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Does the Community Rating System Work? Evidence from Two Gulf Coast States

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Does the Community Rating System Work? Evidence from Two Gulf Coast States

Abstract

The Community Rating System (CRS) was introduced to encourage community-level flood mitigation and increase household-level National Flood Insurance Program (NFIP) participation. It is not clear, however, if and to what extent community participation in the CRS increases household participation in the NFIP and decreases damage claims payments. We employ genetic matching methods and estimate Mundlak-style panel regression models that control for key geospatial, socioeconomic, and time effects to isolate the CRS treatment effect on these outcomes. Results show a positive and significant effect of CRS participation on NFIP participation. CRS effect on damage claims payments is negative but not significant.

Keywords: Community Rating System (CRS); damage claims payments; fixed effects; flood insurance; flood mitigation; flood risk; genetic matching; Mundlak; National Flood Insurance Program (NFIP)

JEL Codes: C23, Q54, Q58

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Abstract

The Community Rating System (CRS) was introduced to encourage community-level flood mitigation and increase household-level National Flood Insurance Program (NFIP) participation. It is not clear, however, if and to what extent community participation in the CRS increases household participation in the NFIP and decreases damage claims payments. We employ genetic matching methods and estimate Mundlak-style panel regression models that control for key geospatial, socioeconomic, and time effects to isolate the CRS treatment effect on these outcomes. Results show a positive and significant effect of CRS participation on NFIP participation. CRS effect on damage claims payments is negative but not significant.

Introduction

The Community Rating System (CRS) was created in 1990 to encourage both community-level flood mitigation and household-level participation in the National Flood Insurance Program (NFIP). CRS participation, which is undertaken at the community level, is optional, and provides a mechanism by which residents living in a participating community can earn flood insurance premium discounts if the community undertakes additional flood mitigation actions. Although the CRS program aims to encourage NFIP participation and reduce future flood damages, it is not clear if and to what degree participation in the CRS affects these outcomes, and whether these effects are consistent across states.

Several papers have addressed the effects of the CRS, but there are some gaps that we attempt to fill in this paper. Zahran et al. (2009) and Petrolia, Landry, and Coble (2013) find a positive 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, except for Michel-Kerjan and Kousky (2010), 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. We are 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. This paper also makes a subtle methodological contribution. Past studies have employed various sets of control variables to isolate the effect of CRS, but to the best of our knowledge, have not taken additional steps to isolate the treatment effect. Matching is a method that seeks to balance a sample between treatment group (i.e., units that received program intervention) and control group (i.e., units that did not receive program intervention) observations. Genetic matching, proposed by Diamond and Sekhon (2013), is a unique matching approach that employs a search algorithm to locate a metric distance that optimizes covariate balance. With genetic matching, for each covariate, weights are assigned to the calculated metric distance between the treated units and the control units. The weights determine the contribution of the units to achieving balance (Diamond and Sekhon 2013). We employ this method to pre-process the data, using key geospatial and socioeconomic indicators during the matching procedure to achieve balance and obtain the final matched sample. Consistent with previous work, we find a positive relationship between CRS participation and NFIP participation. Regarding the relationship between CRS participation and property damage, we find a negative relationship but the effect is not significant.

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 (Federal Emergency Management Agency, 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 (especially in terms of homeowner's purchase of flood insurance), 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 SFHA. 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 into the NFIP program in 1990. In 1995, FEMA also introduced the "Cover America" program, a campaign that promoted awareness of flood risk (Michel-Kerjan 2010). In the year 2004, the National Flood Insurance Act of 1968 was reformed, with the primary goal of reducing payments on repeat-claim properties (FEMA 2017a). 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 2017a). 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 2017a). In 2014, the Biggert-Waters Flood Insurance and Modernization Act was replaced with the Homeowner Flood Insurance Affordability Act. This legislation seeks to reduce premium rates on selected policies and also cancel some rate increases that had previously been implemented (FEMA 2017a).

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. Under the CRS program, there are 19 credit-generating flood mitigation activities organized under four general categories. Series 300 activities are related to providing information on floods and Flood Insurance Rate Map (FIRM) to community residents, as well as promoting flood insurance purchases. Series 400 activities focus on floodplain mapping, including developing new flood elevations and delineating floodways for areas not mapped on FIRMs, and on enforcement of building regulations, with a focus on new developments. Series 500 activities are related to flood damage reduction to existing developments. For example, CRS communities undertake drainage system maintenance and floodplain management. Series 600 activities focus on providing flood warnings, how to respond to emergencies during floods, providing maintenance to levees, and ensuring dam safety (FEMA 2013 b). Depending on the degree to which participating communities undertake these activities, communities are awarded credit points up to the maximum allowed for each activity. An NFIP community can undertake none, some, or all the 19 CRS activities.

