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Community-level flood mitigation effects on household-level flood insurance and damage claims payments

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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 fixed-effects and 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, whereas significant effects on damage claims payments are limited.

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

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I. INTRODUCTION

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 2015). 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 2015). 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). This 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). In an effort to increase both flood mitigation activity at the community level and NFIP participation at the household level, FEMA created the Community Rating System (CRS) in 1990. Participation in the CRS is optional, and provides a mechanism by which residents in a 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 actually affects these outcomes. Zahran et al. (2009) find a positive and significant relationship between increased CRS participation and NFIP participation (policies-in-force). Michel-Kerjan and Kousky (2010) find a negative relationship between increased CRS participation and damage claims payments. Highfield and Brody (2013) find a negative relationship between some, but not all, specific CRS mitigation activities and damage claims payments. Brody et al. (2007a & 2007b) find a negative relationship between increased CRS participation and property damages (measured as the dollar value of total losses from flood events).

However, with the exception of Michel-Kerjan and Kousky (2010), who analyzed the effect of CRS participation on damage claims payments, these studies have focused on within-CRS effects, i.e., how marginal changes in CRS points or class affect NFIP participation (policies-in-force), damages, or damage claims payments. They have not examined the effect of participating (or not) in the CRS. Furthermore, almost all such work has focused on either Florida or Texas. Although Highfield and Brody (2013) used a sample of CRS participating communities across the U.S., they looked only at the effects of specific CRS activities on damage claims payments.

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, such as the use of matching methods. 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, using key geospatial and socioeconomic indicators during the matching procedure to achieve balance and obtain the final matched sample.

In this paper, we depart from earlier studies by looking at the discrete impact of CRS participation (versus non-participation) on NFIP participation (measures 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. Our study area focuses on panel data running from 1994 to 2013 for NFIP communities in Alabama and Mississippi. Overall, we find that participation in the CRS leads to a significant increase in household participation in the NFIP, with relatively greater effects among coastal communities. We find significant effects of CRS participation on damage claims payments only in one of the states studied (Alabama), and only among non-coastal communities.

The rest of the paper is outlined as follows. In Section II we provide a background on NFIP and CRS. The study area and data used to inform our analyses are presented in Section III of the paper. In Section IV, we develop a model framework to link the outcome variables (i.e., NFIP participation and damage claims payments) to our independent variables. We also discuss the genetic matching technique used. The econometric models employed to inform our analyses are discussed in Section V. In Section VI, we present and discuss the results. In Section VII, we conclude and discussion policy implications.

II. BACKGROUND

National Flood Insurance Program (NFIP)

The National Flood Insurance Act of 1968 created the National Flood Insurance Program (NFIP) to provide flood insurance to individuals and businesses. Prior to that, flood insurance was not widely available due in part to adverse selection and high costs of servicing claims when a major flood disaster occurred (Michel-Kerjan and Kousky 2010).

Flood risk designation is accomplished via Flood Insurance Rate Maps (FIRMs), produced by the US Army Corps of Engineers. On the FIRMs, flood risks are classified into two distinct categories: the Special Flood Hazard Area (SFHA) and the area outside of the SFHA, referred to here as the Non-SFHA. As the names imply, SFHA includes high risk areas and the Non-SFHA includes moderate-to-low risk areas. Specifically, the SFHA is the land area covered by the floodwaters of the “base flood” on 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.

The SFHA is further delineated into “A” and “V” zones.[1] V zones are coastal high hazard areas that experience high-velocity wave action (i.e., storm surge), and A zones are inland high hazard areas. Specific zones outside of the SFHA, i.e., the Non-SFHA zones, include B, C, X (shaded and unshaded), and D zones. Zones B and X (shaded) are moderate flood hazard areas,

[1] Actually, the zones in the SFHA include A, AO, AH, A1-30, AE, A99, AR, AR/A1-30, AR/AE, AR/AO, AR/AH, AR/A, VO, V1-30, VE, and V. For the purposes of discussion here, “A” and “V” are sufficient.

whose risk falls between the limits of the base flood and the 0.2-percent-annual-chance (or 500-year) flood. Zone C and X (unshaded) are minimal flood hazard areas with elevation above the 0.2-percent-annual-chance (or 500-year) flood. Zone D is used for areas where there are possible but undetermined flood hazards, or where a community incorporates portions of another community's area where no map has been prepared (FEMA 2016b).

Properties located in flood risk areas that are not mapped onto the FIRM (referred to as "pre-FIRM"), i.e., where no flood maps exist, are eligible to receive subsidized flood insurance policies until FIRMs are created. For areas located on the FIRM, strict building ordinances and actuarial flood insurance rates apply to new developments (Kunreuther and White 1994; Adelle and Leichenko 2011). NFIP policies come in two forms, the actuarial policies and the discounted policies. About a quarter of the entire NFIP policy rates are subsidized on pre-FIRM bases (Bin, Bishop, and Kousky 2012). Flood insurance premia are set nationally, but vary according to flood zone designation and building characteristics such as elevation above base flood.

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

2016c). 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 2016c). 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 2016c). 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 2016c).

Community Rating System (CRS)

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 called “series”, labeled Series 300, 400, 500, and 600, respectively (NFIP CRS Coordinator’s Manual 2013). Activities under series 300 (public information) aim to motivate flood insurance purchase and provide information to residents on how to reduce flood damages. Series 400 activities (mapping and regulations) involves mapping of areas onto FIRMs, protecting floodplains, managing storm water, and ensuring higher standard regulations. Activities under series 500 (flood damage reduction) involve the adoption of good floodplain management plans, relocating flood-prone structures, and maintaining community drainage systems. Series 600 activities (warning and response) seek to provide warnings of possible floods, and also respond to flood events so as to minimize loss of life and property.[2]

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 of 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). In most cases, NFIP communities that enter the CRS program for the first time are rated as class 9 (FEMA 2015), but those that do not earn at least 500 points are eventually re-classified as class 10. Class 10 communities are not eligible for premium discounts, and are treated as non-participating communities. Table 1 reports the premium discounts associated with each CRS class, which differs for SFHA and non-SFHAs. Policy discounts range from 0% to 45%, in 5% increments for residents located in SFHAs. For

[2] Flood mitigation activities may be classified as "structural" or "non-structural". Structural forms consist of large-scale construction projects such as seawalls and channels, while non-structural forms consist of land use planning tools, flood insurance, education and training, and emergency and recovery policies (Highfield and Brody 2013). A Community's preference over the two forms has been shown to be a function of cost. Highfield and Brody (2013) argue that CRS is skewed in favor of non-structural forms. Brody et al. (2009a) found that local jurisdictions in Florida and Texas rely more on non-structural forms, whereas Brody, Kang, and Bernhardt (2010) find that Florida communities rely relatively more on non-structural forms whereas Texas communities rely more on structural forms.

