DOI: 10.1111/risa.14024

ORIGINAL ARTICLE

Does federal flood hazard mitigation assistance affect community rating system participation?

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Abstract

With the inexorable march of climate change, increased flooding is inevitable. Understanding the feedback between federal flood mitigation policies and the ways in which local governments build flood resilience is a significant gap in the literature. In particular, the effect that federal flood mitigation grants have on the intensity of local flood mitigation is nonexistent. This work measures flood risk mitigation by using the level of participation in FEMA's Community Rating System (CRS). Communities that participate in the CRS and undertake mitigation are awarded points; more points imply a higher level of participation. Since its inception in 1990, CRS communities have received considerably more federal pre-disaster flood mitigation grants compared to non-CRS communities. This study assesses the effect of federal pre-disaster flood mitigation grants on the level of participation in the CRS program. We use data on Hazard Mitigation Assistance programs and CRS participation data between 2010 and 2015. We link these data to flood risk and socioeconomic information. Our results indicate (i) federal pre-disaster flood mitigation grants do not appear to significantly influence the level of CRS participation, (ii) the effect of flood risk and socioeconomic factors on the level of CRS participation are mixed, and (iii) the current level of CRS participation is influenced by the previous level of CRS participation, which is not tied to federal pre-disaster flood mitigation grant. These findings add to the growing discussions on the drivers and barriers of local flood risk mitigation.

KEYWORDS

community rating system, dynamic panel model, federal flood mitigation assistance, flood risk mitigation

1 | INTRODUCTION

The widespread and disruptive nature of floods makes addressing flood hazards in the United States important. Data from the National Centers for Environmental Information (NCEI) indicate that flood losses continue to rise at an alarming rate (NCEI, 2020), and that the country's National Flood Insurance Program (NFIP), which is the main issuer of flood insurance in the United States, is not actuarially sound (U.S. Congressional Budget Office, 2017).[1] Mitigation, from elevating homes to limiting development in highly flood-prone areas, is key in improving outcomes (Congressional Research Service, 2019).

One of the ways the Federal Emergency Management Agency (FEMA) encourages participation in the NFIP while encouraging local communities to reduce their flood damage is through the Community Rating System (CRS) (Frimpong et al., 2020). Communities voluntarily participate in the CRS and pursue flood mitigation measures. Each action awards the community points which, when summed, indicates the community's overall level of CRS participation. Residents of participating communities receive a flood insurance premium discount that is, in principle, commensurate with the level of CRS participation by their community. The more points a community receives, the greater their premium discount. The

[1] As of 2020, after a $16 billion debt cancellation, the NFIP is $25 billion in debt (Congressional Research Service, 2020).

CRS activities are nonstructural (e.g., land use regulation, flood mapping, and flood warning and response) and broadly grouped into four categories called series. There are four series of activities—Series 300, 400, 500, and 600. Activities in higher series typically offer more points to generally reflect the fact that more flood damage is being reduced. CRS communities must certify annually that they are still participating in CRS activities, making the program the only one that continuously engages with communities to address flood damage (Frimpong et al., 2020; Michel-Kerjan et al., 2016). If no CRS activity is undertaken in CRS community over the course of a year, its score could fall. A CRS community can increase or maintain its CRS score by showing annually that it is participating in a CRS activity. The cost of participating in CRS activities varies depending on the activities undertaken (Frimpong et al., 2020) and, as a result, CRS communities might elect to strategically engage in less expensive activities to maximize points (Brody et al., 2009; Berke et al., 2014; Michel-Kerjan et al., 2016; Sadiq & Noonan, 2015a; Zahran et al., 2010).

Separate from the CRS, FEMA offers grants for communities to conduct hazard mitigation. Federal funds for mitigation mostly, but not exclusively, flow through the Hazard Mitigation Assistance programs (HMA), which includes the Hazard Mitigation Grant Program (HMGP), Pre-Disaster Mitigation (PDM), and Flood Mitigation Assistance (FMA). The proposed mitigation activities must reduce or eliminate future damage to properties and lives, and the community can, but does not have to be part of the CRS to receive HMA grants. The HMA programs mostly fund nonstructural mitigation activities (e.g., planning, warning and awareness studies, relocation, acquisition of structures, dams and levees infrastructure rehabilitation, and retrofitting) (FEMA, 2020a). The federal cost share for these grants is usually 75% and so local governments' financial support is required. The HMGP, which historically has been the largest among the HMA programs, is usually only available to local governments after a presidential disaster declaration in their jurisdiction. In 2019, FEMA replaced the PDM grant program with the Building Resilient Infrastructure and Communities grant program to expand the financial resources local communities can exploit to bolster hazard mitigation. Except for FMA grant money, CRS communities can improve their CRS points by implementing HMA-funded mitigation projects (FEMA, 2017). The limitation of using FMA grant money to improve CRS points is mandated by the National Flood Insurance Reform Act of 1994 (FEMA, 2017). Outside FEMA, there are other sources of financial assistance including, Community Development Block Grants from the U.S. Department of Housing and Urban Development, grants from the U.S. Army Corps of Engineers, and the U.S. Department of Agriculture's Natural Resources Conservation Service, that CRS communities could use to implement CRS mitigation activities and receive points. However, most of these non-FEMA grants are ex-post recovery spending which has been shown to be less effective compared to pre-disaster grants in reducing property losses (Davlasheridze et al., 2017).

FEMA's 2020 reporting on HMA funding indicates that for flood-related projects, CRS communities have received considerably more grant money compared to their non-CRS counterparts (FEMA, 2020b). This makes intuitive sense because CRS communities (1) hold over 70% of the nation's flood insurance policies (FEMA, 2020c) and (2) may have the capacity to provide the 25% match required as cost share for HMA grants (Brody et al., 2010; Landry & Li, 2012; Sadiq & Noonan, 2015a). Previous research has shown that the level of CRS participation is higher among communities with larger tax base (Li & Landry, 2018), indicating the importance financial resources in local governments' efforts to engage in local flood mitigation. While generally, one would expect that HMA grant money received by CRS communities would bolster flood mitigation efforts (FEMA, 2017), to our knowledge, there is no empirical evidence to show if and to what extent HMA grant money influences the level of CRS participation (as measured by points) and thus the degree to which the community reduces their flood risk.

The CRS program could deliver substantial benefits to the public by reducing flood damages and thus make NFIP solvent and reduce taxpayer burden of funding flood losses. CRS communities hold over 70% of the nation's flood insurance policies (FEMA, 2020c). And so, measuring the effect that federal pre-disaster spending (HMA) has on CRS points is important to understand the effectiveness of government pre-disaster mitigation spending in encouraging communities to reduce flood losses, and provide a mechanism to evaluate flood mitigation programs and ways the government could decrease its post-disaster relief spending.

In this study, we evaluate the degree to which HMA grants influence the level of CRS participation. Given that HMA grants and CRS participation both usually focus on nonstructural activities, we would expect that as more HMA grant funds are awarded, so would CRS participation (as measured by points), all other things equal. However, if these do not have a positive and significant relationship, it may point to two things: (1) local communities use the funds to maintain their status in the CRS as opposed to increasing their participation, thus potentially supplanting funds local governments would otherwise use to maintain CRS status, and/or (2) the CRS, as an instrument for measuring flood damage reduction, is simply too blunt to capture fine-scaled mitigation strategies. We also assess whether there are differential effects of HMA grant money on the level of participation in the various CRS activities undertaken (measured by CRS series points). We assume, all other things equal, that CRS communities increase participation in higher funded CRS activities.

To address this research question, we build a dynamic panel model that predicts the level of CRS participation as a function of FEMA HMA grants, flood risk indicators, and socioeconomic information. We do this by building five different models. We first measure the effect that HMA grants has on the level of CRS participation, and then consider the role it has in the level of participation in each of the four series activities (i.e., Series 300–600). The CRS

TABLE 1 Community Rating System (CRS) activities and correspondence between CRS activities and Hazard Mitigation Assistance (HMA)-funded projects

Activity	Maximum possible points	Related HMA-funded project type
Series 300: Public information		
310–Elevation certificate	166	100.1: Public awareness and education (brochures, workshops, videos, etc.)
320–Map information service	90	
330–Outreach projects	350	
340–Hazard disclosure	80	
350–Flood protection information	125	
360–Flood protection assistance	110	
370–Flood insurance promotion*	110	
Series 400: Mapping and regulations		
410–Floodplain mapping	802	
420–Open space preservation	2020	303.1: Wetland restoration/creation
430–Higher regulatory standards	2042	
440–Flood data maintenance	222	
450–Stormwater management	755	
Series 500: Flood damage reduction activities		
510–Floodplain management planning	622	91.1: Local Multihazard Mitigation Plan
520–Acquisition and relocation	1900	200.1: Acquisition of private real property (structures and land)–Riverine
530–Flood protection	1600	202.1: Elevation of private structures–Riverine
540–Drainage system maintenance	570	218
Series 600: Warning and response		
610–Flood warning and response	395	600.1: Warning systems (as a component of a planned, adopted, and exercised risk reduction plan)
620–Levees	235	500.2: Flood control–berm, levee, or dike
630–Dams	160	500.3: Flood control–dam

Note: Source for CRS activities: FEMA, 2018; Source for HMA funded projects: FEMA, 2020b.
*Introduced in 2013.

participation data covers the entire United States for 2010—2015. Understanding the relationship between HMA grants and CRS participation intensity is thus crucial for advancing flood hazard mitigation and sharpening relevant policy.

