Building Underwater: Effects of Community-scale Flood Management on Housing Development

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Abstract

The Community Rating System (CRS) program was implemented by the U.S. Federal Emergency Management Agency (FEMA) in 1990 as an optional program to encourage communities to voluntarily engage in flood mitigation initiatives. This paper uses national census tract-level data from 1990 to 2010 to estimate whether CRS participation affects housing development patterns. Our results show that participating in the CRS is associated with reduced rates of new housing construction and mobile homes in flood-prone areas. When we separate flood mitigation activities under the CRS program into information-based and regulation-based activities, we find that regulatory approaches are more effective than informational approaches. These results show a general pattern, nationwide and across decades, of community-scale flood management efforts deterring housing development in flood-prone areas.

Keywords: community rating system; flood mitigation; flood risk; housing development

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1. INTRODUCTION

Pressure to develop new housing, often in flood-prone areas, continues in the face of climate change and its impact of the likelihood, severity, and extent of natural disasters (Kousky, 2014). Flood risk largely operates at a scale larger than individual parcels, involving neighbors and other regional land use decisions to determine how flooding occurs and who it affects. Thus, community-scale efforts can play a prominent role in flood management, including shaping where new housing goes. How community-scale flood management activities affect new housing development, especially in flood-prone areas of the community, is a vital question for understanding effectiveness of current management approaches and future flood risk exposure.

To better understand the effectiveness of these community-scale flood management efforts, this paper analyzes the effects on housing development patterns arising from communities' participating in national program aimed at encouraging local flood management across the country. We identify the effects of participation on net growth in new housing and in mobile homes for a panel of census tracts over three decades. Our analysis highlights effect heterogeneity depending on how risky the area is and depending on the nature of the management activities. Flood management's impacts on housing patterns may vary markedly for largely informational or regulatory approaches, for low-risk or high-risk areas, and for mobile homes or new housing.

This analysis yields insights that advance our understanding of local flood management practices and how housing markets respond. Prior work has tended to focus on which communities adopt management practices (e.g., Li and Landry, 2018; Sadiq and Noonan, 2015) or on outcomes of those practices, such as housing price effects (Muller and Hopkins, 2019), insurance take-up rates (Petrolia et al., 2013), damage estimates (Michel-Kerjan and Kousky, 2010, Frimpong et al., 2019), and population changes (Noonan and Liu, 2019). Little is known about how these community-scale efforts affect where new housing and mobile homes locate. Aside from new results about housing impacts, we also show how effectiveness varies by management approach – more mandatory and more informational – which can inform policy tool choices. These results can help guide policymakers seeking to deter ‘building underwater,’ and which approaches are more effective at steering housing development.

To estimate housing impacts, we estimate panel regression model using three decades of census tracts across the United States and detailed information about community flood management efforts. This approach employs time-consistent Census tract boundaries, high-resolution flood risk data, and program participation information for the Community Rating System (CRS) operated by Federal Emergency Management Agency (FEMA). We use a difference-in-difference (DID) approach as our main estimation strategy. The DID results yield robust estimates of CRS participation impacts on housing development. Interacting the CRS treatment with variables detailing the local flood risk and each community’s emphasis on regulatory or informational approaches to CRS allows us to differentiate effects by context. Suggestive evidence indicates that CRS participation does little to affect demolition of older, “grandfathered” buildings.

New homes and mobile homes are less common after community-scale flood management efforts. These effects are strongest where flood risk is greatest within the community and for jurisdictions that favor regulatory approaches over informational ones. These results show a general pattern, nationwide and across decades, of community-scale flood management efforts deterring or diverting housing development to higher ground. Stronger effects from regulatory, rather than information-based, approaches in high-risk areas holds important lessons for policy design. Better understanding how flood policy has shaped development patterns is vital in complex settings where regulations may restrict some development while other efforts may subsidize development in flood-prone areas or reduce information asymmetries that might have deterred development.

This analysis proceeds in the following manner. First, the literature review highlights the recent research on development and flood management. The background on the policy context describes the Community Rating System and how it might influence housing development. Next, the data and empirical approach section outlines the data used and how the modeling approaches capture the hypothesized effects of CRS participation. The empirical results section then presents the baseline model estimates and then the DID estimates, both for new housing construction and for mobile homes. Model extensions identify effect heterogeneity based on informational approaches and consider effects on older housing. After reporting various robustness checks, the conclusion summarizes the findings and points to some implications of these findings.

2. LITERATURE REVIEW

As climate change challenges mount, our understanding of how flood risk management affects housing development continues to grow. In economic terms, the stakes are enormous and continue to increase as more people and property concentrate in high-risk areas (Kousky, 2014). Better understanding adaptation to flood risks, especially in the US, is crucial to reforming policy and management to reduce the considerable flood damage suffered (Bakkensen and Mendelsohn, 2016). The growing economics literature investigating mitigation of and adaptation to flood risks (e.g., Davlasherizde et al., 2017; Li and Landry, 2018; Sant'Anna, 2018; Walsh et al., 2019) offers important, but limited, insights. Kousky and Michel-Kerjan's (2015) overview of the National Flood Insurance Program makes several key observations, including the growth in new housing construction in high-risk areas even as insurance claims are lower where community-based flood risk management efforts are practiced. While the US housing stock grows in high-risk areas, the influence of flood management practices on housing development patterns is not fully explained.

A central concern remains with understanding how public mitigation and management efforts affect private housing development (Kousky, Luttmer, and Zeckhauser, 2006). Bakkensen and Mendelsohn (2016) suggest that policy in the US might be encouraging development in risky areas. Concerns that public policy may inadvertently encourage development in flood-prone areas persist (e.g., Bakkensen and Mendelsohn, 2016), whether that is through post-disaster relief (Buchanan, 1975), provision of subsidized insurance (Kousky, 2019), or other efforts like better information provision (Chivers and Flores, 2002). Recently, both Kousky et al. (2018) and Davlasheridze and Miao (2019) find that post-disaster public assistance reduces flood insurance take-up rates. Davlasherizde, Fisher-Vanden, and Klaiber (2017) describe how ex-ante federal projects can complement or substitute for private adaptation. Some structural projects may substitute for private adaptation behavior, while other programs reduce exposure or improve information to incentivize more adaptation. Thus, while the net effect of ex-ante federal spending is to reduce property value loss, how this affects exposure (e.g., where properties are located) is less clear.

In principle, flood management practices can influence housing development patterns in a variety of ways. Much of the prior research on the economics of local flood management centers on hedonic studies of price effects (e.g., Daniel et al., 2009; Muller and Hopkins, 2019) and on the important role of flood risk information, perceptions, and beliefs (e.g., Petrolia et al., 2013; Gallagher, 2014; Li and Landry, 2018; Bakkensen and Barrage, 2018; Ahmadiani et al., 2019). As public flood risk information can redirect demand toward lower-risk areas (Votsis and Perrels, 2016) and induce sorting, adoption of informational flood management practices stands to shape where housing development occurs. In addition, flood management activities can alter the likelihood or severity of flood events through structural flood defenses, regulating construction, land use restrictions, and other physical risk reduction (Ahmadiani et al., 2019). Wing et al. (2020) show that flood management in the US has reduced vulnerability in Special Flood Hazard Areas (SFHAs) while increasing it outside of SFHAs. Recent work by Walsh et al. (2019) shows how property markets respond to not just changing risks (from sea-level rise) but also to mitigation activities as evidenced in capitalization in housing values.

More direct causal evidence about housing development effects is harder to find (Kousky, 2019). The first empirical study, Cordes and Yezer (1998), finds that participating in the early phase of the NFIP had a positive effect on new housing development across 42 beachfront communities, but that effect disappeared in the regular phase. They attribute this effect to subsidized insurance rates for early development, unlike the higher rates for properties constructed during the regular phase. Browne et al. (2019) find that NFIP participation affects new housing development by reducing development rates in coastal Florida counties while encouraging more development in inland Florida. They speculate that regulatory costs drive their results, though they lack good measures to test this directly. Still, these minimal flood management practices regulate development in ways that raise construction costs while mitigating flood losses, which can affect the types and locations of new housing. The present analysis complements Cordes and Yezer (1998) and Browne et al. (2019) by focusing on more intensive community-scale flood management activities, which allows us to both explicitly address the endogeneity of community participation in these programs and also differentiate between the regulatory and informational effects. Further, we expand the analysis to include the whole country at a smaller geographic scale, which allows identification of within-community effects. These effects may differ by the type of housing as well, as markets for multi-unit housing and standalone properties can react differently to flood risk information (Meldrum, 2016). For example, mobile home parks tend to sort into areas with different flood vulnerability (Horney et al., 2010) and their residents may perceive flood risks differently (Whitehead, 2009)

Analyses of local flood management activities in the US under the nationwide Community Rating System indicate how these practices can help shape behavior. Prior studies of CRS impacts have centered on property damage and insurance demand (Dixon et al., 2006; Zahran et al., 2010) and claims (e.g., Michel-Kerjan and Kousky, 2010; Frimpong et al., 2019; Highfield and Brody, 2017; Muller and Hopkins, 2019). Recent interest in the CRS include analyses of trends in CRS activities (Ahmadiani et al., 2019) and its impacts on local income inequality (Noonan and Sadiq, 2018) and population growth (Noonan and Liu, 2019). None of these studies, however, examines CRS activities' effects on new or vulnerable housing. Kousky (2019) emphasizes the absence of evidence of the CRS inducing land-use changes. Yet the intended outcomes of CRS activities – better information, reduced risk, reduced insurance premiums – should affect housing supply in participating communities, especially in floodplains.

Several recent studies have begun to unpack the various ways that different communities participate in the CRS. This is especially important given hypothesized effects differ across informational, structural, regulatory, and other general categories of flood management activities. Details about a community's types of activities are leveraged in recent work by Fan and Davlasheridze (2016), Li and Landry (2018), Noonan and Liu (2019), Ahmadiani et al. (2019), and Muller and Hopkins (2019). A common theme in these studies is differentiating between informational aspects of the local flood management efforts (e.g., public outreach about risks, insurance), zoning and regulatory aspects, and infrastructural improvements. Muller and Hopkins (2019) examine the effects of informational programs in CRS communities, finding that they cause heightened sensitivity to flood risk for residents. Though Fan and Davlasheridze (2016) report that individuals value public informational programs most, it may be the regulatory aspects that most influence development patterns (Noonan and Liu, 2019; Browne et al., 2019). Additional background information on the CRS program provides context for how this analysis leverages detailed data on community flood management activities to identify which sorts of activities influence housing development patterns.

3. Background on Community Rating System

The Community Rating System (CRS) was created by FEMA in 1990 as an incentive-based, voluntary program designed to recognize and encourage local, community-scale floodplain mitigation activities exceeding the minimum NFIP standards. To participate in the program, communities need to adopt and implement creditable flood mitigation activities that are classified into four broad categories: series 300 (public information), series 400 (mapping and regulation), series 500 (flood damage reduction), and series 600 (warning and response). Based on the 2013 CRS coordinator's manual, the four categories embrace 19 specific flood mitigation activities. FEMA uses a point system to encourage mitigation activities. Each activity earns a score based on the degree to which it is implemented. Table 1 provides the description of the four categories, and lists the 19 mitigation activities and their maximum credit points.

[INSERT TABLE 1 ABOUT HERE]

A community's total CRS score is the sum of all points it earned across all 19 activities. The CRS program places participating communities into one of ten classes based on its total score. Up to 4,500 points are awarded. Every 500 points earns a higher class rating, with scores ranging from 0-499 for Class 10, 500-999 for Class 9, and up to a 4,500 for Class 1 (where 10 is the lowest class, and 1 is the highest class). For example, a community with 550 points earned is placed into Class 9, while a community with 2,200 points earned is placed into Class 6.

An important incentive for improving a community's class rating is the discounted flood insurance premiums for property owners of participating communities. Premium discounts depend on the class that a community is placed and whether a building is located in a special flood hazard area (SFHA).[3] Class 10 communities receive no discount because their corresponding points do not meet the NFIP's minimum requirements. Class 9 communities are the first to receive a discount, which starts at 5% inside the SFHA, and discounts in each Class after 9 increase in increments of 5% until the maximum 45% is reached. Properties outside of SFHA are eligible for discounts of 5% (for classes 7-9) or 10% (classes 1-6) on insurance premiums. These premium discounts are designed to encourage local governments to engage in flood mitigation activities to benefit local residents. Table 2 shows CRS classes, credit points and corresponding flood insurance premium discounts.

[INSERT TABLE 2 ABOUT HERE]

[3] SFHA refers to an area with a 1% or greater chance of flooding within any given year.

