Flood disaster management policy: An analysis of the United States Community Ratings System

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Abstract:

In 1990 the US Federal Emergency Management Agency created the Community Ratings System (CRS) to engage local governments to enhance community flood resilience. CRS encourages community flood risk management activities by discounting flood insurance premiums commensurate with the level of flood management measures implemented. Using a national sample of communities, this study empirically identifies factors motivating both communities' decision to participate and intensity of participation in CRS. The results indicate that local capacity, flood risk factors, socio-economic characteristics, and political economy factors are significant predictors of CRS participation. Further, factors predicting participation in CRS differ from factors predicting CRS scores.

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Flood Disaster Management Policy: An Analysis of the United States Community Ratings System

1. Introduction

Water disaster management in the United States (US), and flood disaster management in particular, generally involves both local and national-level policies and institutions. Much can be learned from analyzing the US experience with improving its flood disaster management. Historically, the US has suffered considerable losses, both in terms of lives lost and property damage, to flooding events. For example, the 30-year average for flood-related deaths and flood damage from 1982 to 2011 are 95 fatalities and $8.20 billion, respectively (National Weather Services [NWS], 2013). The devastation caused by flooding is also reflected in Presidential Disaster Declarations, where over 80 percent of presidentially declared disaster losses are engendered by flooding (Landry & Li, 2012). As a result of persistent increases in flood losses and the unavailability of private flood insurance (Federal Emergency Management Agency [FEMA], 2011), the federal government passed the National Flood Insurance Act (NFIA) in 1968, which established the National Flood Insurance Program (NFIP). One of the goals of NFIP is to reduce future flood losses by encouraging communities to adopt and enforce floodplain management ordinances in exchange for federally backed flood insurance (FEMA, 2011). As of December 2011, approximately 5.6 million residential and commercial insurance policies were in force, totaling $1.26 trillion in coverage (FEMA, 2013). Although the NFIP has been successful in providing support to flood victims, some argue that the NFIP subsidized insurance premiums may be encouraging more losses or development in high-risk areas (e.g., Thomas & Leichenko, 2011; Kousky & Kunreuther 2013; Goodwin, 2013). In order to reduce flood losses, which are still substantial (FEMA, 2013), in 1990, FEMA created the Community Ratings System (CRS) through the NFIP. CRS is a voluntary program that encourages communities to engage in additional flood risk management activities by offering communities discounted flood insurance premiums commensurate with the level of flood management measures implemented.

The relatively new CRS marked a departure in using a federal program (NFIP) to directly engage local governments in integrating flood risk reduction into their plans and to enhance community flood resilience. Better understanding CRS performance promises to respond, in part, to two of the five research priority areas identified in Gopalakrishnan (2013): mainstreaming risk reduction policies and capacity building and resilience. Although researchers have studied the factors that motivate communities to participate in CRS within single states (Brody, Zahran, Highfield, Bernhardt, & Vedlitz, 2009; Landry & Li, 2012), there is only one study to our knowledge on the factors that motivate communities to participate in CRS for a national sample. Previous research into the factors motivating participation in the CRS typically looked only at single state case studies and did not assess the "intensity" of participation as measured by the CRS scores. Results for particular state case studies may not generalize well to the nation as a whole. We examine participation of cities, towns, villages, and townships across the nation. Further, participation and the intensity of participation are closely linked community decisions yet have different determinants. As a result, this study attempts to empirically answer two questions: (1) *what factors motivate communities to participate in CRS?* (2) *What factors predict CRS scores conditional on CRS participation?* A good understanding of what factors motivate communities to not only participate in CRS, but also attain high CRS scores can help policy makers to develop targeted policies to address flood risks and subsequently reduce flood losses. Using national data on historical CRS participation, the 1990 Census, financial data from the 1992 Census of Governments, climate and topographical information from the United States Department of Agriculture (USDA), and other data sources, we analyze the determinants of CRS participation and CRS scores. We estimate two basic empirical models: (1) a logit model to explain why some communities opt to participate and others do not; (2) a tobit model and a Cragg (double-hurdle) model to explain the CRS score achieved, given that the community participated. We use these models to test several competing hypotheses – local government capacity, flood risk factors, socio-demographic factors, and political economy factors – that explain why communities participate as they do. The results indicate that local capacity, flood risk factors, socio-demographic characteristics, and political economy factors are significant predictors of CRS participation. In addition, the results indicate that the factors that motivate communities to participate in CRS are not the same factors that predict CRS scores.

After a brief background description of the NFIP and CRS, we present a review of relevant literature followed by a discussion of the methodological approach, including the dataset used to answer the research questions. Next, we present our findings and discuss the results. Finally, we conclude with policy implications of our results and outline an agenda for future research on community flood risk mitigation.

