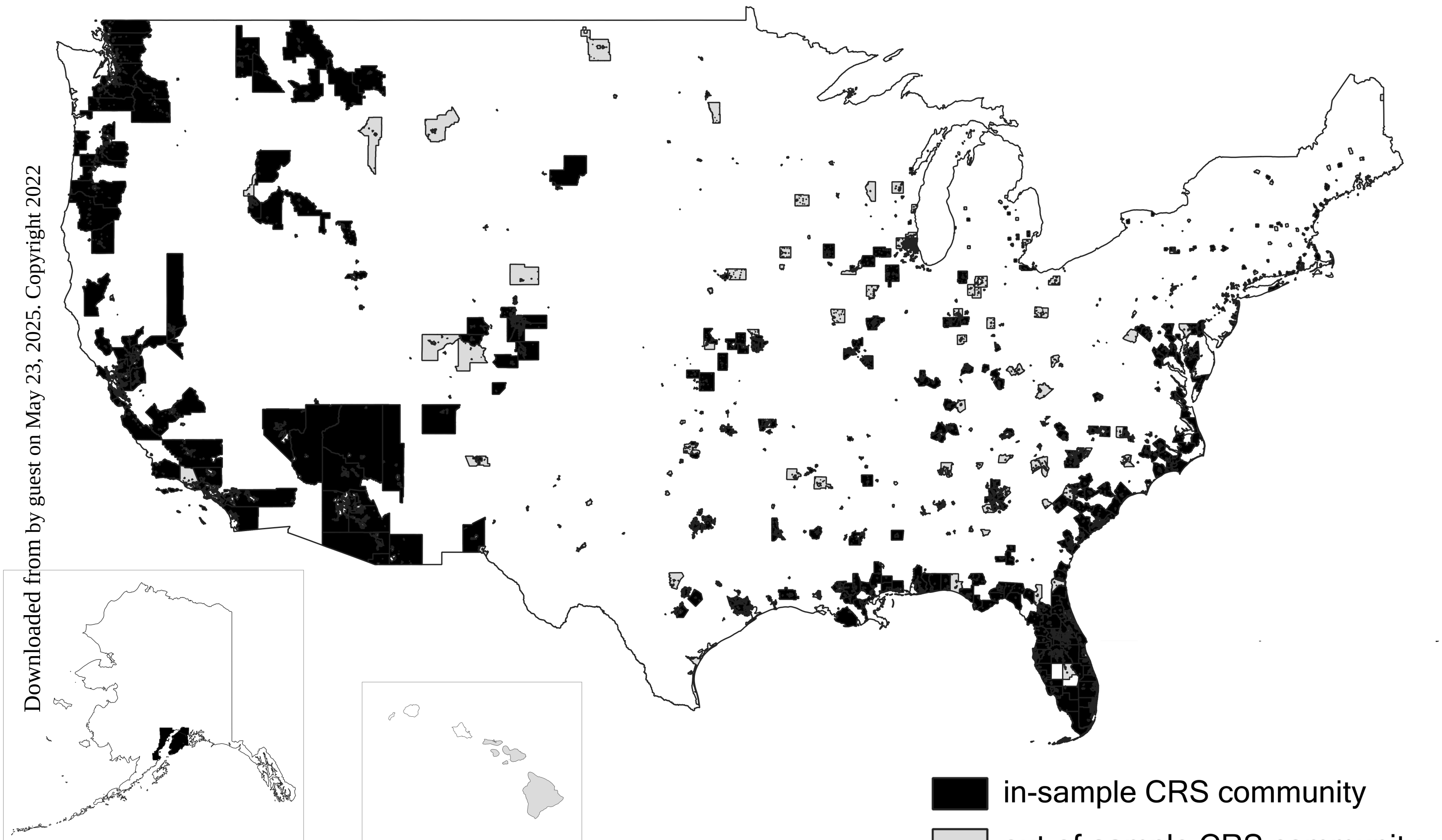
[xxv] Put differently, a one standard deviation increase in risk communication points leads to a 1.4 percent increase in insurance demand. A one standard deviation increase in hazard mitigation points leads to a 3 percent decrease in insurance demand. The difference in the two magnitudes reflect differences in achievable points and average points earned from each activity as shown in Table 1 and Figure 3. Comparing 100 point increases better reflects relative monetary outlays for each activity type.

