The Spillover Effect of FEMA's Community Rating System

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Abstract

The Community Rating System (CRS) was established to encourage community to voluntarily conduct higher standard floodplain management. Participating communities are rewarded with flood insurance discounts based on CRS points earned through CRS eligible activities. This paper examines an overlooked question by previous research: whether there is spillover effect of the CRS program regarding flood damage reduction, as well as the potential mechanism of this spillover effect. Results indicate non-significant average treatment effect, but there is a lagged, short-term spillover effect. For non-CRS communities, having a CRS neighbor leads to about $0.5 million reduction in annual flood damage a few years after the treatment. This impact is possibly because of community's learning from their CRS neighbors by investing more on flood risk mitigation activities.

Keywords: Flood risk, flood damage, spillover effects, community rating system
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1 Introduction

There is concern that climate change increases the frequency and intensity of extreme weather events such as flooding, which leads to a predicted increase of annual property damage by 13% - 17.4% in the next two decades (Liu et al., 2015). In total, from 1980 to 2021, 35 flooding have caused $161.9 billion dollars (CPI adjusted) of damage and about 624 deaths in the U.S. (NCEI, 2021). There is also evidence shows that at national level, the flood damages are increasing and high damage years become more frequent (Cartwright, 2005). Some potential reasons of the rising flood damage include both natural factors such as higher precipitation extremes and seal level rise (Davenport et al., 2021; Hinkel et al., 2014) and human factors such as increased population and accumulation of wealth in coastal areas (Brody et al., 2010; Pielke Jr et al., 2008).

Due to the large damage caused by flooding on human beings and properties, the National Flood Insurance Program (NFIP) was established to provide access to primary flood insurance and reduce comprehensive flood risk and damage in 1968. The Community Rating System (CRS) was established to encourage communities to follow higher standards and implement better floodplain management, as well as support the NFIP with low participation rate and solvency issues (Frimpong et al., 2020). The CRS program rewards voluntarily participated communities through NFIP premium discounts based on the type of floodplain management activities undertaken (FEMA, 2017b). Both of these programs are currently managed by the Federal Emergency Management Agency (FEMA).

The CRS has been found to be associated with higher flood insurance uptake, lower flood claims and property damage (Frimpong et al., 2020; Highfield and Brody, 2017; Highfield et al., 2014). Previous research has shown that a lot of factors affect the participation and level of CRS, such as population, local government tax revenue, household income, education, race, age and so on (Li and Landry, 2018; Sadiq and Noonan, 2015; Landry and Li, 2012). On the other hand, there are also some unintended consequences due to the CRS, such as more development in flood prone areas and income inequality (Noonan and Sadiq, 2018;

Brody et al., 2007). However, most of these research only focus on the local effect within a CRS community in terms of promoting insurance purchase and reducing flood damage. Due to the investment in flood risk mitigation activities, it's possible that these activities could help reducing flood risk and damage of nearby non-CRS communities. Based on the type of flood management activities, they may generate beneficial or adverse externalities to nearby regions (Chang, 2017, 2008). For example, the wetland management and conversion upstream may affect downstream flood claims (Taylor and Druckenmiller, 2022). If this spillover effect exists, then the benefits/costs of the CRS may be underestimated.

I examine whether joining in the CRS has spillover effect on neighbor non-CRS communities. In other words, do non-CRS communities located near CRS communities experience less damage after flooding than those who don't? If there is spillover effect, what's the channel of this effect? To answer these questions, I collect and construct a unbalanced community-year level panel data set using different data sources. I use damage records from FEMA's flood insurance claims data. I use CRS historical data and Community Status Book from FEMA to decide the entry year when a community joined the CRS. I merge the CRS historical data with National Flood Hazard Layer (NFHL) to identify whether a NFIP community has a CRS neighbor in a given year in ArcGIS. I also collect demographic data from American Community Survey (ACS) and Decennial Census, and annual precipitation from PRISM. To control for flood size, I construct an flood frequency analysis using USGS gauge record data following Lee (2021)'s method, which avoid limitations such as subjectivity and limited cover period of other available dataset (Gourley et al., 2013).

The fact that only a small part of NFIP communities joined in the CRS program and they participated in different years allows me to adopt a Difference-in-Difference (DID) and event study specification to estimate the causal effect of having CRS neighbor community on flood damage of non-CRS communities. A simple two way fixed effect model suggests a insignificant negative effect and the treatment effect may become larger for non-CRS community with more than one CRS neighbors. Similarly, the instrument-variable (IV) estimates show a larger negative and insignificant effect after controlling for the potential endogeneity of having a CRS neighbor. To overcome the concern of the biased TWFE estimator given the staggered treatment setting (Goodman-Bacon, 2021), I then adopt alternative methods proposed by Sun and Abraham (2021) and Liu et al. (2021) that estimate dynamic treatment effect and are robust to this concern as baseline specifications. The results provide evidence that non-CRS communities with CRS neighbor experience about $0.5 million less annual flood damage than those who don't. The short-lived effect is only found a few years after the treatment. The results are robust to a series of robustness checks including (1) different estimation method (2) different way of defining neighbor relationship (3) different binning option (4) estimation using sub-sample. I find larger spillover effect for communities with less population and lower income. I also find that this effect is mainly driven by insurance claims located in Special Flood Hazard Area (SFHA) within a community.

I then examine two possible mechanism of this spillover effect. The first possibility is information spillover: households and local government learn from their CRS neighbors when making decisions on conducting flood mitigation activities. The event study results show that having CRS neighbor has no effect on households' behavior of purchasing flood insurance. I find that community/local government that have CRS neighbors are more likely to join the CRS program, indicating that the learning process mainly happen at community level instead of household level. The second possibility is the direct physical externality due to flood mitigation activities conducted by CRS communities, especially those that could increase water store capacity or reduce flow velocity within a community. I test the impact of total CRS points earned from structural CRS activities on neighbors' flood damage. I find no evidence that those CRS activities have direct impact on neighbor communities' flood damage.

This research contributes to three strands of literature. First, this paper contributes to the literature evaluating the effectiveness of the CRS (Frimpong et al., 2020; Highfield and Brody, 2017; Highfield et al., 2014; Brody et al., 2008, 2007). To my best knowledge, this is the first paper that examines the spillover effect of the CRS program, which enhances more thorough understanding of the benefits of the CRS program. Brody et al. (2007) find that one unit increase in CRS rating has led to a reduction in average flood damage by about \$303,525. Highfield et al. (2014) find that structures in CRS communities experience about 88% reduction in flood damage than those not in the program. More recently, Frimpong et al. (2020) find that CRS communities with class 5 experience about \$125,000 lower annual flood damages. While most of these studies focus on the impact of the CRS program on flood damage within CRS communities, this paper provide evidence that non-CRS communities may also benefit from their neighboring CRS communities.

Second, it adds to the literature examining the spillover effect of public policy. Previous studies show that public policy may have spillover effect on different economic outcomes outside the targeted areas. Yilmaz et al. (2002) find that telecommunications investment in a state has negative impact on other states' output growth rate. Similarly, Pereira and Roca-Sagalés (2003) find that public capital formation in one region has spillover effect on the private output in other regions. Dundas and Lewis (2020) find that private protection choices have spillover effect to their neighbors under the setting of coastal land-use policy, which caused about %8 reduction of neighboring land value. This paper shows that the CRS program not only affects participating communities but also their neighbor communities by inducing more community-level investment in flood mitigation projects.

Third, it also broadly relates to the literature about how households form and update their beliefs on the risk of infrequent natural disasters, especially for flooding. Atreya et al. (2013) find that household respond to recent major flood events, which is reflected in the property price discounts. Gallagher (2014) show that flood insurance take-up increases right after a flood not only in communities that directly impacted by the flood, but also in neighbor communities that's not impacted but within the same media market. Instead of examining the impact of flood events on households' belief, this paper shows the impact of another potential information source: flood-related policies in their neighbor communities.

The results indicate that households don't respond to this kind of information because either this information is not strong enough to remind them of flood risk or because the higher insurance premium in non-CRS communities.

The paper proceeds as follows. Section 2 provides background of the NFIP and the CRS. Section 3 describes the data and provides some descriptive analyses. Section 4 lays out the empirical strategy. Section 5 presents the results and section 6 discussed potential mechanism. Section 7 concludes.

2 Background

National Flood Insurance Program (NFIP) was established in 1968 when the National Flood Insurance Act (NFIA) was passed. It aims to provide households access to flood insurance, reduce financial risk brought by flooding, as well as encourage local communities to take activities to mitigate and reduce comprehensive flood risk. Communities could voluntarily participate in NFIP by adopting a flood map and implementing flood plain management activities to reduce future flood risk. The residents of a NFIP community are then eligible to purchase flood insurance.

Some reforms and adjustments have been made to better achieve the goals of the NFIP. For example, the pass of the Flood Disaster Protection Act (FDPA) in 1973. It made the purchase of flood insurance mandatory for property owners located in Special Flood Hazard Area (SFHA) with federally regulated mortgage loan to encourage the participation in the NFIP (Kousky, 2018). SFHA is a collection of flood zones defined by FEMA as having 1% or higher frequency of being flooded in any given year and shown on a Flood Insurance Rate Map (FIRM). It's usually refereed as "100-year flood zone" and is the standard used by NFIP on flood plain management and mandated flood insurance purchase. The CRS program was established in 1990 with three main goals: reduce and avoid flood damage to insurable property, strengthen and support the insurance aspects of the NFIP, and foster comprehensive floodplain management (FEMA, 2017b). CRS encourages NFIP communities to implement flood management activities beyond the minimum requirement of NFIP, and help expand the policy base (FEMA, 2017b). As of 2021, over 22,000 communities have joined the NFIP, and about 7% of them have joined the CRS (FEMA, 2017a). Although the percentage of CRS participants seems low, they account for over 70% of the total NFIP flood insurance policies (FEMA, 2017a).

Communities earn CRS points through CRS credited activities, which determines CRS class and discount level of flood insurance. The CRS class ranges from 1 to 9, with 1 being the highest class and represents 45% discount for communities located in SFHA, and 10% discount for those located in Non-Special Flood Hazard Area (NSFHA) (FEMA, 2017b). Table 1 shows the CRS points needed for each CRS class and associated discount varied across flood zones. CRS credited activities fall in four series: public information, mapping and regulations, flood damage reduction, and warning and responses (FEMA, 2017b). Table 2 shows the activities within each category.

3 Data

The data used are mainly from FEMA. I received the CRS historical data from FEMA through FOIA request. The CRS historical data includes information about all communities that have participated in CRS: CRS class, total CRS points earned, and points earned from 4 category of CRS credited activities. I first create a data table showing annual CRS communities change from 1998 to 2018 using CRS historical data and add it to the NFIP community map extracted from National Flood Hazard Layer (NFHL). For 1991-1997, I use CRS entry date in NFIP Community Status Book to decide the year a community joined the CRS before 1998. I then create the key variable-neighbor using ArcGIS. I identify all non-CRS communities that share border line with at least one CRS community in a given year as having a CRS neighbor. I also calculate the distance of each community to its nearest CRS community in a given year and define "neighbor" based on the distance. Figure B1 provides an example about how treatment (neighbor relationship) is determined in 2018. The community 135158 in purple is a CRS community in 2018. The communities in green are non-CRS communities. The treated units are community 010184, 010250, 130293, 130338, and 130396 that partially share a border with the CRS community. The rest of non-CRS communities are control units. In addition, I download National Hydrography Dataset Plus (NHDPlus-V2) from Environmental Protection Agency (EPA). As a national geospatial surface water framework, it provide information which makes it easier to conduct upstream and downstream navigation, analysis, and modeling (McKay et al., 2015). It allows me to identify the stream network across NFIP communities. I use the identity tool in ArcGIS to determine which part of a stream is within which community. I use the flowing link across main streams to determine the upstream-downstream relationship between two communities. Thus I could define "having a CRS neighbor" in a more conservative way: if a non-CRS shares border with at least one CRS community, and it is located downstream of that CRS community.

For flood damage data, I received FIRM NFIP Redacted Claims data with the unique identifier - community number from FEMA through FOIA request. The same data without community number are available through the OpenFEMA Dataset (FEMA, 2021). This is the best available data set in terms of providing consistent and accurate approximation of observed flood damage according to FEMA. It records 2 million claims transactions since 1978, including information about community number, date of loss, number of policies, flood zone, claim amount, insurance coverage on buildings and contents, and elevation condition of the building. I first restrict data to single-family houses from 1991 to 2018. I calculate total claim by adding together amount paid on building claim, content claim, and increased cost of compliance claim. I then add all total claims within a community to get community-year level claims.

For flood history at community level, I conduct flood frequency analysis using daily flow records from over 3000 United States Geological Survey (USGS) stations. I construct the data set following Lee (2021)'s method, which includes 4 steps: (1) fit gauge-specific flood frequency distribution with Log-Pearson III distribution using annual peak flow records of each gauge. (2) convert daily instantaneous peak flow to quantiles estimated from the fitted distribution from step (1). (3) take the annual maximum value of quantiles for each gauge and convert them to recurrence interval. Generally, the recurrence interval of quantile x is 1/(1-x). For example, if a gauge's discharge is at 95% of the fitted distribution, it corresponds to a 20-year flood, which means this kind of flood happens every 20 years on average. (4) link community to flood history data and calculate community-year-level flood size by taking the average of 3 nearest gauges of each community using inverse distance as weights. More details about the process of flood frequency analysis are in Appendix A.

I collect census block group level demographic data from American Community Survey (ACS) through NHGIS (Manson et al., 2017) including total population, percentage of black population, percentage of bachelor degree holder, median age and median household income. Since it's 5 year estimates, I calculate 5 periods average for each year whenever possible. For example, the population of census block x in 2011 is the average of the population from 5 year estimates of 2007-2011, 2008-2012, 2009-2013, 2010-2014, and 2011-2015. I intersect census block group map and NFIP community map in ArcGIS, and calculate geographic weights indicating the share of a census block group located in a community. A simple example is shown in Figure B2. For 1991-2008 where ACS is not available, I use the Decennial Census data from 2000 and 1990. I also include annual precipitation from PRISM climate group as control variables (PRISM Climate Group, 2015).

I merge all data mentioned above at community-year level through community number. Table 3 reports the summary statistics of the data. About 27.9% of NFIP community have at least one neighbor CRS community. It's worth mentioning that flood damage is very dispersed with mean of $0.394 million and standard variation as large as $11.5 million. This dispersion in flood damage is most likely due to Hurricane Sandy - the second largest and costliest Atlantic hurricane in the US (McCoy and Zhao, 2018). The mean flood damage is about \$3.56 million for 2012 and \$0.31 million for the rest of the years. The data set starts with over 22,000 NFIP communities before any community joining the CRS. The number of CRS communities increased from 272 in 1991 to 1,502 in 2018, which leads to treated non-CRS communities increased from 1,106 to 3,898 communities. However, because not all communities were hit by flood every year, after merging in the NFIP claim data, we end up with 74 treated units in 1991 to 726 treated units in 2018. In total, 203 communities dropped out of the program after entering the CRS program. This is not a big concern because even for those participants that dropped out, over 90% of them stayed in the program for at least 5 years, which provides enough variation to estimate a short-term effect for those treated units. The retention rate is lower here maybe because of longer time dimension, compared to (Michel-Kerjan et al., 2016)'s finding that about 99% of participated CRS communities stay in the program from 1998 to 2011.

