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Factors Affecting Community Rating System Participation in the National Flood Insurance Program: A Case Study of Texas

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by

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Abstract

Since the 1960s, the frequency and cost of floods have, on average, increased in the United States. Concurrent with this increase in flood losses has been an increase in flood insurance claims paid out by the National Flood Insurance Program (NFIP). The existing literature shows that participation in the NFIP's Community Rating System (CRS) program successfully lowered flood losses and NFIP insurance claims in the participating communities. In spite of these successes, community participation in the CRS is low and the NFIP is currently more than $20 billion in debt. By identifying factors predicting participation and related barriers to entry into the program, policy-makers could devise strategies to increase program participation, possibly resulting in lower flood losses and insurance claims.

Only a few studies have examined factors that affect a community's adoption and participation in the CRS program. This dissertation provides additional evidence on CRS participation by using data from Texas from 1980 to 2020 to examine factors that predict initial community adoption, which is defined as joining the program in its first three years (from 1991 to 1993), and participation in 2020. Other studies on CRS participation have not explored the influence that program implementation has on CRS participation, nor have they explored whether factors influencing participation change over time. Results showed that the number of flood insurance claims, claims paid per household, population size, educational attainment, share of renters, and poverty rate all have significant effects on an early adopting community's participation in the CRS program in 1991, after the program was implemented. Results of a participation model using 2020 data showed that

population density becomes a significant factor for early adopters in 2020. Conversely, population size and poverty rate, which were significant factors in 1991, become nonsignificant in 2020. Regarding subsequent joiner participation in 2020, recent claims paid per household and external influence significantly predict participation.

In addition to analyzing predictors of CRS participation in the program's initial years and in 2020, this research offers another perspective on CRS participation by analyzing if early adopter communities differ from subsequent joiners using data from the year that each joined. This research shows that early adopters differed from subsequent joiners on population size and share of renters. Collectively, these results suggest that policy-makers would be successful in encouraging communities with higher population densities located near recent flood events to join the CRS. At the same time, non-participant communities located away from clusters of CRS communities will likely require additional incentives to join. In addition, these results suggest that future studies of CRS participation should consider including time of joining in their research design and analysis.

Dedication

To my partner in life, and primary care oceanographer, Ana.

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1 Introduction

Since the 1960s, the frequency and cost of floods have, on average, increased in the United States (Brody, Zahran, Highfield, Bernhardt, & Vedlitz, 2009). By the end of 2014, average annual flood losses in the United States approached nearly ten billion dollars, making flooding the nation's costliest natural disaster (Kousky, Kunreuther, LaCour-Little, & Wachter, 2020; National Academies of Sciences & Medicine, 2019). Concurrent with this increase in flood losses has been an increase in flood insurance claims paid out by the National Flood Insurance Program (NFIP) (Federal Emergency Management Agency [FEMA], 2021g). As of 2022, this increase in flood insurance claim payments has led to substantial indebtedness – on the order of $20.5 billion – for the National Flood Insurance Program (Bradt & Kousky, 2020; Horn & Webel, 2022). Consistent with national trends, flood damages and flood insurance claims paid in Texas are also rising, albeit at a higher rate than the nation as a whole (ASU Center for Emergency Management and Homeland Security [ASU-CEMHS], 2022; FEMA, 2021g). Overall, Texas ranks first amongst states in property damages due to flood-related events from 1980 through 2020, accounting for 24.8% of the total. Florida ranks second with 19.1% and Louisiana ranks third with 18.7%.

According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the number and severity of flood-causing storms is changing worldwide and is expected to get worse in some places and better in others (Jiménez Cisneros et al., 2014). In general, the central United States is expected to experience fewer flood events while the coastal regions are expected to experience more.

Nonetheless, even if flood events are rarer in the central states, the impacts of flood events are expected to increase as a result of rising exposure and vulnerability. In other words, even with fewer flood events, areas may experience more severe flood events owing to, for example, more intense rainfall, less adaptive physical environments, and more vulnerable populations. The flood damages and NFIP data presented in chapters 2 and 3 tend to support this claim.

Given the high – and potentially increasing – levels of flood loss in Texas, and the overall indebtedness of the NFIP, state and federal policies that encourage the adoption of cost-effective flood mitigation measures are critical. The literature shows that a community's participation in the NFIP's Community Rating System (CRS) program – a voluntary program that rewards communities that exceed the NFIP's minimum requirements regarding flood mitigation – is linked to successfully lowering flood loss and NFIP insurance claims in that community (Frimpong, Petrolia, Harri, & Cartwright, 2020; Gourevitch & Pinter, 2022; Highfield & Brody, 2017). When analyzing the impact of CRS participation as a binary variable of participation and non-participation, results indicate that, all things being equal, CRS participants on average had a 41.6% reduction in flood claims compared to non-participants (Highfield & Brody, 2017). When analyzing CRS participation based on level of participation (as measured by program points earned for implementing various mitigation measures), the connection between CRS participation and lower flood loss, in general, is valid at higher levels of participation (Brody, Zahran, Highfield, Grover, & Vedlitz, 2007; Brody, Zahran, Maghelal, Grover, & Highfield, 2007; Frimpong et al., 2020; Gourevitch & Pinter, 2022; Highfield & Brody, 2013; Michel-Kerjan & Kousky, 2010).

In spite of the links between CRS participation and lower levels of flood loss and insurance claims, participation in the CRS is still low (Highfield & Brody, 2013, 2017; Sadiq, Tyler, & Noonan, 2020). The participation rate for communities in Texas is just 5.6%. A review of CRS adoption trends in Texas, suggests that the rate of adoption has been increasing in recent years and factors explaining participation recently may be different than those predicting participation when the program was implemented (see chapter 3).

By identifying factors predicting participation and related barriers to entry into the program, policy-makers could devise strategies to increase program participation, possibly resulting in lower flood losses and insurance claims. Given factors that predict policy adoption in general, including governing capacity, perceived problem threat, and influence of nearby communities (Berry & Berry, 2018), results presented here could be applicable to policy areas with similar threat characteristics. These characteristics include a perceived threat that increases over time, potentially high levels of public loss, and insufficient levels of private protection through mitigation or insurance. One such area might be wildfire mitigation.

Because the CRS has been shown to reduce flood loss in communities, the participation rate in the CRS nationally and within Texas is low, and few studies have analyzed CRS participation in relation to non-participation in Texas, this dissertation explores the general theme of understanding factors that predict community participation in the Community Rating System flood mitigation program in Texas. I concentrate on incorporated communities in Texas, many of which have experienced substantial upheaval and loss due to disastrous flooding over the last several decades. Building upon the studies of Landry and Li (2012) and Li (2012), in which they use a case study approach to analyze CRS participation in North Carolina, I also use a case study approach to investigate factors known to correlate with CRS participation in Texas.

The primary goals of this dissertation then are to describe factors that predict CRS participation amongst incorporated communities in Texas and to understand if there are differences between early adopters and subsequent joiners.[1] In doing so, I intend to answer the following research questions.

1. Which factors predict CRS participation among NFIP communities in Texas?
2. How do subsequent joiners of CRS differ from initial participants in Texas?

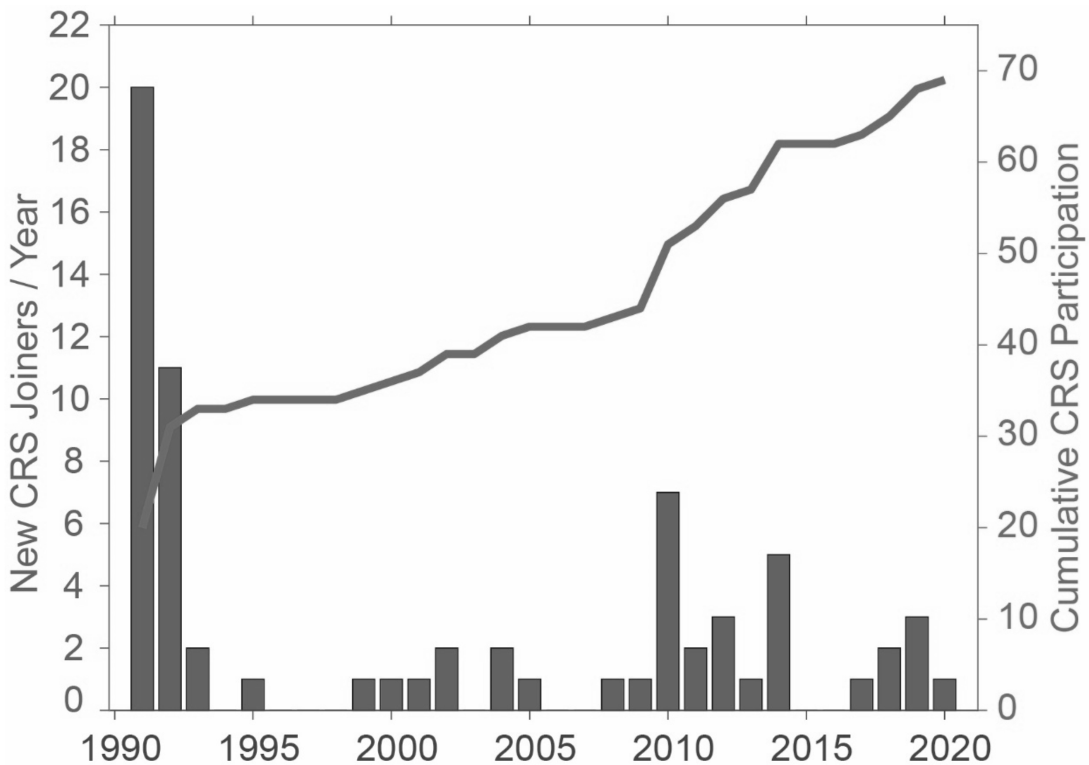
I explore which factors predict CRS participation in Texas at two points in time – 1991 and 2020 – in order to broadly understand community participation and to provide a foundation for the subsequent analysis and discussion about whether there is a difference between initial participants and subsequent joiners on the factors of interest. The second question uses the same factors from the first question to determine if communities that join CRS at later times have similar characteristics as those that joined in the initial cohort.

[1] Through this dissertation I use the terms 'early adopter' and 'early participant' interchangeably. Additionally, 'initial cohort' refers to the group of communities that are early adopters. 'Subsequent joiners' may also be referred to as 'late adopters.'

My research differs from earlier studies on CRS participation and provides a meaningful contribution to the collection of studies on CRS participation by differentiating between early and late adopters in investigating factors that impact CRS participation, by exploring how factors predicting participation differ at certain points in time (1991 and 2020), and by focusing on the case of Texas. Other studies on CRS participation have not attempted to identify the influence that program implementation has on CRS participation, nor have they identified factors influencing participation that change over time.

I suspect that early adopters – those that join in the first three years of the program – may differ in important ways from the subsequent joiners, or those that join after the first three years. I chose the three-year cutoff due to an observed clustering of communities that joined in the first three years of the program (Figure 1.1). Twenty communities joined in 1991, eleven joined in 1992, two joined in 1993, and no communities joined in 1994.

Figure 1.1 New CRS Joiners and Cumulative Participation (1991-2020)



Source: (FEMA, 2021b)

In other CRS participation studies, the year or range of years used to determine participation status seems to be based primarily on Census data availability (Asche, 2013; Frimpong, Reilly, & Niemeier, 2022; Landry & Li, 2012; Li, 2012; Paille, Reams, Argote, Lam, & Kirby, 2016; Sadiq & Noonan, 2015b). This strategy is understandable from the perspective of research feasibility, but analyzing data at such a point in time may lessen the influence that the implementation of the program itself might have on CRS participation – as suggested by Sadiq and Noonan (2015a) – and implies that the influence of policy adoption has little or no impact. Research on the diffusion of innovations and early adopters (Berry & Berry, 2018; Wejnert, 2002), a qualitative analysis of CRS participation by Sadiq, Tyler, and Noonan (2020), and research on the influence of NFIP policy changes on outcomes – such as the increase in flood insurance uptake following the passage of the Flood Disaster Protection Act of 1973 (Horn & Webel, 2022) – suggest that timing is indeed relevant when analyzing CRS participation.

Finally, by selecting Texas as my study area, I add to the small, but growing number of studies describing CRS participation and non-participation on sub-national levels (Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Paille et al., 2016; Posey, 2008, 2009). In doing so, I am also able to describe participation on a jurisdictional level that receives relatively little attention, the incorporated community. Although several studies on CRS participation have focused on the county as the unit of analysis (Asche, 2013; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Paille et al., 2016), the number of counties participating in the CRS in Texas is too small to permit reliable statistical analysis. Of the 69 communities participating in CRS in Texas as of 2020, 65 were incorporated communities and only four were counties. By contrast, of the 1,395 NFIP communities in Texas as of 2020, 1,150 were incorporated communities, 224 were counties, and the remaining 21 were utility, improvement, or drainage districts.

The remainder of this dissertation is divided into five additional chapters. In the following chapter, I describe the history and development of flood risk mitigation in the United States, and particularly of the National Flood Insurance Program and the Community Rating System. I also describe the relevant literature on factors predicting CRS participation. In chapter three, I describe the state of flood risk management in Texas. In chapter four, I describe my research design, including the conceptual framework and variable selection, the hypotheses, the study area and sample, data collection and data processing, and, finally, the methods I used to analyze the data. In chapter five I present the results of the data analysis, followed by a discussion of the results and concluding remarks in chapter six.

2 Flood Risk Management, the NFIP, and the CRS

In order to explain factors related to CRS participation in Texas, I first present an overview of flood risk management in the United States, or what Gilbert White called in his doctoral dissertation, "the flood problem in the United States" (White, 1942). I then discuss the National Flood Insurance Program, which was authorized by Congress in 1968 as a way for the federal government to incentivize the local adoption of floodplain management standards and for communities to gain access to affordable flood insurance (Horn & Webel, 2022). Finally, I discuss the Community Rating System, its relationship to the NFIP and, importantly, the factors that predict CRS participation.

