Community-Level Flood Mitigation Effects on Household-Level Flood Insurance and Damage Claims

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

By
Eugene Frimpong

A Thesis
Submitted to the Faculty of Mississippi State University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Agricultural Economics in the Department of Agricultural Economics

Mississippi State, Mississippi
August 2016
Community-level flood mitigation effects on household-level flood insurance and
damage claims

By

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The Community Rating System (CRS) was introduced to encourage flood mitigation and increase National Flood Insurance Program (NFIP) participation via premium discounts. It is not clear, however, how additional mitigation and premium discounts affect NFIP participation and damage claims payments.

We employ matching methods and log-linear regression framework to estimate the impact of CRS participation (versus non-participation) on outcomes. We also analyze the effect of individual CRS mitigation activities on outcomes. We do so while controlling for key geospatial, socioeconomic, and time effects.

Results show a positive and significant effect of CRS participation on NFIP participation, but no significant effect on damage claims payments. Outreach and flood data maintenance activities have positive effect on NFIP participation while floodplain mapping and flood protection have negative effect. Flood protection information and storm water management have negative effect on damage claims payments while floodplain management planning and acquisition and relocation have positive effect.
DEDICATION

This research is dedicated to my uncle, Mr. George Ofori, my aunt, Madam Felicia Gyamfi, my mother Madam Esther Gyamfi, and my siblings, McClean Nana Frimpong and Michael Frimpong.
ACKNOWLEDGEMENTS

I have come this far with this research because of the guidance I received from my major professor, Dr. Daniel R. Petrolia, and my committee members, Dr. Ardian Harri and Dr. Keith H. Coble. I am highly indebted to these great people.

I would also like to acknowledge Mississippi Alabama Sea Grant Consortium (MASC) for funding this research and Mr. John Cartwright for all the help with the geospatial and socioeconomic data used in this research. Lastly, I would like to convey my sincere gratitude to Mr. Benjamin Sanderson and Dr. Li Xiaofei.
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INTRODUCTION

The National Flood Insurance Program (NFIP) was created in 1968 to provide assistance to communities and homeowners by identifying risk, managing floodplains, and providing residents with affordable flood insurance (Brody et al. 2013). Property owners can participate in the NFIP by purchasing flood insurance policies given that their communities are participating in the NFIP. A Community’s participation in the NFIP implies undertaking some standard flood mitigation activities, including enforcement of building and zoning ordinances (Federal Emergency Management Agency (FEMA) 2015).

The NFIP has seen several reforms over the years aimed at either increasing participation (especially in terms of homeowner’s purchase of flood insurance policy), or reducing insured damage claims, or both. For example, in 1973, property owners with federally-backed mortgages were mandated to purchase flood insurance if the property is located in a special flood hazard area (SFHA). The year 1983 saw the introduction of the write-your-own program which allowed insurance companies to write and market flood insurance policies. The Community Rating System (CRS) was introduced into the NFIP program in 1990. In 1995, FEMA also introduced the “Cover America” program, a campaign that promoted awareness of flood risk (Michel-Kerjan 2010). In the year 2004, the National Flood Insurance Act of 1968 was reformed. The reform was to ensure that
losses to properties for which claims payments have been made on several instances are reduced (FEMA 2016). Some specifics to this reform were the introduction of a pilot flood mitigation program for properties experiencing higher damages, and also FEMA to fund flood mitigation activities for these properties (FEMA 2016). The year 2012 saw the Biggert-Waters Flood Insurance and Modernization Act introduced to NFIP (Center for Insurance Policy and Research 2012; FEMA 2016). This reform aimed at restructuring premium rates, enforce the compulsory flood policy purchase for federally-backed mortgages and also address issues of mitigation among others. In 2014, the Biggert-Waters Flood Insurance and Modernization Act was replaced with the Homeowner Flood Insurance Affordability Act of 2014. This legislation seeks to reduce premium rates on selected policies and also cancel some rate increases that had previously been implemented (FEMA 2016).

In this research, we focus on the CRS. The goal of the CRS program is to encourage both local hazard mitigation activities (Petrolia, Landry, and Coble 2013) and also increase NFIP participation (i.e., increase policies-in-force) among CRS participating communities. Under the CRS program, there are 19 credit-generating flood mitigation activities organized under four general categories called “series”, labeled Series 300, 400, 500, and 600, respectively. Series 300 activities are related to providing information on floods to community residents, information on Flood Insurance Rate Map (FIRM) to community residents and promoting flood insurance purchases. Series 400 activities focus on floodplain mapping. These activities involve developing new flood elevations, and delineating floodways for areas not mapped on FIRMs. Series 400 activities are related to the enforcement of building regulations, especially to new
developments. Series 500 activities are related to flood damage reduction to existing developments. For example, under series 500, CRS communities undertake drainage system maintenance and floodplain management. Series 600 activities focus on providing flood warnings, how to respond to emergencies during flood, providing maintenance to levees, and ensuring dam safety (FEMA 2013).

An NFIP community can undertake none, some, or all of these 19 CRS activities and earn program credits according to the degree to which each activity is undertaken. First, an NFIP community performs a self-assessment to determine if its level of mitigation exceeds the NFIP minimum. It then applies to the CRS program for the CRS program to access the degree of mitigation practices. Should CRS officials be satisfied that the community’s mitigation practices exceeds the base-level flood migration, then the community residents (i.e., individual property owners, including businesses) get an opportunity to earn premium discount on individual policy. A higher degree of flood mitigation (higher CRS overall points) will earn a higher percentage discount on individual flood policy premia. Specific details of the program will be discussed in Chapter 2.

Despite the benefits to participating communities and their residents, the CRS program has suffered from low participation since its inception. Of the over 22,000 NFIP communities, only 5% of these communities also participate in the CRS program (FEMA 2016). Studies that have researched the likelihood of a community to participate in the CRS program have shown that characteristics spanning from hydrology of the community to socio-economics of the community’s residents may influence communities’ participation in the CRS program (Brody et al. 2009; Landry and Li 2012;
Sadiq and Noonan 2015). On the other hand, out of the total 5,583,461 NFIP policies-in-force in the US, 3,779,513 (68%) are in CRS-participating communities (FEMA 2016). Thus, although few NFIP communities are participating in the CRS program, more than two thirds of NFIP policies-in-force are in CRS participating communities.

Although the CRS program aims to encourage NFIP participation and reduce future flood damages, it is not clear if and to what degree participation in the CRS actually affects outcomes. Past research that have looked into this question have analyzed the effect of overall CRS credit points on NFIP participation (Zahran et al. 2009), how the degree of CRS mitigation practice affects the proportion of magnitude of claims (i.e., magnitude of claims divided by coverage purchased, and magnitude of claims divided by property value) (Michel-Kerjan and Kousky 2010), and the relationship between specific CRS mitigation activities and damage claims payments (Highfield and Brody 2013). On the other hand, Brody et al. (2007) have looked at how the degree of CRS mitigation practice affects flood damages (measured as the dollar value of total losses form flood events). Zahran et al. (2009) finds a positive and a significant relationship between overall CRS credit points and NFIP policies-in-force. In their study, control variables such as median home value, college educated, floodplain, coastal county, flood frequency, and flood property damage were also positive and significant in explaining NFIP policies-in-force. Michel-Kerjan and Kousky (2010) finds a negative relationship between higher degree of CRS mitigation practice and the dependent variables (i.e., magnitude of claims divided by coverage purchased, and magnitude of claims divided by property value). Control variables such as the number of floors a house has, building elevation, basement, and the location of the house (Special Flood
Hazard Area/ Non-Special Flood Hazard Area) were also negative and statistically significant in explaining the proportion of magnitude of damage claims payments. Highfield and Brody (2013) find a negative relationship between some specific CRS mitigation activities and damage claims payments. Control variables (floodplain area, soil permeability, precipitation, surge event, and population) used in their study was also statistically significant in explaining damage claims payments. In Brody et al. (2007) study, results show a negative relationship between flood damage and the degree of CRS mitigation practice of counties.

However, with the exception of Michel-Kerjan and Kousky (2010) who looked at the discrete impact of different degrees of CRS mitigation practice on outcomes, these past studies have focused mostly on within CRS-participating communities, i.e., how marginal increases in overall CRS credit points affects either NFIP participation (policies-in-force), damage claims payments, or flood damages. Past studies have mostly used only control variables to isolate the effect of CRS on outcomes whiles focusing on within CRS communities. That is, to the best of our knowledge, no study has tried to isolate the treatment effect of CRS participation (versus non-participation) on outcomes using matching methods. The above-mentioned studies (except Michel-Kerjan and Kousky 2010; Highfield and Brody 2013) have also used county-level data. However, results at the county-level might not apply to individual NFIP communities. Also, with the exception of Highfield and Brody (2013), past studies have concentrated on the state of Florida (Brody et al. 2007; Zahran et al. 2009; Michel-Kerjan and Kousky 2010), and Texas (Brody et al. 2007). That is, their findings may not apply to other states. Although Highfield and Brody (2013) considered a sample of CRS participating communities
across the U.S., they only looked at the effects of specific CRS activities on damage claims payments. In addition, the longest and recent time frame past research have considered is the period 1999 to 2009.

In this present research, we depart from earlier studies by looking at the discrete impact of CRS participation versus non-participation on NFIP participation (policies-in-force), and damage claims payments. Like past studies, we also control for key geospatial and socioeconomic variables. However, we also contribute to the literature by controlling for variables that were not accounted for in past studies, including percent of land area in specific flood zones. Our study area focuses on NFIP communities in Alabama, and Mississippi of which little is known. We use more current community-level panel data (1994 to 2013) in our research.

In estimating the impact of a program on outcomes, it is suggested that for comparison, the units that received the program, and those that did not receive the program should share similar characteristics so as to eliminate program selection bias (Rosenbaum and Rubin 1983; Rubin and Thomas 2000; Stuart and Greene 2008). To accomplish this, the literature suggests using matching methods (Rosenbaum and Rubin 1983; Rubin and Thomas 2000; Stuart and Green 2008). Matching seeks to find from a pool of nonparticipating units (in our case, non-CRS communities), candidates that have similar characteristics as that of the participating units (in our case CRS participating communities). That is, to estimate the discrete impact of CRS participation versus non-participation on outcomes, we employ matching methods in selecting non-CRS participating communities. This is an addition to existing literature as past studies that
have answered the question as to if and to what degree participation in the CRS affects outcomes have not employed matching in their studies.

In a different analysis, we estimate the effect of community-level specific CRS mitigation activities on both NFIP participation and damage claims payments. Highfield and Brody (2013) only looked at the effect of community-level specific CRS mitigation activities on damage claims payments (they did not consider the effect on NFIP participation). Also, Highfield and Brody (2013) only looked at some selected activities.

This current research provides estimates on the discrete impact of CRS participation (versus non-participation) on NFIP participation (policies-in-force) and damage claims payments. Also in this research, analysis on the effect of individual CRS mitigation activities on NFIP participation and on damage claims payments is provided.
CHAPTER II
THE NATIONAL FLOOD INSURANCE PROGRAM (NFIP), AND COMMUNITY RATING SYSTEM (CRS)

In this chapter, we present an overview of the National Flood Insurance Program (NFIP), and the Community Rating System (CRS). We also look at some factors affecting CRS participation.

The National Flood Insurance Program (NFIP)

Flood insurance was not widely available to individuals prior to 1968, due in part to selection and high costs of servicing claims when a major flood disaster occurred (Michel-Kerjan and Kousky 2010). The National Flood Insurance Act of 1968 introduced the National Flood Insurance Program (NFIP) to provide flood insurance to individuals and businesses. In 1983 the “Write-Your-Own” program was introduced, which gave private insurance companies the authority (by FEMA) to prepare and market flood insurance policies, although the federal government retains, responsibility for the settling claims (Michel-Kerjan and Kousky 2010; Michel-Kerjan 2010).

Flood-risk designation is accomplished via Flood Insurance Rate Maps (FIRMs), produced by the US Army Corps of Engineers. On the FIRMs, flood risks are classified into two distinct categories: the Special Flood Hazard Area (SFHA) and the area outside of the SFHA, referred to here as the Non-SFHA. As the names imply, SFHA includes high risk areas and the Non-SFHA includes moderate-to-low risk areas. In specific
terms, the SFHA is the land area covered by the floodwaters of the “base flood” on FIRM. The “base flood” is the flood having a one percent chance of being equaled or exceeded in any given year. This is the regulatory standard, also referred to as the "100-year flood," and the SFHA is thus also referred to as the “100-year flood zone”. The base flood is the national standard used by the NFIP and all federal agencies for the purposes of requiring the purchase of flood insurance and regulating new development. Base Flood Elevation (BFE), which is the computed elevation to which floodwater is anticipated to rise during the base flood, is typically shown on FIRM.

The SFHA is further delineated into specific “zones”, including Zones A, AO, AH, A1-30, AE, A99, AR, AR/A1-30, AR/AE, AR/OA, AR/AH, AR/A, VO, V1-30, VE, and V. V zones (all the aforementioned zones beginning with the letter “V”) are coastal high hazard areas that experience high-velocity wave action (i.e., storm surge), and A zones (those beginning with the letter “A”) are inland high hazard areas.

Specific zones outside of the SFHA, i.e., the Non-SFHA zones, include B, C, X (shaded and unshaded), and D zones. Zones B and X (shaded) are moderate flood hazard areas, whose risk falls between the limits of the base flood and the 0.2-percent-annual-chance (or 500-year) flood. Zone C and X (unshaded) are minimal flood hazard areas with elevation above the 0.2-percent-annual-chance (or 500-year) flood. Zone D is used for areas where there are possible but undetermined flood hazards, or where a community incorporates portions of another community’s area where no map has been prepared (FEMA 2016).

Properties located in flood risk areas that are not mapped onto the FIRM (pre-FIRM), i.e., where no flood maps exist, are eligible to receive subsidized flood insurance
policies until FIRMs are created. For areas located on the FIRM, strict building ordinances and actuarial flood insurance rates apply to new developments (Kunreuther and White 1994; Adelle and Leichenko 2011). NFIP policies come in two forms, the actuarial policies and the discounted policies. About a quarter of the entire NFIP policy rates are subsidized on pre-FIRM bases (Bin, Bishop, and Kousky 2012). Flood insurance premiums vary across flood zones, but are individually adjusted for community residents depending on building characteristics such as elevation above base flood and the community’s involvement in local flood mitigation activities.

NFIP participation is compulsory for properties located in SFHAs that have federally-backed mortgages. The compulsory purchase of flood insurance policies was enacted by the Flood Disaster Protection Act of 1973 in response to Hurricane Agnes, which struck the Atlantic Coast in 1972, and revealed that most community residents, especially those in SFHAs did not have flood insurance (Michel-Kerjan and Kousky 2010). Other reforms to the NFIP have evolved over the years with the idea of increasing NFIP participation (policies-in-force): Cover America in 1995, Flood Insurance Reform and Modernization Act in 2007, and Homeowner Flood Insurance Affordability Act of 2014. In 1990 the NFIP introduced the Community Rating System program to encourage both local flood mitigation activity and NFIP participation.

**The Community Rating System (CRS) program**

To participate in the CRS program, a community must first be a participant of the National Flood Insurance program (NFIP). Participation in the CRS is voluntary. A community’s participation in the CRS gives its residents an opportunity to earn premium discounts on their individual policies. Thus the CRS links community-level flood
mitigation with household-level NFIP participation. CRS participating communities undertake flood mitigation activities that exceed the standard NFIP mitigation practices at the community-level. In general, flood mitigation activities may take a structural or non-structural form. Structural forms are centered on large-scale construction to include but not limited to, seawalls and channels, while the non-structural form address plans and policies such as land use planning tools, flood insurance, education and training, and emergency and recovery policies (Highfield and Brody 2013). Communities’ preferences for the two forms of flood mitigation activities has been shown to be a function of the cost involved in undertaking these activities. Highfield and Brody (2013) make the claim that CRS is more skewed toward non-structural techniques of flood mitigation. In a study by Brody et al. (2009), it was found that local jurisdictions in Florida and Texas use more non-structural flood mitigation techniques compared to the structural techniques. However, Brody, Kang, and Bernhardt (2010) also note that Florida’s measures of flood mitigation are more of the non-structural approach compared to that of Texas.

Table 2.1 contains a summary of the 19 individuals CRS activities. The activities are such that those categorized under series 300 (public information) are to motivate flood insurance purchase and also provide information to community residents as to how to reduce flood damages. Series 400 activities (mapping and regulations) involves mapping of areas onto FIRMs, protecting floodplains, managing storm water, and ensuring higher standard regulations. Activities under series 500 (flood damage reduction) involve the adoption of good floodplain management plans, relocating flood-prone structures, and maintaining community drainage systems. Series 600 activities (warning and response) seek to provide warnings of possible floods, and also respond to
flood events so as to minimize loss of life and property. Depending on the degree to which participating communities undertake these activities, communities are awarded credit points up to the maximum allowed for each activity.
<table>
<thead>
<tr>
<th>Series</th>
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<th>Activity Number</th>
<th>Maximum Activity credit points</th>
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<td>Map Information Service</td>
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<td>Outreach Projects</td>
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<td>350</td>
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<td>Hazard disclosure</td>
<td>c340</td>
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<td></td>
<td>Flood Protection Information</td>
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<td>Flood Protection Assistance</td>
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<td>Flood insurance Promotion</td>
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<td><strong>400: Mapping and Regulations</strong></td>
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<td>Flood Data Maintenance</td>
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<td></td>
<td>Storm Water Management</td>
<td>c450</td>
<td>755</td>
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<tr>
<td><strong>500: Flood Damage Reduction</strong></td>
<td>Floodplain Management Planning</td>
<td>c510</td>
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<td>Acquisition and Relocation</td>
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<td>Flood Protection Maintenance</td>
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<td>Drainage System Maintenance</td>
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<td><strong>600: Warning and Response</strong></td>
<td>Flood Warning and Response</td>
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<td>Levee Safety</td>
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<td></td>
<td>Dam Safety</td>
<td>c630</td>
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Source: NFIP CRS Coordinator’s Manual (2013)

Communities are rated based on the overall CRS credit points they receive for practicing CRS mitigation activities, ranging from 10 (lowest level of participation) to 1.
(highest). For every 500–point-increment in overall credit points, the CRS class improves (decreases). In most cases, NFIP communities that enter the CRS program for the first time are rated as class 9 (FEMA 2015), but those that do not earn at least 500 points are eventually re-classified as class 10. Class 10 communities are not eligible for premium discounts, and are classified as non-participating communities.

Table 2.2 reports the premium discounts associated with each CRS class, which differs for SFHA and non-SFHAs. Policy discounts range from 0% to 45%, in 5% increments for residents located in SFHAs. For residents in non-SFHAs, the policy discount is 10% if the community receives a class rating of 1 through 6. For communities rated class 7 through 9, residents in non-SFHAs receive a 5% discount1.

---

1 Community residents in flood zones B, C, and X with Preferred Risk Policies do not receive CRS premium discounts (FEMA, 2016). Residents of Emergency Program communities are also not eligible for CRS premium discounts
<table>
<thead>
<tr>
<th>Classes</th>
<th>Overall CRS points</th>
<th>Discount (%) in SFHA</th>
<th>Discount (%) in Non-SFHA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4,500+</td>
<td>45</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>4,000 – 4,499</td>
<td>40</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>3,500 – 3,999</td>
<td>35</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>3,000 – 3,499</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>2,500 – 2,999</td>
<td>25</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>2,000 – 2,499</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>7</td>
<td>1,500 – 1,999</td>
<td>15</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>1,000 – 1,499</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>500 – 999</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>499 and below</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: NFIP CRS Coordinator’s Manual (2013)
CHAPTER III
STUDY AREA AND DATA

In this chapter, we focus on the study area of the research, the data used to inform the analysis, and how the data were processed for analysis.

Study area

NFIP communities in the states of Alabama and Mississippi are the focus. The total number of NFIP policies-in-force in Alabama in 2013 was 58,383 of which 32,519 were from CRS participating communities. Mississippi had a total of 74,299 policies-in-force, out of which 52,866 were from CRS participating communities. In Alabama, 12 out of 428 NFIP communities participate in the CRS program while in Mississippi 31 out of 330 NFIP communities participate (FEMA 2013). In Figure 3.1, we show the distribution of CRS participation by communities in Alabama and Mississippi. Participation in the CRS is indicated by the color green. Although both coastal and noncoastal communities participate in the CRS program, there is greater participation density in the coastal areas. We focus on Alabama and Mississippi as the project is funded by the MS-AL Sea Grant Consortium (MASGC). Having said this, there are other reasons that make these states good candidates for analysis. First, Alabama and

---

2 An NFIP “community” may be an incorporated city, town, township, borough or village, any incorporated area of a county, or an entire county. It is simply a distinct geographical entity for the purpose of administering the NFIP and CRS program in that locality. In some places, an entire county is a “community”, whereas in others, a county contains multiple “communities”, depending on the need of the program.
Mississippi are coastal states which make them vulnerable to storm-surge related floods. Also Alabama and Mississippi were known to be part of five states (i.e., Texas, Florida, Louisiana, Mississippi and Alabama) with high damage claims payments (Bin, Bishop, and Kousky 2012).