4 Empirical Model

I start by describing the challenges of estimating the causal effect of having CRS neighbor on flood damage. First, non-CRS with and without CRS neighbors may be different from each other in terms of unobservable characteristics. Thus ordinary least squares (OLS) estimates are subject to bias due to omitted variables. My first approach uses a Difference-in-Difference model with two-way fixed effects. I include community fixed effect and time fixed effect to control for the time-invariant community-specific unobservables and common time trends across communities. The assumption here is that conditional on covariates and community fixed effects, those treated and control units would have similar trend regarding flood damage, in the absence of the treatment.

Second, Since the CRS program is voluntary, the treatment here: decision of joining the CRS is made by individual NFIP community. Although Noonan et al. (2020) show that the decision of joining the CRS program is not affected by their neighbors' characteristics or behaviors, there may be some correlated unobservables between CRS communities and their neighbor non-CRS communities. In other words, even if I control for observables and community fixed effects, the treatment here may be driven by time-varying unobservables. For example, if some exogenous shock affect two neighboring community A and B, which causes A joined the CRS and B implement flood mitigation activities but not join the CRS. Then *Neighbor* in equation 1 could be correlated with the error term, which cause biased estimates. My second approach adopts an instrumental variable (IV) approach to confront the potential endogeneity of joining the CRS. Considering that house buyers in SFHA with federally backed mortgages are required to purchase flood insurance, and the CRS provides premium discount, a community with higher house turnover rate may have higher percentage of households that support their community joining the CRS. The house turnover rate is the percentage of sold houses divided by total available houses on the market in a given year. I use the 1-year lag turnover rate as instrument for community's decision of joining the CRS. I obtain national property transaction data from CoreLogic Solutions. I keep those arms-length transactions of single homes and drop observations missing longitude, latitude, sale date, and year of built. I first overlay every property with NFIP community map in ArcGIS using longitude and latitude. Within each community, I calculate approximate total available houses for year t by adding up all house transactions before year t minus houses built in year t. Then I calculate turnover rate as the ratio of number of houses sold to total available houses for each year from 1990 to 2017.

Last, there are many treatment and control groups with varying treatment times here, this staggered setting may cause bias for simple two-way fixed effect (TWFE) estimator through heterogeneous treatment effect over time or group and dynamic treatment effect (Baker et al., 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). Goodman-Bacon (2021) shows that the TWFE estimator equals to a weighted averages of all possible two-group/two-period DID estimators, and the comparison between early-treated units (as control group) and latertreated units (as treatment group) may cause bias when average treatment effect varies over time. This issue is very likely under the setting of this paper. For example, the treatment effect may be different for large and small NFIP communities. In addition, number of CRS neighbors, as well as their CRS class may increase over time, which may lead to larger treatment effect. My third approach use the method proposed by Sun and Abraham (2021) that's robust to treatment heterogeneity.

4.1 Difference-in-Differences Specification

The base strategy is to estimate the impact of having a neighbor CRS community on flood damage using a Difference-In-Difference (DID) model:

$$Y_{it} = \alpha_i + \beta_1 \text{Neighbor}_{it} + \gamma_i X_{it} + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} is total flood damage ($ million) for community i in year t. $Neighbor$ is a dummy variable and equals to 1 if a NFIP community i is treated: have a neighbor CRS community in year t. β_1 is the coefficient we are interested of, which measures the spillover effect of CRS program. To be specific, the spillover effect is average flood damage difference between treated and control groups, conditional on households in a community being hit by a flood with flood insurance. X_{it} includes number of policy in force, and community demographic characteristics. Historical flood size and annual precipitation are included to control for flood risk. Another concern is that if treated units purchase insurance for higher valued contents and buildings or if they are more likely to elevate their homes, then even the similar flood would lead to higher/lower damage for treated and control communities. So I also include total insurance amount in dollars on the contents and building, as well as % of elevated buildings as control variables. α_i is community fixed effect capturing unobserved characteristics of each community. δ_t is year fixed effect account for unobservable yearly trends that affect all communities. ϵ_{it} is the idiosyncratic error.

4.2 IV Specification

The 2SLS model estimated using the IV method is given by:

$$
\begin{aligned}
Y_{it} &= \alpha_i + \beta_1 \text{Neighbor}_{it} + \gamma_i X_{it} + \delta_t + \epsilon_{it} \\
Neighbor_{it} &= \eta_i + \pi_1 \text{Turnover}_{it} + \phi_i X_{it} + \theta_t + \upsilon_{it}
\end{aligned} \tag{2}
$$

where the second-stage is the same as equation 1, but here in the first-stage I use community-level house turnover rate to instrument a community's decision of joining the CRS, i.e. a community has a CRS neighbor. $Neighbor$ is a dummy variable and equals to 1 if a NFIP community i joined the CRS in year t. $Turnover$ is the house turnover rate for community i in year t-1 . I include the same control covariates, year fixed effect and community fixed effect in the first-stage and second-stage regressions. The exclusion assumption here is that house turnover rate in community A only affects its probability of joining the CRS, but has no direct effect on its neighbor B's annual flood damage.

The first-stage and second-stage model need to be estimated separately here for two reasons. First, in the first-stage, I model the decision of joining the CRS program for all communities. While the second-stage equation only includes non-CRS communities. Secondly, the covariates used in these regressions are different. For the first-stage estimation, I exclude number of policy in force, total insurance amount on buildings and contents, and % of elevated houses because they are likely the consequences of joining the CRS instead of driving factors. I then estimate the second-stage equation using predicted value of $Neighbor$ from the first-stage results.

4.3 Staggered Difference-in-Differences Specification

To alleviate the possible bias because of staggered adoption, and check the validity of parallel trend assumption as well as the existence of dynamic effect over time. I estimate the "interaction-weighted" (IW) estimators proposed by Sun and Abraham (2021) that's robust to treatment heterogeneity in the following event study section. I estimate the event study version of equation 1:

$$Y_{it} = \alpha_i + \sum_{t=-k}^{-2} \mu_l D_{i,t}^l + \sum_{l=0}^{L} \mu_l D_{i,t}^l + \gamma_i X_{it} + \delta_t + \epsilon_{it} \tag{3}$$

where Y_{it} is total flood damage of community i in year t. $D_{i,t}^l = \mathbb{I}[t - E_i = l]$ is an indicator for unit i being l periods away from the year when treatment begins. α_i and δ_t are community and year fixed effect. ϵ_{it} is the idiosyncratic error. I remove $D_{i,t}^{-1}$ to avoid multicollinearity problem (Sun and Abraham, 2021; Borusyak and Jaravel, 2017). For periods distant from the treatment time, I bin the $D_{i,t}^l$ for periods more than 8 years away from the treatment year. I choose to bin the end periods because on one hand, number of observations decrease as getting closer to the end of the relative period. On the other hand, pooling the spillover effect over multiple event years could increase statistical power (Gallagher, 2014). The coefficient μ_l estimated here could be interpreted as the change in total flood damage in community i relative to the year before it starts to have a CRS neighbor community. Standard errors are clustered at community level.

The three assumptions required for identification of Sun and Abraham (2021) are likely to hold here. (1) Parallel trend. The assumption here is that, with or without CRS neighbor, the annual flood damage in treated and untreated non-CRS communities are similar, conditional on covariates. Previous research have found that flood risk and previous flood experience affect community's decision of participating in the CRS (Li and Landry, 2018; Sadiq and Noonan, 2015; Landry and Li, 2012). In other words, those CRS communities generally have higher flood risk than those non-CRS communities. So non-CRS communities as a whole are likely to have similar and lower flood risk, thus experience similar and lower flood damage relative to CRS communities. (2) No anticipatory behavior. As already mentioned above, the treatment here is essentially a decision made by other community. These non-CRS communities are very unlikely to take actions by predicting their neighbor community's decision of joining the CRS. (3) Heterogeneous treatment effect. The CRS program has been established for over 20 years, those non-CRS communities may respond to the fact that their neighbor community joining the CRS differently based on the time of treatment, as well as their community characteristics. I'll test some of these assumptions in the next section.

5 Results and Discussion

5.1 Main Estimates

Table 4 reports the results of the base model of equation 1. As expected, more households purchasing flood insurance generally means higher total claims and payments. The negative coefficient for annual precipitation and flood size may indicate that those NFIP community with higher risk of being flooded may already realize the risk and spend more money on flood mitigation activities, although they are very small and not significant. The key variable of interest is neighbor. The results show that on average, a NFIP community with a CRS neighbor community experience less flood damage than a NFIP community that doesn't have a CRS neighbor, although it becomes non-significant after adding community fixed effect. Column (4) in table 4 shows the impact of treatment intensity. The negative coefficient indicates that having more than one CRS neighbors may have larger effect on flood damage, although it's not significant either. Column (2) in table 5 reports the first-stage relations in 2SLS estimates. The weak instrument test statistic (88.57) shows that turnover rate has significant positive effect on community's likelihood of joining the CRS. Column (1) in table 5 reports the Two-Stage least squares (2SLS) estimates of estimating equation 2. The spillover effect is estimated at -0.51, which is very similar to the baseline estimate of the two-way fixed effect model and still not significant. The insignificant coefficients from two-way fixed effect model and IV estimation may indicate that the average treatment effect over such a long period (i.e. over 10-20 years) is too small to be captured, compared to the direct impact of CRS activities on flood damage reduction within CRS communities.

Since the average treatment effect is not significant and to explore the dynamic treatment effect that may vary across time and cohorts, I then focus on the results using Sun and Abraham (2021)'s method in figure 1 afterwards. I use never-treated units, i.e. non-CRS communities that never have CRS neighbors as controls. As figure 1 shows, there is no discernible difference of flood damage between treated and control groups before treatment. I find a small negative treatment effect in year 7 (-0.496) after the treatment. The delayed treatment effect may indicate the existence of indirect spillover effect. In other words, it takes time for neighbor communities observe and learn from their neighbors after their neighbors' participation in the CRS. It also takes time for those newly conducted activities by non-CRS communities to take effect until next flood event that affect the community.

5.2 Robustness Check

As mentioned in the data section, the drop out of CRS participants may cause some treated units change to untreated, which may bias the results. I first drop all those non-CRS communities that experience treatment status from 1 to 0 at some point and re-estimate equation 3, the results are in figure 2.

I first try an alternative method proposed by (Liu et al., 2021), which also deals with heterogeneous treatment effects or unobserved time-varying confounders issues, as complementary evidence to the base model specification. They also provide easier way of plotting dynamic treatment effect, along with diagnostic tests. The results of the "counterfactual estimators" are in figure 3. The Wald test shows that the no pre-trend assumption likely holds here ($p = 0.62$). Similarly, I find negative and non-significant average treatment effect on the treated (-0.016). I find significant negative treatment effect in year 4 (-0.398), and year 8 (-0.309). To test the validity of identifying assumptions, I also conduct a placebo test to check the overall validity of identifying assumptions of the "counterfactual estimators". I use the default periods setting by assuming that the treatment time start 2 periods before the actual treatment year and re-estimate equation 3 to test whether the average treatment effect in the placebo periods are different from zero. The results are in figure 4 and we fail to reject the null hypothesis that the placebo effect is zero ($p = 0.223$).

I then try different ways of defining CRS neighbors for non-CRS communities in ArcGIS. The results shown in table 4 and figure 1 define neighbor as two communities at least share part of their boarders. Now I first calculate the distance between each non-CRS community and its nearest CRS community and then define neighbor if the shortest distance is 0. I then re-estimate equation 3 and the results are in Figure 5. The estimated coefficient for year 7 is less significant here. Similarly, I also report results in figure 6, where a non-CRS community has a CRS neighbor if they share borders and it is located downstream of that CRS community. The results are similar to figure 1.

As mentioned earlier, one reason that I focus on the results using Sun and Abraham (2021)'s method is that they allow me to bin end periods that's away from treatment time. I now check whether different binning choices affect results. Figure 7 reports the event study results so that -11 (11) on the horizontal axis is a bin for observations that in year -27 to -11 (11 to 27), which is similarly to figure 1. Having a CRS neighbor community still has a small and short-termed negative impact on flood damage.

As discussed before, the average flood damage in 2012 is much larger than the rest of the years in our sample ($3.56 million vs. $0.31 million), which may bias the results. I simply drop the data in 2012 to check whether the results are driven by these observations with greater claim values. Figure 8 reports similar results to the event study results reported in figure 1.

I then check whether there is heterogeneous effect. I estimated equation 3 separately for large and small community, and for high-income and low-income community. The criteria is being above or below the median value of community population and annual household income. The results are reported in figure 9 and 10. I found larger treatment effect for smaller community and low-income community. In other words, a smaller or low-income NFIP community is more likely to benefit from having a neighbor CRS community. The results provide evidence of heterogeneous treatment effect and again justifies the necessity of estimating a dynamic effect model instead of a TWFE model. One potential concern is that, households located in SFHA and NSFHA have different flood risk and experience different flood damage, even within the same community. Comparing the flood damage across communities that contain both SFHA and NSFHA may generate biased results. I estimate equation 3 separately for SFHA and NSFHA. Figure 11 shows the results. The general results hold and the spillover effect for SFHA is slightly larger than NSFHA. This reflects the fact that most of the NFIP policies are held and flood mitigation activities are conducted within SFHA.

6 Potential Mechanism

I find that joining the CRS program has negative impact on neighboring non-CRS communities' flood damage a few years after treatment. There are two potential mechanisms could cause this delayed spillover effect. First, information spillover or indirect impact. Non-CRS communities, as well as households could observe their neighbor communities joining the CRS program. They may learn form this new information about flood risk and more options of implementing better floodplain management. Second, protection spillover or direct impact. Some of the activities taken by CRS communities may directly lower the flood risk and flood damage of their neighbor communities. This physical externality due to CRS activities is different from learning mechanism in the way that non-CRS communities benefit from having CRS neighbor by doing nothing.

6.1 Information Spillover

6.1.1 Learning Behavior of Households

In general, homeowners tend to neglect the potential impact of events with high damage but low probability such as flood and thus are reluctant to purchase flood insurance (Botzen and van den Bergh, 2012). Hence educating households about real flood risk or required information disclosure related to flood risk during housing transactions are important and suggested in improving the efficiency of the NFIP (Chivers and Flores, 2002). Previous research have show that households update their belief of flood risk after a significant flood event, as reflected in the temporally price drop of property located in 100-year flood zone (Atreya et al., 2013).

Household update their expectations on future flood based not only on their own flood history but also flood experience of their neighbors (Gallagher, 2014). The difference here is that the information is not from flood itself but from a neighbor community's decision of joining the CRS program, which may also remind household of flood risk and lead to flood mitigation activities. The change in households' perception of flood risk is measured using total number of flood insurance in force within a community. I first examine whether having a CRS neighbor community have impact on flood insurance take-up. Figure 12 shows the event study results. I binned periods longer than 10 years away from the treatment year. Most of the estimated coefficients before treatment are not different from 0. The figure indicates that having a CRS neighbor community has no significant effect on flood insurance take-up.