2.1 Flood Risk Management

Gilbert White is considered one of the most influential scholars regarding flood mitigation and management in the United States and his dissertation, *Human Adjustment to Floods: A Geographical Approach to the Flood Problem in the United States* (White, 1942), is the basis for what would become, by the end of the 1970s, the 'dominant' methodology for assessing hazard and risk management (Macdonald, Chester, Sangster, Todd, & Hooke, 2012). His methodology, first introduced in a previous article (White, 1936) and expanded upon in his dissertation, is a comprehensive evaluation of adjustments to floods and the costs and benefits of flooding and flood mitigation measures. Previously, cost-benefit estimates of such measures bordered on guesswork, often based on estimated damages that tended to overestimate certain types of benefits – those that he called *special benefits* – while largely ignoring other types of benefits – what he called *general benefits*. Citing their lack of reliability and substantial influence on the calculation of benefits, White also criticized the use of probability analyses of hydrologic data (equivalent to today's 100- and 500-year floodplains). In relation to costs, White criticized the lack of attention paid to potential damages incurred due to the implementation of engineering mitigation measures, the use of overly optimistic estimates of the operational life of mitigation measures, and inappropriate allocation of the fair share of mitigation costs. White's dissertation, completed in 1942 and re-published in 1945, presents a comprehensive assessment of "the flood problem," providing the foundation of what would eventually be referred to as flood risk management.

Flood risk management is a strategy that focuses on reducing the impacts of floods as opposed to preventing floods altogether (Bergsma, 2019). The shift towards a policy of flood risk management did not occur until the passage of the National Flood Insurance Act of 1968 (FEMA, 2021c). Before that, the primary method for managing floods was the construction and maintenance of dams, levees, floodways, and similar measures to control the movement of water. According to White (1942), this engineering approach was, up until 1936, largely at the direction of state and local governments. On several occasions, the federal government authorized and funded specific large-scale projects like the construction of flood control measures on the Lower Mississippi and Sacramento Rivers. The passage of Flood Control Act of 1936 marked the beginning of the shift of flood control responsibility from the state and local level to the national level.

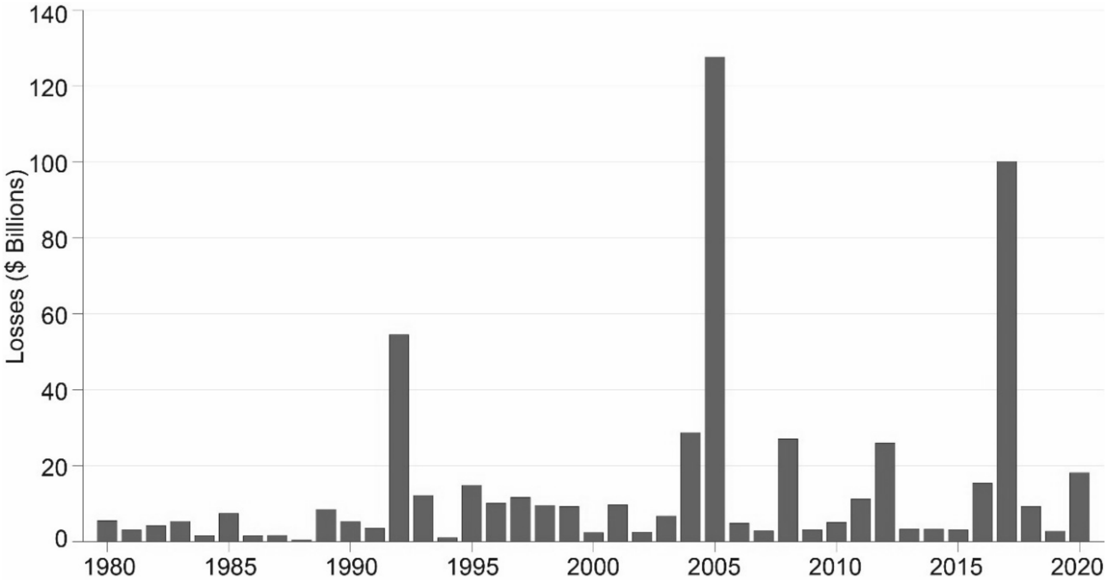
The focus on structural mitigation continued until the 1950s when a series of devastating floods prompted the federal government to consider White's approach, which centered on the range of adjustments that societies and people have to cope with floods (Bergsma, 2019; Macdonald et al., 2012). With the passage of the 1968 Act, the federal government adopted the concept of floodplain management, which focuses on identifying flood risk, managing land use, and providing flood insurance in accordance with the identified risk. This marked the federal government's acceptance of non-structural approaches to flood mitigation.

Research on the impacts of flood mitigation measures has demonstrated the importance of non-structural measures in limiting the negative impacts of flood events on communities (Brody, Bernhardt, Zahran, & Kang, 2009; Brody, Blessing, Sebastian, & Bedient, 2014; Brody, Zahran, Highfield, et al., 2007; Fan & Davlasheridze, 2014; Highfield & Brody, 2017). Non-structural mitigation measures – which include tools like land use planning, wetland preservation and restoration, and information dissemination about flood insurance and flood risk (Bergsma, 2019; Brody, Highfield, & Kang, 2011) – provide communities with effective protections against the consequences of flooding that are more affordable than structural mitigation measures like the construction of flood channels, dams, and levees (Brody, Bernhardt, et al., 2009). Furthermore, non-structural flood mitigation strategies are linked to lower property damages and insurance claims and fewer deaths resulting from flood events (Brody, Highfield, & Blessing, 2015; Brody, Sebastian, Blessing, & Bedient, 2018; Michel-Kerjan & Kousky, 2010; Zahran, Brody, Peacock, Vedlitz, & Grover, 2008).

In spite of these findings on the effectiveness on non-structural flood mitigation, the current system of mitigating against flood damage and loss in the United States is built on a system that has perversely encouraged growth and development in areas with elevated levels of flood risk (Brody et al., 2011). The stated reasons for this outcome include out-of-date flood risk maps and flood insurance pricing that subsidizes locating homes and businesses in risky areas. Consistent with this description of perverse outcomes, in the past twenty years, and particularly since Hurricane Katrina struck New Orleans in 2005, flooding in the United States has resulted in a clear increase in property damages (Figure 2.1). From 1980 through 1999, property damages as a result of flood-related events[2] totaled approximately $142 billion (2020 dollars).[3] From 2000 through 2020, the value of property damages from flood-related events was approximately $402 billion, almost triple what it was in the previous two decades. Just two years, 2005 and 2017, the years of Hurricanes Katrina and Harvey, respectively, account for 41.7% of the total losses during these four decades. If 1992, the year of Hurricane Andrew, is added, these three years account for 51% of all flood losses from 1980 through 2020.

[2] I classify flood-related events as floods, hurricanes/tropical-storms, coastal, and tsunami from the SHELDUS database.
[3] Unless otherwise stated, dollar values presented throughout the text are 2020 real dollars.

Figure 2.1 Estimated Annual Property Losses from Flooding Nationwide (2020 dollars)



Source: The Spatial Hazard Events and Losses Database for the United States, Version 20.0 (SHELDUS) (ASU-CEMHS, 2022)

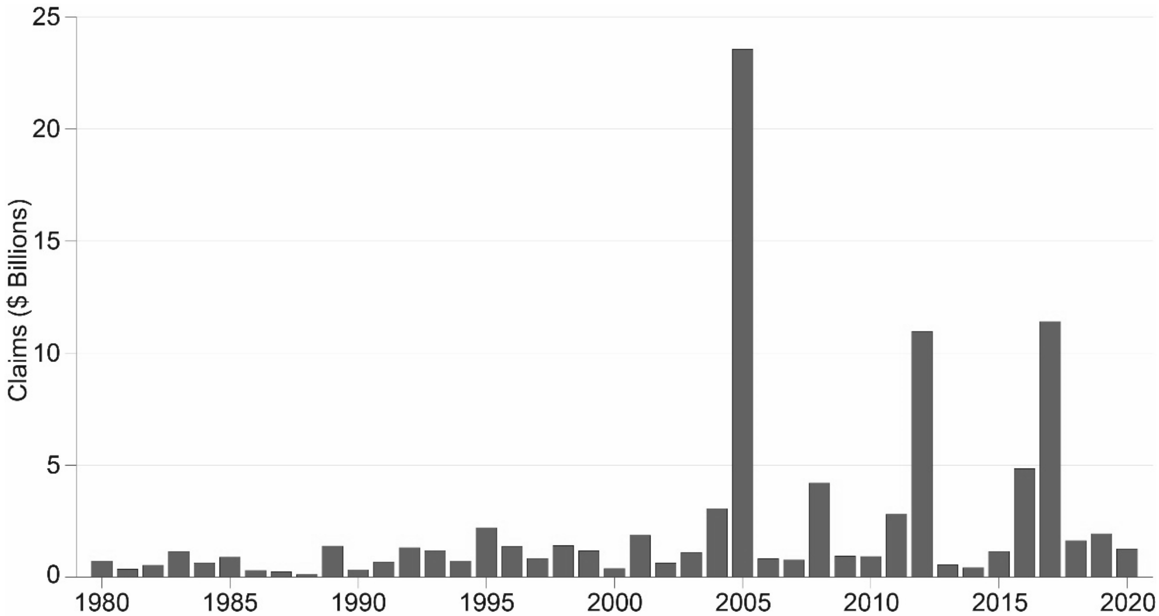
2.2 National Flood Insurance Program

In order to protect against flood losses like those described above, Congress established the National Flood Insurance Program with the passage of the National Flood Insurance Act of 1968 (FEMA, 2021c). The Act was passed in order to address inadequate protection against personal hardship and financial distress caused by increasing exposure to flood losses ("The national flood insurance act of 1968," 1968). The federal government recognized that, at the time, existing government programs were inadequate to address flood losses, the private insurance industry lacked the incentives to make flood insurance available to those in need, and there was a need for a unified flood management program to encourage responsible land use that minimized flood exposure. Over the years, the NFIP has been strengthened in various ways, such as requiring that homes financed through federally backed mortgages have the appropriate level of flood insurance and requiring that communities participate in order to be eligible for certain types of disaster assistance (Brody et al., 2011).

In order for residents to be eligible to purchase flood insurance through the NFIP, the community in which they live must participate in the program. For a community to participate, it must adopt land use controls that restrict development in flood-prone areas, guide development to areas that are not susceptible to flooding, assist in reducing flood damage, and help to improve the land management of flood prone areas (Horn & Webel, 2022). Part of this process is identifying and mapping land at high risk for flooding, which is defined as having a one percent chance of flooding each year. This area of high flood risk is often referred to as the 100-year floodplain or the Special Flood Hazard Area (SFHA).

In spite of these efforts, data on residential flood insurance claims paid through the NFIP from 1980 to 2020 shows that flood insured claims paid, like flood losses in general, have, on average, both increased and become more volatile in recent years (Figure 2.2). Whereas insurance claims paid from 1980 through 1999 totaled approximately $17.5 billion, the amount paid from 2000 through 2020 totaled just over $75 billion. The number of claims during those same time periods increased from 918,094 to 1,460,087. Although the value of claims increased by more than four times the earlier value, the number of claims has increased by just 1.6 times. Consistent with other research, this suggests that, on average, the value of each individual claim has increased substantially over the years (Bradt & Kousky, 2020).

Figure 2.2 Annual Insured Flood Claims Paid by the National Flood Insurance Program Nationwide (2020 dollars)



Source: (FEMA, 2021g)

Furthermore, just three years – 2005, 2012, and 2017 – account for nearly half the value of all claims from 1980 to 2020. These years coincide with Hurricanes Katrina, Sandy, and Harvey, respectively. Collectively, the amount of insured flood losses from these three years is nearly $46 billion.

As of 2022, this increase in flood insurance claim payments has led to substantial indebtedness – on the order of $20.5 billion – for the National Flood Insurance Program (Bradt & Kousky, 2020; Horn & Webel, 2022). It was not until after Hurricane Katrina in 2005 that the NFIP began to accumulate substantial amounts of debt, which required Congress to authorize increases to the NFIP's borrowing limit (Horn, 2021). The most recent debt limit increase, to $30.425 billion, occurred in 2013 following Hurricane Sandy. That the NFIP has not exceeded this limit again is mainly attributable to a

Congressionally authorized cancellation of $16 billion in NFIP debt in 2017, the year Hurricane Harvey struck the Texas coast.

To address this increasing debt and to promote adjustments to flood insurance premiums so they reflect the true risk of flooding, Congress passed the Biggert-Waters Flood Insurance Reform Act of 2012. The act required that the NFIP pay down its debt over the next ten years (something that did not occur), improve flood risk mapping to better reflect actual risk, and adjust rates and eliminate subsidies (Bergsma, 2019; Kousky & Golnaraghi, 2020). More recently, the NFIP is implementing Risk Rating 2.0, which is a program that effectively eliminates zone-based flood risk mapping and insurance pricing. Instead, properties are assessed individually for flood risk and pricing, removing the former subsidization of flood insurance for high-value homes (Linder-Baptie, Epstein, & Kousky, 2022).

2.3 Community Rating System

In 1987, the NFIP's Flood Insurance Administrator sought to establish a program that would reward participating communities that exceeded the NFIP's minimum requirements for reducing community flood losses, facilitated more accurate insurance ratings, and increased community awareness of flood insurance (FEMA, 2008). A task force was established and, over the next three years, these basic tenets evolved into the establishment and implementation of the Community Rating System. Based on the task force's recommendations, a weighted list of activities under the categories of public information, mapping and regulatory, flood damage reduction, and flood preparedness was created to serve as the basis of the CRS scoring and incentive structure.

Communities are scored based on the weighted credits they received for their level of participation in each activity. Activities and maximum scores for each activity can be found in Table 2.1. Their score earns them a CRS classification from 1 to 10 (with 1 being the best) and a corresponding reduction in flood insurance premiums (up to 45%) for residents in the community holding NFIP flood insurance policies. The data presented in Table 2.1 suggest that communities tend to favor certain activities over others. Whereas 100% of participating communities have earned points under activity 430 (Higher Regulatory Standards), less than 1% of communities have earned points under activity 620 (Levee Safety). I suspect the low participation rate in activity 620 is due to the low number or lack of levees in many communities. Nonetheless, the range of activities that a community selects is generally related to the highest number of points that the community can earn for the least amount of effort (Brody, Zahran, et al., 2009; Sadiq & Noonan, 2015b; Zahran, Brody, Highfield, & Vedlitz, 2010). The stepped nature of the class scoring system illustrated in Table 2.2 suggests that communities will favor the easiest activities to get them to the next highest class.