This high damage claims payments could be as a result of Hurricane Katrina which occurred in 2005. Moreover, unlike Florida and Texas, no study has been conducted to find out the effect of CRS on NFIP participation and damage claims payments in these two states. Although Highfield and Brody (2013) considered Alabama and Mississippi in their sample for CRS communities, its focus of analysis did not consider NFIP participation.
Figure 3.1 A map showing CRS participation across Alabama and Mississippi
Source: John Cartwright, Geosystems Research Institute, Mississippi State University

Data and Variables

Two separate community-level panel data sets were utilized in our study. First, to estimate the effect of community-level CRS participation (versus non-participation) on household-level NFIP participation (as measured by policies-in-force), and damage claims (as measured by damage claims payments), we used data for the period 1994-2013. Second, to estimate the effect of specific community-level CRS mitigation activities (among CRS-participating communities only) on household-level NFIP participation and damage claims, we use data for the period 1998-2013. These time periods were chosen for the following reasons. First, although the CRS program began in 1990, the early years of the program were more of an experimental stage to establish the
viability of the program (Pat Skinner, personal communication, March 22, 2016). Thus participation in the early years was very low (Highfield and Brody 2013). Also the period from 1998 to 2013 was considered in estimating the effect of specific CRS mitigation activities because of lack of available data on specific CRS mitigation activities on earlier years. Data on NFIP were obtained from Janice Mitchell FEMA Region 4 office. CRS data were also obtained from Bill Lesser, FEMA CRS coordinator. Data on geospatial variables and socioeconomic variables (for the periods 2000-2013) were also obtained by John Cartwright (Geosystems Research Institute, Mississippi State University). Specifically, Cartwright’s geospatial data were from the US Geological Survey (U.S. Geological Survey 2015) and PRISM Climate Group (PRISM Climate Group 2015). Data on socioeconomic variables for the other periods (1991-2009) were obtained from the American Community Survey (American Community Survey 2015).

Dependent Variables

**NFIP policies-in-force**

Annual data on the number of NFIP policies-in-force were obtained from the Federal Emergency Management Agency (FEMA 2015) (Janice Mitchell, FEMA Region 4). NFIP policies-in-force was measured as the annual total number of NFIP policies-in-force recorded for an NFIP community. The distribution of the number of policies-in-force variable was not normal (i.e., skewness = 5.493, kurtosis = 37.427, and Shapiro Wilk normality test of 0.333 (p-value of 0.000)). Hence we log transformed to approximate a normal distribution.
**Damage claims payment**

We obtain data on damage claims payments from the Federal Emergency Management Agency (FEMA 2015) (i.e., specifically, from Janice Mitchell FEMA Region 4). We measure damage claims payment as the total dollar amount of damage claims payments recorded for a given NFIP community in a given year. Similar to the policies-in-force variable, the damage claims payments variable had a skewness of 23.974, kurtosis of 641.637, and a Shapiro-Wilk test of 0.051 (p-value of 0.000). As such, we log transform this variable to approximate a normal distribution.

**Independent Variables**

Our independent variables can generally be grouped into three: our treatment-CRS variables, geospatial controls, and socioeconomic controls. For our CRS variables, we have CRS participation and specific CRS mitigation activities.

**CRS variables**

**CRS participation**

To estimate the effect of CRS participation versus nonparticipation on outcomes, our independent variable of interest is *CRS participation*. This is measured as a binary variable that is equal to 1 if an NFIP community is participating in the CRS program in a given year and 0 otherwise. A community’s participation in CRS is based on the year in which a community enters the program. With the exception of one community (*Decatur* in Alabama) that dropped out of the CRS program in 2006, communities did not enter, exit, and re-enter the program. As mentioned earlier, since early years of the program were experimental, we consider years after 1993.
Community-Level Specific CRS Mitigation Activities

To estimate the effect of community-level specific CRS mitigation activities on outcomes, a vector of community-level specific CRS mitigation activities is used as our independent variables of interest. Data on community-level specific CRS mitigation activity were obtained from FEMA (2015) (Janice Mitchell FEMA Region 4). Out of the 19 specific CRS mitigation activities, we concentrate on 17 specific CRS mitigation activities. We drop the flood insurance promotion \( (c370) \) activity from our analysis because there were no data available on this activity for the periods considered in this research. The levee safety \( (c620) \) activity was dropped because there were no variations in levee safety data. The activities retained are elevation certificate \( (c310) \), map information service \( (c320) \), outreach projects \( (c330) \), hazard disclosure \( (c340) \), flood protection information \( (c350) \), flood protection assistance \( (c360) \), floodplain mapping \( (c410) \), open space preservation \( (c420) \), higher regulatory standards \( (c430) \), flood data maintenance \( (c450) \), floodplain management planning \( (c510) \), acquisition and relocation \( (c520) \), flood protection \( (c530) \), drainage system maintenance \( (c540) \), flood warning and response \( (c610) \), and dams \( (c630) \). Specific CRS mitigation activities were measured according to the points a community receives by FEMA for undertaking each activity. This variable is scaled (divided) by 100 in all econometric models. Specific CRS mitigation activity points were further divided by 100.
**Geospatial variables**

**Mississippi**
Mississippi is defined as 1 if an NFIP community is in Mississippi and 0 otherwise (Alabama). We identify a community in Mississippi and Alabama based on the state code associated with the community.

**Coast**
Coast is defined as 1 if an NFIP community is a coastal community and 0 if otherwise. We identify an NFIP community as a coastal community if the community is in a coastal county. The identification of a county as a coastal county is based on the National Oceanic Atmospheric Administration’s (NOAA) classification of a coastal community for census purpose (US Census Bureau 2016).

**Slope**
We utilize mean value of the slope variable in this research. The database from which the mean was computed was the National Elevation dataset (U.S. Geological Survey 2015). The slope variable was measured in degrees. It was calculated as the maximum rate of change from a given grid cell to its neighbors. Lower slope values depict flatter areas and higher slope values show steeper area. Data on slope were measured at the community-level based on a 4 kilometer grid cell. Mean value was computed by John Cartwright using the zonal statistics of the ArcGIS software.

**Stream density**
We make use of the mean value of stream density. Data from the National Hydrography dataset (U.S. Geological Survey 2015) was used in computing mean value.
Stream density was measured as the length of a stream divided by the square kilometers of an area. The stream density variable was measured at the community-level, and was based on a 4 kilometer grid cell. The computation was done by John Cartwright using the zonal statistics of the ArcGIS software. We convert the unit scale of stream density from squares kilometers to square miles by multiplying the square kilometer value by 1.609344.

**Elevation**

Data on elevation were from the National Elevation dataset (U.S. Geological Survey 2015). This was originally measured in meters above sea level as the highest point of community. However, we convert from meters to feet by multiplying the meters values by 3.2808399. Measurement was at the community-level. Data on elevation were on 4 kilometer grid cell bases. The mean values of the elevation were calculated by John Cartwright using the zonal statistics of the ArcGIS software. The elevation variable was further scaled (divide) by 100.

**Precipitation**

We utilize the PRISM Climate group database (PRISM Climate Group 2015) in computing the mean values of precipitation. The precipitation variable was measured as the annual amount of rainfall a community receives in millimeters. We convert from millimeters to inches by multiplying by 0.03937008. Data on precipitation were based on a 4 kilometer grid cell. The zonal statistics of the ArcGIS software was used in computing the mean values.
**Special Flood Hazard Area (SFHA)**

Data on these flood zones were obtained from FEMA (2016). We specify the variable SFHA as a combination of all “A” and “V” flood zones, which includes, A, AE, AO, AH, and VE. The flood zones were measured as the percent of land area in a community classified as located in the respective flood zones.

**Non-Special Flood Hazard Area (Non-SFHA)**

We use data from FEMA (2016): to measure the Non-SFHA variable. This variable was a combination of flood zones B and C. Similar to the SFHA variable, we measure the flood zones as the percent of land area in a community classified as flood zone B or C.

**Socioeconomic Variables**

**Coverage**

This is the amount of coverage that a policy covers. This variable is measured in US dollars. Data on coverage were obtained from FEMA (2015) (Janice Mitchell, FEMA Region 4). We further scale (divide) by 10,000,000 and log transform to approximate a normal distribution.

**Education**

We use percent college educated in a community. Data on percent college educated were from two sources. That is, the years 1994-2009 data were from the 1990 and 2000 US Census Bureau (2015). For the years 2010-2013, we calculate percent college educated as total number of people in a community with either a bachelor’s, master’s, professional, or doctorate degree, divided by the population and multiplied by
100. Data used in computing percent college educated were from the American Community Survey (2015). The American Community Survey data were obtained by John Cartwright.

**Household income**

The household income variable was measured in US dollars. The years 1994-2009 median income data were from the 1990 and 2000 US Census Bureau (2015). The years 2010-2013 household income data which were obtained by John Cartwright were from the American Community Survey (2015). The household income variable was further scaled (divided) by 1000.

**Number of households**

For 1994-2009 we use data from the 1990 and 2000 US Census Bureau (2015). For the years 2010-2013, we use data from the American Community Survey (2015). Data on number of households were at the community-level. Where an NFIP community bears the name of a county and within the county there is another NFIP community (a city or a town, etc.), we subtract the city or town’s number of households from the county’s total number of households to obtain the number of households for the NFIP community that bears the county name. For example, for the NFIP community called “Oktibbeha County”, we subtract Starkville’s (which is an NFIP community distinct from “Oktibbeha County” NFIP community) total number of household from the total number of households in “Oktibbeha County” to obtain the number of households for “Oktibbeha County”. We further scale (divide) by 1000
In Tables 3.2 we present a summary of the dependent variables (number of policies-in-force and damage claims payments), the CRS variables (CRS participation, SFHA, and non-SFHA), geospatial variables, and socioeconomic variables. Tables 3.3 present the summary of community-level specific CRS mitigation activities variables used in this research.

Table 3.2 Summary of dependent, CRS, geospatial, and socioeconomic variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables (N = 5860)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Policies-in-force</td>
<td>Units (1000s)</td>
<td>337.564</td>
<td>1025.239</td>
<td>0.000</td>
<td>10150.</td>
</tr>
<tr>
<td>Damage Claims Payments</td>
<td>US $</td>
<td>632408.7</td>
<td>1.08e+07</td>
<td>0.000</td>
<td>3.74e+08</td>
</tr>
<tr>
<td><strong>Independent variables (N = 293)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>Binary</td>
<td>0.107</td>
<td>0.288</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td><strong>Geospatial variables (N = 293, except for precipitation N = 5860)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mississippi</td>
<td>Binary</td>
<td>0.512</td>
<td>0.501</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Coast</td>
<td>Binary</td>
<td>0.171</td>
<td>0.377</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Slope</td>
<td>Degree</td>
<td>2.645</td>
<td>1.697</td>
<td>0.116</td>
<td>8.212</td>
</tr>
<tr>
<td>Stream density</td>
<td>miles</td>
<td>1.472</td>
<td>0.397</td>
<td>0.000</td>
<td>2.593</td>
</tr>
<tr>
<td>Elevation</td>
<td>Feet (100s)</td>
<td>345.734</td>
<td>234.188</td>
<td>1.042</td>
<td>1198.619</td>
</tr>
<tr>
<td>Precipitation</td>
<td>inches</td>
<td>57.589</td>
<td>10.934</td>
<td>25.603</td>
<td>170.795</td>
</tr>
<tr>
<td>SFHA (A &amp; V)</td>
<td>% land area</td>
<td>0.218</td>
<td>0.177</td>
<td>0.000</td>
<td>0.938</td>
</tr>
<tr>
<td>Non-SFHA (B &amp; C)</td>
<td>% land area</td>
<td>0.754</td>
<td>0.214</td>
<td>0.000</td>
<td>0.987</td>
</tr>
<tr>
<td><strong>Socioeconomic variables (N = 293)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coverage</td>
<td>US $</td>
<td>5.31e+07</td>
<td>1.93e+08</td>
<td>0.000</td>
<td>2.26e+09</td>
</tr>
<tr>
<td>Education</td>
<td>% college educated</td>
<td>16.004</td>
<td>9.210</td>
<td>4.190</td>
<td>68.820</td>
</tr>
<tr>
<td>Income</td>
<td>US $</td>
<td>29.863</td>
<td>10.123</td>
<td>10.344</td>
<td>97.020</td>
</tr>
<tr>
<td>Household</td>
<td>1000 Units</td>
<td>11.560</td>
<td>21.265</td>
<td>0.146</td>
<td>236.841</td>
</tr>
</tbody>
</table>
Table 3.3  Summary of community-level specific CRS mitigation activities

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Public Information Activities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation Certificate (c310)</td>
<td>65.517</td>
<td>13.388</td>
<td>0</td>
<td>142</td>
</tr>
<tr>
<td>Map Information Service (c320)</td>
<td>134.697</td>
<td>24.197</td>
<td>0</td>
<td>140</td>
</tr>
<tr>
<td>Outreach Project (c330)</td>
<td>114.521</td>
<td>74.109</td>
<td>0</td>
<td>350</td>
</tr>
<tr>
<td>Hazard Disclosure (c340)</td>
<td>13.788</td>
<td>18.995</td>
<td>0</td>
<td>66</td>
</tr>
<tr>
<td>Flood Protection Info. (c350)</td>
<td>31.358</td>
<td>18.375</td>
<td>0</td>
<td>102</td>
</tr>
<tr>
<td>Flood Protection Ass. (c360)</td>
<td>24.7758</td>
<td>28.969</td>
<td>0</td>
<td>68</td>
</tr>
<tr>
<td><strong>Mapping and Regulations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Floodplain Mapping (c410)</td>
<td>5.261</td>
<td>17.237</td>
<td>0</td>
<td>167</td>
</tr>
<tr>
<td>Open Space Preservation (c420)</td>
<td>71.600</td>
<td>76.092</td>
<td>0</td>
<td>388</td>
</tr>
<tr>
<td>Higher Regulatory Standards (c430)</td>
<td>226.502</td>
<td>197.026</td>
<td>0</td>
<td>885</td>
</tr>
<tr>
<td>Flood data Maintenance (c440)</td>
<td>58.523</td>
<td>48.993</td>
<td>0</td>
<td>180</td>
</tr>
<tr>
<td>Storm Water Management (c450)</td>
<td>47.229</td>
<td>50.345</td>
<td>0</td>
<td>225</td>
</tr>
<tr>
<td><strong>Flood damage reduction activities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Floodplain Management Planning (c510)</td>
<td>70.320</td>
<td>78.489</td>
<td>0</td>
<td>257</td>
</tr>
<tr>
<td>Acquisition and relocation (c520)</td>
<td>66.667</td>
<td>171.573</td>
<td>0</td>
<td>812</td>
</tr>
<tr>
<td>Flood Protection (c530)</td>
<td>2.682</td>
<td>13.037</td>
<td>0</td>
<td>84</td>
</tr>
<tr>
<td>Drainage System Maintenance (c540)</td>
<td>197.369</td>
<td>113.902</td>
<td>0</td>
<td>330</td>
</tr>
<tr>
<td><strong>Warning and Response Activities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flood Warning and response (c610)</td>
<td>40.919</td>
<td>61.587</td>
<td>0</td>
<td>205</td>
</tr>
<tr>
<td>Dam Safety (c630)</td>
<td>40.349</td>
<td>31.182</td>
<td>0</td>
<td>68</td>
</tr>
</tbody>
</table>

N = 528
Data processing

All of the above data were merged into a single dataset by cross-referencing FEMA community identification codes, community name, state FIPS (Federal Information Processing Standard) codes, county FIPS codes, American National Standards Institute (ANSI) codes, FIPS entity codes, and year. The merging process was done using Microsoft Excel and ArcGIS software, in cooperation with John Cartwright. NFIP communities with less than 20 policies-in-force in more than 18 periods were dropped from the dataset. Omission of these observations was necessary because some NFIP communities had zero or single-digit policies-in-force.
CHAPTER IV
MATCHING

This chapter introduces and discusses the matching process used in the research. We look at the general concept of matching, and the main matching methods within the matching literature. We also discuss how we applied matching to our dataset, and present a results summary on the outcome of the matching.

In the matching literature, studies that have evaluated the impact of program interventions have shown the importance of selecting units that received, and those that did not receive, program intervention in a way such that selection bias is eliminated (Rosenbaum and Rubin 1983; Rubin and Thomas 2000; Stuart and Green 2008). To do this, the literature suggests using matching to obtain balance (Rubin 1980; Rosenbaum and Rubin 1983). By balancing, one ensures that the distributions of the covariates (here the control variables) for the treatment group (i.e., units that received program intervention) and the control group (i.e., units that did not receive program intervention) do not differ. It is when balance is achieved that one can compare the treatment group to the control group to determine the impact of the program. Thus matching is used to select units (both from the control group and treatment group) that share similar characteristics (Rubin 1980; Rosenbaum and Rubin 1983). Although one matches on covariates of units from the treatment group and that of the control group, matching becomes difficult when there are more than two covariates. To overcome this, three main
approaches have been identified in the matching literature: matching on metric distance (Mahalanobis-metric distance) (Rubin 1980), matching on propensity scores (Rosenbaum and Rubin 1983), and genetic matching (Diamond and Sekhon 2013).

As a scalar quantity, the Mahalanobis metric-distance (MD) measures the multivariate distance existing between the units of the treatment group and that of the control group (Rubin and Thomas 2000; Diamond and Sekhon 2013). Assuming there are $X$ covariates for units $i$ and $j$ of the treatment group and the control group, respectively, the MD between the covariates is specified as

$$
MD_{(X_i, X_j)} = \sqrt{\left( X_i - X_j \right)^T Z^{-1} \left( X_i - X_j \right)}
$$

where $Z$ is the sample covariance of the covariates $(X)$. Generally, the Mahalanobis metric-distance performs better (in terms of balancing) when covariates are ellipsoidally distributed (Rubin 1980; Diamond and Sekhon 2013). Also, an increase in the number of covariates matched on could distort the ability of the Mahalanobis metric-distance matching to find units with similar distribution of covariates (Gu and Rosenbaum 1993; Rubin and Thomas 2000).

As an alternative, one may match on the propensity scores as suggested by Rosenbaum and Rubin (1983) if the covariates are distributed non-ellipsoidally. The propensity score measures the likelihood that a unit will receive the treatment, conditioned on the covariates. Following Rosenbaum and Rubin (1983), we define the propensity score $P(X)$ as

$$
P(X) \equiv \text{Prob} \left( \text{treatment} = 1 \mid X \right)
$$
To estimate the propensity score in equation 8, a probit or logit function is used. However, the choice of a probit or logit function does not lead to significant differences in propensity scores (Caliendo and Kopeining 2008). A poorly-specified propensity score model could worsen the balancing situation and also bias the estimates of the outcome (Diamond and Sekhon 2013).

A more general form of the Mahalanobis metric distance is the genetic matching, as proposed by Diamond and Sekhon (2013). What makes the genetic matching unique is that unlike the other matching methods, it uses a search algorithm in locating a metric distance that optimizes covariate balance. With the genetic matching, for each covariate, weights are assigned to the calculated metric distance between the treated units and the control units. The weights determine the contribution of the units to achieving balance (Diamond and Sekhon 2013). Following Diamond and Sekhon (2013), the generalized Mahalanobis distance is defined as

$$GMD_{(x_i, x_j, w)} = \sqrt{(x_i - x_j) W Z^{-1/2} \left(Z^{-1/2}\right)' (x_i - x_j)'}$$ \hspace{1cm} (4.3)

where $Z^{-1/2}$ is the sample covariance of the covariates (Cholesky decomposition of $Z$), and $X$ is still defined as the covariates. The covariates could be replaced with estimated propensity scores or one can include both the estimated propensity scores and the covariates. $W$ is the weight matrix which is positive definite with the off-diagonal elements being zero.

