Working Paper Number 19 – 1 | March 2019

Flood Insurance and Claims: The Impact of the Community Rating System

Eugene Frimpong
East Carolina University
frimponge16@students.ecu.edu

Daniel R. Petrolia (corresponding author)
Mississippi State University
d.petrolia@msstate.edu

Ardian Harri
Mississippi State University
ah333@msstate.edu

John H. Cartwright
Mississippi State University
johnc@gri.msstate.edu

Department of Agricultural Economics
Mississippi State University
Box 5187 Mississippi State, MS 39762
Phone: (662) 325-2049
Fax: (662) 325-8777
www.agecon.msstate.edu

Flood Insurance and Claims: The Impact of the Community Rating System

Eugene Frimpong
Graduate Student
Coastal Resources Management Ph.D. Program
East Carolina University
379 Flanagan
Greenville, NC 27858
frimponge16@students.ecu.edu

Daniel R. Petrolia (corresponding author)
Associate Professor
Dept. of Agricultural Economics
Mississippi State University
Box 5187
Mississippi State, MS 39762
662.325.2888
d.petrolia@msstate.edu

Ardian Harri
Associate Professor
Department of Agricultural Economics
Mississippi State University
Box 5187
Mississippi State, MS 39762
ah333@msstate.edu

John H. Cartwright
Research Associate
Geosystems Research Institute
Mississippi State University
High Performance Computing Building, 204
Mississippi State, MS 39762
johnc@gri.msstate.edu

MASGP-19-013
Acknowledgements: This publication was supported by the U.S. Department of Commerce's National Oceanic and Atmospheric Administration under NOAA Award NA10OAR4170078 and the Mississippi-Alabama Sea Grant Consortium. This work also supported by the National Institute of Food and Agriculture and the Mississippi Agricultural and Forestry Experiment Station via Multistate Project W-3133 "Benefits and Costs of Natural Resources Policies Affecting Ecosystem Services on Public and Private Lands" (Hatch Project MIS-033140). The views expressed herein do not necessarily reflect the views of any of these agencies.

Flood Insurance and Claims: The Impact of the Community Rating System

Abstract

The Community Rating System (CRS) was introduced to encourage community-level flood mitigation and increase household-level flood insurance uptake through the National Flood Insurance Program (NFIP). Using historical data of policies-in-force and flood damage claims from 1998-2014 for all NFIP communities in Alabama and Mississippi, we estimate the relationship between community participation in the CRS and the number of policies-in-force, as well on flood damage claims. We find a significant, positive, and generally increasing effect of CRS participation on insurance uptake. Reduced flood damage claims are found to be limited to communities with a very high level of CRS participation (Class 5) only.

Introduction

The Community Rating System (CRS) was created by the Federal Emergency Management Agency (FEMA) in 1990 to bolster the performance of the National Flood Insurance Program (NFIP). The NFIP was established in 1968 with goals to reduce future flood losses by encouraging communities to undertake floodplain management activities in exchange for federally-backed flood insurance.

But the NFIP has struggled with low participation and solvency issues. To combat these, the CRS was established as a voluntary program to encourage additional floodplain management that exceeds minimum NFIP standards. One of the central incentives for CRS participation is premium discounts for individual policyholders in the communities, with greater discounts given for greater participation. Thus, the CRS has the goals of reducing flood damages to insurable property, and by offering lower premiums to participating communities, encouraging flood insurance uptake. Additionally, the CRS is unique in the world in that represents the only national program that systematically encourages communities to better prepare for flood events, quantitatively scores communities across a number of flood resilience activities, and links scores to reduction of insurance premiums for residents in those active communities (Michel-Kerjan, Atreya, and Czajkowski 2016).

The relative importance of the CRS to the NFIP can appear small, depending on the statistic considered. First, the CRS program is at least financially neutral (CBO 2017), so does not represent a budget burden for FEMA. On the other hand, the CRS program may be financially positive.[1] Second, of the more than 22,000 NFIP communities in the U.S., only 5% of them participate in the CRS (FEMA 2017a). But this is a misleading statistic, because policies are not uniformly distributed across communities. A more useful statistic is that out of the 5.6 million NFIP policies-in-force, 68% of them are in CRS-participating communities (FEMA 2017a). Thus, administration of the bulk of NFIP policies are affected, one way or another, by the CRS, and the program may represent a financial gain for the NFIP, even if, as Cunniff (2018) points out, the CRS is not a widely-recognized program and remains under-utilized.

The objective of this paper is to contribute to the small, but growing body of literature evaluating the effectiveness of the CRS. This follows the consensus of a panel of experts convened in 2017 that a stronger body of evidence on the effectiveness of CRS was needed (Cunniff 2018). Zahran et al. (2009) and Petrolia, Landry, and Coble (2013) find a positive

[1] FEMA adjusts all premium rates upward to offset income lost as a result of the discounts. If community mitigation efforts reduce claims, then the premium adjustment is larger than needed and yields additional income to the NFIP (CBO 2017).

relationship between CRS participation and *NFIP participation*. Michel-Kerjan and Kousky (2010) and Brody et al. (2007a & 2007b) find a negative relationship between CRS participation and property damage. Highfield and Brody (2013) find a negative relationship between some, but not all, specific CRS mitigation activities and property damages.

However, most of these studies have focused on within-CRS effects, i.e., how marginal changes in the degree of CRS participation affects outcomes. In other words, they focused only on communities that had already chosen to participate in the CRS – ignoring communities that had not – and asked whether more intense participation resulted in better outcomes.

We, however, ask a broader question: does participating in the CRS at all affect outcomes? Answering this question requires the inclusion of both communities that participate in the CRS and those that do not. This paper is also the first to analyze the effect of CRS participation on both *NFIP participation* and flood damage claims simultaneously; previous studies examined one or the other, but not both. Furthermore, most of the work has focused on the state of Florida, and to a lesser extent, Texas. This is not surprising, given that Florida leads the nation in the number of NFIP policies and in CRS participation. However, it does sow some doubt as to whether the results found for Florida (and Texas) carry over to other states, particularly to states that have relatively lower NFIP and CRS participation rates. To fill this particular gap, we focus on the states of Alabama and Mississippi, states that are geographically adjacent to Florida, but where NFIP and CRS participation is much more limited. Additionally, these states are among the poorest states in the Union, again differentiating them from Florida.

We employ control variables that account for socioeconomics and physical flood risk, and adapt an empirical strategy that models the appearance of large cluster of zeros in *NFIP* *participation* and *Damage claims payments* data. Consistent with previous work, we find a positive relationship between CRS participation and *NFIP participation*. Regarding the relationship between CRS participation and flood damage claims, our findings are consistent with previous work, but more limited in scope. We find CRS participation associated with lower flood damage claims, but only among communities that have achieved CRS class 5 status.