2 | COMMUNITY RATING SYSTEM IN PRACTICE AND THEORY

CRS communities are distinct geographic entities that can include those incorporated and unincorporated areas of counties, cities, towns, villages, and boroughs that participate in the National Flood Insurance Program. The CRS is the only flood mitigation program that integrates insurance with mitigation (Li & Landry, 2018), and participation in the program is voluntary. The activities that CRS communities can participate in are nonstructural and are categorized into four series (Table 1).[2] Series 300 activities are informational (e.g., providing residents information on flood risk and insurance), Series 400 activities focus on regulatory enactment and enforcement (e.g., floodplain mapping), Series 500 activities include those that reduce flood damage (e.g., acquisition and relocation of at-risk homes and structures), and Series 600 activities include those aimed at minimizing the effects of residential flooding (e.g., levee and dam maintenance) (FEMA, 2018). For each activity undertaken, the community receives some fraction of the maximum allowed points conditioned on the extent of mitigation; in the end, the cumulative number of points reflects the degree of CRS participation. It is worth mentioning that, in some cases, activities under different series would have to be undertaken simultaneously to receive credit. For example, a CRS community participating

[2] "Some CRS activities may be implemented by the state or a regional agency rather than by the community. For example, some states have hazard disclosure laws that are creditable under Activity 340 (Flood Hazard Disclosure). A community in those states will receive those credit points when it applies for CRS credit and demonstrates that the law is effectively implemented within its jurisdiction" (FEMA, 2018).

TABLE 2 Community Rating System (CRS) class and discounts

Class	Discount for SFHA (%)	Discount for non-SFHA (%)	Credit points required
1	45	10	4500+
2	40	10	4000–4499
3	35	10	3500–3999
4	30	10	3000–3499
5	25	10	2500–2999
6	20	10	2000–2499
7	15	5	1500–1999
8	10	5	1000–1499
9	5	5	500–999
10	0	0	0–499

Source: FEMA, 2013.

in Series 500 activity is required to also participate in flood protection information activity (Series 300), though they will receive credit for both activities (FEMA, 2017). To participate in the program, NFIP communities have to submit yearly documentation showing active participation in CRS activities. State designated Insurance Services Office (ISO)/CRS specialists review these documents in collaboration with FEMA and either approve or deny premium discounts for residents. As part of the application review process, ISO visits the NFIP community to verify that CRS participation is active. If communities do not engage in mitigation over the course of a year, they could lose points (depending on the types of points awarded in the past) or face elimination from the program.

There are 10 levels of CRS participation; the cumulative points awarded to the community determine the level. The entry level is Class 9 and the highest level of participation is Class 1 (Table 2). NFIP communities that do not participate in CRS activities or do not obtain the minimum CRS credit are assigned to Class 10. Premium discounts for residents depend on the level of CRS participation. For residents in the Special Flood Hazard Area (SFHA)[3], the discount is between 0% and 45%, while the discount is between 5% and 10% for residents outside the SFHA (FEMA, 2018). As of 2020, Roseville, California is the only CRS community to achieve CRS Class 1.

Past studies suggest that an NFIP community's decision to join the CRS program is driven largely by flood risk and socioeconomic factors (Asche, 2013; Landry & Li, 2012; Posey, 2009; Sadiq & Noonan, 2015a; Sadiq et al., 2020). There are a few papers that also find that increased participation in CRS encourages NFIP participation (Borsky & Henninghausen, 2022; Frimpong et al., 2020; Petrolia et al., 2013; Zahran et al., 2009) and reduces flood losses and damage claims payment (Frimpong et al., 2020; Gourevitch & Pinter, 2022; Highfield & Brody, 2013, 2017; Highfield et al., 2014; Michel-Kerjan & Kousky, 2010).

[3] SFHA is an area that has a high risk of flooding. FEMA requires that the NFIP's floodplain management regulations are enforced in SFHA, and that flood insurance purchase be mandatory.

Related to our study, Brody et al. (2009) used CRS data spanning 1999–2005, flood risk, and socioeconomic data to examine the factors affecting Florida counties' level of CRS participation. Their findings show that proportion of land area in floodplain, flood frequency, flood property damage, population density, nonprofit assets per capita, household income, and education are important factors. Zahran et al. (2010) using the same data found that CRS communities are discount-seeking, with mitigation efforts partially driven by the nonlinear incentive design of the program. Similar to Brody et al. (2009), Zahran et al. (2010) also found the proportion of land area in floodplain, flood frequency, flood property damage, population density, nonprofit assets per capita, household income, and education to be significant predictors of CRS points. Sadiq and Noonan (2015b) expanded the analyses by analyzing a national sample of CRS communities to determine whether the factors that affect communities' decision to join the CRS program also affect the level of CRS participation. Their results indicate that factors that predict whether an NFIP community will participate in the CRS program differ from factors that predict CRS points.

Focusing on the state of Louisiana, Paille et al. (2016) also found that higher CRS participation is associated with higher median home values. Factors including the number of floods, local government revenue, and elevation, however, were not significant predictors of CRS participation. Li and Landry (2018) tested whether the current level of CRS participation is influenced by the previous level of participation, while controlling for flood risk and socioeconomic factors, in the State of North Carolina. This indicates the degree to which communities actively seek to maintain their CRS status. They noted that indeed the current level of CRS participation depends on the previous level. They also noted that flood risk and socioeconomic factors including risk index, tax revenue, staff, unemployment, crime rate, population density, income, and percent of senior citizens determine CRS participation. While these studies have contributed to our understanding on the factors that influence the level of participation in the CRS, to the authors' knowledge, no study has evaluated the role that HMA grants have on CRS status and participation. Like Li and Landry (2018), we also test whether the current level of CRS participation depends on previous participation by estimating a dynamic panel model. However, unlike Li and Landry, we use a national dataset, in addition to other differences.

3 | CORRESPONDENCE BETWEEN CRS ACTIVITIES AND HMA-FUNDED PROJECT TYPE

The 19 creditable activities identified across the four CRS series can be mapped partially to one or more project types funded under FEMA's Hazard Mitigation Assistance programs (see Table 1) (FEMA, 2013). To illustrate, CRS activities under series "300—Public Information" map to the HMA project type "100.1: Public Awareness and Education." Likewise, CRS activity "420—Open space preservation," under Series 400, maps to HMA project type "303.1: Wetland restoration/creation." To receive credit for activity 420, CRS communities have to visually demonstrate that areas to be credited are designated as open space preservation (FEMA, 2013). CRS communities may also receive larger credits for HMA-funded property acquisition projects and structure retrofits (FEMA, 2013).

4 | DATA

To evaluate the role that HMA grants have on CRS participation (as measured by a community's score), we use 2010–2015 panel data at the CRS community level. We consider CRS communities that have and have not received HMA funding for the timeframe under consideration. CRS data for 1108 CRS communities that continuously participated in CRS during 2010–2015 and are in United States mainland are obtained by professional courtesy. Ninety very small CRS communities, however, are not in the FEMA CRS community data layer and 49 lack precipitation data. Thus, the final data analyzed consist of 969 communities (Figure 1), and as might be expected, most are in coastal regions. The unit of analysis is CRS community. CRS communities' geographic areas (incorporated and unincorporated areas of counties, cities, towns, villages, and boroughs) do not always cleanly overlay with other more common spatial designations, such as census areas. As we discuss later, to collect information at the spatial scale we need, we overlay CRS community shapefiles from FEMA with shapefiles from other relevant datasets.

For our dependent variables, we separately consider both CRS points (i.e., the total points accrued across all series) and CRS series points (Series 300, Series 400, Series 500, Series 600). Using boxplots, we see the distribution of total CRS points, HMA, and points in each series over the CRS communities (Figure 2A,B). Also displayed in the figures are the means (shown as line plot–dashes). It is clear from the boxplots in Figure 2A,B that the median total CRS points and series points in a given year do not appreciably change within any of the series. It is also clear that there are long tailed distributions for the total CRS points and for the 400 and 500 Series. That is, there are significant outliers. Overall, our CRS data show that 89% (863 out of 969) of CRS communities record a change in CRS points.