After estimating the Mahalanobis distance (MD), the propensity scores ($P(X)$), or the generalized Mahalanobis distance (GMD), a matching algorithm is used to select the units from the control and treatment groups (Diamond and Sekhon 2013). Various
matching algorithms have been discussed in the literature (Sianesi 2001; Stuart and Greene 2008; Dehejia and Wahba, 2002; Diamond and Sekhon 2013) to include nearest-neighbor, radius, caliper, and stratification. The Nearest-neighbor matching may involve matching with replacement or without replacement. The matching algorithm is performed such that for every unit of the treated group, \( m \) units from the control group are identified and matched. Although with replacement a greater number of units from the control group are kept, one cannot rule out biasness in estimates (Stuart and Green 2008; Dehejia and Wahba 2002). The closer the distance or the propensity scores the better the match. For Radius matching algorithm, a neighborhood (radius) for the treated, and control group is defined, and all treated and control units that fall in the neighborhood are seen as matches. The choice of neighborhood can affect the matching efficiency. For example, a smaller neighborhood can increase matching efficiency.

However, one may lose both treated and control units. The caliper matching algorithm can be seen as a combination of nearest-neighbor and radius matching algorithm. Thus, for caliper matching algorithm, a control unit is matched to the treated unit if, for example, the control unit’s propensity score falls within a given caliper. Within the caliper, one could use the nearest-neighbor to find matches. Stratification matching involves grouping, for example the estimated propensity scores, into blocks based on variations in the scores. The grouping is done such that, within a block, the treated and control group will have the same average propensity scores. The problem with this matching method is that it throws away units from both groups if either of them is not found to belong to a block.
Studies that have examined causal relationships using panel data have also employed matching in their studies (Girma, Greenaway, and Richard Kneller 2004; Yasar and Rejesus 2005; Wagner 2002). In this research we employ the genetic matching. We use the nearest neighbor matching algorithm to select units from the treatment group and control group. Specifically, for each treated unit we identify three units \( m = 3 \) from the control group that are closer in distance. We mention here that we perform matching on a subset of our dataset. Thus we consider units (NFIP communities both treated and control) for the year 2013 when performing the GenMatch. This was to ensure that we maintain a dataset that is balanced (i.e., balanced in terms of each NFIP community having the same number of periods, 1994-2013) after the matching for further regression analysis. Although this may have some limitation to our findings, most of the pre-treatment covariates we match on are time-invariant. Thus since the values of most covariates do not change over time for a given NFIP community, matching using data on one year period (2013) shouldn’t lead to any significant change in results if any. We choose the year 2013 because in 2013, most NFIP communities had joined the CRS program.

We use the \( R \) (version 3.3.0) statistical package in performing the GenMatch. First, we categorize our data into CRS participating communities (treatment group) and non-participating communities (control group). The categorization is based on community’s participation during the most recent year observed (i.e., 2013). We estimate the average treatment effect on the treated (ATT) of CRS participation on NFIP policies-in-force rate. Estimating the ATT here was not our primary aim. However, this was used in the process of obtaining our matched sample. We included estimated propensity
scores, higher order, and interaction terms of the covariates that were continuous, in the GenMatch function in R. The GenMatch algorithm then assigns weights to the covariates such that, the weights depict the importance of the covariates in achieving balance. The weights generated by GenMatch were then fed into the Match function in R, together with the covariates. In both the GenMatch and the Matched functions in R, we use the nearest neighbor with replacement. The Match function yields a final set of weights that identify our final matched sample (where control units are weighted based on the number of times each is used as a match, and where all treatment units received a weight of one). We present the covariates used in the matching process in Table 4.1.

Table 4.1 Covariates used in the GenMatch.

<table>
<thead>
<tr>
<th>Time-invariant pre-treatment covariates</th>
<th>Time-varying pre-treatment covariates</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFHA</td>
<td>Education</td>
</tr>
<tr>
<td>non-SFHA</td>
<td>Income</td>
</tr>
<tr>
<td>Slope</td>
<td>Households</td>
</tr>
<tr>
<td>Stream density</td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td></td>
</tr>
<tr>
<td>Mississippi</td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td></td>
</tr>
</tbody>
</table>

We exclude the precipitation variable from the set of pre-treatment covariates when performing the genetic matching because it reduces balance. As recommended by Ho et al. (2007), although by theory one has to account for all variables that otherwise
would have been used in a regression, not all pre-treatment covariates are to be used especially when including them in the matching process leads to inefficiency (balance).

**Summary of Matching Results**

In Table 4.2, we show the means of the covariates before and after the matching. It is clearly seen from Table 4.2 that, unlike the means of the covariates for the control group that varies before and after the matching, that of the treatment group stay constant before and after the matching. Thus all the units from the treatment group found matches from the control group but not the vice versa.

<table>
<thead>
<tr>
<th>Variables</th>
<th>mean of treatment</th>
<th>mean of control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before match</td>
<td>After match</td>
</tr>
<tr>
<td>Coast</td>
<td>0.488</td>
<td>0.488</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.721</td>
<td>0.721</td>
</tr>
<tr>
<td>SFHA</td>
<td>0.297</td>
<td>0.297</td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>0.661</td>
<td>0.661</td>
</tr>
<tr>
<td>Slope</td>
<td>1.978</td>
<td>1.978</td>
</tr>
<tr>
<td>Stream density</td>
<td>1.279</td>
<td>1.279</td>
</tr>
<tr>
<td>Elevation</td>
<td>218.780</td>
<td>218.780</td>
</tr>
<tr>
<td>Income</td>
<td>44646</td>
<td>44646</td>
</tr>
<tr>
<td>Education</td>
<td>0.179</td>
<td>0.179</td>
</tr>
<tr>
<td>Household</td>
<td>14265</td>
<td>14265</td>
</tr>
</tbody>
</table>
In Figure 4.1, we also show the distribution of the covariates before and after matching. We expect that after matching, the distribution of pre-treatment covariates will be similar for CRS participating communities, and non-participating communities. To examine the appropriateness of our matching, we follow Ho et al. (2007) to construct quantile-quantile plots (QQ-plot) of the pre-treatment covariates used in the genetic matching. For binary variables coastal and Mississippi, we exhibit the distributions using the histogram. Shown are the distributions of covariates before and after matching. In the QQ plots, points more proximal to the 45° line depict good matches, whereas points more distant to the 45° line indicate poor matches between the treatment units and the control units. With the histogram, for a good match, the bars for the treated and the control units should be at par or close to that relative to before matching. A visual examination of the QQ plots shows that, pre-treatment covariates such as elevation, slope, SFHA, income, and education for CRS participating (treatment group) and non-participating communities have similar distribution after the genetic matching was done relative to before the matching. On the other hand, the distribution of pre-treatment covariates such as stream density and non-SFHA for CRS participating and non-participating communities were not the best both prior to matching and after matching. The histogram shows good distribution for coast and Mississippi after matching.
Figure 4.1  QQ plots showing the distribution of pre-treatment covariates before and after matching
Figure 4.1 (continued)
CHAPTER V
CONCEPTUAL FRAMEWORK

In this chapter, we discuss the conceptual framework for the research. Our analysis is conducted at the community level, and thus we rely heavily on previous research also conducted at the community, county, or other aggregate level. However, our analysis can nevertheless be informed by previous research conducted at the individual level, under the assumption that behavioral relationships at play at the individual level are reflected in the relationships at the community level. In fact, our community-level data are merely the product of thousands of insurance purchase decisions made at the individual level. At the community level, the explanatory variables will be aggregate measures, and these aggregate measures may serve as reasonable proxies for the effects, on average, at the individual level. For example, if a higher-income household is hypothesized to be more likely to purchase insurance, *ceteris paribus*, then a community with higher median income is hypothesized to be more likely to have a higher rate of insurance at the community level. We present a summary of the literature on factors affecting the choice to purchase flood (and closely related) insurance, and develop some testable hypotheses based on past findings.

**Demand for Insurance**

In the insurance literature, different theories (expected utility, prospect theory, subjective expected utility, and random utility theory) have been used to explain peoples’
demand for insurance and/or, coverage level (Smith 1968; Smith and Baquet 1996; Coble et al. 1996; Marquis and Long 1995; Kriesel and Landry 2004; Schmidt and Zank 2007; Landry and Jahan-Parvar 2011; Petrolia, Landry, and Coble 2013; Petrolia et al. 2015). These theories assume that a rational individual makes decisions based on utility maximization. On a general note, individuals’ utility for insurance and coverage demand has been defined over factors such as wealth, insurance prices, education, risk preferences, and subjective risk perception (Smith and Baquet 1996; Coble et al 1996; Marquis and Long 1995; Browne and Hoyt 2000; Landry and Jahan-Parvar 2011; Kousky 2011; Petrolia, Landry, and Coble 2013; Petrolia et al 2015). Smith and Baquet (1996) observed in their study that farm operators’ level of education is positively related to their decision to demand for multiple peril crop insurance. Coble et al. (1996) finds a negative relationship between crop producers’ wealth and the likelihood that they will purchase crop insurance. Smith and Baquet (1996) mention that wealthier farm operators are more likely to self-insure than buy insurance. Marquis and Long (1995) finds income to be positively related to demand for health insurance by non-employment based workers. Petrolia et al. (2015) also finds a positive relationship between the log of income and wind insurance purchase. They also find that relative to non-coastal residents, a positive relationship exists between residents from the coastal zone and wind insurance purchase. In that same study, they find a positive relationship between homeowners’ risk aversion and wind insurance purchase. Specific to flood insurance demand, Browne and Hoyt (2000), and Kriesel and Landry (2004), analyzed factors affecting demand for flood insurance and finds a negative relationship between insurance price and flood insurance demand. Other factors such as income have also been found to be positively related to
flood insurance demand (Browne and Hoyt 2000; Kriesel and Landry 2004; Kousky 2011; Petrolia, Landry, and Coble 2013). Kriesel and Landry (2004) also find that artificial flood mitigation (seawalls) has a positive effect on NFIP participation. On the other hand, Petrolia, Landry, and Coble (2013) find a negative relationship between flood mitigation (CRS score) and insurance demand. Browne and Hoyt (2000) also find a negative effect of federal spending on flood mitigation on flood insurance demand. The study by Petrolia, Landry, and Coble (2013) finds a positive relationship between individuals located in SFHA and insurance demand. Dixon, Macdonald, and Zissimopoulos (2007) who looked at commercial wind insurance in the Gulf States have mentioned that rising demand for insurance for properties in the Gulf and Atlantic Coast can be explained by the increasing population growth and property values.

In this research we follow Petrolia, Landry, and Coble (2013) in assuming that homeowners’ decision to purchase a flood insurance policy can be conceptualized on the bases of subjective expectation of utility. We first assume that the individual homeowner in community $i$ aims at maximizing subjective expectation of utility for flood insurance such that the decision to take-up or no-take-up of flood insurance policy can be stated as

$$ EU_{ri}^{take-up/no-take-up} = (P(C, F, H, B), \gamma(G), S) $$  (5.1)

Where $P$ is the insurance premium, $C$ is the CRS credit points in community $i$, $F$ is the various flood zones in community $i$, $H$ represents hydrological factors such as rainfall, and $B$ is building characteristics. Gamma ($\gamma$) represents the property owner’s subjective perception of flood risk. $G$ is the geospatial setting of community $i$, and $S$ is the socioeconomic characteristics of the individual in community $i$. We assume that insurance premium ($P$) is itself a function of CRS class ($C$) (the CRS class depends on
the overall CRS points), flood zone (F), building characteristics (B), and hydrological factors such as rainfall (H). Homeowners’ subjective perception of flood risk (γ) is assumed to be a function of factors including but not limited to geospatial factors (G).

Homeowner (r) will choose to take-up flood insurance policy if the subjective expectation of utility of taking-up flood insurance policy is greater than the subjective expectation of utility of not taking-up flood insurance policy. That is, \( EU_r(\text{take-up}) > EU_r(\text{no-take-up}) \).

However, our data is aggregated at the community-level. Thus, we assume that if individual homeowner’s subjective expectation of utility for flood insurance policy is greater than not taking-up flood insurance policy, then each take-up of flood insurance policy adds to the number of flood insurance policies (NFIP policies-in-force) in community \( i \) and vice versa. That is individual homeowners’ flood insurance policy take-up is seen as a share of the aggregate number of NFIP policies-in-force in community \( i \).

We therefore assume that the aggregate number of NFIP policies-in-force (Q) in community \( i \) at time \( t \) is defined as

\[
Q_{it} = \sum_{i=1}^{n} q_{rit}.
\]  

(5.2)

Where, \( q_{rit} \) is 1 if individual homeowner \( r \) takes-up NFIP policy and 0 if no-take-up of NFIP policy in community \( i \) at time \( t \).

In our conceptual framework, we assume that as a proxy for homeowners’ perception of flood risk, homeowners residing in coastal communities, low-lying areas or floodplains, communities with higher percentage of land area covered by water, and communities with high annual rainfall will have a higher perception of flood risk relative to residents in; non-coastal communities, communities with higher elevation, and
communities that observe less annual rainfall, all else equal. As a matter of fact, these variables may serve as an objective measure of flood risk which makes them good proxies for individuals’ subjective measures of flood risk. Hence these variables could influence homeowner’s flood insurance purchase.

**Damage claims payments**

Differences in individual’s wealth could also affect decision to file for damage claims. Thus since people’s marginal utility decrease as their wealth increases, it is logical to expect wealthier policy holders to have lower motivation of filing for damage claims (Cummins and Tennyson 1996). However, one could also expect that when a damage event occurs, claims payments made to wealthy individuals will be higher, relative to low income earners given that wealthier people have larger coverage. With regards to floods, factors such as heavy rains, and other storm surge events resulting from hurricanes are seen as determinants of claims payments (Spekkers et al., 2013). Michel-Kerjan, and Kousky (2010) notes that the average claim payments varied for V flood zones, and A flood zones in Florida, with the V flood zones having a greater amount of claims payments. That is, it is assumed that the flood zone area of the household affects damage claims payments. In regards to this, since V flood zones are related to the coastal areas and A flood zones are related to the non-coastal areas (although both zones are classified as high flood risk zones (SFHA)), it can be hypothesized that damage claims payments are of different magnitudes among coastal and non-coastal areas. Highfield and Brody (2013) also find a positive relationship between precipitation and damage claims payment. Highfield and Brody (2013) also find population to be positively related to damage claims payments.
Similar to policies-in-force which we observe at the community-level, damage claims payments made to individual household is assumed to adds-up to the aggregate at the community-level. That is, we assume that for every addition to the number of policy holders filing for damage claim, total claims payments increases. Hence we state that $d_{rit}$, the damage claims payment made to individual household $(r)$ in community $(i)$ at time $(t)$, is aggregated across individual claimers within the community at time $t$ as

$$D_{it} = \sum_{r=1}^{n} d_{rit} \quad (5.3)$$

where $r = 1, 2, \ldots, n$, and $t = 1, 2, \ldots, T$.

Based on findings from past studies (Smith 1968; Smith and Baquet 1996; Coble et al. 1996; Marquis and Long 1995; Kriesel and Landry 2004; Schmidt and Zank 2007; Landry and Jahan-Parvar 2011; Petrolia, Landry, and Coble 2013; Petrolia et al. 2015), on factors that affects demand for insurance and also factors that affects damage claims payments (Cummins and Tennyson 1996; Michel-Kerjan and Kousky 2010; Highfield and Broody 2013), we assume that at the aggregate level, NFIP policies-in-force and damage claims payments $(y_i)$, are a function $(f)$ of flood mitigation (CRS), geospatial factors of the community, and socioeconomic factors. That is,

$$y_i = f(\text{CRS, Coast, Mississippi, Precipitation, Elevation, Slope, Stream density, SFHA, Non-SFHA, Coverage, Education, Income, and Household}) \quad (5.4)$$

**Hypotheses**

Based on our conceptual framework, and what past studies have found, we hypothesize the following relationships in Table 5.1.
Table 5.1  Hypothesized relationships between dependent and independent variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition of variables</th>
<th>Hypothesized signs on NFIP participation</th>
<th>Hypothesized signs on Damage Claims</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRS</td>
<td>1 = CRS Community, 0 = otherwise</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Coast</td>
<td>1 = located in NOAA-designated coastal county, 0 = otherwise</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Mississippi</td>
<td>1 = Mississippi community, 0 = otherwise</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Annual amount of rainfall in inches</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Elevation</td>
<td>Highest point of a community in</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Slope</td>
<td>Maximum rate of change from a grid cell to its neighbor</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>Stream density</td>
<td>Length of stream divided by square miles of an area within the community</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>SFHA</td>
<td>Percent of land area in flood zones A + V</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>Percent of land area in flood zones B + C</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Education</td>
<td>% College educated</td>
<td>+</td>
<td>?</td>
</tr>
<tr>
<td>Income</td>
<td>Median household income ($)</td>
<td>+</td>
<td>?</td>
</tr>
<tr>
<td>Households</td>
<td>Number of households</td>
<td>?</td>
<td>?</td>
</tr>
</tbody>
</table>
CHAPTER VI
ECONOMETRIC MODEL AND ESTIMATION

In this chapter of the research, we discuss the econometric model as well as method of estimation. The chapter begins by introducing the various models for panel data and estimation. The chapter ends with the empirical model and estimation approach for the research and model selection process.

Modelling Panel Data

To begin with, a simple econometric model would be such that

\[ y_i = \alpha + x_i'\beta + \varepsilon_i \]

(6.1)

where \( y_i \) is the dependent variable, \( \beta \) is a vector of parameters to be estimated, \( x_i \) is a vector of independent variables, and \( \varepsilon_i \) is the error term. However, given that our data are a panel, we need to account for the time series aspect. Thus the model above only accounts for cross-section. Panel data are data with repeated observations (responses) on an individual unit. That is, it has a cross sectional-dimension (N) and a time series dimension (T) (Wooldridge 2002). Some advantages of using panel data are that it gives room to account for individual heterogeneity, and also good for studying dynamic relationships (Greene 2012; Wooldridge 2002). There are some challenges in using panel data. Panel data have issues of autocorrelation, heteroskedasticity, and endogeneity
To account for both the cross-section and time series dimension, we may rewrite equation 6.1 as,

\[ y_{it} = x_{it}'\beta + z_i'\alpha + \epsilon_{it} \]  

(6.2)

where, \( y_{it} \) is the dependent variable we seek to explain, \( x_{it} \) is a vector of covariates, \( \beta \) is a vector of parameters, \( z_i \) is a vector of observed or unobserved factors (heterogeneity or individual effects), \( \alpha \) is the associated vector of parameters, and \( \epsilon_{it} \) is the error term. The subscripts \( i \) and \( t \) are the units (in our case, the communities) and time (year) respectively. Should \( z_i \) be unobserved, then

\[ y_{it} = x_{it}'\beta + c_i + \epsilon_{it} \]  

(6.3)

where \( c_i \) is the unobserved heterogeneity. The vector of covariates may include variables that remain constant over time but vary across individual units, variables that are constant over time and across individual units, variables that change over time and across individual units and those that vary over time but constant across individual units.

Panel data may be modeled as pooled (also known as population average model), fixed-effects, or random-effects model. The fixed-effects and random-effects models are usually referred to as unobserved effects models (Wooldridge 2002; Greene 2012; Baltagi 2008). Mundlak (1978) proposes an approach for modeling panel data when unobserved heterogeneity is assumed. This approach is seen as a settlement of the differences between the fixed-effects and the random-effects model (Greene 2012). The distinction between pooled, fixed-effects, random-effects, and Mundlak’s (1978) model is made based on the assumption that underlies the conditional mean, \( E[c_i|x_i] \), of the
unobserved heterogeneity \( (c_i) \) in equation 6.3. We discuss these models (pooled, fixed-effects, random-effect, and Mundlak’s approach) next.

**Pooled model**

The pooled model (population averaged model), assumes that

\[
E[c_i | x_i] = h(x_i) = \alpha, \quad \text{where} \quad \alpha \text{ is a constant.}
\]

That is, there are no unobserved individual-specific effects \( (c_i) \) in the pooled model. It is referred to as the population averaged model because it assumes there is no heterogeneity in the model, and that all units have the same constant (intercept). From equation 6.3, a pooled model can be specified as

\[
y_{it} = x_i'\beta + \alpha + \epsilon_{it} \quad (6.4)
\]

The pooled model further assumes that

\[
E[\epsilon_{it} | x_{i1}, x_{i2}, \ldots x_{iT}] = 0 \quad \text{(strict exogeneity)}, \quad \text{Var}[\epsilon_{it} | x_{i1}, x_{i2}, \ldots x_{iT}] = \sigma^2 \quad \text{(homoscedasticity)}, \quad \text{Cov}[\epsilon_{it}, \epsilon_{is} | x_{i1}, x_{i2}, \ldots x_{iT}] = 0 \quad \text{if} \quad i \neq j, \quad \text{and} \quad t \neq s \quad \text{(no serial correlation).}
\]

Here both time-varying, time-invariant variables, and time-period dummies can be estimated.