Background

The National Flood Insurance Program (NFIP) was created in 1968, with the goal of reducing the impact of flooding on private and public structures by providing affordable insurance to property owners and by encouraging communities to adopt and enforce floodplain management regulations (FEMA 2013a). A community that chooses to participate in the NFIP is required to undertake some standard flood mitigation activities, including enforcement of building and zoning ordinances (FEMA 2013a). Individual property owners within that community are then eligible to purchase flood insurance.

Participation in the NFIP, however, has lagged behind expectations (Thomas and Leichenko 2011), which has led to continuous program reforms that aim at increasing participation via programmatic changes, mandatory NFIP participation, as well as premium rate adjustments (Thomas and Leichenko 2011). The NFIP has seen several reforms over the years aimed at either increasing participation, or reducing insured damage claims, or both. For example, in 1973, property owners with federally-backed mortgages were mandated to purchase flood insurance if the property was located in a Special Flood Hazard Area (SFHA).[2] The "Write-Your-Own" program was introduced in 1983, which allowed insurance companies to write and market flood insurance policies while the federal government retained responsibility for the settling of claims. The Community Rating System (CRS) was introduced in 1990. In 1995, FEMA introduced the "Cover America" program, a campaign that promoted awareness of flood risk (Michel-Kerjan 2010). In 2004, the National Flood Insurance Act of 1968 was reformed, with the primary goal of reducing payments on repeat-claim properties (FEMA 2017b). Some specifics to this reform were the introduction of a pilot flood mitigation program for properties experiencing higher damages, and FEMA-funded flood mitigation activities for these properties (FEMA 2017b). The Biggert-Waters Flood Insurance and Modernization Act was passed in 2012, and aimed at restructuring premium rates, enforcing the compulsory flood policy purchase for federally-backed mortgages, and addressing other mitigation issues (Center for Insurance Policy and Research 2012; FEMA 2017b). In 2014, the Biggert-Waters Flood Insurance and Modernization Act was replaced with the Homeowner Flood Insurance Affordability Act. This

---

[2] SFHA is the land area covered by the floodwaters of the "base flood" on flood insurance rate maps (FIRMs). The "base flood" is the flood having a one percent chance of being equaled or exceeded in any given year. This is the regulatory standard, also referred to as the "100-year flood," and the SFHA is thus also referred to as the "100-year flood zone". The base flood is the national standard used by the NFIP and all federal agencies for the purposes of requiring the purchase of flood insurance and regulating new development. Base Flood Elevation (BFE), which is the computed elevation to which floodwater is anticipated to rise during the base flood, is typically shown on FIRMs.

legislation sought to reduce premium rates on selected policies and also cancel some rate increases that had previously been implemented (FEMA 2017b).

Of all of the initiatives to bolster NFIP performance, the CRS stands out as the only one that engages communities on a continual basis to address flood risk (Michel-Kerjan, Atreya, and Czajkowski 2016). To participate in the CRS program, a community must first be a participant of the NFIP. Participation in the CRS is voluntary, and residents of a participating community are eligible for premium discounts on individual policies. Thus, the CRS links community-level flood mitigation with household-level NFIP participation. Implementing the flood mitigation activities requires some financial commitment (Brody et al. 2009), and so it is not surprising that Li and Landry (2018) find that CRS communities with larger tax revenues undertake more CRS mitigation activities. Also, previous research has found that characteristics spanning from hydrological to socio-demographic may influence community participation in the CRS (Brody et al. 2009; Landry and Li 2012; Sadiq and Noonan 2015).

Communities are assigned a “class” based on the number of CRS activity credits earned, ranging from 9 (entry-level) to 1 (highest). For residents located in SFHAs, policy discounts range from 5% (Class 9) to 45% (Class 1). For residents in non-SFHAs, the discount is 5% for Classes 7 through 9, and 10% for Classes 6 or better.

Study Area and Data

Data on NFIP policies-in-force, coverage, claims paid (in dollars), and CRS participation status were obtained directly from FEMA for all 675 NFIP-participating communities in Alabama and Mississippi having at least one policy-in-force during the period 1998-2014.

Geospatial data layers were obtained from various sources. *Elevation* (measured in meters above sea level) and *Slope* (measured in degrees) data were obtained from the National Elevation dataset (U.S. Geological Survey 2015a). *Slope* was calculated as the maximum rate of change from a given grid cell to its neighbors. *Stream density* data (measured as the maximum length of a stream divided by the square kilometers of an area) were obtained from the National Hydrography dataset (U.S. Geological Survey 2015b). *Precipitation* data (measured as annual rainfall in millimeters) were obtained from the Parameter-elevation Relationships on Independent Slopes Model (PRISM 2015). Data on NFIP flood zones (measured as percent of land area classified a particular flood zones) were obtained from FEMA (2016). *SFHA* is defined as the sum of all land in A, AE, AO, AH, and VE zones. (Non-SFHA is comprised of zones B and C). Total number of housing units, median home value, median household income, percent college-educated, and median age for Census Year 2010 were obtained from ESRI demographic data sources (which includes the 2010 Census and 2008-2012 American Community Survey data). All data layers were overlain with the FEMA NFIP community layer to compute NFIP community-specific values. All geospatial data were based on a 4 kilometer grid cell, and means were calculated using zonal statistics of ArcGIS. Data on number of county-level federal declared disaster days were obtained from FEMA's Summary of Disaster Declarations and Grants dataset, excluding declaration days classified as "fire". Each county's disaster days were assumed to apply to all NFIP communities falling within that county, and were thus assigned.

Thirty very small NFIP communities were not in the FEMA NFIP community data layer, seventeen lacked census data, and two lacked both. Each of these communities was merged with its respective county-level NFIP community, resulting a total of 626 NFIP communities being used in the analysis, 359 in Alabama and 267 in Mississippi. The scale of an NFIP community varies from place to place, so although their names generally coincide with the local municipality or county, their geography is not necessarily the same. A given NFIP community may be an incorporated city, town, township, borough or village, any incorporated area of a county, or an entire county; it is simply a distinct geographical entity for the purpose of administering the NFIP programs in that locality. We depart from most of the previous NFIP work and retain NFIP communities as our unit of analysis, rather than aggregating up to the county level. This was feasible because, as discussed above, all of our data, except for number of declared disaster days, were in a GIS format and we could overlay all data with the FEMA NFIP community layer.

Figure 1 shows the distribution of CRS participating communities (in green) for Alabama and Mississippi. In Alabama, 12 out of 359 NFIP communities participate in the CRS program, whereas in Mississippi, 31 out of 267 NFIP communities participate (FEMA 2013b). As is evident from the figure, participation is higher among coastal communities. The total number of NFIP policies-in-force in Alabama in 2014 was 57,3131, of which 33,446 were in CRS participating communities. Mississippi had a total of 71,694 policies-in-force, out of which 51,417 were in CRS participating communities. Among the Gulf States, Alabama and Mississippi have the lowest number of CRS participating communities, although Texas has the lowest participation rate (4%). Florida has both the highest number of participating communities (216) as well as the highest participation rate (47%). Figure 2 shows the number of CRS-participating communities over time for Alabama and Mississippi, as well as the mean CRS class achieved. Although the number of CRS-participating Mississippi communities has nearly doubled, from sixteen to thirty-one, the number of participating Alabama communities has increased by only four, from ten to fourteen, with multiple dips in-between. Of those participating, however, the figure shows a decreasing (that is, improving) trend in average CRS class in both states, but with Mississippi doing relatively better.