Our independent variables are organized into policy variable, flood risk variables, socioeconomic variables, and year fixed-effects (Table 3). The policy variable is the level of HMA funding, which we construct using FEMA's "Hazard Mitigation Assistance projects" dataset (FEMA, 2020b). The dataset which spans from 1989 to 2021 includes funding in each program administered through HMA (HMGP, PDM, and FMA). Data for Severe Repetitive Loss (SRL) and Repetitive Flood Claims (RFC) grants are also included in this open dataset but excluded from our analysis because SRL and RFC were eliminated from the HMA program by the passage of the Biggert-Waters Flood Insurance Reform Act of 2012 and are relatively small in number.[4] We also exclude FMA from the analysis because CRS communities do not get credit for implementing FMA-funded mitigation activities (FEMA, 2017). Spending through the HMGP between 1989 and 2019 comprises about 80% of FEMA's HMA dataset; PDM accounts for 12%, FMA is 7%, and RFC and SRL combined is 1%. We exclude all nonflood project types. FEMA's HMA raw data are not at the CRS community level, and so to obtain yearly HMA grant funding at the CRS community level, we first match unique project identifiers in FEMA's "Hazard Mitigation Assistance projects" dataset to project identifiers in FEMA's "Hazard Mitigation Assistance Projects by NFIP CRS Communities" dataset. We then aggregate the federal cost share at the CRS community level over all the projects approved in a given year. Finally, we lag HMA funding by 2 years since most HMA typically funds buyout projects, which can take as long as 18 months to complete (Robinson et al., 2018). However, we recognize that different mitigation projects could take different time periods to complete and for CRS communities to receive credit. As such, we also consider different lagged periods as a robustness check and report the results in the Appendix. That is, in all we use HMA data from 2005 to 2014.

As we discuss later, our econometric model requires that only variables that are time variant are included in our analysis. This means that our control variables including, flood risk and socioeconomic variables should vary across the years considered. So, for the flood risk variables, we obtain *Precipitation* data from PRISM Climate Group's 4-kilometer resolution gridded daily precipitation (PRISM, 2020). Specifically, we measure *Precipitation* as the maximum daily precipitation in millimeters over the course of the year. By

[4] SRL grant program was authorized by the Flood Insurance Reform Act of 2004 to provide funding to reduce or eliminate long-term flood risk to severe repetitive loss structures insured under NFIP. The RFC grant program is like SRL with the goal of reducing or eliminating long-term flood risk to structures and make NFIP solvent. CRS communities could use SRL and RFC to buyout or relocate severe repetitive loss structures. We also estimated our models considering SRL and RFC and the findings are not significantly different.

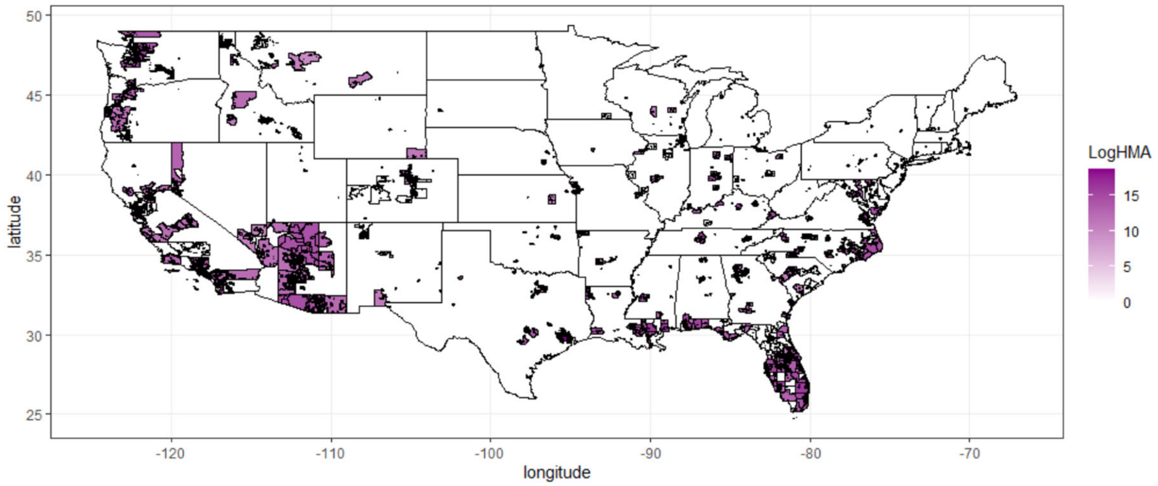

FIGURE 1 Spatial distribution of study Community Rating System (CRS) communities and Hazard Mitigation Assistance (HMA) levels

TABLE 3 Summary of variables, definition, and data source

Variables	Definition	Unit	Data source
Dependent variables			
CRS points	Total number of CRS points earned		
Series 300	Total number of CRS points earned for undertaking Series 300 activities		
Series 400	Total number of CRS points earned for undertaking Series 400 activities		
Series 500	Total number of CRS points earned for undertaking Series 500 activities		
Series 600	Total number of CRS points earned for undertaking Series 600 activities		
Independent variables			
Policy variable			
HMA	Total flood-related grants under FEMA's Hazard Mitigation Assistance	$	FEMA
Flood risk variables			
Precipitation		Millimeters	
NFIP claims rate	Ratio of NFIP claims and to coverage for a given year		FEMA
Socioeconomic variables			
Income	Estimated median household income in the past 12 months	$	ACS
Population density	Number of people per square miles		Imputed
Housing unit	Estimated count of housing units		ACS
Age	Estimated median age	Years	ACS
Property tax	Estimated median real estate taxes paid	$	ACS
	Year fixed-effects		
Yr2010	=1 if year is 2010, = 0 otherwise		
Yr2011	=1 if year is 2011, = 0 otherwise		
Yr2012	=1 if year is 2012, = 0 otherwise		
Yr2013	=1 if year is 2013, = 0 otherwise		
Yr2014	=1 if year is 2014, = 0 otherwise		
Yr2015	=1 if year is 2015, = 0 otherwise		

Abbreviations: CRS, Community Rating System; FEMA, Federal Emergency Management Agency; HMA, Hazard Mitigation Assistance; NFIP, National Flood Insurance Program; SFHA, Special Flood Hazard Area.

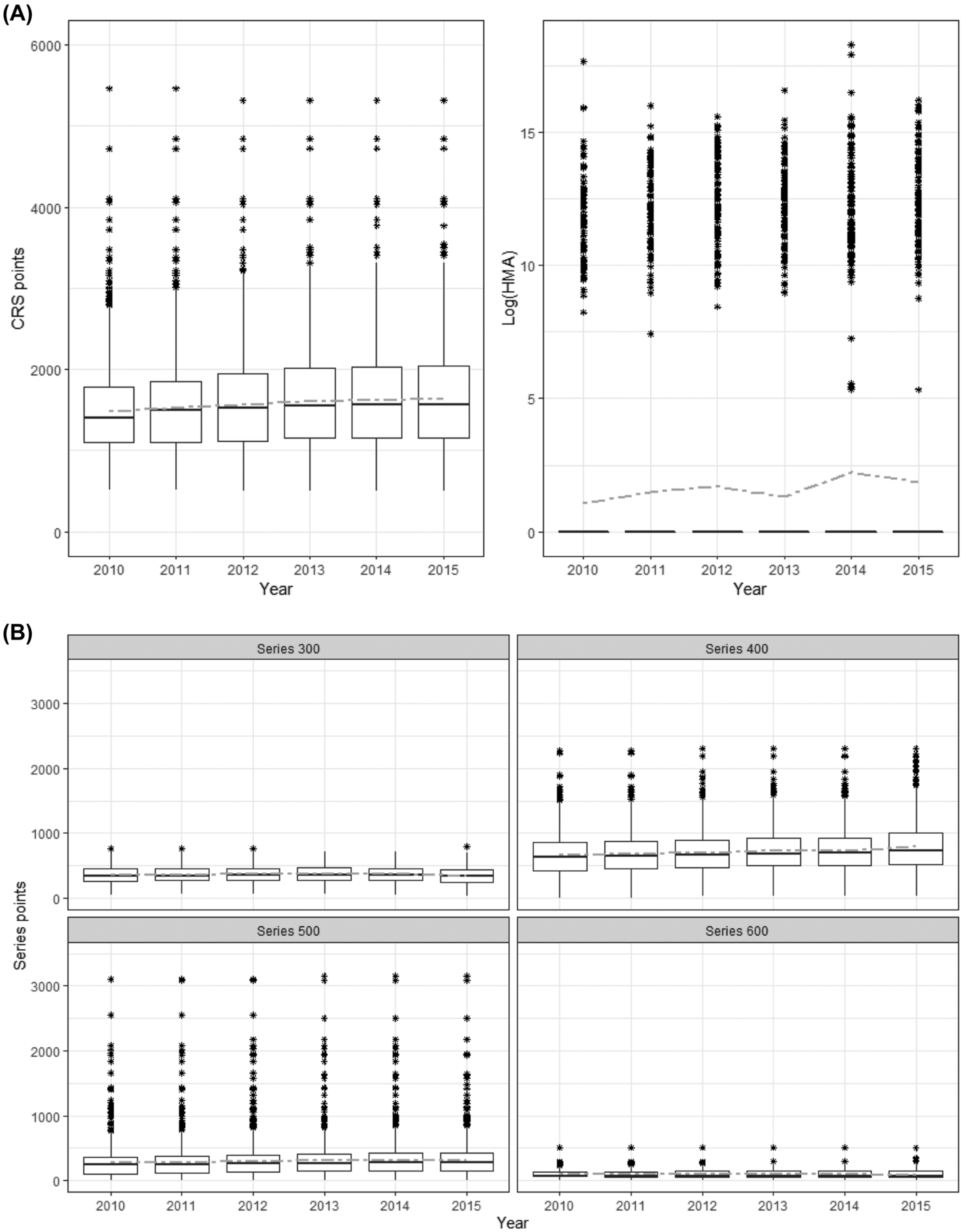

FIGURE 2 (A) Box plots showing distribution of Community Rating System (CRS) points (left) and Log(HMA) (right). The line plot (shown in dashes) represents the means. (B) Box plots showing distribution of Series 300, 400, 500, and 600. The line plot (shown in dashes) represents the means

using maximum daily precipitation, we are able to better account for abnormal rainfalls in a given year. We expect communities that receive more precipitation in the previous year or 2 years to increase CRS participation.

