THE NATIONAL FLOOD INSURANCE PROGRAM AND HOUSING DEVELOPMENT IN THE STATE OF GEORGIA

by

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(Under the Direction of Susana Ferreira)

**ABSTRACT** 

We estimate the effects of community participation in the NFIP on county-wide housing development in the state of Georgia using fixed-effect panel data methods linking program participation dates with housing permit records. We find that program participation has no effect on housing development across all counties, a weakly negative effect in noncoastal counties, and a stronger negative effect in the 500-year floodplains of coastal counties. We find that participation in the Community Rating System is correlated with changes in housing development that outweigh and, in some instances, counteract that of the base NFIP base program.

INDEX WORDS: Housing development, Disaster aid, Flood insurance

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# CHAPTER 1

### INTRODUCTION

A critical component of a prosperous society is the ability to protect its population against the inevitability of natural disasters and provide tools for the management of those risks. From 1995-2015, flooding events were not only the most frequent but also the costliest natural disaster worldwide (Wallemacq et al., 2015). During the same period, in the US floods affected over 17 million people (67% of all affected by weather disasters), resulting in damages of over \$423 billion (in 2010 \$), or 63% of the total damages of weather disasters (EM-DAT, 2018). In 2017 three tropical cyclones: Hurricanes Harvey, Maria, and Irma, were largely responsible for a new US annual record damages from weather disasters exceeding \$300 billion (NOAA, 2018).

In the United States, the National Flood Insurance Program (NFIP), administered by the Federal Emergency Management Agency (FEMA), aims to help communities manage the financial risk of flooding events and to reduce federal expenditures for disaster assistance by offering property owners in participating communities flood insurance. The extent to which the NFIP helps reduce future flood damages by pricing flood risk is, however, an empirical question.

Participating in the NFIP could result in either a net increase or decrease in the overall amount of new housing development through a number of different mechanisms affecting supply and demand. On the one hand, households within a community that participates in the NFIP are required to purchase flood insurance for access to federally-backed mortgages. This could reduce the willingness to pay for housing and thus reduce the demand for housing. In addition, a

community's participation in the NFIP should decrease the supply for new housing due to raised construction costs for meeting the more stringent, flood-resistant building codes in areas designated as Special Flood Hazard Areas (SFHAs). On the other hand, subsidizing flood insurance and thus the cost of risk to homeowners should have a positive effect on housing demand.

The NFIP does indeed offer some of its policyholders premium rates for flood insurance that is lower than the actuarially fair price of risk for a property. This was done to promote program participation among homeowners as well as to encourage floodplain management in participating communities. These subsidized rates generally went to properties located in high-risk flood zones that were built prior to the creation of the flood hazard maps that delegate premium prices for different locations. In other words, these properties were "grandfathered" into the program and are offered subsidized premium rates. FEMA estimated that 17% of the NFIP properties were paying premiums below the actuarially fair rate as of June 2019 (Government Accountability Office, 2020). These subsidies can end up being extremely costly for the program when providing coverage for repetitive loss properties (i.e., properties that have flooded twice or more in a 10-year period since 1978). About 1% of policies have been for repetitive loss properties, yet their claims make up roughly 25-30% of annual payouts (FEMA, 2016). Currently, the NFIP is in debt to the US Treasury for \$20.5 billion.

In this article, we analyze the effect of participation in the NFIP on housing development in Georgia. The methods employed here will determine the net change in housing permits stemming from the three supply/demand shifting mechanisms mentioned above. While our analysis will not comment on whether the NFIP has led to a more efficient or inefficient level of housing development in the state of Georgia or distinguish between the individual contributions

of the supply/demand shifters, it will identify reduced form estimates for how the program affects housing development within the state. These estimates will be quite useful for policy analysts and legislators considering that the NFIP continues to be a point of contention among lawmakers and is frequently modified by the US Congress to improve its financial stability.

In 2012, the Biggert-Waters Act was passed into law. The law aimed to remove subsidies given to NFIP policy holders in flood-prone areas that had been "grandfathered in" over time. Essentially, policy holders with properties built prior to the establishment of flood rate maps or properties in areas that had recently been redesignated to reflect a higher flood risk would have their subsidized premium rates phased out over a 5-year period. In response, the 2014 Homeowner Flood Insurance Affordability Act was enacted to lower the rate at which these grandfathered property owners would lose their subsidized premiums. The maximum rate at which these grandfathered properties' premiums could rise was set to a maximum of 18% (FEMA, 2020). Despite all of the debate and political controversy over the NFIP's financial structure, the program is still bankrupt today.

In its attempt to provide access to affordable flood insurance policies, the NFIP as it stands today is not actuarially sound. Even after the 2012 Biggert-Waters Act decreasing subsidies for certain properties, intense hurricane seasons have demonstrated the ability to crush the NFIP's financial standing. Extreme weather events in the last few years cost the United States an estimated \$306 billion in 2017, \$91 billion in 2018, and \$45 billion in 2019 (NOAA, 2021). With consecutive events like these leaving large groups of flood insurance policy holders with claims to be paid, the NFIP is bankrupt as of January 2021. The program owes \$20.5 billion to the US Treasury despite Congress forgiving \$16 billion of debt in 2017 (Government Accountability Office, 2021). Moreover, projected sea-level rise and a predicted increase in the

intensity and frequency of climate-change-induced extreme weather events, by further increasing flood risk exacerbate the financial peril of the program if its issues cannot be remedied quickly (Valacer, 2015). With this in mind, our reduced form estimates will provide useful information on the potential unanticipated effects of the program on housing development which our lawmakers can utilize to improve the program's financial standing.

The state of Georgia provides a particularly exciting opportunity for researchers to study the program's effects on housing development. Georgia is growing and developing quickly compared to other states' population growth trends. Between 2018 and 2019, the latest data was available, Georgia had the 11<sup>th</sup> fastest growing statewide residential population in the United States at 1.011% in just one year (US Census Bureau, 2019). That means that more residents are going to be susceptible to the risk of flooding in Georgia especially in its coastal region with a higher risk of flooding. Coastal areas of the United States average twice the rate of development compared to interior areas (NOAA, 2016).

Georgia's 110 miles of coastline along its southeastern edge grants the opportunity to identify how the program's effect on housing development changes in coastal counties. These areas are of particular importance due to their increasing risk to flood events in the face of climate-induced sea level rise. Between 8-17% of the local population within Georgia's six coastal counties are now living in areas affected by sea level rise depending on sea level projections for the year 2100 (Hauer et al., 2015). In short, not only is the coast more susceptible to flooding, but higher rates of development in these areas means there is a greater potential for floods to cause damage along the coast as well.

There are other characteristics to the state of Georgia that make it a favorable study area as well. With 77 NFIP policies per 10,000 people, it is the 18th highest state in terms of policies

per capita as of 2020. For comparison, Louisiana is the highest at 1084 policies per 10,000 people. Georgia is also the 15th highest state in terms of policies per total area at 1.4 policies per square mile, while the state of Florida is the highest at 26.29 (Federal Emergency Management Agency, 2021). Essentially, while Georgia is not the largest contributor to overall NFIP participation, it is a state with far higher participation rates both per capita and per square mile than the average state in the country.

Georgia also has an extremely large number of counties for a state its size. That comes in handy when dealing with our measurements for housing development which are available at the county level. With 159 counties, the only state with more counties per square mile than Georgia is Virginia. This allows us to obtain more observations and precision in our estimates than we otherwise would be able to in other states since a large portion of variables used in this analysis are collected at the county level.

#### CHAPTER 2

### LITERATURE REVIEW

At this time, there are three other academic studies that have investigated the relationship between the NFIP and *housing* development specifically. The first is a report from the Comptroller General of the United States in 1982 when asked to investigate whether the NFIP was stimulating development along coastal floodplains. After travelling to one coastal barrier island community in the states of Delaware, Texas, Maryland, South Carolina, and Florida, the researchers concluded that the NFIP program was not the principal reason for increases in development to these barrier island communities but merely a marginal one after looking over the development trends of these communities. It is important to note that these researchers did not provide strong statistical analysis to uphold their conclusion on this point and that they themselves admit that their findings cannot be extended to other communities that participate in the NFIP (Government Accountability Office, 1982).