The dependent variable here is the total number of policies within a non-CRS community that are affected by flood. One concern is that it may be different from the actual total number of policies within a community since there may be households that purchased flood insurance but never filed a claim. Although this won't affect the main results considering that number of policies affected by flood should still be a good approximation of total number of policies in a community. I provide additional evidence by instead using the total number of policies from FIMA NFIP Redacted Policies through OpenFEMA Dataset and re-estimate the same event study model. The results are shown in B3 and similarly I didn't find significant impact on flood insurance take-up. Note that now I only use data from 2009 to 2018 because the NFIP policies data before 2009 are not complete thus may be inaccurate.

One explanation is that households don't use the information that their neighbor community joined the CRS as reminder of flood risk, thus they don't respond to it by starting purchasing flood insurance. Another explanations is that although they received the information, but decide not to purchase flood insurance because of the relative higher premium due to lacking of CRS discount. As previous research showed, better CRS class usually means higher level of flood insurance purchase (Brody et al., 2017; Petrolia et al., 2013). While over 70% of all NFIP policies are written in CRS communities (FEMA, 2017a), households in non-CRS communities may be underinsured because of inadequate risk communication or higher premium.

6.1.2 Learning Behavior of Community/Local Government

Like people learn from each other, governments also learn by observing their neighbors to make more successful policies (Callander and Harstad, 2015). Local government may be affected by their neighbor's policy or performance when making policy decisions. For example, Baicker (2005) shows that state spending is influenced by their neighbor state's spending, and interstate mobility best predicts this spillover effect. Shi and Xi (2018) find that number of accidental death due to coal mining in a city is positively related to the accidental death in its neighbor cities. They also find that this spillover effect is likely a result of relative performance evaluation which leads to promotion competition in China. Similarly, Mitchell and Stewart (2014) shows that in the US, both learning and political competition affect inter-county policy diffusion.

While the flood insurance take-up may indicates households learn from their CRS neighbors, flood mitigation projects may represent learning behavior at community or local government level. A NFIP community or local government may tend to take more actions regarding flood mitigation by observing and learning from their neighbor CRS communities. One example is that downstream counties tend increase their levee elevation after the levee elevation increase by upstream counties (Wang, 2021). To test this hypothesis, I first examine the impact of having a CRS neighbor on CRS participation. In other words, for a NFIP community, whether its neighbor joined the CRS increases its probability of joining. I estimate the following two-way fixed effect model:

$$Y_{it} = \alpha_i + \beta_1 \text{Neighbor}_{it} + \gamma_i X_{it} + \delta_t + \epsilon_{it} \tag{4}$$

where Y_{it} is a binary variable and equals to 1 if a community i have joined the CRS in year t. *Neighbor* is a dummy variable and equals to 1 if a NFIP community i is treated: have a neighbor CRS community in year t. β_1 is the coefficient we are interested of, which indicates the learning behavior of NFIP communities from their CRS neighbors. Historical flood size and annual precipitation are included to control for flood risk and previous flood experience. I also control for community demographic characteristics, such as population, % of black population, household income, education, and age. α_i is community fixed effect capturing unobserved characteristics of each community. δ_t is year fixed effect account for unobservable yearly trends that affect all communities. ϵ_{it} is the idiosyncratic error.

The results of estimating equation 4 is in table 6. Having a CRS neighbor increases the probability of a NFIP community of joining the CRS by about 4.5%. This small coefficient indicates that at least some NFIP community learn from their CRS neighbors and implement similar activities in order to get premium discount and reduce flood damage. One possible explanation for this small effect is related to the potential costs of participating in the CRS program. For example, some main reasons of not joining in the CRS include lack of stuff/resources, and extra administrative and time burden (Sadiq et al., 2020). To participate in the CRS, a community need to submit a letter of interest to state specialist first and show that they could earn at least 500 points through eligible activities. Upon the approval of FEMA regional office, a community verification visit is scheduled. After the specialist reviewing all the CRS activities, the total CRS credits and CRS class are assigned to the community by FEMA, which is effective on May 1st, or October 1st. In addition, CRS communities need to recertify all the activities that receive CRS points annually (FEMA, 2017b). These non-CRS communities thus may choose to invest their restricted resources in conducting and managing flood adaptation projects, and not to invest extra resources on applying for the CRS accreditation. Another possible explanation is that the benefits of premium discount after joining in the CRS may not be large enough considering the relatively lower insurance take-up in these communities.

6.2 Protection Spillover

Generally there are two type of flood mitigation techniques. Structural approaches use engineering methods to control flood, such as building levees and dams, while non-structural approaches adjusting human and community activities, such as flood risk education and awareness and insurance programs (Brody et al., 2010). Brody et al. (2007) find that non-structural activities are more effective in reducing flood losses than dams. The hypothesis here is that these structural CRS activities may directly lower their neighbor communities' flood damage. For example, some activities included in the flood damage reduction category that may have spillover effect on near communities include activities such as flood protection projects, and drainage system maintenance. It's possible that CRS community directly control flood through structural activities, which may help reduce flood severity of their neighbor communities.

I test this hypothesis by estimating equation 1 and adding total CRS points earned by neighbor CRS communities from structural activities. Based on the description of each CRS activities, I include the following activities as structural activity: 310 Elevation Certificates, 420 Open Space Preservation, 430 Higher Regulatory Standards, 450 Stormwater Management, 530 Flood Protection, 540 Drainage System Maintenance, 620 Levees, and 630 Dams. The results are reported in column (1) table 7. Points earned from structural CRS activities have small negative impact on flood damage, although they are not significant. In addition, to better capture the possible protection effect of these CRS activities, I use a more conservation way to define "neighbor": a non-CRS community has a CRS neighbor if they share border and if it is located downstream of that CRS community. I then drop observations that are treated under the "old" definition but not treated under the "new" definition of "neighbor" and re-estimate equation 1 and adding total CRS points earned by neighbor CRS communities through structural activities. Adding the upstream-downstream relationship helps distinguish the impact of those CRS activities that directly help reduce flood damage of downstream non-CRS communities. If this mechanism is true, we should expect a larger spillover effect after adding upstream-downstream relationship. The results are reported in column (2) table 7 and are similar to the results in column (1). I find no evidence that structural CRS activities have significant on flood damage of their non-CRS neighbors. This again confirms that the protection spillover is unlikely the possible mechanism here.

One possible explanation is that there isn't adequate investment in activities that actually reduce flood risk in CRS communities. For example, 28% and 13% of CRS communities have, on average, earned 8.7% and 4.6% of maximum possible points through acquisition and reallocation, and flood protection from the 500 series: Flood Damage Reduction Activities (FEMA, 2017b). As previous studies showed, because of the incentive structure of the CRS, it's possible that CRS communities tend to choose CRS those activities that are less costly and help reaching a better CRS class more easily, but not necessarily those help reducing flood damage (Zahran et al., 2010; Brody et al., 2009). This lack of incentive may have hindered CRS communities' willingness to invest in activities that could generate positive externalities to their non-CRS neighbors.

7 Conclusion

Local government is playing a critical role in floodplain management and increasing community resilience to future flood hazards (Landry and Li, 2012). It's important to investigate the effectiveness of the investments in local flood hazard mitigation under the setting of the CRS. It could be helpful in promoting local investment and even better multi-jurisdictional cooperation if the mitigation activities taken after joining the CRS could benefit not only local community but also neighbor communities.

Previous study have assessed the effectiveness of the CRS on reducing flood damage. Most of these studies find that participating in the CRS helps reducing flood loss, property damage, or individual claims (Highfield and Brody, 2017; Highfield et al., 2014; Brody et al., 2007). Even just implementing minimal CRS eligible activities leads to individual claims amount reduction (Kousky and Michel-Kerjan, 2017). While communities having a CRS class of 5 or better experience most significant reduction of flood damage (Michel-Kerjan and Kousky, 2010). All these studies evaluate the CRS's impact on reducing flood loss within CRS communities, one remaining unanswered question is that whether this impact is completely localized or there is spillover effect.

This paper examine the spillover effect of CRS program. I find a significant short-term negative effect of having a CRS neighbor community on flood damage. This effect is stronger for community with less population and community with lower income. The spillover effect is driven mainly by flood damage experienced in SFHA within a community. Two possible explanations of the existence of the spillover effect are information interaction and protection spillover. The first mechanism indicates that local government learn from their CRS neighbors and invest more on flood mitigation projects. In addition, there is no evidence that households receive this information and start purchasing flood insurance. The latter mechanism assumes that a CRS community may help reducing flood damage of its neighbor NFIP communities through some structural activities but no significant effect is found for this hypothesis.

These results have some important policy implications on issues and reform of the current CRS program. First, although the overall effectiveness of the CRS program on reducing flood losses has been proved, the spillover effect should also be taken into consideration in the future cost-benefit analysis. Second, the overall participation rate of the CRS program remains low (Frimpong et al., 2020; Highfield and Brody, 2017). The results of this paper provides new perspective of promoting participation in the CRS for state government. Encouraging some communities to join the CRS first may help inducing better floodplain management in flood mitigation projects in their neighbor communities. This could help reduce general flood risk and flood damage. Third, to maximize the potential benefits of CRS activities, it's important to encourage communities to implement activities that have positive externalities, especially those that actually reduce flood damage but have relative higher costs, One way of solving this is boosting inter-community cooperation on flood damage reduction projects.

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Main Tables

Table 1: Overview of CRS Program

Class	Credit Points	Premium Reduction	
		SFHA	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	0-499	0	0

Notes: Source: Data from FEMA (FEMA, 2017b)

Table 2: Maximum Points and Average Earned per CRS Activity

Activity	Maximum Points	Average Points Earned
300 Public Information Activities		
310 Elevation Certificates	116	38
320 Map Information Service	90	73
330 Outreach Projects	350	87
340 Hazard Disclosure	80	14
350 Flood Protection Information	125	38
360 Flood Protection Assistance	110	55
370 Flood Insurance Promotion	110	39
400 Mapping and Regulations		
410 Flood Hazard Mapping	802	60
420 Open Space Preservation	2,020	509
430 Higher Regulatory Standards	2,042	270
440 Flood Data Maintenance	222	115
450 Stormwater Management	755	132
500 Flood Damage Reduction Activities		
510 Floodplain Mgmt. Planning	622	175
520 Acquisition and Relocation	2,250	195
530 Flood Protection	1,600	73
540 Drainage System Maintenance	570	218
600 Warning and Response		
610 Flood Warning and Response	395	254
620 Levees	235	157
630 Dams	160	35

Notes: Source: Data from FEMA (FEMA, 2017b)

Table 3: Summary Statistics

Variable	N	Mean	St. Dev.	Min.	Max.
TotDamage ($million)	48,590	0.392	11.52	0	1,955
Neighbor	48,590	0.279	0.449	0	1
NumPolicy	48,590	11.12	134	1	14,358
BldCoverage ($million)	48,590	1.387	21.86	0	2,660
CntCoverage ($million)	48,590	0.299	5.128	0	637
Elevated (%)	48,590	0.171	0.309	0	1
Precipitation (Inches)	48,590	807	650	0	4,076
FloodSize	48,590	10.34	19.18	1	100
Population (1,000s)	48,590	14.04	131	0	8,473
Black (%)	48,590	0.099	0.166	0	1
Age	48,590	39.14	5.197	0	74.08
CollegeGrads (%)	48,590	0.273	0.231	0	0.923
HouseholdIncome ($1000s)	48,590	48.06	26.14	0	247

Notes: This table reports the summary statistics of the unbalanced panel data sample from 1991-2018. All variables are at NFIP community-year level. TotDamage is community annual flood damage and is in million dollars. Neighbor is and indicator and equals to 1 if a non-CRS community has at least one CRS community neighbor in a given year. BldCoverage and CntCoverage are insurance amount in million dollars on the buildings and contents, respectively. Elevated is thee percentage of elevated buildings within a community. Flood size is measured in recurrence interval. For example, 10 indicates the flood on average happens once every 10 years. Population is in 1000 people.

Table 4: The Spillover Effect of the CRS on Flood Damage

	(1) Total Damage	(2) Total Damage	(3) Total Damage	(4) Total Damage
Neighbor	-0.344*	-0.349*	-0.0737	
	(0.139)	(0.139)	(0.0643)	
Neighs				-0.213
				(0.121)
NumPolicy	0.0559	0.056	0.0638*	0.0638*
	(0.0292)	(0.0304)	(0.0307)	(0.0307)
BldCoverage	-0.395	-0.396	-0.419	-0.419
	(0.273)	(0.277)	(0.269)	(0.269)
CntCoverage	2.223*	2.225*	2.173*	2.174*
	(0.918)	(0.914)	(0.871)	(0.872)
Elevated	-0.158	-0.154	-0.159	-0.156
	(0.0972)	(0.107)	(0.0939)	(0.091)
Precipitation	-0.00006	-0.0003	-0.0004*	-0.0004*
	(0.00004)	(0.0002)	(0.0002)	(0.0002)
FloodSize	-0.0042	-0.0035	-0.0088	-0.0088
	(0.0025)	(0.0026)	(0.0047)	(0.0047)
Population	0.0015	0.0014	0.0019	0.002
	(0.0017)	(0.0013)	(0.0014)	(0.0014)
Black	-0.39**	-0.286*	-0.769	-0.748
	(0.128)	(0.117)	(0.424)	(0.415)
Age	0.011	0.012	0.0177*	0.0177*
	(0.0075)	(0.0082)	(0.0079)	(0.0079)
CollegeGrads	-0.451**	-0.8**	-1.293*	-1.278*
	(0.17)	(0.317)	(0.509)	(0.504)
HouseholdIncome	-0.001	-0.001	-0.0004	-0.0003
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	-0.378	-0.136	-0.183	-0.134
	(0.316)	(0.253)	(0.283)	(0.286)
Year		Yes	Yes	Yes
Community			Yes	Yes
R^2	0.851	0.852	0.869	0.869
N	48,590	48,590	45,873	45,873

Notes: This table reports results from equation 1. Neighbor is a dummy variable and equals to 1 if a NFIP community has a neighbor CRS community in a given year. Neighbors is the number of CRS neighbors of a NFIP community in a given year. Robust standard errors clustered at community level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 5: IV Estimates of The Spillover Effect of the CRS on Flood Damage

	(1) Total Damage	(2) Neighbor
Neighbor	-0.51	
	(1.73)	
Turnover		0.0286***
		(0.0038)
NumPolicy	0.0676*	
	(0.033)	
BldCoverage	-0.422	
	(0.266)	
CntCoverage	2.105*	
	(0.854)	
Elevated	-0.205	
	(0.118)	
Precipitation	-0.0004*	-0.000001***
	(0.0002)	(0.0000001)
FloodSize	-0.0098	0.00004**
	(0.0051)	(0.00001)
Population	0.0019	0.0001***
	(0.0014)	(0.00001)
Black	-0.912	0.0138***
	(0.57)	(0.0021)
Age	0.0222*	-0.00005***
	(0.0092)	(0.0001)
CollegeGrads	-1.506**	0.062***
	(0.579)	(0.0037)
HouseholdIncome	-0.00001	0.0002***
	(0.0024)	(0.00003)
Constant	-0.333	0.0499***
	(0.377)	(0.0025)
Year	Yes	Yes
Community	Yes	Yes
R^2	0.872	
N	35,942	431,059
Weak identification		88.57