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.[3]

The CRS program is updated every three years. However, some minor changes to the program occur on yearly basis (FEMA 2016f). The recent major update to the CRS program occurred in 2013. The goal of the changes were 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 CRS activity 420 (Open Space Preservation) have increased whereas points available for CRS activity 320 (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 2013b).

Despite the potential benefits to participating communities and their residents, the CRS program, like the NFIP, appears to suffer from low participation, although it depends on how

[3] Residents in flood zones B, C, and X, are also typically eligible for so-called "Preferred Risk Policies" that are cheaper than the standard policies in these non-SFHA zones. Residents with such policies are not eligible to receive CRS premium discounts (FEMA 2013a). Residents that have made repeated claims and/or received multiple federal flood relief disaster payments are not eligible for Preferred Risk Policies. Residents of Emergency Program communities, which are communities where flood hazard information is not available and/or no FIRMs exist, are also not eligible for CRS premium discounts. Residents in Emergency communities have a restricted amount of coverage that is less than the actuarial rates (FEMA 2016e).

participation is measured. Of the more than 22,000 NFIP communities in the U.S., only 5% of them participate in the CRS (FEMA 2016d). 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 2016d). 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. 2009b; Landry and Li 2012; Sadiq and Noonan 2015).

III. STUDY AREA AND DATA

The states of Alabama and Mississippi are located on the Gulf of Mexico coast of the United States. Figure 1 shows the distribution of CRS participation by communities in Alabama and Mississippi.[4] 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 2013a). 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.

Data on NFIP policies-in-force, damage claims payments, CRS, geospatial and socioeconomics were merged into a single dataset by cross-referencing FEMA community

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[4] 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.

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. The merging process was done using Microsoft Excel and ArcGIS software. NFIP communities that did not have at least 20 policies-in-force for at least two periods were omitted from the analysis.

Table 2 presents the variables, their description, unit of measurement, and data source. 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.

IV. MODEL FRAMEWORK

Based on findings from past studies (Smith 1968; Smith and Baquet 1996; Coble et al. 1996; Marquis and Long 1995; Kriesel and Landry 2004; Schmidt and Zank 2007; Zahran et al. 2009; Landry and Jahan-Parvar 2011; Petrolia, Landry, and Coble 2013; Gallagher 2013; Petrolia et al. 2015; Cummins and Tennyson 1996; Brody et al. 2007a and 2007b; Michel-Kerjan and Kousky 2010; Highfield and Brody 2013; Brody, Highfield, and Blessing 2015), 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*. Specifically, let Equation 1 describe the relationship between outcome *y* (i.e., *NFIP participation*, measured as the number of NFIP policies-in-force in a community in a given year; or *Damage claims payments*, measured as total dollar value of claims in a community in a given year) and the set of explanatory variables:

$$y = f\left(\begin{array}{l} CRS, Years\ in\ CRS, Coverage, A\ \ flood\ zones, V\ \ flood\ zone, B\ \ flood\ zone, C\ \ flood\ zone, \\ Coast, Mississippi, Slope, Elevation, Stream\ density, Precipitation, Household, \\ Income, Education, Community\ \ fixed-effects, Year\ \ fixed-effects \end{array} \right) \qquad [1]$$

The *CRS* variable, *Years in CRS*, and *Coverage* are the policy variables. *Coverage* only enters the damage claims model while *Years in CRS* enters the NFIP participation model. The *Community fixed-effects* and *Year fixed-effect* are to account for individual community heterogeneity and year effects respectively. The geospatial variables we include in our models are *A flood zones*, *V flood zone*, *B flood zones*, *C flood zones*, *Coast*, *Mississippi*, *Slope*, *Elevation, Stream density,* and *Precipitation*. We include *Precipitation* only in the NFIP participation model. Socioeconomic variables are *Household, Income, and Education*.

Cummins and Tennyson (1996) mention that because people's marginal utility decreases as wealth increases, it is expected that wealthier policyholders would have lower motivation for filing damage claims. However, one could also expect that when a damage event occurs, claims payments made to wealthy individuals will be higher, relative to low income earners given that wealthier people have higher coverage. As such, to control for the different levels of coverage, we include dollar amount of *Coverage* in our damage claims payments model.

We include the variables *A flood zones, V flood zone, B flood zone, and C flood zone* in both NFIP participation and damage claims models. *A and V flood zones* are associated with SFHA and *B* and *C flood zones* associated with non-SFHA. Petrolia, Landry, and Coble (2013) find a positive relationship between individuals located in SFHAs and flood insurance demanded. Michel-Kerjan and Kousky (2010) find that damage claims payments increases in SFHA relative to non-SFHA, noting higher average claim payments in V zones relative to A zones. We include in our models the variable *Coast*. Zahran et al. (2009) finds a positive relationship between proximity to the coast and NFIP policies-in-force, and Petrolia et al. (2015) finds the same with regard to wind insurance purchase. We include *Precipitation* in our damage claims model. Gallagher (2013) finds that flood insurance uptake increases immediately after a community experiences flooding, and Brody et al (2007a and 2007b), Spekkers et al. (2013), Highfield and Brody (2013), and Brody, Highfield, and Blessing (2015) find that *Precipitation* has a positive effect on property damage, damage claims, damage claims payments, and insured flood losses, respectively. We also include a *Slope* variable in our models. Highfield and Brody (2013) find that slope has a positive effect on damage claims payments in SFHAs, whereas Brody, Highfield, and Blessing (2015) find a negative effect on insured losses (except for in the V zone). We include an *Elevation* variable as well. Although not in geospatial terms, Michel-Kerjan and Kousky (2010) find that *Elevation* of a building has a negative effect on damage claims payments. We include a *Stream density* variable. Zahran et al. (2009) controlled for stream density but did not find any effect on NFIP participation, and Brody et al. (2007a) found no effect between stream density and property damage.

For socioeconomic factors, we include *Households*, *Income*, and *Education* in our models. Dixon, Macdonald, and Zissimopoulos (2007) argue that rising demand for insurance for properties in the Gulf and Atlantic Coast can be explained by the increasing population growth and property values. With regards to damage claims payments, Highfield and Brody (2013) find population to be positively related to damage claims payments, and Brody, Highfield, and Blessing (2015) find a positive relationship between *Households* and insured flood losses. Browne and Hoyt (2000); Kriesel and Landry (2004); Kousky (2011); and Petrolia, Landry, and

Coble (2013) find *Income* to be positively related to flood insurance demand, whereas Coble et al. (1996) find a negative relationship between crop producers' wealth and the likelihood that they will purchase crop insurance. Related to this finding, Smith and Baquet (1996) note that wealthier farm operators are more likely to self-insure. Marquis and Long (1995) find *Income* to be positively related to demand for health insurance by non-employment based insurance (i.e., workers who do not receive health insurance as work benefit). Petrolia et al. (2015) find a positive relationship between the log of *Income* and wind insurance purchase. Smith and Baquet (1996) observed in their study that farm operators' level of *Education* is positively related to their decision to demand multiple-peril crop insurance. Brody, Highfield, and Blessing (2015) find *Income* to be positively related to insured flood losses. We also include *Education* in our damage claims payments model.