One research review article conducted by the American Institutes for Research notes that the differences in methodology as well as the sample locations used in different studies make it difficult to make a conclusive statement that the program's effect on development (not just housing development) is either positive or negative (Rosenbaum & Boulware, 2006).

A more concrete analysis pertaining specifically to housing development conducted by Cordes and Yezer (1998) found that NFIP participation stimulates beachfront development in the form of a 50% increase in building permits across 42 communities in six states along the east

coast (excluding Georgia) that were studied for 33 years of observation. This study is in-line with the hypothesis of the task at hand which is that subsidized flood insurance participation will likely increase levels of housing development, but it fails to include non-coastal study areas in its analysis.

Finally, the most relevant study to the current paper investigates the effect of NFIP participation on housing development across communities in the state of Florida. Browne et al. (2018) finds that across all participating communities, NFIP membership leads to an increase in housing development in the average Florida community by 16%. It is important to note, however, that these effects differ for coastal communities. In coastal Florida communities, NFIP participation leads to a 65% decrease in housing development while non-coastal communities participating in the NFIP experience a 37% increase. These results conflict with the prior study conducted by Cordes and Yezer who found a significant positive development effect among their beachfront properties, all of which are inherently located in coastal communities. Clearly, in the state of Florida, the effect of NFIP membership on housing development is different between coastal and non-coastal communities.

This study will add to the above academic literature by investigating the unintended consequences of the NFIP program on housing development in the state of Georgia. Because of the conflicting results between the two previous academic studies, it will be interesting to see if the difference in signs between coastal and non-coastal effects on housing development are the same in Georgia as they were in Florida or if this phenomenon is particular to that state. Furthermore, this study will be conducted over a larger time frame in order to comment on the relationship between housing development and the Community Rating System, an add-on program to the NFIP introduced in 1990 that the previous study excludes from their results. This

information will aid regulators as they continue to amend the NFIP by lending insight as to whether or not the program incentivizes further development of housing. As Browne et al. (2018) mention in their study, a quantitative assessment of how a national policy changes real-world resource allocations is not only rare but extremely useful when trying to find ways to improve the Bill.

#### CHAPTER 3

## BACKGROUND ON THE NFIP

There are a number of reasons that flood insurance is not supplied efficiently by the private sector. Flood events are predictable based on the location of the homeowner's property. This leads to adverse selection in the private insurance market because those trying to purchase flood insurance are more likely to be those with properties in locations with high risk of flooding. Furthermore, when flood events do occur, they tend to be catastrophic for the insurer in the sense that not only is one house flooded and deserving of an insurance payout but dozens of homes within a flooded town or neighborhood deserve their payouts simultaneously. It's also commonplace that homeowners' risk perception with respect to flooding is less than the true chance of flood, and their willingness to pay for flood insurance is often less than the actuarially fair premium (Thistlethwaite et al., 2020).

In the end, the lack of access to private insurers willing to help homeowners finance their flood risk meant more government funds were being spent on disaster relief when severe storm events swept through the United States. After a myriad of flood-inducing storm and earthquake events in the 1950s and 60's, topped with the particularly expensive cleanup of Hurricane Betsy in September of 1965, the demand for government-subsidized flood insurance gained enough political momentum to enact legislation in the form of the NFIP Act of 1968. (Felton et al., 1971).

The NFIP's two main goals are: (1) provide access to primary flood insurance to allow the transfer of some financial risk from property owners to the federal government; and (2) reduce the nation's overall flood risk through floodplain management standards (Congressional Research Service, 2020). Homeowners may purchase flood insurance through the program only after their community has first joined the NFIP. Residential single-family homes (or individuals living in multi-family properties) can secure coverage for up to \$250,000 for damage to the building and up to \$100,000 in coverage for belongings within the building. For commercial properties, those limits are \$500,000 for the building as well as \$500,000 for the building's contents (Federal Emergency Management Agency). As of 2021 in the state of Georgia, there are a total of 81,585 policies in force, coverages of \$22.7 billion, and \$56.2 million in premiums and federal policy fees collected annually (Federal Emergency Management Agency, 2021).

The program is funded through the receipt of premiums, fees, and surcharges from its policyholders, annual appropriations for specific flood hazard mapping, and borrowing from the United States Treasury when the program's costs exceed that which is contained in its National Flood Insurance Fund, which it must pay back with interest. Today, the maximum amount the NFIP may borrow from the Treasury is 30.425 billion dollars. For the first time in history, the NFIP was forgiven \$16 billion of its debt so that it could begin paying back damages from Hurricane Harvey, Irma, and Maria in 2017. As it stands today, the NFIP is not actuarially sound as it still owes \$20.5 billion to the Treasury (Congressional Research Service, 2020). In other words, there is a great deal of improvement for the NFIP as a whole for it to succeed in its goal to reduce our country's flood risk.

#### **CHAPTER 4**

## DATA AND METHODOLOGY

We have an unbalanced panel dataset of 159 Georgian counties annually from 1970 to 2019. The data is unbalanced due to the fact that the housing permit data used to gauge housing development was unreported by some counties in specific years (63 different counties total). There are 636 observations out of 7,950 total containing missing housing permit values (8.13%), leaving 7,304 valid observations for our testing.

There are two reasons that the housing permit data could be unreported in a particular year: 1) The county was not designated as a permit-issuing place, or a jurisdiction that issues building permits. Areas where no authorization is required to construct a new privately owned unit are not included in the Census's Building Permit Survey. This primarily pertains to counties with low levels of population density. 2) The county or one of its subsidiary communities simply failed to submit their building permit report that particular year. Communities' submission of their data to the annual Building Permit Survey record is not required by law as it is with the decennial Census report.

Luckily, the impact of these missing observations to the integrity of our analysis is likely to be minimal. Upon closer inspection, it seems that these 63 counties with at least one missing observation had both lower levels of population and density when compared to that of the whole sample. The average Georgia county throughout the years 1970-2019 had an average population of 46,080.8 people per county. The average population of only the counties with missing permit

observations was found to be 14,187.2, or 69.2% less people than that of the average county. Similarly, Georgia's counties had an average population density of 0.228 people per county per acre while the average of those counties with at least 1 missing housing permit observation is 0.0700 or 69.3% less people per acre than that of the average county. Clearly, these 8% counties that have failed to report their housing permit data are those with lower levels of both population and population density, and thus their participation in the NFIP would have an impact on less people and therefore housing development.

We also compared the NFIP participation rates of the counties with missing observations to the average counties. Program participation was reported at the community level, yet housing permits were reported at the county level. In response, we must use county-level observations of NFIP participation. Ideally, our analysis could be kept at the community level to maintain a higher level of detail. Instead, we must relate the average proportion of NFIP participation in communities with the average level of community housing construction at the county level. This allows us to adapt to the mismatch between community and county-level data and observe broad trends in participation and development but not spatially explicit changes at the community level.

In our analysis, we utilize two dates to measure NFIP program participation: FIRM dates and join dates. The FIRM date is the date that the date that a community's Flood Insurance Rate Map first became available, and the day that they were able to join the NFIP's Regular Program. The join date is the date that a community actually joined the NFIP. The average county had a FIRM date participation proportion of 0.464 and a join participation date of 0.445, while the counties with missing housing permit observations had an average FIRM date participation proportion of 0.406 and a join participation proportion of 0.392, or 12.5% and 12.0% less communities participating in the NFIP than the overall county average.

During the time period from 1970-2019, 557 communities began to participate in the NFIP. Communities are free to leave the program at any time, but notably not a single community in Georgia has left the NFIP once it has joined. Figure 1 below illustrates the rate at which new communities joined the program each year. In the program's first 15 years, we see gradual increases in communities' participation rates as flood maps became available and the program gained popularity, peaking in 1986. Another large spike is seen in 2010, just one year after Atlanta's experienced disastrous flooding in 2009. Atreya et al. (2015) find that Georgia's rates of household flood insurance purchases increase for up to three years after a flooding event has occurred, so this spike in 2010 is to be expected.