Communities are then assigned a “class” based on the overall CRS credit points earned, ranging from 10 (lowest level of participation) to 1 (highest). For every 500–point-increment in overall credit points, the CRS class improves (i.e., decreases). These “classes” are now used as a metric to determine how resilient a community is to flood-related disasters (Atreya and Kunreuther 2016; Michel-Kerjan, Atreya, and Czajkowski 2016). Policy discounts range from 0% to 45%, in 5% increments for residents located in Special Flood Hazard Areas (SFHAs), and whereas for residents in non-SFHAs, the policy discount is 5% if the community is rated class 7 through 9, and 10% if rated 6 or better.[1]

The CRS program is updated every three years, although some minor changes occur on a yearly basis (FEMA 2016). The recent major update to the CRS program occurred in 2013. The goal of the changes was to reduce liabilities, improve disaster resiliency and sustainability of communities, integrate a "whole community" approach to emergency management, promote natural and beneficial functions of floodplains, increase understanding of risk, and strengthen adoption and enforcement of disaster-resistant building codes. These changes are expected to have different degrees of impacts on CRS communities. For example, points available for open space preservation have increased whereas points available for map information service have decreased. Additionally, communities will now be required to earn a higher number of points to maintain their CRS participation status, i.e., to achieve a Class 9 (entry-level) status (FEMA 2013c).

Despite the potential benefits to participating communities and their residents, the CRS

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[1] 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.

program, like the NFIP, appears to suffer from low participation, although it depends on how participation is measured. Of the more than 22,000 NFIP communities in the U.S., only 5% of them participate in the CRS (FEMA 2017b). On the other hand, out of the 5.6 million NFIP policies-in-force in the U.S., 68% of them are in CRS-participating communities (FEMA 2017b). Thus, although few NFIP communities participate in the CRS, more than two thirds of NFIP policies-in-force are in CRS-participating communities. 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).

Study Area and Data

Data were collected for years 1998-2013 for all 758 NFIP-participating communities in Alabama and Mississippi. An 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 and CRS programs in that locality. Although all of these communities are considered to be "participating", many are effectively non-participants with none or only a few policies-in-force. Consequently, we dropped observations for communities with fewer than 20 policies-in-force in more than 18 years, resulting in a total of 293 effectively-participating communities in the final data set. Figure 1 shows the distribution of CRS participation by communities in Alabama (in the middle) and Mississippi (first from the left). Participation in CRS is shown in green (pink indicates no CRS participation). Although both coastal and noncoastal communities participate in the CRS program, there is greater participation density in the coastal areas. In Alabama, 12 out of 428 NFIP communities participate in the CRS program, whereas in Mississippi, 31 out of 330 NFIP communities participate (FEMA 2013b).

The total number of NFIP policies-in-force in Alabama in 2013 was 58,383, of which 32,519 were in CRS participating communities. Mississippi had a total of 74,299 policies-in-force, out of which 52,866 were in CRS participating communities. Among the Gulf States, Alabama and Mississippi have the lowest number of CRS participating communities (but not in terms of participation rate: Texas participation rate is 5% less that of Mississippi). In Florida (first from right of Figure 1) for example, about 216 out of 458 communities participate in CRS.

Using Microsoft Excel and ArcGIS software, data on NFIP policies-in-force, damage claims payments, CRS participation, and geospatial and socioeconomics were merged into a single dataset by cross-referencing FEMA community identification codes, community name, state Federal Information Processing Standard (FIPS) codes, county FIPS codes, FIPS entity codes, American National Standards Institute (ANSI) codes, and year.

Table 1 presents the variables and their descriptions. Data on CRS, policies-in-force, and damage claims were obtained from FEMA. Data on geospatial variables were obtained from National Oceanic and Atmospheric Administration (NOAA 2018), United States Geological Survey (USGS 2015a and 2015b), Parameter-elevation Relationships on Independent Slopes Model (PRISM 2015), and US Census Bureau (2016a). Socioeconomic variables data, which were based on the 1990, 2000, 2010 census, were obtained from American Community Survey (ACS 2013) and US Census Bureau (2016b). Except for *Mississippi*, *Coast*, *Number of floods*, and *Number of hurricanes*, geospatial variables were measured based on a 4-km grid cell. The distribution of the dependent variables (i.e., NFIP policies-in-force and damage claims payments) were not normal, and were consequently log-transformed to approximate a normal distribution.