**Fixed-effects model**

Unlike the random-effects model, the fixed-effects model allows the individual heterogeneity to be correlated with the observed independent variables (Greene 2012). For the fixed-effects model, it is assumed that \( E[c_i | x_i] = h(x_i) = \alpha_i \). The fixed-effects model can be specified as

\[
y_{it} = x_i'\beta + \alpha_i + \epsilon_{it} \quad (6.5)
\]
where $\alpha_i$ represents a constant term for a particular unit. Thus fixed-effects models assume that $E[\mu_i | x_i] \neq 0$, hence $\text{Cov}[\mu_i, x] \neq 0$. The unobserved heterogeneity is assumed to be absorbed into the error term $\varepsilon_{it}$. It is important to mention that for the fixed-effects model, time-invariant covariates cannot be estimated because they are confounded with the unit-specific constants (Wooldridge 2002; Greene 2012). Only time-varying variables and time-period dummies are allowed. A fixed-effect model maybe a one-way or a two-way fixed-effect. A one-way fixed-effects model have different constant for the individual units, and the two-way fixed effects model contains a constant for each of the individual units as well as a constant for each of the individual time period.

**Random-effects model**

The random-effects model, assumes the presence of unobserved individual-specific effects (individual heterogeneity) are not correlated with the independent variables. Thus, for random-effects model, $E[c_i | x_i] = 0$. From equation 6.3 the random-effect model is

$$y_{it} = x'_{it} \beta + (\alpha + \mu_i) + \varepsilon_{it}$$

(6.6)

where $\alpha$ is the average of the unobserved-individual heterogeneity, and $\mu_i$, which is allowed to vary cross individual units, is the random unobserved-individual heterogeneity. The random-effects model further assumes that, $E[\mu_i | x_i] = E[\varepsilon_i | x_i] = 0$ (strict exogeneity), $E[\varepsilon^2_{it} | x_i] = \sigma^2_{\varepsilon}$, $E[\mu^2_i | x_i] = \sigma^2_{\mu}$, $E[\varepsilon_{it}\mu_i | x_i] = 0$ for all $i, t,$ and $j$, and
E[ε_{it}ε_{js}|X] = 0 \text{ if } t \neq s \text{ or } i \neq j. \text{ For random-effects model, time-variant variables, time-invariant variables, and time-period dummies can be estimated (Wooldridge 2002; Greene 2012).}

**Mundlak (1978) approach**

The assumption Mundlak (1978) approach makes about the conditional mean of the unobserved heterogeneity is that, \( E[c_i | X_i] = h(X_i) = \bar{x}'\gamma \). From equation 6.3, the model for Mundlak’s approach of dealing with the heterogeneity is specified as,

\[
y_{it} = x_{it}'\beta + \bar{x}'\gamma + \mu_i + \epsilon_{it} \tag{6.7}
\]

Unlike the fixed-effects model and the random-effects model, the Mundlak (1978) approach attempts to account for heterogeneity via group-mean variables. I.e., he adds to the model variables whose observed values are the means over time for each individual of the time-varying variables already included in the model. For example, if an income variable is included in the model that varies over time, then an additional group-mean income variable would also be included that repeats the mean of a given individual’s income over all of that individual’s observations. The Mundlak approach is similar to the random-effects model just that here, the correlation between the observed covariates and the unobserved heterogeneity are addressed by adding the group-means of the time-varying covariates (Greene 2012). As noted by Greene (2012), the Mundlak approach can be used as a compromise between the fixed and random-effects models. This model can include both time-varying and time-invariant variables, as well as time-period dummies.
Empirical Models and Estimation

We construct our empirical models based on the objectives of the research. To begin with, we first let

\[ y_{it} = \begin{cases} \log \text{ of NFIP policies - in - force} \\ \log \text{ of damage claims payments} \end{cases} \] (6.8)

Based on our conceptual framework, we specify our base econometric model for estimating the effect of CRS participation on the log of NFIP policies-in-force and on the log of damage claims payment as

\[ y_{it} = \alpha + x_{it}'\beta + \varepsilon_{it} \] (6.9)

where, \( \alpha \) is the intercept, \( x_{it} \) is a vector of time-varying and time-invariant independent variables: CRS, income, education, number of households, precipitation year, Mississippi, coast, slope, stream density, elevation, special flood hazard area (SFHA), and non-special flood hazard area (non-SFHA). Other independent variables we include when considering the log of NFIP policies-in-force are; time trend and a dummy for Post-Katrina. For log of damage claims payments, we add to the independent variables, year dummies and log of coverage amount. \( \beta \) is a vector of parameters to be estimated. The subscripts \( i \) and \( t \) are the communities and the response year respectively. \( \varepsilon \) is the error term in the model.

In a different analysis where we estimate the effect of community-level specific CRS mitigation activities on outcome, we replace the CRS variable (a binary variable) with the specific CRS mitigation activities (continuous variables).
Testing for model assumptions

To effectively estimate and test for the relationship that exist between the dependent variable and the independent variables, the assumptions that underlie the various panel data models must be considered. When issues of serial autocorrelation, heteroskedasticity, and contemporaneous correlation the estimates become inefficient and also standard errors are biased. That is, we test for possible serial correlation, heteroskedasticity, and contemporaneous correlation. We use Wooldridge’s test for serial correlation (Wooldridge 2002) and the Pesaran (2004) test for contemporaneous correlation. To test for the presence of heteroskedasticity, we use White’s general test for heteroskedasticity. The Hausman test is used to test the fixed-effects model assumption against the random-effects model assumption. However, the fixed-effects model is limited in that effects of time-invariant variables that may be of interest to the researcher cannot be estimated.

Serial autocorrelation occurs when the errors are correlated across-tome within a unit. The Wooldridge (2002) test for serial correlation uses the residuals obtained from estimating the regression by first-differencing. The residuals are then regressed on the lag of the residuals and a test that the parameter of the lagged residuals is equal to -0.5 is carried out. Where there is no serial correlation, the $\text{Corr} \left[ \Delta \epsilon_{it}, \Delta \epsilon_{it-1} \right] = -0.5$. The test is ultimately performed under the null hypothesis that, there is no serial correlation (Wooldridge 2002; Drukker 2003).

The Pesaran (2004) test for contemporaneous correlation or cross-section dependence is used when one has a large number of units (N) and a relatively small number of time periods (T). Cross-sectional dependence may occur due to common
shocks and other unobserved factors that are assumed to be part of the error term. This test is based on a pair-wise correlation coefficient. The null hypothesis to be tested here is that, $\text{Corr} \left[ \varepsilon_u, \varepsilon_{jt} \right] = 0$. In other words, $\varepsilon_u$ and $\varepsilon_{jt}$ are independently distributed and serially uncorrelated (Pesaran 2004; Hoyos and Sarafidis 2006).

White’s test for heteroskedasticity performs better in situations where the errors are not normally distributed. The White test does not require the specification of the structure of the heteroskedasticity (White 1980; Greene 2012). The null hypothesis to be tested here is that the errors are homoscedastic (constant variance of the errors) the test is based on a chi-squared distribution with $k-1$ degrees of freedom (Greene 2012). The letter $k$ is the number of parameters.

To test if there are no individual-effects and that the pooled model (base model) is preferred to the random-effects or fixed-effects model, the Breusch-Pagan (B-P) Lagrange multiplier test is used to test the null hypothesis that there are no individual-effects. The computation of the test statistic is based on the residuals from the pooled model. The Breusch-Pagan Lagrange multiplier test uses the chi-square test statistic with 1 degree of freedom. Where the value of the test statistic is large, the individual-effects model is preferred to the base model (pooled) (Greene 2012). An alternative to the Breusch-Pagan test is the Baltalgi-Li test which is also based on a chi-squared test statistic. Where the data is balanced, the two approaches are the same (Greene 2012).

The Hausman (1978) specification test for fixed and random-effects model test the null hypothesis that the unobserved heterogeneity are correlated with the observed independent variables (Greene 2012). In other words, the null hypothesis is that the
preferred model is random-effects. The Hausman test uses the chi-square test statistic distribution with k-1 degrees of freedom (Greene 2012).

For the Mundlak (1978) approach, we follow Wu’s (1973) variable addition test to test the null hypothesis that the parameters of the means of the time-varying variables included in the model are not different from zero. The test statistic is based on a chi-square distribution. Wu’s test is also seen as an alternative to the Hausman test for random-effects vs. fixed-effects (Greene 2012).

We test for the presence of serial autocorrelation, contemporaneous correlation, and heteroskedasticity using Stata (v.14.1). Specifically, in Stata, to test for serial correlation using the Wooldridge (2002) approach, we use the \textit{xtserial} command (Drukker 2003). To test for contemporaneous correlation, we use the \textit{xtcsd} command in Stata (Hoyos and Sarafidis 2006). White’s general test for heteroskedasticity is performed using the \textit{estat imtest, white} command in Stata.

The Breusch-Pagan (B-P) Lagrange multiplier test is obtained after running the pooled model in NLOGIT. Similarly, the Wu’s test statistic is reported after running the Mundlak’s random-effects model by including means of time-varying variables in the random-effects model in NLOGIT.

**Results on Model assumption test**

Presented in Table 6.1 are the results on the tests for serial correlation, contemporaneous correlation, heteroskedasticity, test for pooled vs random or fixed-effects, test for random vs. fixed-effects, and the Wu’s test for the inclusion of means of time-varying independent variables. From the results, we find the presence of serial correlation, contemporaneous correlation, and heteroskedasticity, when considering the
unmatched and matched data for estimating CRS participation effects on NFIP policies-in-force. The results also show evidence of contemporaneous correlation and heteroskedasticity when we consider the unmatched data for estimating effects of CRS participation on damage claims payments. For matched data we find only heteroskedasticity. For data including claims greater than zero only, we find evidence of serial correlation and heteroskedasticity. We also find serial correlation and heteroskedasticity for the specific CRS mitigation activities effects on NFIP policies-in-force. We do not find serial and heteroskedasticity for specific CRS mitigation activities effects on damage claims payments.

Results on the tests for assumptions on the individual effects (pooled vs random or fixed-effects, random vs. fixed-effects, and test for the inclusion of the means for time-varying independent variables) also show that, for both unmatched and matched data for the effects of CRS participation on NFIP policies-in-force, the random-effects or the fixed-effects is preferred to the pooled model. The Hausman test for random-effects vs. fixed-effects shows that the fixed-effects model is preferred to the random-effects model. Results on Wu’s test also favors the fixed-effects model since we reject the null hypothesis that the parameters of the group means are equal to zero. That is, the test shows that the Mundlak’s random-effects model does not mimic a standard random-effects model, but rather a fixed-effect model.

With regards to the effect of CRS participation on damage claims payments (unmatched data), we observe from the results in Table 6.1 that, the individual effects model (random or fixed-effects) is preferred to the pooled model. The Hausman test result indicates that the fixed-effects specification is the preferred model, and Wu test
also the group-mean effects are significant. This finding indicates that the Mundlak approach can be used to mimic the fixed-effects model while also allowing for the estimation of time-invariant geospatial variable effects. Considering the effect of CRS participation on damage claims payments (matched data), the test results show that the fixed-effects or random-effects is preferred to the pooled model. The Hausman test for fixed-effects vs. random-effects indicates that the random-effects model is preferred to the fixed-effects model, and the Wu test also fails to reject the null hypothesis that the parameter estimates for the group means are equal to zero, hence the standard random-effects model is the preferred model. For data on damage claims payments greater than zero, the test results show that the fixed-effects or random-effects are preferred to the pooled model. Hausman test favors the fixed-effects model but the Wu test also rejects the null hypothesis that the parameters of the group means are zero. That is, the fixed-effects and the Mundlak’s approach are preferred.

Considering specific CRS activities effects on NFIP policies-in-force (unmatched), results show that the fixed-effects and random-effects is preferred to the pooled model but Hausman test favors the fixed-effects to the random-effects. The Wu test also shows that the Mundlak’s group-mean effects are significant. With regards to specific CRS activities effects on damage claims payments, test results from Table 6.1 shows that there are no individual effects in the model. Thus, the pooled model is preferred to the fixed-effects or the random-effects.
Table 6.1 Results on model assumption tests

<table>
<thead>
<tr>
<th>Data</th>
<th>Wooldridge Test for Serial Correlation.</th>
<th>Pesaran Test for Contemporaneous Correlation.</th>
<th>White Test for Heteroskedasticity</th>
<th>Breusch-Pagan Test for Pooled vs. fixed/random-effects</th>
<th>Hausman Test for Fixed-effects vs. Random-effects</th>
<th>Wu Test for group means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>F(1, 292) = 609.65 ***</td>
<td>Corr. coeff. = 109.11***</td>
<td>$\chi^2(151) = 35929.54^{***}$</td>
<td>$\chi^2(7) = 127.03^{***}$</td>
<td>$\chi^2 = 46.79^{***}$</td>
<td></td>
</tr>
<tr>
<td>(N = 5,860)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matched</td>
<td>F(1, 91) = 233.90 ***</td>
<td>Corr. coeff. = 30.02***</td>
<td>$\chi^2(151) = 1791.14^{***}$</td>
<td>$\chi^2 = 55.89^{***}$</td>
<td>$\chi^2 = 38.41^{***}$</td>
<td></td>
</tr>
<tr>
<td>(N = 1,840)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS participation effects on policies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unmatched</td>
<td>F(1, 292) = 1.48</td>
<td>Corr. coeff. = 4.07***</td>
<td>$\chi^2(367) = 672.85^{***}$</td>
<td>$\chi^2(15) = 26.96^{**}$</td>
<td>$\chi^2 = 26.85^{***}$</td>
<td></td>
</tr>
<tr>
<td>(N = 5,860)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matched</td>
<td>F(1, 91) = 0.001</td>
<td>Corr. coeff. = -2.44</td>
<td>$\chi^2(367) = 30.67^{***}$</td>
<td>$\chi^2(11) = 3.79$</td>
<td>$\chi^2 = 12.71^{*}$</td>
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<tr>
<td>(N = 1,840)</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Claims &gt; 0</td>
<td>F(1,178) = 117.64***</td>
<td>N/A</td>
<td>$\chi^2(367) = 64.08^{***}$</td>
<td>$\chi^2(25) = 50.62^{***}$</td>
<td>$\chi^2 = 23.02^{***}$</td>
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</tr>
<tr>
<td>(N = 1,807)</td>
<td></td>
<td>(data unbalanced)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS participation effects on claims payments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unmatched</td>
<td>F(1, 43) = 31.30***</td>
<td>N/A</td>
<td>$\chi^2(291) = 1246.28^{***}$</td>
<td>$\chi^2(23) = 64.50^{***}$</td>
<td>$\chi^2 = 1011.31^{***}$</td>
<td></td>
</tr>
<tr>
<td>(N = 528)</td>
<td></td>
<td>(data unbalanced)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specific CRS activities effects on policies-in-force</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unmatched</td>
<td>F(1, 43) = 3.73*</td>
<td>N/A</td>
<td>$\chi^2(527) = 1.37$</td>
<td>$\chi^2(23) = 28.27$</td>
<td>$\chi^2 = 18.29$</td>
<td></td>
</tr>
<tr>
<td>(N = 528)</td>
<td></td>
<td>(data unbalanced)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specific CRS activities effects on claims payments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance
Panel Model Estimation in the presence of Heteroskedasticity and Autocorrelation

Where serial autocorrelation and heteroskedasticity exists, the robust variance matrix estimator can be used (Wooldridge 2002). The estimator is said to be valid in cases where one has issues of heteroskedasticity or serial correlation (Wooldridge 2002). The rule in using the robust variance matrix estimator is that the time or year period \(T\) must be fixed or small relative to the number of units \(N\). The robust variance matrix estimator is specified for a pooled OLS model as

\[
\hat{\text{AVar}}(\beta) = \left[ \sum_{i=1}^{N} X_i' \hat{\varepsilon}_i \right]^{-1} \left[ \sum_{i=1}^{N} X_i' \hat{\varepsilon}_i \hat{\varepsilon}_i' X_i \right] \left[ \sum_{i=1}^{N} X_i' \hat{\varepsilon}_i \right]^{-1} \tag{6.10}
\]

where \(\hat{\text{AVar}}\) is the estimated asymptotic variance, \(\hat{\beta}\) is the parameter estimates, and \(\hat{\varepsilon}\) are the residuals.

For the fixed-effects model it is specified as

\[
\hat{\text{AVar}}(\beta_{FE}) = (\hat{X}_i' \hat{X}_i)^{-1} \left[ \sum_{i=1}^{N} \hat{X}_i' \hat{\varepsilon}_i \hat{\varepsilon}_i' \hat{X}_i \right] (\hat{X}_i' \hat{X}_i)^{-1} \tag{6.11}
\]

where \(\hat{X}_i\) indicates only independent variables that vary over time. The difference between the two equations is that, for fixed-effect estimator only the time demeaned errors \(\hat{\varepsilon}_u\) can be estimated and not \(\varepsilon_u\) (Wooldridge 2002). For random-effects model the robust variance matrix estimator can be specified as

\[
\hat{\text{AVar}}(\beta) = \left[ \sum_{i=1}^{N} X_i' \hat{\Omega}^{-1} X_i \right]^{-1} \left[ \sum_{i=1}^{N} X_i' \hat{\Omega}^{-1} \hat{v}_i \hat{v}_i' \hat{\Omega}^{-1} X_i \right] \left[ \sum_{i=1}^{N} X_i' \hat{\Omega}^{-1} X_i \right]^{-1} \tag{6.12}
\]

where \(\hat{\Omega} = \sigma^2 \hat{I}_T + \sigma^2 \hat{J}_T \hat{J}_T'\) which equal the variance covariance matrix. \(\sigma^2\) is the estimated variance which is constant, \(I\) is an identity matrix is, and \(\hat{J}_T\) is a \(T \times T\) matrix with...
elements that are unity. $\hat{\nu}$ are estimated residuals from the random-effect estimator. Using the robust variance matrix estimator may lead to larger standard errors (Wooldridge 2002)

**Estimating the empirical models**

Based on the results obtained after testing for model assumptions (pooled vs. random or fixed-effects, random vs. fixed-effects, and Mundlak’s random-effects) we settle on estimating the empirical models using the estimation approaches as summarized in Table 6.2. As mentioned earlier, the Mundlak’s random-effects approach is a compromise between the random-effects and the fixed-effects model (Greene 2012). Although it retains the specification of the random-effects model, the assumption $E[c_i \mid X_i] = 0$ made under the random-effects does not apply to the Mundlak’s random-effects approach. Thus, results from the Mundlak’s approach are closer to the fixed effects approach. However, unlike the fixed-effects, the Mundlak’s approach allows for the estimation of time-invariant variables. For example, if we consider the unmatched data, for CRS participation effect on NFIP policies-in-force, the parameter estimate for CRS based on random-effects model and fixed-effects-model are 0.792 and 0.660 respectively. On the other hand, the estimate from the Mundlak’s random-effects approach is 0.642. That is, we observe that the difference in the magnitude of the estimates for the random-effects model to the fixed-effects model is clearly distinctive. On the other hand, the estimate from the Mundlak’s random-effect approach is very close to that of the fixed-effects. Again, consider the matched data (for NFIP policies-in-force), the parameter estimate for CRS for the random-effects, fixed-effects, and
Mundlak’s random-effects models, respectively, are 1.147, 1.018, and 1.058. That is, the parameter estimate for Mundlak’s random-effects is similar to the fixed-effects.

We estimate the parameters for the models (pooled, Mundlak’s random-effects, and fixed-effects) using the NLOGIT (version 5) routine for estimating linear regression models for panel data as described in Greene (2012). We apply the robust command to account for the autocorrelation and heteroskedasticity where necessary. We estimated the Mundlak’s random-effects approach by including means of time-varying variables in the model and use the random-effects option in NLOGIT. Where matched data are used, a weighting variable is specified. In all we estimate 12 models.