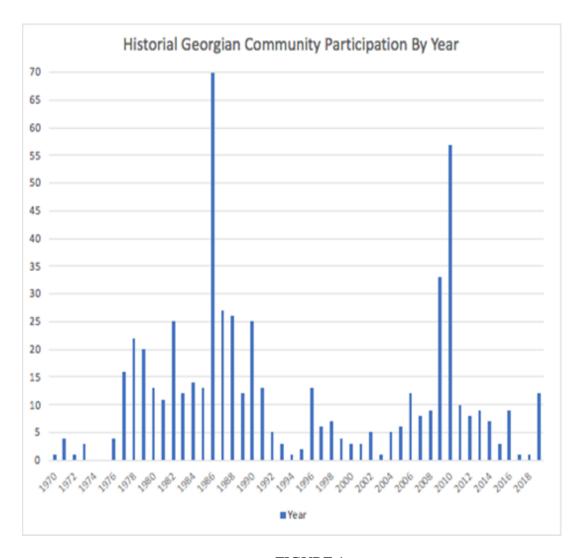


FIGURE 1

Unlike the Florida study, the analysis of the NFIP in Georgia requires a longer study period due to the fact that a significant portion of its participant communities joined in the past twenty years. In Florida, nearly all communities that have joined today did so before 2000, which is not the case in Georgia. Therefore, our analysis will be using every year for which we can obtain data, from 1970-2019, as well as a shortened time period from 1970-1989 to compare our results to the Browne et al. Florida analysis.

Individuals within a community have the opportunity of purchasing NFIP flood insurance anytime they wish *after* their community has formally joined the NFIP. Thus, as with Browne et

al. (2018), we are measuring how the *opportunity* to purchase flood insurance affects housing development in the area. Before communities can join the NFIP's "Regular Program", FEMA must produce a Flood Insurance Study (FIS) as well as a Flood Insurance Rate Map (FIRM). These are maps of the community that designate high risk (100-year floodplain), low risk (500-year floodplain) flood zones and SFHAs. Once these flood areas have been designated, they are each assigned premium rates that participating homeowners will pay in exchange for flood insurance coverage with prices varying depending on the estimated level of flood risk within a particular area. Upon FEMA's completion of this Flood Insurance Rate Map, the community is now allowed entry into the "Regular Program" of the NFIP. Communities are allowed to request that a FIRM map be produced, but FEMA is required by law to produce FIRMs for communities considered at "high-risk" of flooding. It is possible for a community to join the NFIP prior to receiving a FIRM, but they must enter through the "Emergency Program" which has different premium rates and requirements as opposed to the "Regular Program" for communities who join after their FIRM has been provided.

Ideally, we would like for the date that each community joins the NFIP to be randomly assigned. For this reason, we will focus only on communities that have joined via the Regular Program in order to eliminate selection effects from communities who choose to join the Emergency Program whenever they want. This includes 21 out of the 577 communities that will be dropped (3.63%). If membership dates were determined by any sort of variables that are correlated with the growth and development of the community that we can't control for in our modelling, then we would be estimating a correlation rather than identifying the effect of participation on housing development. 420 of the 577 (73%) communities that have joined the NFIP in Georgia did so on the exact same day that their FIRM was identified. Thus, it would

seem that for the large majority of the participating communities, it was the flood insurance mapping process that determined their membership date.

In our analysis, we use the "FIRM date" (i.e., the date in which a community's FIRM is identified by the NFIP allowing them to join the Regular Program) as well as the actual "join date" (i.e., the date in which the community actually joins the Regular Program). The difference between the two is illustrated in Figure 2. As more FIRMs are identified, a higher proportion of the average county's population is eligible to participate in the NFIP or "covered." This is represented by the orange line. Similarly, as this happens more and more communities begin to participate in the program by formally joining. Since most communities joined the program the same day their FIRM was identified, these two lines are very close together. As with Figure 1, Figure 2 shows a large increase in program participation until about the late 1990, slowed growth for a number of years, and finally a surge around 2009 that eventually tapers off until 2018. We use the FIRM date as well as the join date to eliminate possible selection bias from entering into the program after the FIRM is provided by FEMA. While the join date may better reflect the actual participation rate in the NFIP program, it opens up the possibility for an endogeneity bias since the communities themselves are choosing when to join. The FIRM date, on the other hand, eliminates this selection bias but may be a bit less accurate in representing program participation. We utilize both dates in our analysis to see to what extent our results are robust across the two different participation measurements.

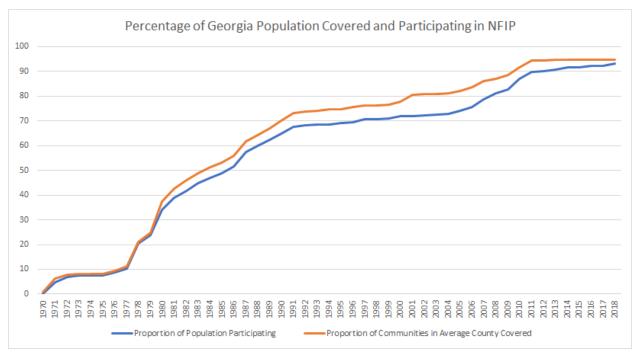


FIGURE 2

We know that the majority of communities joined as soon as their FIRMs were made available, but how was this mapping process prioritized? FEMA representatives indicate that there were a few different factors that went into determining the prioritization of providing communities with their FIRMs (Browne et al., 2018) These factors included the availability of flood plain data, economic growth, and the potential for flood destruction. If the potential for flood destruction is higher in areas with more floodplain acreage as well as coastal counties, then these variables will serve as good proxies to control for these selection biases. We need to test to what extent chronological order in the FIRM mapping process is correlated with economic growth, floodplain area, and coastal status.

Table 1 shows the Spearman rank correlation coefficients between a community's membership date (both the date their FIRM was identified as well as the date they formally joined the program) and the encompassing county's real income growth rate lagged by one year. The earlier the participation date, the lower the ranking (earliest joining community ranked 1).

Here, the lag of income growth is used as a proxy for economic growth. Similarly, the rank correlation coefficients between membership dates and a dummy variable for whether the encompassing county was a coastal county were calculated (1 if coastal county, 0 otherwise). Finally, the rank correlation coefficients between membership dates and the proportion of the encompassing county's land in 100 and 500-year floodplains were calculated. Table 1 summarizes these results below.

**Table 1: NFIP Participation Dates Correlations** 

All communities- even "Emergency Program" communities

Variable	FIRM Participation Date	Join Date
County Real Income Growth, Lagged 1 Year (years 1971-2020)	-0.3096*** p-value < 0.0000	-0.2683*** p-value < 0.0000
County Real Income Growth, Lagged 1 Year (years 1971-1989 before CRS)	0.1130* p-value = 0.0572	0.0791 p-value = 0.1822
Coastal	-0.2121*** p-value < 0.0000	-0.2191*** p-value < 0.0000
Proportion of County Land Area in 100 Year Floodplain	-0.1155 *** p-value = 0.0055	-0.1566 *** p-value = 0.0002
Proportion of County Land Area in 500 Year Floodplain	5619 *** p-value < 0.0000	-0.4784 *** p-value < 0.0000

<sup>\*\*\*\*, \*\*,</sup> and \* represent significance at the 1%, 5%, and 10% levels, respectively. P-values are below.

If the community participation date is prior to July 1st of year X, it is given a year value corresponding with it for the analysis is year X. If the community participation date is on or later than July 1st of year, it is grouped into year X+1.

The results in Table 1 are consistent with the FEMA representative's statements about the factors involved in determining which communities to map first when looking at the whole sample. It is apparent that FEMA did prioritize flood mapping in coastal areas as well as areas with higher proportions of floodplain land in the county. In fact, in the first seven years of the program, five of the ten communities to have FIRMs identified by the NFIP were in coastal counties. That's quite significant considering that only six of Georgia's 159 counties are along the coast. We can also see this statistically in the negative correlation coefficients for the FIRM date as well as the join date (-.2930 and -.2951, respectively). Their *p*-values indicate both of these correlations are significant at the 1% level. This is in line with our assumptions since we can expect coastal counties to experience more flood events than non-coastal counties. Similarly, the larger the proportion of 100-year floodplain in a county, the sooner its communities began participating. The correlation coefficients are negative in magnitude and statistically significant for the 100- and the 500-year floodplain proportions, when using the FIRM date or the join date. We control for these factors in our regression analysis below.