Empirical Model

Building on past studies, we assume that at the aggregate level, NFIP policies-in-force and damage claims payments are a function of flood mitigation activities undertaken (i.e., CRS), geospatial factors of the community, and socioeconomic factors. The dependent variables are *NFIP participation* and *Damage claims payments.* The independent variables are categorized as policy-related, geospatial, socioeconomic, and fixed-effects (by community and year). Our variable of interest is *CRS*. The *CRS* variable, *Class 5, 6, 7, 8, and 9, and Series 300, 400, 500, and 600* are the policy variables. Because *NFIP participation* is likely increasing in previous-year claims (see Gallagher 2014), we condition *NFIP participation* on lagged claims payments. Also, because claims are likely increasing in coverage, we condition claims on the NFIP coverage in dollars. The *Community fixed-effects* and *Year fixed-effect* are to account for individual community heterogeneity and year effects, respectively.

In estimating the impact of a program on outcomes, it is suggested that for comparison, the units that received the program, and those that did not receive the program should share similar characteristics so as to eliminate program selection bias (Rosenbaum and Rubin 1983; Rubin and Thomas 2000; Stuart and Greene 2008). To accomplish this, the literature suggests using matching methods (Rosenbaum and Rubin 1983; Rubin and Thomas 2000; Stuart and Greene 2008; Li, Vyn, and McEwan 2016; Qian et al. 2016).

Matching is a method that seeks to balance a sample between treatment group (i.e., units that received program intervention) and control group (i.e., units that did not receive program intervention) observations.[2] Here, balance means that the differences in the distributions between the covariates (here the control variables) for the treatment group and the control group are minimized. Although one matches on covariates of units (here, communities) from the treatment group and that of the control group, matching becomes difficult when there are more than two covariates. To overcome this, three main approaches have been identified in the matching literature: matching on metric distance (e.g., Mahalanobis-metric distance) (Rubin 1980), matching on propensity scores (Rosenbaum and Rubin 1983), and genetic matching (Diamond and Sekhon 2013). Here, we employ the genetic matching approach of Diamond and Sekhon (2013), which is a more general form of the Mahalanobis metric distance approach. With genetic matching, for each covariate, weights are assigned to the calculated metric distance between the treated units and the control units. The weights determine the contribution of the units to achieving balance (Diamond and Sekhon 2013).

We use the GenMatch algorithm included in the statistical package *R* (version 3.3.0). First, we categorize our data into CRS participating communities (treatment group) and non-participating communities (control group). The categorization is based on a community's participation during the most recent year observed (i.e., 2013) to ensure that we maintain a

[2] Matching techniques can be used to pre-process the data, or to estimate treatment effects directly. Pre-processing the data using matching methods and then estimating the program effect on outcomes using a difference-in-difference (DID) regression framework based on the matched sample is preferred (Yasar and Rejesus 2005). Ravallion and Chen (2005) have also demonstrated the benefit of preprocessing data to achieve balance between treated and controlled group, and then estimating the policy effect via a DID estimator.

balanced panel, i.e., that each NFIP community has the same number of observations. We included estimated propensity scores, higher order, and interaction terms of the covariates that were continuous, in the GenMatch function in R.

Covariates used during the matching procedure included: *SFHA-V*, *SFHA-A*, *non-SFHA* (i.e., non-SFHA-*B* and *C* combined), *Coast*, *Mississippi*, *Slope*, *Elevation*, *Stream density*, *Household*, *Income*, and *Education*.[3] The GenMatch algorithm assigns weights to the covariates such that the weights depict the importance of the covariates in achieving balance. The weights generated by GenMatch were then fed into the Match algorithm in *R*, together with the covariates. In both the GenMatch and the Match functions in *R*, we use the nearest neighbor with replacement option. Specifically, for each treated unit we identify three units ($m = 3$) from the control group that are closest in distance. The Match function yields a final set of weights that identify our final matched sample (where control units are weighted based on the number of times each is used as a match, and where all treatment units received a weight of one). As desired, the means of the covariates for the control group are closer to the means of the treatment group after matching. In all, our final data set contained a total of 113 communities observed over a period of 16 years.

To examine the effectiveness of the matching procedure, we followed Ho et al. (2007) to construct quantile-quantile (QQ) plots of the pre-treatment covariates used in the genetic

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[3] We exclude the *Precipitation* variable from the set of pre-treatment covariates when performing the genetic matching because it reduces balance. As recommended by Ho et al. (2007), although by theory one must account for all variables that otherwise would have been used in a regression, not all pre-treatment covariates are to be used especially when including them in the matching process leads to inefficiency and reduces balance.

matching. For binary variables *Coast* and *Mississippi*, we exhibit the distributions using histograms. Results indicated that genetic matching improved the distributions of variables *SFHA-A*, *Coast*, *Mississippi*, *Slope*, *Elevation*, *Household*, *Income*, and *Education*, whereas for the variables *SFHA-V*, *non-SFHA*, and *Stream Density*, distributions did not improve much. Table 2 contains the weighted summary statistics of the variables after matching used in the econometric model, and reports the expected signs for the independent variables.