1.1 The National Flood Insurance Program

The recognition of the potential consequences of flooding prompted the US federal government to initially engage in structural mitigation measures - levees, seawalls, dams, etc. - to control flooding and provide relief assistance to disaster victims (FEMA, 2011). However, this strategy was neither successful in reducing flood losses nor discouraging communities from building in flood-prone areas (Brody et al., 2010; FEMA, 2011). To make matters worse, the private market was not providing affordable flood insurance for water damage from flooding and other storms because of the seasonality of floods, uncertainty of flood risk, and high flood risk (Kunreuther, 1996; FEMA, 2011; Kousky, Olmstead, Walls, Stern, & Macauley, 2011). Due to the increasing disaster losses and unavailability of insurance coverage from the private sector, on 1 August 1968, the US Congress established the NFIP through the passage of NFIA, to provide flood insurance to communities. Communities can participate in the NFIP by adopting and enforcing floodplain management ordinances in exchange for federally backed flood insurance (FEMA, 2011).

In addition to providing flood insurance to communities, NFIP also develops Flood Insurance Rate Maps (FIRM), which depict the base flood elevations, flood zones, and floodplain boundaries of the nation’s communities. FIRMs help homeowners/renters and insurance companies identify flood risks (FEMA, 2002). Recognizing that buildings constructed prior to the adoption of FIRM were not likely to have known about flood risks, pre-FIRM buildings receive subsidized insurance rates. In exchange for subsidized insurance rates for pre-FIRM buildings, communities are expected to protect new construction from floods by implementing floodplain management ordinances (FEMA, 2002).

There have been several amendments to NFIP since its creation in 1968. Realizing that communities were not participating in NFIP at high rates voluntarily, Congress added the Mandatory Flood Insurance Purchase Requirement in 1973. This amendment mandates “ … federally insured or regulated lenders … to require flood insurance on all grants and loans for acquisition or construction of buildings in designated Special Flood Hazard Areas (SFHAs) in communities that participate in the NFIP" (FEMA, 2002, p. 3). SFHA is a piece of land in a floodplain that has a 1 percent or greater chance of flooding in any given year (also known as the 100-year flood occurrence) (FEMA, 2002). This 1973 requirement engendered an increase in the number of communities participating in NFIP from 2,200 in 1973 to 15,000 in 1977 (FEMA, 2002). In 1994, the National Flood Insurance Reform Act (NFIRA) added additional measures to increase compliance of the mandatory purchase requirement, to codify the CRS, and to require FEMA to reassess the FIRMs every 5 years, among other measures (FEMA, 2002). More recently, the US Congress enacted the Biggert-Waters Flood Insurance Reform and Modernization Act of 2012. Changes made by this act include premium rate structure reforms, a requirement for FEMA to develop a reserve fund, and the development of an ongoing mapping program that will continuously update floodplain maps (National Association of Insurance Commissioners, 2012). This 2012 act was in response to recent flood disasters in the US, like Hurricane Katrina and Super storm Sandy that resulted in billions of dollars in flood damage. In the aftermath of these disasters, it was clear that many individuals had not purchased flood insurance (King, 2013). As a matter of fact, only 18 percent of all Americans have flood insurance (Stellin, 2012). In addition, it seems that many people misunderstand their flood risk and often underestimate the probability that a flood could occur, thereby decreasing the likelihood that they will obtain the mandatory insurance coverage (King, 2013).

[TABLE 1 HERE]

1.2 The Community Rating System

The CRS program, which was implemented in 1990, is supposed to give additional incentives to communities to go beyond the NFIP requirements to address flood risks. The program has three main objectives: reduce flood losses, strengthen accurate insurance ratings, and foster awareness of flood insurance (King, 2013). When communities participate in CRS, they not only reduce their flood risks they also enjoy discounted premiums (up to 45 percent) on federally required flood insurance based on their community's CRS score (see Table 1). To date, over 1,200 communities from all 50 states are participating voluntarily in the CRS program, achieving a wide range of ratings (FEMA, 2013). The 19 credited activities to be completed by communities fall into four major categories; public information activities, mapping and regulations, flood damage reduction activities, and warning and response (see Table 2). Public information activities promote the purchase of insurance, advise people about their flood hazards, and provide information on how to reduce risks. Mapping and regulation activities increase the protection to new development, while flood damage reduction activities address the risks present in current structures. Lastly, the warning and response activities are those that prepare communities to respond during flood events (FEMA, 2013).

[TABLE 2 HERE]

2. Literature Review

Improving flood disaster management policies involves better understanding current policy frameworks. Since the creation of NFIP, researchers have studied various aspects of this program. For example, researchers have examined the problems and the potential of NFIP (Anderson, 1974), the proposed changes for the NFIP (United States General Accounting Office (GAO), 1983), and the demand for flood insurance (Browne & Hoyt, 2000). Others have looked at the participation in NFIP by coastal communities (Landry & Jahan-Parvar, 2011; Petrolia, Landry, & Coble, 2013) and flood risk perception in lands protected by 100-year levees (Ludy & Kondolf, 2012). Similarly, researchers have studied different aspects of CRS. For instance, Brody et al. (2009) used the CRS as a case study to understand policy learning for flood mitigation. These researchers found that local jurisdictions do learn from histories of flood risks (Brody et al., 2009). In addition, Posey (2009) used the CRS as a proxy for adaptive capacity and examined whether the socio-economic status (SES) of individuals in a community is a determinant of adaptive capacity at the municipal level. Posey's results suggest an association between average individual SES and adaptive capacity of the collective (i.e., participation in CRS) (Posey, 2009). In addition, Zahran, Weiler, Brody, and Lindell (2009) examined the correlation between flood insurance purchases by households and the flood mitigation measures implemented by local governments participating in CRS in Florida. Their results indicate a strong correlation between household flood insurance purchase and local government mitigation activities. Furthermore, Zahran, Brody, Highfield, and Vedlitz (2010) studied the relationship between the non-linear nature of the incentive inherent in CRS and observed changes in CRS scores. Their results indicate that adoption of mitigation measures by Florida communities are driven by the non-linear incentive nature of CRS. Finally, Landry and Li (2012) studied the influence of local capacity, hydrological risk factors, and flood experience on community hazard mitigation decisions in North Carolina counties (participation in CRS was used as a measure of community hazard mitigation decisions). Landry and Li's (2012) results suggest positive relationships between flood history and CRS participation, as well as between physical risk factors and CRS participation, among other findings.