Notes: This table reports results from equation 2. Column (1) reports 2SLS estimates instrumenting CRS participation with 1-year lag house turnover rate. Column (2) reports the corresponding first-stage estimates. Neighbor is a dummy variable and equals to 1 if a NFIP community joined the CRS in a given year. Robust standard errors are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 6: The Impact of CRS Neighbor on CRS participation

	(1) CRS participation
Neighbor	0.0445***
	(0.0037)
Precipitation	-0.000003*
	(0.000001)
FloodSize	-0.000001
	(0.000001)
Population	0.00012*
	(0.00006)
Black	0.0101**
	(0.0038)
Age	0.0005
	(0.0001)
CollegeGrads	0.0606
	(0.007)
HouseholdIncome	0.0001
	(0.0001)
Constant	0.0354***
	(0.0046)
Year	Yes
Community	Yes
R^2	0.811
N	623,978

Notes: This table reports results from equation 4. The dependent variable is CRS participation, which equals to 1 is a community has joined the CRS in a given year. Neighbor is a dummy variable and equals to 1 if a NFIP community has a neighbor CRS community. Flood size is measured in recurrence interval. For example, 10 indicates the flood on average happens once every 10 years. Robust standard errors clustered at community level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 7: The Impact of CRS Activities on Flood Damage

	(1) Total Damage	(2) Total Damage
Neighbor	0.019	-0.0502
	(0.0849)	(0.104)
Structural	-0.0001	-0.0001
	(0.0001)	(0.0001)
NumPolicy	0.0638*	0.0881*
	(0.0307)	(0.028)
BldCoverage	-0.419	-0.501
	(0.269)	(0.235)
CntCoverage	2.174*	2.005*
	(0.872)	(0.707)
Elevated	-0.16	-0.216*
	(0.0939)	(0.0919)
Precipitation	-0.0004*	-0.0005*
	(0.0002)	(0.0002)
FloodSize	-0.0088	-0.0113**
	(0.0047)	(0.0044)
Population	0.002	0.0021
	(0.0014)	(0.0013)
Black	-0.758	-0.489
	(0.419)	(0.324)
Age	0.0176*	0.0138*
	(0.0079)	(0.0061)
CollegeGrads	-1.289*	-1.946*
	(0.508)	(0.429)
HouseholdIncome	-0.0001	-0.0012
	(0.0024)	(0.0024)
Constant	-0.186	-0.232
	(0.283)	(0.272)
Year	Yes	Yes
Community	Yes	Yes
R^2	0.869	0.895
N	45,873	45,591

Notes: This table reports coefficient estimates of equation 1 and add CRS points earned from structural CRS activities. In column (1), Neighbor is a dummy variable and equals to 1 if a NFIP community has a neighbor CRS community in a given year. In column (2), Neighbor is a dummy variable and equals to 1 if a NFIP community has a neighbor CRS community and if it is located downstream of that CRS community in a given year. Robust standard errors clustered at state level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Main Figures

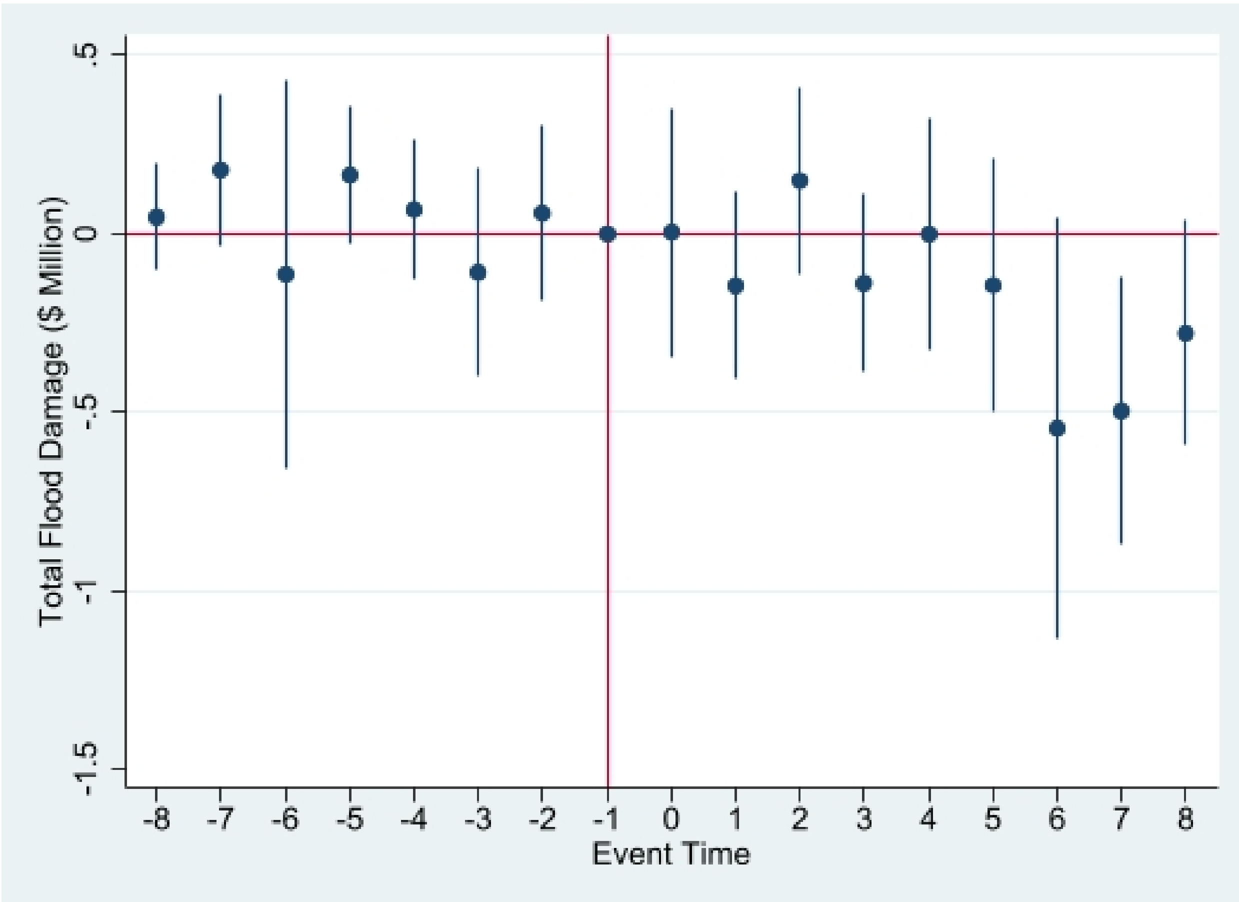


Figure 1: The Spillover Effect of the CRS on Flood Damage

Notes: This figure shows the results of event study estimating equation 3. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

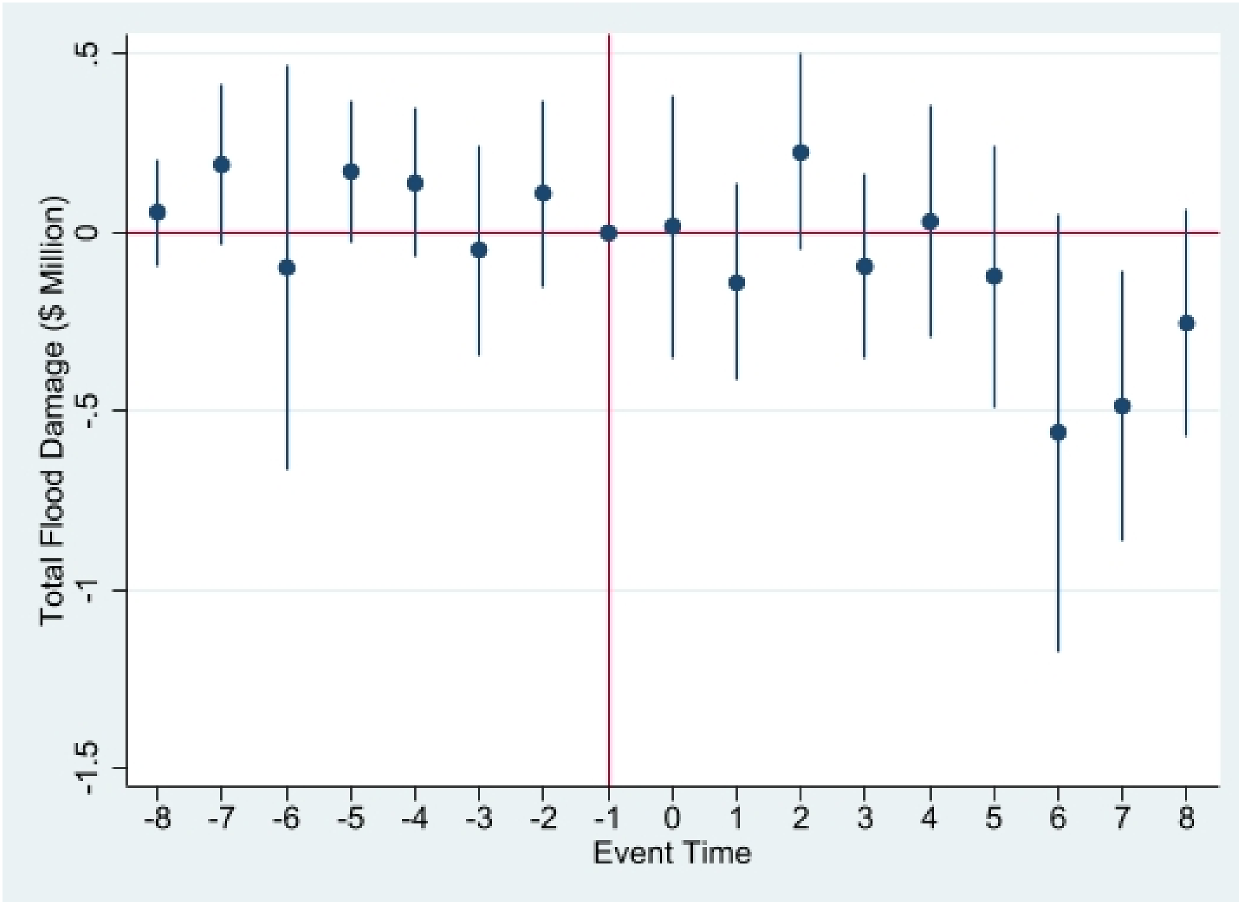


Figure 2: The Spillover Effect of the CRS on Flood Damage - No Treatment Reversal

Notes: This figure shows the results of event study estimating equation 3. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

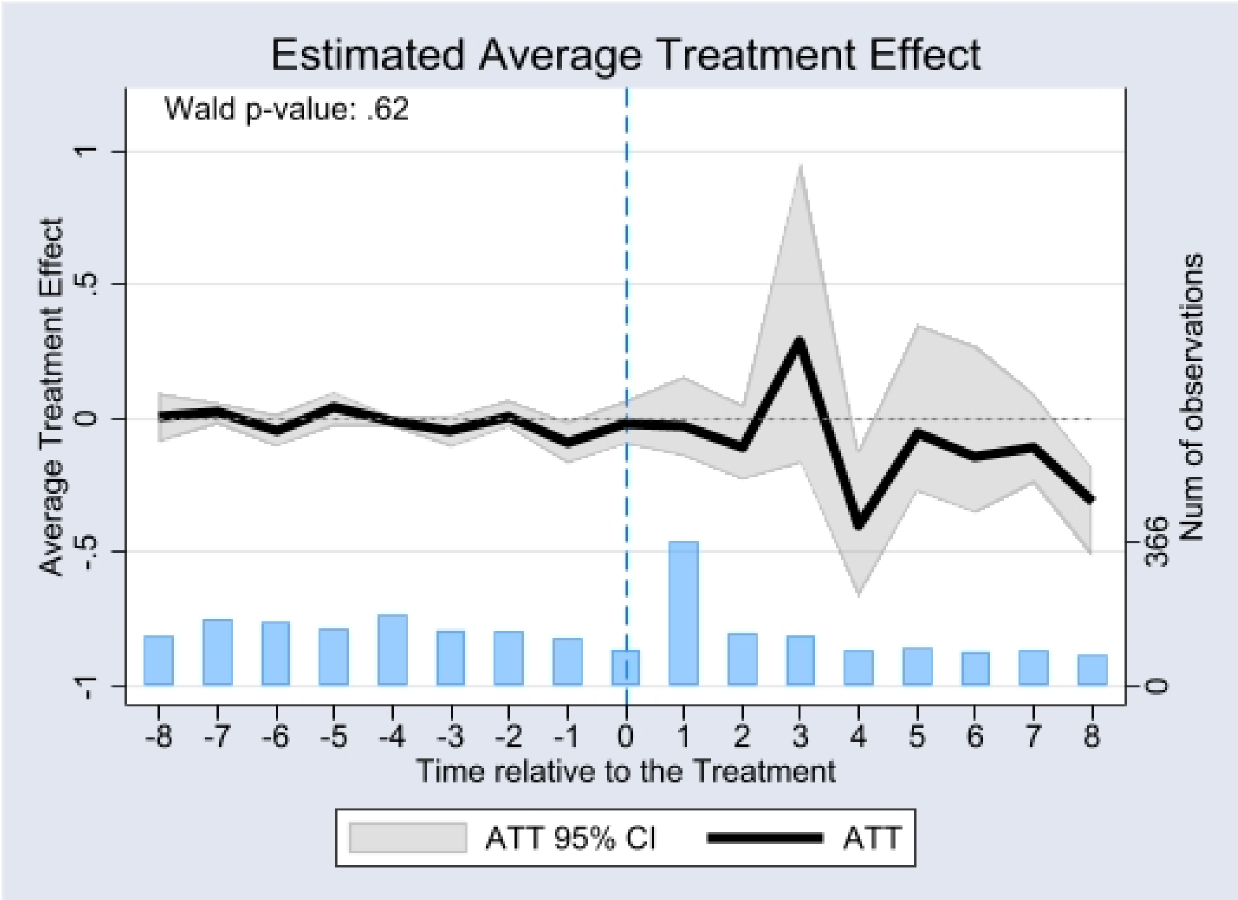


Figure 3: The Spillover Effect of the CRS on Flood Damage - Counterfactual Estimators

Notes: This figure shows the dynamic treatment effect estimating equation 3 using the framework of counterfactual estimation proposed by (Liu et al., 2021). The dependent variable is total flood damage for community i in year t. I only keep estimates for 10 periods before and after treatment year for display purpose. The black line shows the estimated average treatment effect. The grey shadow show the 95% confidence interval. The bar plot at the bottom illustrates the number of treated units at the given time period relative to the treatment year. Standard errors are clustered at community level.