Another metric that we use to capture flood risk is *NFIP claims rate*. This is ratio of NFIP claims payment to the coverage amount. Both values come from FEMA's "FIMA NFIP Reduction Claims" dataset (FEMA, 2020d). Because the smallest unit of this dataset is the Zone Improvement Plan (ZIP) code, we aggregate NFIP claims payments and coverage amount at the CRS community level by overlaying ZIP code shapefiles on NFIP community shapefiles. We include

NFIP claims rate to assess the extent to which communities respond to prior flood damages; it serves as a proxy for property damage relative to the community's assets. The *NFIP claims rate* is lagged 1 and 2 years. We assume that communities with higher *NFIP claims rate* in the previous year or 2 years will increase current CRS participation, all other things equal. In previous studies of factors influencing the level of CRS participation, property damage was found to be a significant determinant of CRS participation (Brody et al., 2009; Zahran et al., 2010).

Our socioeconomic variables include data on *Income*, *Population density, Housing units*, *Age*, and *Property tax* from the American Community Survey (ACS) 5-year data (U.S. Census, 2020). *Income* is the median household income; *Population density* is the total number of people per square mile of CRS community area; *Housing units* captures the total number of housing units; *Age* is the median age of the population, and finally *Property tax* is the median real estate tax. We overlay ACS data at the census tract level on NFIP community shapefiles to obtain data at the CRS community level. For *Income*, *Age*, and *Property tax*, we use the maximum value that intersects the NFIP community shapefiles, and for *Housing units* we aggregate across all census tracts that intersect with the NFIP community shapefiles. Like *Housing units*, for *Population density*, we aggregate across census tracts, and further divide by CRS community area. *Income*, *Population density, Housing units*, and *Age* accounts for the effect of community characteristics on local hazard mitigation while capturing the influence of human and social capital on local hazard mitigation. Household income and population density have been found to be important predictors of CRS participation (Brody et al., 2009; Li & Landry, 2018; Zahran et al., 2010). Other studies have also found property tax to be an important predictor of CRS participation (Li & Landry, 2018; Paille et al., 2016; Sadiq & Noonan, 2015b). *Property tax* is used as a proxy for local capacity to implement mitigation projects. We presume that communities with larger income, population density, number of housing units, median age of the population, and tax base will engage more in local hazard mitigation and increase CRS points. Finally, we construct year fixed-effects variables for the years under consideration 2010–2015. Table 4 presents the summary statistics and expected signs for our variables of interest, and all monetary values are nominal. For the study period considered, the average *CRS points* is about 1573. The minimum (502) and maximum (5463) *CRS points* suggest that our data consist of CRS communities in both the entry level (class 9) and the highest level of participation (class 1). On average, the number of points earned in public information activities (*Series 300*), mapping and regulation (*Series 400*), flood damage reduction activities (*Series 500*), and flood warning and response activities (*Series 600*) are approximately 361, 714, 297, and 96, respectively, suggesting that flood warning and response is the least participated activity series. Regarding our policy variable, *HMA*, CRS communities in our study period have received an average of about \$74,511 in *HMA* grants and maximum of \$46,520,404. The minimum is \$0. The mean *Precipitation* is 93.74 mm and the mean *NFIP claims rate* is 0.04. The mean value for *Income* is approximately \$101,225, and the minimum and maximum are \$22,385 and \$250,001. For *Population density*, the mean value is about 130.36 while the minimum and maximum values are 0.28 and 6735.85 respectively. The mean number of *Housing unit* in the CRS communities in our study period is approximately 4742, and the minimum and maximum are 135 and 136,041. The average *Age* (about 52 year) in the CRS communities and for the period studied suggest the population is in the mature working age group. The minimum age is 30 years, while the maximum age is 83. The last of our socioeconomic variables, *Property tax*, has a mean value of about \$4,521 and a minimum and maximum of \$326 and \$10,001, respectively. Finally, our year fixed-effects variables (*Yr2010-Yr2015*) which are dummy variables have a mean of 0.17 and minimum and maximum values of 0 and 1, respectively.

5 | EMPIRICAL MODEL AND ESTIMATION

Our interest is in the relationship between *HMA* and the total *CRS points* and between *HMA* and each CRS series points. To accomplish this, we build a dynamic panel model (Arellano & Bond, 1991) and estimate parameters using the Arellano-Bover/Blundell-Bond (ABBB) two-step Generalized Method of Moments (GMM) estimator (Arellano & Bover, 1995; Blundell & Bond, 1998). The dynamic panel model is preferred to a host of panel models because it simultaneously addresses two issues in our panel data. First, our dependent variables, *CRS points* and the CRS activity series (Series 300, Series 400, Series 500, Series 600) are presumed to be state dependent (autoregressive). That is, the current level of CRS participation depends on the previous level of participation (Li & Landry, 2018). The second issue is that *HMA* is potentially endogenous (reverse causality). That is, CRS communities may be receiving more HMA grant money because they are participating in CRS and the amount of HMA grant money a community receives may depend on the community's level of CRS participation. If these issues are unaddressed, our estimates will be potentially biased and inconsistent.

We specify our initial dynamic panel model as,

$$ln(y_{it}) = \gamma ln(y_{i,t-1}\ ) + \varphi ln(h_{i,t-2}) + \delta ln(f_{i,t-1,2}) + \beta ln(s_{it}) + u_{it}, \tag{1}$$

$$u_{it} = \eta_i\ + \lambda_t + \varepsilon_{it}, \tag{2}$$

where $ln(y_{it})$ and $ln(y_{i,t-1})$ represent log of a *CRS points* or CSR activity series (300-600) and its lag, for CRS community i at year t. Recall that five models in total are created. γ, φ, δ, and β are parameters to be estimated. $ln(h_{i,t-2})$ is the

TABLE 4 Summary statistics of variables

Variables	Unit	Median	Mean	SD	Min	Max	Exp. Sign
	Dependent variables						
CRS points		1531	1573	623	502	5463	
Series 300		351	361	130	38	795	
Series 400		675	714	335	0	2309	
Series 500		257	297	292	0	3152	
Series 600		71	96	63	0	510	
	Independent variables						
	Policy variable						
HMA	$	0	74511.78	76,8037.70	0	46,520,404	+
	Flood risk variables						
Precipitation	Millimeters	83.95	93.74	53.57	8.73	471.46	+
NFIP claims rate		0.01	0.04	0.08	0	2.09	+
	Socioeconomic variables						
Income	$	89,850	101,225.50	44,557.82	22,385	250,001	+
Population density		79.65	130.36	242.98	0.28	6735.85	+
Housing unit		2435	4742.28	7908.13	135	136,041	+
Age	Years	51	52.93	9.24	30	83.60	+
Property tax	$	3812	4521.79	2852.44	326	10,001	+
	Year fixed-effects						
Yr2010–Yr2015		0	0.17	0.37	0	1	

Note: Sample size is 969. In the regression model, variables are log transformed. A constant is added to variables with a minimum value of zero before log transforming.

log of the level of *HMA* grants awarded to community i in year $t-2$. It is endogenous because causality may run in both directions as previously explained. We lag the level of *HMA* grants awarded to community i by 2 years because many HMA projects (e.g., buyouts) take approximately 2 years to complete. As a robustness check, we also lag the level of HMA grants by different years (1, 3, 4, and 5 years, see the Appendix). $ln(f_{i,t-1,2})$ is the log of the vector of exogenous flood risk variables for community i, again lagged by 1 and 2 years with the assumption that past levels of flood risk influence current CRS participation level, and $ln(s_{it})$ is the log of the vector of exogenous socioeconomic variables for community i in year t. u_{it} is the error term and is composed of community-specific effects, η_i, year fixed-effects, λ_t, and an idiosyncratic error term, ε_{it}.