Empirical Model

Building on past studies, we assume that at the aggregate level, *NFIP participation* (NFIP policies-in-force) and *Damage claims payments* are a function of CRS participation, geospatial factors, and socioeconomic factors. Because the nature of these two variables differ, specifically, that *NFIP participation* is a count variable and *Damage claims payments* is continuous, the empirical models differ.

In the *NFIP participation* model, the dependent variable (y) is the count of number of policies-in-force for a given year (t) in community i. So our empirical strategy was to identify a model that accounts for both the panel and count nature of the data. Our policies-in-force counts are overdispersed, that is, the variance is larger than the mean, which would suggest that a negative binomial would perform better than a Poisson. However, the fixed and random effects of a negative binomial models apply to the distribution of the dispersion parameter, not to the $X_i'\beta$, thus the panel Poisson models allow for estimation of true fixed- and random-effects models that the panel negative binomial models do not.

Additionally, we have a variety of control variables, including NFIP flood-zone variables, geospatial variables, and demographic variables. We find that our NFIP flood-zone variables are fairly highly correlated with our geospatial variables, and that model performance can be negatively affected depending upon the set of variables specified. Thus, we tested a variety of models based on these issues. The key result of these alternative models is that the CRS effect, which is of central importance here, is robust to model specification. We do find, however, that the effect of some other control variables differs across models, with some variables taking on incredible estimated values. We conclude that the inconsistent results are due to highly collinear time-invariant variables, and that the fixed-effects Poisson, that captures all of these effects as community fixed effects and year fixed effects, offers the cleanest and most straightforward results. But again, we emphasize that the CRS effects, of which we are particularly interested here, are robust to model choice.

Following Cameron and Trivedi (2013) and Allison (2009), the fixed-effects Poisson model for *NFIP participation* is $y_{it} \mid \mathbf{x}_{it}, \alpha_i \sim Poisson\left[\alpha_i \lambda_{it}\right]$, where α_i , the community fixed effect, is unobserved and possibly correlated with $\mathbf{x}_{it}$, and $\lambda_{it} = \exp\left(\mathbf{x}'_{it}\boldsymbol{\beta}\right)$. The vector of time-varying independent variables, $\mathbf{x}_{it}$, contains: *Class 9*, *Class 8*, *Class 7*, *Class 6*, *Class 5*, *Disaster days, Disaster days one year prior*, and *year fixed-effects.* The fixed-effects Poisson estimator is the vector $\boldsymbol{\beta}$ that solves the first-order conditions $\sum_{i=1}^{n}\sum_{t=1}^{T}\mathbf{x}_{it}\left(y_{it} - \frac{\overline{y}_i}{\overline{\lambda}_i}\lambda_{it}\right) = \mathbf{0}$. For alternative models we tested and report in the Appendix, we also included time-invariant independent variables: *SFHA, Waterfront, Mississippi, Income, Home value, Education,* and *Age*. These models also include *Log(Housing units)* as an exposure variable (that is, with coefficient fixed at 1). Because our exposure variable is time-invariant, its effect in the fixed-effects Poisson model would be absorbed into the community fixed effects.

The *Damage claims payments* variable is of a continuous nature, and the data contain an abundance of zeroes. Of the 10,642 observations of policies-in-force for 626 communities over 17 years, 2,010 are zeroes. Of the 8,632 remaining observations, only 1,724 have non-zero flood damage claims. To accommodate these data, we adopt a Two-Part-Model (2PM), which assumes that the zero and positive claims values derive from two different data generating processes (Cameron and Trivedi 2001). In application, the 2PM first estimates the likelihood of observing a positive value via a logit model, followed by an OLS estimation conditional on the positive values of the dependent variable (Buntin and Zaslavsky 2004). We also estimate a Cragg Hurdle model, which operates much the same way and yields similar results, as well as linear fixed-effects and random-effects regressions on log(Total Paid), which ignores non-claim observations. The raw coefficients are also consistent with those of the 2PM, although this model is not equipped to account for non-claim observations to calculate the correct marginal effects. These alternative results are reported in the Appendix.

Following Belotti et al. (2015) and Buntin and Zaslavsky (2004), we specify the first part of the 2PM for the *Damage claims payments* as a logit model, $\Pr\left(y_{it} > 0 \middle| \mathbf{x}_{it}\right) = F\left(\mathbf{x}_{it}'\boldsymbol{\lambda}\right)$, where y_{it} is *Damage claims payments*, *F* is the logit function, and $\mathbf{x}_{it}$ is a vector of independent variables: *Class 9*, *Class 8*, *Class 7*, *Class 6*, log(*Coverage*), *SFHA*, *Waterfront*, *Mississippi*, *Precipitation*, *Elevation*, *Slope*, *Stream density*, *Disaster days*, *Disaster days one year prior*, *Income*, *Home value*, *Education*, *Age*, and *year fixed-effects*. $\boldsymbol{\lambda}$ is the vector of associated parameters. The second part of the model is $\ln(y_{it} | y_{it} > 0, \mathbf{x}_{it}) = \mathbf{x}_{it}'\boldsymbol{\gamma} + \varepsilon_{it}$ where $\mathbf{x}_{it}$ are as defined above, $\boldsymbol{\gamma}$ is vector of parameters to be estimated, and ε_{it} is the error term. The expectation is $E\left(y_{it} \middle| y_{it} > 0, \mathbf{x}_{it}\right) = \exp\left(\mathbf{x}_{it}'\boldsymbol{\gamma} + 0.5\sigma^2\right)$, where σ^2 is the variance of the distribution of ε_{it}. The overall expectation of the 2PM is the product of the expectations of the first and second part, $E\left(y_{it} \middle| \mathbf{x}_{it}\right) = \Pr\left(y_{it} > 0 \middle| \mathbf{x}_{it}\right) E\left(y_{it} \middle| y_{it} > 0, \mathbf{x}_{it}\right)$.

Heteroskedasticity and autocorrelation are accounted for using clustered standard errors (Wooldridge 2002; Greene 2012). The use of the robust covariance matrix estimator for a fixed number of time periods and large number of units relative to the number of time periods, which is the case here, results in no loss of information or properties even if there is no correlation or heteroscedasticity. Table 1 presents the summary of variables and their descriptions and Table 4 contains the summary statistics of the variables used in the econometric model, and reports the expected signs for the independent variables.

Results

Effects of CRS Participation on NFIP Participation

Table 3 reports the results of the *NFIP participation* model, based on a panel Poisson model, community and year fixed effects, and robust standard errors. As noted earlier, results regarding CRS participation effects, which is of central interest here, are robust across alternative models, although we do find differences across models on a small number of supporting variables (see Appendix for alternative model estimates).