The CRS is a voluntary federal program for communities – counties or municipalities – to opt into, encouraging them to go above and beyond the minimal expectations of the NFIP.[4] Eligibility for CRS requires that communities comply with the rules and regulations of the NFIP for at least one year. Thus, the term "community" in this context and throughout this analysis refers to local governments – either counties or incorporated places like cities and towns – that can participate in the CRS. To begin the application, local governments can submit a letter of interest to their state's Insurance Services Office (ISO) and document that their flood protection activities qualify for more than 500 points. If the application is approved, an ISO specialist will schedule a verification visit to determine the community's class by evaluating how the flood mitigation activities were implemented. After the evaluation the ISO specialist submits the report to FEMA to verify his findings and notify the applicant community of its initial classification in the CRS tier system.

The CRS program requires that each participating community recertify each year to ensure that it is continuing to perform the mitigation activities for which it has earned credit. The recertification allows communities who have implemented additional creditable activities to receive a higher tier ranking and thus a greater discount on insurance premiums. Conversely, communities who did not properly or fully implement the promised activities may downgrade to a lesser ranking. In addition to recertification, audits are performed every few years to review the activities and points earned of communities (FEMA, 2013). Therefore, the program is a form of quantifiable and continuously updated tool reflecting local communities' flood mitigation efforts.[5] In general, the CRS has attracted more participating communities each year, and communities that join the CRS rarely if ever drop from the program (Michel-Kerjan et al., 2016). This voluntary program is notable for its strong persistence and tendency for participating communities to slowly ratchet up their activities over time (Li and Landry, 2018).

Participation in CRS may yield a variety of societal and environmental benefits other than the reduction in flood insurance premiums. Other benefits that accrue more broadly include reduced flood damage to humans and properties, better risk information disclosure, enhanced public awareness about flood risks, and better infrastructure for managing floods and responding to flood events. Participation may also promote stricter building codes, land

[4] Consistent with CRS usage, we use the term "community" to refer to either counties or municipalities throughout. Tribal areas can also be eligible to join the CRS. Only a few have joined.
[5] At present, more than 1,400 communities have participated in CRS, and most communities entered the program in the class range 9 to 7 (FEMA, 2017).

use rules and development restrictions that make the community more sustainable and resilient. While some of these benefits are concentrated to SFHA areas, others are more proportional to local flood risks, and some are more diffused to the broader area.

4. Data and Empirical Approach

4.1 Data Sources

The data used in this paper come from a variety of sources. The tract-level decennial census data from 1990 to 2010 are obtained from the Geolytics, Inc. Neighborhood Change Database (NCDB) file. Geolytics re-codes data from earlier years to 2010 census tract boundaries to maintain a geographically consistent panel. The CRS participation data from 1998 to 2013 are obtained from FEMA, which records the total CRS points, class and the points awarded for each of the 19 creditable activities for each community.[6] Flood risk data come from FEMA's national flood hazards layer, downloaded in 2017, as highly detailed digital flood insurance rate maps (dFIRMs) mapped onto tract boundaries. We characterize flood risk as the share of each tract's area that overlaps an SFHA that represents at least 1% annual chance of flooding. Although this limits our flood risk measure to a time-invariant risk measure that covers most (87%) of the US population in 2010, the SFHAs from the FIRMs represent official and widely known information about local flood risks that link directly to flood insurance premiums and policy. The Spatial Hazard Events and Loss Database for the United States (SHELDUS) provides county-level flood property damage estimates. As shown later, we use these data to construct tract-level weighted flood property damage. Table 3 reports variable descriptions and their sources.

[INSERT TABLE 3 ABOUT HERE]

4.2 Baseline Estimation

The main purpose of this study is to examine the effects of flood mitigation activities under the CRS program on local development patterns. Using panel data for Census years (1980 – 2010) at the tract level, baseline model takes the following fixed-effects form:

[6] Although the first cohort of CRS-participating communities began after the 1990 Census, FEMA did not provide detailed annual data on CRS participants prior to 1998.

$$Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_1 CRS_{jt} + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt} \qquad (1)$$

where i indexes tracts, j indexes communities (county or city), and t indexes decennial censuses 1990, 2000 and 2010.[7] θ_t is census year fixed effects, and α_i is tract fixed effects to control for any time-invariant unobservable heterogeneity. ε_{it} is the idiosyncratic error that changes across time for each tract. Standard errors are clustered at the community level (county or city) to account for serial correlation. This two-way fixed-effects specification exploits variation within tracts over time to study the effect of the CRS program.

Y_{ijt} represents the outcome variables. We create two dependent variables to measure local development. The first is percent of new housing units built in the last five years in a tract. The second is percent of mobile homes/trailers in a tract.[8] We consider mobile homes in this analysis because it is a class of housing particularly sensitive to flooding.

The key explanatory variable is CRS participation. This participation decision is taken by the much larger community, typically a municipality or county, that contains the tract. We are interested in seeing whether tract-level changes of new construction and mobile homes are associated with whether the broader community participated in the CRS. We first create a dummy variable CRS_{jt} that equals to 1 if the host community j of tract *i* has participated in CRS during the census period, and 0 otherwise. Tracts are considered to participate in the CRS if they are either in a place or a county that participates in year *t*. Note that this *CRS* variable only varies by the community in which the tract *i* is situated; *CRS* does not vary among tracts in the same participating community. As an alternative, we create a continuous variable *CRS Points* that equals to the total credit points earned through all 19 activities by tract *i*'s host community *j*.[9] Higher points indicate greater flood mitigation efforts in the community.

$\boldsymbol{X}'_{\boldsymbol{ij,t-1}}$ is a vector of time-varying, tract-level demographic characteristics that are predictive of changes in new housing units and mobile homes. *Housing Value* is measured as

[7] One advantage of our dataset is that it provides a small unit of observation at the tract level, avoiding aggregation errors arising from using average values across a wider area such as a county. Also, note that *t* measures time decadally across three decennial censuses (1990, 2000, 2010), while the panel dataset also includes 1980 Census data because the $\boldsymbol{X}$ control variables are lagged by one time period.

[8] The denominator for both variables is total housing units for a tract in a census year.

[9] Because the dependent variables in this analysis are only available decadally, we simply use CRS participation status and total points earned at the time of census years 2000 and 2010 in the data, although FEMA provides annual CRS information for each community. We do not expect this to be a major issue because of the very strong temporal persistence in CRS participation and CRS scores for communities (Michel-Kerjan et al., 2016; Li and Landry, 2018).

the log of the mean housing value. *Poverty* is measured as the poverty rate. *Unemployment* is measured as the number of unemployed divided by total number in the labor force. *Population Density* is measured as the total tract population divided by total land area. *Renters* is measured as the share of total housing units that are rentals. *Vacant* is measured as the share of total housing units that are vacant. These control variables are 10-year lagged to mitigate possible simultaneity concerns, and reflect economic vitality of the previous decade.[10]

A potential confounding variable in our model is flood damage. Property loss and casualties from past flooding events may drive communities to participate in CRS to avoid further flood loss. Meanwhile, flooding damage may significantly influence development and relocation decisions made by developers and property owners. To control for this factor, we use a variable $Damage_{ijt}$ that is measured as the total flood damage over the previous five years for a county. The raw variable is provided by SHELDUS. It is then weighted by a tract's share of county's area, population, and flood risk to form a time-varying, tract-level measure.[11] We adjust it to 2013 dollars to make sure that the damages coincide with the end of the CRS participation data.

One limitation of the specification in equation (1) is that it assumes a uniform CRS program effect on development across all tracts within a broader community. This situation is unlikely because there is large flood risk heterogeneity within a community. Many CRS activities target buildings and properties within SFHAs to obtain the highest marginal benefits of mitigation efforts. Therefore, we expect to observe a much stronger program effect in flood-prone areas than in low-risk areas.

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[10] A small portion of tracts have missing values on these demographic characteristics in certain census years. In this case, we use other census years' values of the tract to interpolate or extrapolate its missing observations.

[11] For purposes for flood risk-weighting historic flood damage, we employ a risk measure from FEMA (1996). The FEMA flood risk data are computed from a 1km by 1km grid cell map onto census block groups, taking the mean value of the flood risk metric across the cells in each block group. Then, flood risk of each census tract is equivalent to the mean value of these block groups' flood risk value. This variable has several advantages in measuring flood risk. First, it characterizes local flood hazard conditions with a continuous measure at scales much smaller than cities or counties. Using a continuous measure for flood risk in risk-weighting flood helps characterize flood risks outside of SFHA "floodplains," where much of flood damage in fact occurs. Second, its calculation uses data that largely predate communities joining the CRS program, so it avoids overcontrolling for possible CRS effects on flood risk. Further, because its risk measure is independent of SFHA status, it mitigates potential endogeneity concerns insofar as housing development might lead to subsequent changes in floodplain designations. The weighting formula from Noonan and Liu (2019) is $Damage_{ict} = MA_{ct}(w_{it}/w_{ct})$, where MA_{ct} is the five-year moving average of property damage in county c in year t from SHELDUS, weight w_{it} is flood risk × area × population in tract i for year t, and w_{ct} is the sum of w_{it} across all tracts in county c in year t. This weighting approach treats each component (risk, area, population) equivalently, a simple assumption that may not hold. Thus, a tract with double the population will have double the *Damage* of another tract in the same county with the same risk and area. With flood risk defined using the raster flood risk measure, *Damage* apportions county-level flood damage to tracts based on their relative flood risk and land area and share of county population, which is also time varying.

To reflect this risk heterogeneity across tracts, we use a set of *Risk* interaction terms to extend equation (1) into the following model:

$$Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_0(Risk_i \times \theta_t) + \gamma_1 CRS_{jt} + \gamma_2(CRS_{jt} \times Risk_i) + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt} \quad (2)$$

For $Risk_i$, we use the (land area) share of each tract that occupies a 100-year floodplain. This variable is time-invariant but varies across tracts. Although we cannot insert this variable independently into the model after tract fixed effects are controlled for, we can estimate the coefficient of the interaction term $(CRS_{jt} \times Risk_i)$. This interaction allows for the impact of CRS to vary by flood risk.

4.3 Difference-in-Differences Estimation

The specification in equation (2) lends itself to a difference-in-differences (DID) estimator. In this DID approach, after defining $HighRisk_i$ as a dummy variable to indicate flood-prone tracts (i.e., more than 10% of the tract's area occupies a 100-year floodplain), we model the outcome as:

$$Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_0(HighRisk_i \times \theta_t) + \gamma_1 CRS_{jt} + \gamma_2(CRS_{jt} \times HighRisk_i) + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt} \quad (3)$$

Equation (3) is a close analog of equation (2) while also taking on the familiar form of a difference-in-difference-in-differences (DDD) estimator.[12] Here, $\hat{\gamma}_2$ represents the differences estimator to indicate how CRS participation differentially affects flood-prone regions of the community in contrast with the rest of the community. We can also directly estimate equation (2) where *Risk* is defined as a continuous measure of flood risk, which is represented by the variable *SFHAshare*.

By focusing our attention on the estimate of differential CRS effects in high- versus low-risk tracts ($\hat{\gamma}_2$), this approach controls for other trends affecting all tracts in a community

[12] We model a basic DID model as $Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_0 CRSever_j + \gamma_1 CRS_{jt} + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt}$, where $CRSever_j$ is a dummy variable indicating whether the host community *j* has ever been in the CRS and CRS_{jt} is the time-varying measure of CRS status or $CRSever_j \times \theta_t$. With tract-level fixed effects, γ_0 is not identified as *CRSever* drops out. This reduces to equation (1), where the $\hat{\gamma}_1$ coefficient is the difference-in-differences estimate. To refine the definition of the treatment and control groups to account for varying levels of flood risk and how the CRS program may differentially affect high-risk areas, we can expand this base DID model to a difference-in-difference-in-differences (DDD) model. We include the $HighRisk_i$ dummy and a full set of interactions to arrive at: $Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_0 CRSever_j + \gamma_1 HighRisk_i + \gamma_2 CRS_{jt} + \gamma_3 HighRisk_i \times \theta_t + \gamma_4 CRS_{jt} \times Risk_i + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt}$. With tract-level fixed effects, this reduces to:
$Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_2 CRS_{jt} + \gamma_3 HighRisk_i \times \theta_t + \gamma_4 CRS_{jt} \times HighRisk_i + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt}$. This analog of equation (2) highlights the *CRS*×*Risk* coefficient for the interaction term as identifying the DDD estimate.

– regardless of the relevance of CRS flood-management activities – and tests whether CRS effects differ for those flood-prone areas relative to less risky areas. CRS activities within a particular community should focus on flood-prone areas, so not all tracts within a participating community will necessarily receive the CRS treatment. Hence, low-risk tracts in CRS communities can serve as a control group for the high-risk tracts that CRS activities target. This can help mitigate concerns that a community may opt to join the CRS because of expected trends in the community's future housing development. Identifying the effect of joining the CRS in flood-prone tracts relative to other, low-risk tracts in CRS communities helps to control for changes in other community-level factors that might influence housing development, such as other local regulation and regional economic conditions.