The ABBB two-step[5] GMM estimator is one of few "advanced" estimators that can estimate our parameters in Equation 1 (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). The ABBB is a first-difference estimator that builds on earlier GMM estimators by expanding the number of instruments[6] that the estimator uses to address the issue of endogeneity in the dynamic panel model (Arellano & Bover, 1995; Blundell & Bond, 1998). This increases the efficiency of our parameter estimates (Arellano & Bover, 1995; Blundell & Bond, 1998). Similar to the Arellano and Bond (1991), GMM estimator, the ABBB is designed for panel datasets with large panels and small time periods like ours; we have 969 CRS communities and six 1-year periods (2010–2015). Because the GMM estimator is a first-difference estimator, community-specific effects, η_i, in Equation 2 are removed, and Equations 1 and 2 are combined to yield a single equation of the form,

$$ln(\Delta y_{it}) = \gamma ln(\Delta y_{i,t-1}) + \varphi ln\left(\Delta h_{i,t-2}\right) + \delta ln\left(\Delta f_{i,t-1,2}\right) + \beta ln(\Delta s_{it}) + \lambda_t + \varepsilon_{it}, \quad (3)$$

where Δy_{it} (i.e., $y_{it} - y_{i,t-1}$) is the first difference of *CRS points* or CRS activity series, y_{it}, $\Delta y_{i,t-1}$ is the first-difference of the lagged levels of CRS points or CRS activity series, $y_{i,t-1}$, $\Delta h_{i,t-2}$ is the first-difference of the level of HMA grant money, $\Delta f_{i,t-1,2}$, and Δs_{it} is the first-difference of the levels of socioeconomic variables. The ABBB uses a variety of instruments from the model to address endogeneity. First, it uses the lags, except for the first one, of the levels of the dependent (*CRS points* or CRS activity series) and endogenous independent variable (*HMA*) as

[5] There is also a one-step procedure. However, it is inefficient (Hwang & Sun, 2018).

[6] Instruments are variables that are not part of the explanatory variables in the main equation but are correlated with the endogenous independent variables. They are used to estimate causal relationship.

instruments (Arellano & Bond, 1991). In addition, it uses the first differences of the exogenous variables (flood risk and socioeconomic variables) as instruments (Arellano & Bover, 1995; Blundell & Bond, 1998). We specify five models—one for CRS participation overall, and one for each of the 300–600 Series degree of participation, and perform the specification tests, including Sargan test for overidentifying restrictions and Arellano and Bond (1991) test for serial correlation. Although not obvious here, each model uses 40 instruments to address endogeneity. Standard errors are estimated using WC-Robust estimators (Windmeijer, 2005) to address potential downward bias of standard errors that may arise because of the two-step estimation.

6 | RESULTS

6.1 | Effects of HMA, flood risk, and socioeconomic information on total CRS points

We present our model specifications in Tables 5 and 6 and include our model diagnostics. The diagnostics include the Wald Test for joint significance of the independent variables, the Sargan test for overidentifying restrictions, and the Arellano and Bond Test (1991) for serial correlation. Based on these diagnostics, we can reject the null hypothesis of no valid instruments at the 1% significance level for all models. We can also reject the null hypothesis of no first-order serial correlation, but fail to reject the null hypothesis of no second-order serial correlation at 1% significance level. This supports our model specification; a second-order serial correlation would have implied that the lagged endogenous variables used as instruments are invalid and thus, the dynamic panel model specification would be wrong (Arrelano & Bond, 1991).

Our first model (Table 5) presents the model specification for total *CRS points*. The estimated coefficients for this model represent the percent change in the level of CRS participation (as measured by total *CSR points*) for a one percent change in the independent variable. Note that this interpretation does not apply to the constant and the year fixed-effects coefficients. Notably, our primary variable of interest, *HMA*, is positive as hypothesized but not significant. This suggests that HMA funding has no significant effect on the level of CRS participation. In fact, only the lagged dependent variable ($CRS\ points_{one\ year\ prior}$), *Precipitation lagged one year*, *NFIP claims rate lagged one year, Yr2014*, and *Yr2015* coefficients are significant. Consistent with Li and Landry (2018), the estimated coefficient on the lagged total *CRS points* is positive and significant. This suggests that the current level of CRS participation depends on the previous level of participation. Specifically, a 1% increase in the previous year's *CRS points* results in a 0.96% increase in current year *CRS points*. The fact that the magnitude on the lagged CRS points is less than one implies that after some initial number of points has been achieved, additional improvements are more difficult to achieve (i.e., diminishing returns) (Li & Landry, 2018). Our

TABLE 5 This table presents the dynamic panel regression results for Hazard Mitigation Assistance (HMA) effect on Community Rating System (CRS) points, controlling for flood risk, socioeconomic factors, and year fixed-effects. The results indicate a positive but insignificant correlation between HMA and CRS points. Except for socioeconomic variables, flood risk variables and year fixed-effects are significant predictors of CRS points

Variables	Coefficients
Log(CRS points$_{one\ year\ prior}$)	0.962***
	(0.024)
Log(HMA$_{two\ years\ prior}$)	0.003
	(0.002)
Log(Precipitation$_{one\ year\ prior}$)	−0.012**
	(0.005)
Log(Precipitation$_{two\ years\ prior}$)	0.001
	(0.006)
Log(NFIP claims rate$_{one\ year\ prior}$)	0.070*
	(0.037)
Log(NFIP claims rate$_{two\ years\ prior}$)	0.012
	(0.035)
Log(Income)	−0.025
	(0.032)
Log(Population density)	−0.002
	(0.014)
Log(Housing units)	0.015
	(0.020)
Log(Age)	0.023
	(0.057)
Log(Property tax)	0.012
	(0.021)
Yr2012	−0.001
	(0.004)
Yr2013	−0.001
	(0.005)
Yr2014	−0.016***
	(0.005)
Yr2015	−0.013**
	(0.006)
Constant	0.337
	(0.431)
Wald test (χ^2)	4883.430***
Sargan test (χ^2)	31.988*
First-order autocorrelation	−9.647***
Second-order autocorrelation	1.561
Observations	4845
Number of CRS communities	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
***$p < 0.01$;
**$p < 0.05$;
*$p < 0.1$.

TABLE 6 Presented in this table are the dynamic panel regression results looking at the differential effects of Hazard Mitigation Assistance (HMA) on Community Rating System (CRS) series. Except for Series 300, the results indicate a positive but insignificant correlation between HMA and the activity series. HMA has a positive and significant effect on public information on flood risk and insurance activities (Series 300). The effect of flood risk, socioeconomic variables, and year fixed-effects on the series are mixed

Variables	X = 300	X = 400	X = 500	X = 600
Log(Series $X_{\text{one year prior}}$)	0.984***	0.666***	0.938***	0.905***
	(0.038)	(0.068)	(0.049)	(0.081)
Log($HMA_{\text{two years prior}}$)	0.013*	0.002	0.051	0.016
	(0.008)	(0.005)	(0.032)	(0.024)
Log($Precipitation_{\text{one year prior}}$)	0.004	−0.018**	−0.019	−0.007
	(0.008)	(0.008)	(0.035)	(0.026)
Log($Precipitation_{\text{two years prior}}$)	0.010	−0.011	−0.008	−0.033
	(0.009)	(0.010)	(0.037)	(0.030)
Log(NFIP claims $rate_{\text{one year prior}}$)	0.082	0.068	−0.035	0.467**
	(0.053)	(0.078)	(0.289)	(0.215)
Log(NFIP claims $rate_{\text{two years prior}}$)	0.081	0.052	−0.103	0.519**
	(0.054)	(0.077)	(0.230)	(0.240)
Log(Income)	−0.002	0.023	−0.039	−0.018
	(0.055)	(0.054)	(0.185)	(0.173)
Log(Population density)	0.037	0.064*	0.095	0.288
	(0.046)	(0.035)	(0.153)	(0.240)
Log(Housing units)	0.002	−0.004	0.050	0.027
	(0.041)	(0.045)	(0.133)	(0.125)
Log(Age)	0.014	0.116	−0.061	−0.296
	(0.086)	(0.173)	(0.282)	(0.304)
Log(Property tax)	0.020	0.012	0.130	−0.089
	(0.048)	(0.049)	(0.186)	(0.142)
Yr2012	−0.001	0.007	0.060*	−0.013
	(0.008)	(0.007)	(0.034)	(0.021)
Yr2013	−0.004	0.017**	0.015	−0.008
	(0.008)	(0.008)	(0.024)	(0.021)
Yr2014	−0.021***	0.004	−0.007	−0.041
	(0.008)	(0.010)	(0.027)	(0.029)
Yr2015	−0.091***	0.042***	−0.039	−0.387***
	(0.012)	(0.012)	(0.034)	(0.058)
Constant	−0.343	1.240	−0.752	1.269
	(0.800)	(0.913)	(3.201)	(2.850)
Wald test (χ^2)	1174.83***	421.92***	624.86***	552.76***
Sargan test (χ^2)	21.882	38.446*	36.382*	22.086
First-order autocorrelation	−7.291***	−3.372***	−7.153***	−4.335***
Second-order autocorrelation	−0.492	−0.526	−1.239	2.187**
Observations	4,845	4,845	4,845	4,845
Number of CRS communities	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

estimate of this year-to-year effect of participation is larger than that found by Li and Landry (2018), but their work focuses on the State of North Carolina between the years of 1999 and 2010.