Results are reported as IRRs, that is, as e^{β} rather than β, to make interpretation more convenient. IRRs are positive by definition, and interpreted relative to a base of 1; an example is given below. The results on classes 9, 8, 7, 6, and 5 indicate that the rate of *NFIP participation* is significantly greater across all CRS classes (all coefficients exceed one) relative to non-CRS communities, and that *NFIP participation* generally increases as class status increases (although results indicate a slight dip for *Class 8* relative to *Class 9*). The estimated IRR of 1.287 on *Class 9*, for example, indicates that *NFIP participation* in entry-level CRS communities (that is, *Class 9* communities) is greater than that of non-CRS communities by a factor of 1.287. Similarly, *NFIP participation* in *Class 5* communities is greater by a factor of 1.566.

Additionally, one-sided tests of parameter equivalence (not shown in table) indicate that the coefficient on *Class 5* is significantly greater than that of all other classes. In short, results indicate a generally increasing rate of *NFIP participation* from the lowest, entry-level class (9) up to the highest class (5), and that *NFIP participation* is significantly greater among *Class 5* communities relative to all others. These results are consistent across alternative models.

Regarding declared disaster days, we find that *NFIP participation* is significantly affected by the number of declared disaster days in the previous year, but not the current year. However, the magnitude of the effect is quite small (less than 1 percent). Alternative models yield the same results.

Effect of CRS Participation on Damage Claims payments

Table 4 presents the *Damage claims payments* results, based on the 2PM. As mentioned earlier, the 2PM produces two results; estimates from a binary logit model predicting a claims event, and estimates from an OLS regression predicting magnitude of claims conditional on a claims event. Given that we are most interested in predicting the magnitude of damage claims payments, we report and discuss the OLS estimates and relegate the logit results to the Appendix (see Model 1in Table A2. However, the reported marginal effects take into account both equations.

Results indicate a negative relationship between flood damage claims and Classes, 7, 6, and 5, respectively, but the effect is significant among *Class 5* communities only. Specifically, we find that annual average sum of flood damage claims for *Class 5* communities is $125,000 lower than that of non-CRS communities, representing a 5.8 percent reduction from the mean flood claim of $2.1 million.

As expected, results indicate a positive and significant effect of *Coverage* on *Damage claims payments*. Although the sign is as expected, there is no significant relationship between *SFHA* land area and *Damage claims payments*. Brody et al. (2007a) also found a positive but insignificant effect between *SFHA* and flood damages, whereas Highfield and Brody (2013) found a significant relationship.

The coefficient on *Waterfront* is positive and significant as expected, indicating *Damage claims payments* are $50,116 higher in waterfront communities. Coefficient on *Mississippi* is also positive and significant, indicating that *Damage claims payments* are $55,831 higher in Mississippi relative to Alabama. The coefficients on *Precipitation* and *Slope* are both significant and positive, whereas the coefficients on *Elevation* and *Stream density* were not significant. Highfield and Brody (2013) also found a significant and positive effects of precipitation and slope. They argue that steeper slopes result in rainfall concentration, leading to high stream peaks and mean annual flow.

The coefficient on *Disaster days* is significant and positive, although the coefficient on *Disaster days one year prior* is not significant. The result indicates that one additional flood disaster day increases *Damage claims payments* by $4,097. On socioeconomic variables, the coefficients on *Income*, *Education*, *Age,* and *Home value* are not significant. On the other hand, the coefficient on *Housing units* is positive and significant, indicating that for each 1000-unit increase in housing, annual average sum of *Damage claims payments* increases by $462.

Discussion

Our results indicate that the CRS program in these states is consistent with what has been observed elsewhere. Our findings that *NFIP participation* is higher among CRS communities, and increasing with the intensity of CRS participation is consistent with the two papers in the literature that address this question. Petrolia, Landry, and Coble (2013), who conducted a survey of Gulf Coast households in 2010, found that, with the exception of Florida, the likelihood of a household to hold a flood policy increased linearly with CRS class status. It should be noted that their sample was also dominated by Florida (61 percent); Alabama and Mississippi households combined accounted for less that 5 percent of their sample. Similarly, Zahran et al. (2009), who focused on Florida during the years 1999-2005, found that *NFIP participation* increases linearly with CRS points earned. Points earned is merely a continuous measure of CRS participation, whereas class status represents more discrete changes. Our discrete specification also allowed us to test whether the relationship among classes is non-linear, which bore some fruit: we found that although *NFIP participation* rates tend to increase with class status, the rates are not significantly different among Classes 9, 8, 7, and 6. However, we also found that *NFIP participation* in *Class 5* communities is significantly higher than the others, with a rate of participation at least 18 percent higher than other CRS communities.

Our finding that magnitude of flood damage claims is significantly lower among *Class 5 CRS* communities only is identical to what Michel-Kerjan and Kousky (2010) found for Florida during the years 2000-2005. They found that claims rates are between 7 and 9 percent lower among *Class 5* communities, which is just slightly higher than our estimate of a 5.8 percent reduction. Brody et al. (2009) and Zahran et al. (2010) provide plausible explanations for the lack of significance at the lower CRS classes: they argue that the design of the CRS program motivates communities to be selective in mitigation activities that will only help reach the next discount level, but which may not necessarily reduce damages significantly. Thus, it is possible that communities pick off the "low hanging fruit" to achieve the lower classes, and it is not until working to obtain *Class 5* status that communities begin to undertake meaningful flood-mitigation activities.

Brody et al. (2007a), who examined 54 coastal Florida counties between 1997 and 2001, found a much broader, and larger, CRS effect. They report that their estimates imply a $303,525 reduction in county-level value of flood damages for each one-unit improvement in CRS class status. Assuming then that the Class 5 effect is five times that figure, that implies a reduction of over $1.5 million. They report a mean flood event value of $2.6 million, implying a 58 percent reduction from the mean, which is an order of magnitude higher than our study (5.8 percent) and Michel-Kerjan and Kousky (7-9 percent). Part of this may be explained by difference in measurement: they were using SHELDUS flood damage values, which are more general than our measure, which was limited to NFIP flood damage claims. Additionally, their unit of analysis was the county, whereas ours was the community. Brody et al. (2007b), who examined 37 counties in eastern Texas between 1997 and 2001, found a similarly broad and large CRS effect. They estimated a $38,989 reduction for each improvement in CRS class, implying a $194,945 reduction for *Class 5* communities (a 46-percent reduction based on an average flood event of $423,766).

Although Highfield and Brody's (2013) findings are consistent with ours in that they show a significant relationship between CRS participation and flood damage reduction, a direct dollar comparison is more difficult because they modeled CRS participation by points earned for individual CRS activities. They find that CRS effects on flood damages are limited to particular mitigation activities only, including freeboard requirements, open space preservation, and flood protection, depending on model specification. Although they report marginal dollar reductions associated with these activities, the extrapolation to a scale similar to ours (note that a CRS class improvement is associated with earning 500 additional CRS activity points) would yield artificially large and implausible effects, because the reported reductions are for activities with significant and large effects only, not mean effects, and relative CRS class status is indeterminate. However, FEMA records indicate that only 28% and 13% of CRS communities, respectively, have earned points related to open-space preservation and flood protection (FEMA 2017c), which bolsters the argument given above that many of the activities that actually reduce flood risk are not frequently undertaken.