Table 2.1 CRS Activities and Points Awarded as of 2016

Activity	Maximum Possible Points	Maximum Points Earned	Average Points Earned	Percentage of Communities Credited
300 Public Information Activities				
310 Elevation Certificates	116	116	38	96%
320 Map Information	90	90	73	85%
330 Outreach Projects	350	350	87	93%
340 Hazard Disclosure	80	62	14	84%
350 Flood Protection Information	125	125	38	87%
360 Flood Protection Assistance	110	100	55	41%
370 Flood Insurance Promotion	110	110	39	4%
400 Mapping & Regulatory Activities				
410 Additional Flood Data	802	576	60	55%
420 Open Space Preservation	2,020	1,603	509	89%
430 Higher Regulatory Standards	2,042	1,335	270	100%
440 Flood Data Maintenance	222	249	115	95%
450 Stormwater Management	755	605	132	87%
500 Flood Damage Reduction Activities				
510 Floodplain Management Planning	622	514	175	64%
520 Acquisition and Relocation	2,250	1,999	195	28%
530 Flood Protection	1,600	541	73	13%
540 Drainage System Maintenance	570	454	218	43%
600 Flood Preparedness Activities				
610 Flood Warning Program	395	365	254	20%
620 Levee Safety	235	207	157	0.5%
630 Dam Safety	160	99	35	35%

Source: 2017 CRS Coordinator's Manual (FEMA, 2017)

As part of the verification process, communities participating in the CRS must submit proof of activities performed to an independent organization which audits and verifies each community's points and class. As evidenced by the 641-page CRS Coordinator's Manual (Federal Emergency Management Agency, 2017), the program's scoring system is very complicated. Although not visible here, under each activity listed in Table 2.1, there are several elements that are individually scored. The hazard disclosure activity, for example, is composed of four underlying elements. Because some element scores are multiplicative, or somehow dependent on scores from another element, determining a community's total score for an activity is not simply a matter of adding each of the element scores.

Table 2.2 CRS Classes, Points, and Premium Discounts

		Premium Reduction	
CRS Class	Points	In SFHA	Outside SFHA
1	4,500+	45%	10%
2	4,000 – 4,499	40%	10%
3	3,500 – 3,999	35%	10%
4	3,000 – 3,499	30%	10%
5	2,500 – 2,999	25%	10%
6	2,000 – 2,499	20%	10%
7	1,500 – 1,999	15%	5%
8	1,000 – 1,499	10%	5%
9	500 – 999	5%	5%
10	0 – 499	0	0

Source: 2017 CRS Coordinator's Manual (FEMA, 2017)

This scoring and incentive system is intended to promote the implementation of community flood mitigation measures and the awareness of flooding in accordance with the Community Rating System's three primary goals (FEMA, 2017):

1. Reduce and avoid flood damage to insurable property;
2. Strengthen and support the insurance aspects of the National Flood Insurance Program; and
3. Foster comprehensive floodplain management.

To better explain how the scoring system works, I have entered the activity scores of three communities in Texas to provide an example of results at three different class levels. Table 2.3 presents the activity scores of Dallas (class 5), Friendswood (class 7), and El Paso (class 9) from 2016. As a class 5 community, Dallas has, on average, higher scores than the other two communities. Dallas scores particularly well in open space preservation (activity 420), which, itself, is made up of eight additional elements. These elements are open space preservation, deed restrictions, natural functions open space, special flood-related hazards open space, coastal erosion open space, open space incentives, low-density zoning, and natural shoreline protection. In reviewing the underlying data, I could see that nearly all of Dallas's points within the open space preservation activity fall under one element. By comparison, neither Friendswood, nor El Paso have received any points for elements under the open space preservation activity.

Table 2.3 CRS Scores Dallas (Class 5), Friendswood (Class 7), and El Paso (Class 9) in October 2016

Activity	Maximum Possible Points	Dallas Class 5	Friendswood Class 7	El Paso Class 9
300 Public Information Activities				
310 Elevation Certificates	116	86	11	16
320 Map Information	90	90	0	50
330 Outreach Projects	350	200	33	12
340 Hazard Disclosure	80	15	15	15
350 Flood Protection Information	125	58	36	36
360 Flood Protection Assistance	110	55	0	0
370 Flood Insurance Promotion	110	0	0	0
400 Mapping & Regulatory Activities				
410 Additional Flood Data	802	62	10	0
420 Open Space Preservation	2,020	1043	0	0
430 Higher Regulatory Standards	2,042	253	271	103
440 Flood Data Maintenance	222	179	141	124
450 Stormwater Management	755	112	83	62
500 Flood Damage Reduction Activities				
510 Floodplain Management Planning	622	50	204	0
520 Acquisition and Relocation	2,250	105	646	21
530 Flood Protection	1,600	0	12	0
540 Drainage System Maintenance	570	265	0	0
600 Flood Preparedness Activities				
610 Flood Warning Program	395	0	0	0
620 Levee Safety	235	0	0	0
630 Dam Safety	160	22	0	22

Source: 2017 CRS Coordinator's Manual (FEMA, 2017), (FEMA, 2021b)

According to the data presented in Table 2.2, Dallas's class 5 ranking suggests that its total score lies somewhere between 2,500 and 2,999 points. Indeed, according to the underlying data, its score is 2,842. With this class ranking, Dallas residents will receive a 10% or 25% discount on their flood insurance premiums based on whether their home is located outside or inside the SFHA.

The flood insurance premium reductions for residents are the primary incentives for communities joining the CRS program. Even with these incentives, it seems that many communities choose not to participate due to the substantial administrative burden that is perceived. In a survey of floodplain managers and CRS coordinators by Sadiq, Tyler, and Noonan (2020), lack of resources was the most common reply for non-participant when asked why their community did not participate in the CRS.

These responses are worrisome given the insurance premium discounts for residents, the evidence that CRS participants experience lower levels of flood loss (Frimpong et al., 2020; Gourevitch & Pinter, 2022; Highfield & Brody, 2017), and the already low number of NFIP communities participating in the CRS (Table 2.4). Of the 22,534 NFIP communities in 2021, only 1,729 or 7.7% participated in CRS. With 70 of its 1,260 NFIP communities participating in the CRS, Texas falls below national percentage; only 5.6% of NFIP communities in Texas participate in CRS. With 70 CRS communities, and accounting for 4% of all CRS communities nationally, Texas ranks sixth amongst states based on its share of CRS communities.

Table 2.4 NFIP and CRS Community Participation by State, 2021

State	# of NFIP Comms.	# of CRS Comms.	CRS as a % of NFIP in State	% of NFIP Comms. Nationally	Rank	% of CRS Comms. Nationally	Rank
Alabama	434	19	4.4%	1.9%	19	1.1%	27
Alaska	32	7	21.9%	0.1%	49	0.4%	45
Arizona	106	34	32.1%	0.5%	43	2.0%	18
Arkansas	424	23	5.4%	1.9%	20	1.3%	23
California	528	104	19.7%	2.3%	15	6.0%	3
Colorado	255	52	20.4%	1.1%	33	3.0%	9
Connecticut	177	19	10.7%	0.8%	39	1.1%	27
Delaware	50	11	22.0%	0.2%	46	0.6%	40

State	# of NFIP Comms.	# of CRS Comms.	CRS as a % of NFIP in State	% of NFIP Comms. Nationally	Rank	% of CRS Comms. Nationally	Rank
Florida	468	263	56.2%	2.1%	16	15.2%	1
Georgia	579	58	10.0%	2.6%	12	3.4%	7
Hawaii	4	2	50.0%	0.0%	50	0.1%	50
Idaho	174	23	13.2%	0.8%	40	1.3%	23
Illinois	893	75	8.4%	4.0%	6	4.3%	5
Indiana	451	36	8.0%	2.0%	18	2.1%	16
Iowa	688	13	1.9%	3.1%	8	0.8%	34
Kansas	468	46	9.8%	2.1%	16	2.7%	12
Kentucky	359	42	11.7%	1.6%	24	2.4%	13
Louisiana	318	47	14.8%	1.4%	28	2.7%	10
Maine	992	22	2.2%	4.4%	5	1.3%	25
Maryland	147	16	10.9%	0.7%	41	0.9%	31
Massachusetts	341	25	7.3%	1.5%	25	1.4%	22
Michigan	1,060	28	2.6%	4.7%	4	1.6%	20
Minnesota	625	13	2.1%	2.8%	10	0.8%	34
Mississippi	334	32	9.6%	1.5%	26	1.9%	19
Missouri	681	15	2.2%	3.0%	9	0.9%	32
Montana	136	13	9.6%	0.6%	42	0.8%	34
Nebraska	418	7	1.7%	1.9%	21	0.4%	45
Nevada	35	10	28.6%	0.2%	48	0.6%	43
New	219	6	2.7%	1.0%	38	0.3%	48
New Jersey	553	109	19.7%	2.5%	14	6.3%	2
New Mexico	104	11	10.6%	0.5%	44	0.6%	40
New York	1,505	53	3.5%	6.7%	2	3.1%	8
North Carolina	594	102	17.2%	2.6%	11	5.9%	4
North Dakota	334	12	3.6%	1.5%	26	0.7%	38
Ohio	755	15	2.0%	3.4%	7	0.9%	32
Oklahoma	403	18	4.5%	1.8%	22	1.0%	29
Oregon	261	35	13.4%	1.2%	32	2.0%	17
Pennsylvania	2,474	37	1.5%	11.0%	1	2.1%	14
Rhode Island	40	11	27.5%	0.2%	47	0.6%	40
South Carolina	238	47	19.7%	1.1%	35	2.7%	10
South Dakota	235	8	3.4%	1.0%	36	0.5%	44
Tennessee	402	20	5.0%	1.8%	23	1.2%	26
Texas	1,260	70	5.6%	5.6%	3	4.0%	6
Utah	227	12	5.3%	1.0%	37	0.7%	38
Vermont	246	7	2.8%	1.1%	34	0.4%	45
Virginia	291	28	9.6%	1.3%	30	1.6%	20
Washington	292	37	12.7%	1.3%	29	2.1%	14
West Virginia	278	13	4.7%	1.2%	31	0.8%	34
Wisconsin	561	17	3.0%	2.5%	13	1.0%	30
Wyoming	85	6	7.1%	0.4%	45	0.3%	48
Total	22,534	1,729					

Source: (FEMA, 2021a; FEMA, 2021e)

In spite of low participation rates amongst NFIP communities, Highfield and Brody (2017) report that CRS communities account for approximately 68% of all NFIP flood insurance policies. A more recent Federal Emergency Management Agency (FEMA) Fact Sheet states that more than 70% of NFIP policies are accounted for by CRS communities (Federal Emergency Management Agency, 2021a). This data suggests that although few NFIP communities also participate in the CRS, those that do participate in the CRS have a high proportion of the NFIP policy holders compared to those communities that do not participate in the CRS.

2.3.1 Factors impacting CRS participation

In this subsection, I review the literature on CRS participation and identify the factors that predict CRS participation. I also discuss these factors in the context of my research presented here. Table 2.5 presents an overview of the literature on CRS participation and the variables that significantly predict CRS participation. I limit the studies to those where CRS participation is the dependent variable measured as a binary outcome or as a function of class or activity points. I include one qualitative study in which community floodplain managers were asked what factors influenced their community to join or not join the CRS (Sadiq, Tyler, & Noonan, 2020). Several studies were excluded due to issues with their research design or lack of clarity regarding the variables analyzed (Husein, 2012; Mayunga, 2010). I included one study with questionable claims (for example, that the CRS was established in 1998), primarily due to its discussion of policy diffusion (Noonan, Richardson, Sadiq, & Tyler, 2020), a concept similar to one that I incorporate in my study.

An earlier literature review by Sadiq, Tyler, Noonan, et al. (2020) served as the basis for my literature review and I supplemented their listing with a search of “community rating system” in Web of Science and Google Scholar. In general, the twelve studies selected cover both smaller (census places and municipalities) and larger (counties and metropolitan statistical areas) geographical areas. The sample sizes in the studies range from 35 to 28,147 depending on the location studied. The works of Landry and Li (2012) and Li (2012) are foundational pieces referenced by most others and were, along with Asche (2013), the inspirations for my own research design.

Some of the most common significant predictors of CRS participation are related to flood risk, flood loss, and insurance claims. In general, communities with higher levels of these variables are more likely to participate in the CRS (Asche, 2013; Frimpong et al., 2022; Li & Landry, 2018; Posey, 2008, 2009; Sadiq & Noonan, 2015a). Flood risk is operationalized in different ways across the studies. Asche (2013) operationalizes flood risk as “total insured losses from the ten years prior to the observed year in each of the NFIP communities.” Landry and Li (2012) and Li (2012) incorporate similar cumulative ten-year variables that sum the total number of floods and the total value of property damage over that time period. As I describe in section 4.1, I use a similar approach for two variables (number of claims paid and total claims paid per household) within my past experience domain. Frimpong et al. (2022) operationalizes flood risk as a one-year lagged ratio of NFIP claims to coverage. Amount of precipitation also falls under their conceptualization of flood risk. Landry and Li (2012) and Li (2012) use one-year and two-year lagged variables of the number of flood events and also of the value of property damage to again describe what they call flood experience. They base these lagged variables on the notion of windows of opportunity in which a disaster prompts hazard mitigation (Berkes, 2007; Kingdon, 1984). Although Landry and Li did not find significance with some of the lagged variables, I incorporate the same concepts into the variables within my triggering event window domain. Instead of one- and two-year lags, however, I incorporate a one-to-three-year lag window and a four-to-six-year lag window. I do this primarily as a result of visually observing what appear to be lags of similar time periods in Figure 3.3. Posey (2008, 2009) incorporates the number of flood insurance claims, number of flood insurance losses (per capita), amount paid to flood insurance claimants, amount paid to flood insurance claimants (per capita), number of flood insurance policies, and number of flood insurance policies (per capita). Posey uses a very long time scale (1978-2007) in calculating these variables, a time scale that I believe is too long to be meaningful for community decision-making purposes. Sadiq and Noonan (2015a) operationalize flood risk as mean flood risk in reference to NFIP risk maps. I attempted to include percent of land area in the SFHA as a variable in my models, but unfortunately, 146 communities were missing digital flood maps. Landry and Li (2012) and Li (2012) reported similar issues when trying to calculate a flood risk variable for their study of North Carolina counties. Instead, I operationalized flood risk as a dummy variable indicating the presence of a digital flood map.