**Summary of empirical models and estimation approach**

In Table 6.2, we present a summary of the various empirical models estimated in this research as well as the estimation approaches used.
Table 6.2  Summary of empirical models and estimation approach

<table>
<thead>
<tr>
<th>Empirical model</th>
<th>Estimation approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effects of CRS participation on NFIP policies-in-force (unmatched data)</td>
<td>Mundlak’s random-effects and Fixed-effects</td>
</tr>
<tr>
<td>Effects of CRS participation on NFIP policies-in-force (matched data)</td>
<td>Mundlak’s random-effects and Fixed-effects</td>
</tr>
<tr>
<td>Effects of CRS participation on damage claims payments (unmatched data)</td>
<td>Mundlak’s random-effects and Fixed-effects</td>
</tr>
<tr>
<td>Effects of CRS participation on damage claims payments (matched data)</td>
<td>Random-effects</td>
</tr>
<tr>
<td>Effects of CRS participation on damage claims payments (claims&gt;0, unmatched)</td>
<td>Mundlak’s random-effects and Fixed-effects</td>
</tr>
<tr>
<td>Effects of community-level specific CRS mitigation effects on NFIP policies-in-force (unmatched data)</td>
<td>Mundlak’s random-effects and Fixed-effects</td>
</tr>
<tr>
<td>Effects of community-level specific CRS mitigation effects on damage claims payments (unmatched data)</td>
<td>Pooled</td>
</tr>
</tbody>
</table>
Presented in this chapter of the research are the results from the estimated models as well as discussion of the results. Given that our dependent variable is log transformed; this presents us with a log-linear model (Gujarati and Porter 2009). The coefficients of the independent variables of a log-linear model can be interpreted as the relative change in the dependent variable given an absolute change in the independent variable. When the coefficients of the independent variables are multiplied by 100, this gives us a percent change in the dependent variable given a change in the independent variable. That is, this provides a partial elasticity (Gujarati and Porter 2009). Where the dependent and independent variable are both in a log transformation, the parameter estimate of the independent variable can be interpreted as elasticity. That is a percentage change in the dependent variable given a percentage change in the independent variable (Gujarati and Porter 2009). However, where the independent variable is a binary variable (in our case an example is the variable CRS) the interpretation is different. That is, for binary independent variables, the coefficient gives a multiplicative shift of the regression equation. Thus, a percent change in \( E[y|x,d] = 100\%[\exp(\beta) - 1] \) given a change in the binary variable (Greene 2012).
Effects of CRS participation on NFIP Participation (log of Policies-in-force)

Under this sub-heading, we present results for the effect of CRS participation on NFIP participation, using both unmatched and matched data. First, we look at results for the unmatched data.

Unmatched data

Table 7.1 reports the results of the Mundlak random-effects and fixed-effects models. The results show a positive and a significant relationship between CRS participation and NFIP policies-in-force for both the Mundlak’s random-effects and the fixed-effects estimation approach. That is we see that a discrete change in CRS participation increases the number of NFIP policies-in-force by 90.0 percent (i.e., $100\%[e^{0.642} - 1]$) and 93.5 percent (i.e., $100\%[e^{0.660} - 1]$) respectively, ceteris paribus. This finding is similar (not in magnitude but in direction) to that of Zahran et al. (2009), who found a positive and significant relationship between overall CRS points and natural log of number of policy holders in Florida. Also, the results show that overall, there is an increase in the number of NFIP policies-in-force overtime. However, the interaction of the CRS variable and the time trend variable (CRS x Time trend) shows that the growth over time is slower for CRS communities. Results based on the fixed-effects estimation approach show that overall, the number of policies-in-force increases after hurricane Katrina although the growth in the number NFIP policies-in-force is greater for CRS communities, as indicated by the variable CRS x Post-Katrina ceteris paribus.

Shifting to the socioeconomic variables, results show a positive and significant effect between income and the number of NFIP policies-in-force. Thus, ceteris paribus a $1000$ increase in income increases the number of NFIP policies-in-force by 1.60 percent
(i.e., 100% x 0.016) in both estimation approaches. This relationship is in line with our hypothesized expectation. Past studies (Marquis and Long 1995; Brown and Hoyt 2000; Petrolia et al. 2015) have also found income to be positively related to insurance demand. Although education had the expected sign (positive) as also found by Smith and Baquet (1996), our estimate is not significant.

For geospatial variables, the results show a negative relationship between Precipitation and the number of NFIP policies-in-force for both estimation approaches. This finding is not as expected given that we hypothesized a positive relationship. However, this could be explained as, for precipitation to cause damages one expects extreme amounts. Because the other geospatial variables are time-invariant, they appear in the Mundlak random-effects model only. The variables Coast and SFHA are positive and significant in influencing NFIP policies-in-force. Specifically, relative to non-coastal communities, number of policies-in-force in coastal communities’ increase by 115.3 percent as expected. But the growth in the number of NFIP policies-in-force is slower for coastal communities during hurricane Katrina although not significant. The results also show that a one percent increase in land area in SFHA increases the number of NFIP policies-in-force by 2.1 percent, ceteris paribus. The relationship between SFHA and NFIP participation (number of policies-in-force) is as expected given that this area has high flood risk. Petrolia, Landry, and Coble (2013) also find demand for flood insurance to increase in SFHA. Although, elevation and non-SFHA are negatively related to the number of NFIP policies-in-force, as hypothesized, they are not significant. Stream density show up as negatively related to the number of NFIP policies-in-force but this is not what we expected. Slope also comes out as negative in explaining the number of
NFIP policies-in-force. The reason for this relationship could be that, homeowners’ properties are located along slopes where the risk of flood is minimal.

Table 7.1  NFIP policies-in-force (unmatched data)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mundlak’s Random-effects</th>
<th>Fixed-effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Robust std. errors</td>
</tr>
<tr>
<td>Time-Varying Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>0.642**</td>
<td>0.256</td>
</tr>
<tr>
<td>CRS×Time trend</td>
<td>-0.037***</td>
<td>0.012</td>
</tr>
<tr>
<td>CRS×Post-Katrina</td>
<td>0.178</td>
<td>0.122</td>
</tr>
<tr>
<td>Time-Trend</td>
<td>0.043***</td>
<td>0.006</td>
</tr>
<tr>
<td>Post-Katrina</td>
<td>0.106**</td>
<td>0.050</td>
</tr>
<tr>
<td>Education</td>
<td>0.009</td>
<td>0.006</td>
</tr>
<tr>
<td>Household</td>
<td>0.006</td>
<td>0.005</td>
</tr>
<tr>
<td>Income</td>
<td>0.016***</td>
<td>0.004</td>
</tr>
<tr>
<td>Precipitation</td>
<td>-0.002**</td>
<td>0.001</td>
</tr>
<tr>
<td>Time-Invariant Geospatial Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td>0.767**</td>
<td>0.307</td>
</tr>
<tr>
<td>Coast×Post-Katrina</td>
<td>0.106</td>
<td>0.111</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.194</td>
<td>0.174</td>
</tr>
<tr>
<td>Slope</td>
<td>-0.044</td>
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<tr>
<td>Elevation</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Stream Density</td>
<td>-0.314</td>
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</tr>
<tr>
<td>SFHA</td>
<td>2.136***</td>
<td>0.486</td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>-0.210</td>
<td>0.350</td>
</tr>
<tr>
<td>Constant</td>
<td>3.329**</td>
<td>1.651</td>
</tr>
</tbody>
</table>

Mundlak Group Means

| CRS                    | 1.339***    | 0.307                 |
| Education              | 0.012       | 0.011                 |
| Household              | 0.021**     | 0.008                 |
| Income                 | 0.001       | 0.010                 |
| Precipitation          | -0.014      | 0.030                 |

R²: 0.537  0.921
N: 5860  5860

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance.
Matched data

In Table 7.2, we report results on the effects of CRS participation of NFIP policies-in-force for matched data. The results are based on Mundlak’s random-effects and fixed-effects models. The results for both approaches show a positive relationship and significant between CRS participation and NFIP policies-in-force. That is, a discrete change in CRS participation increases the number of NFIP policies-in-force by 188.1 percent and 176.8 percent respectively, ceteris paribus. In both estimation approaches, the time trend variable show that overall, the number of NFIP policies-in-force increases by 4.9 percent but the growth of the number of NFIP policies-in-force for CRS communities over time (as shown by the variable, CRS x Time trend) is slower, ceteris paribus.

Among the socioeconomic variables, income still remains the only significant socioeconomic variable influencing the number of NFIP policies-in-force as shown in Table 7.2. In both estimation approaches, a $1000 increase in income increases the number of NFIP policies-in-force by 1.1 percent. This positive relationship follows our hypothesized relationship between income and the number of NFIP policies-in-force. The negative relationship between education and the number of NFIP policies-in-force is not what we expected. The estimate however, is not significant. Household also shows up positive but not significant. This positive effect is not surprising because where properties are located in SFHA insurance purchase is mandatory for federally backed mortgages. Hence if household increase in such area, then we can expect flood policies to also increase.
Although precipitation is significant in both estimation approaches, the sign is not as expected. That is, we observe that in both estimation approaches, a one inch increase in precipitation reduces the number of NFIP policies-in-force by 0.2 percent, *ceteris paribus*. The slope variable is also found to be negative and significant in explaining NFIP policies-in-force. That is, a one degree increase in the slope reduces the number of NFIP policies-in-force by 39.3 percent, *ceteris paribus*. One reason that accounts for this finding is that properties are located along the slope rather than the base of the slope which makes them less prone to floods. SFHA is positive and significant in explaining the number of NFIP policies-in-force. This finding is as expected given the high flood risk nature of SFHA. That is we observe that a one percent increase in land area in SFHA increases the number of NFIP policies-in-force by 3.4 percent *ceteris paribus*. Elevation and stream density are also positive but not significant. The positive relationship between elevation and the number of NFIP policies-in-force is in line with our hypothesis. Also the positive relationship existing between stream density and the number of NFIP policies-in-force is as expected given that communities with bigger stream density are prone to flood risk.
Table 7.2  NFIP policies-in-force (matched data)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>robust std. errors</th>
<th>Coefficient</th>
<th>robust std. errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mundlak’s Random-effects</strong></td>
<td></td>
<td></td>
<td><strong>Fixed-effects</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Time-Varying Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>1.058***</td>
<td>0.332</td>
<td>1.018***</td>
<td>0.268</td>
</tr>
<tr>
<td>CRS×Time trend</td>
<td>-0.042**</td>
<td>0.019</td>
<td>-0.042***</td>
<td>0.016</td>
</tr>
<tr>
<td>CRS×Post-Katrina</td>
<td>0.021</td>
<td>0.101</td>
<td>0.033</td>
<td>0.097</td>
</tr>
<tr>
<td>Time trend</td>
<td>0.049***</td>
<td>0.012</td>
<td>0.049***</td>
<td>0.012</td>
</tr>
<tr>
<td>Post-Katrina</td>
<td>0.108</td>
<td>0.085</td>
<td>0.083</td>
<td>0.072</td>
</tr>
<tr>
<td>Education</td>
<td>-0.00033</td>
<td>0.008</td>
<td>-0.001</td>
<td>0.010</td>
</tr>
<tr>
<td>Household</td>
<td>0.002</td>
<td>0.003</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td>Income</td>
<td>0.011**</td>
<td>0.005</td>
<td>0.011*</td>
<td>0.006</td>
</tr>
<tr>
<td>Precipitation</td>
<td>-0.002**</td>
<td>0.001</td>
<td>-0.002*</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Time-Invariant Geospatial Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td>0.582</td>
<td>0.456</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast×Post-Katrina</td>
<td>-0.085</td>
<td>0.173</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.052</td>
<td>0.383</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>-0.393***</td>
<td>0.128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>0.002</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stream density</td>
<td>0.127</td>
<td>0.426</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SFHA</td>
<td>3.436***</td>
<td>0.830</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>-0.152</td>
<td>0.496</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.345</td>
<td>3.516</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mundlak Group Means</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS mean</td>
<td>1.083***</td>
<td>0.341</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education mean</td>
<td>0.019</td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household mean</td>
<td>0.023***</td>
<td>0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income mean</td>
<td>0.004</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Precipitation mean</td>
<td>0.041</td>
<td>0.061</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.598</td>
<td>0.922</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( N )</td>
<td>1840</td>
<td>1840</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance.

Effects of CRS participation on Damage Claims (log of Damage Claims Payment)

Here also we consider unmatched and matched data. We first report results based on the unmatched data.
Unmatched data

In Table 7.3, we show results for Mundlak’s random-effects and fixed-effects estimation approach. Based on the two estimation approaches, we find a positive but not significant relationship between CRS participation and damage claims payments. Although this result is not significant, we did not expect a positive relationship. The positive relationship could be due to the fact that most CRS communities are coastal communities that are severely affected by tidal wave actions. Moreover, since NFIP participation is high for CRS communities as we found in the previous results (Table 7.1 and 7.2), it is not very surprising to see a positive relationship between damage claims payments and CRS participation. Although we do not report here, we observed from our data that most CRS communities are above CRS class 7 which means the degree of mitigation practice is low. The parameter estimate for the log of coverage also shows a positive and significant relationship between the amount of coverage purchased and damage claims payments. That is, we observe that a percent change in the amount of coverage purchased increases damage claims payments by 0.5 percent, ceteris paribus.

For socioeconomic variables, both the Mundlak’s random-effects and the fixed-effects approaches show a positive and significant relationship between households and damage claims payments. That is, a 1000 increase in households increase damage claims payments by 3.5 percent, ceteris paribus. Highflied and Brody (2013) find a positive relationship between population and total damage claims payments. Both estimation approaches also show a positive relationship between education and damage claims payments but not significant. Although this relationship is not significant, the positive relationship could mean that education leads to higher earnings which also empower
people to flood policy and properties that have high value. As such a damage event will increase claims damage payments. For both estimation approaches, we also find income to be positive but not significant in explaining damage claims payments. Although this finding is not significant, the positive relationship is intuitive because, within a community, wealthier households may have a higher property value and therefore can claim higher damage claim payments when a damage event occurs.

On geospatial variables, for both estimation approaches, we find precipitation to be positive and significantly related to damage claims payments. That is, a one inch increase in precipitation increases damage claims payments by 13.3 percent, *ceteris paribus*. This finding is in line with our hypothesized relationship between precipitation and damage claims payments. Spekkers et al. (2013), find a positive relationship between precipitation and the number of damage claims. For the time-invariant geospatial variables, results are reported for only the Mundlak’s random-effects approach. We find a positive and significant relationship between coast and damage claims payments as hypothesized. A discrete change in coast increases damage claims by 277.4 percent, *ceteris paribus*. Coastal communities are exposed to high wave velocity actions; this finding is therefore not surprising. The results also show a positive and significant relationship between Mississippi and damage claims payments. That is relative to Alabama, damage claims in Mississippi increase by 207.3 percent, *ceteris paribus*. This result may be explained by the fact that Mississippi has a longer coast line relative to Alabama hence any hurricane or wave action should have a greater impact on Mississippi. Also flooding from the Mississippi river could account for the differences. Slope is positive but not significant in predicting damage claims payments. Although this
is not significant, the reason for this relationship is that properties in a community may be located at the base of a slope which makes them prone to floods, *ceteris paribus*. The negative relationship between elevation and damage claims payments is as expected, although the parameter estimate is not significant. The results also show that stream density is negative but not significant in predicting damage claims payments. This finding is not in line with our hypothesis. SFHA shows up as positively related to damage claims payments but not significant. The positive relationship between SFHA and damage claims payments is in line with our hypothesis significant. Non-SFHA is negative in explaining damage claims payments as expected, the parameter estimates is however not significant. Since non-SFHA is an area with moderate or minimal flood risk, this relationship found is not surprising.

We observe here that unlike the effects of CRS participation on NFIP policies-in-force, we include year dummies and report their estimates when considering the effects of CRS participation on damage claims payments. This is because here we find parameter estimates for different years to be significant and different from each other in explaining damage claims payments. For both estimation approaches, the parameter estimate for the year 2005 shows up as positive and significant as expected. That is, relative to the year 1994, the year 2005 saw damage claims payments increase by 278.5 percent *ceteris paribus*. This result is not surprising given the fact that hurricane Katrina which destroyed properties mostly in the coastal communities and its surrounding communities occurred that year. Bin, Bishop, and Kousky (2012) notes that Alabama and Mississippi are states two states among five to have recorded high damage claims payments due to hurricane Katrina. Parameter estimates for other years such as 1995, 1998, 1999, 2000,
2003, and 2011 are also positively related to damage claims payments but are not significant. For both estimation approaches, the parameter estimates for the years 2002, 2006, 2008, 2009, 2012, and 2013 are negative and significantly related to damage claims payments. More interestingly, we see a decline in damage claims right after the year 2005 (hurricane Katrina year) which is not surprising.

Table 7.3  Damage claims payments (unmatched data)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>robust std. errors</th>
<th>Coefficient</th>
<th>robust std. errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time-Varying Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>0.703</td>
<td>0.670</td>
<td>0.703</td>
<td>0.691</td>
</tr>
<tr>
<td>Log(coverage)</td>
<td>0.482***</td>
<td>0.108</td>
<td>0.482***</td>
<td>0.111</td>
</tr>
<tr>
<td>Education</td>
<td>0.007</td>
<td>0.026</td>
<td>0.007</td>
<td>0.027</td>
</tr>
<tr>
<td>Household</td>
<td>0.035**</td>
<td>0.015</td>
<td>0.035**</td>
<td>0.016</td>
</tr>
<tr>
<td>Income</td>
<td>0.017</td>
<td>0.017</td>
<td>0.017</td>
<td>0.017</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.133***</td>
<td>0.011</td>
<td>0.133***</td>
<td>0.011</td>
</tr>
<tr>
<td><strong>Time-Invariant Geospatial Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td>1.328**</td>
<td>0.507</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mississippi</td>
<td>1.309***</td>
<td>0.235</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>0.152</td>
<td>0.111</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>-0.0004</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stream density</td>
<td>-0.319</td>
<td>0.275</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SFHA</td>
<td>0.665</td>
<td>0.762</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>-0.188</td>
<td>0.535</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Year dummy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>0.438</td>
<td>0.294</td>
<td>0.438</td>
<td>0.302</td>
</tr>
<tr>
<td>1996</td>
<td>-0.263</td>
<td>0.293</td>
<td>-0.263</td>
<td>0.301</td>
</tr>
<tr>
<td>1997</td>
<td>-0.404</td>
<td>0.281</td>
<td>-0.404</td>
<td>0.289</td>
</tr>
<tr>
<td>1998</td>
<td>0.496</td>
<td>0.328</td>
<td>0.496</td>
<td>0.338</td>
</tr>
<tr>
<td>1999</td>
<td>0.435</td>
<td>0.33</td>
<td>0.435</td>
<td>0.339</td>
</tr>
<tr>
<td>2000</td>
<td>0.720</td>
<td>0.448</td>
<td>0.72</td>
<td>0.461</td>
</tr>
<tr>
<td>2001</td>
<td>-0.438</td>
<td>0.383</td>
<td>-0.438</td>
<td>0.394</td>
</tr>
<tr>
<td>2002</td>
<td>-1.221***</td>
<td>0.379</td>
<td>-1.221***</td>
<td>0.39</td>
</tr>
<tr>
<td>2003</td>
<td>0.209</td>
<td>0.41</td>
<td>0.209</td>
<td>0.422</td>
</tr>
<tr>
<td>2004</td>
<td>-0.295</td>
<td>0.439</td>
<td>-0.295</td>
<td>0.452</td>
</tr>
</tbody>
</table>
Table 7.3 (continued)

<table>
<thead>
<tr>
<th>Year</th>
<th>B (CRS)</th>
<th>B (Household)</th>
<th>B (Income)</th>
<th>B (Precipitation)</th>
<th>R²</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>1.331***</td>
<td>0.405</td>
<td>1.331***</td>
<td>0.417</td>
<td>0.310</td>
<td>5860</td>
</tr>
<tr>
<td>2006</td>
<td>-1.170***</td>
<td>0.413</td>
<td>-1.17***</td>
<td>0.425</td>
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<td></td>
</tr>
<tr>
<td>2007</td>
<td>-0.448</td>
<td>0.47</td>
<td>-0.448</td>
<td>0.485</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>-0.813**</td>
<td>0.385</td>
<td>-0.813***</td>
<td>0.396</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>-0.967**</td>
<td>0.407</td>
<td>-0.967***</td>
<td>0.419</td>
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<td></td>
</tr>
<tr>
<td>2010</td>
<td>-0.722</td>
<td>0.497</td>
<td>-0.722</td>
<td>0.512</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>0.260</td>
<td>0.468</td>
<td>0.26</td>
<td>0.482</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>-1.038**</td>
<td>0.515</td>
<td>-1.038*</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td>-2.191***</td>
<td>0.501</td>
<td>-2.191***</td>
<td>0.516</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.355</td>
<td>2.521</td>
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<td></td>
</tr>
</tbody>
</table>

**Mundlak Group Means**

<table>
<thead>
<tr>
<th>Mean</th>
<th>CRS mean</th>
<th>Education mean</th>
<th>Household mean</th>
<th>Income mean</th>
<th>Precipitation mean</th>
<th>Log(coverage) mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.119</td>
<td>0.501</td>
<td>-0.009</td>
<td>0.829</td>
<td>0.030</td>
<td>-0.136***</td>
<td>0.025</td>
</tr>
<tr>
<td>0.551***</td>
<td>0.043</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance.