In addition to the DID approach, we also use a matching procedure to restrict the sample to a set of observations that reduce imbalance in covariates between the treated and control tracts (i.e., those tracts in CRS communities vs. those not in CRS communities). We apply a coarsened exact matching (CEM) method (Iacus et al., 2012) that restricts the sample to observations that balance better in terms of covariates while reducing model dependence, estimation error, and other statistical concerns. We estimate the matched sample of treated and untreated tracts using covariates (***X***) measured in 1990, prior to the implementation of the CRS program, before we estimate the model in equation (2).[13] Table A1 presents means for the treatment and control tracts from the full and matched samples. Compared with the results in full sample, means of most variables are closer across the treatment and control tracts using the matched sample.

Our final panel data include 62,291 unmatched and 49,971 matched tracts for the census years 1990 to 2010.[14] Table 4 shows the descriptive statistics for both the full sample and for the matched sample. Focusing on the CEM matched sample, on average, a tract has 9.6 percent of new housing built in the last five years, and 7.5 percent of mobile homes. Just over 12 percent of tracts' areas, on average, sit in SFHAs. The CRS participation rate of about 23% reflects how most tracts were not in participating communities in any given year. (Note that the participation rate was 0% in 1990.)

[INSERT TABLE 4 ABOUT HERE]

[13] Because all the covariates that we used for CEM are continuous, we use the default binning algorithm, the Sturge's rule, to coarsen the continuous variables into a fixed number of bins.

[14] A very small number of tracts have missing values in the dependent variables in certain census years. We do not interpolate these missing values.

Table 5 shows participation rates in more recent years, at the community- and tract-levels of analysis. While only a little more than 5% of all eligible communities participate in the CRS, this low rate belies the scope of this voluntary program. That small share of communities encompasses a disproportionate share of the population, including over a third of US population and of all census tracts. Table 5 also shows the persistence of participation in the CRS. Although the program expanded from 2000 to 2010, adding more tracts and a greater share of the US population, it retained the vast majority of its participants. Over 95% of the communities (and tracts) participating in 2000 also participated in 2010.

[INSERT TABLE 5 ABOUT HERE]

4.4 CRS and Its Impact on Development

Before describing our empirical analysis, we want to briefly discuss the conceptual model of the relationship between CRS-incentivized mitigation activities and new housing construction, as it guides the empirical specifications outlined earlier. One policy goal of the CRS program is to redirect development away from floodplains to abate the potential for catastrophic losses. To receive discounted flood insurance premiums, CRS participants need to ensure a genuine commitment by implementing a bundle of floodplain management mitigation activities. These activities may have an immediate effect on development. Land use regulations such as zoning ordinances, building codes, development restrictions, and open-space preservation may directly discourage developers from starting new homes in floodplains. Some activities such as transfer of development rights and bonuses for avoiding floodplains provide incentives to encourage developers and property owners to keep flood-prone lands free of development. Greater hazard disclosure provides property owners, including mobile home owners, with information to make better decisions such as relocating to safer areas. Acquisition, relocation and demolition of mobile homes would directly move these risky properties to areas outside the floodplains. Particular interest may be paid to removing older, at-risk homes from floodplains. These combined effects are supposed to reduce the shares of new housing and mobile homes in CRS communities. Further, because most CRS activities target high-risk areas inside the SFHA, this negative effect should be more evident in flood-prone areas within CRS communities. If these policy goals are reached, we should see that CRS communities will have less new housing construction and mobile homes than non-CRS communities, and this reduction is more apparent in risky tracts. Empirically, we should find that $\gamma_1 < 0$ and $\gamma_2 < 0$ in equation (2) and (3).

On the other hand, previous studies have found that flood risk programs may create perverse outcomes that are counterproductive to public interests. Specifically, there is empirical evidence that poorly designed federal programs might actually attract private investment and housing development into high-risk areas (Burby, 2001; Bagstad et al., 2007; Zahran et al., 2010; Chakraborty et al., 2014). The CRS program is no exception. Improved flood management infrastructure, tighter regulations and proactive mitigation activities might indirectly encourage development and population growth in floodplains by making the areas safer for habitation. Better flood warnings and risk information disclosure may encourage more floodplain development because of reducing flood uncertainty. Providing discounts on flood insurance premiums to households, the CRS program is also likely to facilitate in-migration and development in flood-prone areas if the households are attracted by discounted insurance premiums. In these scenarios, the total cost of flood damage would increase, not decrease, because of drawing more households and development into high-risk areas. If these unintended consequences occur, we should observe that $\gamma_1 > 0$ and even $\gamma_2 > 0$ in equation (2) and (3). Given these countervailing arguments, the net effect of the CRS program on development remains an open empirical question. This theoretically ambiguous direction motivates our empirical inquiry.

5. Main Results

Table 6 reports DDD estimates of the relationships between CRS participation, local flood risk, and the outcome variables as described in equation (2), based on the CEM matched sample.[15] The unit of observation is a tract for each census year. Standard errors are clustered at the community level (unique combination of counties and cities) to account for serial correlation within communities.[16] All specifications include tract and year fixed effects.

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[15] Columns (1) and (3) in Table A2 report OLS estimation results for equation (1). The results show that, on average, CRS participation has negative and statistically significant effects on housing development and mobile homes, after controlling for tract fixed effects, census year fixed effects, and the demographic characteristics. As described above, equation (1) assumes a uniform CRS participation effect on housing development across all tracts within the community.

[16] Errors clustered by group use the unique county-and-city combinations to define 'community' groups. Thus, all tracts in a given county but outside of any city are assigned to the same group.

[INSERT TABLE 6 ABOUT HERE]

We first find that CRS participation has a negative effect on housing development in flood-prone areas when estimating equation (3). Column (1) shows that, assuming very safe areas, CRS participation is associated with a decreased share of new housing construction by 0.5 percentage points, though this estimate is not statistically significantly different than zero. Column (3) shows that CRS participation is associated with a decreased share of mobile homes by 0.5 percentage points, a statistically significant effect. Table 4 reports that the standard deviation of share of mobile homes is 0.115, so this modest effect size is about 0.042 of a standard deviation in the outcome variable.

More relevant to its policy goals, we test whether CRS flood management activities discourage housing development in flood-prone areas. The coefficients on the interaction terms are consistently significant and negative, indicating that this negative program effect is stronger in high-risk areas. More specifically, column (1) results show that CRS participation is expected to decrease share of new housing in flood-prone areas by 0.134 standard deviations. Expressed in terms of semi-elasticity, it translates into a 17.6% decrease in share of new housing. Correspondingly, column (3) results show that CRS participation is expected to decrease the share of mobile homes in flood-prone areas by 0.109 standard deviations, and its semi-elasticity is about 16.7%.

Furthermore, in examining the results of columns (2) and (4) in Table 6, where flood risk is measured as a continuous measure, we see that the negative effect of CRS grows stronger as flood risk increases. Given that among tracts in CRS communities the average high-risk tract (i.e., *SFHAshare* > 0.1) has an *SFHAshare* of 0.344 and the average low-risk tract's *SFHAshare* is 0.023, results in column (2) imply that typical low-risk tracts' share of new housing construction fall by 0.7 percentage points after their community joins the CRS, while typical high-risk tracts in those communities see their share of new housing construction fall by 1.3 percentage points. Expressed in terms of semi-elasticity, it translates into a 13.3% decrease in the share of new housing for high-risk tracts and a 7.7% decrease for low-risk tracts. Similar effects for the share of mobile homes reflects declines of 0.6 percentage points for typical low-risk tracts compared to 1.0 percentage points for high-risk counterparts. This risk heterogeneity effect accords with the fact that most CRS mitigation activities seek to restrict development in SFHAs to reduce potential flood damage.

Table A3 in the Appendix reports the effects from the control variables. Recall that the empirical model uses lags of all control variables, by 10 years for the socioeconomic factors and 5 years for flood damage. We find that almost all of them have significant effects. For example, poorer, higher unemployment rate areas tend to attract constructions of new housing and mobile homes. Past property damage due to flooding significantly predicts more new construction, perhaps to replace the damaged housing stock.

The difference-in-differences approach addresses concerns that tracts in communities that join the CRS may be very different in the first place from those that do not join (i.e., the first difference) and may have already been on a different development trajectory (i.e., the second difference). The DID approach to estimating a model like equation (1) can identify the effect of the CRS "treatment," but this requires assuming that the CRS and non-CRS tracts would have experienced parallel trends in the absence of the CRS program. To test this assumption, we examine the trends in *New Construction* and *Mobile Homes* in the decades prior to joining the CRS program and compare those trends for tracts in communities that would eventually join the CRS with those that never have. Figure 1 visually depicts the results of this analysis. Prior to the advent of the CRS, tracts whose community would one day join the CRS exhibit similar trends in the housing development outcome variables as tracts in communities never joining the CRS. This gives us some confidence that the DID estimation approach is appropriate here. Treatment and control tracts follow similar, largely parallel trends prior to 2000, the first census year in which CRS participation could affect outcomes. Prior to 2000, both treatment and control tracts experienced declining shares of new construction, with the rate of decline slowing after 1990. And prior to 2000, both groups experienced rising and then falling shares of mobile homes.

[INSERT FIGURE 1 ABOUT HERE]

We also use a flexible event study framework to estimate the effect of CRS participation on changes in new housing and mobile homes. Following our main specification of equations (1) and (2), we can set up the following panel event study equation:

$$Y_{\mathrm{ijt}} = \sum_{\tau=-2}^{1} \beta_\tau W_{j\tau} + \alpha_i + \theta_t + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt} \qquad (4)$$

The variables of interest are the event time indicator variables $W_{j\tau}$, which indicate that the given community is a given number of census periods *before* or *after* the census year of CRS participation. For example, for communities that participated in CRS in 2000, then we have τ = -1, 0, 1 for census years 1990, 2000 and 2010.[17] The indicator variable W_{j0} equals 1 if community j participated in CRS in that census year.

We normalize β_{-1} as zero when estimating the equation. So the estimated coefficients can be interpreted as the impact of CRS on the dependent variable relative to the census year before CRS participation.

The estimated event time indicator coefficients along with their confidence intervals are plotted in Figure 2.[18] The reference year (τ = -1) is a decade before the CRS participation census year. Consistent with the results in Table 6, Figure 2 shows that high-risk areas after participating in CRS have significantly lower shares of new housing and mobile homes relative to the reference year. This trend is more pronounced as time passes (τ = 1), suggesting that CRS participation has enduring effects on housing development and mobile homes. By contrast, the pre-event lead coefficients are small and statistically insignificant and, therefore, do not provide evidence of pre-trends. We further test the null hypothesis that $\beta_{-2} = \beta_{-1}$ by normalizing β_0 as zero, and the p-values of both equations are higher than 0.85 so we cannot reject the hypothesis.

[INSERT FIGURE 2 ABOUT HERE]

In addition, we implement the CEM matching technique to further improve the comparability of the sample of "treated" and "control" tracts in our sample. Moreover, our primary interest lies with the *CRS*×*Risk* interaction term in the DDD model, because we are most interested in whether CRS participation affects housing development in flood-prone areas more than low-risk tracts in CRS communities. Thus, even if the differencing strategy estimates an average effect of CRS participation (γ_1) that includes some omitted-variable bias reflective of some community-scale unobservables that affected development trajectories, our

[17] For most communities, CRS participation occurred in 2000, but a small number of communities participated in CRS in 2010. So we can observe τ=-2 for these communities.

[18] Following the specifications in Table 6 and Figure 1, the tracts located in CRS participating communities and with *SFHAshare* equal or greater than 0.1 are considered as the treated units. Also, the results are based on the matched sample of treated and untreated tracts after applying a coarsened exact matching (CEM) method.

focus on differential effects (by *Risk*) within those CRS communities (γ_2) helps mitigate concerns that community-level unobservables bias the results.

We also consider several other robustness checks for the DDD analysis in Table 6. First, we examine whether the results are sensitive to the threshold chosen in determining which tracts are at "high risk" for flooding. While Table 6 reports results for *HighRisk* when *SFHAshare* > 0.1, Table A4 in the Appendix reports results for thresholds set at 0, 0.05, 0.15, and 0.2. The results all show roughly comparable results for the coefficient of interest, though the effects may be fading as the *HighRisk* treatment groups is more narrowly defined.[19]

Our second robustness check uses CRS total points to replace the dummy variable *CRS*. More points earned indicate stronger mitigation efforts in the community. To reduce skewness, we transform *CRS Points* to log form. This alternative specification yields qualitatively similar results, as reported in Appendix Table A5. Again, we find negative effect of CRS on new construction and mobile homes, and this effect is more significant in flood-prone areas.