Socioeconomic and demographic variables were also shown to be significant predictors of CRS in several studies (Asche, 2013; Fan & Davlasheridze, 2014; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Noonan et al., 2020; Paille et al., 2016; Posey, 2008, 2009; Sadiq & Noonan, 2015a). Population, owner occupancy rate, and income were found to be significant by Asche (2013). Within that study, larger population size, lower owner occupancy rate, and higher income were significant predictors of CRS participation. Fan and Davlasheridze (2014) found that age and educational attainment were significant predictors of CRS participation. The percent of residents 65 years and older and the percent of college graduates were positively associated with participation. Like Fan and Davlasheridze, Landry and Li (2012) and Li (2012) had similar findings. In addition, they also found higher housing density to be associated with CRS participation in three studies (Landry & Li, 2012; Li, 2012; Li & Landry, 2018). Furthermore, in their later study, Li and Landry (2018) found lagged unemployment, income, and age were significant predictors of CRS participation when measured by CRS activity points. A study by Paille et al. (2016) indicated that CRS participation was significantly related to housing value. As home prices increased, communities were more likely to participate in CRS. Posey (2008, 2009) found the concept of affluence, defined by income, college attainment, median rents, median home values and poverty rate, to be a significant predictor of CRS participation. Sadiq and Noonan (2015a) developed a comprehensive model in which they found property tax, housing value, household income, age of house, rent share, longevity of residence, educational attainment, share of the population that is white, and share of the population under the age of 18 to be significant predictors of CRS participation. Given the possibility of multicollinearity amongst several variables, I interpret these results with caution. Considering the finding from these studies, and in reference to the Pearson's r correlation matrix in Table 4.1, I selected population size, population density, education, rent share and poverty rate as variables within the community demographics domain in my models. As detailed in subsection 4.1.2, I discarded median home value and median income as a result of high correlations.

Finally, the concept of external influence was described by Noonan et al. (2020) in the context of policy diffusion. They operationalized policy diffusion as non-participating communities following the lead of neighboring CRS participants and later joining. The authors compared communities that were immediately bordering each other, therefore removing the influence of communities located nearby, but not bordering. Landry and Li (2012) and Li (2012) include as similar variable, CRS neighbor, which they operationalize as the percentage of neighboring counties that are CRS counties.

A study on innovative flood mitigation policy adoption in Oregon (Hamlin, 2018) suggests that regional policy diffusion is related to influences and competition between communities along with the presence or absence of policy networks amongst clustered or regional communities. Recognizing the complexity of the diffusion of policy and innovation, I therefore incorporate and expand beyond Noonan et al. (2020), Landry and Li (2012), and Li (2012) by conceptualizing external influence as a continuous variable of distance to the nearest CRS community. By incorporating a continuous variable, I can arguably capture the regional influences that may predicted CRS participation.

Table 2.5 CRS Participation Studies with Sample Information and Significant Variables

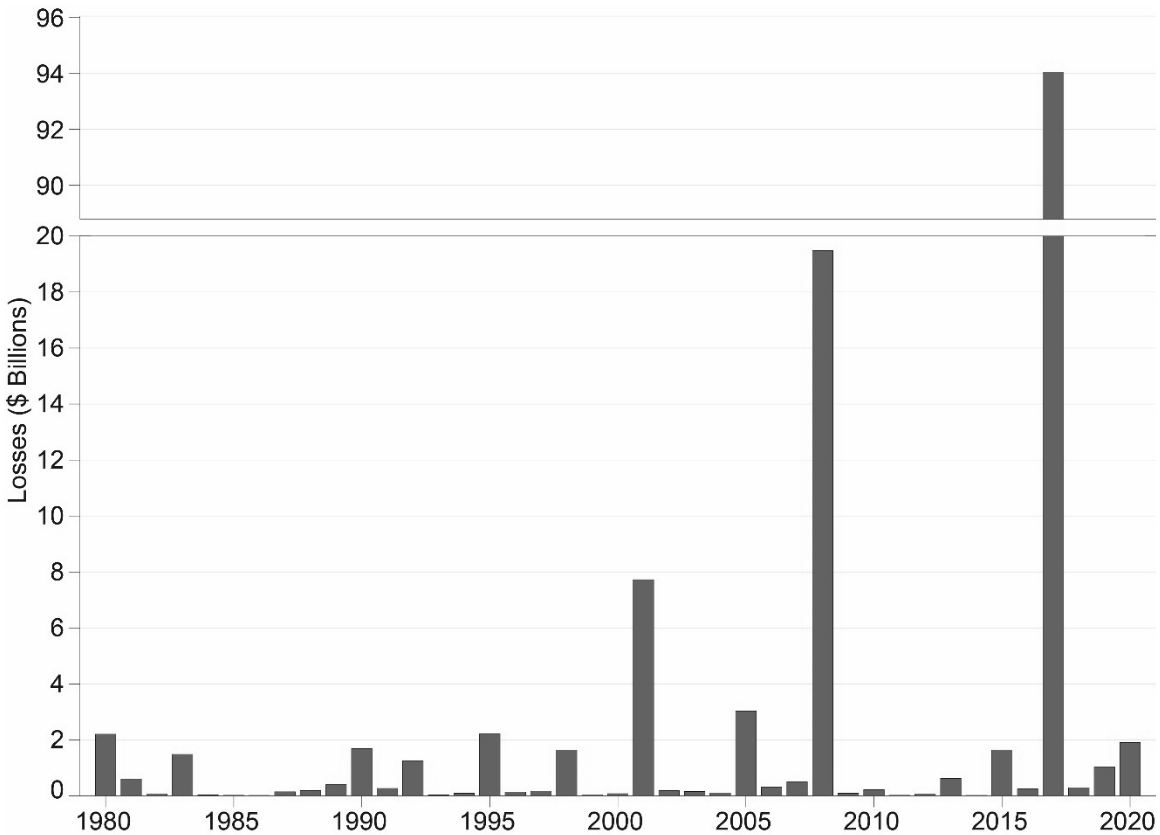
Source	Unit of Analysis	N	Location	Time-frame	Dependent Variable	Significant Independent Variables
Asche (2013)	Counties	548	Nationwide	2004-2009	CRS participation (0/1)	Flood risk Population Income % Owner occupied
Fan and Davlasheridze (2014)	Metropolitan statistical areas	281	Nationwide	2000	Value of CRS program	% 65 and older % College graduate
Frimpong et al. (2022)	CRS communities	969	Nationwide	2010-2015	CRS points	CRS points (t-1) Precipitation (t-1) Claims rate (t-1)
Landry and Li (2012); Li (2012)	County-level; multi-jurisdiction aggregation	100	North Carolina	1991-2002	CRS participation (0/1)	Precipitation % of county covered by water CAMA county Property tax Housing density % 65 and older % College graduate % of CRS in county
Li and Landry (2018)	County-level; multi-jurisdiction aggregation	100	North Carolina	1999-2010	CRS points	CRS points (t-1) Flood (t-1) Risk index (t-1) Staff Crime (t-1) Unemployment (t-1) Population density Income % 65 and older
Noonan et al. (2020)	NFIP Communities	18,095	Nationwide	1998-2013	CRS participation (0/1)	(Incomplete data) Population density Housing value % Renters Flat topography
Paille et al. (2016)	Parishes	35	Southern Louisiana	2010	CRS Points	Housing value % of CRS in county/parish
Posey (2008); Posey (2009)	Municipalities with NFIP claim(s)	10,916	Nationwide; coastal New Jersey	2007	CRS participation & class	Affluence Flood risk

Source	Unit of Analysis	N	Location	Time-frame	Dependent Variable	Significant Independent Variables
Sadiq and Noonan (2015a)	Census place	28,147	Nationwide	1990/ 2012	CRS participation & points	Property tax Housing value Household income Home year built % Renters Stay share % High school % White % Child Ruralness Humidity Topography % Water Plains (0/1) WaterXtopography HumidityXplains HumidityXtopo Flood Risk
Sadiq, Tyler, and Noonan (2020)	NFIP community	100	Nationwide	2018	(*qualitative*) CRS participation	(*qualitative*) Flood insurance discounts Lack of resources

3 The NFIP and CRS in Texas

As shown in Figure 3.1 and Figure 3.2 below, flood damages and flood claims paid have risen sharply in Texas since 2000. Property damages due to flood-related events from 1980 through 1999 totaled approximately $6.9 billion (Figure 3.1). Property damages totaled approximately $130.6 billion from 2000 through 2020, more than 18 times the amount from the previous two decades. This increase is primarily the result of Tropical Storm Allison, Hurricane Ike, and Hurricane Harvey in 2001, 2008, and 2017, respectively. Average annual flood losses between 2010 and 2020 amounted to almost ten billion dollars and the vast majority of those losses occurred in 2017 when Hurricane Harvey hit southeast Texas and the Houston region. Damages from 2017, alone, accounted for just under $94 billion (Figure 3.1), or 68% of the total property damages from flood-related events in Texas from 1980 through 2020 and 17% of damages nationwide during the same period. By one calculation, total damages associated with Hurricane Harvey (including flood losses) amounted to approximately $125 billion, making it the second most costly disaster in US history (EOTS, 2018, p. 4). By comparison, property damages in Louisiana and Mississippi in 2005 – the year of Hurricane Katrina – totaled just over $104 billion. As mentioned earlier, Texas ranks first amongst states in property damages due to flooding from 1980 through 2020, accounting for nearly a quarter of the national total.

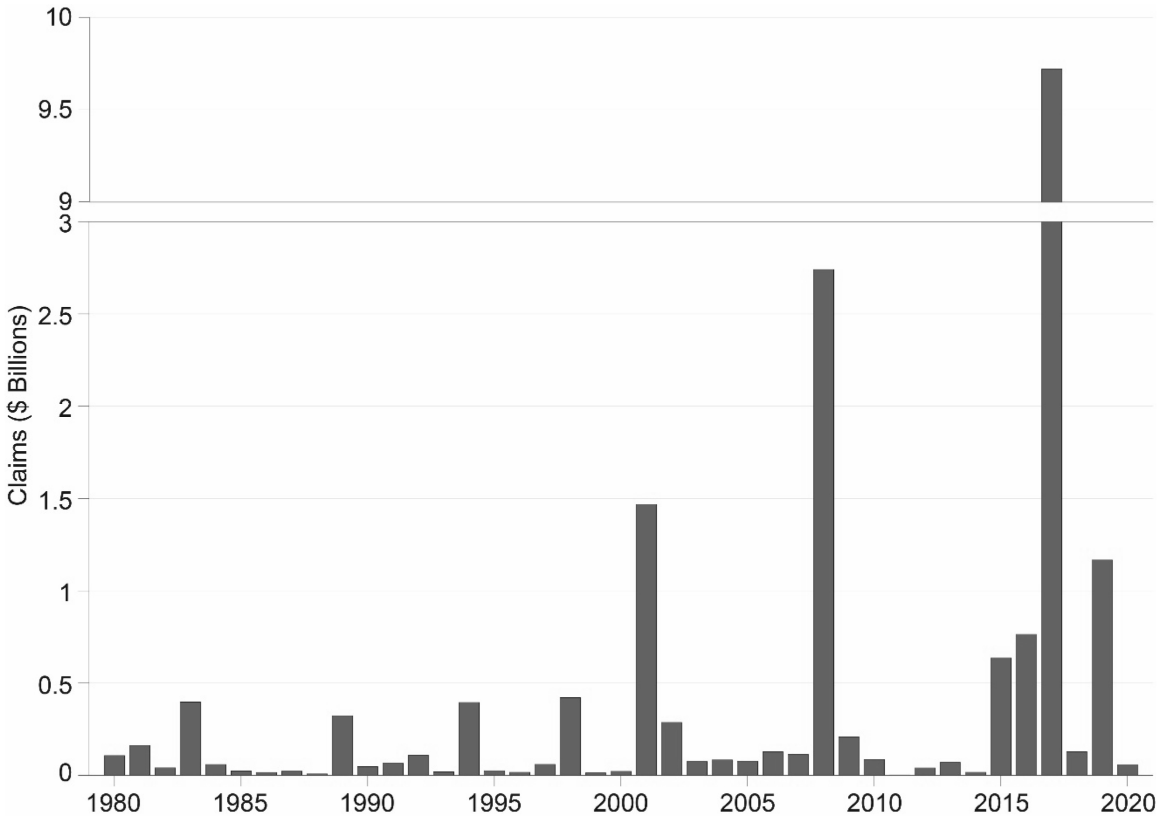
Figure 3.1 Estimated Annual Property Losses from Flooding in Texas (2020 dollars)



Source: SHELDUS (ASU-CEMHS, 2022)

Flood claims paid in Texas during the same periods paint a similar picture (Figure 3.2). Of the $20.2 billion in NFIP flood claims paid from 1980 through 2020, nearly $18 billion – or 88.5% - were paid out from 2000 through 2020. As with property damages, most flood claims were paid out in 2001, 2008, and 2017. Claims paid during these three years totaled $13.9 billion. Elevated flood insurance claims are also visible in years 2015, 2016, and 2019, though these amounts are overshadowed by the huge losses from Hurricane Harvey in 2017. Losses in 2015 and 2016 are generally the result of heavy rains and flash floods not associated with a named storm. Losses in 2019 are generally associated with Tropical Storm Imelda.