V. MATCHING

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 Green 2008). 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. 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).

Generally, the Mahalanobis metric-distance performs better (in terms of balance) when covariates are ellipsoidally distributed (Rubin 1980; Diamond and Sekhon 2013). However, an increase in the number of covariates matched on could distort the ability of the Mahalanobis metric-distance approach to find units with similar distribution of covariates (Gu and Rosenbaum 1993; Rubin and Thomas 2000). Alternatively, one may match on the propensity scores as suggested by Rosenbaum and Rubin (1983) if the covariates are distributed non-ellipsoidally. A poorly-specified propensity score model, however, could worsen balance and also bias the estimates of the outcome (Diamond and Sekhon 2013). Genetic matching, proposed by Diamond and Sekhon (2013), is a more general form of the Mahalanobis metric distance approach. What makes genetic matching unique is that unlike other matching methods, it uses a search algorithm to locate a metric distance that optimizes covariate balance.

Regardless of the method used, a matching algorithm is needed to select units from the control and treatment groups (Diamond and Sekhon 2013). Various matching algorithms, including nearest-neighbor, radius, caliper, and stratification have been discussed in the literature (see Sianesi 2001; Stuart and Greene 2008; Dehejia and Wahba, 2002; Diamond and Sekhon 2013).

Here, we employ the genetic matching approach of Diamond and Sekhon (2013). 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). Following Diamond and Sekhon (2013), the generalized Mahalanobis distance is defined as

$$GMD_{(\boldsymbol{k}_i,\boldsymbol{k}_j,\boldsymbol{w})} = \sqrt{\left(\boldsymbol{k}_i - \boldsymbol{k}_j\right)\boldsymbol{w}\boldsymbol{z}^{-1/2}\left(\boldsymbol{z}^{-1/2}\right)'\left(\boldsymbol{k}_i - \boldsymbol{k}_j\right)'} \quad [2]$$

where $\boldsymbol{z}^{-1/2}$ is the sample covariance of the covariates (Cholesky decomposition of $\boldsymbol{z}$), and $\boldsymbol{k}$ is the vector of covariates. The covariates could be replaced with estimated propensity scores or one can include both the estimated propensity scores and the covariates. $\boldsymbol{w}$ is the weight matrix, which is positive definite with zero off-diagonal elements.

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 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: *A flood zones*, *V flood zone*, *B* and *C flood zone* (i.e., *B* and *C flood zone* combined), *Coast, Mississippi, Slope, Elevation, Stream density, Household, Income, and Education*.[5] The

[5] 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 has to account for all variables that otherwise would have been used in a regression,

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). Table 3 reports the means of the covariates before and after the matching. For the treatment group, means of the covariates are necessarily the same before and after matching. For the control group, the means of the covariates for the control group are closer to the means of the treatment group after matching. For example, the treatment group mean for *Elevation* is 218.78. Before matching, the mean of the control group is 367.73, but after matching is 224.06, as shown in Table 3.

To examine the effectiveness of the matching procedure, we follow Ho et al. (2007) to construct quantile-quantile (QQ) plots of the pre-treatment covariates used in the genetic matching. For binary variables *Coast* and *Mississippi*, we exhibit the distributions using histograms. Figure 2 contains the QQ plots of the covariates before and after matching. In the QQ plots, points more proximal to the 45^{o} line depict good matches, whereas points more distant to the 45^{o} line indicate poor matches, between the treatment units and the control units. With the histogram, for a good match, the bars for the treated and the control units should be level or nearly level relative to before matching. A visual examination of the QQ plots shows that pre-treatment

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not all pre-treatment covariates are to be used especially when including them in the matching process leads to inefficiency and reduces balance.

covariates such as *A flood zones, Slope, Elevation, Household, Income,* and *Education* have improved distributions after the genetic matching was done relative to before. On the other hand, the distributions of pre-treatment covariates *V flood zone, B and C flood zone, and Stream Density,* do not improve much. The histograms indicate improvements in the distributions for *Coast* and *Mississippi*. Table 4 contains the weighted summary statistics of the variables used in the econometric model, and reports the expected signs for the independent variables.

VI. ECONOMETRIC MODEL

The data comprise a panel (i.e., has a cross-section (*N*) and a time-series dimension (*T*)). Let

$$y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + c_i + \varepsilon_{it} \qquad [3]$$

where, y_{it} is the dependent variable (*NFIP participation and Damage claims payments*) we seek to explain, $\boldsymbol{x}_{it}$ is a vector of covariates. Specifically, the vector contains the policy-related variables CRS_j , where, for the NFIP participation model, *j = Alabama Coastal communities pre-Katrina, Alabama non-coastal pre-Katrina, Alabama coastal post-Katrina, Alabama non-coastal post-Katrina, Mississippi coastal pre-Katrina, Mississippi non-coastal pre-Katrina, Mississippi coastal post-Katrina,* and *Mississippi non-coastal post-Katrina; and for the Damage claims payments model, j = Alabama coastal communities, Alabama non-coastal, Mississippi coastal, and Mississippi non-coastal.* The vector also contains the policy-related variables *Years in CRS* and *Coverage*; geospatial variables *A Flood Zones, V Flood zone, B Flood Zone, C Flood Zone, Coast, Mississippi, Coast × Mississippi, Slope , Elevation, Stream density,* and *Precipitation;*

socioeconomic variables *Household, Income,* and *Education*. $\boldsymbol{\beta}$ is a vector of parameters, c_i is the unobserved heterogeneity (i.e., *Community* and *Year fixed-effects*), and ε_{it} is the error term. The subscripts i and t are the units (in our case, the communities) and time (year), respectively.[6]

Panel data models vary based on the assumption that underlies the conditional mean, $E\left[c_i \middle| x_i\right]$, of the unobserved heterogeneity $\left(c_i\right)$ in equation 3. That is, we may have a pooled model, $E\left[c_i \middle| x_i\right] = h\left(x_i\right) = \alpha$, where α is a constant for all individual units, hence no individual unobserved heterogeneity, or a fixed-effects model which assumes that $E\left[c_i \middle| x_i\right] = h(x_i) = \alpha_i$, where α_i represents a constant term for a particular unit. The random-effects model assumes that, $E\left[c_i \middle| x_i\right] = 0$ (Wooldridge 2002; Greene 2012). Unlike the fixed-effects model, random-effects does not allow the individual unobserved heterogeneity to be correlated with the independent variables (Greene 2012). It is 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 2012). Another model variation is the Mundlak (1978)

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[6] The econometric model as shown in equation 4 is analogous to the difference-in-differences (DD) approach. The DD seeks to compare changes in outcomes between a group that receives treatment (CRS participating communities) and those that did not receive the treatment (non-CRS communities) (Carpenter 2004, and Ravallion and Chen 2005). Unlike the traditional DD 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 DD gives one the freedom to control for other covariates.

approach, which is similar to the random-effects model. However, here, the correlation between the observed covariates and the unobserved heterogeneity are addressed by adding as covariates group-means of the time-varying covariates (Greene 2012). For example, if an income variable is included in the model that varies over time, then an additional group-mean income variable would also be included that repeats the mean of a given individual's income over all of that individual's observations. Thus, this approach assumes that $E[c_i \mid \boldsymbol{x}_i] = h(\boldsymbol{x}_i) = \bar{\mathbf{x}}_i'\boldsymbol{\gamma}$. As noted by Greene (2012), the Mundlak approach can be used as a compromise between the fixed and random-effects models.