The negative and significant coefficient on *Precipitation lagged one year* suggest that for communities that receive greater precipitation in the previous year, *CRS points* is lower. Our model indicates that a 1% increase in precipitation in the preceding year reduces current *CRS points* by 0.012%. This effect, however, dissipates in the subsequent preceding year as indicated by the coefficient on *Precipitation lagged two years*. Li and Landry (2018) interacted precipitation with floodplain (i.e., precipitation × floodplain) and found a negative and significant relationship between the product and CRS points.[7] A possible argument for this finding is that as the level of risk increases, mitigation becomes more expensive and so communities abandon mitigation (Li & Landry, 2018). It could also be possible that as communities engage in less costly CRS activities that offer lower CRS points (low hanging fruits), the remaining CRS activities that could lead to higher CRS points become more expensive to undertake. Thus, communities may decide to maintain their current level by undertaking the "low hanging fruits" (Frimpong et al., 2020). Another interpretation might be that a singular event does not prompt further activities; instead, it is seen as an unusual occurrence. The positive and significant coefficient on *NFIP claims rate lagged one year* is in line with our hypothesis. That is, a 1% increase in NFIP claims rate in the preceding year corresponds to a 0.07% increase in *CRS points*. But the effect dissipates in the subsequent preceding year as indicated by the coefficient on *NFIP claims rate lagged two years*. Brody et al. (2009), who studied Florida counties, also noted that flood property damage is positively associated with higher CRS points. This could imply that as more individuals personally experience the impacts of a flood, there is a greater collective agreement and local government momentum to engage in hazard risk reduction.

Surprisingly, our socioeconomic variables do not significantly influence CRS points. The negative signs on *Income* and *Population density* are contrary to our hypotheses, though are not significant at a 10% level, and contradict the findings of past research (Brody et al., 2009; Li & Landry, 2018). The different findings might partly be explained by the differences in the scale of measurement of the variables. As mentioned earlier, we analyze data at the CRS community level while previous research use county-level data (Brody et al., 2009; Li & Landry, 2018). Another possible explanation is the differences in data periods. We studied CRS data from 2010 to 2015, while previous research studied CRS data from 1999 to 2005 (Brody et al., 2009) and 1999 to 2010 and 2002 to 2008 (Li & Landry, 2018). Li and Landry (2018) had mixed finding when examining different years and durations, which reinforces why differences in time periods considered could be influencing the differences in findings in our study and that of past research. For example, for the periods 1999 to 2010, Li and Landry (2018) found a positive and significant association between tax per capita and the level of CRS participation. On the contrary, for the data periods 2002 to 2008, their estimate for tax per capita is insignificant.

The positive signs for *Housing unit*, *Age*, and *Property tax* are consistent with our hypotheses, though these are not considered significant by the model. The results for the year fixed-effects (year dummies) are negative and indicate that the improvement in the level of CRS participation for 2014 and 2015 is significantly lower compared to 2011.[8] As mentioned earlier, this could be due in part to the 2013 changes to the CRS program that resulted in the adjustment of credit for some CRS activities and the introduction Flood Insurance Promotion activity to Series 300 (FEMA, 2013).

6.2 | Effects of HMA, flood risk, and socioeconomic information on the different CRS activity series

Table 6 has our model specifications for each of the CRS series. Our model diagnostics indicate that we can reject the null hypothesis of no valid instruments at 1% significance level for all the models. Additionally, we reject the null hypothesis of no first-order serial correlation, and fail to reject the null hypothesis of no second-order serial correlation at 1% significance level, providing confidence in our model specification.

Except for *Series 300*, we find a positive, but statistically insignificant, relationship between *HMA* and the activity series. To the extent that HMGP makes up about 80% of HMA grants, the lack of significance on *HMA* for *Series 400* (mapping and regulation activities) and *Series 600* (warning and response activities) is not surprising. HMGP money funds mostly acquisition and relocation projects, which is one of the activities with the highest maximum points under *Series 500* (flood damage reduction activities). Thus, to find no significant relationship between *HMA* and the level of participation in activity *Series 500* is unexpected and warrants further investigation. The positive and weakly significant relationship between *HMA* and *Series 300* (public information on flood risk and insurance activities) is not surprising. We find that 1% increase in *HMA* leads to 0.013% increase in *Series 300* participation. Public information on flood risk and insurance activities is popular among CRS communities because they are comparatively less expensive to undertake. Another possible explanation could be that CRS communities take advantage of HMA-funded activities under Series 500 (flood damage reduction activities) to simultaneously undertake Series 300 activities (public information on flood risk and insurance activities) and secure points. Recall that CRS communities can simultaneously secure

[7] In a separate model, we considered the product of precipitation and floodplain, and the coefficient was negative but insignificant.

[8] For example, the coefficient on Yr2014 should be interpreted as exp (−0.016) = 0.98%.

points for *Series 300* while undertaking *Series 500* activities (FEMA, 2017).

For all of the CRS series models, the lagged series coefficient is positive and significant at 1% significance level. However, as expected, the effects vary across series. The coefficient on the lagged series is lower for *Series 400* (0.666) compared to that of *Series 300* (0.984), *Series 500* (0.938), and *Series 600* (0.905), implying that it is difficult to improve participation in *Series 400* activities compared to *Series 300, 500*, and *600*. *Series 400* and *500* activities are more expensive and difficult to implement (Brody et al., 2009; Li & Landry, 2018; Sadiq & Noonan, 2015a).

The flood risk variables do not seem to influence participation in the activity series. Among the series, we find that *Precipitation* significantly and negatively influences the level of participation in only mapping and regulation activities (*Series 400*), while *NFIP claims rate* influences only warning and response activities (*Series 600*). That is, CRS communities that receive greater precipitation in the previous year participate less in mapping and regulation activities (*Series 400*). A finding that is unexpected and warrants further investigation. Li and Landry (2018) who interacted precipitation with floodplain found a negative correlation between the product (i.e., precipitation × floodplain) and *Series 300*, *400*, and *500*. The positive and significant sign on *NFIP claims rate* for the two lagged periods is consistent with our hypothesis. Generally, we also find that socioeconomic variables are not important factors influencing the level of participation in the activity series. Past research shows that the effect of socioeconomic variables on activity series is mixed (Brody et al., 2009; Li & Landry, 2018). We find that only *Population density* influences mapping and regulation activities (*Series 400*), and the positive sign and significance on population density are in line with our hypothesis. Past research found a positive relationship between population density and the activity series (Brody et al., 2009; Li & Landry, 2018). Finally, the year fixed-effects indicate that compared to 2011, communities are generally increasing participation in mapping and regulation activities (*Series 400*) at a higher rate compared to participation in public information on flood risk and insurance activities (*Series 300*), flood damage reduction activities (*Series 500*), and warning and response activities (*Series 600*).

6.3 | Robustness of results

To check our models' robustness, we examine whether the results on *HMA* are sensitive to lags. Particularly, we estimate our five models with the level of *HMA* lagged 1, 3, 4, and 5 years, and present the results in Tables A1–A5. Overall, the results are consistent with those from the presented models. *HMA* grant money received in the previous 1, 3, 4, and 5 years does not significantly affect the level of CRS participation as shown in Table A1. The signs on the *HMA* coefficient in Table A1, however, are mixed. In our presented results, the sign is positive but insignificant.

7 | DISCUSSION AND CONCLUSIONS

We assess the impact of FEMA's HMA grant programs on FEMA's CRS. We use 2010 through 2015 data on FEMA's CRS and link these data to flood risk and socioeconomic information. Although scholars have assessed the factors that affect the level of CRS participation, we present the results of what we believe to be an initial empirical study that tests the link between FEMA's HMA and the level of CRS participation. That is, the results in this study speak to local communities' responsiveness to flood risk mitigation due to availability of federal and local financial resources, and changes in flood risk and socioeconomics.

Our results reveal that, overall, HMA does not appear to significantly influence the level of CRS participation, although the relationship is positive. Consistent with Li and Landry (2018), the dynamic panel model suggests that previous level of CRS participation, flood risk and to some extent socioeconomic factors influence the level of CRS participation. The lack of significant effect of HMA on the level of CRS participation suggests a couple of things. First, it could be that the CRS program is not designed to capture the fine-scaled effects that incremental federal flood mitigation funding is likely to produce. Local authorities may also be strategically using HMA funding to largely maintain their status in the CRS program, rather than to expand mitigation efforts. Recall that the CRS program is designed such that local authorities have to renew their participation in the program annually.

Our findings suggest two main recommendations for policy. First, federal pre-disaster flood mitigation grant programs should be implemented in a way that encourages local communities to use HMA grants to expand flood risk mitigation and increase CRS participation in contrast to simply maintaining their status in the CRS program. Second, the disconnect between federal pre-disaster flood mitigation grant and the level of CRS participation indicates a need for programmatic changes to the CRS program that are able to capture the effect of incremental flood mitigation grants that CRS communities receive. Since FEMA is far and away the largest provider of community-level flood mitigation assistance and manages the CRS at the federal level, FEMA has the opportunity to influence both programs to achieve the desired flood resiliency in local communities.