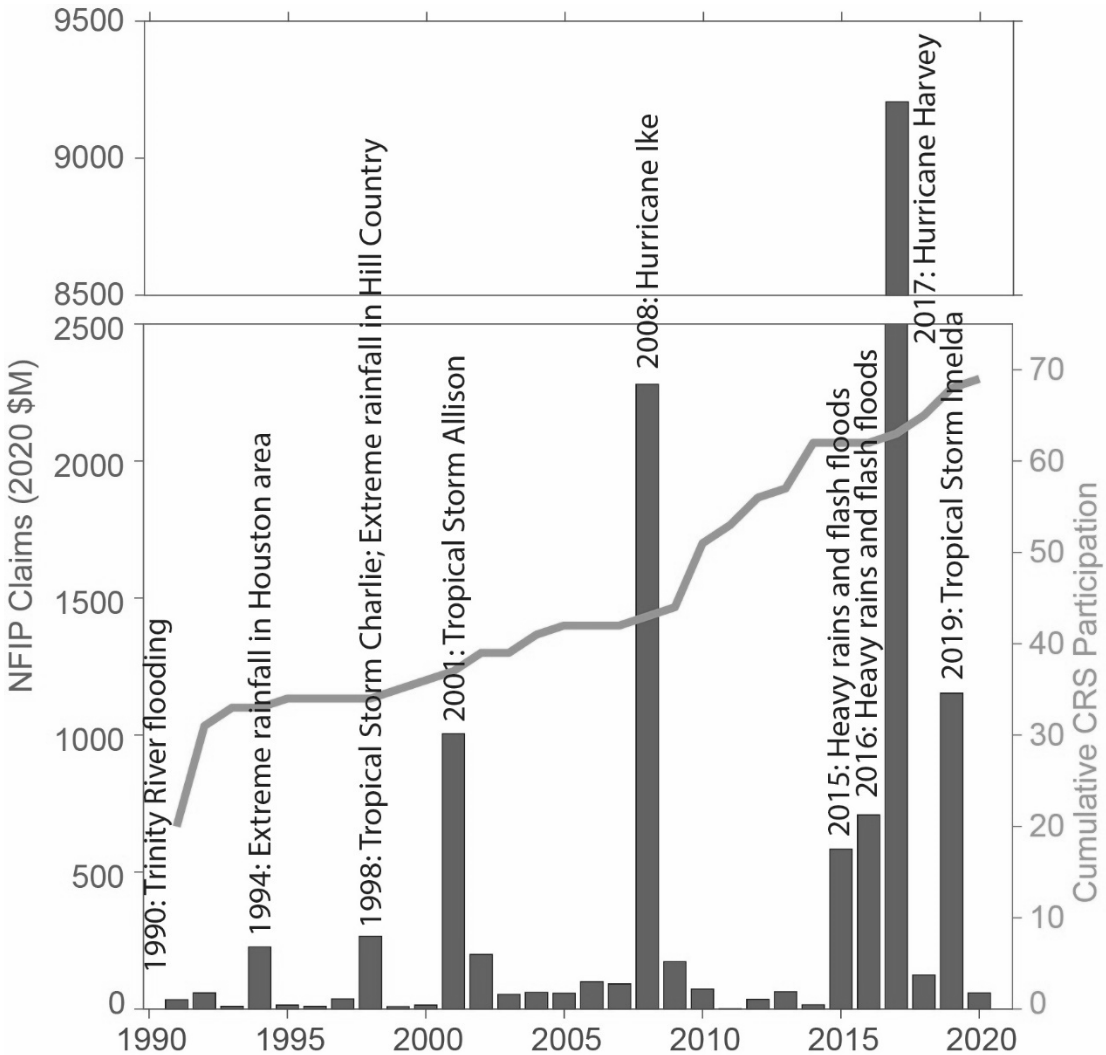
Figure 3.2 Annual Insured Flood Claims Paid by the National Flood Insurance Program in Texas (2020 dollars)



Source: (FEMA, 2021g)

According to Figure 3.3, nearly half of the communities that are currently CRS participants joined in the first three years of the program. This was followed by a gradual increase in participation until 2009, after which there was a noticeable increase in the rate of joining. This period of increased adoption followed Hurricane Ike in 2008 and continued until about 2015. Another increase seems to have started in 2017, the same year Hurricane Harvey struck the Houston area.

Figure 3.3 Cumulative Number of CRS Participants, Annual NFIP Claims Paid, and Significant Flood Events in Texas between 1990 & 2020



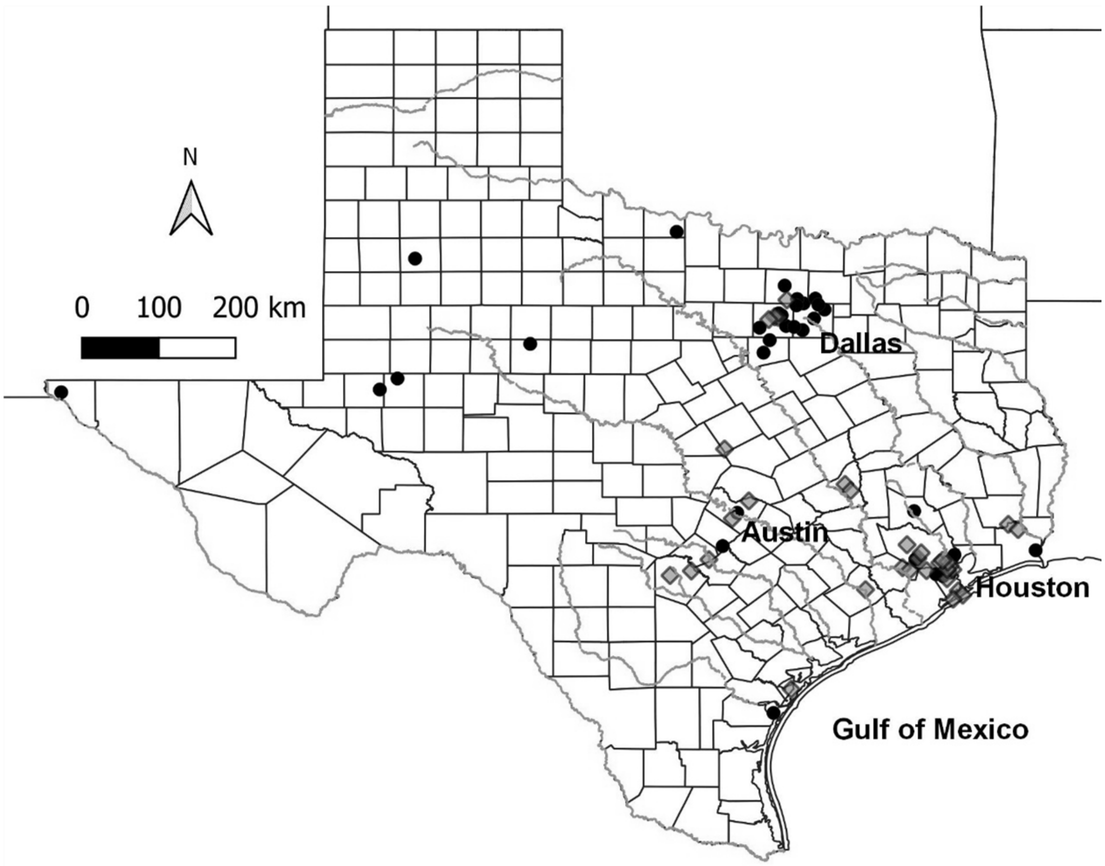
Source: (FEMA, 2021b; FEMA, 2021g)

According to FEMA, a community is defined as "any State or area or political subdivision thereof, or any Indian tribe or authorized tribal organization, or Alaska Native village or authorized native organization, which has authority to adopt and enforce flood plain management regulations for the areas within its jurisdiction" ("Emergency management assistance, general provisions," 2020). As a result of this definition, there can be a wide range of jurisdictional authorities, land areas, and population sizes amongst the communities that participate in CRS. In Texas, however, the jurisdictional authority of CRS communities primarily includes towns and cities. Of the 69 CRS communities, only four are counties. This could be explained by the fact that counties in Texas generally lack land use planning and zoning authority (Brody et al., 2011). Several counties have enacted the equivalents of flood control districts which have authorities allowing them to participate in CRS. The four participating counties are: Bastrop, Burnet, Guadalupe and Harris counties.

3.1 CRS Participation Over Time (Early Versus Late Adopters)

Figure 3.4 shows the location of the 65 incorporated CRS communities in Texas as of 2020. This does not include the four participating counties mentioned above, which, as described Chapter 4, were not included in this study. Approximately three quarters of the CRS communities are clustered around three urban areas: Dallas-Fort Worth, Houston, and the Austin-San Antonio corridor. When viewed through the lens of early adopters (those communities that joined between 1991 and 1993) and subsequent joiners (those that joined after 1993), the picture is slightly different. Sixteen of the 33 early adopters are clustered near the city of Dallas, seven are around Houston, and two are in the Austin-San Antonio corridor. Of the top 50 NFIP communities, as measured by total amount of claims paid per household from 1981 through 1990, only five joined the CRS in the initial cohort. All five of these communities – Kemah, Friendswood, Baytown, Conroe, and League City – are located in the Houston area. According to the NFIP flood insurance claim data, this area was heavily impacted by Tropical Storm Allison in 1989 (FEMA, 2021g).

Figure 3.4 CRS Communities in Texas as of 2020



Note: Circles represent early adopting communities, or those that joined between 1991 and 1993; diamonds represent subsequent joiners, or those that joined after 1993; excludes counties participating in CRS.

The late adopter communities in the Houston area seemed to join in response to several triggering events. Several communities joined after another Tropical Storm Allison led to severe flooding in the Houston area in 2001. Five of the top twenty communities most impacted by Allison, as measured by total claims paid per household, had already joined the CRS before the tropical storm arrived. Over the next five years, four more communities in the top twenty – Deer Park, Houston, Seabrook, and Pearland

– joined the CRS. Harris County, which includes Houston, also joined during that time.

Several more communities joined after Hurricane Ike made landfall in 2008 over Galveston, just south of Houston. Of the top twenty communities impacted by Ike, four were already CRS participants when the hurricane struck. These communities are Kemah, Seabrook, Tiki Island, and La Porte. Three more communities in the top twenty joined between 2010 and 2014. These communities are Dickinson, Galveston, and Shoreacres. The Houston-area communities of Sugar Land, Missouri City, Pasadena, and Taylor Lake Village also joined during this period, though they were not severely impacted by Hurricane Ike. Hurricane Harvey in 2017 may also be a triggering event, though it is too early to tell with data only through 2020. Nonetheless, the larger geographic extent and substantially higher levels of flood loss from Hurricane Harvey may require looking beyond just the Houston area to understand its potential impact on CRS adoption and participation.

Although the cluster of early adopter communities around Dallas are not part of the top 50 as measured by total amount of claims paid per household from 1981 through 1990, these communities are located near the Trinity River, which topped its banks in 1990 due to intense rainfall. This flood event was the primary contributor to Texas having the sixth highest level of annual property damage per capita due to flooding in any state up through 2020 (ASU-CEMHS, 2022). The low number of NFIP insured flood losses in that year could be attributed to either a low number of homes and small businesses impacted or, alternatively, low numbers of NFIP flood insurance policies amongst these groups. The four late adopter communities in the Dallas area – Fort Worth, Haltom City, Richland Hills, and Flower Mound – joined between 2012 and 2019. None of these communities experienced substantial flooding in the ten years prior to joining the CRS.

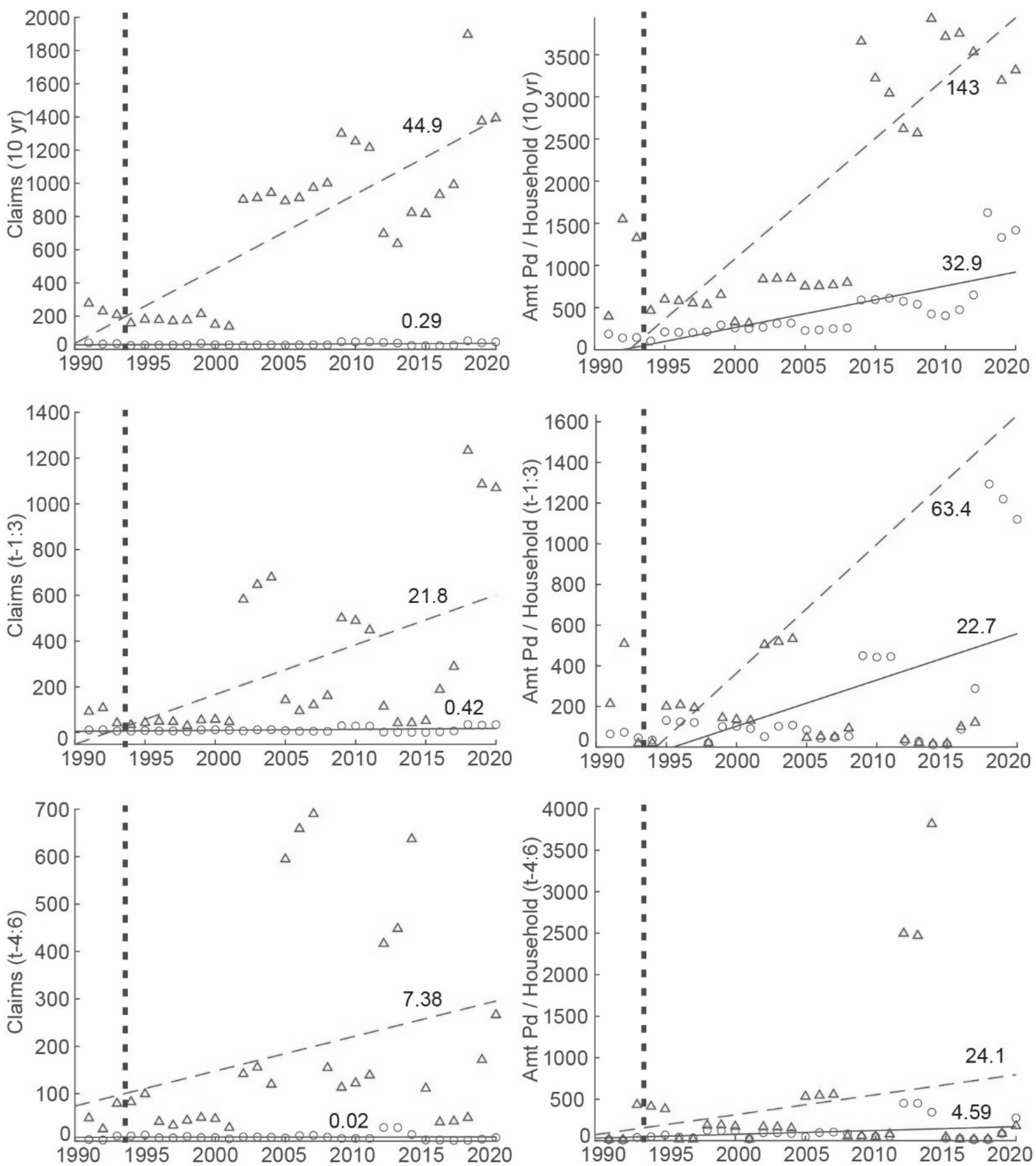
Within the Austin-San Antonio corridor, neither early adopter community (Austin or San Marcos) experienced substantial flooding in the previous ten years before joining. The communities near the Guadalupe River, which bisects the corridor, are subject to regular flooding resulting in increased numbers of flood insurance claims (FEMA, 2021g). This is especially true for the city of New Braunfels, which experienced substantially higher levels of insured flood loss in 1998, 2002, and 2010. Four of the five late adopter communities in the area, including New Braunfels, joined the CRS between 2010 and 2013. Although these communities did not experience high levels of insured flood loss like New Braunfels, their adoption of the CRS program may have been impacted by observing the experiences of neighboring communities like New Braunfels.(FEMA, 2021g) A complete listing of communities participating in the CRS in Texas can be found in Table A.1 of Appendix A. This listing also shows the year of joining and level of participation by year (since 1998) as measured by their CRS class.