Researchers have measured local capacity in terms of resource availability, such as the number of trained staff in a community (Kunreuther & Roth, 1998). Previous studies on risk reduction have established a positive relationship between resources (time, money, man-power, etc.) and adoption of risk-reducing measures at the household (Mileti, 1999), community (May & Birkland, 1994; Brody et al., 2010), and organizational levels (Mileti, Darlington, Fitzpatrick, & O'Brien, 1993; Dahlhamer & D'Souza, 1997; Meyer-Emerick & Momen, 2003; Sadiq, 2010). In the light of these findings, we expect a positive relationship between local capacity (e.g., payroll, property tax revenue, and capital outlay) and participation in CRS.

Prior studies have measured community flood risk in several different ways depending on data availability. For example, Posey (2009) measured flood risk by the number of flood insurance policies, the amount of payments made to satisfy flood claims, and flood insurance claims filed; while Zahran et al. (2010) measure flood risk by flood frequency and flood property damage. According to the findings of these studies and others, communities that faced higher flood risks are more likely to undertake flood mitigation measures (Posey, 2009; Zahran et al., 2010; Landry & Li, 2012). As a result, we expect a positive relationship between flood risk factors (e.g., percent of community area covered by water, topography, and humidity) and participation in CRS.

In addition, researchers have found significant relationships between socio-demographic factors - educational level, percentage of senior citizens in a community, population density - and local flood risk mitigation (Zahran et al., 2010; Landry & Li, 2012). Based on these studies, we expect a significant relationship between socio-demographic factors (e.g., educational attainment, racial composition, share of residents who are children) and CRS participation.

Landry and Li (2012) argue that wealthier communities (measured as median household income or housing values) may put less pressure on local government to adopt flood mitigation measures because they themselves undertake personal protective measures against flood. Rentership rates and the share of new residents (who likely have new mortgages governed by NFIP mandates) are also linked to local collective action. We expect a significant relationship between political economy factors (e.g., housing values, share of housing units that are rentals, household income, and turnover rates) and CRS participation.

Only one of these prior NFIP and CRS studies looks at the predictors of CRS participation using national scale data. By examining the factors that motivate communities to participate voluntarily in CRS using national data, we hope to produce generalizable results. In addition, none of the aforementioned studies has examined whether or not the determinants of CRS participation are the same as the determinants of CRS scores. Based on our literature review and the need to contribute to this important, but scanty literature on CRS participation specifically and the study of risks in general, we posit the following hypotheses:

2.1 Hypotheses

- H1: Local capacity: communities with more financial resources (e.g., payroll, property tax revenue, and capital outlay) are more likely than communities with less financial resources to participate in CRS and score higher CRS scores *ceteris paribus*.
- H2: Flood risk factors: communities with higher flood risks (e.g., percent of community area covered by water, topography, and humidity) are more likely than communities with lower flood risks to participate in CRS and score higher CRS scores *ceteris paribus*.
- H3: Socio-demographic factors: the likelihood and intensity of a community's participation in CRS is influenced by socio-demographic characteristics (e.g., educational level, racial composition, and share of residents who are children).
- H4: Political-economy factors: the likelihood and intensity of a community's participation in the CRS depends on expected capitalization gains (e.g., housing values and share of housing units that are rentals) and residents' ability to influence local policies (e.g., household income and turnover rates).

3. Methodology

3.1 Data

We combined five data sources to inform the analysis. Data on CRS participation is obtained from the 2013 *CRS Coordinator's Manual* (FEMA, 2013) and FEMA. Underlying flood risk data from US Department of Transportation (US DOT) (1996) offers very high resolution (1 km grid cell) rankings of flood risk (on a 0-100 scale) that use underlying topography and hydrography of the area. This flood hazard rank variable derives from a formula that equally weights annual flooding frequency ranked from 0-100 (which itself is an area-weighted average of flooding by soil map units within the 1km grid cell) and their potential scour depth ranked from 0-100. Scour depth reflects erosion hazard based on 100-year flood flow, sediment size, and stream shape characteristics (Williams, Carreon, & Bradley, 1992). Thus this flood hazard risk variable captures both the frequency and the intensity of flooding. This flood risk measure has three advantages: (i) it derives from data and computations that largely predate the start of the CRS program, (ii) it offers a rich quantitative scale for flood risk, and (iii) it provides spatial resolution much smaller than cities or counties, which allows better distributional characterization of flood risk (see footnote 2). The Natural Amenities Index, which contains data on the physical characteristics of counties like topography, climate, and water coverage, are taken from USDA's Economic Research Service. Information about the population and housing stock of communities is obtained from 1990 block-group level Census data from United States Census Bureau. Finally, information about government expenditures and revenues is taken from the 1992 Census of Governments, the earliest available Census data on local governments' finances.