Overall, this study adds to the growing discussion on drivers and barriers of local flood risk mitigation and sheds light on the effect of federal financial assistance on local flood risk mitigation. That is, findings and discussions in this study presents an important subject for further investigation and discussions. Some potential avenues for future research are to consider extending the dataset to cover a broader period (preferably 1999–2021), which should also expand the number of CRS communities. As of 2021 about 1500 (out of 22,000 NFIP communities) participate in the CRS program. A follow-up study should consider exploring other control variables, especially socioeconomic variables, that vary over time. Our control variables were limited by the econometric approach taken and the time frame considered. Future research should also consider other non-FEMA flood mitigation grants that CRS communities could use to implement CRS activities and receive credit, such as grants from the USACE. At this point, we have established, to some degree, a correlation between HMA spending and CRS points. However, further studies are required to provide a deeper understanding of the correlation between federal flood mitigation spending and the level of CRS participation.

ACKNOWLEDGMENTS

This research was supported by the National Academies Gulf Research Program Early-Career Research Fellowship. The support of the sponsor is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations presented in this study are those of the authors and do not necessarily reflect the views of the National Academies. The research was conducted during the time when Dr. Eugene Frimpong was employed by the University of Maryland. We thank Dr. Sam Brody (Texas A&M Galveston) for his insights and for providing CRS data. Finally, we gratefully acknowledge and thank the three anonymous reviewers for their thoughtful comments.

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How to cite this article: Frimpong, E., Reilly, A. C., & Niemeier, D. (2022). Does federal flood hazard mitigation assistance affect community rating system participation? *Risk Analysis*, 1–20. https://doi.org/10.1111/risa.14024

APPENDIX

A1-A5

TABLE A1 In this table, we test for different lag periods of Hazard Mitigation Assistance (HMA) on Community Rating System (CRS) points. The results we find are generally consistent with what were discussed in the study. Surprisingly HMA lagged 1 and 4 years have a negative but insignificant effect on CRS points

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Log(CRS points$_{\text{one year prior}}$)	0.954***	0.962***	0.933***	0.917***	0.941***
	(0.020)	(0.024)	(0.032)	(0.038)	(0.041)
Log(HMA $_X$)	−0.001	0.003	0.002	−0.006	0.001
	(0.003)	(0.002)	(0.004)	(0.004)	(0.006)
Log(Precipitation$_{\text{one year prior}}$)	−0.011**	−0.012**	−0.011**	−0.011**	−0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log(Precipitation$_{\text{two years prior}}$)	0.002	0.001	−0.001	0.004	−0.001
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Log(NFIP claims rate$_{\text{one year prior}}$)	0.066*	0.070*	0.067*	0.070*	0.059
	(0.037)	(0.037)	(0.038)	(0.039)	(0.042)
Log(NFIP claims rate$_{\text{two years prior}}$)	0.009	0.012	0.001	0	0.008
	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)
Log(Income)	−0.003	−0.025	−0.029	−0.029	−0.025
	(0.031)	(0.032)	(0.032)	(0.034)	(0.032)
Log(Population density)	−0.001	−0.002	0.026	0.012	0.012
	(0.012)	(0.014)	(0.020)	(0.020)	(0.023)
Log(Housing units)	−0.005	0.015	0.007	−0.018	−0.005
	(0.017)	(0.020)	(0.021)	(0.027)	(0.033)
Log(Age)	0.002	0.023	0.005	0.002	0.001
	(0.054)	(0.057)	(0.057)	(0.057)	(0.057)
Log(Property tax)	−0.003	0.012	−0.004	0.004	0.004
	(0.022)	(0.021)	(0.026)	(0.026)	(0.031)
Yr2012	0.000	−0.001	−0.002	0.002	−0.001
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Yr2013	0.002	−0.001	0.002	0.006	0.0001
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)

(Continues)

TABLE A1 (Continued)

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Yr2014	−0.011**	−0.016***	−0.013***	−0.009	−0.012
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Yr2015	−0.010	−0.013**	−0.014*	−0.005	−0.011
	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
Constant	0.485	0.337	0.734	1.044*	0.735
	(0.366)	(0.431)	(0.498)	(0.604)	(0.649)
Wald test (χ^2)	6504.810***	4883.430***	2396.52***	2481.88***	3524.85***
Sargan test (χ^2)	34.719	31.988*	34.223	29.501	34.458
First-order autocorrelation	−9.8789***	−9.647***	−9.635***	−9.447***	−9.171***
Second-order autocorrelation	1.614	1.561	1.614	1.438	1.629
Observations	4845	4845	4845	4845	4845
Number of CRS communities	969	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

TABLE A2 This table compares the effect of different lagged periods of Hazard Mitigation Assistance (HMA) on Series 300. Except for HMA lagged 2 years, we find an insignificant relationship between the different HMA lags and Series 300

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Log(Series $300_{\text{one year prior}}$)	0.986***	0.984***	0.949***	0.933***	0.940***
	(0.034)	(0.038)	(0.051)	(0.064)	(0.060)
Log(HMA_{X})	0.003	0.013*	−0.006	−0.007	−0.007
	(0.006)	(0.008)	(0.008)	(0.008)	(0.005)
Log($\text{Precipitation}_{\text{one year prior}}$)	0.007	0.004	0.006	0.003	0.009
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Log($\text{Precipitation}_{\text{two years prior}}$)	0.012	0.010	0.010	0.011	0.011
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)
Log(NFIP claims $\text{rate}_{\text{one year prior}}$)	0.047	0.082	0.078	0.058	0.051
	(0.047)	(0.053)	(0.050)	(0.051)	(0.058)
Log(NFIP claims $\text{rate}_{\text{two years prior}}$)	0.082	0.081	0.091*	0.080	0.083
	(0.052)	(0.054)	(0.052)	(0.049)	(0.057)
Log(Income)	0.005	−0.002	0.012	0.009	−0.003
	(0.046)	(0.055)	(0.045)	(0.049)	(0.049)
Log(Population density)	0.030	0.037	−0.003	−0.023	−0.016
	(0.040)	(0.046)	(0.046)	(0.039)	(0.041)
Log(Housing units)	−0.015	0.002	0.026	0.061	0.056
	(0.036)	(0.041)	(0.035)	(0.057)	(0.060)
Log(Age)	−0.004	0.014	0.010	0.013	0.014
	(0.076)	(0.086)	(0.077)	(0.079)	(0.081)
Log(Property tax)	0.020	0.020	0.011	0.033	0.0362
	(0.037)	(0.048)	(0.039)	(0.035)	(0.035)
Yr2012	−0.006	−0.001	−0.003	−0.007	−0.006
	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)
Yr2013	−0.012*	−0.004	−0.012**	−0.009	−0.008
	(0.007)	(0.008)	(0.005)	(0.008)	(0.006)
Yr2014	−0.015**	−0.021***	−0.016**	−0.021**	−0.011
	(0.006)	(0.008)	(0.006)	(0.008)	(0.009)
Yr2015	−0.089***	−0.091***	−0.085***	−0.090***	−0.091***
	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)
Constant	−0.213	−0.343	−0.220	−0.455	−0.408
	(0.602)	(0.800)	(0.587)	(0.697)	(0.782)
Wald test (χ^2)	2067.2***	1174.83***	421.92***	624.86***	896.20***
Sargan test (χ^2)	39.753**	21.882	35.213	26.451	28.728
First-order autocorrelation	−7.380***	−7.291***	−7.115***	−6.372***	−6.753***
Second-order autocorrelation	−0.437	−0.492	−1.017	−0.123	−0.499
Observations	4845	4845	4845	4845	4845
Number of CRS communities	969	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

TABLE A3 This table compares the effect of different lagged periods of Hazard Mitigation Assistance (HMA) on Series 400. We find no significant relationship between the various lagged periods of HMA and Series 400