Testing for Model Assumptions

To test for panel effects (i.e., to test a pooled model against a random- or fixed-effects panel model), the Breusch-Pagan (B-P) Lagrange multiplier test is used (Greene 2012). The Hausman test (Hausman 1978) is then used to test the null hypothesis of random effects against fixed effects. Wu's variable addition test (Wu 1973) is also used 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 test 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.

Results on the tests for assumptions on the individual effects show that for the NFIP policies-in-force model, we reject the null hypothesis of no panel effects (Breusch-Pagan statistic, $\chi^2 = 4340.31$, df = 1). The Hausman test for random-effects vs. fixed-effects shows that the null hypothesis of random-effects is rejected (Hausman statistic, $\chi^2 = 39.81$, df = 12). Result on Wu's variable addition test (Wald statistic, $\chi^2 = 97.97$, df = 12) indicates a rejection of the null hypothesis that individual effects are not correlated with the regressors (i.e., the Mundlak's approach does not mimic a random-effects model, but rather a fixed-effects model). Therefore, we report results based on the Mundlak's approach for the NFIP participation (number of policies-in-force) model. Considering the damage claims payments model, we reject the null hypothesis of no panel effects (Breusch-Pagan statistic, $\chi^2 = 59.44$, df = 1). The Hausman test (Hausman statistic, $\chi^2 = 24.26$, df = 9), indicates that we fail to reject the null hypothesis of random-effects and the Wu's variable addition test result (Wald statistic, $\chi^2 = 37.23$, df = 9) also indicates a rejection of the null hypothesis that individual effects are not correlated with the regressors (i.e., the Mundlak's approach is preferred although at a weak level of significance).

Based on the results of the tests for correlation and heteroscedasticity, we find the presence of serial correlation (Wooldridge statistic, F = 287.09, df = 1, 112), contemporaneous correlation (Pesaran statistic, Z = 10.38), and heteroscedasticity (White statistic, $\chi^2 = 1369.50$, df = 586) in the NFIP policies-in-force model. The results also show evidence of heteroscedasticity (White statistic, $\chi^2 = 901.77$, df = 554) but no serial correlation (Wooldridge statistic, F = 0.31, df = 1,112) and contemporaneous correlation (Pesaran statistic, Z= -2.83) in the damage claims payments model. 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.

We estimate all models, with robust standard errors, using NLOGIT 5 software (Greene 2012). Matching weights serve as the regression weights. Here, the matching weights enter the regression as follows:

$$\boldsymbol{b}_w = \left[\sum_i w_i \boldsymbol{x}_i \boldsymbol{x}_i'\right]^{-1} \left[\sum_i w_i \boldsymbol{x}_i y_i\right] \qquad [4]$$

where $\boldsymbol{b}_w$ is the vector of estimated parameters, w are the matching weights and $\boldsymbol{x}$ and y are as previously defined.

VII. RESULTS

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

In Table 5, we report results on the effects of CRS participation on NFIP participation (log of number of policies-in-force), based on the fixed-effects and Mundlak's approach. Reported are the raw coefficients, robust standard errors, and marginal effects. Marginal effects are calculated by exponentiating the raw coefficient.[7] Although the fixed-effects approach has a much better overall model fit in terms of R^2 value, the results are strikingly similar, making it possible to discuss both sets of results simultaneously. The Mundlak model allows for inclusion and interpretation of additional policy-relevant time-invariant variables. Additionally, although we discuss results based on the matched sample, we also estimate models using the full unmatched sample, reported in the Appendix. We find that models based on matched data out-perform those

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

based on the full, unmatched data set: matched results have better fit statistics and a greater number of significant coefficients on policy variables (i.e., *NFIP participation* and *Damage claims payments*).

The results show a positive and significant relationship between CRS participation and NFIP participation (policies-in-force) for coastal Alabama both pre- and post-Katrina, and for coastal Mississippi post-Katrina. Specifically, we find that, pre-Katrina, the number of NFIP policies-in-force is 63% higher in coastal Alabama communities participating in the CRS, and 90% higher post-Katrina.[8] In coastal Mississippi, there is no significant effect pre-Katrina, but there is a 64% increase in the number of NFIP policies-in-force post-Katrina.   Zahran et al. (2009), also find a positive relationship between increased CRS participation and NFIP participation. Unexpectedly, we find a significantly lower number of policies-in-force for non-coastal Alabama communities pre-Katrina (15% lower), but find no other significant CRS effects among non-coastal communities. Also somewhat surprisingly, the coefficient of *Years in CRS* is negative and significant. That is, for every additional year in *CRS* participation, *NFIP policies-in-force* declines by 10%. This result may reflect the fact that, as the time between major storm events increases, residents tend to let their coverage lapse.

The Mundlak's approach which reports estimates on time-invariant geospatial variables shows that, as expected, *A and V flood zones* have a positive and significant relationship with *NFIP participation*. However, only the coefficient on A flood zones is significant. That is, *ceteris paribus*, a 10-percent increase in the proportion of land in a community that is in an *A*

[8] For example, the CRS effect for coastal Alabama pre-Katrina is exp(0.49) = 1.63, i.e., a 63% increase over the base case (i.e., non-CRS communities in Alabama pre-Katrina).

flood zone increases *NFIP participation* by 37 percent.[9] Parameter estimates on *B and C flood zones* are negative but not significant. *B and C flood zones* are non-SFHA (i.e., have less flood risk compared to *A and V flood zones*). The coefficients on *Coast* and *Mississippi* are not individually significant, but the interaction between them is positive and significant, implying higher *NFIP participation* among coastal Mississippi communities. Parameter estimates on *Slope*, *Elevation*, and *Stream density* are also negative but only *Slope* and *Elevation* significantly affect *NFIP participation*. The coefficient on the *Slope* variable indicates that a one degree increase in the mean *Slope* of a community reduces the number of NFIP policies-in-force by 31 percent, *ceteris paribus.* Also, a 100-foot increase in *Elevation* reduces NFIP policies-in-force by 18 percent, *ceteris paribus*. The negative relationship between *Elevation* and *NFIP participation* is as hypothesized. On *Stream density*, Zahran et al. (2009) also find no effect between stream density and NFIP policies-in-force.