6. Extensions

6.1 Informational and Regulatory Mitigation Activities

Flood mitigation activities under the CRS program can be broadly defined as two types: information-based (series 300) and regulation-based (series 400, 500 and 600). The former focuses on providing the public with information needed to increase flood hazard awareness to motivate actions to reduce flood damage. The latter focuses on adopting and reinforcing concrete flood control regulations to prevent loss of life and property damage to new development, or to reduce flood damage to existing buildings. An interesting policy question is whether these two categories of activities yield different program effects. This question is not answered from previous analysis.

Because implementing regulation-based activities, such as open space preservation, higher regulatory standards, zoning ordinances, building codes, acquisition or relocation of

[19] Note that Table A4 also contains results for the models where risk is measured continuously with SFHAshare because the CEM procedure still relies on *HighRisk* to obtain the matched sample.

flood-prone structures, is expected to have a more immediate impact on discouraging development than information-based activities, one hypothesis is that the negative CRS program effect identified before is more evident if a community favors regulatory activities. To test this hypothesis, we expand equation (2) by including a full set of interaction terms for the information variable, $Information_{jt}$, to indicate the strength of information-based activities in the community. It has the following specification:

$$Y_{\mathrm{ijt}} = \alpha_i + \theta_t + \gamma_0(Risk_i \times \theta_t) + \gamma_1(CRS_{jt} \times Information_{jt}) + \gamma_2 CRS_{jt} + \gamma_3\left(CRS_{jt} \times Risk_i\right) + \gamma_4\left(CRS_{jt} \times Risk_i \times Information_{jt}\right) + \boldsymbol{X}'_{\boldsymbol{ij,t-1}}\phi + \varepsilon_{ijt} \quad (5)$$

where $Infomation_{jt}$ represents percentage of total credit points earned from information-based activities for a community (and equals zero for tracts in non-participating communities). Specifically, we define that the six activities from public information (series 300 level) are information-based, and the remaining thirteen activities from other three categories (series 400, 500 and 600 levels) are regulation-based. We calculate total credit points earned from the 300 level activities, and then divide it by the total credit points earned by a community. Higher value means that the community relies more on informational activities (and thus less regulatory activities) to achieve CRS points. Similar to CRS_{jt}, $Information_{jt}$ only varies with community j in which the tract i is situated. In a nutshell, this model assumes that the marginal effect of CRS on new housing and mobile homes depends not only on flood risk heterogeneity, but also on the choice of mitigation activities types.

Table 7 reports the results. To conserve space, we only present the coefficients on CRS and its interaction terms. Columns (1) and (3) in Table 7 parallel columns (1) and (3) in Table 6, except that they include two more terms, $CRS_{jt} \times Info_{jt}$ and $CRS_{jt} \times HighRisk_i \times Info_{jt}$. The dummy variable *Info* equals 1 if *Information* is greater than 0.3.[20] Similarly, columns (2) and (4) parallel those columns in Table 6, except that they include continuous variables $CRS_{jt} \times Information_{jt}$ and $CRS_{jt} \times SFHAshare_i \times Information_{jt}$. Thus, these models estimate equation (5). This specification allows for the effects of informational activity intensity to depend on flood-risk heterogeneity among tracts.

[INSERT TABLE 7 ABOUT HERE]

[20] We select 0.3 as the threshold because the mean and median of percentage of information activities are close to 0.3 for CRS participating communities.

To understand that how CRS activities' effect vary by flood risk within the community, we turn our attention to the *Risk* interaction terms in Table 7. In all models, the negative effect of $CRS_{jt} \times Risk_i$ remains significant and negative. CRS participation generally reduces the share of new housing construction and mobile homes and this effect is amplified in flood-prone tracts. This effect holds regardless of whether risk is measured in a discrete (columns 1 and 3) or continuous (columns 2 and 4) manner.

Although the baseline effect of joining the CRS remains negative and significant in all models in Table 7, the effect of the information intensity (discrete or continuous) uninteracted with flood risk is only significant for the mobile homes models. Communities that join the CRS via more information-intensive activities tend to see the share of mobile homes increase. These results support the hypothesis that series 400 to 600 regulatory activities are more effective than series 300 informational activities on discouraging development among mobile homes, though this effect is statistically insignificant for new construction. Holding everything else constant, a 10 percent point increase of adopting regulatory activities is associated with a decreased share of mobile homes by 0.2 percentage points for tracts with *SFHAshare* equal to 0. Interestingly, these results imply that the negative CRS program effects on housing development (evident in the CRS coefficients in tables 6 and 7) would be lessened for mobile homes if a community emphasizes adopting informational activities, but informational activities' effects on new housing construction are more targeted to flood-prone areas.

Whether different sorts of CRS activities – informational or regulatory – affects this relationship can be seen in the triple-interaction terms. CRS effects in high-risk tracts may not vary much by the reliance on informational activities when information is treated as a dummy variable. For continuous measures (columns 2 and 4), however, the triple-interaction term indicates that this negative effect of CRS in riskier tracts significantly weakens as communities rely more on informational activities. Both new construction and mobile homes models exhibit this positive and statistically significant coefficient. These results confirm our hypothesis that the effect of CRS on development depends on both flood risk heterogeneity and the types of mitigation activities adopted. Communities favoring regulatory activities would yield a stronger effect on discouraging development than those favoring informational activities. This difference is more significant in flood-prone areas of CRS communities.

Figure 3 further visualizes the marginal effect of CRS on new housing construction and mobile homes, using the estimated coefficients from columns (2) and (4) in Table 7. Equation

(5) indicates that the marginal effect of CRS hinges on the values of the variables *Risk* and *Information*. To simplify the exposition, we use two cutoff points 0.17 and 0.43 of *Information* to represent two types of CRS communities: one favors adopting regulatory activities (0.17), and the other favors adopting informational activities (0.43).[21] The variable *Risk* is displayed along the horizontal axis, where higher values indicate flood-prone areas, like the tracts with higher proportion of SFHAs.

[INSERT FIGURE 3 ABOUT HERE]

The figure shows that for communities favoring regulatory activities, the marginal effects of CRS on new housing and mobile homes are always negative, and the effects are stronger in risky areas. This result agrees with the policy goals of the CRS program. However, for communities favoring informational activities, the marginal CRS effect on mobile homes is much flatter than that of communities favoring regulatory activities. The marginal CRS effect on new housing is even upward-sloping. This result indicates that, compared with 300 series informational activities, those regulatory activities have stronger impacts on diverting new construction and mobile homes away from risky areas.

We also examine these models with an alternative definition of *New Construction*, based on housing built in the past 10 years (rather than 5), to assess if the results are sensitive to the definition of "new." The results of estimates for the models in tables 6 and 7 (columns 1 and 2) are available in appendix Table A6. They show results that are essentially unchanged from the main findings here.

These findings provide initial empirical evidence that adopting different types of mitigation activities may yield significantly different impacts on development. We offer several plausible explanations. First, regulatory activities in series 400 to 600, especially those land use regulations and development restrictions, are effective in restricting developers from starting new homes in floodplains. Acquisition and relocation activities are also effective in encouraging property owners to relocate to safer areas. These regulatory activities have direct and immediate impacts on diverting new construction and mobile homes away from risky areas. Second, although series 300 informational activities provide better flood risk disclosure and flood protection assistance to the public, they exert little direct influence

[21] We select 0.17 and 0.43 here because they are the first and last deciles in the distribution of the percentage of informational activities implemented by CRS participating communities in our data.

on restricting development in floodplains. Instead, better flood warnings and risk information system may encourage more floodplain development because these activities reduce flood uncertainty. Third, discounted insurance premiums might attract development and households into floodplains because of a strong price effect. This effect would be reinforced if a community fails to undertake enough regulatory activities to restrict development in SFHAs.

As an incentive-based voluntary program, the CRS program provides local governments with latitude to select from a menu of mitigation activities to receive discounted insurance premiums. Because costs of flood mitigation are high while benefits are long-term and uncertain, local governments may disproportionately pursue those least-cost, "low-hanging fruit" activities to minimize mitigation costs. Unfortunately, prior studies have found that CRS communities do appear to favor series 300 informational activities for accumulating points, because points in this series are easier and cheaper to achieve than those regulatory activities that entail more significant, expensive interventions (Brody et al. 2009; Zahran et al. 2010; Ahmadiani et al., 2019). Apparently, this is counterproductive because it undermines the goal of CRS to limit population growth and development in flood-prone areas. A policy implication derived from this analysis is that the CRS program should encourage communities to adopt more meaningful mitigation strategies. In particular, the federal government should recalibrate the CRS reward structures to give more weight in assigning credits to reward regulatory mitigation activities if restricting floodplain development is a priority for a community.

6.2 Demolition Effect on Old Buildings

Another interesting policy question is whether the CRS program facilitates demolition or relocation of dilapidated, old properties from floodplains. There are at least two reasons that the program should pay particular attention to old properties. First, old properties can be more vulnerable to flood damage because they lack flood-resistant structures, and their technical standards are outdated. If a disaster occurs, these buildings account for a higher share of claims filed and losses paid. Second, old, pre-FIRM properties usually qualify for discounted flood insurance rates defined by pre-FIRM or "grandfathering" policies provided by the NFIP.[22] The owners of these properties pay much lower rates than NFIP risk-based

[22] NFIP defines pre-FIRM properties as those constructed prior to the date of the community's initial FIRM or prior to January 1, 1975.

rates even though their buildings were mapped into a higher-risk zone, so long as the building maintains a flood insurance policy. Thus, they pay rates not commensurate with the true risk of flood damage, indicating that governments collect insufficient premiums to cover expected losses. With flood risk increasing over time in many places, grandfathering of old buildings will make the NFIP program financially unsound.

The CRS program recognizes that demolition of buildings in floodplains is especially effective at reducing flood damage because it is a permanent form of mitigation. Its series 500 Flood Damage Reduction activities credit the demolition or relocation of buildings outside the floodplains. Previous literature devotes little attention to examine this demolition effect on old buildings. This study attempts to fill this void. We define old buildings in a tract as the housing units built prior to 1970. To account for tract heterogeneity, we use 1990 as the base year, and compute the ratios of old housing units in the census years (1990, 2000, 2010) over that in 1990. This variable equals to 1 for all tracts in 1990, and should decrease over subsequent decades. Ahmadiani et al. (2019) show a similar downward trend in the frequency of pre-FIRM houses. If CRS activities speed up demolition of old buildings, we should observe that the ratio decreases more rapidly in CRS-participating communities.

We run the same regressions for equations (2) and (5) using the old building ratio as a new dependent variable. As reported in Table A7 in the Appendix, the estimation results show that the coefficient for CRS (γ_1) is positive and statistically significant, whereas the interaction term (γ_2) is positive and marginally significant for column (2). Contrary to our expectation, removing old, pre-FIRM properties tends to happen less often in CRS-participating communities. Also, we do not find that old properties situated in flood-prone areas are more likely to be relocated or removed. The models including informational activities suggest that information may help reduce the number of these older buildings, but not differentially so in flood-prone areas. These results imply that the CRS program fails to provide enough incentives for local communities to engage in relocating or demolishing old properties. It is also possible that many communities choose to retrofit existing flood-prone buildings to receive credits, which reduces the demand for demolition. In a nutshell, our preliminary results suggest that there is little demolition effect of CRS on old housing units. Certainly, more rigorous tests in this area should be carried out in future research.

7. Limitations

Despite showing consistently negative effects of CRS participation on our housing development indicators in flood-prone areas, these analyses hinge on important assumptions that point to promising areas for future research. First, our key variables rely on measures that offer only a limited a perspective on potentially richer underlying relationships. Our outcome variables – the shares of new housing constructed in the past five years and of mobile homes – capture important indicators of housing development impacts but are limited in their granularity by being measured only at the aggregate (tract) level and only decadally from the census. These measures can characterize broader trends across a large country like the US and over many decades, although these relationships should also be examined using higher frequency, parcel-level data. This can be especially useful in identifying the lag time for community-scale flood management efforts to affect housing development patterns.[23] Similarly, our measure of *Risk* has advantages in terms of broad coverage, geographic precision, and relevance for policy and insurance requirements and premiums. But SFHA-based risk measures are often criticized for characterizing flood risk in crude categories, and digital flood maps with complete US coverage predating the CRS program are unavailable. Future research would do well to use alternative measures of risk to examine other approaches, within-tract variation in risk, and changing risk over time. Community-level activities like the CRS can affect where housing development occurs, but they can also influence flood risk itself through changes in infrastructure and policy.

In addition, limitations in measuring community-scale flood management efforts suggest another path for future research. Using detailed program participation data for the CRS offers considerable information about the nature of the "treatment," but this likely under-estimates the effects of serious community-scale efforts. If CRS activities include efforts that predate the program, such as long-term protections for open space, then our CRS treatment effect likely understates the full effect of new community flood management efforts. Our approach also does not account (beyond the DDD estimator) for communities' discretion in which activities they pursue under CRS, which recommends caution in interpreting the *Information* effects in Table 6. Furthermore, non-CRS communities may also be undertaking some flood management activities, insufficient to qualify for or uninterested in joining the CRS, which can also lead to underestimating the *CRS* effects in a

[23] Our data allows us to consider alternative definitions of "new" housing construction, such as the share of housing units constructed in the past 10 years. Using a decade-long window for *New Construction* yields very similar results. Using a one-year window for *New Construction*, on the other hand, produces generally insignificant results – likely owing to too short a time lag.

model that cannot account for those activities. More comprehensive accounting for the many possible ways communities can address flood risk can help identify more effective and efficient policies.