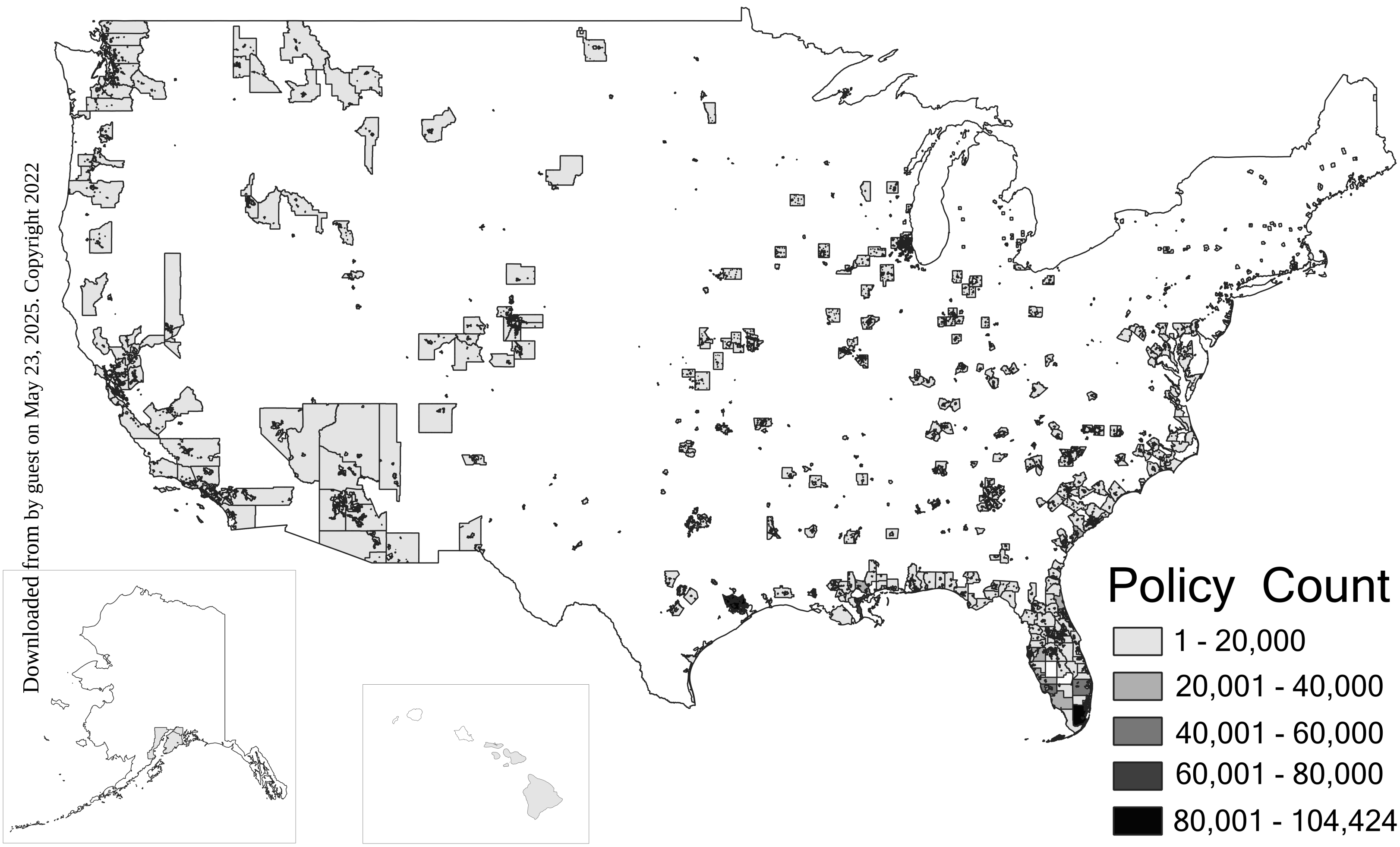
[xxvi] See a technical note of Sergio Correia (2015) http://scorreia.com/research/singletons.pdf} and the references within on this issue.

[xxvii] SHELDUS data is available at its website: https://cemhs.asu.edu/sheldus.

[xxviii] American Community Survey's education information is available on the American FactFinder website: https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml.

[xxix] Hazard information comes from the CEPTCommunityData portal: https://www.arcgis.com/home/item.html?id=407442d5e8dc447aabe2b09fb698adad.


in-sample CRS community
out-of-sample CRS community


Policy Count
1 - 20,000
20,001 - 40,000
40,001 - 60,000
60,001 - 80,000
80,001 - 104,424