Summary and Conclusions

To the best of our knowledge, we present the first joint analysis of the impact of *CRS participation* (versus non-participation) on *NFIP participation* and *Damage claims payments*. Consistent with previous studies, we find that higher NFIP participation is in fact associated with communities participating in the CRS. Also consistent with some of the literature, we find that reduced flood damage claims is associated only with those communities with very high levels of CRS participation. So, overall, this analysis indicates that the CRS program does appear to be achieving its goal of increasing *NFIP participation* among CRS-participating communities in Alabama and Mississippi, and is having some success in reducing flood risk, at least to the extent that reduced flood claims reflects reduced risk. The other positive trend we observe is that both the number of communities participating in the CRS has increased over time, and that the average

CRS class has increased over time, which, taken in tandem with the aforementioned effects, means that the program's reach is expanding.

However, the number of CRS-participating communities in Alabama and Mississippi remains low, which means that the positive effects of the CRS program are not being realized in those non-participating communities. It is beyond the scope of our work to ascertain what factors drive CRS participation, but the recent work of Li and Landry (2018), who focused on North Carolina, provides some insights. They find that communities with lower levels of crime and unemployment, and greater median household income, tax revenues, and population density are more likely to undertake flood mitigation activities and participate in the CRS. As noted earlier, our study states rank among the poorest in the U.S. (Alabama ranks 47th in median household income and Mississippi ranks dead last), and both have very low CRS participation rates (3% and 9% of NFIP communities participate in the CRS, respectively).

As mentioned in the introduction, the CRS does not represent a budget burden for FEMA, and may even be a financial positive. So the efficiency of the program relative to its cost to FEMA is not really at issue. On the other hand, communities may spend a great deal of money in the pursuit of CRS points, so it remains a crucial issue to understand the extent to which the activities promoted by the CRS actually increase flood resiliency. Given the recent (2013) changes to the CRS program, future studies should investigate the extent to which these recent changes are impacting its effectiveness. Our research should serve as a guide to subsequent work focused on the CRS program, the NFIP, and flood hazards and mitigation in general.

References

Allison, P. D., 2009. *Fixed Effects Regression Models*. Newbury Park, CA: Sage.

American Community Survey (ACS). 2013. Census data. http://www.census.gov/programs-surveys/acs/data/summary-file.2013.html.

Belotti, F., Deb, P., Manning, W. G., and Norton, E. C., 2015. twopm: Two-part models. *The Stata Journal* 15 (1): 3-20.

Brody, S. D., Zahran, S., Maghelal, P., Grover, H., and Highfield, W. E., 2007a. The rising costs of floods: Examining the impact of planning and development decisions on property damage in Florida. *Journal of the American Planning Association* 73: 330-345.

Brody, S. D., Zahran, S., Highfield, W. E., Grover, H., and Vedlitz, A. 2007b. Identifying the impact of the built environment on flood damage in Texas. *Disasters* 32: 1-18.

Brody, S. D., Zahran S., Highfield, W. E., Bernhardt, S. P., and Vedlitz A. 2009. Policy learning for flood mitigation: A longitudinal assessment of community rating system in Florida. *Risk Analysis* 29: 912-929.

Buntin, M. B. and Zaslavsky, A. M., 2004. Too much ado about two-part models and transformation? Comparing methods of modeling medicare expenditures. *Journal of Health Economics* 23: 525-542.

Center for Insurance Policy and Research. 2012. http://www.naic.org/documents/cipr_events_2012_cipr_summit_overview.pdf.

Cameron, A. C. and Trivedi, P. K., 2001. *Essentials of count data regression. In A companion to theoretical econometrics*, 331. Edited by Baltagi, G. H.

Cameron, A. C. and Trivedi, P. K., 2013. *Regression Analysis of Count Data*. 2nd ed. New York: Cambridge University Press.

Congressional Budget Office (CBO), 2017. *The National Flood Insurance Program: Financial Soundness and Affordability*. Congress of the United States, September. https://www.cbo.gov/publication/53028.

Cunniff, S.E., 2018. Improving FEMA's Community Rating System to encourage investment in coastal natural infrastructure to reduce storm damages. *Shore & Beach* 86(2): 27-32.

Federal Emergency Management Agency (FEMA). 2013a. Joining the National Flood Insurance Program. http://www.fema.gov/media-library-data/20130726-1629-20490-5244/fema_496.pdf.

Federal Emergency Management Agency (FEMA). 2013b. The National Flood Insurance Program Community Rating System Coordinator's manual. http://www.fema.gov/media-library/assets/documents/8768.

Federal Emergency Management Agency (FEMA). 2016. NFIP/CRS update. https://www.fema.gov/media-library-data/1456858373947-34333001905c96988f8ec721a8e60005/January_February_CRS-NFIP_Update_newsletter.pdf.

Federal Emergency Management Agency (FEMA). 2017a. FEMA fact sheet. http://www.fema.gov/media-library-data/1455710459301-048a67862580037b30cd640a802a9053/FY16_FMA_Fact_Sheet.pdf.

Federal Emergency Management Agency (FEMA). 2017b. Flood insurance reform. https://www.fema.gov/flood-insurance-reform.

Federal Emergency Management Agency (FEMA). 2017c. National Flood Insurance Program Community Rating System Coordinator's Manual. https://www.fema.gov/media-library-data/1493905477815d-794671adeed5beab6a6304d8ba0b207/633300_2017_CRS_Coordinators_Manual_508.pdf

Greene, H. W. 2012. *Econometric analysis*. Seventh edition. Pearson Education, Edinburgh, England.

Highfield, W. E. and Brody, S. D. 2013. Evaluating the effectiveness of local mitigation activities in reducing flood losses. *Natural Hazards* 14: 229-236.

Li, J. and Landry, E. C., 2018. Flood risk, local hazard mitigation, and the community rating system of the National Flood Insurance Program. *Land Economics* 94: 175-198.

Landry, E. C. and Li, J. 2012. Participation in the Community Rating System of NFIP: An empirical analysis of North Carolina counties. *Natural Hazards Review* 13: 205-220.

Michel-Kerjan E. O. and Kousky, C. 2010. Come rain or shine: Evidence on flood insurance purchases in Florida. *The Journal of Risk and Insurance* 77: 369-397.

Michel-Kerjan, E. O. 2010. The National Flood Insurance Program. *The Journal of Economic Perspective* 24: 165-186.

Michel-Kerjan, E. O., Atreya, A., and Czajkowski, J. 2016. Learning over time from FEMA's Community Rating System (CRS) and its link to flood resilience measurement. Working Paper, No. 2016-11.