Third, spatial interdependence remains an intriguing and implicit aspect of this analysis. Our approach cannot differentiate between heterogeneous effects by local flood risk (i.e., uniform CRS policies having differential effects between high- and low-risk tracts) and heterogeneous treatment of local flood-related policy (i.e., CRS policies targeting high- and low-risk areas differently). Just as changes in housing development in one area can imply displacement of that development to other areas in its community or elsewhere, flood management efforts or the lack thereof can affect "downstream" flood risks and management challenges for neighboring communities. Future research would do well to further investigate these spillovers. Our results that show differential effects by flood risk within the same CRS community suggest that displacement may be an important aspect, especially when nearby communities face competitive pressures for development and economic growth (and fiscal and environmental externalities may affect incentives). Examining how these spillovers push development to "higher ground" or to havens of lower regulation is an important area for future study.

8. Conclusions

The analysis presented here contributes to the small literature providing empirical evidence on the effects of community flood management practices on housing development patterns. It leverages national, spatially refined datasets and design features in the CRS, where decisions to participate in the CRS are taken at a larger geographic scale than tracts and within-community variation in flood risks and demographics allow for identification of differential effects of CRS activities in various contexts.

We use a DID approach as our main estimation strategy. Interacting the CRS treatment with variables detailing the local flood risk and each community's emphasis on regulatory or informational approaches to CRS allows us to differentiate effects by context. Our main conclusion is that participating in the CRS is associated with reduced rates of new housing construction and mobile homes in more flood-prone areas. This effect is weaker where communities emphasize informational programs, suggesting that more regulatory approaches are more effective. These findings complement with Browne et al.'s (2019) findings for the NFIP's effects in Florida communities. Yet flood management concerns more than just new homes; it also concerns existing homes. These results can help inform local adoption decisions as flood managers seek to alter housing development patterns or relocate vulnerable residences (e.g., mobile homes, older pre-FIRM homes). On average across the national sample and these decades, some CRS activities tend to reduce the frequency of mobile homes in flood-prone areas, though they do little to influence older homes' removal. Measures of effectiveness in altering exposure to flood hazards can also help guide CRS design, including point allocations for various activities. Future work estimating effects of more specific activities could further refine the incentive system.

In the appendix, we also conduct an instrumental variables (IV) analysis as a robustness check to our main DID estimations. To address the potential endogeneity problem that CRS participation is likely to be endogenous to housing development and population migration, we use county-level share of Hispanic residents to instrument for CRS participation. The validity of this IV is based on recent findings that communities with significant Hispanic populations are more likely to participate in CRS because of disproportionate exposure to flood risks. The fixed-effect IV regressions yield qualitatively similar results to the DID results. (I.e., CRS participation is associated with reduced rates of new housing construction and mobile homes in more flood-prone areas, and this effect is more pronounced in communities that emphasize regulation-based flood mitigation activities.) See the appendix for more details about the IV approach.

These results highlight the importance of community flood management to influencing where new housing development occurs. Although communities undertaking these sorts of activities appear to have minimally different new construction rates in low-risk areas, new homes are less common in flood-prone areas. These results are consistent with reducing migration in risky areas (Noonan and Liu, 2019). Building fewer, and more resilient homes (Wing et al., 2020) in harm's way may be just the sort of result needed to improve the flood damage curves in the US. Relatively less housing supply in high-risk portions of CRS communities combined with roughly lower prices (Muller and Hopkins, 2019) suggests that demand for housing in these areas may also be falling. This would be consistent with residents' increased sensitivity to flood risk and a growing marginal willingness to pay to avoid flood risk over time (Daniel et al., 2009). These positive CRS effects might not amount to much in the aggregate, however, if participation is rare and considerable flood damage occurs outside of CRS jurisdictions. The CRS is just one piece of a more complex set of policies related to flood management, including the broader NFIP and federal mitigation and relief payments. Thus, while this analysis identifies effects of CRS participation on housing development patterns, future research would do well to provide evidence of the effects of other policies on housing patterns.

REFERENCES

Ahmadiani, M., Ferreira, S., Landry, C.E., 2019. Flood insurance and risk reduction: market penetration, coverage, and mitigation in coastal North Carolina. Southern Economic Journal. 85 (4), 1058-1082.

Bagstad, K. J., Stapleton, K., D'Agostino, J. R, 2007. Taxes, subsidies, and insurance as drivers of United States coastal development. Ecological Economics. 63 (2), 285-298.

Bakkensen, L.A., Barrage, L., 2018. Flood risk belief heterogeneity and coastal home price dynamics: Going under water? (No. w23854). National Bureau of Economic Research.

Bakkensen, L., Ma, L., 2019. Sorting over flood risk and implications for policy reform. Working paper. Last accessed 21 April 2020. http://www.laurabakkensen.com/wp-content/uploads/2019/10/Bakkensen_Ma_2019.pdf

Bakkensen, L.A., Ding, X., Ma, L., 2019. Flood risk and salience: New evidence from the Sunshine State. Southern Economic Journal. 85 (4), 1132-1158.

Bakkensen, L.A., Mendelsohn, R.O., 2016. Risk and adaptation: evidence from global hurricane damages and fatalities. Journal of the Association of Environmental and Resource Economists. 3 (3), 555-587.

Brody, S.D., Zahran, S., Highfield, W.E., Bernhardt, S.P., Vedlitz, A., 2009. Policy learning for flood mitigation: A longitudinal assessment of the community rating system in Florida. Risk Analysis. 29 (6), 912-29.

Browne, M.J., Dehring, C.A., Eckles, D.L., Lastrapes, W.D., 2019. Does national flood insurance program participation induce housing development? Journal of Risk and Insurance. 86 (4), 835-859.

Buchanan, J.M., 1975. The Samaritan’s Dilemma. In Altruism, Morality, and Economic Theory. E. Phelps. New York: Russell Sage, 71–85.

Burby, R. J., 2001. Flood insurance and floodplain management: The US experience. Environmental Hazards. 3 (3–4), 111–122.

Chakraborty, J., Collins, T.W., Montgomery, M.C., Grineski. S.E., 2014. Social and spatial inequities in exposure to flood risk in Miami, Florida. Natural Hazards Review. 15 (3) 04014006.

Chivers, J., Flores, N.E., 2002. Market failure in information: the National Flood Insurance Program. Land Economics. 78 (4), 515-521.

Cordes, J.J., Yezer, A.M., 1998. In harm's way: does federal spending on beach enhancement and protection induce excessive development in coastal areas? Land Economics. 128-45.

Daniel, V.E., Florax, R.J., Rietveld, P., 2009. Flooding risk and housing values: An economic assessment of environmental hazard. Ecological Economics. 69 (2), 355-365.

Davlasheridze, M., Fisher-Vanden, K., Klaiber, H.A., 2017. The effects of adaptation measures on hurricane induced property losses: Which FEMA investments have the highest returns? Journal of Environmental Economics and Management. 81, 93-114.

Davlasheridze, M., Miao, Q., 2019. Does governmental assistance affect private decisions to insure? An empirical analysis of flood insurance purchases. Land Economics. 95 (1), 124-145.

Dixon, L., Clancy, N., Seabury, S.A., Overton, A., 2006. The national flood insurance Program's market penetration rate, estimates and policy implications. RAND Corporation. Retrieved from http://www.rand.org/content/dam/rand/pubs/technical_reports/2006/RAND_TR300.pdf

Fan, Q., Davlasheridze, M., 2016. Flood risk, flood mitigation, and location choice: evaluating the national flood insurance program's community rating system. Risk Analysis. 36 (6), 1125-1147.

Federal Emergency Management Agency (FEMA). 1996. Natural disaster study: National pipeline risk index technical report (Task 2). Retrieved from https://www.npms.phmsa.dot.gov/data/data_natdis.htm. Accessed April 1, 2014

Federal Emergency Management Agency (FEMA). 2013. National Flood Insurance Program (NFIP) community rating system (CRS) coordinators' manual.

Federal Emergency Management Agency (FEMA). 2014. National Flood Hazard Layer.

Federal Emergency Management Agency (FEMA). 2017. Community rating system (CRS) fact sheet.

Frimpong, E., Petrolia, D.R., Harri, A., Cartwright, J., 2019. Flood insurance and claims: the impact of the community rating system. Available at SSRN: https://ssrn.com/abstract=3175910 or http://dx.doi.org/10.2139/ssrn.3175910

Gallagher, J., 2014. Learning about an infrequent event: evidence from flood insurance take-up in the United States. American Economic Journal: Applied Economics. 6 (3), 206-233.

Highfield, W.E., Brody, S.D., 2017. Determining the effects of the FEMA community rating system program on flood losses in the United States. International Journal of Disaster Risk Reduction. 21, 396-404.

Horney, J.A., MacDonald, P.D., Van Willigen, M., Berke, P.R., Kaufman, J.S., 2010. Individual actual or perceived property flood risk: Did it predict evacuation from Hurricane Isabel in North Carolina, 2003? Risk Analysis. 30 (3), 501-511.

Iacus, S. M., King, G., & Porro, G. 2012. Causal inference without balance checking: Coarsened exact matching. Political Analysis. 20 (1), 1-24.

Kousky, C., 2014. Informing climate adaptation: A review of the economic costs of natural disasters. Energy Economics. 46, 576-592.

Kousky, C., 2019. The role of natural disaster insurance in recovery and risk reduction. Annual Review of Resource Economics. 11, 399-418.

Kousky, C., Luttmer, E.F., Zeckhauser, R.J., 2006. Private investment and government protection. Journal of Risk and Uncertainty. 33 (1-2), 73-100.

Kousky, C., Michel-Kerjan, E.O., 2015. Examining flood insurance claims in the United States: six key findings. Journal of Risk and Insurance. 84 (3), 819-50.

Kousky, C., Michel-Kerjan, E.O., Raschky, P.A., 2018. Does federal disaster assistance crowd out flood insurance? Journal of Environmental Economics and Management. 87, 150-64.

Landry, C.E., Li, J., 2012. Participation in the community rating system of NFIP: Empirical analysis of North Carolina counties. Natural Hazards Review. 13 (3), 205-220.

Li, J., Landry, C.E., 2018. Flood risk, local hazard mitigation, and the community rating system of the national flood insurance program. Land Economics. 94 (2), 175-98.

Maldonado, A., Collins, T.W., Grineski, S.E., Chakraborty, J., 2016. Exposure to flood hazards in Miami and Houston: are Hispanic immigrants at greater risk than other social groups? International Journal of Environmental Research and Public Health. 13 (8), 775.

Meldrum, J.R., 2016. Floodplain price impacts by property type in Boulder County, Colorado: Condominiums versus standalone properties. Environmental and Resource Economics. 64 (4), 725-750.

Michel-Kerjan, E.O., Kousky, C., 2010. Come rain or shine: Evidence on flood insurance purchases in Florida. Journal of Risk and Insurance. 77(2), 369-397.

Michel-Kerjan, E.O., Atreya, A., Czajkowski, J., 2016. Learning over time from FEMA's Community Rating System (CRS) and its link to flood resilience measurement. Working Paper #2016-11, Risk Management and Decision Processes Center, The Wharton School, University of Pennsylvania.

Muller, N.Z., Hopkins, C.A., 2019. Hurricane Katrina floods New Jersey: the role of information in the market response to flood risk (No. w25984). National Bureau of Economic Research.

Noonan, D.S., Liu, X., 2019. Heading for the hills? Effects of community flood management on local adaptation to flood risks. Southern Economic Journal. 86 (2), 800-822.

Noonan, D.S., Sadiq, A.A., 2018. Flood risk management: exploring the impacts of the community rating system program on poverty and income inequality. Risk Analysis. 38 (3), 489-503.

Petrolia, D.R., Landry, C.E., and Coble, K.H., 2013. Risk preferences, risk perceptions, and flood insurance. Land Economics. 89 (2), 227-245.

Sadiq, A.A., Noonan, D.S., 2015. Flood disaster management policy: an analysis of the United States Community Ratings System. Journal of Natural Resources Policy Research. 7 (1), 5-22.

Sant'Anna, A.A., 2018. Not so natural: unequal effects of public policies on the occurrence of disasters. Ecological Economics. 152, 273-281.

Smith, V.K., Carbone, J.C., Pope, J.C., Hallstrom, D.G., Darden, M.E., 2006. Adjusting to natural disasters. Journal of Risk and Uncertainty. 33 (1-2), 37–54.