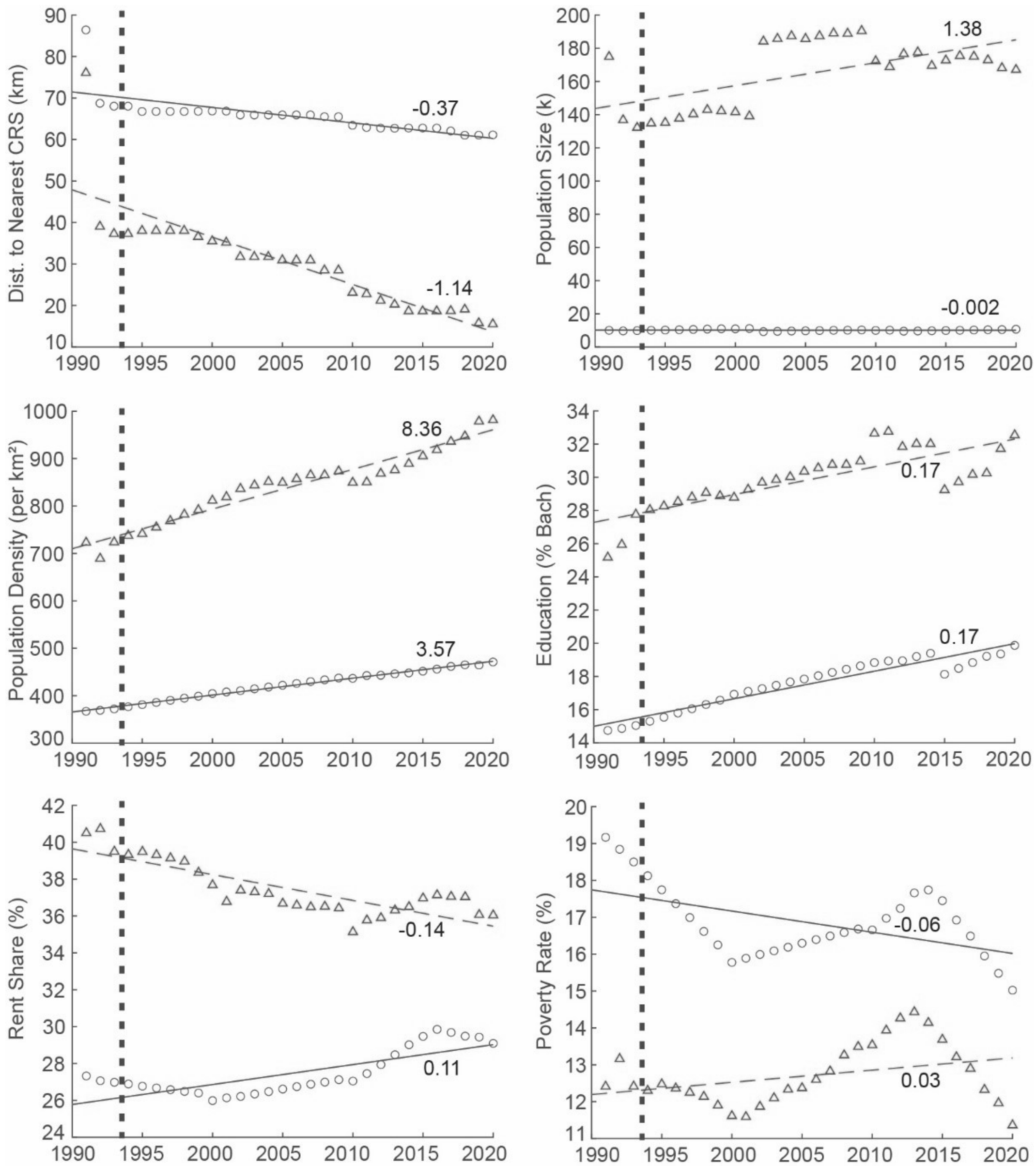
In spite of these observations, understanding the extent to which the flood events mentioned above had an impact on CRS adoption is difficult without analyzing community records regarding CRS adoption or, alternatively, asking community stakeholders with knowledge of the decision to adopt. The data presented here, along with the analysis presented in the following chapters, provide a foundation for qualitative studies addressing CRS participation in Texas. Such studies could provide information about the community decision-making process surrounding CRS adoption, as well the motivators and barriers for and against adoption that could be used by policy-makers to encourage participation in this program. (Sadiq, Tyler, & Noonan, 2020; Sadiq, Tyler, Noonan, et al., 2020).

3.2 Predictors of CRS Participation Over Time

I have created a series of graphs to illustrate the differences between CRS participants and non-participants in Texas on modeled variables over time (Figure 3.5). I have included a vertical hashed line at the year 1993 to differentiate between the early adopter and late adopter/subsequent joiner years. These variables fall within the domains of past experience, triggering event windows, flood risk, and community demographics, which I use in my statistical models and describe in section 4.1. I have plotted the average scores per year by group and I have overlayed the line of best fit for each group. I have also included the slope for each line to provide a numerical indication of how much the groups are converging or diverging. Generally, these data show that CRS participants are diverging from non-participants on variables related to the number of flood claims paid, the value of flood claims paid per household, population size, and population density. The slopes for the percentage of renters and poverty rates are converging, indicating that CRS participants and non-participants are, on average, becoming more similar on these variables. These observations suggest that, overall, CRS participants and non-participants are changing in different ways over time based on the measured variables and that consideration of time of joining for CRS participation studies is warranted.

Figure 3.5 Changes in Modeled Variables over Time for CRS Participants and Non-participants





Notes: triangles = participants; circles = non-participants; lines of best fit and their slopes are also included: dashed line for participant and solid line for non-participant best-fit; vertical dashed line shows the separation between early adopters and subsequent joiners.

4 Research Design

As stated in chapter 1, my research questions are the following:

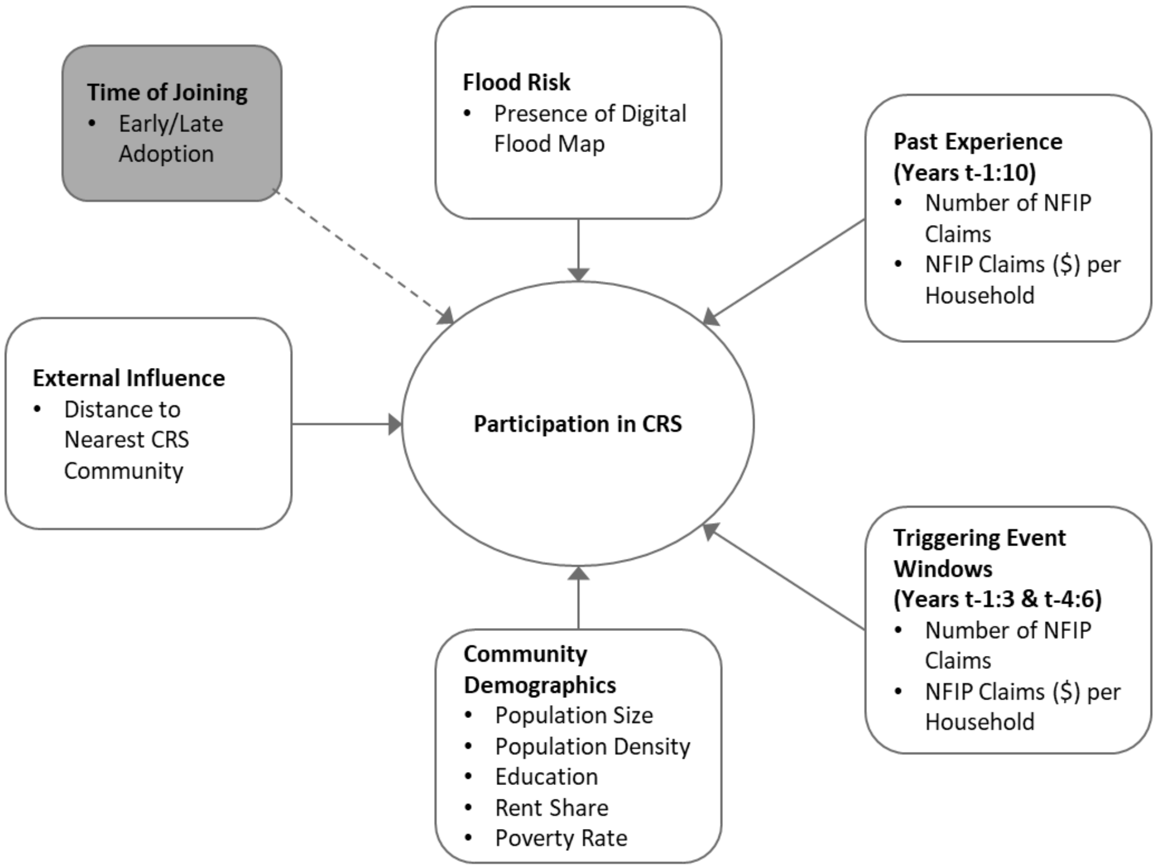
1) Which factors predict CRS participation among NFIP communities in Texas?
2) How do subsequent joiners of CRS differ from initial participants in Texas?

The following sections outline the research design that I used to answer these questions. I begin with a description of the conceptual framework and variables that I selected for this study. This is followed by the hypotheses that I propose for the subsequent statistical tests. I then describe the study area – Texas – and the sample that I selected. In the last two sections of the chapter, I describe the data collection and processing methods that I used to prepare the data and the analytical methods that I used to ultimately assess the hypotheses and answer the research questions.

4.1 Conceptual Framework

The primary outcome that I describe in this dissertation is community participation in the Community Rating System in Texas. In order to explore this outcome in the context of the research questions stated above, I focus on six domains – time of joining, past experience, triggering event windows, flood risk, external influence, and community demographics (Figure 4.1). These six domains generally correspond to variable groupings used by Landry and Li (2012) (flood experience, environmental and risk control, and social) and, to a certain extent, by Paille et al. (2016) (socioeconomics, government capacity, and exposure). I isolate past experience and triggering event windows due to correlations between the variables across these domains. In addition, I include a separate domain for external influence. In defining these domains and variables separately, I am able to test the effect of these domains on the outcome variables independently and compare them to each other.

Figure 4.1 Conceptual Framework



Within these six domains, I include relevant independent variables drawn from the literature on CRS participation described in Chapter 2. I describe these domains and the included variables in subsection 4.1.2 below. Before that, however, I describe the process that I used to determine which variables drawn from the literature would be appropriate if placed in the statistical models together. In summary, I created a correlation matrix that I used to eliminate independent variables that were not significantly correlated with the outcome (CRS participation) or, alternatively, that were highly correlated with each other.

4.1.1 Variable Selection Process

While selecting variables from the literature to include in the fully specified models, I suspected that several variables would be highly correlated and violate assumptions of multicollinearity associated with logistic regression if they were placed in the model together (Cohen, Cohen, West, & Aiken, 2003; Hilbe, 2016). Since the variables within the triggering event windows domain are effectively a subset of the variables within the flood experience domain, I expected to find high correlation coefficients amongst these pairs. Due to the well-established connection between education and income (Ashenfelter & Rouse, 1999), I suspected that variables related to education, income, and, incidentally, home value and poverty would be highly correlated. I also suspected that the total number and total value of NFIP flood insurance claims in a community would be highly correlated with population size. It stands to reason that, all things being equal, a community with a higher population size and, therefore, higher number of households, would have a higher number of flood claims. Research suggests that the number of claims and average claim value are increasing over time (Bradt & Kousky, 2020), but I assumed that these increases would not substantially impact correlations between the number and total value of NFIP flood insurance claims and population size.

In order to determine which independent variables were highly correlated with each other – and correlated with the dependent variable – I created a correlation matrix displaying the Pearson's correlation coefficient and significance for each pair of variables (Table 4.1). In general, the independent variables that I selected for further modeling were those that were significantly correlated with the dependent CRS participation variable ($p < .10$) and not highly and significantly correlated with each other ($r > .60$; $p < .10$).

The variables that were not significantly correlated with the CRS participation ($p > .10$) – and, therefore, not included in subsequent models – were the three amount paid per claim variables (each representing different time periods), total claims paid per household for the triggering event window from four to six years prior, and the flood risk variable represented by percentage of community land within the special flood hazard area. Because the other variables for total claims paid per household – flood experience over the previous ten years and the triggering event window over the previous three years – were significantly correlated, I kept total claims paid per household for the triggering event window from four to six years prior.

Twelve independent variable combinations had correlation values exceeding .60, which is the cutoff value I used to further cull variables that could be problematic if they were included in the logistic regression models. Typically, correlation coefficients ranging from .10 to .29, from .30 to .49, and .50 or greater are considered to have small, medium, and large effects, respectively (Myers, Well, & Lorch, 2010). Although .60 is generally considered a high cutoff value, I wanted to first review any correlations in the .50 to .60 range before deciding whether to reject a particular variable. This was especially true for any variable combinations in which I had already rejected one of the variables. Based on these criteria, I debated removing the three variables for number of claims since they were highly correlated with each other and with population size. Due to their significance in Posey (2008, 2009) when included with population, I kept them in the model. As expected, variable pairs crossing the flood experience and triggering event windows domains were highly correlated. Rather than remove some of these variables to reduce multicollinearity, however, I decided to not include variables from both domains in the subsequent models at the same time (with the exception of the fully specified models).