Econometric Model

The data comprise a panel (i.e., has a cross-section (*N*) and a time-series dimension (*T*)). Panel data models vary based on the assumption that underlies the conditional mean of the unobserved heterogeneity. One may specify a pooled model which assumes no individual unobserved heterogeneity; a fixed-effects model, which assumes that unobserved heterogeneity conditional on covariates is fixed for each unit; or a random-effects model, which assumes that the expected unobserved heterogeneity conditional on covariates is zero (Wooldridge 2002; Greene 2012a).

Unlike fixed-effects, random-effects does not allow the individual unobserved heterogeneity to be correlated with the independent variables (Greene 2012a). It is also important to mention that for the fixed-effects model, time-invariant covariates cannot be estimated because they are confounded with the unit-specific constants (Wooldridge 2002; Greene 2012a). Another model variation is the Mundlak (1978) approach, which is similar to the random-effects model, but allows for correlation between the observed covariates and the unobserved heterogeneity by adding as covariates group-means of the time-varying covariates (Greene 2012a). Li, Vyn, and McEwan (2016) refer to the Mundlak's approach as "Correlated Random-Effects", and as noted by Greene (2012a), the Mundlak approach can be used as a compromise between the fixed and random-effects models.

We tested for panel effects (i.e., to test a pooled model against a random- or fixed-effects panel model) using the Breusch-Pagan (B-P) Lagrange multiplier test (Greene 2012a), the Hausman test (Hausman 1978) to test the null hypothesis of random effects against fixed effects, and Wu's variable addition test (Wu 1973) to test if the individual effects are correlated with the regressors after including the means of time-varying variables and testing the joint hypothesis that the parameters on the group means are not different from zero. We also tested for the presence of serial correlation, contemporaneous correlation, and heteroscedasticity using Wooldridge's test (Wooldridge 2002), the Pesaran (2004) test, and White's general test (White 1980), respectively.

Based on the aforementioned tests, for the NFIP policies-in-force model, we reject the null hypotheses of no panel effects and random effects. We also reject the null hypothesis that individual effects are not correlated with the regressors (i.e., that Mundlak's approach does not mimic a random-effects model, but rather a fixed-effects model). For the damage claims payments model, we also reject the null hypothesis of no panel effects, and fail to reject the null hypothesis of random-effects. Additionally, we reject the null hypothesis that individual effects are not correlated with the regressors.

Tests indicate the presence of serial correlation, contemporaneous correlation, and heteroscedasticity in the NFIP policies-in-force model, and indicate heteroscedasticity and contemporaneous correlation, but no serial correlation in the damage claims payments model. Based on these findings, we estimate all models with robust standard errors, using NLOGIT 5 software (Greene 2012b). Where serial autocorrelation and heteroscedasticity exists, the robust covariance matrix estimator is used (Wooldridge 2002). This estimator is valid in cases where one has issues of heteroscedasticity or serial correlation (Wooldridge 2002). The use of the robust covariance matrix estimator and related test statistics, 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. Matching weights serve as the regression weights.

One potential limitation of this work is that our modeling efforts, matching and panel data methods, address selection on observables only, and fail to account for selection on unobservables. It may be that CRS is endogenous, given that it may be correlated with the error term, i.e., that there exist one or more unobserved factors affecting both flood insurance purchase and CRS participation. The consequence is that the CRS effect reported here will be inconsistent, and to the extent that the unobserved factors have a positive influence, biased upward, leading to overestimates of the CRS effect. To address this, we would need one or more instruments, i.e., variables that explain CRS participation but not flood insurance purchase. Unfortunately, we have concluded that no instruments exist that satisfy the exclusion restriction. Because our data are measured at the community level, we argue that any variable that influences CRS participation is likely to also influence flood insurance purchase. A recent paper (Kousky, Michel-Kerjan, and Raschky 2018) instrumented federal disaster aid using swing counties in presidential elections, to address the endogeneity problem associated with federal disaster aid in explaining flood insurance uptake. The argument is that decisions on federal disaster aid are at least partly politically motivated. CRS participation, however, is much less likely to be influenced by national politics. Furthermore, both Alabama and Mississippi are solid "red" states, so swing counties are of much less consequence. One possible candidate instrument that we did try was Federal Mitigation Assistance (FMA) grants made to communities. One could argue that these grants, which fund "projects and planning that reduces or eliminates long-term risk of flood damage to structures insured under the NFIP" (FEMA 2018), could influence a community's decision to participate in CRS, but not influence a homeowner's decision to purchase a flood policy. However, we find that this is, at best, a weak instrument, being either not significant or only marginally significant even under the most favorable conditions, and weak instruments do not generally perform well, having poor finite sample properties (biased). Additionally, weak instruments exacerbate any potential inconsistency resulting from even a small violation of the exclusion condition.