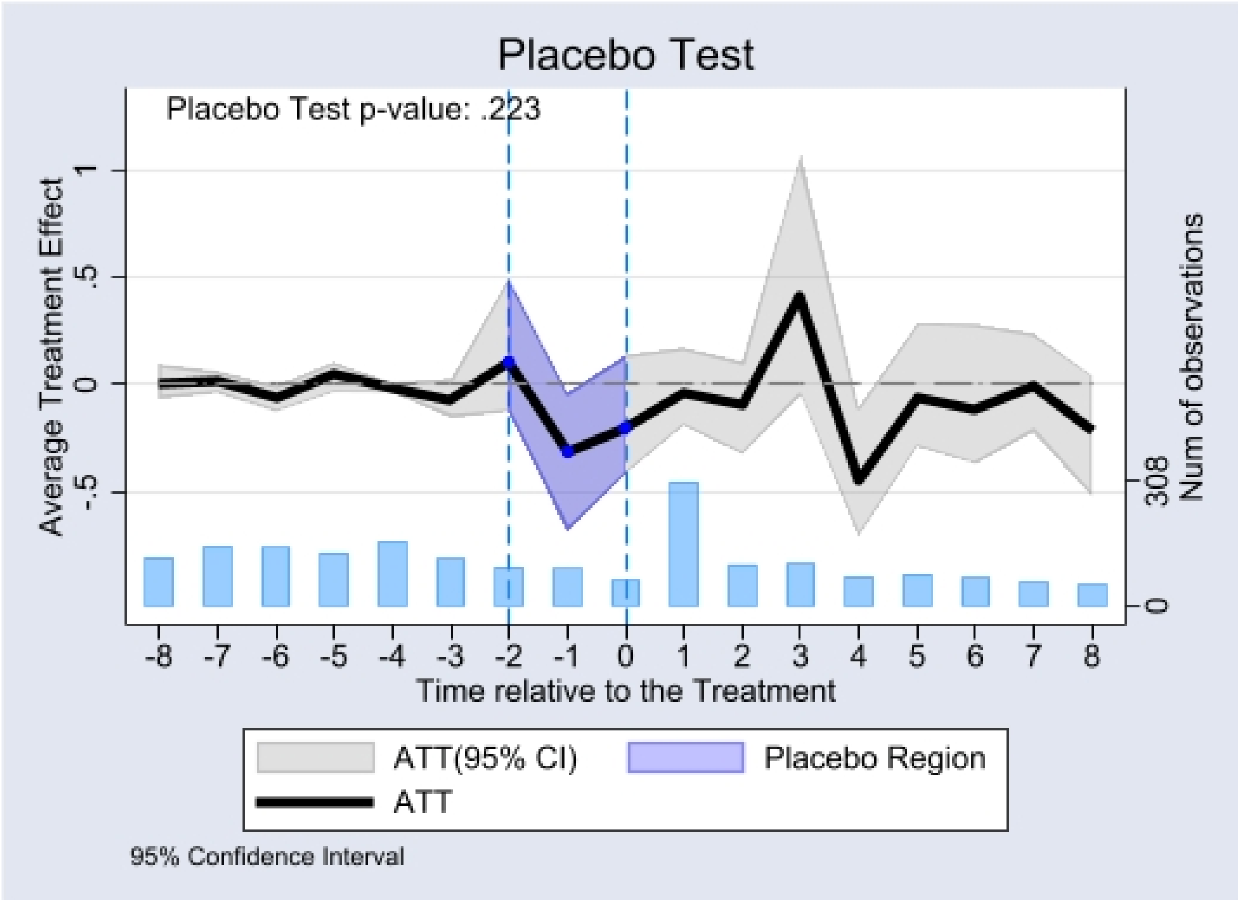


Figure 4: The Spillover Effect of the CRS on Flood Damage - Placebo Test

Notes: This figure shows the results of placebo test. Periods [-2,0] are set as placebo periods. The p-value of the t-test for the placebo test is shown at the top-left corner. I only keep estimates for 10 periods before and after treatment year for display purpose. The black line shows the estimated average treatment effect. The grey shadow show the 95% confidence interval. The bar plot at the bottom illustrates the number of treated units at the given time period relative to the treatment year. Standard errors are clustered at community level.

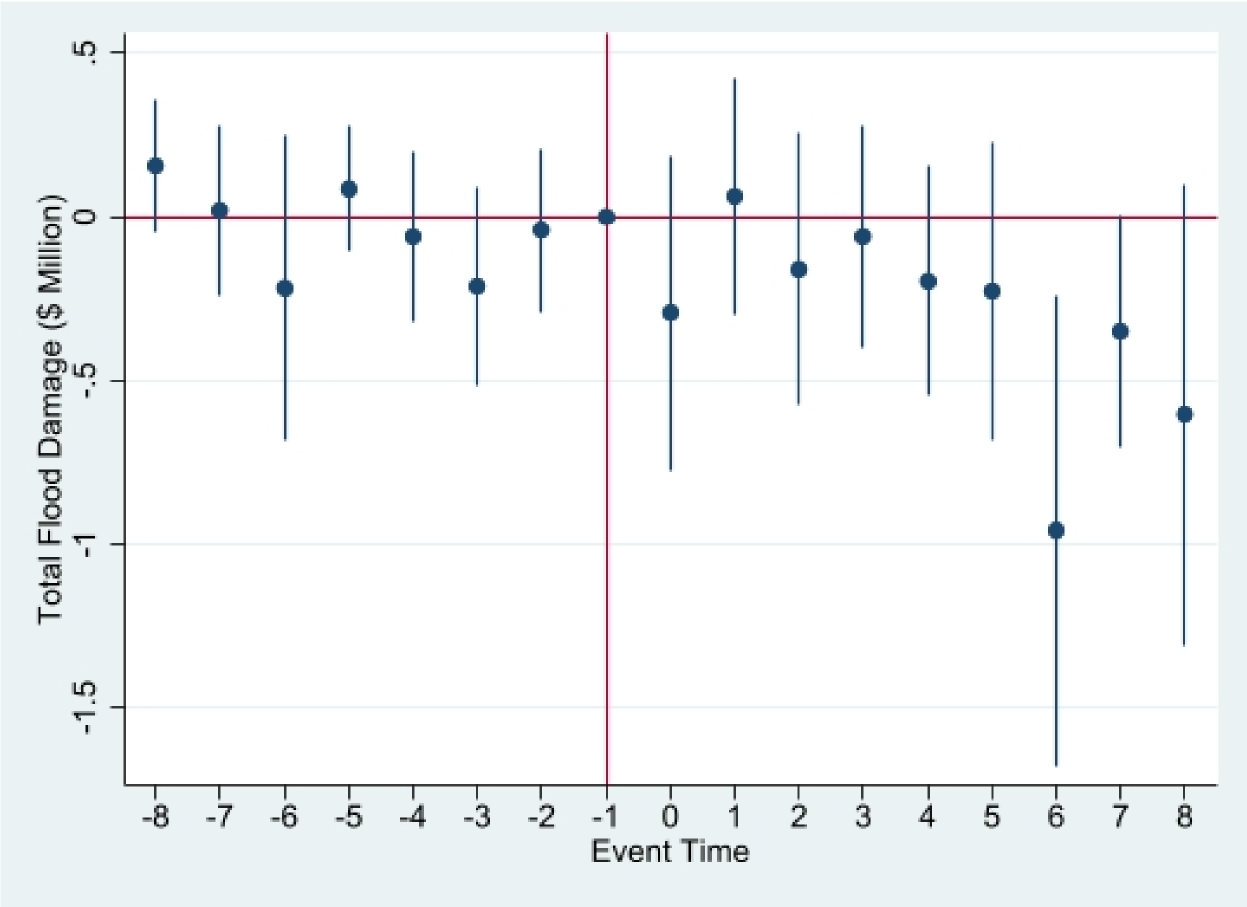


Figure 5: The Spillover Effect of the CRS on Flood Damage – Neighbor Defined Using Distance

Notes: This figure shows the results of event study estimating equation 3 while defining neighbor using shortest distance between non-CRS communities and CRS communities. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

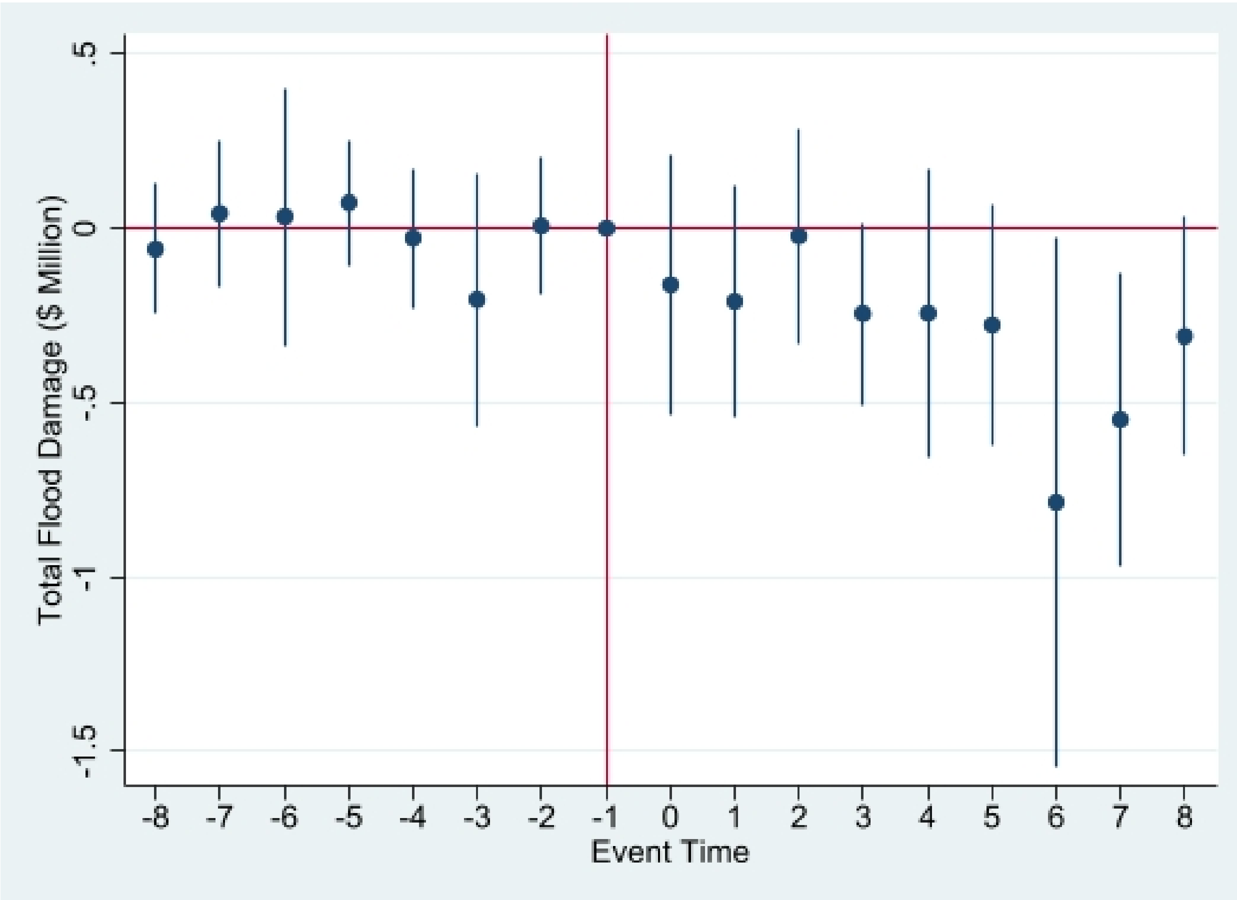


Figure 6: The Spillover Effect of the CRS on Flood Damage – Neighbor Defined Using Upstream-Downstream Relationship

Notes: This figure shows the results of event study estimating equation 3 while defining neighbor if a non-CRS communities shares border with at least one CRS community and it is located downstream of that CRS community. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

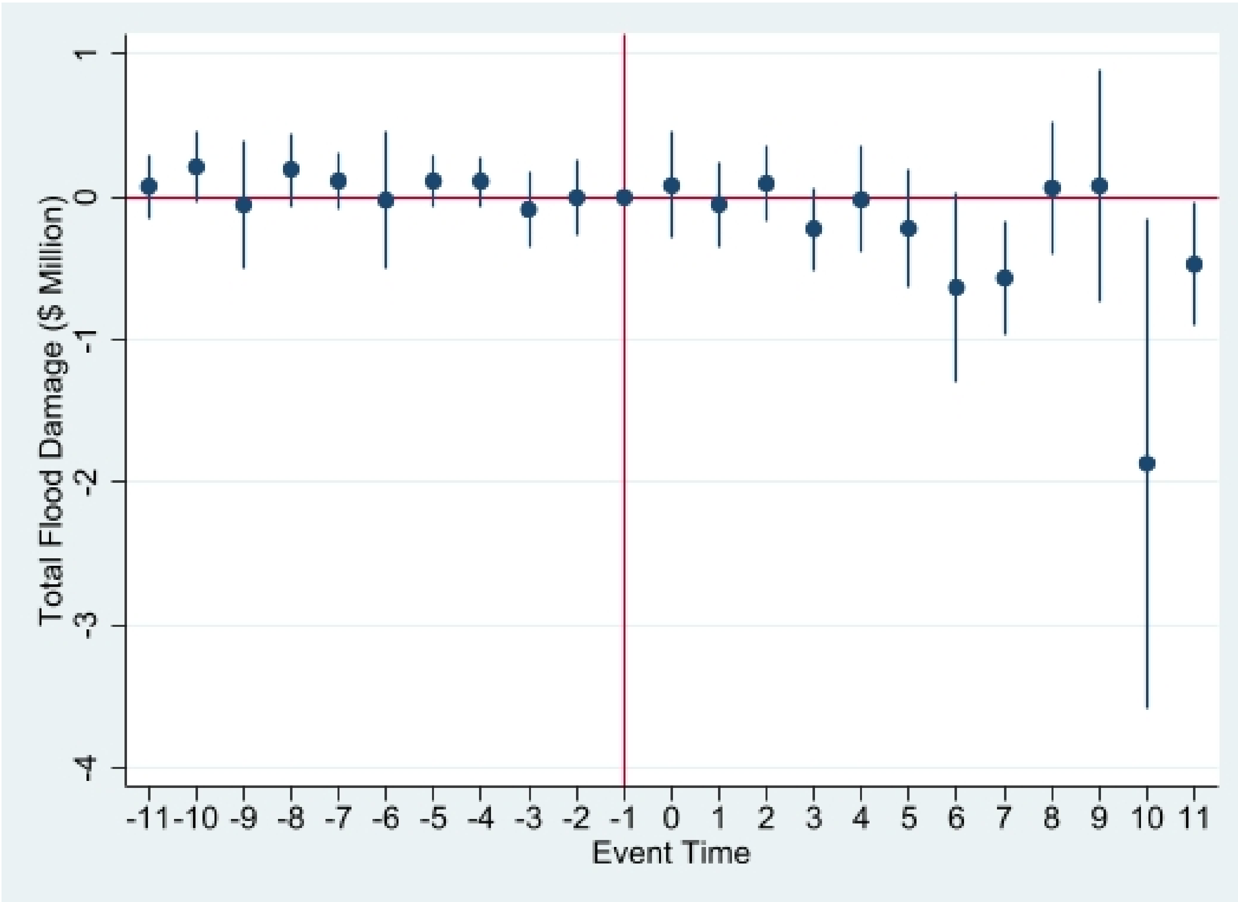


Figure 7: The Spillover Effect of the CRS on Flood Damage - Different Binning Option