Among the socioeconomic variables, log(*Household*) has a positive and significant effect on *NFIP participation*: a 10 percent increase in the number of *Households* in the community increases the number of *NFIP policies-in-force* by 10 percent, *ceteris paribus*.[10] The finding on the relationship between *Household* and the number of *NFIP policies-in-force* is consistent with the argument made by Dixon, Macdonald, and Zissimopoulos (2007). Although the positive sign between *Income* and *NFIP participation* is as expected, the relationship is not significant. The coefficient on *Education* is not significant in explaining the number of *NFIP policies-in-force*.

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[9] The marginal effect is calculated as $\exp(3.138/10) = 1.37$.

[10] The marginal effect is calculated as $1.10^{0.91} = 1.09$.

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

Results presented in Table 6 are based on the Fixed-effects and Mundlak's approach. We find a significant effect of *CRS* participation among non-coastal Alabama communities only. Specifically, we find that such communities have 90% lower claims (in terms of value).[11] We tested for, but found no significant differences in *CRS* effects on damage claims pre- and post-Katrina. No other significant *CRS* effects on damage claims were found. The parameter estimate for log(*Coverage*) is positive and significant in explaining *Damage claims payments* under the Mundlak specification only. That is *ceteris paribus*, a 1-percent increase in total *Coverage* in the community leads to a 0.2 percent increase in *Damage claims payments*.

On geospatial variables, results from the Mundlak's approach show that the variables *A flood zones*, *V flood zone*, and *B flood zone* have a positive relationship with *Damage claims payments* but only *V flood zone* is significant. That is, a 10-percent increase in land in the V flood zone increases damage claims payments by 58 percent, *ceteris paribus*. With the exception of *B flood zone*, the positive coefficients are as hypothesized. We have no ready explanation for why this might be the case for *B flood zone.* Parameter estimate on *C flood zone* is negative as expected but it is not significant. The coefficient on *Coast* is also positive and significant as hypothesized. Specifically, *Damage claims payments* are 442 percent higher for coastal communities compared to noncoastal communities. The coefficients on *Mississippi* and the

[11] Birmingham, Decatur, Hoover (a suburb of Birmingham), Homewood (a suburb of Birmingham), Huntsville, and Pell City are the only non-coastal Alabama communities participating in the CRS. The sample contains a high number (50) of observations with zero claims for these communities.

Coast×Mississippi interaction are also positive but not significant. The coefficient of *Slope* is positive and significant. Highfield and Brody (2013) also find a positive relationship between *Slope* and total *Damage claims payments*, although their estimate is not significant. Brody, Highfield, and Blessing (2015) on the other hand find a negative relationship between *Slope* and insured damage losses (except for losses in V-flood zones). The parameter estimate for *Elevation* is negative as expected, but not significant. Unexpectedly, the coefficient on *Stream Density* is also negative and significant. Brody et al. (2007a) find no effect between *Stream density* and property damage. We find a positive and significant relationship between *Precipitation* and *Damage claims payments* as hypothesized. However, it is significant only for the fixed-effects model. That is, a 1-inch increase in *Precipitation* increases *Damage claims payments* by 19 percent, *ceteris paribus*. Both Highfield and Brody (2013) and Spekkers et al. (2013) find a positive relationship between *Precipitation* and *Damage claims payments* and the number of damage claims, respectively. Brody et al (2007a & 2007b) also finds that *Precipitation* has a positive effect on property damage.

On socioeconomic variables, both the fixed-effects and the Mundlak's approach show a positive relationship between log(*Household*) and *Damage claims payments*. However, only the result from Mundlak's approach is significant. That is, a 10 percent increase in the number of *Households* in the community increases *Damage claims payments* by 6 percent, *ceteris paribus*. We find no significance for, *Income* in both estimation approaches, although the relationship is positive. Brody et al. (2007b) also find a positive but not significant relationship between *Income* and property damage (measured in dollars) from floods. Although results show a positive relationship between *Education* and *Damage claims payments*, it is only significant for the

Mundlak approach. That is, *ceteris paribus,* a 1 percent increase in the percent of college educated increases damage claims payments by 21 percent.

VIII. 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 in order to mitigate comparison bias. This study is also the first to provide empirical findings specific to the states of Alabama and Mississippi.

We find that participation in the *CRS* program increases participation in the *NFIP*. We also find that growth in *NFIP participation* does not increase as the tenure of a community in CRS increases. We find that overall, *NFIP participation* is higher among coastal communities in Mississippi compared to coastal communities in Alabama. We can only speculate as to why this might be the case. The NOAA Office for Coastal Management reports that Alabama has a larger coastal population than Mississippi (595,257 vs. 370,702), and more coastline miles (607 vs. 359), but that Mississippi experienced a slightly higher number of billion-dollar disasters between 1980 and 2016 (62 vs. 57), and perhaps this last fact is the underlying reason (NOAA 2016a and b). The finding on the impact of *CRS* participation (versus non-participation) on *NFIP participation* appears to support the goal of the CRS program in improving *NFIP participation*. This implies that premium discounts awarded on individual policies in CRS communities may indeed be motivating residents to purchase flood policies.

With regards to *CRS* effects on *Damage claims payments*, we find a significant effect of *CRS* participation on *Damage claims payments* only for Alabama non-coastal communities. Although one of the goals of the *CRS* program is to reduce damages to insured properties, we find very limited evidence for such effects in our study area, especially in the coastal zone, where we find no significance in either Alabama or Mississippi. This lack of significant impact of *CRS* participation on *Damage claims payments* (with the exception of non-coastal Alabama) 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.

Overall, the analysis this paper provides indicates that the CRS program appears 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 indicate that there may be some disconnect between CRS participation and reduced damage claims. Having said this, although FEMA might be witnessing an increase in household *NFIP participation*, its 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 consider investigating how the changes to the program have impacted 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

CRS Credit Points Earned, Classification Awarded, and Premium Discounts

Classes	Overall CRS points	Discount (%) in SFHA	Discount (%) in Non-SFHA
1	4,500+	45	10
2	4,000 – 4,499	40	10
3	3,500 – 3,999	35	10
4	3,000 – 3,499	30	10
5	2,500 – 2,999	25	10
6	2,000 – 2,499	20	10
7	1,500 – 1,999	15	5
8	1,000 – 1,499	10	5
9	500 – 999	5	5
10	499 and below	0	0

Source: NFIP CRS Coordinator’s Manual (2013)

TABLE 2

Description of Variables

Variables	Unit	Description	Source
		Dependent Variables	
Policies-in-force[a]	(1000s)	Annual total number of NFIP policies-in-force.	FEMA
Damage claims payments[b]	US $	Annual total damage claims payments.	FEMA
		Independent variables	
		Policy variables	
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
Years in CRS	units	= 1 for the first year in CRS, =2 for the second year, etc. = 0 if no CRS participation.	
Coverage	$US	Annual total amount of coverage purchased and scaled (divide) by 10,000,000.	FEMA
		Geospatial variables [c]	
A flood zone	%	Measured as the percent of land area in a community classified as A flood zones.	FEMA
V flood zone	%	Measured as the percent of land area in a community classified as V flood zones.	FEMA
B flood zone	%	Measured as the percent of land area in a community classified as B flood zone.	FEMA
C flood zone	%	Measured as the percent of land area in a community classified as C flood zones.	FEMA
Coast	Binary	= 1 if NFIP community is a NOAA-designated coastal community, = 0 otherwise.	NOAA
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

TABLE 2 (continued)

Stream Density	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
		Socioeconomic variables	
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
		Fixed-effects variables	
Post-Katrina	Binary	= 1 if year > 2005, = 0 otherwise (Pre-Katrina)	
Community fixed-effects			
Year fixed-effects	Binary	=1 for 1994, 0 otherwise, 1 for 1995, 0 otherwise, etc.	