Another possible set of instruments are dummy variables when there is a change in the CRS status of a certain community. Change of CRS status may include entry into the program and/or a change in the CRS class. The argument here is that changes in CRS status occur rather infrequently and definitely not every year. To the extent that these changes in CRS status reflect the effect of unobserved factors like community awareness or increased awareness about the CRS program, then such a variable could serve as an instrument for these unobserved factors. To these ends, we include a dummy variable, *CRS Change in Status*, to capture these unobserved effects.

Results

Effects of CRS Participation on NFIP Participation (log of number of policies-in-force)

In table 3, we report results on the effects of CRS participation on NFIP participation (log of number of policies-in-force), based on Mundlak's approach. While Mundlak coefficients are similar with fixed-effects results, standard errors are larger with fixed-effects. Again, Mundlak's approach allows for inclusion and interpretation of additional policy-relevant time-invariant variables, so we opted to report the Mundlak results.[4] Additionally, we find that models based on matched data out-perform those based on the full, unmatched data set: matched results have better fit statistics. Consequently, we report results using the matched sample. Reported are the raw coefficients, robust standard errors, and marginal effects. Marginal effects are calculated by exponentiating the raw coefficient.[5]

The results show a positive and significant relationship between CRS participation and NFIP participation (policies-in-force) as hypothesized. Specifically, we find that *NFIP participation* in CRS communities is 14% higher compared to communities not participating in CRS, *ceteris paribus*.[6] Coefficient on *Class 5* is positive and significant, implying that, *NFIP participation* is 57% higher among CRS communities rated class 5 compared to those in class 9, *ceteris paribus*. Coefficients on *class 6*, *7*, and *8* are not significant, indicating no significant

[4] The econometric model estimated is analogous to the difference-in-differences (DID) approach, which seeks to compare changes in outcomes between a group that receives treatment and those that did not (Carpenter 2004, and Ravallion and Chen 2005). Unlike the traditional DID that has two time periods (before and after), for panel data (with more than two time periods) where the treatment assignment is arbitrary, a set of year dummies are included in the regression framework (Imbens and Wooldridge 2007). Also, as noted by Gruber (1994), using a regression framework other than the traditional DID gives one the freedom to control for other covariates.

[5] Exceptions are log-transformed coefficients, which have a different transformation and interpretation. Examples are provided below.

[6] For example, the CRS effect is *exp* (0.13) = 1.14, i.e., a 14% increase over the base (i.e., non-CRS communities).

effect on NFIP participation over and above that of entry-level Class 9. Coefficients on lagged log claims variables (i.e., Log *Claims 1, 2, 3, 4, and 5 Years Prior*) are all positive and significant, indicating that, *ceteris paribus*, increased claims in one year lead to increased policy uptake in subsequent years. Our results indicate that the effect lasts for up to five years, with an estimated 0.1% increase in policies-in-force for every 10% increase in damage claims payments in each of the previous five years.

As expected, *SFHA (i.e.,* combination of *SFHA-V* and *SFHA-A)* has a positive and significant relationship with *NFIP participation*, however the effect dissipates as the percent of land area under *SFHA* increases (as depicted by the negative quadratic term). Contrary to our hypothesis, we find the coefficient on *Coast* to be negative and significant, implying lower *NFIP participation* among coastal communities. The coefficient on *Mississippi is* negative but not significant. Parameter estimates on *Slope* is negative and significant, indicating that a one degree increase in the mean *Slope* of a community reduces the number of NFIP policies-in-force by 29%, *ceteris paribus*. Coefficients on *Elevation* and *Precipitation* are positive but not significant in explaining *NFIP participation*. *Stream density* coefficient is negative but not significant. Surprisingly, we find that the coefficient on the *Number of floods* is negatively correlated with *NFIP participation.* On the other hand, as expected, the coefficient on *Number of hurricanes* is positive and significant in affecting *NFIP participation*. That is, *ceteris paribus*, one additional hurricane event increases *NFIP participation* by 3%. *Change of CRS status* instrument is not significant.

Among the socioeconomic variables, log(*Household*) has a positive and significant effect on *NFIP participation*: a 10% increase in the number of *Households* in the community increases the number of *NFIP policies-in-force* by 8%, *ceteris paribus*.[7] The positive and significant relationship between *Income* and *NFIP participation* is as expected. This indicates that a $1000 increase in annual median *Income* increases *NFIP participation* by 1%. The coefficient on *Education* is negative and significant in explaining the number of *NFIP policies-in-force*. We hypothesized a positive relationship.