Stock, J.H., Yogo, M., 2005. Testing for weak instruments in iv regression. In: Andrews, D.W.K., Stock, J.H. (Eds.), Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas Rothenberg. Cambridge University Press, 80–108.

Troy, A., Romm, J., 2006. An assessment of the 1998 California natural hazard disclosure law (AB 1195). Policy Research Program, California Policy Research Center, University of California.

Votsis, A., Perrels, A., 2016. Housing prices and the public disclosure of flood risk: a difference-in-differences analysis in Finland. The Journal of Real Estate Finance and Economics. 53 (4), 450-471.

Walsh, P., Griffiths, C., Guignet, D., Klemick, H., 2019. Adaptation, Sea Level Rise, and Property Prices in the Chesapeake Bay Watershed. Land Economics. 95 (1), 19-34.

Whitehead, J.C., 2009. Hurricane risk perceptions and preparedness. Encyclopedia of Psychology of Decision Making. 811-824.

Wing, O.E., Pinter, N., Bates, P.D., Kousky, C., 2020. New insights into US flood vulnerability revealed from flood insurance big data. Nature Communications. 11.1444.

Zahran, S., Brody, S.D., Highfield, W.E., Vedlitz, A., 2010. Non-linear incentives, plan design, and flood mitigation: The case of the Federal Emergency Management Agency's Community Rating System. Journal of Environmental Planning and Management. 53 (2), 219-239.

Table 1: CRS Categories of Activities and Credit Points Awarded

Activities	Descriptions	Maximum Possible Points
300 Public Information		
310 Elevation Certificates	Activities that advise the public about flood hazard, flood insurance and flood protection measures.	116
320 Map Information Service		90
330 Outreach Projects		360
340 Hazard Disclosure		80
350 Flood Protection Information		125
360 Flood Protection Assistance		110
370 Flood Insurance Promotion		110
400 Mapping and Regulations		
410 Floodplain Mapping	Activities that enact and enforce regulations that exceed the National Flood Insurance Program's (NFIP's) minimum standards, so that more flood protection is provided for new and existing development.	802
420 Open Space Preservation		2,020
430 Higher Regulatory Standards		2,042
440 Flood Data Maintenance		222
450 Stormwater Management		755
500 Flood Damage Reduction		
510 Floodplain Mgmt. Planning	Activities that address reducing flood damage to existing buildings. Measures include acquiring, relocating, or retrofitting existing buildings; maintaining and improving drainageways and retention basins.	622
520 Acquisition and Relocation		1,900
530 Flood Protection		1,600
540 Drainage System Maintenance		570
600 Warning and Response		
610 Flood Warning and Response	Activities that address emergency warnings, evacuation plans and safety protocols for dams, levees, and other flood protection structures.	395
620 Levees		235
630 Dams		160

Source: FEMA (2013).

Table 2: CRS Classes, Credit Points and Premium Discounts

Class	Credit Points	Premium Reduction	
		In SFHA	Outside 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

Source: FEMA (2013).

Table 3: Variable Definitions and Data Sources

Variable Name	Definition	Data Source
Dependent Variables		
New construction	Share of housing units in a tract that are built in the last five years (0 to 1)	US Census (Geolytics)
Mobile homes/trailers	Share of housing units in a tract that are mobile homes or trailers (0 to 1)	US Census (Geolytics)
Independent Variables		
CRS (dummy)	1 if a community is participating in CRS, and 0 if not	FEMA (2013)
CRS points	Totals CRS points for the participating community in which the tract resides	FEMA (2013)
Risk (0 to 1)	Share of each tract's area that overlaps an SFHA that represents at least 1% annual chance of flooding	FEMA (2014)
Information (0 to 1)	Percentage of information-based (series 300) activities for the participating community	FEMA (2013)
CRS × Risk	Interaction between CRS and flood risk	FEMA (2013)
CRS × Information	Interaction between CRS and percentage of information-based activities	FEMA (2013)
CRS × Risk × Information	Triple interaction between CRS, flood risk, and percentage of information-based activities	FEMA (2013)
Control Variables		
Property damage	Total flood damage over the previous five years, weighted by a tract's share of county's area, population, and risk, adjusted to 2013$	SHELDUS
Poverty rate	Tract poverty rate	US Census (Geolytics)
Housing value	Log of mean housing value in a tract	US Census (Geolytics)
Population density	Total tract population divided by total land area	US Census (Geolytics)
Unemployment rate	Number of unemployed divided by total number in the labor force in a tract	US Census (Geolytics)
Renters	Share of total housing units that are renter occupied in a tract	US Census (Geolytics)
Vacant homes	Share of total housing units that are vacant in a tract	US Census (Geolytics)

Table 4: Descriptive Statistics

	Full Sample		Matched Sample	
Variable	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
Dependent Variables				
New construction	0.089	0.121	0.096	0.126
Mobile homes	0.073	0.118	0.075	0.115
Independent Variables				
CRS	0.220	0.414	0.235	0.424
SFHAshare	0.121	0.19	0.127	0.189
HighRisk (dummy)	0.334	0.472	0.358	0.479
Information	0.063	0.128	0.066	0.13
Info (dummy)	0.088	0.283	0.092	0.289
Control Variables				
Property damage (million $)	0.014	0.467	0.014	0.500
Poverty rate	0.136	0.115	0.112	0.091
Housing value (log)	11.079	1.102	11.314	0.865
Population density	0.002	0.004	0.001	0.001
Unemployment rate	0.063	0.059	0.053	0.045
Renters	0.311	0.202	0.273	0.165
Vacant home	0.095	0.091	0.083	0.071
Observations	185,448		149,347	

Table 5: Rates of Participation in CRS by Year

	Participating in		
Unit	2000	2010	both 2000 & 2010[b]
Communities[a]	5.1	6.3	95.4
Tracts	28.8	35.4	99.1
Population	29.1	37.0	99.2

[a] FEMA Community Status Report (https://www.fema.gov/flood-insurance/work-with-nfip/community-status-book), downloaded 1 June 2021, indicates 18,183 eligible communities. Detailed CRS participation data from FEMA indicate 926 and 1148 participating communities in October 2000 and October 2010, respectively.

[b] This column represents the share of the communities, tracts, or population participating in the CRS in 2000 that were still participating in 2010.

Table 6: CRS Program Effects on New Construction and Mobile Homes

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
CRS	-0.0050	-0.0070**	-0.0049***	-0.0060***
	(0.0034)	(0.0033)	(0.0014)	(0.0013)
CRS x HighRisk	-0.0119***		-0.0076***	
	(0.0036)		(0.0016)	
CRS x SFHAshare		-0.0170**		-0.0121***
		(0.0083)		(0.0041)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,971	49,971	49,971	49,971
Observations	149,347	149,347	149,347	149,347

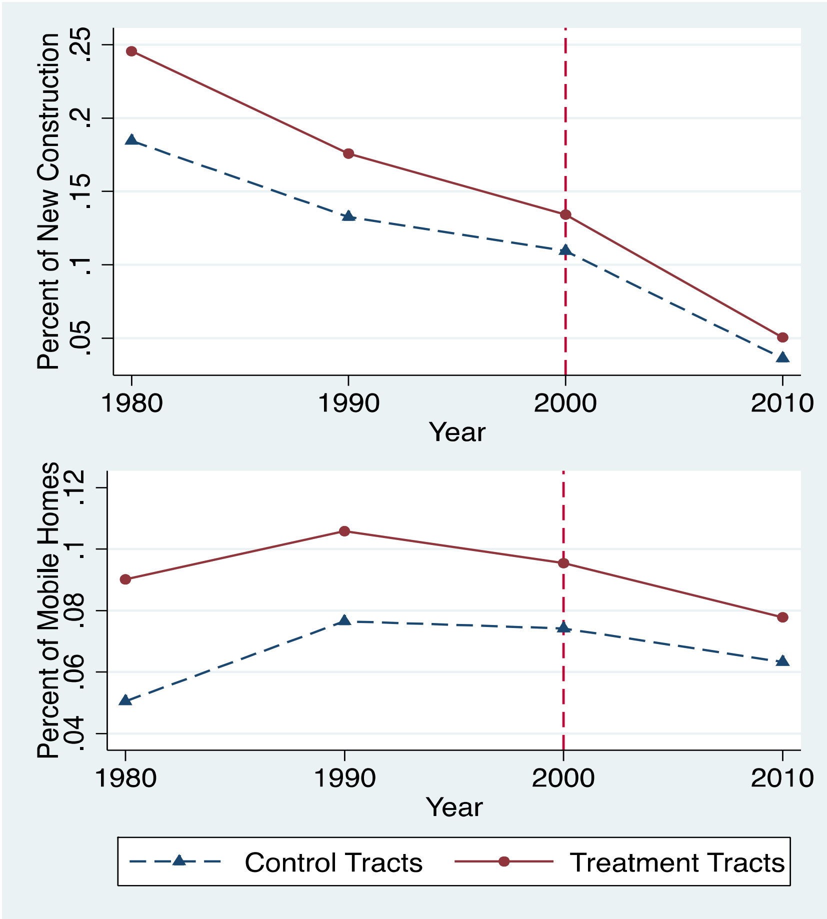
Notes: Estimated coefficients from DID regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables are percent of houses built in the last five years in a tract, and percent of housing units that are mobile homes in a tract. Units are tract/census year. *HighRisk* is a dummy variable that equals one if the tracts with *SFHAshare* equal or greater than 0.1. Standard errors clustered at the community level are in parentheses. See Eq. (2) for the specification.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table 7: Heterogeneity of CRS Activities on New Construction and Mobile Homes

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
CRS	-0.0077*	-0.0143*	-0.0057***	-0.0112***
	(0.0046)	(0.0074)	(0.0016)	(0.0026)
CRS x Info	0.0062		0.0042***	
	(0.0058)		(0.0014)	
CRS x HighRisk	-0.0120**		-0.0085***	
	(0.0048)		(0.0019)	
CRS x HighRisk x Info	-0.0006		0.0013	
	(0.0057)		(0.0016)	
CRS x Information		0.0249		0.0214***
		(0.0207)		(0.0061)
CRS x SFHAshare		-0.0593***		-0.0253***
		(0.0189)		(0.0083)
CRS x SFHAshare x Information		0.1452***		0.0416**
		(0.0513)		(0.0205)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,971	49,971	49,971	49,971
Observations	148,697	148,697	148,697	148,697

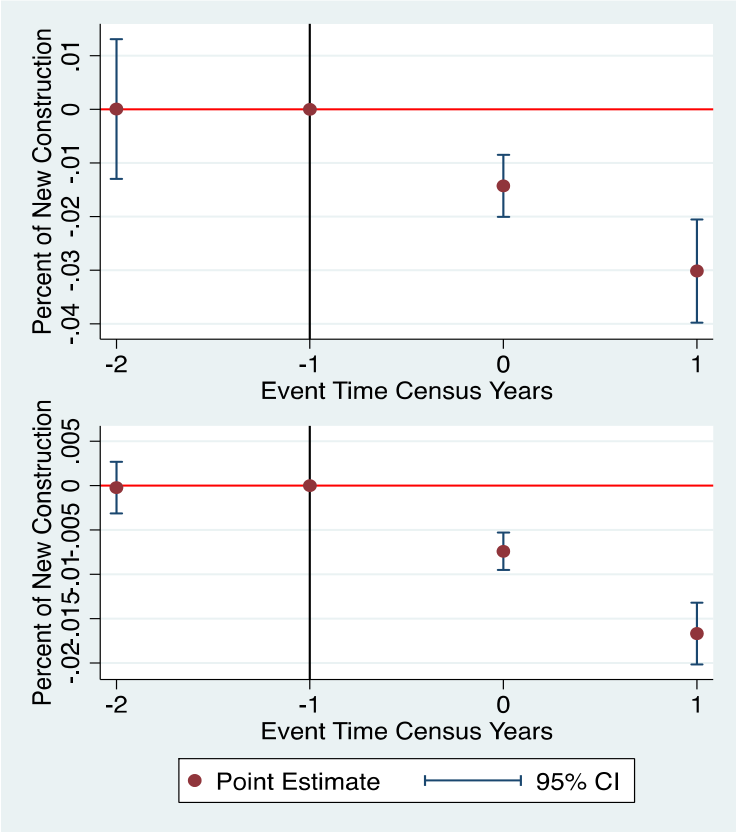
Notes: Estimated coefficients from DID regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables are percent of houses built in the last five years in a tract, and percent of housing units that are mobile homes in a tract. Units are tract/census year. *HighRisk* is a dummy variable that equals one if the tract with *SFHAshare* equal or greater than 0.1. *Info* is a dummy variable that equals one if the tract's *Information* is equal or greater than 0.3. Standard errors clustered at the community level are in parentheses. See Eq. (5) for the specification.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Figure 1: Parallel Trends