**Matched data**

Results presented in Table 7.4 are based on random-effects model. The results show a positive but not significant relationship between CRS participation and damage claims payments. This relationship is not as expected. We hypothesized a negative relationship. The parameter estimate for log coverage is positive and significant in explaining damage claims payments. That is, *ceteris paribus*, a percent change in coverage amount purchased leads to 1.1 percent increases damage claims payments. This result is not surprising as people with more coverage amount are expected to receive higher damage claims payments should a flood damage event occur.
On socioeconomic variables, we find household to be positive and significant in explaining damage claims payments. Specifically, a 1000 increase in household increases damage claims payments by 2.6 percent, \textit{ceteris paribus}. This finding is not surprising as Highfield and Brody (2013) also find a positive and significant relationship between population and total damage claims payments, although not the same magnitude. The parameter estimate for income is positive but not significant. Although this is not significant, this relationship is not surprising because, as explained earlier when income increases, households are able to afford high value properties and when a damage event occurs, higher claims payments are demanded by these households, \textit{ceteris paribus}. Education shows up as negatively related to damage claims but this is not significant. This could mean that homeowners who are educated are more likely to practice individual flood mitigation thereby reducing damage claims payments.

On geospatial variables, we find a positive relationship between precipitation and damage claims payments as hypothesized. A one inch increase in precipitation increases damage claims payments by 10.2 percent, \textit{ceteris paribus}. Highfield and Brody, (2013) also find a positive relationship between precipitation and damage claims payments. Coast shows up as positively related to damage claims payments as we hypothesized, but this is not significant. Parameter estimate for Mississippi also shows that a discrete change in Mississippi leads to an increase of 683.0 percent in damage claims payments, \textit{ceteris paribus}. This finding can be explained by the fact that, Mississippi has a longer shoreline relative to Alabama and as such are more exposed to wave actions. Slope shows up to be positive and significant in predicting damage claims payments. This positive relationship may arise due to the fact that properties are located at the base of
slopes exposing them to floods *ceteris paribus*. Highfield and Brody (2013) also find a positive relationship between slope and total damage claims payments, although their estimate is not significant. Stream density shows up as negative and significant in predicting damage claims payments but this relationship is not what we expected. Results also show that SFHA has positive relationship with damage claims payments as we hypothesized, although the parameter estimate is not significant. As explained earlier in chapter II of this research, this area is an area classified as a high flood risk area, so it is not surprising to see a positive relationship as we hypothesized between SFHA and damage claims payments. Non-SFHA and elevation, although are negative as we hypothesized but the parameter estimates are not significant.

The parameter estimates of year dummies in this model are all (except the year 2005) negatively related to damage claims payments. The dummy for the year 2005, although positively related to damage claims payments, it is not significant. Here also, we see that immediately after the year 2005 (the year hurricane Katrina strikes the Gulf Coast), damage claims payments reduces significantly from the year 2006 to the end of our study period (2013). This finding is not surprising as the hurricane caused damages to many properties.
Table 7.4  Damage claims payments (matched data)

<table>
<thead>
<tr>
<th>Random-effects</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Coefficient</td>
<td>Robust std. error</td>
</tr>
<tr>
<td><strong>Time-Varying Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>0.645</td>
<td>0.479</td>
</tr>
<tr>
<td>Log(coverage)</td>
<td>1.091***</td>
<td>0.166</td>
</tr>
<tr>
<td>Education</td>
<td>-0.024</td>
<td>0.021</td>
</tr>
<tr>
<td>Household</td>
<td>0.026***</td>
<td>0.006</td>
</tr>
<tr>
<td>Income</td>
<td>0.009</td>
<td>0.020</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.102***</td>
<td>0.019</td>
</tr>
<tr>
<td><strong>Time-Invariant Geospatial Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coast</td>
<td>0.490</td>
<td>0.676</td>
</tr>
<tr>
<td>Mississippi</td>
<td>2.058***</td>
<td>0.596</td>
</tr>
<tr>
<td>Slope</td>
<td>0.551**</td>
<td>0.267</td>
</tr>
<tr>
<td>Elevation</td>
<td>-0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>Stream density</td>
<td>-1.558*</td>
<td>0.800</td>
</tr>
<tr>
<td>SFHA</td>
<td>0.068</td>
<td>1.346</td>
</tr>
<tr>
<td>Non-SFHA</td>
<td>-0.082</td>
<td>0.68</td>
</tr>
<tr>
<td><strong>Year dummy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>-1.068*</td>
<td>0.599</td>
</tr>
<tr>
<td>1996</td>
<td>-1.421**</td>
<td>0.577</td>
</tr>
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<td>1997</td>
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<td>1998</td>
<td>-0.887</td>
<td>0.618</td>
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<tr>
<td>1999</td>
<td>-0.627</td>
<td>0.645</td>
</tr>
<tr>
<td>2000</td>
<td>-1.840**</td>
<td>0.715</td>
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<tr>
<td>2001</td>
<td>-0.953</td>
<td>0.596</td>
</tr>
<tr>
<td>2002</td>
<td>-2.479***</td>
<td>0.691</td>
</tr>
<tr>
<td>2003</td>
<td>-0.035</td>
<td>0.679</td>
</tr>
<tr>
<td>2004</td>
<td>-2.113***</td>
<td>0.804</td>
</tr>
<tr>
<td>2005</td>
<td>0.978</td>
<td>0.662</td>
</tr>
<tr>
<td>2006</td>
<td>-4.178***</td>
<td>0.655</td>
</tr>
<tr>
<td>2007</td>
<td>-3.670***</td>
<td>0.777</td>
</tr>
<tr>
<td>2008</td>
<td>-2.608***</td>
<td>0.626</td>
</tr>
<tr>
<td>2009</td>
<td>-2.727***</td>
<td>0.662</td>
</tr>
<tr>
<td>2010</td>
<td>-4.443***</td>
<td>0.697</td>
</tr>
<tr>
<td>2011</td>
<td>-2.287***</td>
<td>0.817</td>
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Table 7.4 (continued)

<p>| | | |</p>
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<td>-2.354***</td>
<td>0.816</td>
</tr>
<tr>
<td>2013</td>
<td>-4.591***</td>
<td>0.767</td>
</tr>
<tr>
<td>Constant</td>
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<td>1.612</td>
</tr>
<tr>
<td>R²</td>
<td>0.289</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1840</td>
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</table>

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance.

Positive damage claims payments

Table 7.5 show results based on only positive damage claims payments (those greater than zero). The estimation approach used here are the Mundlak’s random-effects and the fixed-effects approach. Across the two estimation approaches, results show that damage claims payments are reducing among CRS participating communities, although this is not significant. This finding is in line with our hypothesis. One of the goals of the CRS is to reduce flood damages among participating communities through local-level flood mitigation practices. The parameter estimate for log of coverage amount purchased shows up as positive and significant in predicting damage claims. Specifically we find that a percent increase in coverage amount purchased, increases the percent of damage claims payments by 0.7 percent ceteris paribus.

Considering the socioeconomic variables, we find that education and household have positive a sign although only household is significant in explaining damage claims payments. The positive relationship between household and damage claims payment could mean that increase in households increases the demand of insurance policy which subsequently increases damage claims payments due to the occurrence of a flood damage event, ceteris paribus. Also, the positive relationship we see between education and damage claims payments is intuitive in that, higher education can affect earnings and
subsequently influence demand for flood policy and properties, *ceteris paribus*. Results also show a negative relationship between income and damage claims payments. Although in our hypothesis we were uncertain about the sign, this finding can be supported by fact that policy holders’ motivation to file for damage claims payments can reduce as they become wealthier (Cummins and Tennyson 1996).

Precipitation, the only geospatial variable that is time-varying in our research shows up as positive and significant in explaining damage claims payments. That is, we find that a one inch increase in precipitation increases damage claims payments by 6.6 percent, *ceteris paribus*. This relationship is in line with our hypothesis. Highfield and Brody (2013) also find a positive relationship between precipitation and total damage claims payments, although not of the same magnitude.

For both estimation approaches, year dummies for 1995, 1998, 1999, 2005, and 2011 are all positive and significant in explaining damage claims payments. Although these years are all positive and significant, the magnitude of the parameter estimate for year 2005 stands out. That is, we observe that for the Mundlak’s random-effects approach, the year 2005, relative to year 1994, damage claims payments increases by 513.5 percent whiles for the fixed-effects, damage claims payments increases by 637.4 percent, *ceteris paribus*. This outstanding effect can be attributed to hurricane Katrina. We also find that for the years 1996, 1997, 2001, 2002, 2006, 2007, 2009, and 2013, damage claims payments are reducing relative to the year 1994. However, only the year 2009 is significant in explaining damage claims payments.
Table 7.5  
Damage claims payments (positive claims: non-zero)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>robust std. errors</th>
<th>Coefficient</th>
<th>robust std. errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mundlak’s Random-effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>Time-Varying Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRS</td>
<td>-0.161</td>
<td>0.278</td>
<td>-0.163</td>
<td>0.303</td>
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<tr>
<td>Log(coverage)</td>
<td>0.682***</td>
<td>0.121</td>
<td>0.687***</td>
<td>0.145</td>
</tr>
<tr>
<td>Education</td>
<td>0.031</td>
<td>0.02</td>
<td>0.024</td>
<td>0.023</td>
</tr>
<tr>
<td>Household</td>
<td>0.011*</td>
<td>0.006</td>
<td>0.010</td>
<td>0.007</td>
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<tr>
<td>Income</td>
<td>-0.014</td>
<td>0.012</td>
<td>-0.020</td>
<td>0.013</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.066***</td>
<td>0.009</td>
<td>0.068***</td>
<td>0.011</td>
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<tr>
<td><strong>Time-Invariant Geospatial Variables</strong></td>
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<tr>
<td>Coast</td>
<td>0.824***</td>
<td>0.229</td>
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<tr>
<td>Mississippi</td>
<td>0.186</td>
<td>0.140</td>
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<tr>
<td>Slope</td>
<td>0.098</td>
<td>0.065</td>
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<tr>
<td>Elevation</td>
<td>-0.0003</td>
<td>0.001</td>
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<tr>
<td>Stream density</td>
<td>0.000</td>
<td>0.192</td>
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<tr>
<td>SFHA</td>
<td>0.911</td>
<td>0.571</td>
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<tr>
<td>Non-SFHA</td>
<td>0.416</td>
<td>0.447</td>
<td></td>
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<tr>
<td><strong>Year dummy</strong></td>
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</tr>
<tr>
<td>1995</td>
<td>0.740***</td>
<td>0.246</td>
<td>0.708***</td>
<td>0.273</td>
</tr>
<tr>
<td>1996</td>
<td>-0.291</td>
<td>0.274</td>
<td>-0.289</td>
<td>0.290</td>
</tr>
<tr>
<td>1997</td>
<td>-0.139</td>
<td>0.248</td>
<td>-0.145</td>
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<td>1998</td>
<td>0.993***</td>
<td>0.287</td>
<td>1.011**</td>
<td>0.322</td>
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<tr>
<td>1999</td>
<td>0.797**</td>
<td>0.326</td>
<td>0.973**</td>
<td>0.385</td>
</tr>
<tr>
<td>2000</td>
<td>0.436</td>
<td>0.363</td>
<td>0.761*</td>
<td>0.392</td>
</tr>
<tr>
<td>2001</td>
<td>-0.218</td>
<td>0.31</td>
<td>-0.032</td>
<td>0.345</td>
</tr>
<tr>
<td>2002</td>
<td>-0.222</td>
<td>0.316</td>
<td>-0.187</td>
<td>0.36</td>
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<tr>
<td>2003</td>
<td>0.392</td>
<td>0.319</td>
<td>0.530</td>
<td>0.379</td>
</tr>
<tr>
<td>2004</td>
<td>0.022</td>
<td>0.351</td>
<td>0.244</td>
<td>0.386</td>
</tr>
<tr>
<td>2005</td>
<td>1.814***</td>
<td>0.394</td>
<td>1.998***</td>
<td>0.441</td>
</tr>
<tr>
<td>2006</td>
<td>-0.200</td>
<td>0.344</td>
<td>-0.080</td>
<td>0.403</td>
</tr>
<tr>
<td>2007</td>
<td>-0.462</td>
<td>0.458</td>
<td>-0.343</td>
<td>0.518</td>
</tr>
<tr>
<td>2008</td>
<td>0.174</td>
<td>0.33</td>
<td>0.271</td>
<td>0.36</td>
</tr>
<tr>
<td>2009</td>
<td>-0.725**</td>
<td>0.336</td>
<td>-0.683*</td>
<td>0.414</td>
</tr>
<tr>
<td>2010</td>
<td>0.191</td>
<td>0.416</td>
<td>0.221</td>
<td>0.554</td>
</tr>
<tr>
<td>2011</td>
<td>0.891**</td>
<td>0.350</td>
<td>1.026**</td>
<td>0.436</td>
</tr>
<tr>
<td>2012</td>
<td>0.228</td>
<td>0.355</td>
<td>0.482</td>
<td>0.453</td>
</tr>
<tr>
<td>2013</td>
<td>-0.510</td>
<td>0.380</td>
<td>-0.450</td>
<td>0.504</td>
</tr>
<tr>
<td>Constant</td>
<td>7.776***</td>
<td>1.122</td>
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Table 7.5 (continued)

<table>
<thead>
<tr>
<th></th>
<th>Mundlak Group Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRS mean</td>
<td>0.220</td>
</tr>
<tr>
<td>Education mean</td>
<td>-0.028</td>
</tr>
<tr>
<td>Household mean</td>
<td>-0.008</td>
</tr>
<tr>
<td>Income mean</td>
<td>0.012</td>
</tr>
<tr>
<td>Precipitation mean</td>
<td>-0.047***</td>
</tr>
<tr>
<td>Log(coverage) mean</td>
<td>-0.412***</td>
</tr>
</tbody>
</table>

| R²                   | 0.268               | 0.423               |
| N                    | 1807                | 1807                |

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance.

Effect of Community-level Specific CRS Mitigation activities on NFIP participation (log of policies-in-force)

Results presented under this heading apply to only CRS participating communities. That is, we focus on within CRS communities to analyze the relative effects of the individual CRS mitigation activities on NFIP participation. From Table 7.6, we present results based on the Mundlak’s random-effects and the fixed-effects estimation approaches. While results from the Mundlak’s random-effects approach shows a negative but insignificant relationship between elevation certificate activity, and the number of NFIP policies-in-force, parameter estimate from the fixed-effects estimation approach shows a negative but also significant relationship. For elevation certificate (c310) activity, CRS communities receive credit points for ensuring that new buildings in flood risk areas are elevated above some base-level. It is therefore not surprising to observe a negative and significant relationship (based on the fixed-effects). That is, when property owners have buildings elevated above some base-level, they feel safer and therefore don’t see the need to buy flood policy ceteris paribus. Map information service (c320) also shows up as negative for the Mundlak’s random-effects.
and positive for the fixed-effects approach but not significant under the two estimation approaches. This activity makes available information regarding flood insurance rate maps (FIRM) to community residents. In both estimation approaches, outreach project (c330) activity is positive and significant in explaining the number of NFIP policies-in-force. This finding is as expected because the outreach project activity involves the dissemination of information regarding flood hazard, flood insurance, as well as flood protection measures to community residents. Hazard disclosure (c340), flood protection information (c350), and flood protection assistance (c360) are all negative but not significant in explaining the number of NFIP policies-in-force. Hazard disclosure (c340) involves notifying potential homeowners of flood-prone areas hence the negative relationship between hazard disclosure (c340) and the number of NFIP policies-in-force is not surprising. Also, for flood protection information (c350) activity, CRS communities are supposed to make available at the community libraries or website, flood protection information such as flood insurance, as such the negative relationship between this activity and the number of NFIP policies-in-force is not as expected. Flood protection assistance (c360) activity involves providing property owners with technical advice as to effective ways of securing their buildings from flooding. The negative relationship found between flood protection assistance and the number of NFIP policies-in-force could mean that homeowners feel secured when given such technical advice hence might prefer not to purchase flood policy.

Results based on the two estimation approaches show that floodplain mapping (c410) activity is negative and significant in explaining the number of NFIP policies-in-force. This relationship is as expected given that this activity involves the provision of
new flood elevation standards and delineating flood ways for areas that are not yet mapped onto FIRM. That is elevation, and delineation of flood ways reduces flood risk hence not surprising that this activity is negatively related to the number of NFIP policies-in-force. Open space preservation (c420) activity also show up as negative but not significant in predicting the number of NFIP policies-in-force. CRS communities that practice this activity ensure that undeveloped floodplains are protected from any future developments; hence it is intuitive that this activity is negatively related to the number of NFIP policies-in-force. For Mundlak’s random-effects, higher regulatory standards (c430) activity is negatively related to the number of NFIP policies-in-force but shows up positive for the fixed-effects estimation approach. However, they are not significant. This activity involves establishing regulations that seek to protect areas with special flood hazards, as well as provide standards for coastal constructions. Also, for both estimation approaches, parameter estimates for flood data maintenance (c440) activity are positive and significant. For CRS communities that practice flood data maintenance activity, CRS credit points are awarded for data management such as storing data on flood and property on computers. The data are made available to insurance companies for insurance rating purposes. The positive relationship between flood data maintenance activity and the number of NFIP policies-in-force is therefore not surprising as this activity can provide information to the insurance company so as to adjust premium. The result also shows a positive relationship existing between storm water management (c450) and number of NFIP policies-in-force but this is only significant for fixed-effects estimation approach. This activity involves the regulation of new constructions in the water-shed to reduce soil erosion and improve water quality, as well
as ensure good post-development runoffs. We are not surprised to see the effect to be positive.

Floodplain management planning (c510) turns out to be negatively related to the number of NFIP policies-in-force but this is only significant for the Mundlak’s random-effects. This finding is as expected because this activity involves the adoption and implementation of flood hazard mitigation. That is where flood hazard mitigation leads to a reduction of flood damages, demand for flood policy will reduce *ceteris paribus*. We also find that for both estimation approaches, there is a negative relationship between acquisition and relocation (c520) but this is not significant. This activity involves acquiring or relocating buildings from flood-prone areas. The sign is as expected since this activity reduces flood risk hence there will be no need of buying flood policy. For both estimation approaches, we find a negative and significant relationship between flood protection (c530) activity and the number of NFIP policies-in-force. Flood protection activity involves the provision of protection such as floodproofing and elevation to already existing properties in a floodplain. Since this is a way of mitigating against flood risk, it is expected that as communities practice this activity homeowners’ flood risk will reduce and therefore lead to a reduction in flood policy demand, *ceteris paribus*. Considering Mundlak’s random-effects approach, we find drainage system maintenance (c540) to be negatively related to the number of NFIP policies-in-force but this is not significant. On the other hand, the fixed-effects approach shows a positive relationship. This activity involves a periodic removal of debris in drainage system, and inspections of channels hence it is expected that removal of debris will clear the drainage system and
therefore give free passage to runoffs thereby reducing flood risk and hence reduce the number of NFIP policies-in-force, *ceteris paribus*.

In both estimation approaches, parameter estimates for flood warning and responses (c610) and dam safety (c630) are negative but not significant in explaining the number of NFIP policies-in-force. For flood warning and response (c610), community residents receive early warnings of possible floods as well as flood response plans which makes them more prepared ahead of any flood impact. Dam safety activity ensures that dams are properly managed to prevent any possible collapse. Although the parameter estimates for these activities are not significant, the signs are as expected. That is, these activities can reduce the damage caused by the floods thereby reducing flood risk and subsequently, the number of NFIP policies-in-force.

With regards to the control variables, the two estimation approaches show that overall number of policies-in-force increases over time, although not significant. On the other hand, in the two estimation approaches, the Post-Katrina variable is found to be positive and significant. That is, we find that a discrete change in Post-Katrina increases the number of NFIP policies-in-force by 37.2 percent (for fixed-effects approach) whiles for Mundlak’s random-effects, the increase is 15.3 percent, *ceteris paribus*. Gallagher (2013) has shown that flood insurance demand increases after a flood event has occurred.

For the two estimation approaches, parameter estimates for education and household show that they are positively related to the number of NFIP policies-in-force, although the estimates are not significant. Again, this finding is not surprising as Smith and Baquet (1996) also find a positive and significant relationship between education and
demand for crop insurance indicating that education has a positive effect on insurance demand.

On the socioeconomic controls, we find that for both estimation approaches, the relationship between income and the number of NFIP policies-in-force is positive and significant. That is we find that a $1000 increase in income increases the number of NFIP policies-in-force by 0.8 percent. This finding supports that of past studies (Browne and Hoyt 2000; Petrolia et al. 2015) that have found a positive relationship between income and demand for insurance.