Effect of CRS Participation on Damage Claims payments (log of Damage Claims Payment)

Results are presented in table 4. Although, as expected, the coefficient for *CRS* participation is negative, the effect is not significant. Furthermore, none of the individual *Series* variables are significant either, indicating no significant relationship between CRS participation in general, or specific CRS activities (as captured by the *Series* variables) and *Damage claims payments*. Highfield and Brody (2013) finds a negative and significant relationship between some but not all activities under *Series 400*, and insured flood damages. Again, they find no significant effect between *Series 500 activities* and insured flood damages. The parameter estimate for log(*Coverage*) is positive and significant in explaining *Damage claims payments*. That is *ceteris paribus*, a 1% increase in total *Coverage* in the community leads to a 0.2% increase in *Damage claims payments*. Again, we note that the instrument *Change of CRS status* is not significant.

On geospatial variables, results show that *SFHA* has a positive relationship with *Damage claims payments*, although the effect is not significant. The coefficient on *Coast* is positive and significant as hypothesized. Specifically, *Damage claims payments* are 610% higher for coastal communities compared to noncoastal communities. The coefficient on *Mississippi* is also positive

[7] The marginal effect is calculated as $1.10^{0.76} = 1.08$.

and significant. The positive effect indicates that *Damage claims payments* are 530% higher for communities in Mississippi compared to those in Alabama, *ceteris paribus*. The coefficient of *Slope* is positive and significant. The parameter estimate for *Elevation* is not significant. Unexpectedly, the coefficient on *Stream Density* is also negative and significant. We find a positive and significant relationship between *Precipitation* and *Damage claims payments* as hypothesized. That is, a 1-inch increase in *Precipitation* increases *Damage claims payments* by 17%, *ceteris paribus*. As hypothesized, the parameter estimates for *Number of floods* and *Number of hurricanes* are both positive and significant. That is, one additional flood and hurricane event, respectively, increases *Damage claims payments* by 43% and 353%.

On socioeconomic variables, results show a positive but not significant relationship between log(*Household*) and *Damage claims payments*. We find a positive and significant relationship between *Income* and Damage claims payments. Results show a positive but not significant relationship between *Education* and *Damage claims payments*.

Summary and Conclusions

To the best of our knowledge, we present the first analysis on the impact of *CRS participation* (versus non-participation) on *NFIP participation* (measured as total number of policies-in-force in a community in a year) and *Damage claims payments* (measured as total dollar value of claims in a community in a year), respectively. We employ genetic matching methods to group CRS and non-CRS communities with similar characteristics to mitigate comparison bias.

We find that participation in the CRS program increases *NFIP participation.* This finding implies that premium discounts awarded on individual policies in CRS communities may indeed be motivating residents to purchase flood policies, although it could also reflect heightened awareness of flood risk in CRS communities. With regards to *CRS* effects on *Damage claims payments*, we find no significant effect of *CRS* participation on *Damage claims payments*, although the relationship is negative. Although one of the goals of the *CRS* program is to reduce damages to insured properties, we find no evidence for such effects in our study area. The lack of significant impact of *CRS participation* on *Damage claims payments* may be at least partly explained by the fact that in cases of severe flood damage events (like Hurricane Katrina), the impact of the damage event could overwhelm any mitigation effects.

This study is the first to provide empirical findings specific to states other than Florida and Texas, and potentially more importantly, states with very different circumstances. 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* (3% and 9% of NFIP communities participate in the CRS, respectively). Additionally, our study states have much less coastal exposure, with 8 out of 67 Alabama counties holding a NOAA coastal designation and 12 out of 82 Mississippi counties thus designated. Although Texas also has very low *CRS participation* (4%), and less coastal exposure (41 NOAA coastal counties out of 254), it has a much higher median household income level (ranking 26th). Florida, on the other hand, ranks lower in median household income (39th), but has the highest *CRS participation* (47%), and all but 6 of its 67 counties are NOAA-coastal designated.