The unit of analysis for this study is a Census place, which includes cities, towns, townships or other Census-designated places (henceforth referred to as "places"), which captures roughly half of the CRS-participating communities. While the CRS invites participation from "communities" – which includes both counties and incorporated cities and towns – the analysis here is restricted to places. About 4% of the 28,000-plus places in the US participate in the CRS. For some data available at the county level, each place can be associated with a host county by the United States Census Bureau (1990). This, coupled with the use of more spatially refined Census data from 1990 (i.e., block groups), enables the exploration of the broader distribution of socio-economic variables within a community (rather than relying on simple means or medians at the larger place-level). It is both possible and likely that place-average values of predictors like property values or flood risk will perform less well than peak values within the place.

All variables are taken from 1990, or as close to that year as possible, in order to better match the variables to the conditions existing before the start of the CRS program with those after, thereby enabling a causal interpretation to the findings. There is a serious concern that, for a CRS program that began in 1990, that the program's operation has indeed had an impact on a host of participating places' characteristics. An effective CRS would affect flood insurance policies, claims and flood damages, and even migration and development patterns. Accordingly, relatively permanent or preexisting measures of local capacity, flood risks, socio-economic and political factors are employed in order to minimize their endogeneity in models predicting current CRS participation. A consequence of this cautious approach that predicts current participation with "deep lags" of explanatory variables is reduced explanatory power. Significant effects in this model should be interpreted as less proximate causes of CRS participation, but rather as more indirect forces that affect participation perhaps through intermediate mechanisms (e.g., wealthier communities can better afford to start and sustain engaging a federal program). Of course, recent shocks like floods likely drive reactionary participation (Zahran et al., 2010). The influence of more permanent flood risks are captured here without including endogenous post-1990 measures like experienced flood damages or those related to flood insurance maps, policies, or claims – all of which partly result from a community's flood mitigation activities (such as CRS participation).

3.2 Variables

Table 3 shows the dependent and independent variables and their descriptions. The dependent variable for the logit model is CRS participation and the dependent variable for the tobit model and the Cragg - double hurdle model ("craggit") (Cragg, 1971) is the total CRS scores for the communities that were participating in CRS at of 2012.

[TABLE 3 HERE]

3.3 Data analysis

We employ a two-stage nested model. For the participation model, we use a logit model to explain why some communities participate and others do not. Logit is an appropriate model because of the binary nature of the dependent variable. Linear probability models would yield heteroskedastic error term (Wooldridge, 2002).

[TABLE 4 HERE]

To understand the predictors of CRS score conditional on participation, we use both a tobit model and a craggit model. The two-stage Cragg model offers a compelling alternative to a tobit model in this context because the tobit restricts the underlying process or parameters to be the same in determining both participation (in the first stage) and actual score (in the second stage). The craggit, which is a more flexible model than Tobit, allows for distinct processes to determine the participation and the score separately. Cragg's alternative uses a probit for the first stage and a truncated normal for the second. As the tobit model is nested in the craggit model, the Cragg approach is preferred and offers both interesting comparisons with the tobit and a useful demonstration of the value in relaxing some tobit's assumptions. The descriptive statistics for the independent and dependent variables are presented in Table 4.

4. Results

Table 4 shows that 4.2 percent of all communities are participating in CRS as of 2012. This means that out of a total of 28,147 communities, 1,182 communities were participating in CRS as at 2012. For this group of participants, the minimum CRS score obtained is 505 (CRS class 9) and the maximum CRS score obtained is 5,315 (CRS class 1). In other to determine whether there are significant differences between the means of all independent variables for participant and non-participant communities, we run a t-test. The t-test results indicate that there are statistically significant differences ($p < 0.01$) between the two groups on all but three independent variables—humidity, plains, and the interaction between humidity and topography.

The logistic model is estimated using STATA statistical analysis software. Table 5 shows the results of the logistic regression. The pseudo R-square of 41.07 percent indicates a good fit of the logistic regression.

[TABLE 5 HERE]

The result from the logistic regression indicates that local capacity factors are significant predictors of CRS participation. Specifically, the result indicates a positive significant relationship between payroll and CRS participation. The result also shows a significant, but negative relationship between property tax revenue and CRS participation. Capital outlay is not a significant predictor of CRS participation.