With regards to geospatial controls, precipitation is positive in explaining number of NFIP policies-in-force as expected, although this is not significant. Time-invariant geospatial controls reported for Mundlak’s random-effects estimation approach shows that a discrete change in coast leads to an unexpected reduction in the number of NFIP policies-in-force, although this is not significant. However, there is a significant growth of the number of NFIP policies-in-force in the coast after hurricane Katrina, ceteris paribus. We also find that relative to Alabama, the number of NFIP policies-in-force increases in Mississippi, although this is not significant. Parameter estimate for slope shows that a one degree increase in slope reduces the number of NFIP policies-in-force by 70.6 percent. This relationship is as expected because properties located along a slope should have little or no risk of flood since rainwater can easily drain away. The results also show that a one percent increase in land area in SFHA increases the number of NFIP policies-in-force by 4.0 percent. This relationship is as expected given that the SFHA is an area classified as high flood risk area. The parameter estimate for non-SFHA also reveals that a one percent increase in the land area in non-SFHA increase the number of
NFIP policies-in-force by 1.8 percent. Given that non-SFHA is an area of moderate to low flood risk, we expected the number of NFIP policies-in-force to be reducing.

Elevation also shows up as positive but not significant in explaining the number of policies-in-force. This finding is not what we expected, however, communities with high elevation might not necessarily have good slopes which still expose residents to flood.

Table 7.6  NFIP policies-in-force (Unmatched)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>robust std.errors</th>
<th>Coefficients</th>
<th>robust std.errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mundlak’s Random-effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fixed-effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time-Varying Variables</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Elevation Certificate (c310)</td>
<td>-0.046</td>
<td>0.161</td>
<td>-0.295*</td>
<td>0.167</td>
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<td>Map Inf. Service (c320)</td>
<td>-0.079</td>
<td>0.103</td>
<td>0.055</td>
<td>0.110</td>
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<td>Outreach Project (c330)</td>
<td>0.186***</td>
<td>0.071</td>
<td>0.193**</td>
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<tr>
<td>Hazard Disclosure (c340)</td>
<td>-0.214</td>
<td>0.191</td>
<td>-0.120</td>
<td>0.230</td>
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<td>Flood Protection Info.(c350)</td>
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<td>-0.219</td>
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<td>0.135</td>
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<td>Floodplain Mapping (c410)</td>
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<td>Open Space Pres. (c420)</td>
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<td>Higher Reg. Std.(c430)</td>
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<td>0.020</td>
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<td>Flood data Mtn (c440)</td>
<td>0.158***</td>
<td>0.052</td>
<td>0.119*</td>
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<td>Storm Water Mgt (c450)</td>
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<td>0.059</td>
<td>0.129*</td>
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<td>-0.072</td>
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<td>Acquisition &amp; Reloc.(c520)</td>
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<td>Flood Protection (c530)</td>
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<td>-0.509**</td>
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<td>Drainage Sys. Mtn.(c540)</td>
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<td>Post-Katrina</td>
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<tr>
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<td>Mean Higher Reg. Strd (c430)</td>
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<td>Mean Storm Water Mgt (c450)</td>
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<td>0.719</td>
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<tr>
<td>Mean Fldplain Mgt Plannng (c510)</td>
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<tr>
<td>Mean Acquisition &amp; Reloc.(c520)</td>
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<td>Mean Flood Protection (c530)</td>
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<td>Mean Drainage Syst.Mtn (c540)</td>
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<td>Mean Flood Warn. &amp; Resp. (c610)</td>
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<td>Mean Dam Safety (c630)</td>
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<td>Mean of Household</td>
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<tr>
<td>Mean of Precipitation</td>
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<td>0.060</td>
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</table>

| R²                                            | 0.878    | 0.982    |
| N                                             | 528      | 528      |

Note: *** , ** , and * shows significance at 1%, 5%, and 10% levels of significance.
**Effect of Community-level Specific CRS Mitigation activities on the log of Damage Claims Payments**

In Table 7.7 we present results on the estimates of the individual CRS mitigation effects on damage claims payments. The estimates are based on the pooled model. The results show that elevation certificate (c310), damages hazard disclosure (c340), flood protection information (c350), flood protection assistance (c360), higher regulation standards (c430), storm water management (c450), drainage system maintenance (c540), and flood warning and response (c610) are all negatively related to damage claims payments as expected, but only flood protection information (c350) and storm water management (c450) are significant. Although the parameter estimates of some of these activities are not significant they deserve some explanation. The negative effect of elevation certificate (c310) on damage claims payments is not surprising given that the activity ensures that buildings in flood risk areas are elevated above some base-level in order to reduce flood. Highfield and Brody (2013) did not consider this activity in their study. Also, the negative relationship between Hazard disclosure (c340) and damage claims payments is as expected because for this activity, potential homeowners are notified of flood-prone areas so they can avoid any plans of developing the area. That is, when developers avoid developing such high risk areas, then we should expect damage claims payments to decline. This activity is also not considered by Highfield and Brody (2013). The negative relationship between flood protection information (c350) and damage claims payments is as expected since this activity ensures information on floods are provided on community’s website and libraries to inform residents as to how to secure their properties from floods. Also, practicing flood protection assistance (c360) activity ensures that property owners receive technical advice as to effective ways of
securing their buildings from flooding hence the negative effect of this activity on
damage claims payment is intuitive. Again, Highfield and Brody (2013) did not consider
this activity in their study. The relationship between higher regulatory standards (c430)
and damage claims payments is also as expected. This activity involves putting in place
regulations to secure areas with special flood hazards. Highfield and Brody (2013), finds
a positive but not significant relationship between higher regulatory standards (c430) and
total damage claims. For storm water management (c450) activity, CRS communities
that practice Storm water management (c450) activity ensures that new developments do
not lead to soil erosion, and also ensures that good water quality is maintained. Highfield
and Brody (2013) find a positive but not significant relationship between the Storm water
management activity and damage claims payments. The relationship between drainage
system maintenance (c540) and damage claims payments is not surprising because the
periodic removal of debris in drainage system and inspections of channels should reduce
flood risk, hence a reduction in damage claims payments. This activity is not considered
in Highfield and Brody (2013) study. The negative relationship between flood warning
and response (c610) activity and damage claims payments is intuitive because, early
warnings of possible floods as well as flood response plans gives residents enough time
to evacuate the area and if possible relocate mobile properties. Again, Highfield and
Brody (2013) did not account for this activity.

The results also show that map information service (c320), outreach project
(c330), floodplain mapping (c410), open space preservation (c420), flood data
maintenance (c440), floodplain management planning (c510), acquisition and relocation
(c520), flood protection (c530), and dam safety (c630) are all positive in explaining
damage claims payments, but only floodplain management planning (c510), and acquisition and relocation (c520) are significant. The positive relationship found between map information service (c320) activity and damage claims payments is not as expected because provision of flood maps to community residents are supposed to warn them of flood risk areas to avoid. Outreach project (c330) involves providing information on flood hazard and flood protection to residents to help them make better decisions that will reduce flood damages. The positive relationship existing between this activity and damage claims payments is not what we expected. Also the positive effect of floodplain mapping (c410) activity on damage claims payments is not as expected. This activity involves the provision of new flood elevation standards, delineating flood ways, for areas that are not yet mapped onto FIRM. Highfield and Brody (2013) also find a positive relationship between floodplain mapping (c410) and damage claims payments but their estimate is also not significant. The positive relationship between open space preservation (c420) and damage claims payments is not as expected since this activity ensures that undeveloped floodplains are protected from any future developments. In Highfield and Broody (2013) study, they find a negative and significant relationship between open space preservation (c420) and total damage claims payments. CRS communities practicing flood data maintenance (c440) activity ensures that data on floods and property are stored on computers and made available for use, especially by insurance companies for insurance rating purposes. Highfield and Brody (2013) also find a positive relationship between flood data maintenance (c440) and total damage claims payments but their estimated effect is not significant. Also our finding on the relationship between floodplain management planning (c510) and damage claims
payments is not as expected. For this activity, communities adopt and implement flood hazard mitigation with the aim of reducing damage claims. Although Highfield and Brody (2013) find a negative relationship between floodplain management planning (c510) activity and damage claims payments, their estimated effect is not significant. Parameter estimate for acquisition and relocation (c520) is positive and significant in explaining damage claims payments. This finding is not as expected since this activity seeks to reduce damage claims by acquiring and or relocating buildings prone to floods. Highfield and Brody (2013) also find a positive relationship between acquisition and relocation (c520), and damage claims payments but their estimated effect is not significant. The positive relationship between flood protection (c530) and damage claims payments is not as expected because this activity involves the provision of protection such as floodproofing and elevation to already existing properties in a floodplain. Highfield and Brody (2013) find a positive relationship between damage claims classified under non-SFHA and flood protection (c530) activity, although not significant. The positive effect of dam safety (c630) on damage claims payments is surprising given that this activity ensures that dams are prevented from collapsing and thereby not causing any destruction to surrounding properties. Highfield and Brody (2013) did not consider this activity in their study.

The results in Table 7.7 also show that there is a positive and significant relationship between the amount of coverage purchased and damage claims payments. That is we find that a percent increase in the amount of coverage purchased increases damage claims payments by 1.5 percent, *ceteris paribus*. The positive and significant relationship between household and damage claims payments is as expected because
when more households buy flood policy and a flood damage event occurs, then we should expect damage claims payments to also increase, *ceteris paribus*. The parameter estimate for education also shows that it is positively related to damage claims payments although this is not significant. A reason for this positive effect is that, higher education can lead to higher income which can also affects demand for flood policy and or acquire high value properties. This subsequently results in more damage claims payments if a damage event occurs, *ceteris paribus*. Income on the other hand shows up as negative but not significant in explain damage claims payments. As Cummins and Tennyson 1996 notes, increase in wealth of policy holders can reduce their motivation to file for damage claims payments.

For geospatial variables, we find that one inch increase in precipitation increases damage claims payments by 19.0 percent, *ceteris paribus*. Highfield and Brody (2013) also find a positive and significant relationship between precipitation and total damage claims payments. Results also show that damage claims payments are reducing in coastal communities although not significant. This is not as expected given that coastal communities observe high velocity of wave actions. The positive relationship between Mississippi and damage claims payments is intuitive, although the estimate is not significant. That is, because Mississippi’s shoreline extends in great length relative to that of Alabama, properties in Mississippi should be more exposed to wave actions as compared to Alabama. We also observe that the parameter estimate for slope is positive but not significant in explaining damage claims payments. Highfield and Brody (2013) also find a positive but not significant relationship between slope and total damage claims payments. The parameter estimates for elevation, stream density and non-SFHA are all
positive but not significant in explaining damage claims payments. The positive relationship between elevation and damage claims payments is not as expected. However, a community with a high elevation and poor slope will still face some flood risk, *ceteris paribus*. The positive relationship between stream density and damage claims payments is not surprising given that these streams have the potential of getting flooded. Also, the relationship between non-SFHA and damage claims payments is not as expected. This is because the non-SFHA is known to have low or moderate flood risk. Our results also show that one percent increase in land area in SFHA increases damage claims payments by 3.7 percent, *ceteris paribus*. This positive relationship between SFHA and damage claims payments is as expected given the high flood risk nature of SFHA.

Considering the year dummies, with the exception of the years 2000 and 2005, all other years are negatively related to damage claims payments. The years 2000 and 2005, although are positive, they are not significant. The year 2005 is the year when the Gulf Coast experienced hurricane Katrina. The years after 2005 are negative and significant (except for 2008, 2011, and 2012) in explaining damage claims payment.
Table 7.7  Damage claims payments (Unmatched)

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<th>Variables</th>
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<th>std. errors</th>
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<tr>
<td><strong>Time-varying variables</strong></td>
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<td>Elevation Certificate (c310)</td>
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<tr>
<td>Map Inf. Service (c320)</td>
<td>0.479</td>
<td>0.981</td>
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<tr>
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<td>Flood data Mtn(c440)</td>
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<td>Income</td>
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<tr>
<td>Non-SFHA</td>
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<td>1.749</td>
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Table 7.7 (continued)

|--------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|----------|

| R² | 0.467 |
| N  | 528   |

Note: ***, **, and * shows significance at 1%, 5%, and 10% levels of significance
SUMMARY AND CONCLUSIONS

This research is the first (to the best of our knowledge) to analyze the impact of CRS participation (versus non-participation) on NFIP participation and damage claims payments. We employ matching methods to group CRS and non-CRS communities with similar characteristics in order to eliminate comparison bias. Moreover, we are not aware of any study that has analyzed the impact of specific CRS mitigation activities on NFIP participation. This study is also the first to provide empirical findings specific to Alabama and Mississippi.

We find that regardless of the estimation approach used and whether unmatched or matched data are used, participation in the CRS program increases NFIP participation. Zahran et al. (2009) finds a positive relationship between county’s overall CRS points and NFIP participation. We also observe that although overall NFIP participation increases over time, the growth in NFIP participation is slower among CRS communities. That is, we find that the growth in NFIP participation over time for CRS communities is 4.2 percent while overall NFIP participation increase over time is 4.9 percent. Based on the unmatched data, regardless of the estimation approach, we do find that overall NFIP participation significantly increases after hurricane Katrina but the growth in NFIP participation after hurricane Katrina is slower for CRS communities, but only significant for fixed-effects model. This finding is consistent with that of Gallagher (2014) who
finds that peoples’ demand for flood insurance increases after a damage event has occurred. Regardless of using unmatched or matched data, we do not find any difference in NFIP participation between Alabama and Mississippi. Based on the unmatched data, we do find that overall, NFIP participation increases by 115.3 percent for coastal communities relative to non-coastal communities. The finding on the impact of CRS participation (versus non-participation) on NFIP participation appears to support the goal of the CRS program in improving NFIP participation. This implies that premium discounts awarded on individual policies in CRS communities may be motivating residents to purchase flood policies. However, the slow growth of NFIP over time as found in this research also raises some concerns, as this may indicate that policy holders do not keep coverage over time which threatens the goal of the CRS program in increasing NFIP participation. It could also be that NFIP participation rate in CRS communities is already higher, hence limited room for growth relative to non-CRS communities. Michel-Kerjan and Kousky (2010) also notes that over time policy holders drop coverage quickly. This means that policymakers and FEMA authorities may consider extending flood policy contracts over longer periods.

With regards to CRS effects on damage claims payments, regardless of the estimation approach and whether the unmatched or matched data is used, we do not find any significant effect of CRS participation on damage claims payments. This finding is unexpected given that the CRS program also aims to reduce or avoid damages to insured properties. Having said this, our finding regarding a lack of significant impact of CRS participation on damage claims payments can be explained by the fact that the majority (93.0 percent) of CRS communities are rated above Class 5 as of 2013, which implies
that the degree of mitigation practiced is perhaps too low to effect any significant reduction in flood damages. Michel-Kerjan and Kousky (2010) finds that only Class 5 significantly reduces damage claims payments in Florida. For our data, as of 2013, there were 3 communities in Class 5, 9 in Class 6, 4 in Class 7, 18 in Class 8, and 9 in Class 9. We also add that in cases of severe flood damage events (like hurricane Katrina), the impact of the damage event could overwhelm any mitigation effects. We also observe that damage claims payments are high for Mississippi relative to Alabama. This is not surprising, given that Mississippi has a longer coast line relative to Alabama. This indicates that more properties especially along the coast of Mississippi are subject to wave actions compared to Alabama. We find that for unmatched data, there is a significant increase of 277.4 percent in damage claims payments for coastal communities relative to non-coastal communities.

After analyzing the relationships between the individual CRS mitigation activities and NFIP participation, we find that regardless of the estimation approach, increased outreach activity and increased flood data maintenance leads to a significant increase in NFIP participation. These findings are not surprising because activities such as outreach (c330), involves dissemination of information on flood risk and flood insurance which creates the awareness of flood hazard and also the need to buy flood insurance, and hence has a positive relationship with NFIP participation. Also, flood data maintenance (c440), as practiced by CRS communities ensures that records on flood and property are available on computers, the right base maps are used and the right elevation reference marks are adhered to. That is, flood data maintenance (c440) activity can help update FIRMs which can further be used to adjust premiums on individual policy especially
where data shows a reduction in floods and property damages thereby increasing NFIP participation. On the other hand, increased floodplain mapping and increased flood protection reduces NFIP participation. Floodplain mapping (c410) involves the development of new flood elevation, delineating floodways and using more restrictive mapping standards. Hence its positive effects on damage claims payments indicates that community residents are well informed of high flood risk areas as indicated on flood maps and therefore avoid developing or evacuate these areas to safer zones. Also, flood protection (c530) activity contribution to the reduction of NFIP participation indicates that retrofitting of buildings and construction of small flood controls are achieving the aim of reducing flood damages caused to buildings hence property owners feel no need of buying flood policy.

Also, we find that increased flood protection information (c350), and increased storm water management (c450) significantly reduces damage claims payments. That is, the finding on flood protection information (c350, where communities provide flood insurance and flood protection information at the community libraries and also on its website) indicates that the resident are making good use of flood hazard and flood protection information provided in community libraries and on community website. Residents who are well informed on these issues are more likely to seek measures that will reduce flood damages to their property, ceteris paribus. Also, it is not surprising that practicing storm water management (c450, where the community ensures that new developments do not worsen runoff), activity reduces damage claims payments. This is because, once a community put the necessary measures in place to ensure that new constructions are properly positioned, then runoff can be properly directed to follow its
course so as to reduce flooding and hence reduce damage claims payments. Highfield
and Brody (2013) find a positive relationship between this activity and damage claims
payments although their estimate is not significant. On the other hand, increased
floodplain management planning (c510, which involves the preparation, adoption, and
implementation of comprehensive flood hazard mitigation strategies) and increased
acquisition and relocation (c520, acquiring and or relocating buildings from floodplains)
significantly increase damage claims payments. The positive effects of floodplain
management planning (c510) and acquisition and relocation (c520) on damage claims
payments are very surprising as we expected a negative effect. A possible explanation
for the negative effect between floodplain management planning (c510) and damage
claims payments is that since this activity does not involve any structural mitigation it is
likely that its goal of reducing damages might not be achieved. Highfield and Brody
(2013) however find a negative effect between floodplain management planning (c510)
and total damage claims payments but positive effects between floodplain management
planning (c510) and damage claims payments for SFHA, although the effects are not
significant. Highfield and Brody (2013) also find a positive effect between acquisition
and relocation (c520) but not significant. Although flood mitigation activities are
supposed to reduce damages, could also create a perception that a flood risk area is safe
for inhabiting. Brody et al (2007) notes that flood mitigation activities are encouraging
developments in the floodplains thereby leading to flood damages. These findings on the
effects of specific CRS mitigation activities on NFIP participation indicate that not all
CRS activities motivate NFIP participation, and also not all specific CRS activities
reduced damage claims payments.
Overall, the CRS program is achieving its goal of increasing NFIP participation among CRS participating communities. However, communities need to put in more mitigation effort in order to see some significant effect of the CRS program in reducing damage claims payments. Future policy changes to the CRS should focus on encouraging communities to practice more structural mitigation activities.

**Limitations**

Although this research has addressed some important questions that have not been answered in previous studies, there are some limitations to this research that need to be addressed in future studies. First, this study only focused on Mississippi and Alabama as such findings might not apply to other states. However, this research can serve as a guide to studying the effect of CRS participation on outcomes in other states. Thus future research should consider studying a wider set of NFIP communities.

Also, NFIP data used in this research are aggregated at the community-level which in one way or the other restricts analysis at the household-level. Future research should therefore consider using NFIP data at the household-level.