And, indeed, variables related to education, income, and home value were highly correlated with each other ($r > .79$). Poverty rate was also highly correlated with these variables, though with a slightly weaker effect ($r < -.50$). Amongst these variables, education ($r = .19$) had the strongest correlation with the CRS participation variable and, as a result was kept for further analysis. In spite of its strong negative correlation with education ($r = -.51$), poverty rate was also kept due to concerns that the CRS program may exacerbate poverty and income inequality (Noonan & Sadiq, 2018).

Table 4.1 Results of Pearson's Correlation Calculations

Variable	1	2	3	4	5	6	7	8	9	10
1. CRS	–									
2. Number of Claims (10 yrs)	0.082*	–								
3. Claims Paid/ Household (10 yrs)	0.172***	0.126***	–							
4. Claims Paid/Claim 81-90	0.022	0.051	0.129**	–						
5. Number of Claims (yrs 1-3)	0.095**	0.965***	0.129**	0.067	–					
6. Claims Paid/ Household (yrs 1-3)	0.164***	0.111***	0.894***	0.162**	0.164***	–				
7. Claims Pd/Claim (yrs 1-3)	-0.029	0.032	0.075	0.876***	0.079	0.177**	–			
8. Number of Claims (yrs 4-6)	0.182***	0.779***	0.060	0.045	0.759***	0.047	0.002	–		
9. Claims Paid/ Household (yrs 4-6)	0.006	0.030	0.260***	0.107*	0.022	0.344***	0.077	0.135***	–	
10. Claims Pd/ Claim (yrs 4-6)	-0.081	-0.027	0.026	0.543***	-0.029	0.035	0.254***	0.036	0.296***	–
11. Risk map	0.067*	0.053	0.052	0.018	0.051	0.041	0.044	0.061	0.055	-0.081
12. % Land in SFHA	0.038	0.105**	0.165***	0.081	0.079*	0.140***	-0.025	0.027	0.021	-0.168*
13. Distance to Nearest CRS	-0.088**	-0.079*	-0.091**	-0.134**	-0.084**	-0.102**	-0.133*	-0.049	-0.066*	-0.033
14. Population Size	0.275***	0.696***	-0.001	0.005	0.697***	-0.001	0.022	0.659***	-0.005	-0.049
15. Population Density	0.177***	0.094**	-0.010	-0.099*	0.094**	-0.024	-0.092	0.110***	-0.022	-0.126
16. Education	0.194***	0.052	0.008	-0.018	0.063*	0.018	-0.092	0.056	-0.033	-0.048
17. Rent Share	0.199***	0.162***	0.081*	0.028	0.148**	0.064*	0.010	0.194***	0.048	-0.015
18. Median Home Value	0.078*	0.007	0.004	-0.012	0.014	0.009	-0.079	-0.001	-0.012	-0.064
19. Median Income	0.113***	0.018	0.025	-0.005	0.033	0.037	-0.052	0.004	-0.006	-0.107
20. Poverty Rate	-0.105**	-0.017	-0.028	-0.074	-0.034	-0.051	-0.059	-0.006	-0.008	0.031

Variable	11	12	13	14	15	16	17	18	19	20
11. Risk map	–									
12. % Land in SFHA	NA	–								
13. Distance to Nearest CRS	-0.357***	-0.067	–							
14. Population Size	0.063*	-0.010	-0.032	–						
15. Population Density	-0.065*	0.099**	-0.003	0.177***	–					
16. Education	0.194***	0.047	-0.267***	0.100**	0.247***	–				
17. Rent Share	0.051	0.015	0.041	0.236***	0.200***	-0.070*	–			
18. Median Home Value	0.223***	-0.021	-0.314***	0.026	0.162***	0.798***	-0.190***	–		
19. Median Income	0.264***	0.039	-0.410***	0.018	0.135***	0.797***	-0.343***	0.856***	–	
20. Poverty Rate	-0.279***	0.030	0.448***	-0.007	-0.004	-0.511***	0.255***	-0.501***	-0.698***	–

* $p < .1$; ** $p < .05$: *** $p < .01$.

4.1.2 Domains and Selected Variables

As described above, time of joining is a concept that has not drawn much attention in the CRS participation literature. I define time of joining as a dichotomous variable that distinguishes between early adopters – those communities that join CRS in the first three years of the program – and subsequent joiners. Within the literature, factors related to time tend to be analyzed in relation to past flood experience and triggering event windows (Asche, 2013; Frimpong et al., 2022; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Paille et al., 2016; Posey, 2008, 2009). I have not found any studies investigating whether there are empirical differences between early adopters and subsequent joiners in relation to CRS participation. Incidentally, if a community joined CRS in the initial cohort, I assume that the establishment of the program was an influential factor and that the decision to join was based on factors that predate the year that the program was established. As a result, for all communities in the initial cohort, I treat 1991 as the year of joining for data analysis purposes, even if the year of joining was 1992 or 1993.

The domains of past experience and triggering event windows in predicting CRS participation draw upon research by Asche (2013), Li (2012), and Landry and Li (2012). I include two variables that represent experience with flood loss over the previous ten years and four variables that represent triggering event windows for joining CRS. The two flood loss variables are the number of claims submitted during the ten years before joining CRS and the value of claims paid per household in the community during the same time period. The four triggering event window variables are claims submitted during the three years before joining and during the four to six years before joining, as well as claims paid per household in the community during those two time periods. Because the range of years for the triggering event window variables (one through three and four through six) fall within the range of years for the flood experience variables, (one through ten), the triggering event window variables are effectively subsets of the flood experience variables and, therefore, not independent and unrelated. As a result, I try not to include these domains together in any statistical model, with the exception of fully specified models.

Flood risk is operationalized through a single variable – presence of digital flood map. This is a dichotomous variable that I define as whether a community has a digitized flood risk map as of 2021. I originally considered a different variable to represent flood risk – the percentage of land area that lies within the special flood hazard area – but, as stated above, many communities do not have digitized flood risk maps and I could not find a way to obtain or measure the percentage of land within the SFHA for communities that lacked digitized flood maps.

The domain of external influence is operationalized as a single variable, distance to the nearest CRS community. The variable is defined as the distance from the community boundary to the community boundary of the nearest CRS participating community. If a community was participating in CRS at any time during the year in question, then the community is considered a CRS participant for that year. Similar were variables included in CRS participation studies by Landry and Li (2012), Li (2012), and Noonan et al. (2020).

The final domain, community demographics, is composed of five variables that have been included in previous CRS participation studies (Asche, 2013; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Noonan et al., 2020; Paille et al., 2016). These variables are population size, population density, education, rent share, and poverty rate. Population size is self-explanatory and population density is the population size per square kilometer (km^2) in the community. Education, rent share, and poverty rate are the percentages of residents with a bachelor's degree or higher, renter occupied homes in the community, households in the community with household incomes below the federal poverty limit, respectively. Two additional variables – median home value and median income – were considered, but rejected after analyzing correlations with the dependent variable (Table 4.1).

4.2 Hypotheses

In reference to the first research question and based on the supporting literature, I propose the following hypotheses:

Hypothesis 1.1: Communities with higher numbers of flood claims over the previous ten years are more likely to participate in CRS.

Hypothesis 1.2: Communities with higher values of claims paid per household over the past ten years are more likely to participate in CRS.

Hypothesis 1.3: Communities with higher numbers of flood claims over the t-1:3 and t-4:6 triggering event windows are more likely to participate in CRS.

Hypothesis 1.4: Communities with higher values of claims paid per household over the t-1:3 and t-4:6 triggering event windows are more likely to participate in CRS.

Hypothesis 1.5: Communities with digital flood maps (as of 2021) are more likely to join CRS.

Hypothesis 1.6: Communities that are located closer to CRS communities are more likely to participate in CRS.

Hypothesis 1.7: Communities with larger populations are more likely to participate in CRS.

Hypothesis 1.8: Communities with higher population densities are more likely to participate in CRS.

Hypothesis 1.9: Communities with higher percentages of college graduates are more likely to participate in CRS.

Hypothesis 1.10: Communities with higher percentages of renters are more likely to participate in CRS.

Hypothesis 1.11: Communities with lower percentages of households with incomes under the federal poverty level are more likely to participate in CRS.

In reference to the second research question and based on the supporting literature, I expect communities that join CRS later (subsequent joiners) to generally exhibit higher levels of sensitivity to past flood experience and flood risk. This is due to increasing flood risk and increasing awareness of flood risk over time. I also expect the subsequent joiners to generally have lower values on variables related to community demographics – with the exception of poverty rate – when compared to early adopters. The rationale for this expectation is the assumption that early adopters will be more motivated to join CRS based on higher community capabilities and institutional capacity as indicated by higher levels of education and lower levels of poverty. On the other hand, the presence of threat will drive subsequent joiners to join CRS (Berry & Berry, 2018). As a result of these expected differences, I propose the following hypotheses:

Hypothesis 2.1: Early adopters and subsequent joiners will differ on numbers of flood claims in relation to NFIP communities over the ten years prior to joining.

Hypothesis 2.2: Early adopters and subsequent joiners will differ on values of claims paid per household in relation to NFIP communities over the ten years prior to joining.

Hypothesis 2.3: Early adopters and subsequent joiners will differ on numbers of flood claims over the t-1:3 and t-4:6 triggering event windows in relation to NFIP communities.

Hypothesis 2.4: Early adopters and subsequent joiners will differ on values of claims paid per household over the t-1:3 and t-4:6 triggering event windows in relation to NFIP communities.

Hypothesis 2.5: Early adopters and subsequent joiners will differ on likelihood to have digital flood maps (as of 2021) in relation to NFIP communities.

Hypothesis 2.6: Early adopters and subsequent joiners will differ on distance to CRS communities in relation to NFIP communities.

Hypothesis 2.7: Early adopters and subsequent joiners will differ on population sizes in relation to NFIP communities.

Hypothesis 2.8: Early adopters and subsequent joiners will differ on population densities in relation to NFIP communities.

Hypothesis 2.9: Early adopters and subsequent joiners will differ on percentages of college graduates in relation to NFIP communities.

Hypothesis 2.10: Early adopters and subsequent joiners will differ on percentages of renters in relation to NFIP communities.

Hypothesis 2.11: Early adopters and subsequent joiners will differ on percentages of households with incomes under the federal poverty level in relation to NFIP communities.

4.3 Study Area - Texas

Located in the southern United States, and bordering Mexico to the south and the Gulf of Mexico to the southeast, Texas is experiencing climactic changes that are expected to exacerbate flooding in the next 15 years (Nielsen-Gammon, Holman, Buley, & Jorgensen, 2021). Extreme precipitation is expected to increase by 10%-15% in expected frequency and urban flooding is expected to worsen due to this increase and factors related to urban population growth. Furthermore, coastal flooding is expected to increase due to sea level rise and a possible increase in hurricane severity.

As of 2020, the state of Texas had a population of just over 29 million people and its jurisdictions relevant for this study consisted of 254 counties and 1,220 incorporated communities (US Census Bureau, 1990-2018, 2010-2020). Of the 254 counties, 224 actively participated in the NFIP at that time. And of the 1,220 incorporated communities, 1,020 actively participated in the NFIP. A more detailed breakdown can be found in the sampling section below.

I chose Texas as the case study location due to the state's susceptibility to flooding, its large portion of incorporated communities participating in CRS, and for reasons related to convenience. Regarding convenience, I lived in Texas for three years, from 2018 to 2021. During that time, I worked on a project related to flood mapping and mitigation and became familiar with the causes of flooding and range of mitigation efforts in Texas.

Regarding Texas's susceptibility to flooding, the state experiences a high proportion of flood loss in comparison to the rest of the United States. Of the approximately $543.7 billion in property damages related to storms and flooding that have been recorded in the United States since 1980, approximately $137.5 billion – or about 25% – of these damages were in Texas (ASU-CEMHS, 2022). This ranks Texas first in property damages since 1980, followed by Florida, which accumulated $102.7 billion – or about 19% – in damages.

Texas also accounts for a substantial portion of communities participating in NFIP and CRS. In 2021, Texas ranked third amongst all states in the number of NFIP participating communities and ranked sixth in the number of CRS participating communities (Table 2.4). Furthermore, as of 2020, 65 of the 69 Texas communities participating in CRS were incorporated communities. This is relevant due to the fact that many of the studies about CRS participation focus on counties as the unit of analysis (Asche, 2013; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Paille et al., 2016). These studies tend to aggregate communities nested within counties at the county level. The selection of counties as the unit of analysis and the aggregation of communities within counties may be masking differences between counties and incorporated communities on the factors of interest. As a result, selecting Texas as the study area allows me to explore a level of governance – the incorporated community – that has received less scrutiny in the literature about CRS participation.

4.4 Sampling

Because CRS communities are a subset of NFIP communities – meaning that CRS Communities must already participate in the NFIP as a prerequisite to joining CRS – this research focuses primarily on the NFIP community as the unit of analysis. More specifically, I have selected incorporated communities in Texas that were participating in the NFIP as of 6 July 2021, the last time I downloaded the NFIP participant listing. I removed counties due to their low participation rate in CRS in Texas and due the focus on the incorporated community as the unit of analysis. As suggested above, only 4 of the 224 NFIP counties in Texas also participate in CRS. I removed 21 utility districts and similar organizations due to the lack of delineated census data within those jurisdictions. I removed 130 NFIP communities that were only participating on a temporary or emergency basis. Finally, I removed six communities because the datasets contained incomplete or inconsistent data that prevented analysis in some or all of the models. As a result of these limitations, there are 1,014 incorporated NFIP communities in Texas that I analyzed, based on the availability of other data for the model in question.

Table 4.2 Composition of NFIP and CRS Communities for Analysis

Category	NFIP	CRS
NFIP Communities	1,395	69
Counties	- 224	- 4
Utility, Drainage & Improvement Districts	- 21	
Non-Participating Communities	- 130	
Other	- 6	
NFIP Communities for Analysis	1,014	65

Source: Federal Emergency Management Agency (2021a)

4.5 Data Collection and Processing

In order to construct the models with the variables described above, and using the incorporated NFIP community as the unit of analysis, I collected the data from a variety of sources and created mechanisms to connect the datasets since they lacked uniform identifiers. The main data sources for the variables were the Federal Emergency Management Agency, the Census Bureau, and the Social Explorer database of US Census data. Data supporting variable calculations and linking community identifiers were collected from a variety of state, federal, and private sources. Main and supporting data sources are summarized in Table 4.3 and described in more detail below.