Flood risk factors in a community are significant determinants of CRS participation. Measures from the ERS's Natural Amenities Index which capture climate and topography, and their interaction, play some role. Specifically, the percent of community area covered by water and humidity both significantly increase CRS participation. As expected, interaction terms (highly variable topography *and* extensive surface water, highly variable topography *and* more humidity) are negative and significant determinants of CRS participation as communities are less likely to participate in the CRS in steeper or mountainous topography. More water and flatter topography is typically associated with floodplains and more flooding risk, and the results for the interaction terms in Table 5 are consistent with the notion that greater flood risk is associated with CRS participation. Finally, conditional on those basic correlates of flood risk, peak flood risk in the area is also a positive significant determinant of CRS participation.[1] That basic, county-level climate and topography factors play a significant role even after directly controlling for flooding risk suggests other environmental conditions beyond technical flood risk measures can influence community mitigation.

Two out of the three socio-demographic factors are significant predictors of CRS participation. Share of population that is white and the share of population under the age of 18, both significantly decrease CRS participation. Share of population with a college degree is not a significant predictor of CRS participation.

Political-economy factors are significant predictors of CRS participation. Housing values are significant positive predictors of CRS participation, consistent with greater private gains to homeowners from discounted flood insurance. The share of housing units that are rentals significantly decreases CRS participation, as would be expected if renters apply less pressure on community flood risk managers. Conversely, household income and share of residents not relocating significantly decrease CRS participation rates.

We employed a tobit regression to determine the factors that predict the credits or scores that communities get conditional on participating in the CRS program. Because we cannot interpret the tobit coefficients as effect sizes for actual CRS scores, we focus on the significance and direction of the coefficients. The tobit result suggests positive and significant association between CRS scores and payroll, capital outlay on related categories, housing values, educational attainment, humidity, topography, the percent of a community area covered by

[1] As an important aside, given that flood risk (measured at the 1km × 1km grid cell scale) often varies widely within a community, it is interesting to note that the "max-mean" function performed most consistently in the model runs. The grid cell risks can be aggregated to a block-group level (e.g., mean risk, maximum risk) and those neighborhood level risk indicators can be aggregated up to a county level. Taking the highest value among neighborhood risk levels, where neighborhood risk is defined as the average risk in that neighborhood, proved a strong fit in these models.

water, the interaction between humidity and plains, and community flood risk. The tobit results also show a negative and significant association between CRS scores and amount of property tax, household income, share of renters and share of residents not relocating, share of population not finishing high school, share of a community's population that is White, share of population under the age of 18, and ruralness. In addition, plains, the interaction between the percent of a community area covered by water and topography, and the interaction between humidity and topography, all decrease CRS scores.

We employ a Cragg model, which relaxes some tobit assumptions, to better understand whether the factors that motivate communities to participate in CRS are the same factors that determine the CRS scores for communities. The Cragg model results indicate that the factors that influence communities' decision to participate in CRS do not operate similarly in influencing communities' CRS scores. The predictors of CRS participation are indeed different than those determining the intensity of participation. Payroll, household income, share of renters, share of population not finishing high school, share of population that is White, share of population under the age of 18, humidity, topography, plains, percent of community area covered by water, and flood risk are significant determinants of CRS participation but are not significant predictors of CRS score. Additionally, all three interaction terms that significantly predict CRS participation - the percent of a community area covered by water and topography, humidity and plains, and humidity and topography – are not significant predictor of CRS score.

[TABLE 6 HERE]

5. Discussion

The size of the government staff does appear to be positively associated with government capacity to participate in the CRS program, but property tax revenues do not also work in this way. Capital outlay on flood-related infrastructure categories, conversely, is positively associated with CRS participation (in the tobit and craggit models) and likely reflects local capacity or interest in flood risk management. We expect higher property tax revenues to lead to more participation in CRS. Contrary to our expectations, the results from each model indicate a negative and significant relationship between property tax revenue and CRS participation. This finding is at odds with Landry and Li's (2012) finding of a positive relationship between CRS participation and property tax revenue. One possible explanation for this negative relationship is that many places' inability to collect property taxes biases its effects in this sample (unlike Landry and Li (2012), who only analyze counties). Another explanation is that, conditional on payroll and housing values, property tax revenues may better capture the effect of higher tax rates. Finally, it might be that the property tax revenue effect may be proxying for larger communities. Alternative constructions of the property tax variable merit investigations, including a per-household measure (which would better align with Landry and Li's usage) and one that addressed potential nonlinearities (where logging is not an option because, unlike Landry and Li (2012) who study North Carolina counties, many places report $0 in property tax receipts). Unlike an analysis for counties, property tax receipts are not as good a candidate for measuring capacity to participate in CRS as the size of the government's payroll and its capital outlays for water- and sewerage-related infrastructure. That latter, in particular, is a strong and consistent predictor of both participation in CRS and attainment of higher CRS scores. In sum, the negative sign on the coefficient of property tax does not support H1, but the significant and positive sign on the coefficients for payroll and *FlowCapital* does support H1.