Although this research demonstrates the use of matching methods to study the impact of the CRS program on NFIP participation and damage claims payments, matching was performed on a subset of our data (the period 2013). We also note, however, that matching on the full data set (i.e., over all years) leads to a highly unbalanced panel and therefore possess its own challenges for regression analysis.
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US Census Bureau, 2016. [https://www.census.gov/geo/maps-data/data/gazetteer.html](https://www.census.gov/geo/maps-data/data/gazetteer.html)


APPENDIX A

ESTIMATION CODES
Matching Codes (R codes)

rm(list=ls(all=TRUE))
tic <- proc.time()
library("MatchIt")
library("Hmisc")
library("truncnorm")
library("xtable")
library("WhatIf")
library("Matching")
library("snow")
set.seed(37)
crsdata <- read.table("c:/crs/crsdata.csv", header=TRUE,sep="", dec=".", check.names=TRUE)
attach(crsdata)
View(crsdata)

nC <- length(which(crs == 0))
nT <- length(which(crs == 1))

Din <- data.frame(cbind(oid,cid1,miss,coast,crs,hh,inc,educ,
nclaims,paid,pif,premium,cover,pifrate,claimrate,pptmin,pptmax,pptmean,pptstd,elevmin
,elevmax,elevmean,elevstd,slpmin,slpmax,slpmean,slpstd,strdnmin,strdnmax,strdnmean,strdnstd,vzone,azone,bzone,czone))

avzones <- I(vzone+azone)
bzones <- I(bzone+czone)
Y <- crsdata$pifrate

Tr <- crsdata$crs

PSout <- glm(Tr ~ miss + coast + hh + inc + educ + elevmean + slpmean + strdnmean + avzones + bczones, data = Din, family = binomial)

summary(PSout)

PS <- PSout$fitted

XM <- cbind(miss, coast, hh, inc, educ, elevmean, slpmean, strdnmean, avzones, bczones, PS)

XB <- cbind(XM, I(hh^2), I(inc^2), I(educ^2), I(hh*inc), I(hh*educ), I(inc*educ), I(elevmean^2), I(slpmean^2),
            I(strdnmean^2), I(elevmean*slpmean), I(elevmean*strdnmean), I(slpmean*strdnmean),
            I(avzones^2), I(bczones^2), I(avzones*bczones))

cl <- makeCluster(c(rep("localhost", 8)), type = "SOCK")

gen1 <- GenMatch(Tr = Tr, X = XM, BalanceMatrix = XB, estimand = "ATT",
                 M = 3,
                 pop.size = 1000,
                 exact = NULL,
                 replace = TRUE,
                 ties = TRUE,
                 caliper = NULL,
                 fit.func = "pvals", 109
cluster=cl,
unif.seed=37,
int.seed=37)
stopCluster(cl)

m1 <- Match(Tr=Tr, X=XM,
estimand="ATT",
M=3,
exact=NULL,
replace=TRUE,
ties=TRUE,
Weight.matrix=gen1)

matchout <- capture.output(MatchBalance(Tr ~
   hh+inc+elevmean+slpmean+strdnmean+avzones+bczones+I(hh^2)+I(inc^2)+I(hh*inc)+I(elevmean^2)+I(slpmean^2)+I(strdnmean^2)+I(elevmean*slpmean)+I(elevmean*strdnmean)+I(slpmean*strdnmean)+I(avzones^2)+I(bczones^2)+I(avzones*bczones), data =
   crsdata, match.out = m1, nboots = 1000), file="C:/crs/matchout.txt")
iT <- m1$index.treated
iC <- m1$index.control
iAll <- c(iT,iC)

trm1 <- Tr[iAll]
Wopt <- gen1$par
liT <- length(iT)
liC <- length(iC)

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iTu <- unique(m1$index.treated)
liTu <- length(iTu)

iCu <- unique(m1$index.control)
liCu <- length(iCu)

w <- m1$weights

int <- data.frame(cbind(iC,w))

intagg <- aggregate(int,by=list(iC),FUN=sum)

wCagg <- intagg$w

wC <- (wCagg/(length(iTu)))*(length(iCu))

wT <- rep(1,length(iTu))

wvec <- c(wT,wC)

iAllu <- c(iTu,iCu)

oidM <- oid[iAllu]
cid1M <- cid1[iAllu]

Z <- cbind(oidM,cid1M,iAllu,wvec)

write.csv(Z, "c:/crs/wtdata.csv")

png("C:/crs/miss.png")

missm1 <- miss[iAll]

ttm <- table(trm1,missm1)

ttm <- prop.table(ttm,1)

anno <- table(Tr,miss)

anno <- prop.table(anno,1)

tbfaf <- cbind(anno[,2],ttm[,2])
coastm1 <- coast[iAll]

ttm <- table(trm1,coastm1)

ttm <- prop.table(ttm,1)

tto <- table(Tr,coast)

tto <- prop.table(tto,1)

tbfaf <- cbind(tto[,2],ttm[,2])

barplot(tbfaf,ylab="prob",col=c("azure1","azure4"),
main="coast",legend=c("controls","treated"),beside=TRUE,names.arg=c("Before",
"After"))

dev.off()

png("C:/crs/hhbef.png")

qqplot(crsdata$hh[44:294],crsdata$hh[1:43],xlab="controls",ylab="treated",main="#
households BEFORE",ylim=c(0,30000),xlim=c(0,30000))

abline(coef=c(0,1))

dev.off()

png("C:/crs/hhaft.png")

qqplot(crsdata$hh[m1$index.control],crsdata$hh[m1$index.treated],xlab="controls",ylab
="treated",main="# households AFTER",ylim=c(0,30000),xlim=c(0,30000))

abline(coef=c(0,1))

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dev.off()

png("C:/crs/incbef.png")
qqplot(crsdata$inc[44:294],crsdata$inc[1:43],xlab="controls",ylab="treated",main="income BEFORE",ylim=c(20000,60000),xlim=c(20000,60000))
abline(coef=c(0,1))
dev.off()

png("C:/crs/incaft.png")
qqplot(crsdata$inc[m1$index.control],crsdata$inc[m1$index.treated],xlab="controls",ylab="treated",main="income AFTER",ylim=c(20000,60000),xlim=c(20000,60000))
abline(coef=c(0,1))
dev.off()

png("C:/crs/educbef.png")
qqplot(crsdata$educ[44:294],crsdata$educ[1:43],xlab="controls",ylab="treated",main="education BEFORE",ylim=c(0,0.4),xlim=c(0,0.4))
abline(coef=c(0,1))
dev.off()

png("C:/crs/educaft.png")
qqplot(crsdata$educ[m1$index.control],crsdata$educ[m1$index.treated],xlab="controls",ylab="treated",main="education AFTER",ylim=c(0,0.4),xlim=c(0,0.4))
abline(coef=c(0,1))
dev.off()

png("C:/crs/elevbef.png")qqplot(crsdata$elevmean[44:294],crsdata$elevmean[1:43],xlab="controls",ylab="treated",main="mean elevation BEFORE",ylim=c(0,800),xlim=c(0,800))
abline(coef=c(0,1))
dev.off()
png("C:/crs/elevaft.png")
qqplot(crsdata$ele$mean[m1$index.control],crsdata$ele$mean[m1$index.treated],xlab="controls",ylab="treated",main="mean elevation AFTER",ylim=c(0,800),xlim=c(0,800))
abline(coef=c(0,1))
dev.off()
png("C:/crs/slpbef.png")
qqplot(crsdata$slpmean[44:294],crsdata$slpmean[1:43],xlab="controls",ylab="treated",main="mean slope BEFORE",ylim=c(0,7),xlim=c(0,7))
abline(coef=c(0,1))dev.off()
png("C:/crs/slpaft.png")
qqplot(crsdata$slpmean[m1$index.control],crsdata$slpmean[m1$index.treated],xlab="controls",ylab="treated",main="mean slope AFTER",ylim=c(0,7),xlim=c(0,7))
abline(coef=c(0,1))
dev.off()
png("C:/crs/strdnbef.png")
qqplot(crsdata$strdmean[44:294],crsdata$strdmean[1:43],xlab="controls",ylab="treated",main="mean stream density BEFORE",ylim=c(0.5,2),xlim=c(0.5,2))
abline(coef=c(0,1))
dev.off()
png("C:/crs/strdnaft.png")
qqplot(crsdata$strdnmean[m1$index.control],crsdata$strdnmean[m1$index.treated],xlab = "controls",ylab="treated",main="mean stream density AFTER",ylim=c(0.5,2),xlim=c(0.5,2))
abline(coef=c(0,1))
dev.off()

png("C:/crs/avzonesbef.png")
qqplot(avzones[44:294],avzones[1:43],xlab="controls",ylab="treated",main="A+V zones BEFORE",ylim=c(0,0.9),xlim=c(0,0.9))
abline(coef=c(0,1))
dev.off()

png("C:/crs/avzonesaft.png")
qqplot(avzones[m1$index.control],avzones[m1$index.treated],xlab="controls",ylab="treated",main="A+V zones AFTER",ylim=c(0,0.9),xlim=c(0,0.9))
abline(coef=c(0,1))
dev.off()

png("C:/crs/bczonesbef.png")
qqplot(bczones[44:294],bczones[1:43],xlab="controls",ylab="treated",main="B+C zones BEFORE",ylim=c(0,1),xlim=c(0,1))
abline(coef=c(0,1))
dev.off()

png("C:/crs/bczonesaft.png")
qqplot(bczones[m1$index.control],bczones[m1$index.treated],xlab="controls",ylab="treated",main="B+C zones AFTER",ylim=c(0,1),xlim=c(0,1))
abline(coef=c(0,1))
dev.off()

Testing for model assumptions (Stata codes)

**NFIP policies-in-force**

*Unmatched data*

**Serial correlation**

xtserial LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS
EDU SLPMEAN AVZONES BCZONES HH1000 IN
C1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1993

**Contemporaneous correlation**

xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS
EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN
ELVMEAN TIME if YEAR>1993, re
xtcsd, pesaran abs

**heteroskedasticity**

regress LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS
EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN
ELVMEAN TIME if YEAR>1993

set matsize 1000
estat imtest, white
**Hausman test between fixed and random**

. `xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK CRS EDU HH1000 INC1000 PPTMEANI TIME if YEAR>1993,fe`

estimates store fixed

xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK CRS EDU HH1000 INC1000 PPTMEANI TIME if YEAR>1993,re

hausman fixed , sigmamore

**Matched**

**Serial correlation**

`xtserial LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1993 & WVEC3>0`

**Contemporaneous correlation**

`xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1993 & WVEC3>0 , re`

`xtcsd, pesaran abs`

**Heteroskedasticity**

`re`gres`s LOGPIF POSTKAT TIMECRS CRSPOSTK COASTPOK MISS COAST CRS EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1993 & WVEC3>0`

`.estat imtest, white`
Hausman test between fixed vs random effect

```
.xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK CRS EDU HH1000 INC1000
PPTMEANI TIME if YEAR>1993 & WVEC3>0 ,fe
estimates store fixed
.xtreg LOGPIF POSTKAT TIMECRS CRSPOSTK CRS EDU HH1000 INC1000
PPTMEANI TIME if YEAR>1993 & WVEC3 >0,re
hausman fixed ., sigmamore
```

Damage claims payments

Unmatched

Serial correlation

```
xtserial LOGCLAIM MISS COAST CRS EDU SLPMEAN AVZONES BCZONES
HH1000 logCOVERAMT INC1000 PPTMEANI STRDMEAN ELVMEAN D1995
```

Contemporaneous correlation

```
xtdreg LOGCLAIM MISS COAST CRS EDU SLPMEAN AVZONES BCZONES
HH1000 logCOVERAMT INC1000 PPTMEANI STRDMEAN ELVMEAN D1995
```

```xtcsd, pesaran abs```
**Heteroskedasticity**

```
estat imtest, white
```

**Hausman test between fixed-effect and random-effects**

```
estimates store fixed
hausman fixed ., sigmamore
```

**Matched**

**Serial correlation**

```
```
contemporaneous correlation

xtreg LOGCLAIM MISS COAST CRS EDU SLPMEAN AVZONES BCZONES
HH1000 logCOVERAMT INC1000 PPTMEANI STRDMEAN ELVMEAN D1995
xtcsd, pesaran abs

Heteroskedasticity

regress LOGCLAIM MISS COAST CRS EDU SLPMEAN AVZONES BCZONES
HH1000 logCOVERAMT INC1000 PPTMEANI STRDMEAN ELVMEAN D1995
estat imtest, white

Hausman test between fixed-effect and random-effects

xtreg LOGCLAIM CRS EDU HH1000 logCOVERAMT INC1000 PPTMEANI D1995
estimates store fixed
xtreg LOGCLAIM CRS EDU HH1000 logCOVERAMT INC1000 PPTMEANI D1995
hausman fixed , sigmamore
Claims greater than zero

Serial correlation

Heteroskedasticity
estat imtest, white

Hausman Fixed vs Random-effects

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Specific CRS mitigation activities

NFIP policies-in-force

Serial correlation

xtserial LOGPIF POSTKAT COASTPOK C310S C320S C330S C340S C350S C360S C410S C420S C430S C440S C450S C510S C520S C530S C540S C610S C630S MISS COAST CRS EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1997

heteroskedasticity

regress LOGPIF POSTKAT COASTPOK C310S C320S C330S C340S C350S C360S C410S C420S C430S C440S C450S C510S C520S C530S C540S C610S C630S MISS COAST EDU SLPMEAN AVZONES BCZONES HH1000 INC1000 PPTMEANI STRDMEAN ELVMEAN TIME if YEAR>1997 & CRS>0

estat imtest, white

Hausman test between fixed vs random

xtreg LOGPIF POSTKAT C310S C320S C330S C340S C350S C360S C410S C420S C430S C440S C450S C510S C520S C530S C540S C610S C630S EDU HH1000 INC1000 PPTMEANI TIME if YEAR>1997 & CRS>0, fe

estimates store fixed

xtreg LOGPIF POSTKAT C310S C320S C330S C340S C350S C360S C410S C420S C430S C440S C450S C510S C520S C530S C540S C610S C630S EDU HH1000 INC1000 PPTMEANI TIME if YEAR>1997 & CRS>0, re

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Damage claims payments

**Serial correlation**


**Heteroskedasticity**

estat imtest, white

**Hausman test between randome vs fixed-effects**


xtreg LOGCLAIM C310S C320S C330S C340S C350S C360S C410S C420S C430S C440S C450S C510S C520S C530S C540S C610S C630S EDU HH1000 INC1000
Empirical model estimations (NLOGIT Codes)

**CRS participation**

*NFIP policies-in-force*

**Unmatched**

Mundlak’s Random-effects

```
|-> NAMELIST
X =
time,timecrs,
CRS,MISS,COAST,AVZONES,BCZONES,SLPMEAN,ELVMEAN,STRDMEAN,EDU
,HH1000,INC1000,PPTMEANI,postkat, crspostk,
coastpok,CRSMU,EDUMU,HHMU,INCMU,PPTMU,
$ 
|-> REGRESS
; Lhs=logPIF ; Rhs = one, X
; panel
; random
; robust
; Test: CRSMU = 0, EDUMU = 0,HHMU = 0,INCMU = 0,PPTMU = 0 ? Wu's Variable Addition Test
**Fixed-effects**

;sample; all $

;reject; year < 1994 $

;SETPANEl

; Group = CID1

;Pds=ti $

NAMELIST

; X =

time,timecrs,CRS,EDU,HH1000,INC1000,PPTMEANI,postkat,crspostk,

$ 

REGRESS

; Lhs=logPIF ; Rhs = one, X

; panel

; fixed

; robust

$

**Matched**

Mundlak’s Random-effects

sample; all $

reject; wvec3 = 0 $

reject; year < 1994 $

SETPANEl

; Group = CID1
;Pds=ti $

NAMELIST

; X =

time, timecrs,
CRS, MISS, COAST, AVZONES, BCZONES, SLPMEAN, ELVMEAN, STRDMEAN, EDU,
HH1000, INC1000, PPTMEANI, postkat, crspostk, coastpok, CRSMU, EDUMU, HHMU, IN
CMU, PPTMU,$

REGRESS

; Lhs=logPIF ; Rhs = one, X

; panel

; random

; robust

; wts = wvec3

; Test: CRSMU = 0, EDUMU = 0, HHMU = 0, INCMU = 0, PPTMU = 0 ? Wu's Variable

Addition Test

$

Fixed-effects

sample; all $

reject; wvec3 = 0 $

reject; year < 1994 $

SETPANEL

; Group = CID1

;Pds=ti $
NAMELIST

; X =
time, timecrs, CRS, EDU, HH1000, INC1000, PPTMEANI,
postkat, crspostk,

$ REGRESS

Lhs = logPIF ; Rhs = one, X

; panel

; fixed

; robust

; wts = wvec3

$ 

*Damage claims payments*

*Unmatched*

Mundlak’s random-effects

sample; all $

reject; year < 1994$

SETPANEL

; Group = CID1

; Pds = ti $

NAMELIST

; X =

CRS,
MISS, COAST, AVZONES, BCZONES, SLPMEAN, ELVMEAN, STRDMEAN
EDU, HH1000, INC1000, PPTMEAN, LOGCOVER,
CRSMU, EDUMU, HHMU, INCMU, PPTMU, covermu

$ REGRESS
; Lhs = logCLAIM ; Rhs = one, X
; panel
; random
; robust
; Test: CRSMU = 0, EDUMU = 0, HHMU = 0, INCMU = 0, PPTMU = 0,
covermu = 0 ? Wu's Variable Addition Test

$ Fixed-effects
sample; all $
reject; year < 1994 $

SETPANEL
; Group = CID1
; Pds = ti $

NAMELIST
; X =

CRS,
EDU, HH1000, INC1000, PPTMEANI, LOGCOVER,

$ REGRESS
; Lhs = logCLAIM ; Rhs = one, X
; panel
; fixed
; robust

$ Matched

Random-effects sample; all $ reject; wvec3 = 0 $ reject; year < 1994 $ SETPANEL
; Group = CID1
; Pds = ti $ NAMELIST
; X = CRS,
MISS, COAST, AVZONES, BCZONES, SLPMEAN, ELVMEAN, STRDMEAN,
EDU, HH1000, INC1000, PPTMEANI, LOGCOVER,
REGRESS

;Lhs=logCLAIM ; Rhs = one, X
;panel
;random
;robust
; wts = wvec3

Claims greater than zero

Mundlak
sample; all $ reject; year < 1994 $ reject ; logCLAIM = 0 $ SETPANEL ; Group = CID1 ;Pds=ti $
NAMELIST ; X = CRS, MISS, COAST, AVZONES, BCZONES, SLPMEAN, ELVMEAN, STRDMEAN, EDU, HH1000, INC1000, PPTMEANI, LOGCOVER,
CRSMU, EDUMU, HEMU, INC MU, PPTMU, covermu

$ REGRESS
; Lhs = logCLAIM ; Rhs = one, X
; panel
; random
; robust
; Test: CRSMU = 0, EDUMU = 0, HEMU = 0, INC MU = 0, PPTMU = 0, covermu = 0 ? Wu's Variable Addition Test

$ Fixed-effects
sample; all $

reject; year < 1994 $

reject; logCLAIM = 0 $

SETPANEL
; Group = CID1
; Pds = ti $

NAMELIST
; X =

CRS,
EDU, HH1000, INC1000, PPT MEANI, LOGCOVER,

$\$

REGRESS

; Lhs = logCLAIM ; Rhs = one, X

; panel

; fixed

; robust

Specific CRS activities

NFIP policies-in-force

Mundlak’s random-effects

sample; all $ reject; year < 1998 $ reject; crs = 0 $ SETPANEL

; Group = CID1

; Pds = ti $ NAMELIST

; X =

time,

c310s, c320s, c330s, c340s, c350s, c360s, c410s, c420s, c430s, c440s, c450s,
c510s, c520s, c530s, c540s, c610s, c630s, MISS, COAST, AVZONES, BCZONES, SLPMEA N, ELVMEAN, STRDMEAN, EDU, HH1000, INC1000, PPTMEANI, postkat,
coastpok,c310mu,c320mu,c330mu,c340mu,c350mu,c360mu,c410mu,c420mu,c430mu,c440mu,c450mu,c510mu,c520mu,c530mu,c540mu,c610mu,c630mu,EDUMU,HHMU,INU,PPTMU,

$\REGRESS$

; Lhs=logPIF

; Rhs = one, X

; panel

; random

; robust

; Test: c310mu = 0, c320mu = 0, c330mu = 0, c340mu = 0, c350mu = 0, c360mu = 0, c410mu = 0, c420mu = 0, c430mu = 0, c440mu = 0, c450mu = 0, c510mu = 0, c520mu = 0, c530mu = 0, c540mu = 0, c610mu = 0, c630mu = 0, EDUMU = 0, HHMU = 0, INCMU = 0, PPTMU = 0 ? Wu's Variable Addition Test

$\Fixed-effects$

sample; all $\reject$ year < 1998 $\reject$

reject; crs = 0 $

SETPANEL

; Group = CID1

; Pds = ti $

NAMELIST
 ; X =

time, c310s,c320s,c330s,c340s,c350s,c360s,c410s,c420s,c430s,c440s,c450s,
c510s,c520s,c530s,c540s,c610s,c630s, EDU,HH1000,INC1000,PPTMEANI, postkat,
$ REGRESS
; Lhs=logPIF ; Rhs = one, X
; panel
; fixed
; robust
$ 

**Damage claims payments**

*Pooled model*

sample; all $ reject; year < 1998 $ reject; crs = 0 $ SETPANEL
; Group = CID1
; Pds=ti $ NAMELIST
; X =
c310s,c320s,c330s,c340s,c350s,c360s, c410s,c420s,c430s,c440s,c450s,
c510s,c520s,c530s,c540s,c610s,c630s, MISS,COAST, AVZONES,BCZONES, SLPMEAN,ELVMEAN,STRDMEAN,
EDU, HH1000, INC1000, PPTMEANI, LOGCOVER,

$ REGRESS

; Lhs=logCLAIM ; Rhs = one, X

; panel

; pooled

$