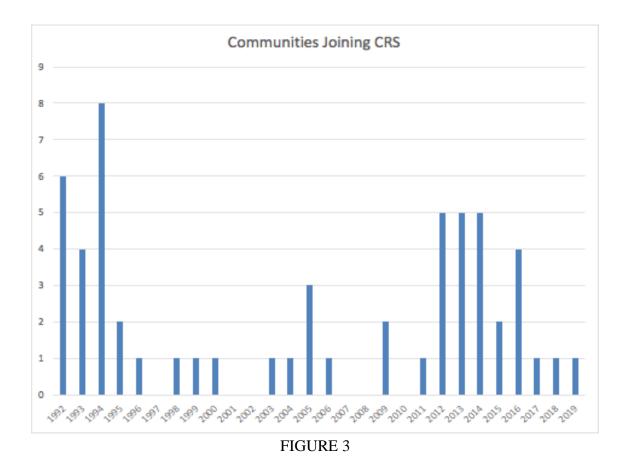
Prior to 1990, it appears that economic growth was not as significantly correlated with the order in which communities were selected for the mapping process, using either the FIRM or the join date (correlation coefficients ~.1, p-values greater than .05). After 1990, the Spearman rank tests show that communities with higher lagged growth rates were prioritized for participation by returning statistically significant negative values (coefficients -.3096 and -.2683, respectively). We will control for this economic growth effect in influencing the mapping process in the regression model below.

This change in Spearman rank results for economic growth could be in response to the introduction of the Community Rating System (CRS), an incentive program added onto the NFIP

that rewards communities with subsidies on their flood insurance in exchange for doing a number of activities.<sup>1</sup> The introduction of the CRS could further incentivize wealthier counties to map their communities and thus expedite their FIRM mapping process. Figure 3 below illustrates the participation rates for the CRS over time. 57 communities have joined the program in our study period, and only three of those communities left the program during our study period: one in 1997, 1998, and in 2018. The majority of Georgia's communities in the NFIP have not joined the CRS.

Another possible solution to overcoming the endogeneity of program participation is to use an instrumental variable for the FIRM dates. Before more detailed FIRM maps were produced, the US Army Corps of Engineers was tasked with identifying high risk communities and providing them with Flood Hazard Boundary Maps (FHBMs) that gave delineated general floodplain locations. Once a community's FHBM was produced, that community could join the Emergency Program, wait until its FIRM was produced later on to join the Regular Program, or not join at all. Like with the FIRMs, FHBMs were drawn for high-risk communities exogenously but other communities who wanted to be in the Emergency Program could take it upon themselves to request that an FHBM be made for them. Thus, FHBMs are not a perfectly exogenous instrumental variable for program participation yet their potential for use should still be explored for future research endeavors using Spearman tests as above.

<sup>&</sup>lt;sup>1</sup> These activities can be summarized into the following: Updating and distributing local floodplain data and maps, promoting natural floodplain functionality, developing a floodplain management plan, reducing flood loss to existing developments, improving emergency preparedness and response, and increasing public information about flood protection options.



As mentioned by Browne et al. in their 2018 Florida study, the CRS could potentially introduce a confounding effect between itself and time fixed effects in our model. Luckily, FEMA keeps track of communities' enrollment in the CRS. We can control for its effects, but we will not be able to claim causality in our results once it has been introduced in 1990 for the reasons discussed above. Therefore, we will estimate one set of models spanning the years 1970-1989, and one set covering the years 1970-2019. The results from the former can be compared to the results of Browne et al. (2018). The latter models will include variables that control for the CRS participation and will only be able to claim correlation in the interpretation of their results.

To estimate the effect of NFIP participation on housing development, we employ the following fixed effect models:

$$HP_{it} = B_0 + B_1 NFIP prop_{it} + B_2 NFIP X 100 Y r_{it} + B_3 NFIP X 500 Y r_{it} + B_4 X_{it} + B_5 \gamma_i + B_6 \delta_t + e_{it} \ (1)$$

To estimate the correlation between NFIP participation and CRS participation with housing development, we employ the following fixed effect models:

$$HP_{it} = B_0 + B_1 NFIP prop_{it} + B_2 PropInCRS_{it} + B_3 NFIPX 100 Yr_{it} + B_4 CRSX 100 Yr_{it} + B_5 NFIPX 500 Yr_{it} + B_6 CRSX 500 Yr_{it} + B_7 X_{it} + B_8 \gamma_i + B_9 \delta_t + e_{it}$$
(2)

Here,  $HP_{it}$  is a dependent variable representing the number of new housing permits (either all units or single-family units) per community in county i during year t.  $NFIPprop_{it}$  is the proportion of communities that are participating in the NFIP (according to either their FIRM date or join date) in county i during year t.  $PropInCRS_{it}$  is the proportion of communities that are participating in the Community Rating System in county i during year t.  $NFIPX100Yr_{it}$  ( $NFIPX500Yr_{it}$ ) is an interaction term between the proportion of county land in the 100 (500) year floodplain and  $NFIPprop_{it}$ .  $CRSX100Yr_{it}$  ( $CRSX500Yr_{it}$ ) is an interaction term between the proportion of county land in the 100 (500) year floodplain and PropInCRS.  $X_{it}$  is a vector of control variables including the single year lag of county population per community in county i during year i, the log of average community real income in county i during year i, and the continuous growth rate of average community real income in county i during year i.  $\gamma_i$  is a vector of county fixed-effect dummy variables.  $\delta_t$  is a vector of year fixed-effect dummy variables.

FIRM and join participation dates were collected from the FEMA Community Status

Book at the community level. CRS participation data was collected from the FEMA CRS

October 2020 Eligible Communities spreadsheet at the community level. County income and
population data were collected from the Bureau of Economic Analysis under the US Department
of Commerce at the county level. 100-year and 500-year floodplain data was collected from the
FEMA Flood Map Service Center at the county level. County-level housing permit data was
collected from the US Census Bureau's Building Permit Survey as well as hard copies of C-40
housing permit construction reports over the years 1970-2019 at the county level.

Table 2 contains sample means and standard deviations over the full sample from 1970 to 2019, excluding the observations in which housing permit data was unavailable. It also distinguishes between the coastal and non-coastal subsamples. Data in these tables span from 1971-2019 because we utilize the lag of population and the growth rate of real income in our analysis. Observations were dropped if they had a missing value for the number "All" housing permits and/or "Single Unit" housing permits that year (646 dropped with 7304 remaining). As might be expected, the coastal counties have far higher proportions of both 100- and 500-year floodplain land than noncoastal counties. Coastal counties have an average of 0.565 and 0.0872 while noncoastal counties have averages of 0.119 and 0.00229, respectively. Coastal counties also have higher average participation rates for the NFIP using either FIRM dates or join dates. The same can be said for coastal counties' average participation rate in the CRS.

**Table 2A: Summary Statistics 1971-1989** 

Variable Description	Mean (Full Sample)	St. Dev (Full Sample)	Mean (Noncoastal Counties)	St. Dev (Noncoastal Counties)	Mean (Coastal Counties)	St. Dev (Coastal Counties)
Communities per county	3.937	2.300	3.908	2.290	4.666	2.437
County real income (log)	8.589	0.499	8.579	0.494	8.827	0.564
County real income continuous growth rate	0.0155	0.0260	0.0152	0.0261	0.0217	0.0232
Population per community	9720.892	20115.63	9715.989	20433.58	9845.918	8752.603
County population	34386.67	71611.85	33619.79	70608.45	53942.3	68216.58
NFIP participation (FIRM) per community	0.131	0.264	0.123	0.252	0.340	0.416
NFIP Participation (join) per community	0.127	0.259	0.119	0.248	0.339	0.416
Proportion of county land in 100-Year floodplain	0.137	0.119	0.120	0.0841	0.567	0.0724
Proportion of county land in 500-Year floodplain	0.00638	0.0231	0.00325	0.0160	0.0861	0.0355
All housing permits per community	81.586	210.649	81.189	214.114	91.078	95.881
Single unit permits per community	54.784	129.543	54.690	131.829	57.063	48.555