Notes: This figure shows the results of event study estimating equation 3. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -11 (+11) is a bin for years -11 to -27 (+11 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

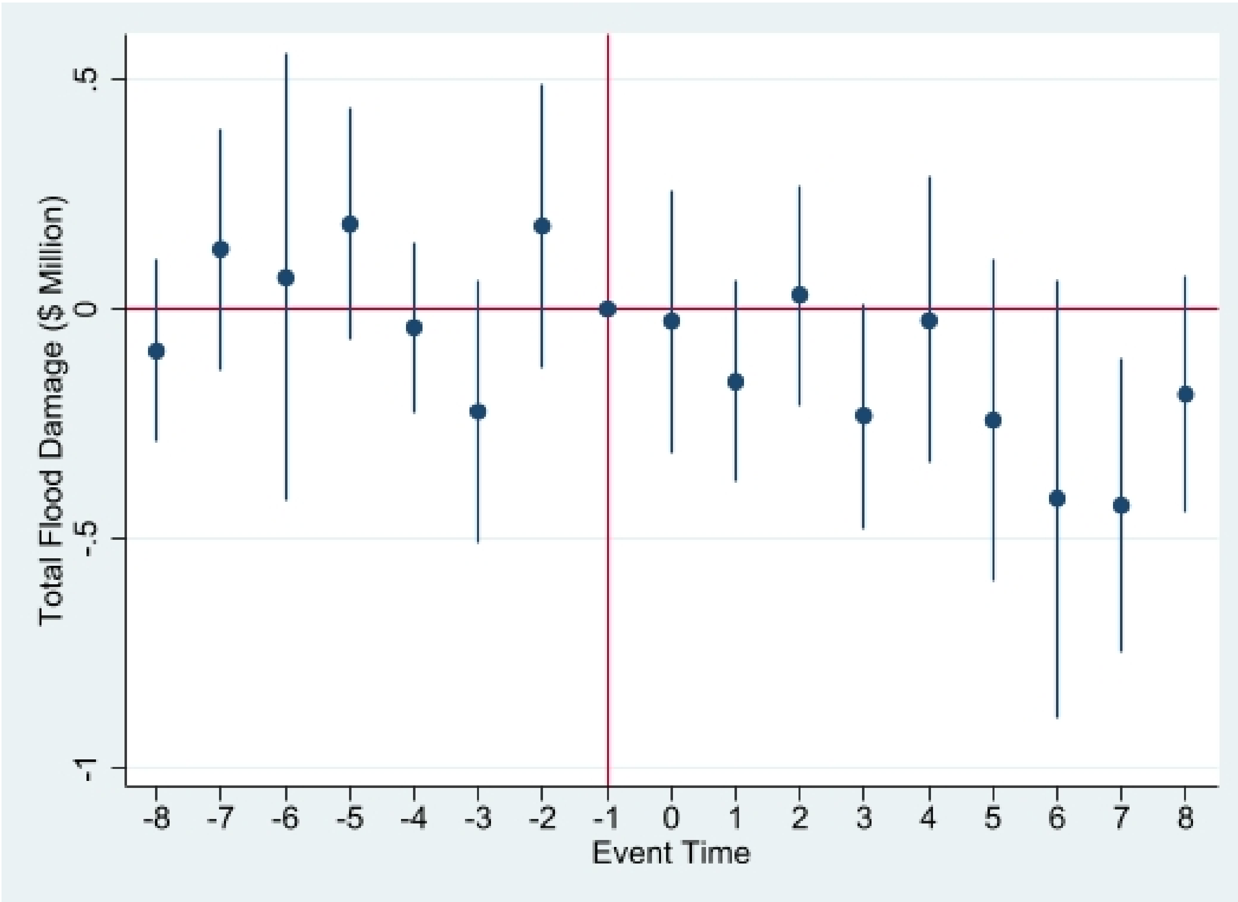


Figure 8: The Spillover Effect of the CRS on Flood Damage - without 2012

Notes: This figure shows the results of event study estimating equation 3 using data from 1991-2018 and dropping all observations in 2012. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

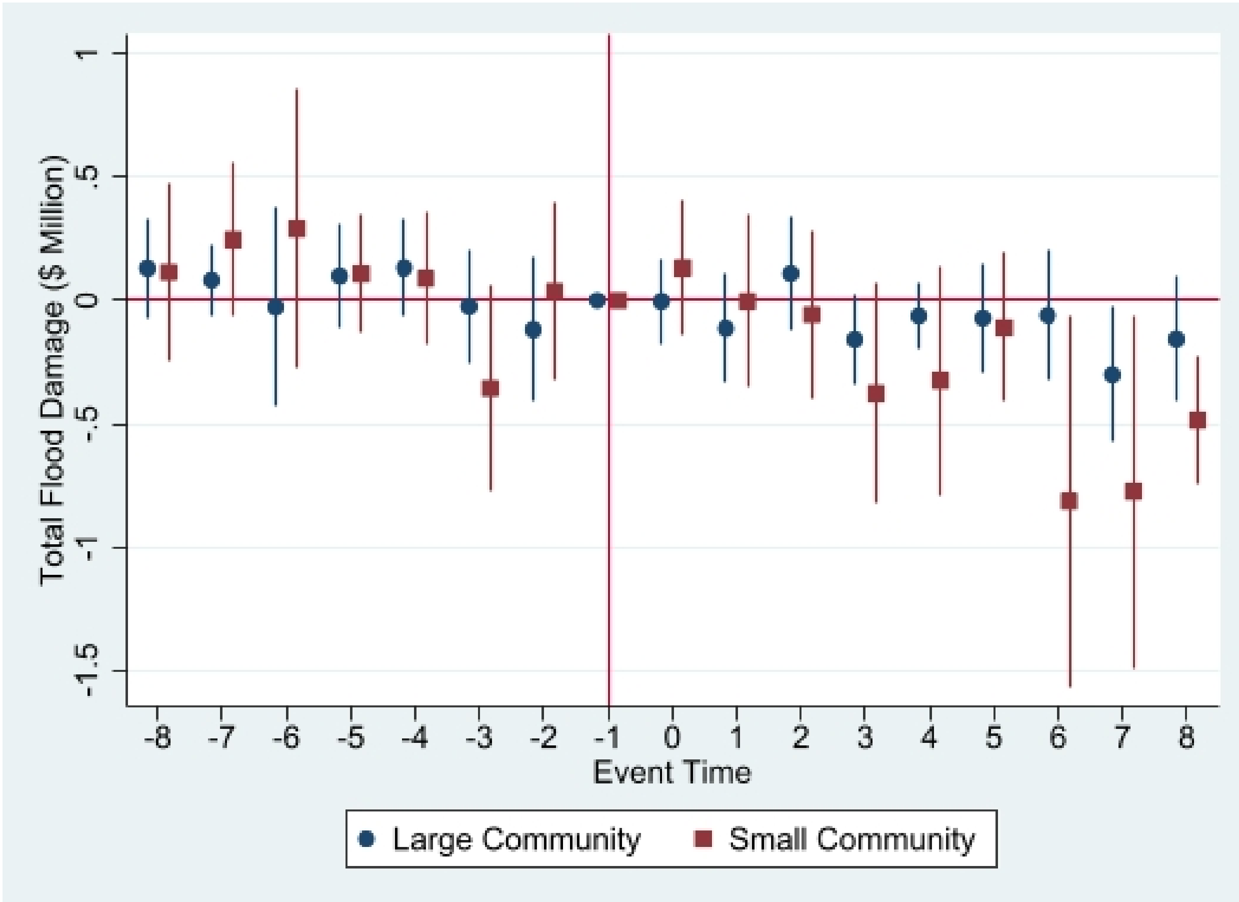


Figure 9: Spillover Effect on Flood Damage of Large and Small Community

Notes: This figure shows the results of event study estimating equation 3 separately for community with population above and below the median value. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

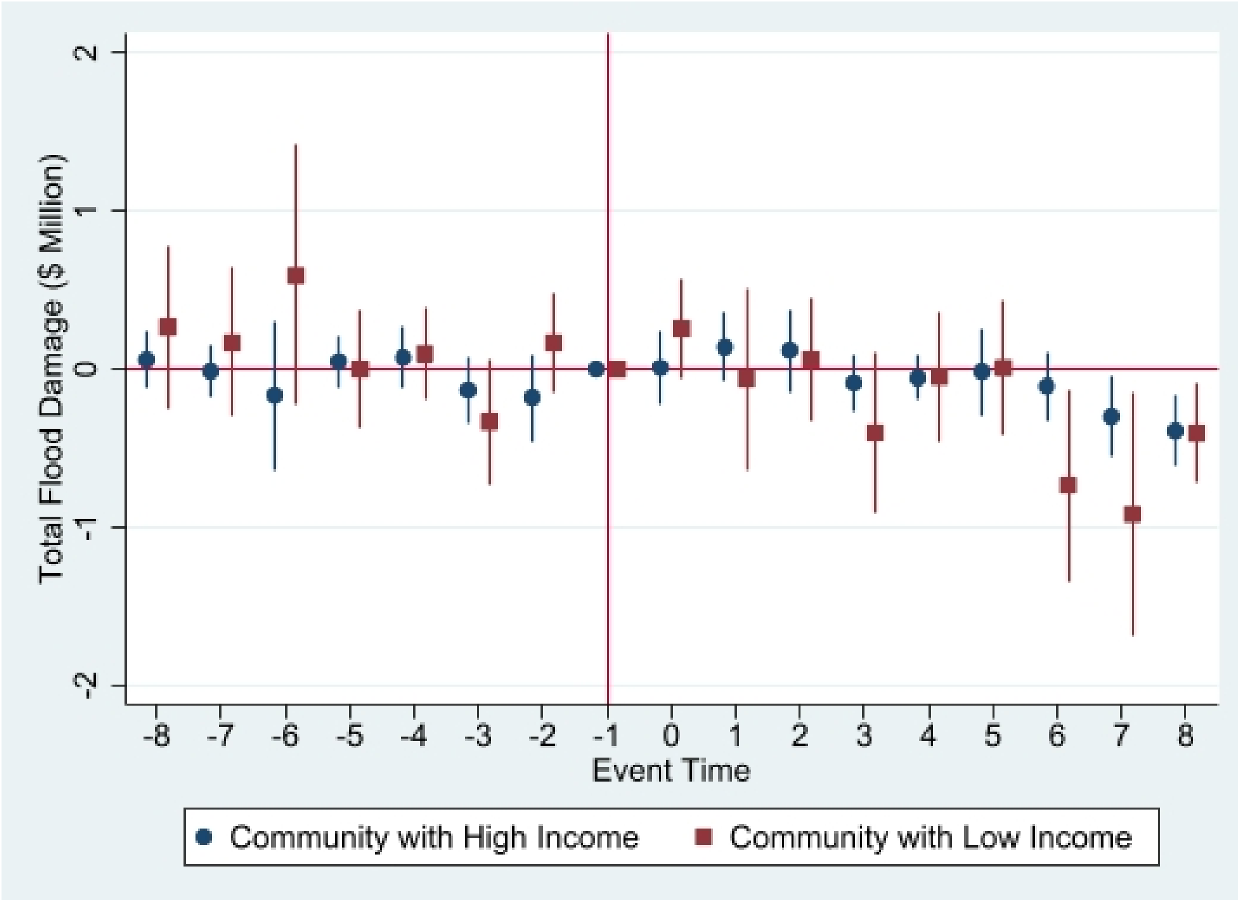


Figure 10: Spillover Effect on Flood Damage of High-Income and Low-Income Community

Notes: This figure shows the results of event study estimating equation 3 separately for community with household income above and below the median value. The dependent variable is total flood damage for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

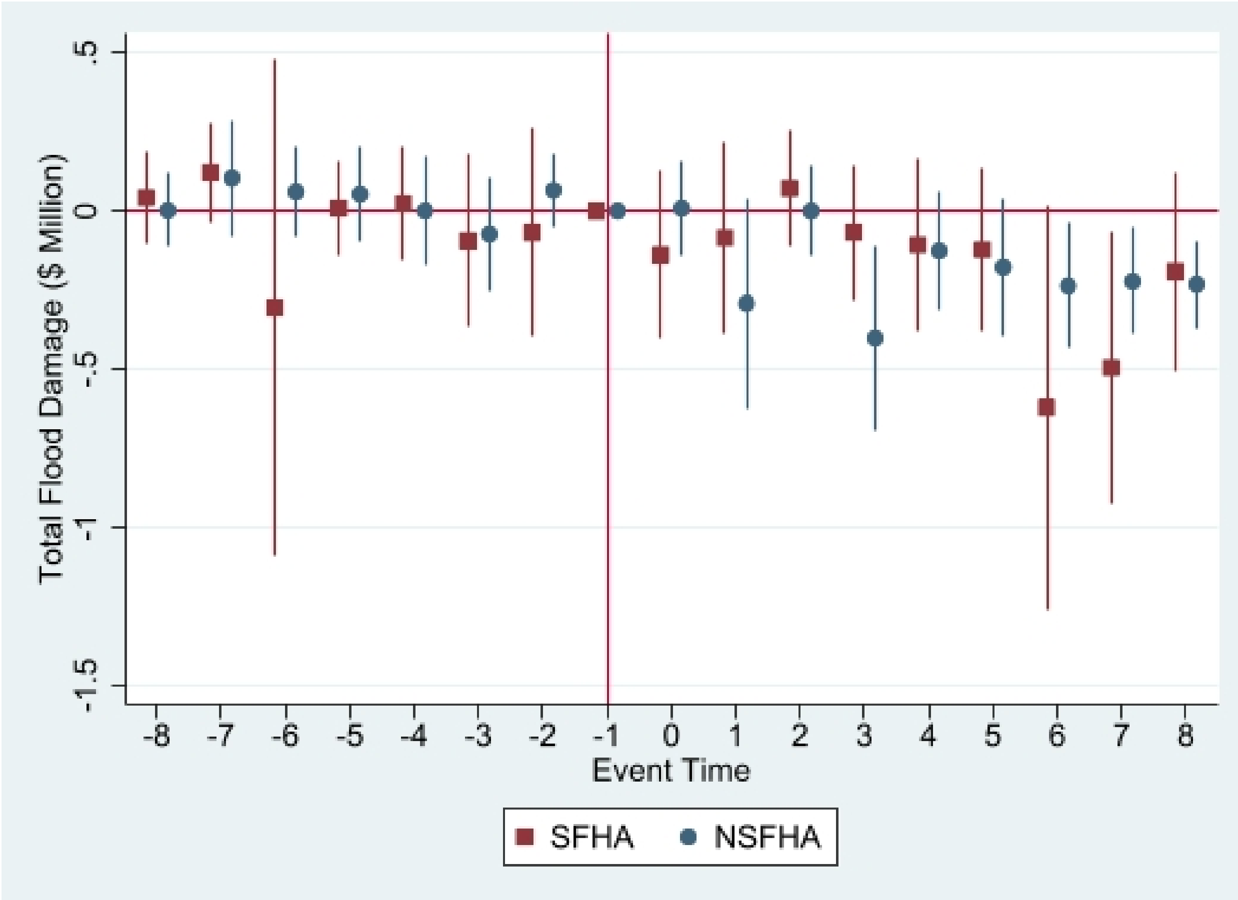


Figure 11: Spillover Effect on Flood Damage of SFHA and NSFHA in Community

Notes: This figure shows the results of event study estimating equation 3 separately for SFHA and NSFHA areas with each community. The dependent variable is total flood damage in SFHA or NSFHA for community i in year t. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.