With regard to flood risk factors, the positive signs on the coefficients of these three variables – percent of community area covered by water, topography, and humidity – indicate support for H2. In other words, communities with higher flood risks are more likely to participate in CRS. A higher percentage of water coverage indicates a higher likelihood of flooding. More humidity, especially in flatter topography, is a strong predictor of participation. These findings are generally consistent with the expectation that combining water flows with flat areas leads to more flooding. That climate and topography measures matter so much in this model is particularly interesting in light of the control for a more technical "flood risk" measure. This result is in line with previous research (Landry and Li 2012) and an important finding to policy makers because it suggests that flood hazard mitigation measures are implemented by communities that are prone to flooding (Landry and Li 2012). It is also important to recognize that communities appear to be influenced by natural characteristics of their environments beyond what technical flood risk metrics capture.

More than government capacity and natural risk drive CRS participation, however. The results also present evidence in support of H3 and H4. Socio-demographic factors like racial composition, education levels, and age profiles play important roles in explaining CRS participation. Furthermore, political and economic variables explain a great deal of the variation in CRS participation, although not always as expected. Specifically, household income is a significant negative predictor of CRS participation - communities with higher household incomes are less likely than communities with lower household incomes to participate in CRS. One explanation is that residents of wealthier places are better able to invest in personal flood mitigation measures and may not see the need to demand that their communities participate in CRS. An alternative explanation is that measures of average income for the region may not be the appropriate income metric and may even be inversely related to the relevant group's income. Income variability among suburban communities appears to play an important role here.

Just as flood risk positively predicting CRS participation is taken to indicate some validity to the overall results, the positive relationship between property values and CRS participation is vital to a political economy approach to understanding CRS. (As flood insurance premiums are proportional to housing value, the benefits from the CRS discounting rise in property values.) Similarly, a greater share of renters is seen to deter participation, something consistent with a Home Voter hypothesis (Fischel, 2001). Newer housing construction and high turnover rates among residents predicts greater and more intense participation in CRS, suggesting that expanding (and perhaps sprawling) communities are most apt to see value in CRS. New homes and recent sales fall under the NFIP purview, making them more likely to have mandatory flood insurance and thus raising the value of CRS participation to communities with more of those residents. Interestingly, these factors associated with private gains to homeowners predict CRS participation but appear unrelated to CRS scores attained. Higher housing values, surprisingly, predict lower CRS scores (and thus lower insurance premium discounts) conditional upon participating at all. The negative role of wealth, even conditional on all the other controls like housing value and education levels, still presents some anomalous results.

It is interesting to note that the factors that motivate communities to participate in the CRS program are generally not the same factors that determine what CRS scores communities that participate in CRS get. For example, flood risk is a significant predictor of CRS participation but is not a significant predictor of the CRS scores attained by communities. Further, greater property values appear to reduce CRS score achievement rather than increase it. The communities that score highest in the CRS program are a special kind of participating communities, that much is clear. Knowing the specific predictors for CRS participation and CRS scores would be useful to policy makers – it might enable them to develop policies that would incentivize communities who are already participating in CRS to attain higher CRS scores. Such incentives should target flood reducing measures that would contribute immensely to reducing community vulnerability to flooding.

6. Conclusion

The US suffers huge losses from flooding, both in terms of lives lost and property damage, every year (Gopalakrishnan, 2013). The recognition of persistent losses and the absence of private flood insurance prompted the US federal government to establish the NFIP in 1968. In 1990, the US federal government established, as part of the NFIP, the Community Ratings System, which is a voluntary program aimed at reducing community flood losses and making communities more resilient to flood disasters. Previous research into the factors motivating participation in the CRS typically looked only at single state case studies and did not assess the "intensity" of participation as measured by the CRS scores. We use national data to understand the factors that motivate communities to participate in CRS. In addition, we examined the factors that predict a first stage of CRS participation and a second stage of CRS scores using several approaches. The results indicate that local capacity, flood risk factors, socio-demographic characteristics, and political and economic factors are significant predictors of CRS participation. In addition, the results indicate that the factors that motivate communities to participate in CRS are not the same factors that predict CRS scores.

This national level analysis offers an opportunity to generalize our findings; something that has not been done enough by previous studies. Nevertheless, there are some limitations of the current study. First, there are some independent variables that previous studies argue are important predictors of CRS participation that are not in our study. For instance, flood experience and percentage of senior citizens (Landry & Li, 2012), population density, reduction per policy holder, and flood property damage (Brody et al., 2009). Second, using total CRS score as our dependent variable does not allow us to see the predictor for each of the four groups of scoring activities (i.e., Series 300, 400, 500, and 600). Finally, our models characterize the participation decisions in a cross-sectional setting; it does not model the dynamics of when communities opt to participate or drop out of the CRS program. Assessing these changes over time remains the focus of future research, especially in light of new local flood risk information.

Despite these limitations, this study contributes to the literature on NFIP and CRS in particular and natural hazard risk reduction in general. We urge researchers to take this national level study a step further by exploring some additional hypotheses about local flood risk map changes, social capital and political activism, and learning from neighboring communities. In addition, decomposing total CRS scores to determine whether different factors motivate communities to focus on some types of activities more than others, can shed light on program efficacy, as well as feasibility of alternative risk management strategies. For example, it would be interesting to know whether high flood-risk communities focus on Series 300 (informational items) more than Series 500 (mostly structural measures).