Note: NOAA is National Oceanic and Atmospheric Administration; USGS is United States Geological Survey; PRISM is Parameter-elevation Relationships on Independent Slopes Model; ACS is American Community Survey; 1990, 2000, and 2010 US Census Bureau/ ACS data were used.

[a] skewness = 4.24, kurtosis = 22.07, and Shapiro-Wilk normality test of 0.40 (p-value of 0.00)

[b] skewness = 17.16, kurtosis = 317.46, and a Shapiro-Wilk normality test of 0.08 (p-value of 0.00)

[c] With the exception of Mississippi and Coast, geospatial variables were measured based on a 4 km grid cell.

TABLE 3

Means of Covariates Before and After Matching

	Mean of Treatment		Mean of Control	
Variables	Before match	After match	Before match	After match
A flood zone	0.234	0.234	0.202	0.229
V flood zone	0.063	0.063	0.003	0.031
B and C flood zone	0.661	0.661	0.770	0.729
Coast	0.488	0.488	0.116	0.447
Mississippi	0.721	0.721	0.474	0.587
Slope	1.978	1.978	2.763	2.112
Elevation	218.780	218.780	367.730	224.060
Stream Density	1.279	1.279	1.506	1.456
Household	14265	14265	69726	15961
Income	44646	44646	38129	44087
Education	0.179	0.179	1.228	0.168

TABLE 4

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	706.02	1536.53	0.00	10150	
Damage Claims	15.63	165	0.00	3740	
Payments (scaled by 100,000)					
		Independent variables			
		Policy variables			
CRS	0.274	0.45	0.00	1.00	+/-
Years in CRS	2.560	5.13	0.00	20.00	+/
Coverage (scaled by 100,000)	1150	2920	0.00	22600	+
		Geospatial variables			
A flood zones	0.25	0.17	0.00	0.68	+
V flood zone	0.03	0.08	0.00	0.61	+
B flood zone	0.06	0.14	0.00	0.86	?
C flood zone	0.64	0.28	0.00	0.96	?
Coast	0.39	0.49	0.00	1.00	+
Mississippi	0.59	0.49	0.00	1.00	?
Slope	2.23	1.51	0.12	6.98	?
Elevation	247.90	196.21	1.04	805.46	-
Stream Density	1.44	0.45	0.00	2.26	+
Precipitation	59.55	11.80	25.73	170.80	/+
		Socioeconomic variables			
Household	13.97	21.369	0.19	156.77	?
Income	32.56	12.837	2.00	96.78	+/?
Education	18.89	11.215	2.10	60.80	+/?
		Fixed-effects variables			
Post-Katrina	0.40	0.49	0.00	1.00	
Community fixed-effects					
Year fixed-effects					

N = 2260. However, geospatial variables (except precipitation) are time -invariant

*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 5

Fixed Effects and Mundlak's Approach Linear Regression Analysis Predicting NFIP Participation

	Fixed-effect			Mundlak		
Variables	Coef.	S. E.	Marg. E.	Coef.	S. E.	Marg. E.
Policy variables						
CRS						
Alabama						
Coastal, Pre-Katrina	0.49***	0.12	0.63	0.49***	0.12	0.63
Non-Coastal, Pre-Katrina	-0.16**	0.08	0.15	-0.16**	0.07	0.15
Coastal, Post-Katrina	0.64***	0.16	0.90	0.64***	0.16	0.90
Non-Coastal, Post-Katrina	0.09	0.11	0.09	0.09	0.11	0.09
Mississippi						
Coastal, Pre-Katrina	-0.17	0.22	0.16	-0.17	0.21	0.16
Non-Coastal, Pre-Katrina	0.13	0.14	0.14	0.13	0.13	0.14
Coastal, Post-Katrina	0.50**	0.24	0.65	0.50**	0.23	0.65
Non-Coastal, Post-Katrina	0.03	0.14	0.03	0.03	0.13	0.03
Years in CRS	-0.05***	0.01	0.10	-0.05***	0.01	0.10
Geospatial variables						
A Flood Zones				3.14***	1.00	0.37
V Flood zone				0.22	1.63	0.02
B Flood Zone				-0.72	0.81	0.07
C Flood Zone				-0.40	0.77	0.04
Coast				-0.58	0.46	0.44
Mississippi				-0.54	0.36	0.42
Coast×Mississippi				1.33**	0.54	2.78
Slope				-0.37***	0.10	0.31
Elevation				-0.002*	0.001	0.18
Stream density				-0.55	0.35	0.42
Socioeconomic variables						
Log(Household)	0.91***	0.26	0.09	0.91***	0.24	0.09
Income	0.01	0.01	0.01	0.01	0.01	0.01
Education	-0.002	0.01	0.002	-0.002	0.01	0.002
Year fixed-effects	Yes			Yes		
Mundlak Group Means	No			Yes		
Constant				4.18***	0.84	
R^2	0.95			0.74		
N	2260			2260		

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

TABLE 6

Fixed Effects and Mundlak's Approach Linear Regression Analysis Predicting Damage claims Payments

	Fixed-effects			Mundlak		
Variables	Coef.	S. E.	Marg. E.	Coef.	S. E.	Marg. E.
Policy variables						
CRS						
Alabama						
Coast	0.79	2.09	1.20	0.79	2.04	1.20
Non-Coast	-2.34***	0.28	0.90	-2.34***	0.28	0.90
Mississippi						
Coast	0.64	0.74	0.90	0.64	0.72	0.90
Non-Coast	0.90	2.19	1.46	0.90	2.13	1.46
Log(Coverage)	0.19***	0.04	0.002	0.17***	0.02	0.002
Geospatial variables						
A Flood Zones				0.39	1.58	0.04
V Flood zone				4.54*	2.52	0.58
B Flood Zone				1.68	1.33	0.18
C Flood Zone				-0.18	1.20	0.02
Coast				1.69*	1.03	4.42
Mississippi				0.76	0.54	1.14
Coast×Mississippi				0.66	0.95	0.94
Slope				0.47*	0.28	0.60
Elevation				-0.002	0.002	0.18
Stream density				-1.35**	0.57	0.74
Precipitation	0.17***	0.02	0.19	0.65	0.59	0.92
Socioeconomic variables						
Log(Household)	0.65	0.65	0.06	0.05*	0.03	0.01
Income	0.05	0.04	0.05	0.02	0.04	0.02
Education	0.02	0.04	0.02	0.19***	0.04	0.21
Year fixed-effects	Yes			Yes		
Mundlak Group Means	No			Yes		
Constant				-4.56	4.47	
R^2	0.47			0.36		
N	2260			2260		