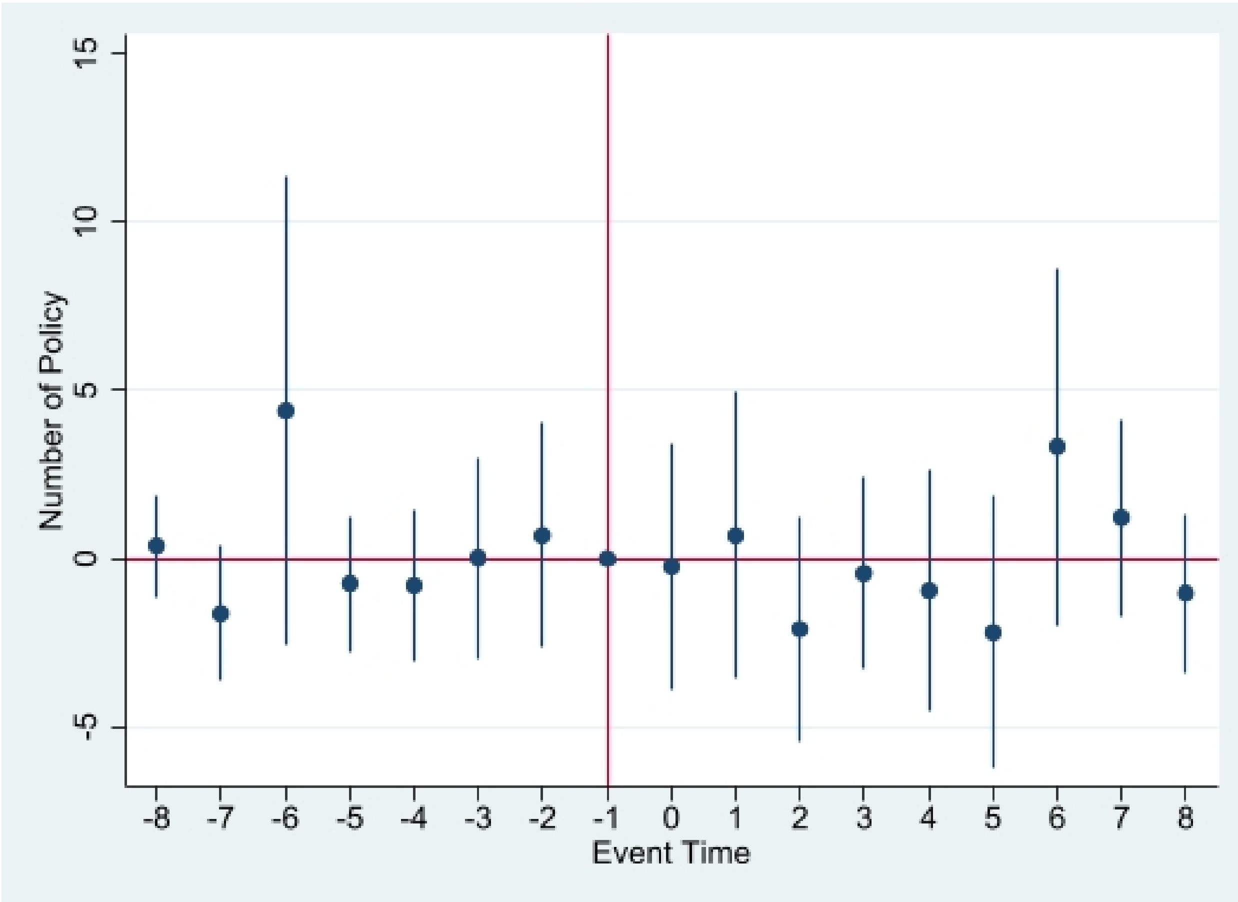


Figure 12: The Spillover Effect of the CRS on Flood Insurance Take-up

Notes: This figure shows the results of event study estimating equation 3 but using number of policy in force of community i in year t as dependent variable. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at state level.

A Appendix A Flood History Data Construction

The data construction here basically follow the USGS guideline (England Jr et al., 2019) and the procedure of Lee (2021), except two main differences: (1) Instead of estimating daily instantaneous peak flow using mean daily flow and drainage area through the Fuller method (Fuller, 1914), I approximate daily instantaneous peak flow using a slope-based method which only requires mean daily flow and performs well (Chen et al., 2017). (2) I only use 3882 gauge stations from USGS.

One potential database of flood history is the Unified Flash Flood Database (Gourley et al., 2013), which utilizes different data sources such as USGS discharge records, National Weather Service (NWS) storm reports, and the Severe Hazards Analysis and Verification Experiment (SHAVE) questionnaire responses, and convert them to flood events. Similar to Lee (2021), two main reasons that I didn't use this data are: (1) this database doesn't cover the whole study period from 1991-2018 of this paper (2) the flood threshold used makes it difficult to do cross-station comparison and potential bias due to missing records of instantaneous peak flow.

A.1 Procedure

First, I estimate site-specific flood size distribution. The annual peak flow records are retrieved in R using package "dataRetrieval" De Cicco et al. (2018) and used to fit log-Pearson III distribution. I keep stations with that have latest record after 2017 and earliest record before 1991. I then keep stations with at least 10 observations before 1991. Then I calculate thresholds of flood size from the quantiles of the estimated distribution using records before 1991. A annual peak flow at 90% of the fitted distribution indicates it's a 10-year flood $\frac{1}{1-0.9}$ or such an event would on average happen every 10 years.

Second, I convert daily instantaneous peak flow to quantiles estimated from the fitted distribution from step (1). The issue here is that there are a lot of missing values for daily instantaneous peak flow (IPF), which is important to identify flood events. Chen et al. (2017) propose a slope-based method to predict instantaneous peak flows. The method basically use the mean daily flow in day t, t-1, and t+1 to predict the IPF in day t. This method is easier to implement than the Fuller method because it only requires mean daily flow data. Figure A1 gives an example for step 1 and 2 for USGS site 01010000. The red line is the fitted log-Pearson III distribution for this site. A discharge in a given day greater than the threshold of 90th value: 36549.52 indicates a 10-year flood.

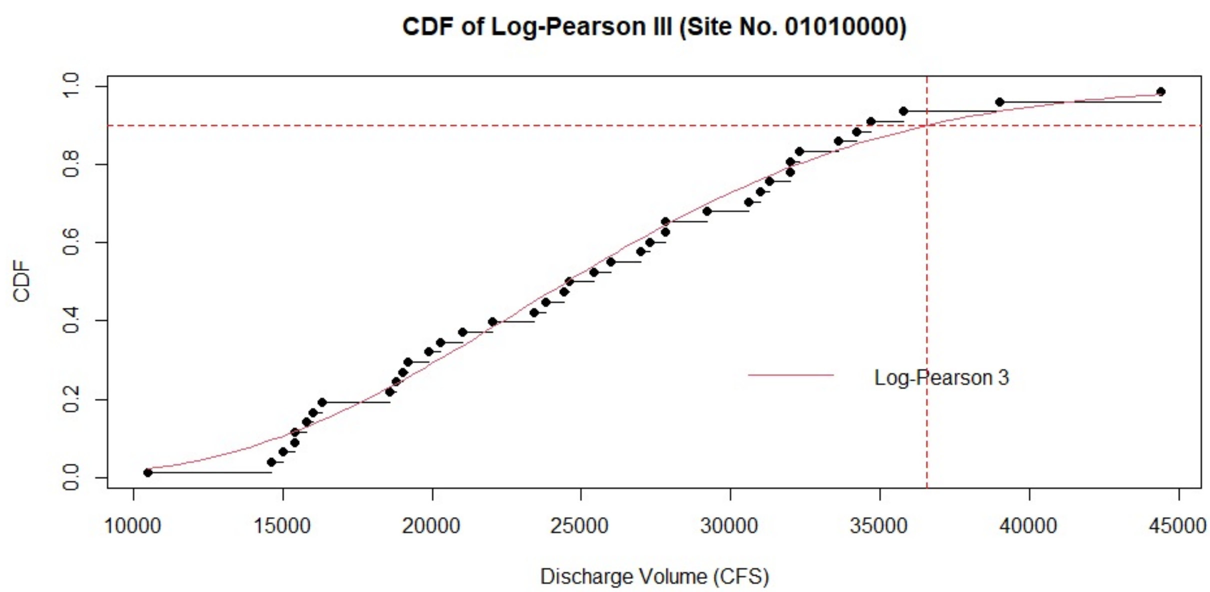


Figure A1: Flood Frequency Analysis Example

Third, I take the maximum vale of converted quantiles for each site in each year and translate it to flood recurrence level. By doing this, I get flood size for each year. The xth quantile here could be interpreted as $\frac{1}{1-x}$-year flood (Lee, 2021).

Finally, I assign 3 nearest gauge to each community and calculate community-year-level flood size by taking average of the flood size of the 3 stations using the distance between the centroid of a community to 3 nearest stations as weights. Figure A2 shows the distribution of distance between 3 nearest gauge stations and each community. Over 90% of the stations are within 34 miles and the median distance is 13.5 miles.

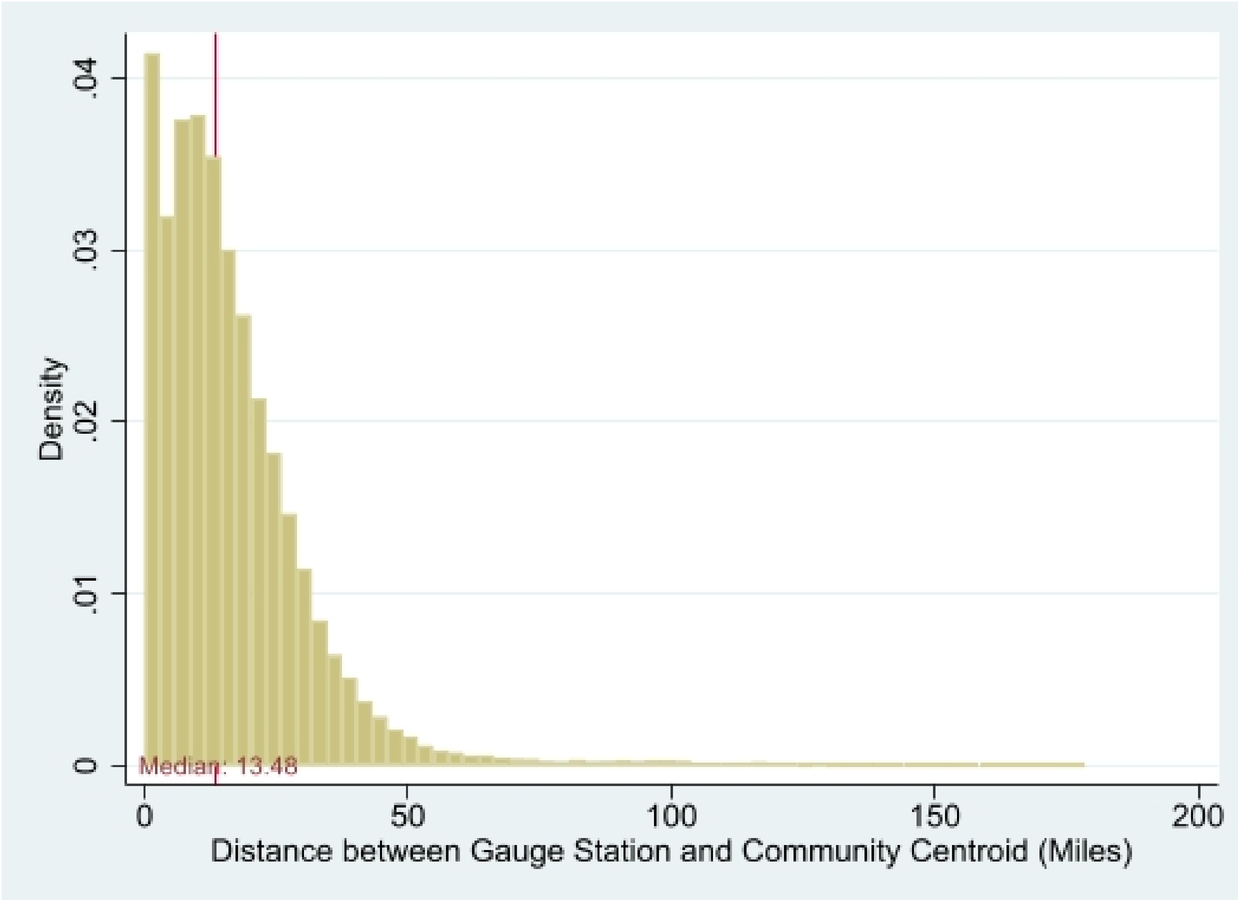


Figure A2: Distribution of Distance Between Gauge Station and Community

A.2 Data Validation

Figure A3 shows the distribution of flood size. As expected, the distribution is dominated by small-scale floods. To validate the data, I check the number of 10-year and 30-year flood over the study period: 1991-2018. By definition, 10-year and 30-year flood should on average happen about three times and once during almost 30 years. Figure A4 shows that on average each community experienced about 2.14 times of 10-year flood and 1.03 times of 30-year flood over 28 years.