**Table 2B: Summary Statistics 1971-2019** 

Variable Description	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
	(Full Sample)	(Full Sample)	(Noncoastal Counties)	(Noncoastal Counties)	(Coastal Counties)	(Coastal Counties)
Communities per county	4.048	2.328	4.018	2.319	4.767	2.428
County real income (log)	8.829	0.531	8.817	0.528	9.118	0.532
County real income continuous growth rate	0.0116	0.0192	0.0114	0.0193	0.0161	0.0182
Population per community	13299.04	24813.48	13301.79	25242.88	13231.93	9632.162
County population	49922.39	104814.2	49066.61	105718	70758.57	76962.71
NFIP participation (FIRM) per community	0.492	0.415	0.482	0.413	0.727	0.406
NFIP Participation (join) per community	0.471	0.405	0.460	0.402	0.727	0.407
Proportion of communities in CRS	0.0263	0.126	0.0201	0.105	0.176	0.334
Proportion of county land in 100-Year floodplain	0.137	0.119	0.120	0.0839	0.567	0.0724
Proportion of county land in 500-Year floodplain	0.00638	0.0231	0.00325	0.0160	0.0861	0.0355
All housing permits per community	89.567	249.763	89.342	254.231	95.046	86.790
Single unit permits per community	69.277	201.487	69.187	205.220	71.470	60.179

# **CHAPTER 5**

# **RESULTS**

Our results are split into six tables, tables 3A, 3B, 3C, 4A, 4B, and 4C. Table 3 includes observations from 1970-1989, the years prior to the introduction of the CRS. These results can be compared to that of Browne et al. (1998) and their analysis in the state of Florida. Table 4 includes the entire sample from 1970-2019 while controlling for the CRS. To accommodate for differences in participation effect between coastal and noncoastal counties, these tables are each broken into A, B, and C, representing all counties, noncoastal counties, and coastal counties subsamples, respectively. All variables in these regression models are measured relative to the total number of communities per county.

The total effect of a change in NFIP participation in Table 3 is given by the equation:

$$\Delta HP_{it} = B_1 \Delta NFIP prop_{it} + B_2 \Delta NFIP X 100 Y r_{it} + B_3 \Delta NFIP X 500 Y r_{it}$$
(3)

Table 3A: Years 1970-1989

All Counties

VARIABLES	1: All	2: Single Unit	3: All	4: Single Unit
Beta coefficient	Permits	Permits	Permits	Permits
Het Robust St. Error P-Value	(FIRM Date)	(FIRM Date)	(Join Date)	(Join Date)
NFIPProp	-24.49	-20.23	-30.12	-25.97
ı	(40.19)	(28.10)	(41.58)	(29.48)
	0.542	0.472	0.469	0.378
NFIPX100Yr	-30.00	-13.03	-16.04	1.972
	(109.4)	(72.87)	(111.7)	(76.39)
	0.784	0.858	0.886	0.979
NFIPX500Yr	-301.7	-2.222	-323.4	-43.68
	(459.6)	(275.2)	(463.0)	(283.5)
	0.512	0.994	0.485	0.878
PopPerComLag	-0.000106	0.00187	-3.86e-05	0.00195
1 opi ei comeag	(0.00491)	(0.00262)	(0.00489)	(0.00261)
	0.983	0.475	0.994	0.453
Log Real Community	576.3***	363.8***	577.0***	364.8***
Income	(109.6)	(67.23)	(109.7)	(67.25)
	1.59e-07	6.85e-08	1.56e-07	6.39e-08
Real Community Income	-131.9	-12.77	-131.8	-12.72
Growth Rate	(115.0)	(70.69)	(115.0)	(70.74)
	0.251	0.857	0.252	0.857
Constant	-4,477***	-3,168***	-4,491***	-3,187***
	(645.0)	(437.8)	(642.8)	(436.3)
	0	0	0	0
Observations	2 712	2,712	2 712	2.712
Observations  P. squared	2,712 0.793	0.832	2,712 0.793	2,712 0.833
R-squared F-Stat	29.31	49.52	29.22	49.40
Adjusted R^2	0.778	0.821	0.779	0.821
Trajubiou IC 2	<b>.</b>	~- <b>~-</b>		
$B_1 + B_2 * 100 Avg +$	-30.519	-22.023	-34.379	-25.976
$B_3 * 500Avg =$	0.312	0.282	0.270	0.224
p-value	0.312	0.202	0.270	U.22T

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: Here, participation rates using FIRM dates are on the left in models 1 and 2 while participation rates using the join dates are on the right in models 3 and 4. Coefficients, robust standard errors, and p-values for those coefficients' estimates are listed in every 3 rows. The dependent variable in models 1 and 3 is the number of new housing permits for all units per community in county i during year t and new housing permits for single unit homes in models 2 and 4.  $B_1 + B_2 * 100 \text{Avg} + B_3 * 500 \text{Avg} = \text{displays the estimated change in housing permits if a community was participating in the NFIP and had an average floodplain level across all counties. NFIPProp<sub>it</sub> the proportion of communities that are participating in the NFIP according to their FIRM or join date in county i during year t. NFIPX100Yr<sub>it</sub> is an interaction term between the proportion of 100-year floodplain in and the proportion of communities participating in the NFIP in county i during year t. NFIPX500Yr<sub>it</sub> is similar, but it uses the 500-year floodplain proportion as opposed to the 100-year floodplain. Control variables include county and year fixed effects, the single year lag of county population per community in county i during time t, the log of average community real income in county i during time t, and the continuous growth rate of average community real income in county i during year t. The county and year fixed effects have been omitted from the results tables.$ 

Table 3B: Years 1970-1989
Noncoastal Counties Subsample

VARIABLES	1: All	2: Single Unit	3: All	4: Single Unit
Beta coefficient	Permits	Permits	Permits	Permits
Het Robust St. Error	(FIRM Date)	(FIRM Date)	(Join Date)	(Join Date)
P-Value	-22.94	-37.04	-28.50	-41.60*
NFIPProp	(35.27)	(24.37)	(35.75)	(25.18)
	0.515	0.129	0.425	0.0987
	0.313	0.129	0.423	0.0987
NFIPX100Yr	-52.92	9.418	-39.93	21.94
	(107.9)	(72.60)	(109.3)	(75.84)
	0.624	0.897	0.715	0.772
NFIPX500Yr	-275.2	2,231	-293.5	2,063
	(4,738)	(2,548)	(4,947)	(2,695)
	0.954	0.381	0.953	0.444
	0.000414	0.000593	-0.000351	0.000747
PopPerComLag	-0.000414 (0.00524)	(0.00259)	(0.00524)	0.000747 (0.00258)
	0.937	0.819	0.00324)	0.772
	0.937	0.819	0.947	0.772
Log Real Community	595.9***	397.7***	596.9***	397.0***
Income	(119.8)	(69.82)	(119.7)	(69.60)
	7.04e-07	1.37e-08	6.51e-07	1.31e-08
Real Community Income	-167.2	-52.13	-167.5	-50.72
Growth Rate	(117.7)	(70.14)	(117.5)	(70.00)
	0.156	0.457	0.154	0.469
Constant	-4,545***	-3,016***	-4,553***	-3,011***
Constant	(904.5)	(531.1)	(903.3)	(529.4)
	5.40e-07	1.51e-08	4.98e-07	1.44e-08
	3.400-07	1.510-06	4.960-07	1.440-00
Observations	2,604	2,604	2,604	2,604
R-squared	0.794	0.833	0.794	0.833
F-Stat	27.54	45.41	27.46	45.25
Adjusted R^2	0.779	0.822	0.780	0.822
$B_1 + B_2 * 100 Avg + B_3 * 500 Avg =$	-30.189	-28.658	-34.248	-32.259*
p-value	0.257	0.126	0.212	0.098

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: See notes beneath Table 3A.