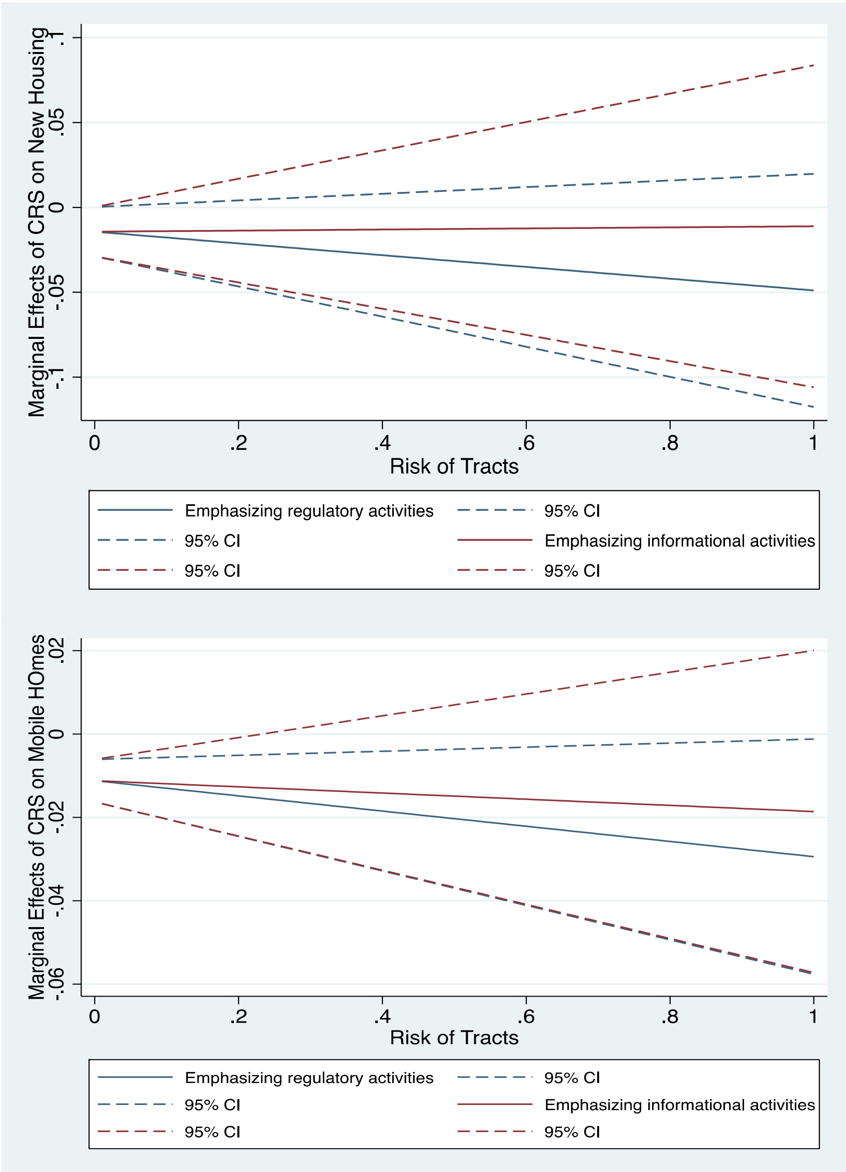
Notes: The figure is constructed based on the CEM matched sample in Table 6. *Treatment Tracts* are the tracts located in CRS participating communities and with *SFHAshare* equal or greater than 0.1 (i.e., *CRS* x *HighRisk* =1). Other tracts are coded as *Control Tracts*.

Figure 2: CRS Participation and Outcomes



Notes: The figure plots event time indicator coefficients along with their confidence intervals from estimation of equation (4). The estimated coefficients can be interpreted as the impact of CRS on the dependent variable relative to the census year before CRS participation. The reference year (τ = -1) is a decade before the CRS participation census year, and is normalized to 0. Following the specifications in Table 6 and Figure 1, the tracts located in CRS participating communities and with *SFHAshare* equal or greater than 0.1 are considered as the treated units. The results are based on the matched sample of treated and untreated tracts after applying a coarsened exact matching (CEM) method.

Figure 3: Marginal Effects of CRS Participation on Dependent Variables



Notes: The figure presents the marginal effect of CRS on new housing construction and mobile homes as a function of tracts' flood risk, based on the estimated coefficients in columns (2) and (4) in Table 7. "Emphasizing regulatory activities" are the communities where *Information* is set to 0.17 (first decile), and "Emphasizing informational activities" are those where *Information* is set to 0.43 (last decile). The dashed lines represent the 95% confidence interval.

Appendix: Instrumental Variable (IV) Estimation

Model Setup

As a robustness check to our main DID estimations, we conduct an instrumental variables (IV) estimation of equation (5). The IV strategy estimates a causal effect of joining the CRS, and tests whether that effect differs for flood-prone tracts, by instrumenting for the potentially endogenous CRS variables. This endogeneity problem deserves our attention since prior literature has documented that CRS participation is likely to be endogenous to housing development and population migration (Landry and Li, 2012; Fan and Davlasheridze, 2016; Sadiq and Noonan, 2015; Noonan and Liu, 2019). The DDD approach relies on an assumption that the treated tracts would have followed a similar trend to the control tracts but for being a flood-prone tract in a community that joined the CRS. The IV approach, by contrast, relies on an assumption that our instruments can isolate the causal effect of joining the CRS. Two conditions must hold for IV estimation. First, the instrument must be a strong predictor of communities' CRS participation. Second, the exclusion restriction requires that the instrument is independent of the error term ε in equations (2) and (5). This is equivalent to say that the instrument has no effect on changes of new construction or mobile homes other than through its effect on CRS participation. It is not hard to find a possible IV to meet the first condition, but it is challenging to select a good IV to meet the second condition. Many factors previously identified as related to communities' flood mitigation efforts (e.g., Landry and Li, 2012; Sadiq and Noonan, 2015; Li and Landry, 2018) may also influence local housing construction. Therefore, some characteristics that predict CRS participation, such as poverty, housing value, income levels, are unlikely to meet the exclusion restriction assumption.

To select a valid IV to instrument for CRS participation, we leverage the design of the CRS program itself – where decisions to participate in the CRS are taken at a community scale (i.e., county or municipality) much larger than the tract-level unit of analysis. For IVs, we employ county-level share of Hispanic residents. Many environmental justice studies find that different ethnic groups have unequal exposure to environmental risk, and Hispanic residents in the US have the greatest likelihood of residing in floodplains, relative to other ethnic groups including Whites, Blacks and Asians (Troy and Romm, 2006; Chakraborty et al., 2014; Maldonado et al., 2016). Similarly, Smith et al. (2006) and Fan and Davlasheridze

(2016) show that Hispanics are more likely to reside in floodplains, and Bakkensen et al. (2019) show different post-flood sorting behavior by Hispanics. Hispanics exhibit greater willingness to pay for CRS participation (Fan and Davlasheridze, 2016) and greater expected welfare losses from losing insurance discounts associated with CRS participation (Bakkensen and Ma, 2019). Based on these findings, it is suggested that communities with significant Hispanic populations are more likely to participate in CRS because of disproportionate exposure to flood risks. We create the IV using county-level share of Hispanic residents because CRS participation decisions are made at the community level.

To meet the exclusion restriction, our underlying assumption is that share of Hispanic population at the broader community level should be exogenous to new housing and mobile homes construction in much smaller geographical areas of tracts, after controlling for tract fixed effects and a host of demographic characteristics.[24] To further satisfy the exclusion restriction, we exclude the count of Hispanic residents in the individual tract and its neighboring tracts when constructing this county-level IV. Specifically, for a given tract i in county c, the IV is constructed as the total count of Hispanic persons in all other tracts in the county c minus the count in tract i and its adjacent tracts, divided by total population of county c.[25]

In summary, we implement complementary empirical approaches to estimate the housing development effects of CRS participation. First, we use a difference-in-differences approach in the main text to identify how housing development patterns differ for flood-prone tracts versus low-risk tracts after joining their community joined the CRS. Second, as a robustness check, we use an instrumental variable regression strategy in this appendix to identify CRS effects on housing development. Both approaches use a tract-level panel dataset spanning several decades and rely on tract fixed effects, a host of time-varying control variables, and a design feature of the CRS whereby participation decisions are made by local governments – counties or municipalities – much larger than the individual tract observations that they contain. In our sample, tracts in participating municipalities and counties on average account for 5.6% and 1.3% of their communities' population, respectively.

[24] A tract is only a very small portion of the whole county. Census tracts usually have between 2,500 to 8,000 persons. On average, a county has 225 tracts. Our data show that the average share of Hispanic population among tracts is 0.12, and the median is 0.04.

[25] This strategy makes sure that the IV varies across tracts within a county. It is also worth noting that this strategy automatically drops counties made up entirely of a single tract. Also, because some neighboring tracts may be in a different county, the calculated "county share" IV no longer has a lower bound of zero.

The IV Results

We first check whether the instrument is relevant, that is, whether it is correlated with CRS participation. Appendix Table A8's bottom panel shows the diagnostics from the first-stage regressions. Because equation (5) has four endogenous variables – *CRS* and its interactions with *Risk, Information,* and the triple interaction term – we use the share of Hispanic persons and its interactions with these variables to form four instrumental variables. We also use the squares of those four IVs as an additional four IVs. This overidentifies the model and allows us to calculate a Hansen's J statistic to test for overidentification. We find that these IVs based on the share of Hispanic population are strong predictors of CRS participation. Table A9 reports the first-stage regression results of CRS participation. After controlling for demographic characteristics and tract fixed effects, increases in Hispanic population in the county are predicted to significantly increase the probability of participating in CRS. These results are consistent with prior studies that find a significant association between Hispanic populations and flood risk of communities. Columns 1 and 3 show that the F-tests for joint significance of the eight excluded instruments in the first-stage regressions have F statistics ranging from 35.04 to 505.54 and p-values close to 0 for *CRS*, $CRS \times Risk$, and $CRS \times Risk \times Information$, which indicates that the IVs are very relevant. Columns 2 and 4 find similar results. We also check whether the IVs are weak. The Kleibergen-Paap F-statistic are 92.14 and 175.32 respectively.[26] The value is far higher than the rule-of-thumb value of 10 that is often used to evaluate whether weak instrument bias is an issue (Stock and Yogo, 2005). We conclude that our instruments appear to be strongly correlated with CRS participation and our estimates are unlikely to suffer from weak instrument bias. Furthermore, overidentifying the model allows calculation of the Hansen's J statistic. For most models, the p-values suggest that we cannot reject the null hypothesis that the instruments are valid and correctly excluded at the 0.05 significance level.[27] We find that the exogeneity test rejects the null hypothesis (that the potentially endogenous regressors are exogenous) for both dependent variables, suggesting that CRS participation may be endogenous conditional on the many control variables and assuming valid IVs.

[26] We use Kleibergen-Paap F-statistic instead of Cragg-Donald F-statistic because the latter is not valid in the presence of non-i.i.d. errors.

[27] It is worth noting that column 2 reports large Hansen J statistic, so we should be cautious about causal inferences based on that specification.

Given these results from diagnostic tests, the IV approach appears to provide another layer of robustness on the models estimated in Table 7. We prefer the fixed-effect OLS estimates in Table 7 over the IV approach because the OLS approach yields more conservative effect sizes and does not rely on assuming valid instruments. In addition, estimating other models – such as the DDD models in Table 6 – with these instruments does not yield similar results. For example, estimating the models in Table 6 via IV regressions produces diagnostics where we cannot reject the null of exogeneity for our CRS variables. Thus, we prefer the OLS estimates in Table 6. When the model diagnostics appear favorable, the IV results presented in the Appendix offer tests of whether the findings reported in Table 7 are robust to instrumenting for endogenous CRS variables.

The estimates shown in Table A8 confirm the negative effects of CRS participation in flood-prone areas on changes in new construction and mobile homes when *Info* is 0.[28] The coefficients for *CRS×HighRisk* and *CRS×SFHAshare* are much larger (in absolute value) than their corresponding values in Table 7, suggesting greater CRS participation effects with *Info* or *Information* equal to 0. The four coefficients on the triple-interaction terms are all positive and significant, confirming that flood-prone areas within CRS communities tend to experience an increase in new housing construction and mobile homes when those communities pursue more informational strategies. The effects sizes are much larger than estimated via OLS in Table 7. This lends some confidence to the interpretation that more information-intensive community flood management may be less effective at discouraging new housing development or mobile homes from locating in more flood-prone areas of a community. The effects in Table A8 indicate that information-intensive CRS participation leads to an increase in the share of new construction (0.056, p-value = 0.001) and mobile homes (0.031, p=0) of a few percentage points – a substantial increase equivalent to about 0.44 and 0.27 standard deviations, respectively.