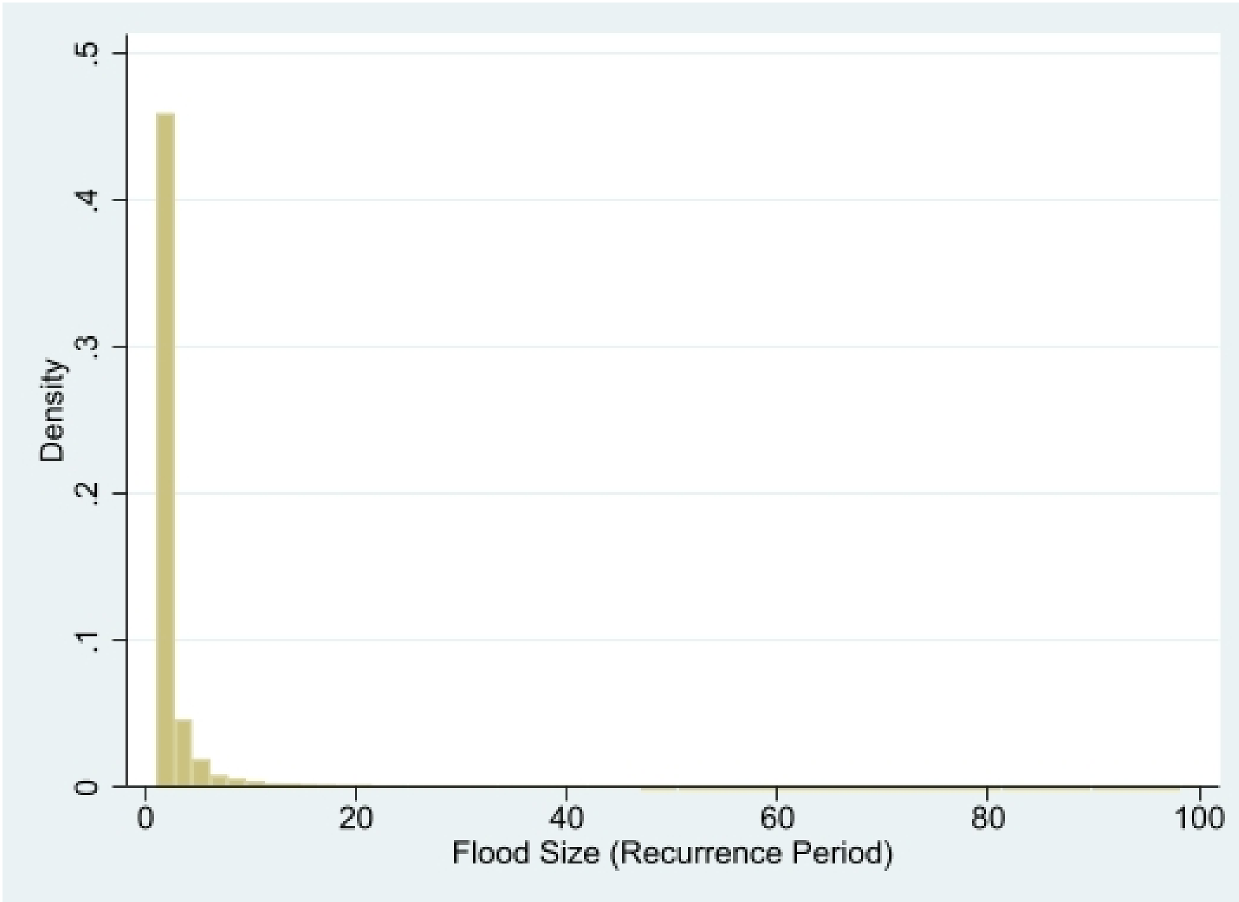
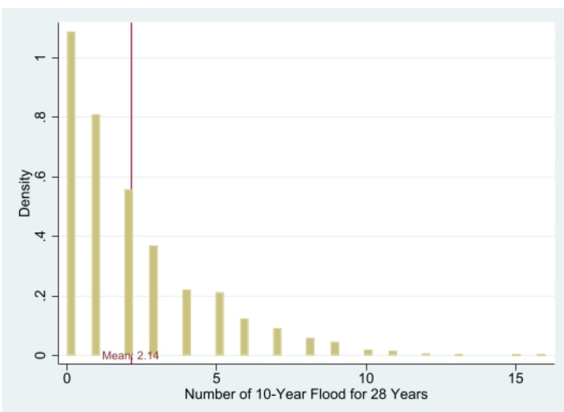
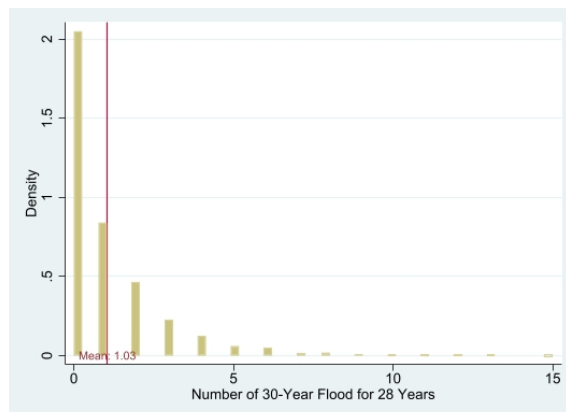


Figure A3: Distribution of Flood Size



(a) Distribution of Number of 10-Year Floods over 28 Years



(b) Distribution of Number of 30-Year Floods over 28 Years

Figure A4: Distribution of Number of Floods

B Appendix B Additional Figures

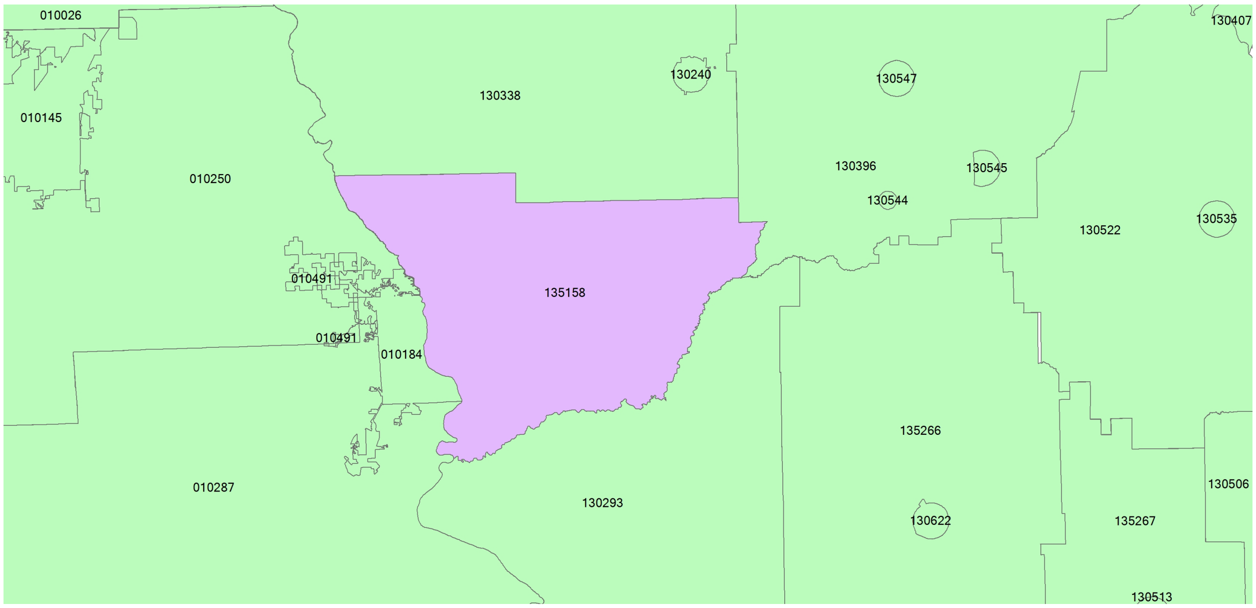


Figure B1: An Example of Treated and Control Communities

Notes: This figure shows an example of treated and control communities in 2018. The community 135158 in purple is a CRS community in 2018. The communities in green are non-CRS communities. The treated units are community 010184, 010250, 130293, 130338, and 130396 that partially share a border with the CRS community. The rest of non-CRS communities are control units.

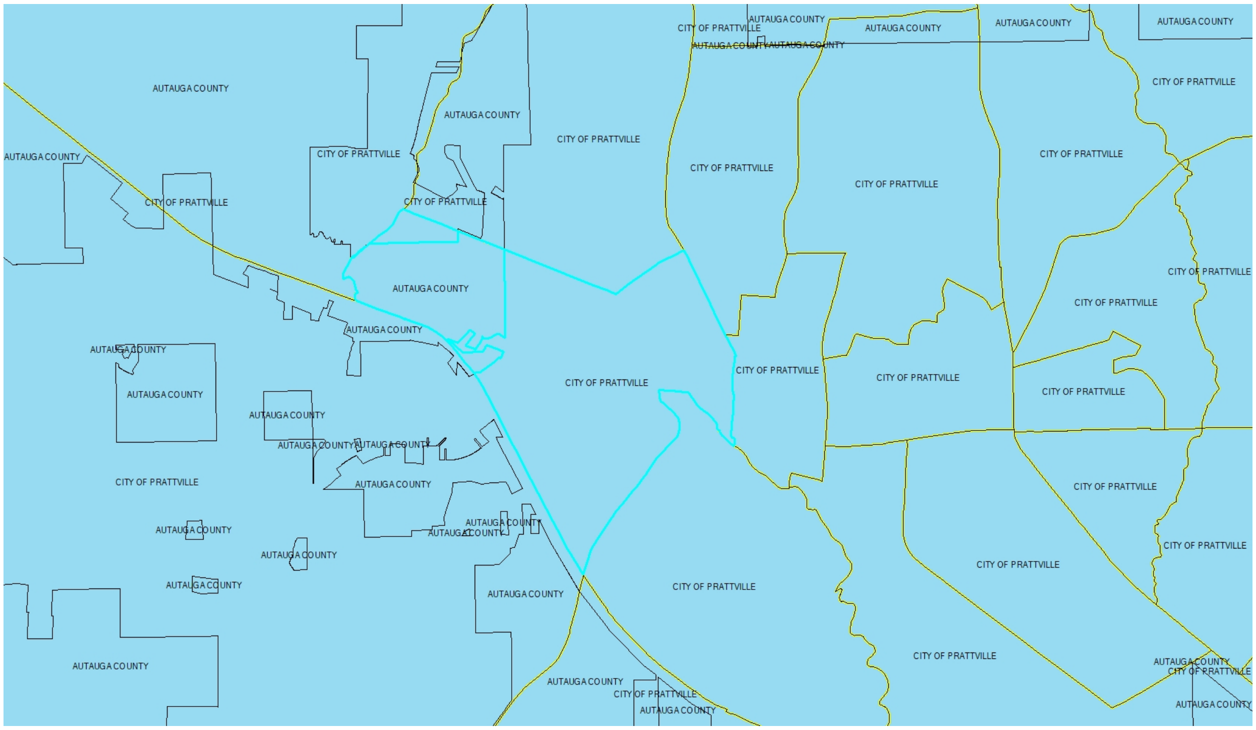


Figure B2: Geographical weight

Notes: This figure shows an example of geospatial weight used to merge in census block group level demographic data. Autauga County (CID:010314) and City of Prattville (CID:010002) are two NFIP communities with black border line. Census block groups are polygons with yellow border line. The highlighted area with blue border line is the intersected area between census block group: 010010201001 with two communities mentioned above. The area of the intersected region is 4.276222, and the areas of the intersected regions with Autauga County and City of Prattville are 0.917327 and 3.256695, respectively. Then census block group: 010010201001 contributes 21.5% to Autauga County and 78.5% to City of Prattville when calculating total population of that community.

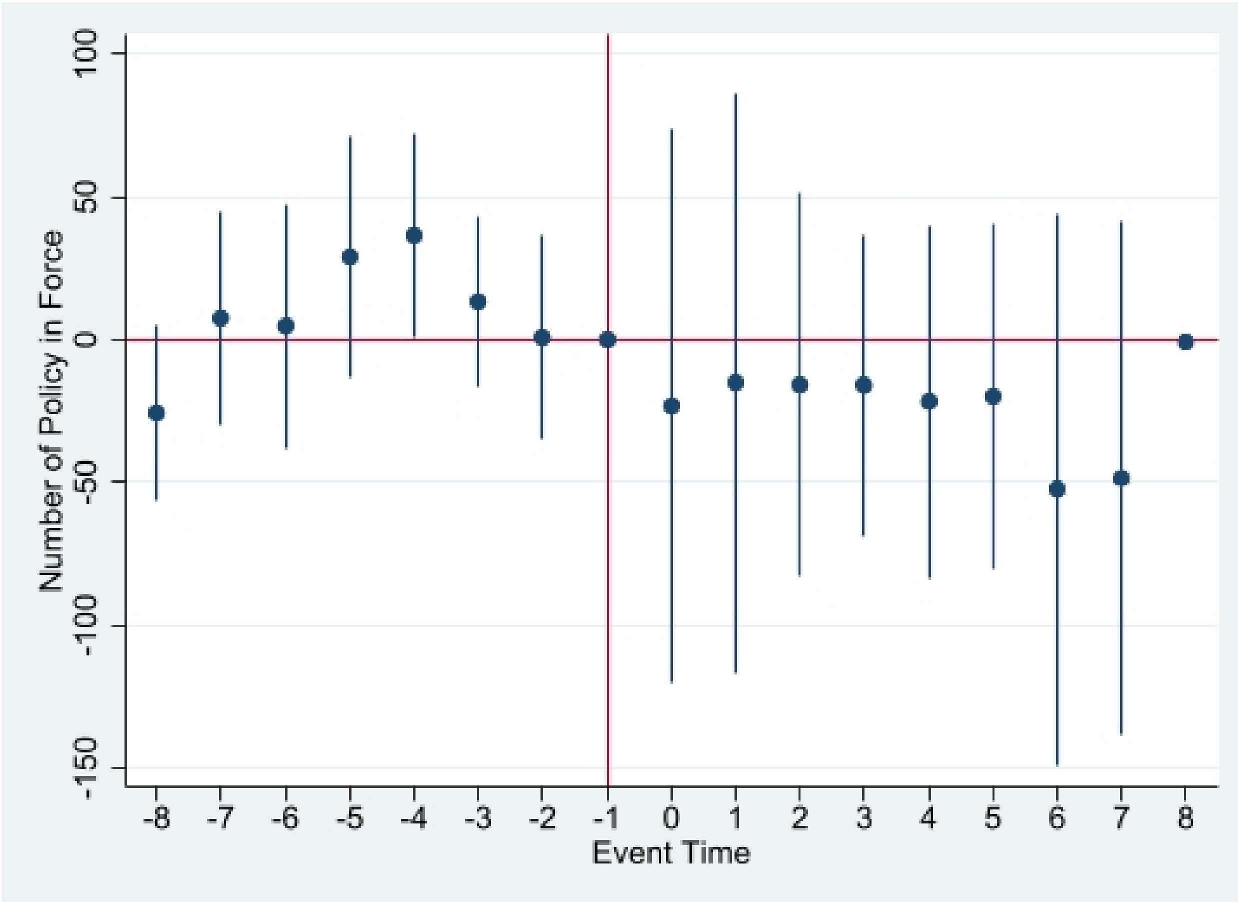


Figure B3: The Spillover Effect of the CRS on Flood Insurance Take-up - Using NFIP Redacted Policies Data

Notes: This figure shows the results of event study estimating equation 3 but using number of policy in force of community i in year t as dependent variable. The number of policy is retrieved from FIMA NFIP Redacted Policies data from 2009 to 2018. The end points on the graph are binned so that -8 (+8) is a bin for years -8 to -27 (+8 to +27). The coefficient for the year before treatment is normalized to zero. The bars show the 95% confidence interval. Standard errors are clustered at community level.