The results of this study shine light on the drivers that motivate public authorities to engage in community risk management for flooding. This is especially important as flood risks and flood induced losses continue to rise. As one of the criticisms of NFIP is that it subsidizes building in floodplains (Goodwin, 2013) and thus exacerbates these losses. The CRS program is especially fascinating as it encourages voluntary community-scale flood risk management by further discounting the flood insurance premiums. With most CRS points earned for informational activities or those that do not actually reduce flood risks, that higher-risk communities tend to participate in the CRS and enjoy discounted premiums raises important questions about the sustainability and efficiency of the program. Understanding how to better promote community-wide risk management and public mitigation efforts remains a major policy challenge for natural disaster risks in general (Gopalakrishnan, 2013). It is our hope that this study will help to galvanize support for increased attention to water disasters as well as spur interest in empirical research to inform water policy to make communities more resilient to water disasters.

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Table 1. CRS classes, credit points, and premium discounts based on location in or outside Special Flood Hazard Areas (SFHA).

CRS Class	**Credit Points**	**Premium Reduction**	
		In SFHA (%)	**Outside SFHA (%)**
1	4,500+	45	10
2	4,000-4,999	40	10
3	3,500-3,999	35	10
4	3,000-3,499	30	10
5	2,500-2,999	25	10
6	2,000-2,499	20	10
7	1,500-1,999	15	5
8	1,000-1,499	10	5
9	500-999	5	5
10	0-499	0	0

Note: Extracted from FEMA (2013). National Flood Insurance Program Community Rating System Coordinator's Manual. http://www.fema.gov/media-library-data/20130726-1557-20490-9922/crs_manual_508_ok_5_10_13_bookmarked.pdf.

Table 2. Credit points awarded for CRS activities.

Activity	Maximum Possible Points	Percent of Communities Credited[a]
300 Public Information Activities		
310 Elevation Certificates	116	100%
320 Map Information Service	90	93
330 Outreach Projects	360	90
340 Hazard Disclosure	80	68
350 Flood Protection Information	125	92
360 Flood Protection Assistance	110	41
370 Flood Insurance Promotion	110	0
400 Mapping and Regulations		
410 Floodplain Mapping	802	50%
420 Open Space Preservation	2,020	68
430 Higher Regulatory Standards	2,042	98
440 Flood Data Maintenance	222	87
450 Stormwater Management	755	83
500 Flood Damage Reduction Activities		
510 Floodplain Mgmt. Planning	622	43%
520 Acquisition and Relocation	1,900	23
530 Flood Protection	1,600	11
540 Drainage System Maintenance	570	78
600 Warning and Response		
610 Flood Warning and Response	395	37%
620 Levees	235	0
630 Dams	160	0

Note: [a] Includes communities credited partially
Extracted from FEMA (2013). National Flood Insurance Program Community Rating System Coordinator's Manual. http://www.fema.gov/media-library-data/20130726-1557-20490-9922/crs_manual_508_ok_5_10_13_bookmarked.pdf.

Table 3. Variable and their descriptions

Variable	**Description**
Dependent variables 1. Participation in CRS 2. Total CRS score	 Communities that were participating in CRS as of 2012 (Dichotomous: 1 for communities currently participating in CRS and 0 for communities not currently participating in CRS.) Total CRS score obtained by each participating community (i.e., the sum of points obtained from the 19 credited activities in Series 300, 400, 500, and 600 sections of the CRS scoring formula.)
Independent Variables	
ln(payroll)	Log of total payroll ($) for each community, 1992
PropTax	Total property tax revenue for each community, 1992
FlowCapital	Sum of annual capital outlay ($) on sewerage, solid waste management, and water transport and terminals, 1992
HousingValue	ln(county's median block-group median housing value, 1990)
HHincome	ln(county's median block-group median income, 1990)
YearBuilt	Mean of county's block group's median year housing built, 1990
RentShare	Mean of county's block group's share of housing units as rentals, 1990
StayShare	Mean of county's block group's share of households living in same home five years earlier, 1990
CollegeShare	Mean of county's block group's share with college degrees, 1990
noHSshare	Mean of county's block group's share not finishing high school, 1990
WhiteShare	Mean of county's block group's share that is white, 1990
ChildShare	Mean of county's block group's population share under age 18, 1990
Ruralness	Rural-urban continuum code from ERS (scales from 1 – 9, with 1 indicating counties in metro areas over 1 million population and 9 indicating completely rural counties with less than 2,500 population and no adjacent metro area)
Humidity	Average relative humidity in July
Topography	Topography code from ERS (scales from 1 for flat plains to 21 for high mountains).
Plains	Dummy variable (from *Topography*) indicating flat, smooth or irregular plains
WaterShare	Percent of county area covered by water
WaterTopo	*WaterShare* × *Topography*
WetPlains	*Humidity* × *Plains*
WetTopo	*Humidity* × *Topography*
Floodrisk	Mean flood risk of block group with highest mean risk in county