Table 3C: Years 1970-1989 Coastal Counties Subsample

NFIPY NFIPX 100 Yr  NFIPX 500 Yr  PopPerComLag  Log Real Community	Permits IRM Date)  48.41 (154.2) 0.754  -49.04 (359.9) 0.892  -965.1 (584.5) 0.103	2: Single Unit Permits (FIRM Date)  52.68 (56.81) 0.357  -24.74 (116.9) 0.833  -490.6**	Permits (Join Date) 45.06 (150.2) 0.765 -38.74 (343.1) 0.910	4: Single Unit Permits (Join Date)  53.87 (57.37) 0.351  -28.78 (119.1) 0.810
P-Value NFIPProp  NFIPX100Yr  NFIPX500Yr  PopPerComLag  Log Real Community	48.41 (154.2) 0.754 -49.04 (359.9) 0.892 -965.1 (584.5)	52.68 (56.81) 0.357 -24.74 (116.9) 0.833	45.06 (150.2) 0.765 -38.74 (343.1)	53.87 (57.37) 0.351 -28.78 (119.1)
NFIPX100Yr  NFIPX500Yr  PopPerComLag  Log Real Community	(154.2) 0.754 -49.04 (359.9) 0.892 -965.1 (584.5)	(56.81) 0.357 -24.74 (116.9) 0.833	(150.2) 0.765 -38.74 (343.1)	(57.37) 0.351 -28.78 (119.1)
NFIPX100Yr  NFIPX500Yr  PopPerComLag  Log Real Community	0.754 -49.04 (359.9) 0.892 -965.1 (584.5)	0.357 -24.74 (116.9) 0.833	0.765 -38.74 (343.1)	0.351 -28.78 (119.1)
NFIPX500Yr  PopPerComLag  Log Real Community	-49.04 (359.9) 0.892 -965.1 (584.5)	-24.74 (116.9) 0.833	-38.74 (343.1)	-28.78 (119.1)
NFIPX500Yr  PopPerComLag  Log Real Community	(359.9) 0.892 -965.1 (584.5)	(116.9) 0.833	(343.1)	(119.1)
PopPerComLag  Log Real Community	0.892 -965.1 (584.5)	0.833	, ,	
PopPerComLag  Log Real Community	-965.1 (584.5)		0.910	0.810
PopPerComLag  Log Real Community	(584.5)	-490.6**		
Log Real Community			-977.6*	-486.6**
Log Real Community	0.103	(205.8)	(571.0)	(206.7)
Log Real Community		0.0196	0.0909	0.0211
= -	0.0235*	-0.00341	0.0236*	-0.00339
= -	(0.0127)	(0.00465)	(0.0127)	(0.00465)
_	0.0678	0.465	0.0659	0.468
Income	326.4**	194.9***	325.6**	194.7***
	(138.8)	(46.52)	(139.0)	(46.82)
	0.0212	7.38e-05	0.0217	8.25e-05
Real Community Income Growth Rate	622.8**	291.9**	625.9**	292.2**
	(273.5)	(132.0)	(274.0)	(131.9)
	0.0255	0.0300	0.0251	0.0297
Constant	-2,615**	-1,502***	-2,609**	-1,501***
	(1,092)	(364.8)	(1,093)	(367.0)
	0.0190	9.52e-05	0.0195	0.000106
Observations	108	108	108	108
R-squared	0.759	0.865	0.759	0.865
F-Stat	12.07	22.52	12.09	22.68
Adjusted R^2	0.666	0.813	0.665	0.813
$B_1 + B_2 * 100 Avg + B_3 * 500 Avg =$	-62.488	-3.591	-61.080	-4.342
p-value		0.804		

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: See below Table 3A.

Table 3A shows that community-level participation in the NFIP between the years 1970 and 1989 did not have a statistically significant effect on housing development across all counties even if we differentiate between FIRM and join participation dates as well as single unit and multi-unit housing permits. For the full sample of communities in table 3A, we find that the single most important determinant of new housing permits per community was the log of real community income adjusted to 2019 dollars. If a community's real income increased by 1%, we estimate that it saw an increase in all new housing permits requests of 576.3 (or 577) when using the FIRM date (join date) model and 397.7 (or 397.0) additional single unit housing permit requests. All four of these coefficients are statistically significant at the 99% confidence level.

Table 3B's results using single unit housing permits and join participation dates indicate that participation in the NFIP to have a negative effect on housing development in areas with no floodplain in Georgia's noncoastal counties. If a community participated in the NFIP and had no 100 or 500-year floodplain, the community saw an estimated 41.6 less permit requests for single-unit structures; however, the results from the Wald Test indicate that in the average noncoastal county with average levels of noncoastal floodplain proportions, this negative effect is weakened to a 32.6 decrease in single unit permit requests per community. In other words, the floodplain effect is working in the opposite direction of the non-floodplain participation effect in noncoastal counties. These results are statistically significant at the 10% alpha level and are not robust across the other three models in Table 3B. Similar to the full sample results in Table 3A, increases in the log of community real income were projected to increase housing permits as well. In noncoastal counties, a 1% increase in community real income brought an estimated 595.9 (or 596.9) additional housing permit requests if using FIRM (or join) dates for NFIP

participation. 397.7 (or 397) of those additional housing permits came from single-unit structures. All four of these estimates are statistically significant at the 1% significance level.

Table 3C finds that participation in the NFIP had a negative effect on housing development in coastal counties for communities located with high proportions of 500-year floodplain. If a coastal community was located entirely in a 500-year floodplain and participated in the NFIP, the community would see a 490.6 (or 486.6) less single unit housing permit requests using the FIRM date (or join date) for participation in addition to the program's non-floodplain effect. These estimate are statistically significant at the 5% level. Similarly, a coastal Georgian community located in the 500-year floodplain that has joined the NFIP saw an additional 977.5 decrease in all of its housing permit requests using the join participation date, and this result was statistically significant at the 10% level. The log of real income and the growth rate of real income were both found to be significant determinants of housing development as well in coastal counties. An estimated 326.4 (or 325.6) more housing permit requests can be expected in communities from a 1% increase in real income when using the FIRM (or join) participation dates. These results were statistically significant at the 5% significance level. 194.9 (or 194.7) of those permits would be for single unit strictures. These results were statistically significant at the 1% level. As for income growth, our models estimate that a 10% increase in the coastal community's real income growth rate would increase the number of housing permit requests by 62.28 (or 62.59 using join dates), and 29.19 (or 29.22 using join dates) of these permit requests would be for single unit structures. All four of these estimates are statistically significant at the 95% confidence level.

The next set of results in tables 4A, 4B, and 4C were calculated using the similar models as those above but over a larger period of time, including when the CRS was available for joining.

The correlation for a change in NFIP participation and housing development for a community that is not in the CRS in Table 4 is given by the equation:

$$\Delta HP_{it} = B_1 \Delta NFIPprop_{it} + B_3 \Delta NFIPX100Yr_{it} + B_5 \Delta NFIPX500Yr_{it}$$
(4)

The correlation for a change in NFIP participation and housing development for a community that is in the CRS in Table 4 is given by the equation:

$$\Delta HP_{it} = B_1 \Delta NFIPprop_{it} + B_2 \Delta PropInCRS_{it} + B_3 \Delta NFIPX100Yr_{it} + B_4 \Delta CRSX100Yr_{it} + B_5 \Delta NFIPX500Yr_{it} + B_6 \Delta CRSX500Yr_{it}$$
(5)

Table 4A: Years 1970-2019 Full Sample

VARIABLES Beta coefficient Het Robust St. Error P-Value	1: All Permits (FIRM Date)	2: Single Unit Permits (FIRM Date)	3: All Permits (Join Date)	4: Single Unit Permit (Join Date)
NFIPProp	44.67***	45.14***	25.66*	30.09***
r	(12.46)	(9.026)	(13.40)	(9.731)
	0.000340	5.82e-07	0.0555	0.00199
PropInCRS	-487.5***	-362.6***	-492.9***	-367.2***
1	(94.85)	(64.95)	(94.88)	(64.95)
	2.83e-07	2.45e-08	2.11e-07	1.63e-08
NFIPX100Yr	75.40*	51.18*	105.4***	73.46***
	(38.70)	(26.32)	(39.66)	(27.14)
	0.0514	0.0519	0.00786	0.00680
CRSX100Yr	980.8***	839.7***	964.9***	827.3***
44	(279.4)	(186.4)	(279.6)	(186.5)
	0.000449	6.79e-06	0.000561	9.24e-06
NFIPX500Yr	-1,464***	-902.2***	-1,572***	-980.6***
	(279.0)	(181.5)	(279.1)	(183.7)
	1.58e-07	6.86e-07	1.83e-08	9.70e-08
CRSX500Yr	-451.9	-779.2*	-348.7	-699.4
	(720.2)	(467.0)	(722.9)	(469.4)
	0.530	0.0953	0.630	0.136
PopPerComLag	0.00591***	0.00533***	0.00588***	0.00530***
1 0	(0.00144)	(0.00111)	(0.00144)	(0.00111)
	3.85e-05	1.52e-06	4.26e-05	1.74e-06
Log of Real	295.2***	221.6***	301.4***	226.5***
Community	(38.53)	(27.64)	(38.51)	(27.62)
Income	0	0	0	0
Real Community	773.1***	717.2***	770.0***	715.2***
Income Growth	(132.7)	(109.8)	(133.0)	(110.3)
Rate	5.91e-09	7.09e-11	7.45e-09	9.45e-11
Constant	-2,127***	-1,600***	-2,169***	-1,633***
	(302.2)	(218.3)	(302.0)	(217.9)
	0	0	0	0
Observations	7,304	7,304	7,304	7,304