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

FIGURE 1

A Map Showing CRS Participation Across Alabama and Mississippi (Source: John Cartwright, Geosystems Research Institute, Mississippi State University)

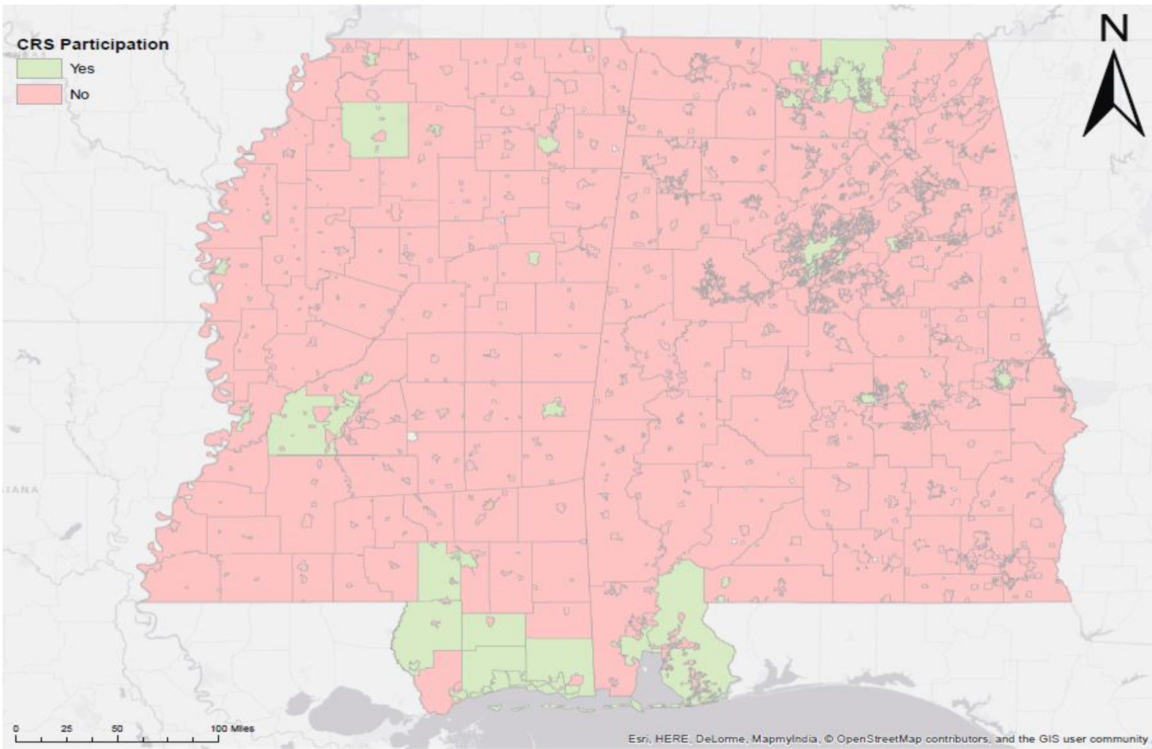


FIGURE 2

QQ Plots Showing the Distribution of Pre-treatment Covariates Before and After Matching

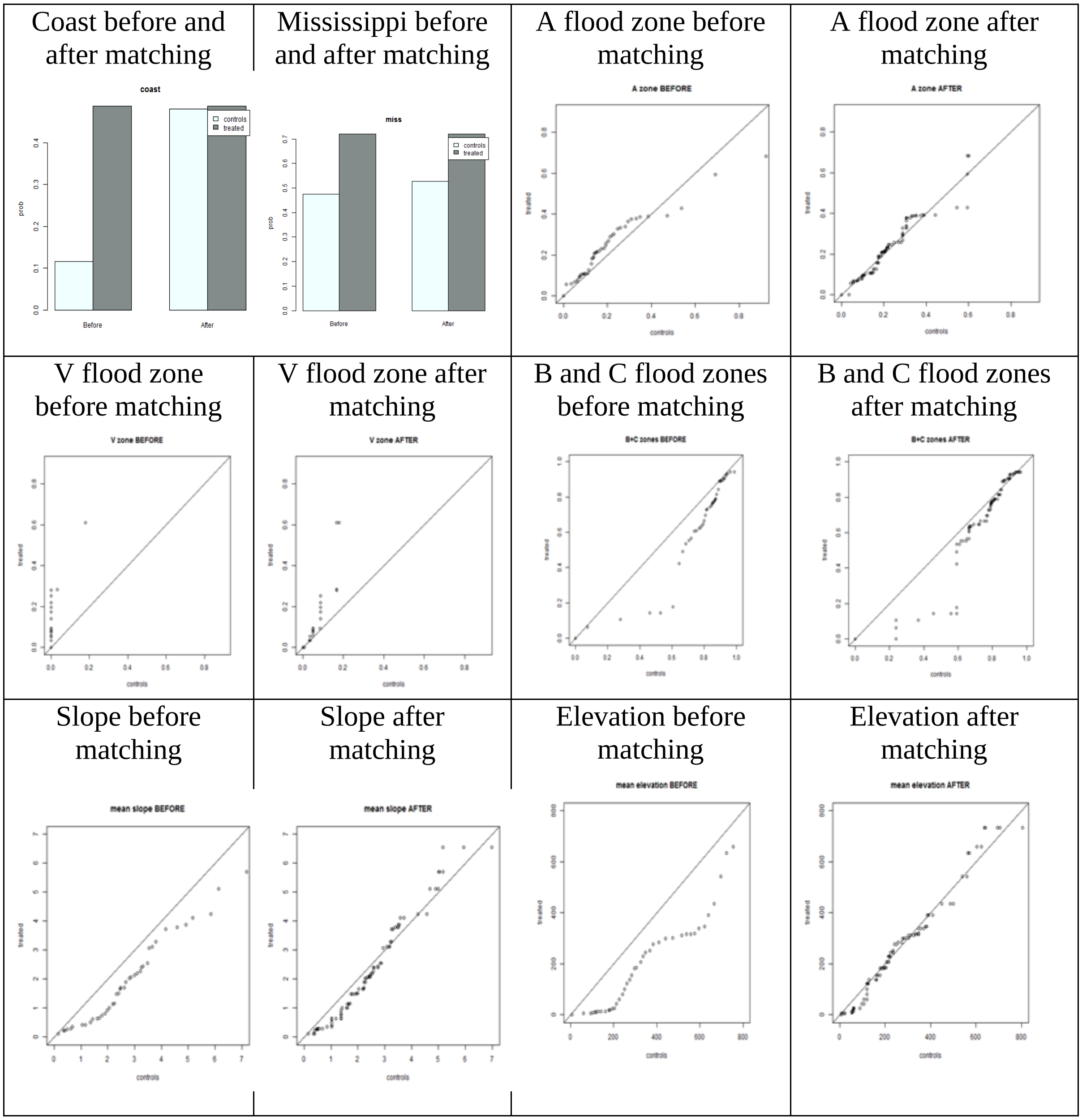
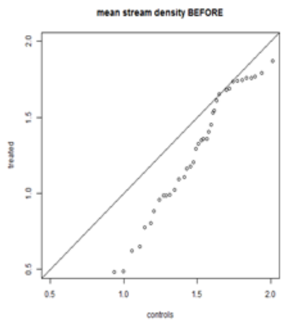
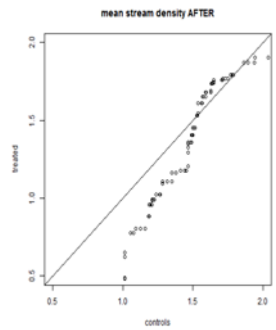