With this in mind, we wish to draw some key distinctions from our findings relative to previous work that are policy relevant. Zahran et al. (2009) found a positive relationship between increased *CRS participation* and *NFIP participation* in Miami-Dade, but their study did not include non-CRS communities. Their data covered the years 1999-2005, so lied between Hurricanes Andrew (1992) and Katrina (2005), so was not capable of detecting any such effects due to these major storms. Their data did span Hurricane Charley (2004) and other lesser storms, but their analysis does not appear to have allowed for any such structural changes due to major storm events. The same can be said of Petrolia, Landry, and Coble (2013), who, although having surveyed households across the five Gulf states, nevertheless had a sample dominated by Florida and Texas respondents, who were surveyed after Hurricane Katrina. They found a significant and positive relationship between *CRS participation* and *NFIP participation*. With regard to the effect of CRS participation on flood damage, our results provide some contrast and more nuance relative to previous work as well. Michel-Kerjan and Kousky (2010), the only other paper to include both CRS- and non-CRS-participating communities in the analysis, found that damage claims were reduced only among (relatively rare) Class 5 CRS communities. Our results may not necessarily contradict theirs because our sample contained very few Class 5 observations, and even when we modeled classes separately in preliminary estimations, we found no such significance. Interestingly, however, is the fact that both our paper and theirs find that Class 5 communities, i.e., communities with a high-degree of CRS participation, stand out in terms of impacts on NFIP outcomes. Highfield and Brody (2013), too, found that *CRS* effects on flood damage were limited; in their case, limited to particular mitigation activities. Brody et al. (2007a and 2007b), however, found more robust effects of the *CRS* on flood damage, but as mentioned earlier, focused on communities in *CRS* only, so the effect of joining the *CRS* was not investigated as it is here. Taking all the aforementioned studies together, program administrators may wish to consider whether the *CRS* needs to be further scrutinized to determine which activities actually result in tangible reductions, and under what circumstances.

Overall, this analysis indicates that the CRS program does appear to be achieving its goal of increasing *NFIP participation* among CRS-participating communities. To the extent that these additional policies cover the bulk of claims made in the event of a flood, our findings imply that increased *NFIP participation* should result in reduced burdens on state and federal agencies to provide emergency post-disaster aid to uninsured households. However, our results also indicate that there may be some disconnect between *CRS* participation and reduced *Damage claims*, a finding at odds with previous work. FEMA's ability to financially sustain the NFIP program is threatened if flood mitigation strategies are not reducing damage claims payments. Given the recent (2013) changes to the CRS program, future studies should investigate the extent to which these recent changes are impacting on outcomes, especially in reducing damage claims payments. This research should serve as a guide to studying the effect of *CRS* participation on outcomes in other states.

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Table 1. Description of variables

Variables	Description
Policies-in-force[a] (units)	Annual total number of NFIP policies-in-force. (FEMA)
Damage claims payments[b] (US $)	Annual total damage claims payments. (FEMA)
CRS (binary)	= 1 if an NFIP community is participating in the CRS program in a given year, = 0 otherwise. Participation is based on the year community enters the CRS program. (FEMA)
Class 5, 6, 7, 8, and 9 (binary)	=1 if a community's CRS class is 5, = 0 otherwise.
Series 300, 400, 500, and 600 (Units)	Total credit points a CRS community earns for participating in respective activities under each series. (FEMA)
Change of CRS status (binary)	= 1 if a community enters the CRS or improves class status, = 0 otherwise.
Coverage ($US)	Annual total amount of coverage purchased and scaled (divide) by 10,000,000. (FEMA)
SFHA (%)	Measured as the percent of land area in a community classified as V flood zones. (FEMA)
Coast (binary)	= 1 if NFIP community is a NOAA-designated coastal community, = 0 otherwise. (US Census Bureau/ ACS)
Mississippi (binary)	= 1 if NFIP community is in Mississippi, = 0 otherwise (Alabama).
Slope (degree)	Maximum rate of change from a given grid cell to its neighbours. (USGS)
Elevation (feet)	Highest point of community above sea level, in 100 feet. (USGS)
Stream density (square miles)	Length of a stream divided by the square kilometers of an area and converted to square miles by multiplying the square kilometers values by 1.609344. (USGS)
Precipitation (inches)	Annual amount of precipitation received in inches. (PRISM)
Number of floods (units)	Includes floods, coast floods and storm surge. (NOAA)
Number of hurricanes (units)	Includes tropical storms and hurricanes. (NOAA)
Household (units)	The annual total number of household recorded for a community and scaled (divide) by 1000. (US Census Bureau/ ACS)
Income ($US)	Annual median income recorded for a community and scaled (divided) by 1000. (US Census Bureau/ ACS)
Education (%)	Percent college educated in a community. (US Census Bureau/ ACS)

[a] Skewness = 3.11, kurtosis = 13.00, and Shapiro-Wilk normality test of 0.52 (p-value of 0.00)

[b] Skewness = 13.26, kurtosis = 197.34, and a Shapiro-Wilk normality test of 0.10 (p-value of 0.00)

Table 2. Weighted summary statistics of dependent and independent variables after matching used in the regression analysis