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Log(Series $400_{\text{one year prior}}$)	0.658***	0.666***	0.660***	0.659***	0.658***
	(0.062)	(0.068)	(0.069)	(0.059)	(0.056)
Log(HMA $_X$)	0	0.002	−0.006	0.004	−0.010
	(0.004)	(0.005)	(0.005)	(0.007)	(0.010)
Log($\text{Precipitation}_{\text{one year prior}}$)	−0.021**	−0.018**	−0.019**	−0.019**	−0.017*
	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
Log($\text{Precipitation}_{\text{two years prior}}$)	−0.010	−0.011	−0.013	−0.012	−0.012
	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
Log(NFIP claims $\text{rate}_{\text{one year prior}}$)	0.084	0.068	0.049	0.106	0.073
	(0.072)	(0.078)	(0.077)	(0.080)	(0.080)
Log(NFIP claims $\text{rate}_{\text{two years prior}}$)	0.016	0.052	0.025	0.036	0.0217
	(0.078)	(0.077)	(0.075)	(0.079)	(0.083)
Log(Income)	−0.014	0.023	0.009	−0.018	−0.024
	(0.052)	(0.054)	(0.051)	(0.056)	(0.059)
Log(Population density)	0.044	0.064*	0.040	0.074**	0.055
	(0.038)	(0.035)	(0.033)	(0.035)	(0.048)
Log(Housing units)	−0.012	−0.004	0.013	−0.003	−0.009
	(0.046)	(0.045)	(0.043)	(0.048)	(0.050)
Log(Age)	0.057	0.116	0.051	0.034	0.018
	(0.159)	(0.173)	(0.167)	(0.157)	(0.166)
Log(Property tax)	0.020	0.012	0.024	0.006	0.011
	(0.050)	(0.049)	(0.048)	(0.048)	(0.059)
Yr2012	0.006	0.007	0.005	0.005	0.009
	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)
Yr2013	0.017**	0.017**	0.012*	0.017*	0.025**
	(0.008)	(0.008)	(0.007)	(0.009)	(0.010)
Yr2014	0.008	0.004	0.004	0.006	0.013
	(0.008)	(0.010)	(0.009)	(0.009)	(0.012)
Yr2015	0.049***	0.042***	0.047***	0.045***	0.048***
	(0.013)	(0.012)	(0.011)	(0.012)	(0.014)
Constant	2.041**	1.240	1.594*	2.092**	2.322***
	(0.853)	(0.913)	(0.879)	(0.898)	(0.883)
Wald test (χ^2)	503.87***	421.92***	488.72***	494.45***	527.05**
Sargan test (χ^2)	38.446**	38.446*	41.099**	25.360	23.250
First-order autocorrelation	−3.391***	−3.372***	−3.395***	−3.454***	−3.437***
Second order autocorrelation	0.301	−0.526	0.757	0.340	0.333
Observations	4845	4845	4845	4845	4845
Number of CRS communities	969	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

TABLE A4 This table compares the effect of different lagged periods of Hazard Mitigation Assistance (HMA) on Series 500. Except for HMA lagged 2 years, all lagged periods of HMA have a negative but insignificant relationship with Series 500. HMA lagged 2 years has a positive but insignificant effect on Series 500

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Log(Series $500_{\text{one year prior}}$)	0.948***	0.938***	0.931***	0.952***	0.959***
	(0.058)	(0.049)	(0.044)	(0.041)	(0.047)
Log(HMA_X)	−0.066	0.051	−0.009	−0.012	−0.010
	(0.041)	(0.032)	(0.012)	(0.009)	(0.009)
Log($\text{Precipitation}_{\text{one year prior}}$)	−0.022	−0.019	−0.002	−0.032	−0.033
	(0.040)	(0.035)	(0.031)	(0.033)	(0.033)
Log($\text{Precipitation}_{\text{two years prior}}$)	−0.013	−0.008	0.011	−0.009	−0.005
	(0.041)	(0.037)	(0.031)	(0.033)	(0.034)
Log(NFIP claims $\text{rate}_{\text{one year prior}}$)	0.022	−0.035	−0.247	−0.062	−0.004
	(0.321)	(0.289)	(0.317)	(0.314)	(0.389)
Log(NFIP claims $\text{rate}_{\text{two years prior}}$)	−0.079	−0.103	−0.107	−0.044	−0.151
	(0.257)	(0.230)	(0.192)	(0.201)	(0.219)
Log(Income)	−0.004	−0.039	−0.113	−0.107	−0.080
	(0.191)	(0.185)	(0.166)	(0.159)	(0.164)
Log(Population density)	0.057	0.095	−0.058	−0.025	0.043
	(0.114)	(0.153)	(0.075)	(0.069)	(0.079)
Log(Housing units)	0.116	0.050	0.076	0.129	0.262*
	(0.155)	(0.133)	(0.127)	(0.124)	(0.137)
Log(Age)	−0.047	−0.061	0.028	0.014	0.182
	(0.322)	(0.282)	(0.266)	(0.269)	(0.264)
Log(Property tax)	0.052	0.130	0.177	0.145	0.122
	(0.165)	(0.186)	(0.141)	(0.121)	(0.142)
Yr2012	0.050	0.060*	0.020	0.011	0.0146
	(0.031)	(0.034)	(0.018)	(0.016)	(0.017)
Yr2013	0.041	0.015	−0.005	0.001	−0.013
	(0.034)	(0.024)	(0.022)	(0.021)	(0.022)
Yr2014	−0.001	−0.007	−0.006	−0.024	−0.037
	(0.029)	(0.027)	(0.022)	(0.021)	(0.024)
Yr2015	−0.008	−0.039	−0.034	−0.061*	−0.092***
	(0.052)	(0.034)	(0.031)	(0.031)	(0.035)
Constant	−0.777	−0.752	−0.238	−0.422	−2.570
	(2.519)	(3.201)	(2.786)	(2.477)	(2.683)
Wald test (χ^2)	466.76***	624.86***	696.41***	808.06***	831.52***
Sargan test (χ^2)	28.198	36.382*	40.896**	29.080	27.549
First order autocorrelation	−6.804***	−7.153***	−7.464***	−7.598***	−7.457***
Second order autocorrelation	0.163	−1.239	−0.820	−1.036	−0.906
Observations	4845	4845	4845	4845	4845
Number of CRS communities	969	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

TABLE A5 This table compares the effect of different lagged periods of Hazard Mitigation Assistance (HMA) on Series 600. All but HMA lagged 4 years have a positive but insignificant relationship with Series 600. HMA lagged four years has a negative but insignificant relationship with Series 600

Variables	X = One year prior	X = Two years prior	X = Three years prior	X = Four years prior	X = Five years prior
Log(Series 600$_{\text{one year prior}}$)	0.973***	0.905***	0.943***	1.002***	1.014***
	(0.088)	(0.081)	(0.070)	(0.043)	(0.055)
Log(HMA $_X$)	0.004	0.016	0.014	−0.004	0.006
	(0.009)	(0.024)	(0.009)	(0.006)	(0.007)
Log(Precipitation$_{\text{one year prior}}$)	−0.022	−0.007	−0.002	0.006	−0.009
	(0.024)	(0.026)	(0.023)	(0.022)	(0.023)
Log(Precipitation$_{\text{two years prior}}$)	−0.034	−0.033	−0.022	0.003	−0.014
	(0.029)	(0.030)	(0.025)	(0.024)	(0.025)
Log(NFIP claims rate$_{\text{one year prior}}$)	0.346*	0.467**	0.435**	0.349*	0.393**
	(0.191)	(0.215)	(0.172)	(0.179)	(0.180)
Log(NFIP claims rate$_{\text{two years prior}}$)	0.301	0.519**	0.492**	0.358	0.334
	(0.274)	(0.240)	(0.234)	(0.241)	(0.229)
Log(Income)	0.050	−0.018	0.026	0.018	0.095
	(0.156)	(0.173)	(0.163)	(0.154)	(0.154)
Log(Population density)	0.177	0.288	0.252	0.171	0.164
	(0.302)	(0.240)	(0.185)	(0.115)	(0.136)
Log(Housing units)	0.104	0.027	0.034	0.056	0.051
	(0.103)	(0.125)	(0.096)	(0.097)	(0.090)
Log(Age)	−0.066	−0.296	−0.349	−0.289	−0.441
	(0.298)	(0.304)	(0.255)	(0.258)	(0.276)
Log(Property tax)	−0.070	−0.089	−0.172	−0.156	−0.204*
	(0.120)	(0.142)	(0.111)	(0.100)	(0.119)
Yr2012	−0.015	−0.013	−0.019	−0.012	−0.011
	(0.014)	(0.021)	(0.012)	(0.011)	(0.013)
Yr2013	−0.021	−0.008	−0.017	−0.020*	−0.019
	(0.018)	(0.021)	(0.013)	(0.011)	(0.015)
Yr2014	−0.028	−0.041	−0.031	−0.021	−0.022
	(0.025)	(0.029)	(0.021)	(0.014)	(0.019)
Yr2015	−0.385***	−0.387***	−0.390***	−0.360***	−0.368***
	(0.061)	(0.058)	(0.052)	(0.048)	(0.051)
Constant	−0.925	1.269	1.515	1.033	1.285
	(2.402)	(2.850)	(2.530)	(2.245)	(2.423)
Wald test (χ^2)	1585.95***	552.76***	614.65***	1268.0***	875.27***
Sargan test (χ^2)	44.309**	22.086	21.810	29.975	29.078
First order autocorrelation	−4.361***	−4.335***	−4.439***	−4.723***	−4.553***
Second order autocorrelation	1.535	2.187**	2.201**	1.811*	1.588
Observations	4845	4845	4845	4845	4845
Number of CRS communities	969	969	969	969	969

Note: Windmeijer (2005) robust standard errors are in parentheses. Note that because ABBB is a first-difference estimator, the first year, 2010 is sacrificed, and 2011 is the reference category.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.