Petrolia, D. R., Landry, C. E., and Coble, K. H. 2013. Risk preferences, risk perceptions, and flood insurance. *Land Economics* 89: 227-245.

Parameter-elevation Relationships on Independent Slopes Model (PRISM). 2015. Precipitation data. http://www.prism.oregonstate.edu/recent/.

Sadiq, A. and Noonan, D. S. 2015. Flood disaster management policy: an analysis of the United States Community Rating System. *Journal of Natural Resources Policy Research* 7: 5-22.

Thomas, A. and Leichenko, R. 2011. Adaption through insurance: lessons from the NFIP. *International Journal of Climate Change Strategies and Management* 3: 250-263.

U.S. Geological Survey (USGS). 2015a. Elevation data. http://nationalmap.gov/3DEP/index.html.

U.S. Geological Survey (USGS). 2015b. Stream density data. http://nhd.usgs.gov/data.html.

Wooldridge, J. M., 2002. *Econometric analysis of cross sectional and panel data*. MIT Press Cambridge, Massachusetts London, England.

Zahran, S., Weiler, S., Brody, S. D., Lindell, M. K., and Highfield, W. E., 2009. Modeling national flood insurance policy holding at the county scale in Florida, 1999-2005. *Ecological Economics* 68: 2627-2636.

Table 1. Variable descriptions

Variables	Description
	Dependent variables
Policies-in-force (count)	Annual total number of NFIP policies-in-force. (FEMA)
Damage Claims Payments ($US)	Annual total damage claims payments. (FEMA)
	Independent variables
	Policy variables
Class 9	= 1 if a community's CRS class is 9, = 0 otherwise
Class 8	= 1 if a community's CRS class is 8, = 0 otherwise
Class 7	= 1 if a community's CRS class is 7, = 0 otherwise
Class 6	= 1 if a community's CRS class is 6, = 0 otherwise
Class 5	= 1 if a community's CRS class is 5, = 0 otherwise
Coverage ($US)	Annual total amount of coverage purchased, scaled by 10,000,000. (FEMA)
	Geospatial variables
SFHA	Measured as the percent of land area in a community classified as A or V flood zones. (FEMA)
Waterfront	= 1 if NFIP community contains a positive share of V flood zones (FEMA)
Mississippi	= 1 if NFIP community is in Mississippi, = 0 otherwise.
Slope	Mean value of the maximum rate of change from a given grid cell to its neighbors (USGS)
Elevation	Mean value of the highest point of community above sea level, in meters, divided by 100 (USGS).
Stream Density	Mean value of the maximum length of a stream divided by the square kilometers of an area (USGS)
Precipitation	Mean of total annual rainfall in kilometers. (PRISM)
Disaster days	Number of county-level federal declared disaster days. (FEMA)
Disaster days one year-prior	One year lag of Disaster days.
	Socioeconomic variables
Income ($US)	Median household income for a community, scaled by 1000. (ACS)
Home value ($US)	Median home value for a community, scaled by scaled by 1000
Housing units	Total number of housing units in a community, scaled by scaled by 1000. (ACS)
Education	Percent college educated in a community. (ACS)
Age	Median age for Census Year 2010

Table 2: Summary statistics of variables used in the regression analyses. Summary statistics for Part 1 of the Damage claims payments model (N = 8,632) are reported in the Appendix.

Variables	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
	NFIP participation model, N=10,642				Damage claims payments model (Part 2), N=1,724			
Policies-in-force (count)	176.024	774.585	0	10,173				
Damage Claims Payments ($)					2,148,737	19,800,000	25	374,000,000
Class 9	0.015	0.120	0	1	0.049	0.215	0	1
Class 8	0.023	0.149	0	1	0.090	0.286	0	1
Class 7	0.008	0.087	0	1	0.038	0.192	0	1
Class 6	0.005	0.068	0	1	0.019	0.137	0	1
Class 5	0.002	0.041	0	1	0.007	0.083	0	1
Log(Coverage)					16.759	2.134	9.210	21.602
SFHA*	0.176	0.160	0	0.969	0.249	0.193	0.004	0.938
Waterfront*	0.042	0.200	0	1	0.166	0.372	0	1
Mississippi*	0.427	0.495	0	1	0.563	0.496	0	1
Slope*	2.820	1.675	0.105	8.715	2.472	1.775	0.116	8.715
Elevation*	1.189	0.755	0.003	5.246	0.934	0.712	0.003	3.715
Stream Density*	0.924	0.268	0	2.050	0.888	0.257	0	1.764
Precipitation	1.450	0.282	0.650	2.470	1.571	0.281	0.747	2.328
Disaster days	10.593	20.646	0	110	15.234	24.321	0	110
Disaster days one year-prior	10.535	20.730	0	110	10.202	19.517	0	100
Income (scaled by 1000)*	3.672	1.380	1.208	13.580	4.024	1.485	1.208	13.583
Home value (scaled by 1000)*	9.863	4.490	2.340	53.850	11.671	5.744	3.380	53.850
Housing units (scaled by 1000)*	8.446	20.767	0.031	301.202	24.001	40.819	0.031	301.202
Education*	0.110	0.066	0	0.538	0.145	0.076	0	0.538
Age*	38.101	4.698	21.800	53.300	37.079	4.092	23.900	53.300

* Omitted from the fixed-effects Poisson model

Table 3. Fixed-effects Poisson Regression results for NFIP participation with bootsrap standard errors, reported as incidence rate ratios (N = 10,642; communities = 626).

Variable	Estimated Incidence Rate Ratio	Bootstrap Standard Error
Class 9	1.287**	0.135
Class 8	1.218**	0.108
Class 7	1.375***	0.167
Class 6	1.386***	0.177
Class 5	1.566***	0.269
Disaster days	1.000	0.0003
Disaster days one year prior	1.002***	0.0004
Community fixed effects	Yes	
Year fixed effects	Yes	
Log likelihood = -69185.072		
Wald chi2 (23) = 319.02		
Prob > chi2 = 0.000		

***, ** shows significance at 1% and 5% level of significance, resp.

Table 4. Two-Part-Model Regression results for damage claims payments. First-step logit results suppressed to simplify presentation (N = 1,724; communities = 626).

Variable	Coefficient	Robust Standard Error	Marginal effects ($)
Class 9	0.217	0.311	25,621
Class 8	0.24	0.23	26,132
Class 7	-0.456	0.288	-31,671
Class 6	-0.044	0.324	-11,875
Class 5	-1.137**	0.538	-125,342
log(Coverage)	0.313***	0.397	46,902
SFHA	0.327	0.379	41,601
Waterfront	0.61**	0.225	50,115
Mississippi	0.417***	0.134	55,831
Precipitation	1.785***	0.284	245,318
Elevation	0.028	0.144	910
Slope	0.105*	0.059	12,616
Stream density	0.045	0.286	-1,157
Disaster days	0.035***	0.004	4,097
Disaster days one year prior	-0.001	0.003	46
Income	-0.067	0.076	-5,876
Home Value	0.03	0.022	2,394
Housing unit	0.003*	0.001	462
Education	-1.094	1.27	-92,443
Age	0.006	0.014	527
Year fixed effects	Yes		
Constant	1.708	1.031	
Log likelihood = -3459.473			
Adjusted R-squared = 0.314			

***, **, and * shows significance at 1%, 5%, and 10% levels of significance, resp. Standard errors are cluster robust. Marginal effects accounts for both parts of the model (Logit and OLS).