FIGURE 2, CONTINUED

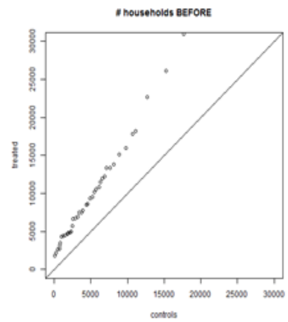
Stream density before matching



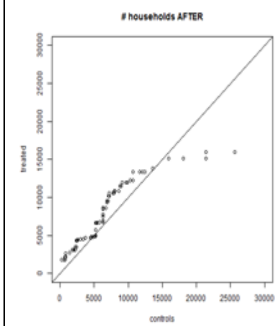
Stream density after matching



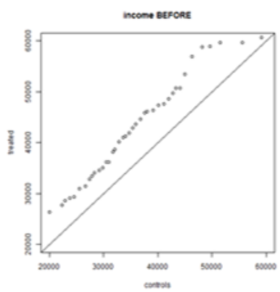
Household before matching



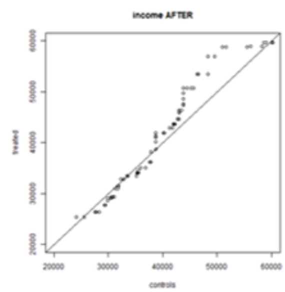
Household after matching



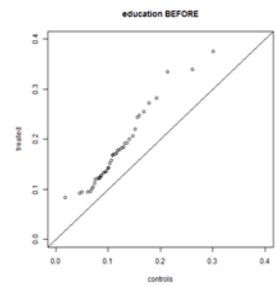
Income before matching



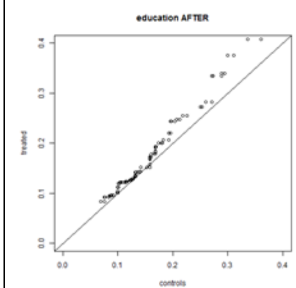
Income after matching



Education before matching



Education after matching



APPENDIX: TABLE A1:

Fixed Effects and Mundlak's Approach Linear Regression Analysis Predicting NFIP Participation based on Full (Unmatched) Sample

	Fixed-effects			Mundlak		
Variable	Coef.	S. E.	Marg. E.	Coef.	S. E.	Marg. E.
			Policy variables			
CRS						
Alabama						
Coastal, Pre-Katrina	0.42***	0.10	0.52	0.42***	0.10	0.52
Non-Coast, Pre-Katrina	0.29	0.34	0.34	0.29	0.33	0.34
Coastal, Post-Katrina	0.53***	0.13	0.70	0.53***	0.13	0.70
Non-Coastal, Post-Katrina	0.43	0.34	0.54	0.42	0.33	0.52
Mississippi						
Coastal, Pre-Katrina	-0.17	0.22	0.16	-0.17	0.21	0.16
Non-Coastal, Pre-Katrina	0.21	0.15	0.23	0.21	0.14	0.23
Coastal, Post-Katrina	0.44*	0.23	0.55	0.44*	0.23	0.55
Non-Coastal, Post-Katrina	0.10	0.16	0.11	0.10	0.15	0.11
Year in CRS	-0.04***	0.01	0.04	-0.04***	0.01	0.04
			Geospatial variables			
A Flood Zones				2.24***	0.44	0.25
V Flood zone				0.48	1.31	0.05
B Flood Zone				0.01	0.41	0.001
C Flood Zone				-1.10***	0.35	0.10
Coast				0.31	0.3	0.36
Mississippi				-0.03	0.18	0.03
Coast× Mississippi				0.73*	0.39	1.08
Slope				-0.06	0.06	0.06
Elevation				-0.001	0.00	0.10
Stream density				-0.43***	0.16	0.35
			Socioeconomic variables			
Log(Household)	0.33***	0.12	0.03	0.33***	0.11	0.03
Income	0.02***	0.01	0.02	0.02***	0.01	0.02
Education	0.01	0.01	0.01	0.01	0.01	0.01
Year fixed-effects	Yes			Yes		
Mundlak Group Means	No			Yes		
Constant				3.07***	0.44	
R^2	0.93			0.63		
N	5860			5860		

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

APPENDIX: TABLE A2:

Fixed Effects and Mundlak's Approach Linear Regression Analysis Predicting Damage claims Payments based on Full (Unmatched) Sample

	Fixed-effects			Mundlak		
Variables	Coef.	S. E.	Marg. E.	Coef.	S. E	Marg. E.
Policy variables						
CRS						
Alabama						
Coast	1.05	2.07	1.90	1.05	2.01	1.90
Non-Coast	0.53	1.70	0.70	0.53	1.65	0.70
Mississippi						
Coast	0.69	0.74	1.00	0.69	0.72	1.00
Non-Coast	1.30	2.00	2.70	1.30	1.94	2.70
Log(Coverage)	0.13***	0.03	0.001	0.13***	0.03	0.001
Geospatial variables						
A Flood Zones				1.71**	0.85	0.19
V Flood zone				2.54	2.24	0.29
B Flood Zone				0.99	0.82	0.10
C Flood Zone				-1.41**	0.59	0.13
Coast				1.14*	0.58	2.13
Mississippi				0.75***	0.27	1.12
Coast×Mississippi				1.26*	0.71	2.53
Slope				0.24**	0.11	0.27
Elevation				-0.001	0.001	0.10
Stream density				-0.58**	0.29	0.44
Precipitation	0.13***	0.01	0.14	0.13***	0.01	0.14
Socioeconomic variables						
Log(Household)	0.89***	0.28	0.09	0.88***	0.27	0.09
Income	0.02	0.02	0.02	0.02	0.02	0.02
Education	0.003	0.03	0.003	0.003	0.03	0.003
Year fixed-effects	Yes			Yes		
Mundalk Group Means	No			Yes		
Constant				-7.89***	2.52	
R^2	0.42			0.31		
N	5860			5860		

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