R-squared	0.721	0.730	0.720	0.729
F-Stat	34.94	40.40	34.69	39.97
Prob > F	0	0	0	0
Adjusted R^2	0.712	0.722	0.712	0.721
In CRS $B_1 + B_2 + 100 Avg(B_3 + B_4) + 500 Avg(B_5 + B_6)$	-310.446***	-206.242***	-332.921***	-224.524***
= p-value	0.000	0.000	0.000	0.000
Out of CRS $B_1 + 100Avg * B_3 + 500Avg * B_5 =$	45.656***	46.397***	30.069**	33.894***
p-value	0.000	0.000	0.011	0.000

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Notes:** See below Table 3A. PropInCRS<sub>it</sub> is the proportion of communities that are participating in the Community Rating System in county i during year t. CRSX100Yr<sub>it</sub> and CRSX500Yr<sub>it</sub> are interaction terms between average community CRS participation in county i in year t and the proportion of county land in either the 100 or 500-year floodplain, respectively. The Wald test "In CRS" gives the correlation between program participation and CRS participation for the average community with average floodplain proportions. The "Out of CRS" Wald test gives the correlation between program participation for the average community with average floodplain proportions.

Results from Table 4A indicate that over the longer period of observation and across all counties, participating in the NFIP is correlated with an *increase* in housing development. Using the FIRM date, we estimate that community participation in the NFIP outside of the floodplain is correlated with a 44.67 unit increase in all housing permits, or 45.14 single unit permits. These results are statistically significant at the 1% significance level. Interestingly, participating in the CRS has an even greater correlation with housing development but in the opposite direction. Using the FIRM participation dates, community participation in the CRS outside of the floodplain is correlated with an additional 487.5 *decrease* in the number of new permit requests, or 362.5 single unit permits. Using the join participation dates, community participating in the CRS with no floodplain is correlated with an additional 492.9 decrease in the number of new

housing permit requests per community, or 367.2 single unit permits. These results are all statistically significant at the 99% confidence level.

For communities located in the 100-year floodplain, participating in the NFIP is associated with an additional increase in housing permits. The same can be said for participation in the CRS, although these estimates are roughly one order of magnitude larger than the NFIP \* 100-year floodplain estimates. For communities in the 500-year floodplain, participating in the NFIP is associated with a large decrease of 1464 (or 1572 using the join dates) new housing permits, or 902.2 (980.6) single unit permits. These results are statistically significant at the 1% significance level. Only one of the four models in 4A finds the CRS x 500-year floodplain interaction term to be statistically significant. Using the FIRM participation dates, a community participating in the CRS and entirely within the 500-year floodplain is correlated with an additional 779.2 decrease in single unit housing permits, and this estimate is significant at the 10% significance level.

The lag of community population is found to be significantly correlated with housing development in all four of the models, but its beta estimates are so small in magnitude that the effect is negligible. Both the log of real community income as well as the real income growth rate are found to be significantly correlated with housing development, and their results can be interpreted the same as in Table 3.

At the bottom of the table, the Wald test for "Out of CRS" can be interpreted as the correlation between housing permits and base program participation for communities that have average floodplain proportions and do not participate in the CRS. For these communities, the models find correlations of 46 additional permits using FIRM dates, and between 30 and 34 additional permits using join dates. All four of these results are statistically significant at the 1%

significance level. The "In CRS" Wald test can be interpreted as the correlation between housing permits and program participation for communities that have average floodplain proportions and do participate in the CRS. For these communities, the four full sample models find a negative correlation in new housing permits of 310 less all permits using FIRM dates or 333 less using join dates. 206 225 These tests also find a negative correlation for single unit structures of 206 using FIRM dates or 225 less using join dates. These results are statistically significant at the 1% significance level. It appears that communities who join both the CRS and the NFIP are correlated with an increased number of permits in the 100-year floodplain, and a decrease in the number of permits in the 500-year floodplain.

Table 4B: Years 1970-2019 Noncoastal Subsample

VARIABLES	1: All	2: Single Unit	3: All	4: Single
Beta coefficient	Permits	Permits	Permits	Unit Permits
Het Robust St. Error	(FIRM Date)	(FIRM Date)	(Join Date)	(Join Date)
P-Value	(PIKWI Date)	(MIXIVI Date)	,	(Join Date)
NFIPProp	56.68***	42.88***	39.51***	27.71***
	(10.44)	(7.753)	(10.97)	(8.071)
	5.88e-08	3.31e-08	0.000321	0.000600
PropInCRS	-355.0***	-240.6***	-367.7***	-249.0***
_	(124.8)	(90.93)	(125.1)	(91.12)
	0.00448	0.00816	0.00330	0.00630
NFIPX100Yr	49.31	57.96**	80.16**	83.62***
	(39.83)	(29.10)	(40.61)	(29.66)
	0.216	0.0465	0.0485	0.00483
CRSX100Yr	1,977***	1,842***	1,996***	1,857***
	(682.1)	(448.2)	(682.1)	(447.5)
	0.00375	4.00e-05	0.00345	3.37e-05
NFIPX500Yr	-8,064**	-2,491	-8,969***	-2,936
	(3,134)	(1,919)	(3,190)	(1,964)
	0.0101	0.194	0.00494	0.135
CRSX500Yr	-23,480***	-24,438***	-23,027***	-24,311***
	(7,339)	(4,934)	(7,432)	(4,982)
	0.00138	7.49e-07	0.00195	1.09e-06
PopPerComLag	0.00673***	0.00576***	0.00674***	0.00575***
-	(0.00152)	(0.00118)	(0.00152)	(0.00118)
	9.16e-06	1.11e-06	8.90e-06	1.17e-06
Log of Community Real	269.7***	203.9***	276.6***	209.6***
Income	(41.37)	(30.23)	(41.37)	(30.24)
	7.66e-11	0	0	0
Community Real Income	855.6***	783.0***	853.8***	780.9***
Growth Rate	(138.9)	(115.3)	(139.2	(115.7)
	7.74e-10	0	9.12e-10	0
Constant	-666.0	-1,159**	-564.1	-1,132**
	(711.2)	(484.3)	(720.1	(490.1)
	0.349	0.0167	0.433	0.0209
Observations	7,016	7,016	7,016	7,016

R-squared	0.726	0.735	0.725	0.734
F-Stat	34.31	39.96	34.08	39.72
Prob > F	0	0	0	0
Adjusted R^2	0.717	0.726	0.717	0.726
In CRS $B_1 + B_2 + 100Avg(B_3 + B_4) + 500Avg(B_5 + B_6)$	-157.517**	-57.138	-183.019***	-76.932
= p-value	0.025	0.274	0.010	0.145
Out of CRS $B_1 + 100Avg * B_3 + 500Avg * B_5 =$	36.391***	41.739***	19.979	28.207***
p-value	0.006	0.000	0.114	0.005

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: See below Table 4A.

Compared to the full sample models in 4A, Table 4B indicates that for noncoastal communities without floodplain, NFIP participation is correlated with a larger increase in housing permit while additional CRS participation is correlated with a smaller decrease in permits. Again, we see that CRS participation and its floodplain interaction estimates dwarf that of the base NFIP program. While the values of the coefficient estimates may vary their general sign and magnitude matches that of Table 4A.