Figure 1. Map showing CRS participating communities in Alabama and Mississippi (Source: FEMA)

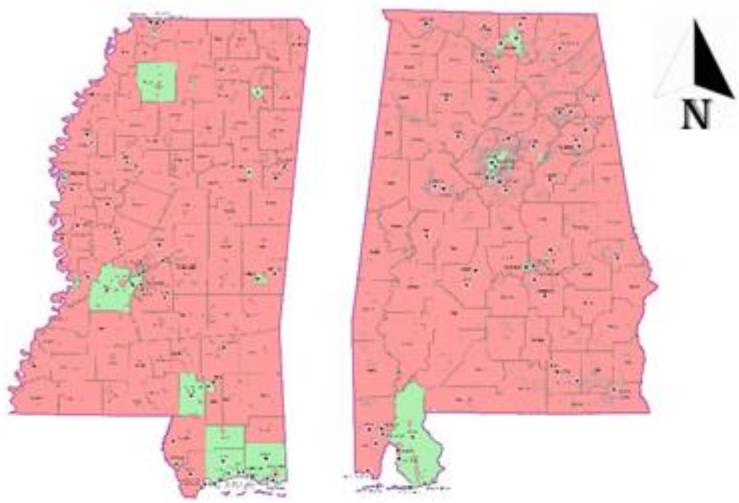
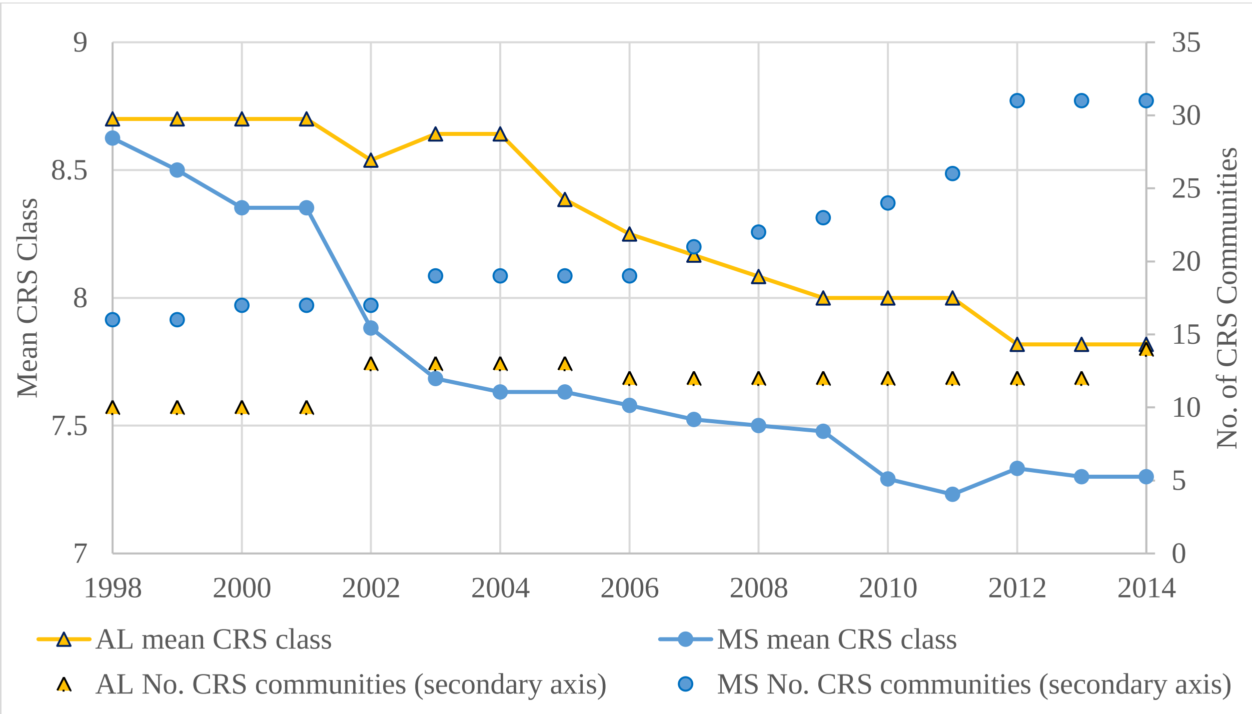


Figure 2. Number of CRS-participating communities and average CRS class for Alabama and Mississippi over time.



APPENDIX

Table A1. Alternative model results for NFIP participation, reported as Incidence Rate Ratios (IRR). Values in Parentheses indicate robust (Poisson, negative binomial, and fractional logit) or bootstrapped (fixed-effects and random-effects negative binomial) standard errors. Log (Housing units) is the exposure variable (N = 10,642; communities = 626).

Variable	Random-effects Poisson	Negative Binomial	Fixed-effects Negative Binomial	Random-effects Negative Binomial	Fixed-effects Fractional Logit
Class 9	1.288*** (0.109)	1.206(0.172)	1.255*(0.161)	1.256**(0.146)	0.397*(0.214)
Class 8	1.218**(0.100)	1.448*(0.220)	1.565***(0.186)	1.473***(0.195)	0.667**(0.261)
Class 7	1.375*** (0.155)	1.712***(0.317)	1.676***(0.227)	1.636***(0.245)	1.137***(0.245)
Class 6	1.385***(0.164)	1.657(0.510)	1.593**(0.312)	1.550***(0.310)	0.967***(0.243)
Class 5	1.564***(0.171)	2.401*(0.995)	2.541***(0.631)	2.365***(0.659)	1.233***(0.206)
Time trend x Non-CRS		1.052***(0.004)	1.045***(0.004)	1.043***(0.004)	
Time trend x Class 9		1.050***(0.010)	1.046***(0.009)	1.046***(0.009)	
Time trend x Classes 5-6-7-8		1.033***(0.009)	1.009(0.009)	1.014(0.010)	
SFHA	193.083***(86.556)		2.347(2.184)	1.505(1.431)	
Waterfront	1.5003*(0.327)		0.154***(0.062)	0.091***(0.038)	
Mississippi	1.231(0.166)		2.167**(0.677)	1.350(0.395)	
Precipitation	1.000**(0.000)			0.942**(0.011)	
Elevation	0.996***(0.001)			0.642*(0.153)	
Slope	1.004(0.056)			0.799**(0.090)	
Stream density	0.458***(0.090)			0.844(0.407)	
Disaster days	1.000(0.000)	1.000(0.0002)	1.001***(0.000)	1.001***(0.000)	0.002***(0.001)
Disaster days one year prior	1.002***(0.000)	1.001***(0.0002)	1.001***(0.000)	1.001***(0.000)	0.004***(0.001)
Income	0.936(0.051)		0.865(0.114)	0.914(0.109)	
Home Value	1.039*(0.023)		0.960(0.056)	0.978(0.049)	