Variables	Mean	Std. Dev.	Min	Max	Expected signs*
		Dependent Variables			
Policies-in-force	766.52	1633.06	0	10150	
Damage Claims	19.26	184.60	0	3744.06	
Payments (scaled by 100,000)					
		Independent variables			
		Policy variables			
CRS	0.29	0.45	0	1	+/-
Class 5	0.01	0.09	0	1	+/-
Class 6	0.03	0.16	0	1	+/-
Class 7	0.05	0.21	0	1	+/-
Class 8	0.13	0.33	0	1	+/-
Class 9	0.08	0.28	0	1	+/-
Series 300	110.94	185.33	0	761	+/?
Series 400	120.14	236.54	0	1135	?/-
Series 500	98.26	199.07	0	1122	?/-
Series 600	24.0	56.06	0	273	?/-
Change of CRS status	0.03	0.17	0	1	?/?
Coverage (scaled by 100,000)	1338.65	3206.76	0	22562.01	+
		Geospatial variables			
SFHA	0.28	0.20	0	0.94	+
Flood	0.39	0.89	0	5.00	+
Hurricane	0.57	1.18	0	6.00	+
Coast	0.39	0.49	0	1	+
Mississippi	0.59	0.49	0	1	?
Slope	2.23	1.51	0.12	6.98	?
Elevation	247.90	196.21	1.04	805.46	-
Stream Density	1.44	0.45	0	2.26	+
Precipitation	58.72	11.91	25.73	89.99	/+
Number of floods	0.39	0.89	0	5	?/+
Number of hurricanes	0.57	1.18	0	6	+
		Socioeconomic variables			
Household	15.09	22.57	0.19	156.77	?
Income	35.01	12.73	2.00	96.78	+/?
Education	19.16	11.26	2.10	60.80	+/?

*Where two signs are shown, the first is the hypothesized sign for the NFIP policies-in-force model and the second, for damage claims payments model.

Table 3. Regression results for NFIP participation

Variables	Coefficients	Std. Errors	Marg. Effects
	Policy variables		
CRS	0.13**	0.07	0.14
Class 5	0.45***	0.13	0.57
Class 6	-0.13	0.09	-0.12
Class 7	-0.04	0.08	-0.04
Class 8	-0.09	0.06	-0.09
Change of CRS status	0.03	0.06	0.03
Claims one year prior	0.01***	0.002	0.001
Claims two years prior	0.01***	0.002	0.001
Claims three years prior	0.01***	0.002	0.001
Claims four years Prior	0.01***	0.002	0.001
Claims five years Prior	0.004**	0.002	0.00
	Geospatial variables		
SFHA	5.11***	1.33	0.05
SFHA squared	-4.24***	1.56	-0.04
Coast	-0.68**	0.31	-0.49
Mississippi	-0.27	0.21	-0.24
Slope	-0.35***	0.08	-0.29
Elevation	0.001	0.001	0.01
Stream density	-0.10	0.22	-0.1
Precipitation	0.001	0.001	0.00
Number of floods	-0.06***	0.01	-0.06
Number of hurricanes	0.03**	0.01	0.03
	Socioeconomic variables		
log (Household)	0.76***	0.07	0.08
Income	0.01**	0.003	0.01
Education	-0.01***	0.003	-0.01
Year fixed-effects	Yes		
Mundlak group means	Yes		
Constant	-0.48	1.93	
R-squared	0.84		
N	1808		

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance. Standard errors are robust.

Table 4. Regression results for damage claims payments

Variables	Coefficients	Std. Errors	Marginal Effects
	Policy variables		
CRS	-0.15	0.98	-0.14
Series 300	0.30	0.27	0.03
Series 400	-0.07	0.10	-0.01
Series 500	0.15	0.14	0.01
Series 600	-0.67	0.51	-0.06
Change of CRS status	-0.31	0.63	-0.27
Log (Coverage)	0.22***	0.08	0.02
	Geospatial variables		
SFHA	1.23	1.44	0.01
Coast	1.96**	0.89	6.10
Mississippi	1.84***	0.57	5.30
Slope	0.41*	0.22	0.51
Elevation	0.0004	0.002	0.004
Stream density	-1.00*	0.60	-0.63
Precipitation	0.16***	0.02	0.17
Number of floods	0.36***	0.14	0.43
Number of hurricanes	1.51***	0.13	3.53
	Socioeconomic variables		
Log (Household)	1.02	0.79	0.10
Income	0.07**	0.03	0.07
Education	0.01	0.04	0.01
Year fixed-effects	Yes		
Mundlak group means	Yes		
Constant	-0.90	5.82	
R-squared	0.40		
N	1808		

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance. Standard errors are robust.

Figure 1. Map showing CRS participating communities in Alabama, Mississippi, and Florida

(Source: FEMA)