One important exclusion restriction assumption in our instrumental variable estimation is that the share of Hispanic population is uncorrelated with the error term in equation (5). We run a falsification test to examine the effect of the share of Hispanic population on new construction and mobile homes, using only the tracts that never participated in the CRS program. The intuition is that if the share of Hispanic population is a valid instrument, it

[28] Columns (2) and (4) in Table A2 report IV estimation results for equation (1). The results are consistent with the OLS results, which show that CRS participation has negative and statistically significant effects on housing development and mobile homes. The results also suggest that the OLS estimates may underestimate the impact of CRS participation.

should only affect the outcome variables indirectly through CRS participation. If the estimation results show that the Hispanic share is a statistically insignificant predictor of the two dependent variables among non-CRS communities, it provides evidence that it is a valid instrument.

The results are reported in Table A10. We find that the coefficients on Hispanic share are small and insignificant across all specifications, regardless of the control variables included or not. These results provide some evidence that the IV should be uncorrelated with the error term in equation (5).

Table A1: Means for Treatment and Control Tracts across Full and Matched Samples

	Full Sample			Matched Sample		
	Treatment Mean	Control Mean	P-value of Difference	Treatment Mean	Control Mean	P-value of Difference
Dependent and Risk Variables						
New construction	0.118	0.085	<0.01	0.12	0.093	<0.01
Mobile homes	0.093	0.07	<0.01	0.093	0.071	<0.01
CRS	0.601	0.166	<0.01	0.599	0.173	<0.01
SFHAshare	0.347	0.09	<0.01	0.336	0.092	<0.01
HighRisk (dummy)	1	0.239	<0.01	1	0.25	<0.01
Control Variables						
Property damage	0.009	0.014	0.073	0.009	0.015	0.08
Poverty rate	0.132	0.138	<0.01	0.124	0.11	<0.01
Housing value	11.13	11.067	<0.01	11.219	11.331	<0.01
Population density	0.001	0.002	<0.01	0.001	0.001	0.013
Unemployment rate	0.059	0.065	<0.01	0.057	0.052	<0.01
Renters	0.307	0.316	<0.01	0.297	0.269	<0.01
Vacant home	0.114	0.093	<0.01	0.105	0.08	<0.01
Observations	23,393	164,339		21,679	128,135	

Notes: This table reports means for the treatment and control tracts from the full and matched samples derived from coarsened exact matching (CEM).

Table A2: OLS and IV Results for Equation (1)

Variables	New Construction		Mobile Homes	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
CRS	-0.0095***	-0.0294*	-0.0078***	-0.0249***
	(0.0030)	(0.0158)	(0.0012)	(0.0057)
Property Damage	0.0005***	0.0004**	0.0002*	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Poverty Rate	0.2807***	0.2609***	0.0927***	0.0757***
	(0.0144)	(0.0198)	(0.0055)	(0.0073)
Housing Value (log)	-0.0422***	-0.0431***	-0.0155***	-0.0162***
	(0.0028)	(0.0028)	(0.0012)	(0.0014)
Population Density	-112.5006***	-108.6712***	-1.2046*	2.0828*
	(9.2613)	(9.9944)	(0.6638)	(1.1451)
Unemployment Rate	0.0616***	0.0714***	0.0254***	0.0338***
	(0.0208)	(0.0202)	(0.0089)	(0.0095)
Renters	-0.1455***	-0.1400***	-0.0278***	-0.0231***
	(0.0167)	(0.0155)	(0.0044)	(0.0047)
Vacant Home	0.0142	0.0150	0.0223**	0.0230**
	(0.0308)	(0.0318)	(0.0094)	(0.0095)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,971	49,768	49,971	49,768
Observations	149,347	149,144	149,347	149,144

Notes: Estimated coefficients from OLS and IV regressions for Eq. (1) based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables are percent of houses built in the last five years in a tract, and percent of housing units that are mobile homes in a tract. Units are tract/census year.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A3: Estimates of Control Variables for Table 6

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
Property Damage	0.0005***	0.0005***	0.0002*	0.0002*
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Poverty Rate	0.2802***	0.2809***	0.0921***	0.0926***
	(0.0143)	(0.0143)	(0.0055)	(0.0055)
Housing Value (log)	-0.0423***	-0.0422***	-0.0156***	-0.0155***
	(0.0028)	(0.0028)	(0.0012)	(0.0012)
Population Density	-113.0285***	-112.8193***	-1.5353**	-1.5167**
	(9.2533)	(9.2415)	(0.6523)	(0.6460)
Unemployment Rate	0.0620***	0.0622***	0.0253***	0.0258***
	(0.0207)	(0.0208)	(0.0089)	(0.0089)
Renters	-0.1460***	-0.1459***	-0.0280***	-0.0282***
	(0.0167)	(0.0167)	(0.0044)	(0.0044)
Vacant Home	0.0136	0.0145	0.0217**	0.0221**
	(0.0310)	(0.0310)	(0.0095)	(0.0095)

Notes: This table reports the coefficients of the control variables in Table 6 of the four models.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A4: Risk Thresholds and CRS Program Effects

SFHAshare Thresholds	New Construction		Mobile Homes	
	CRS x HighRisk	*CRS x SFHAshare*	*CRS x HighRisk*	*CRS x HighRisk*
0	-0.0127**	-0.0209**	-0.0050***	-0.0130***
	(0.0053)	(0.0084)	(0.0018)	(0.0041)
0.05	-0.0123***	-0.0189**	-0.0070***	-0.0124***
	(0.0038)	(0.0083)	(0.0014)	(0.0042)
0.15	-0.0100**	-0.0156*	-0.0080***	-0.0124***
	(0.0039)	(0.0083)	(0.0017)	(0.0041)
0.2	-0.0066*	-0.0142*	-0.0071***	-0.0124***
	(0.0038)	(0.0083)	(0.0020)	(0.0041)

Notes: This table shows the coefficients of the interaction terms in Table 6 from using different thresholds in *SFHAshare* to define control and treated units. For example, when *SFHAshare* threshold is 0.05, *HighRisk* is a dummy variable that equals one if the tract with SFHAshare greater than 0.05, and equals zero otherwise. The coefficient on *CRS x HighRisk in* column (1) would be -0.0123, and the coefficient on *CRS x SFHAshare* in column (2) would be -0.0189. Both are statistically significant.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A5: CRS Total points on New Construction and Mobile Homes

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
CRS Points	-0.0007	-0.0010**	-0.0006***	-0.0008***
	(0.0005)	(0.0005)	(0.0002)	(0.0002)
CRS Points x HighRisk	-0.0018***		-0.0012***	
	(0.0005)		(0.0002)	
CRS Points x SFHAshare		-0.0026**		-0.0019***
		(0.0012)		(0.0006)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,971	49,971	49,971	49,971
Observations	148,697	148,697	148,697	148,697

Notes: Estimated coefficients from DID regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The specifications are the same as those reported in Table 6, except that CRS total points are used to replace *CRS*.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A6: CRS Program Effects on New Construction over 10 Years

Variables	New Construction (last 10 years)		New Construction (last 10 years)	
	(1)	(2)	(3)	(4)
CRS	-0.0109**	-0.0129***	-0.0141**	-0.0118
	(0.0045)	(0.0046)	(0.0060)	(0.0091)
CRS x HighRisk	-0.0160***		-0.0142**	
	(0.0048)		(0.0062)	
CRS x SFHAshare		-0.0260**		-0.0716***
		(0.0113)		(0.0236)
CRS x Info			0.0035	
			(0.0070)	
CRS x HighRisk x Info			-0.0025	
			(0.0071)	
CRS x Information%				-0.0101
				(0.0248)
CRS x SFHAshare x Information%				0.1664***
				(0.0643)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,971	49,971	49,971	49,971
Observations	149,347	149,347	148,697	148,697

Notes: Estimated coefficients from DID regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The specifications are the same as those reported in columns (1) and (2) in Table 6 and 7, except that the dependent variables are percent of houses built in the last ten years in a tract. Units are tract/census year. Standard errors clustered at the community level are in parentheses.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A7: CRS Program Effects on Old Buildings

Variables	Old Building Ratio		Old Building Ratio	
	(1)	(2)	(3)	(4)
CRS	0.0802***	0.0771***	0.1632***	0.3280***
	(0.0296)	(0.0297)	(0.0431)	(0.0773)
CRS x HighRisk	0.0614		0.0254	
	(0.0441)		(0.0586)	
CRS x SFHAshare		0.1714*		0.1013
		(0.1030)		(0.2590)
CRS x Info			-0.1849***	
			(0.0464)	
CRS x HighRisk x Info			0.0362	
			(0.0590)	
CRS x Information				-0.8722***
				(0.1950)
CRS x SFHAshare x Information				0.2157
				(0.6020)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	48,376	48,376	48,376	48,376
Observations	144,960	144,960	144,342	144,342

Notes: Estimated coefficients from DID regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables are ratios of old housing units in the census years (1990, 2000, 2010) over that in 1990 in a tract. Units are tract/census year. Standard errors clustered at the community level are in parentheses.

* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A8: IV regressions for CRS Program Effects

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
CRS	0.0040		-0.0040	
	(0.0109)		(0.0037)	
CRS x HighRisk	-0.0596**		-0.0426***	
	(0.0261)		(0.0098)	
CRS x Info	0.0020		0.0047	
	(0.0167)		(0.0042)	
CRS x HighRisk x Info	0.1100***		0.0731***	
	(0.0407)		(0.0153)	
CRS x SFHAshare		-0.1292**		-0.1254***
		(0.0614)		(0.0259)
CRS x Information		0.0773		0.0594***
		(0.0675)		(0.0175)
CRS x SFHAshare x Information		0.4123**		0.3656***
		(0.1917)		(0.0834)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Number of Tracts	49,768	49,768	49,768	49,768
Observations	148,494	148,494	148,494	148,494
Exogeneity test, p-value	0.004	0.036	0.000	0.000
Hansen's J test (p-value)	0.093	0.020	0.086	0.207
Kleibergen-Paap F-statistic	92.138	175.317	92.138	175.317
First-stage F-statistic for CRS	505.54	505.54	505.54	505.54
First-stage F-statistic for CRS x HighRisk	329.56		329.56	
First-stage F-statistic for CRS x Info	97.41		97.41	
First-stage F-statistic for CRS x HighRisk x Info	35.04		35.04	
First-stage F-statistic for CRS x SFHAshare		149.23		149.23
First-stage F-statistic for CRS x Information		343.88		343.88
First-stage F-statistic for CRS x SFHAshare x Information		81.27		81.27

Notes: Estimated coefficients from IV regressions based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables are percent of houses built in the last five years in a tract, and percent of housing units that are mobile homes in a tract. Units are tract/census year. The models are IV specifications that use a modified 'share of Hispanic population in a county' to instrument for CRS participation, along with interactions with *HighRisk (SFHAshare)*, *Info (Information)*, and *HighRisk×Info (SFHAshare×Information)*, and their squares. Standard errors clustered at the community level are in parentheses.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A9: First Stage IV Results of CRS Participation

Variables	CRS
	(1)
Property Damage	-0.0005 (0.0016)
Poverty Rate	-0.3502*** (0.04)
Housing Value (log)	-0.0177* (0.0096)
Population Density	6.7582 (7.2552)
Unemployment Rate	0.0540 (0.0713)
Renters	0.0678** (0.0311)
Vacant Home	0.0439 (0.0568)
Share of Hispanic	-0.6442*** (0.1434)
Square of Share of Hispanic	0.0036*** (0.0008)
Share of Hispanic x SFHAshare	-0.5115 (0.3278)
Square of (Share of Hispanic x SFHAshare)	0.4442*** (0.093)
Share of Hispanic x Information	20.3581*** (1.4685)
Square of (Share of Hispanic x Information)	-83.7916*** (11.0355)
Share of Hispanic x SFHAshare x Information	2.3376 (1.4319)
Square of (Share of Hispanic x SFHAshare x Information)	-18.5542 (14.1373)

Notes: Estimated coefficients from the first-stage regression results of CRS participation, based on the reduced sample and weights derived from coarsened exact matching (CEM). The dependent variables is CRS participation. Units are tract/census year. Standard errors clustered at the community level are in parentheses. * significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level

Table A10: Results for Falsification Tests of the IV Estimations

Variables	New Construction		Mobile Homes	
	(1)	(2)	(3)	(4)
Hispanic Share	-0.0008	-0.0004	-0.0002	0.0001
	(0.0009)	(0.0004)	(0.0003)	(0.0001)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Census Year Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	No	Yes	No	Yes
Number of Tracts	39,769	39,397	39,769	39,397
Observations	148,402	117,437	148,402	117,437

Notes: Estimated coefficients from IV regressions based on the subsample of tracts that never participated in the CRS. The dependent variables are percent of houses built in the last five years in a tract, and percent of housing units that are mobile homes in a tract. Units are tract/census year.
* significant at the 10 percent level; ** significant at the 5 percent level; *** significant at the 1 percent level