Table A1 continued

Education	18.654**(23.075)		0.011*(0.030)	0.032(0.070)	
Age	0.995(0.010)		1.183***(0.049)	1.161***(0.040)	
Constant	4.711***(2.191)	71.292***(4.441)	0.009***(0.013)	0.049**(0.067)	-5.342***(0.203)
ln(Housing units)	1.000(exposure)		1.000(exposure)	1.000(exposure)	
Year fixed effects	Yes	No	No	No	Yes
Community fixed effects	No	Yes	Yes	No	Yes
	α = 1.056(1.025)	α = 0.086(0.113)		*r* = 0.774(0.063) *s* = 1.120(0.145)	
Log likelihood	= -73337.709		= -31393.755	= -35725.232	
Log pseudolikelihood		= -32847.146			
Pseudo R-squared		= 0.351			
	Wald chi2(34) = 6262.82		Wald chi2(17) = 543.63	Wald chi2(17) = 598.24	Wald chi2(37) = 1.98×10^{14}
	Prob > chi2 = 0.0000		Prob > chi2 = 0.0000	Prob > chi2 = 0.0000	Prob > chi2 = 0.000

***, **, and * shows significance at 1%, 5%, and 10% levels of significance, resp.

Table A2. Part 1 (Logit) of the 2PM and alternative model results for Damage claims payments. Values in Parentheses indicate robust standard errors. (N = 10,642; communities = 1724).

Variable	Part 1 (Logit) of 2PM	Cragg Hurdle		Random effects OLS log(Claims)	Fixed-effects log(Claims)
		Outcome model	Selection model		
Class 9	0.122(0.235)	0.217(0.307)	0.108(0.131)	0.262(0.294)	0.217(0.327)
Class 8	0.020(0.238)	0.241(0.228)	0.078(0.137)	0.196(0.223)	-0.414(0.320)
Class 7	0.857(0.592)	-0.456(0.285)	0.496*(0.300)	-0.428(0.305)	-0.766(0.537)
Class 6	-0.359(0.549)	-0.044(0.321)	-0.141(0.320)	-0.086(0.313)	-0.740*(0.444)
Class 5	-0.185(0.463)	-1.137**(0.532)	-0.039(0.275)	-1.107*(0.525)	-1.478**(0.633)
log(Coverage)	0.668***(0.041)	0.313***(0.000)	0.358*** (0.023)	0.311***(0.039)	0.573***(0.161)
SFHA	0.332(0.352)	0.327(0.375)	0.209(1.197)	0.304(0.381)	
Waterfront	-0.760*** (0.226)	0.610***(0.222)	-0.356***(0.127)	0.633***(0.227)	
Mississippi	0.560***(0.124)	0.417***(0.133)	0.308***(0.068)	0.413***(0.134)	
Precipitation	2.713***(0.225)	1.785***(0.281)	1.500***(0.127)	1.816***(0.285)	2.122***(0.346)
Elevation	-0.103(0.108)	0.028(0.142)	-0.044(0.058)	0.050(0.144)	
Slope	0.070(0.047)	0.105*(0.058)	0.036(0.025)	0.092(0.058)	
Stream density	-0.298(0.230)	0.045(0.283)	-0.150(0.125)	0.091(0.284)	
Disaster days	0.017***(0.003)	0.035***(0.004)	0.010***(0.001)	0.035***(0.004)	0.038***(0.004)
Disaster days one year- prior	0.007***(0.002)	-0.001(0.003)	0.004***(0.001)	-0.001(0.003)	-0.003(0.003)
Income	0.062(0.061)	-0.067(0.079)	0.028(0.034)	-0.070(0.076)	
Home Value	-0.042 (0.031)	0.030(0.022)	-0.023(0.017)	0.032(0.022)	
Education	1.231(0.075)	-1.094(1.256)	0.712(0.613)	-1.057(1.289)	
Age	-0.007(0.013)	0.006(0.014)	-0.005(0.007)	0.007(0.014)	
Housing units	0.010***(0.003)	0.003*(0.001)	0.006***(0.001)	0.003*(0.001)	
Constant	-14.984***(0.926)	1.708*(1.019)	-8.134***(0.505)	1.606(1.029)	-2.109(2.617)
Community fixed effects	No	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Table A2 continued

Log likelihood	= -2896.116	= -22842.433		
Wald chi2(36)	= 1221.30	= 884.82	= 824.58	F(25,353) =15.96
Prob > chi2	= 0.0000	= 0.0000	= 0.000	Prob > F = 0.000
Pseudo R2	= 0.3290	= 0.0713	R-squared= 0.328	R-squared= 0.303

***, **, and * shows significance at 1%, 5%, and 10% levels of significance, resp.

Table A3. Fixed-effects Fractional Logit Regression results for Damage claims payments with robust standard errors, (N = 1,724; communities = 626).

Variable	Coefficient	Robust Standard Error
Class 9	-0.086	0.393
Class 8	0.038	0.442
Class 7	0.106	0.592
Class 6	0.913	0.690
Class 5	-3.385***	0.670
Disaster days	0.059***	0.006
Disaster days one year prior	0.005	0.006
Constant	-3.908***(0.325)	
Community fixed effects	Yes	
Year fixed effects	Yes	
Log pseudolikelihood = -123.2087		
Wald chi2 (318) = 503,000,000,000		
Prob > chi2 = 0.000		
Pseudo R-squared = 0.3648		

*** shows significance at 1% level of significance.

Table A4: Summary statistics of variables used in Part 1 (Logit) of 2PM of the Damage claims payments model (N = 8,632).

Variables	Mean	Std. Dev.	Min.	Max.
Damage Claims Payments ($)	429149.9	8,879,573	0	374,000,000
Class 9	0.018	0.133	0	1
Class 8	0.028	0.164	0	1
Class 7	0.009	0.096	0	1
Class 6	0.006	0.076	0	1
Class 5	0.002	0.046	0	1
Log(Coverage)	14.655	2.302	7.601	21.602
SFHA	0.191	0.166	0	0.969
Waterfront	0.049	0.216	0	1
Mississippi	0.448	0.497	0	1
Slope	2.743	1.671	0.106	8.715
Elevation	1.134	0.716	0.003	5.246
Stream Density	0.922	0.270	0	2.050
Precipitation	1.455	0.283	0.650	2.470
Disaster days	10.761	21.053	0	110
Disaster days one year-prior	10.907	21.341	0	110
Income (scaled by 1000)	3.681	1.373	1.208	13.583
Home value (scaled by 1000)	10.050	4.609	2.340	53.850
Housing units (scaled by 1000)	9.929	22.596	0.031	301.202
Education	0.115	0.068	0	0.538
Age	37.898	4.570	21.800	53.300