Table 4. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Mean (CRS)[a]
Participation in CRS	28147	0.042	0.200	0	1	
Total CRS score	1174	1607.6	645.7	505	5315	
ln(payroll)	28147	8.564	2.918	0.693	20.992	12.91***
PropTax	28147	2705.011	95276.27	0	7898700	13000.42***
FlowCapital	28147	718.134	9808.715	0	729485	5554.70***
HousingValue	28147	10.879	0.441	9.461	13.122	11.19***
HHincome	28147	10.168	0.248	8.995	11.035	10.28***
YearBuilt	28147	1961.437	12.128	1714.127	1982.388	1961.30***
RentShare	28147	0.275	0.0728	0.117	0.839	0.32***
StayShare	28147	0.535	0.0773	0.217	0.783	0.46***
CollegeShare	28147	0.142	0.0627	0.034	0.505	0.18***
noHSshare	28147	0.261	0.082	0.053	0.665	0.23***
WhiteShare	28147	0.876	0.150	0.024	1	0.79***
ChildShare	28147	0.270	0.034	0.122	0.460	0.25***
Ruralness	28147	4.526	2.919	0	9	2.29***
Humidity	28147	56.781	12.200	14	80	59.36
Topography	28147	7.706	6.209	1	21	7.67***
Plains	28147	0.603	0.486	0	1	0.61
WaterShare	28147	4.874	11.465	0	75	11.91***
WaterTopo	28147	27.956	71.913	0	1200	44.13***
WetPlains	28147	35.532	29.435	0	80	40.08***
WetTopo	28147	418.173	352.102	28	1580	384.91
Floodrisk	28147	87.194	12.753	19	99	91.02***

Note: [a] This column contains the mean values of the independent variables for communities participating in CRS.

Table 5. Logistic regression results

Models	**Logistic Regression Coefficient Variables (Robust Std. Err.)**
Variables	
ln(payroll)	.680 ***
	(.021)
PropTax	-8.33e-06***
	(2.92e-06)
FlowCapital	.0000133
	(9.25e-06)
HousingValue	.934***
	(.202)
HHincome	-3.123***
	(.394)
YearBuilt	.014***
	(.005)
RentShare	-4.634***
	(.789)
StayShare	-4.641***
	(.799)
CollegeShare	1.651
	(1.033)
noHSshare	-7.126***
	(1.042)
WhiteShare	-1.737***
	(.417)
ChildShare	-3.976***
	(1.324)
Ruralness	-.051**
	(.023)
Humidity	.023*
	(.012)
Topography	.145***
	(.040)
WaterShare	.032***
	(.004)
Plains	-1.067***
	(.717)
WaterTopo	-.005***
	(.001)
WetPlains	.026**
	(.012)
WetTopo	-.002***
	(.001)

Floodrisk	.011***
	(.004)
Constant	-10.919
	(11.068)
Observations	**28,140**

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 6. Tobit regression and Cragg's double hurdle results

Models **Variables**	**Tobit Regression** **Coefficient (Std. Err.)**	**Cragg Double Hurdle** **Coefficient (Std. Err.)**	
		Participation	Score
ln(payroll)	713.972***	.331***	17.981
	(25.365)	(.010)	(11.240)
PropTax	-.0113***	-4.72e-06***	-.006***
	(.003)	(1.26e-06)	(.001)
FlowCapital	.0263***	.0000105***	.0202***
	(.007)	(3.46e-06)	(.003)
HousingValue	908.905***	.440***	-223.871**
	(200.014)	(.094)	(99.463)
HHincome	-3180.822***	-1.512***	28.269
	(430.569)	(.201)	(216.681)
YearBuilt	8.917***	.005***	-.988
	(3.341)	(.002)	(1.480)
RentShare	-5298.117***	-2.416***	-601.757
	(822.932)	(.385)	(419.568)
StayShare	-5746.344***	-2.54***	-1051.359**
	(818.210)	(.380)	(436.063)
CollegeShare	2491.044**	.937*	1091.935**
	(1114.827)	(.529)	(540.595)
noHSshare	-6894.933***	-3.386***	-337.131
	(1164.905)	(.542)	(648.052)
WhiteShare	-1663.979***	-.755***	-151.530
	(463.056)	(.216)	(256.007)
ChildShare	-3518.382**	-1.929***	-902.743
	(1420.085)	(.686)	(630.078)
Ruralness	-60.716**	-.022**	-50.417***
	(23.642)	(.011)	(11.732)
Humidity	25.012**	.0127**	-8.596
	(12.693)	(.006)	(6.166)
Topography	162.558***	.0763***	1.330
	(41.302)	(.020)	(19.278)
WaterShare	32.204***	.015***	2.229
	(3.657)	(.002)	(1.653)
Plains	-1273.389*	-.667*	39.230
	(716.677)	(.341)	(328.808)
WaterTopo	-4.289***	-.002***	-.189
	(.665)	(.000313)	(.271)
WetPlains	31.466**	.0151**	5.824
	(12.397)	(.006)	(5.912)
WetTopo	-2.308***	-.001***	.231
	(.734)	(.000346)	(.352)
Floodrisk	11.645***	.005***	1.881
	(4.010)	(.002)	(1.969)

Constant	-1524.012	-2.192	6446.719
	(7327.397)	(3.507)	(3210.868)
Observations	**28,140**	**28,140**	**28,140**

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.