For noncoastal communities participating in the base program, located within average amount of floodplain, and not participating in the CRS, the Wald tests find small yet statistically significant positive correlation in housing permits. Participation is correlated with an additional 36 all permits using FIRM dates, or 42 additional single unit permits using FIRM dates and 28 additional single unit permits using join dates. These three estimates are statistically significant at the 1% significance level. For the average noncoastal community participating in the CRS as well as the base program, the Wald test finds a negative correlation between participation and all permits of 158 less all permits using FIRM dates, or 183 less all permits using join dates. These

correlations are statistically significant at the 5% and 1% significance level, respectively. Notice that the overall effect for average noncoastal counties flips from a positive to negative correlation once communities are joining the CRS.

Table 4C: Years 1970-2019 Coastal Subsample

VARIABLES	1: All	2: Single Unit	3: All	4: Single Unit
Beta coefficient	Permits	Permits	Permits	Permits
Het Robust St. Error	(FIRM Date)	(FIRM Date)	(Join Date)	(Join Date)
P-Value NFIPProp	4.080	45.65	0.770	44.73
NEIPPIOP	(99.04)	(40.78)	(98.18)	(40.75)
	0.967	0.264	0.994	0.274
	0.507	0.204	0.774	0.274
PropInCRS	-314.7**	-203.3**	-312.8**	-202.7**
1	(140.5)	(92.49)	(140.4)	(92.47)
	0.0261	0.0290	0.0269	0.0294
NFIPX100Yr	-85.78	-102.9	-75.18	-100.0
	(205.1)	(80.49)	(200.3)	(80.20)
	0.676	0.202	0.708	0.214
CRSX100Yr	697.8***	524.5***	696.0***	524.0***
	(227.9)	(136.0)	(228.0)	(136.0)
	0.00247	0.000150	0.00255	0.000152
NFIPX500Yr	-139.3	54.89	-144.2	53.54
	(241.3)	(113.1)	(240.3)	(113.5)
	0.564	0.628	0.549	0.638
CRSX500Yr	50.48	-63.71	41.83	-66.10
	(558.2)	(388.5)	(557.2)	(388.7)
	0.928	0.870	0.940	0.865
PopPerComLag	-0.0187***	-0.0121***	-0.0186***	-0.0121***
T opi or comeng	(0.00422)	(0.00238)	(0.00415)	(0.00236)
	1.44e-05	7.28e-07	1.23e-05	6.42e-07
Log of Community Real	402.2***	265.2***	401.6***	265.0***
Income	(46.95)	(22.79)	(46.88)	(22.72)
meome	0	0	0	0
C ' D II	220.4	220.5	241.6	221.1
Crawth Page	339.4	220.5	341.6	221.1
Growth Rate	(231.6) 0.144	(139.7) 0.116	(232.0) 0.142	(139.7) 0.115
	U.1 <del>44</del>	0.110	0.142	0.113
Constant	-3,075***	-2,022***	-3,071***	-2,021***
	(363.8)	(173.0)	(363.5)	(172.7)
	0	0	0	0

Observations	288	288	288	288
R-squared	0.718	0.769	0.718	0.769
F-Stat	13.19	17.25	13.15	17.26
Prob > F	0	0	0	0
Adjusted R^2	0.639	0.704	0.639	0.704
In CRS				
$B_1 + B_2 + 100 Avg(B_3 + B_4) + 500 Avg(B_5 + B_6)$	28.570	80.569***	31.005	81.232***
= p-value	0.605	0.003	0.568	0.002
Out of CRS				
$B_1 + 100 Avg * B_3 +$	-56.528	-7.956	-54.254	-7.338
$500Avg * B_5 =$				
p-value	0.207	0.629	0.215	0.650

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: See below Table 4A.

Admittedly, the lower number of observations due to the fact that there exist only six coastal counties in the state of Georgia gives the models in 3C and 4C less power. While not all of the results for our coastal subsample in Table 4C are statistically significant, there are still some noteworthy estimates that are. All four models in Table 4C find a negative correlation between CRS participation and housing development. These four estimates range between –200 and –315, statistically significant at the 95% confidence level, and each of less magnitude than those of the full sample or the noncoastal subsample.

4C finds the interaction between CRS participation and the proportion of land in the 100-year floodplain to be statistically significant at the 99% confidence level across all four models. These values range from 520-700 additional housing permits for communities in the 100-year floodplain and participating in the CRS as well as the NFIP. Notably, all four of these estimates are of lower magnitude than those in the full sample or the noncoastal subsample models.

The results of the linear combination estimates for a community in both the NFIP and the CRS located in a 100-year floodplain are in-line with those from Tables 4A and 4B. The

estimates indicate a positive relationship between these communities' participation and housing development of 301 or 308 all permits (using FIRM or join dates, respectively), and 264 or 266 single unit permits. The results for all permits models are statistically significant at the 10% alpha level while the single unit results are significant at the 1% alpha level.

## **CHAPTER 6**

## **CONCLUSION**

In the state of Georgia, the effect of community-level involvement in the National Flood Insurance Program on nearby housing development was certainly not as strong as it was in Florida over the initial study period up to 1989. Across all counties, there was no statistically significant effect on housing development brought about by the NFIP; however, when we looked specifically at noncoastal counties, we did find that annual single unit housing permits decreased significantly. When we focused only on Georgia's six coastal counties, we found that participating communities exhibited even greater declines in housing permits for areas at higher risk of flooding.

When we look beyond 1989 to the most recent data in 2019 and control for the effect of the Community Rating System, we find that across all counties, main program participation is correlated with an increase in housing development yet communities that choose to participate in the CRS are correlated with reductions in housing development that outweigh and overshadow the former positive development correlation from NFIP participation alone. The CRS's incentive programs are likely even more influential in affecting housing development than the base NFIP program itself, but comparatively, fewer communities participate in the CRS and the self-selection bias into the CRS is likely to be prominent. Both NFIP participation and CRS participation both are both correlated with an increase in housing development for areas within the 100-year floodplain, yet simultaneously both are correlated with a decrease in development

in areas within the 500-year floodplain. This finding is odd, for why would the NFIP and CRS incentivize development in higher risk areas yet disincentivize it in lower risk 500-year floodplains? One possible explanation for this finding is perhaps the negative supply mechanism of the NFIP through increased construction costs dominates in these 500-year floodplain areas while the positive demand mechanism of decreased cost of risk are dominating in the 100-year floodplain areas.

The estimates produced by our 1970-1989 analysis do not support as strong of an effect of flood insurance participation on housing development as in the state of Florida. Indeed, one model even directly conflicts with their findings; Program participation was found to induce housing permits in noncoastal Florida counties, while in Georgia the effect is just the opposite. Thus, it is important to note that the effect of the National Flood Insurance Program is not entirely consistent in different places, or in this case, across state lines. On the other hand, one effect found to be consistent between these two states in particular is that in coastal counties, program participation reduces housing development in areas with high proportions of floodplain acreage.

This analysis cannot test what mechanisms of supply and demand were most significant in driving these decreases in housing development (perhaps it was increased compliance cost from stricter building codes, or reduced willingness to pay for housing), but the question is an exciting opportunity for future research as it would provide lawmakers with a deeper understanding of which particular aspects of the NFIP legislation are most responsible for its effect on development. One way to improve upon this research endeavor would be to find a complete set of housing permit data at the community-level that is listed annually. If we could avoid having to aggregate to the community level in this analysis, we could avoid looking at

broad trends in the NFIP's relationship with development and strengthen the confidence of the results. Another avenue worthy of more investigation is the potential use of FHBMs and their dissemination to high-risk flood communities as an instrumental variable for program participation.

The NFIP has proved to be a costly program for the federal taxpayer thus far, but it aims to accomplish a highly valuable public service. One of the most important goals of the NFIP is to reduce future flood damages for its citizens through the adoption of voluntary floodplain management regulations at the community level. Due to our results indicating that participation has brought about significant levels of reduction for housing development in higher-risk floodplain communities in our coastal counties for three out of four models, we prove that it has succeeded in achieving that goal for the state of Georgia.

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