Table 4.3 Sources of Main and Supporting Data

Sources for Main Data

Data	Timeframe	Source
NFIP Communities	2021	(FEMA, 2021f)
CRS Communities	2000 – 2020	(FEMA, 2021b)
NFIP Claims	1980 – 2020	(FEMA, 2021h)
Flood Risk Maps	2021	(FEMA, 2021d)
Community Boundary Maps	2020	Texas Department of Transportation (2021)
Community Water Area Maps	2021	US Census Bureau (2014)
Community Demographics	1990, 2000, 2010 – 2020	US Census Bureau (1990), US Census Bureau (2010-2020)

Sources for Supporting Data

Data	Timeframe	Source
Census Place Names & Geocodes	1990, 2000, 2010, 2012, 2013, 2014, 2015, 2016, 2017, 2018	US Census Bureau (1990-2018)
Zip Codes	2021	UnitedStatesZipCodes.org (2021)
Consumer Price Index – Urban	1980 – 2020	US Bureau of Labor Statistics (2020)

4.5.1 NFIP Communities

I obtained the listing of NFIP Communities from the NFIP Community Status Report for Texas, which was current when I downloaded it on July 6, 2021. For the purposes of this dissertation, I used five columns from the table: community identity number, community name, county, program, and participating community. I selected the communities that were classified as regular participants in NFIP. Communities that I did not include, for example, were classified as emergency participants that temporarily joined after experiencing a declared flood disaster or were no longer participating in the program. As described in the Sampling section above, of the 1,395 communities listed in the Community Status Report, 1,014 communities were used for analysis.

4.5.2 CRS Communities

Although the NFIP Community Status Report also includes basic information on CRS participation, including CRS entry year and current class rating, I obtained more detailed CRS data directly from FEMA via a Freedom of Information Act request.[4] The dataset includes detailed activity scores and ratings for each community nationwide by year. In general, the data were produced in May, October, or both months for each year requested. I used the October data for each year unless the data were only produced for May of that year; this occurred in 2008, 2009, and 2014. With this level of information, I was able to determine if a community exited the program and how a community's class changed year over year. I used the community identity number from this data to link it to the listing of NFIP communities and other datasets. After filtering for communities in Texas between 1991 and 2020, 69 communities remained. Twenty communities joined in the first year, 1991, and a total of 33 communities joined in the first three years, which I define as the initial cohort. Thirty-six more communities joined between 1994 and 2020. I did not observe any communities dropping out of the program during this time. Please see **Error! Reference source not found.** for a listing of CRS communities in Texas along with their participation years.

4.5.3 NFIP Claims

I downloaded NFIP claims data on June 22, 2021, from OpenFEMA, which is FEMA's online platform that houses publicly available datasets on disaster information, emergency management, individual and public assistance, hazard mitigation, and NFIP

[4] FEMA FOIA Case Number 2021-FEFO-00415, submitted March 5, 2021.

policies and claims. The dataset, FIMA NFIP Redacted Claims (FEMA, 2021g), is constructed using claims data from the NFIP system of record and is redacted by NFIP to remove all personally identifiable information of the policy holders. The dataset contains more than two and a half million records nationwide, but after I filtered the dataset to only include claims in Texas after 1978, approximately 390,000 records remained. The relevant fields that I extracted from the dataset were community name, county code, zip code, year of loss, building claim paid amount, contents claim paid amount, and increased cost of compliance claim paid amount. Upon inspecting the Texas data, I discovered that some records contained community names that were spelled incorrectly or contained combinations of community, county, and zip code that were not possible. For example, an invalid record could contain a community that did not lie in specified county or the zip code may not be part of the specified community.

I used a series of data transformations and filters to create a reliable listing of NFIP claims that could be aggregated and linked to NFIP communities. This series of transformations and filters is outlined in Table 4.4. Due to a large number of records with misspelled community names in the earlier data, I separated the records into two datasets that I later merged. The first dataset contained all claims before 1995, the second dataset contained all claims from the beginning of 1995. This separation allowed me to investigate whether there were any trends with the misspelled or otherwise invalid data in the earlier years.

Within both datasets, I investigated communities with more than 100 claims that were flagged as invalid due to invalid community/county combinations. In general, communities with large numbers of flagged yet valid claims that I could repair tended to be those that were not listed in the file that I used to validate city/county combinations, those with common misspellings of community names, and those where a neighborhood name was used instead of the community's name. The primary reason a community is not in the validation file is that the validation file is a point in time dataset, showing all Census places in Texas as of 2010. A community may not have been incorporated or identified as a Census Place by the Census Bureau in that particular year, but was identified as such in an earlier or later year. For those communities, I manually identified and entered the appropriate community codes to facilitate subsequent data analysis. In the end, I removed 12,700 claims with invalid community/zip code combinations or invalid city/county combinations that I could not manually repair.

Table 4.4 NFIP Claims Selection

Item / Transformation	Number of Records	Percent of Claims
Full dataset	2,516,992	
Remove non-Texas claims	-2,126,387	
Remove claims before 1979	-764	
Texas Claims	389,841	
Texas Claims: 1979-1994	99,718	100%
Remove invalid community/zip & community/county combinations	-8,207	
Valid Texas Claims: 1979 – 1994	91,511	91.8%
Claims grouped by community & year	2,995	
Texas Claims: 1995-2021	290,123	100%
Remove invalid community/zip & community/county combinations	-4,493	
Valid Texas Claims: 1995-2021	285,630	98.5%
Claims grouped by community & year	6,451	
Total Texas Claims: 1979-2021	389,841	100%
Total Valid Texas Claims	377,141	96.7%
Total Claims grouped by community & year	9,446	

The dataset from 1995 onwards contained substantially fewer irreparable misspellings and inconsistencies than the pre-1995 dataset. Of the 99,718 Texas claims from 1979 to 1994, I removed 8,207 records, or 8.2%. Of the 285,630 Texas claims from

1995 through 2021, I removed just 4,493 records, or 1.5%. Of the 3,930 pre-1995 records that I manually repaired, nearly 82% were due to communities not appearing in the 2010 Census places validation file. Of the 17,089 records from 1995 through 2021 that I manually repaired, nearly 95% were due to communities not appearing in the validation file. The larger proportion of irreparable records in the earlier dataset appears to be due to misspellings, which I attribute to less reliable or consistent recording and database technologies in those years. The final dataset containing valid claims contained 377,141 records or 96.7% of the total claims in Texas from 1979 through 2021. I then grouped and summarized these records by NFIP community and year. This resulted in 9,446 records, each representing an NFIP Community with at least 1 flood claim in any year from 1979 through 2021.

4.5.4 Mapping Data

I obtained flood risk maps from FEMA's National Flood Hazard Layer. Although communities are required to have flood risk maps in order to participate in NFIP, not all NFIP communities have digitized flood maps. Of the 1,014 NFIP communities in the sample that I analyzed, 868 had a digitized flood map when I last downloaded the data on July 9, 2021. Due to the large number of communities lacking digitized flood maps, I was not able to include this variable in the full model and instead replaced it with flood map presence – a dummy variable representing community commitment to understanding their flood risk from 1991 to 2020.

In order to calculate distance to the nearest CRS community – as part of external influence domain – I again used the City Boundaries shapefiles maintained by the Texas

Department of Transportation. After linking CRS entry date information for each community, I calculated the closest distance from a community's boundary to the boundary of its nearest CRS neighbor for each year in question. Because the composition of CRS participants and non-participants can change each year, I re-calculated this variable for each community for the years I was considering in each model.

4.5.5 Community Demographics

I used data from the Decennial Census in 1990 and 2000 and data from the 5-year American Community Survey (ACS) from 2010 to 2020 to populate the variables within the community demographics domain. These variables are population size, population density, education, rent share, and poverty rate. I attempted to obtain all data directly from the Census Bureau's website, data.census.gov. At the time that I downloaded the data, however, Decennial Census data from 1990 and 2000 were not available on data.census.gov; not all data had been migrated from the Census' legacy system, American Factfinder. As a result, I download this missing data from the Social Explorer database (US Census Bureau, 1990, 2000). I also downloaded poverty rate data from the 2010 and 2011 ACS from Social Explorer due to unexplained difficulties in obtaining this data directly from the Census website. In order to approximate data for the years between the 1990 and 2000 and between 2000 and 2010, I used a straight-line interpolation calculation. Although this method masks changes in variables that fall outside of the linear projection, it has been recognized as an acceptable solution to calculating variables in years between the Decennial Census (Li, 2012).

An additional issue arises with the use of the 5-year ACS data to represent single years with my models. In reality, data from the 5-year ACS represents the totality of the five-year period ending with the dataset year. It does not represent any single year in that time period, nor does it represent the average of years during that time period. Although there is a conflict in comparing and interpreting Decennial Census data and 5-year ACS data due differences on when data are collected, I approach each type of data with the understanding that they represent different time periods. Additionally, due to the fact that the 5-year ACS data indeed represent the totality of the five-year period, I believe these data may be a better demographic representation of a community during the time period when it is considering joining CRS. ACS data were also used by Asche (2013) and Frimpong et al. (2022) in their studies of CRS participation.

4.5.6 Supporting Data

I obtained three additional datasets to facilitate joining the datasets above, to verify claims data, and to adjust nominal dollar values to 2020 real dollar values. Within datasets and maps from FEMA, with the exception of flood claims data, communities are identified by a community identity number or CID. Datasets and maps from the Census Bureau, on the other hand, identify communities by FIPS codes. Since community names may differ slightly between FEMA and the Census Bureau, I created a linking table containing the FIPS code and CID for NFIP communities in Texas. The basis of this table is the Census Bureau's 1990 – 2018 Place Reference Tables. I validated flood claims data, in part, by confirming that the community name and zip code combinations were valid. In order to do this, I used a private zip code dataset that is made available for free to academic researchers (UnitedStatesZipCodes.org, 2021). Finally, nominal dollar values were adjusted to 2020 real dollar values using the Consumer Price Index – All Urban Consumers (CPI-U) from the U.S. Bureau of Labor Statistics.

4.6 Analytical Methods

The two overarching research questions that I attempt to answer address factors predicting community participation in the Community Rating System in Texas and how those factors differ between initial participants and subsequent joiners. In order to answer these questions, I construct two models using the domains and variables described in section 4.1. The methods used in developing these models and analyzing the data are described in the subsections below. I begin, however, with a discussion of data limitations and analytical methods that I considered before choosing the methods that I ultimately used.

4.6.1 Data and Modeling Considerations

The data that I use for this research constitutes a nearly complete panel dataset of CRS participation variables for the entirety of the CRS program in Texas from 1991 to 2020. I chose, however, to analyze the data using cross-sectional methods for several reasons. The data possess several characteristics that present challenges to longitudinal data analysis and, to a more limited extent, to logistic regression analysis. These challenges are the presence of censored and bounded data, as well as the fact that within the sample, there are only 64 instances of a community joining CRS.

Data is censored when an event can occur – in this case, joining CRS – before or after the study period (Cohen et al., 2003). Because a non-participating community could join at any time after 2020, and therefore would not be captured in the dataset, any longitudinal analysis and conclusions would need to account for this limitation. This issue is referred to as right-censoring. Similarly, the year of joining CRS has a lower-bound of 1991, meaning that communities cannot join before 1991. As a result, the distribution of joining communities by year has a large peak in the initial years and is right-skewed.

Because only 65 communities of the 1,014 NFIP communities in the sample join CRS during the study period, the act of joining is rare in the context of annual opportunities for a community to join over a thirty-year period. Stated differently, there were only 65 acts of joining amongst the approximately 30,000 opportunities (1,014 communities x 30 years) to join. Even by analyzing the dataset using modified cross-sectional methods – as I have done here – the act of joining could still be considered a rare event in the context of logistic regression. King and Zeng (2001) have suggested that a rare event is one that occurs in less than approximately five percent of cases. In the case of Texas, from 1991 to 2020, approximately 6.3% of incorporated NFIP communities joined CRS. Fortunately, the models that I ran did not suffer from a failure to converge – a common problem with rare event datasets. Nonetheless, as noted below, the last model that I ran was a Firth logit analysis of the variables from the best fitting standard logistic regression model. The Firth logit method uses a penalized likelihood function that lessens the impact of biases caused by small sample sizes within logistic regression models (Hilbe, 2016).

For all statistical analyses, I used $\alpha < .1$ as my significance indicator. This is the same level that is used in several other studies on CRS participation (Asche, 2013; Frimpong et al., 2022; Li & Landry, 2018; Noonan et al., 2020; Sadiq & Noonan, 2015b).

4.6.2 Participation in the CRS

In order to answer the first research question about factors predicting CRS participation among NFIP communities in Texas, I compared NFIP communities that joined CRS in the first three years of the program – the initial adopters – with those that did not join. I also compared the initial adopters to non-participants and the subsequent joiners to non-participants in 2020. These groups of communities were compared on the independent variables within the domains of past experience, triggering event windows, flood risk, external influence, and demography. To accomplish this, I first performed Levene's test of equal variance to investigate the possibility of unequal variances amongst variables (Appendix B) and then analyzed boxplots and scatterplots on the same variables to determine the appropriate data transformations that I would use within the participation model. After finding unequal variances amongst variables, I performed a series of one-way, two-sample Welch's t-tests with unequal variances to identify statistically significant differences between participating and non-participating communities on individual variables. Welch's t-test is more appropriate than the standard t-test when variances are not equal across groups (Myers et al., 2010).

I then used the following logistic regression model to predict initial CRS participation as a function of past experience, triggering event windows, flood risk, external influence, and demography:

$$\text{CRS} = f\,(\text{past experience, triggering event windows, flood risk, external influence, demography})$$

$$\text{CRS} = 0 \text{ for early adopters; CRS} = 1 \text{ for non-participants}$$

A total of nine models were executed. The first five models analyzed the variables within each of the five domains by themselves. For example, the first model, analyzing past experience, includes only the number of claims paid in the previous 10 years and the total amount of claims paid per household in the previous ten years as independent variables. Due to correlations between past experience and triggering event window variables, the sixth model includes past experience, flood risk, external influence, and community demographics. Model 7 is similar to Model 6, but replaces past experience with triggering event window. Model 8 is the full model with all domains, ignoring issues of multicollinearity. Finally, Model 9 performs the Firth logit function described above on the best fitting, non-full model. This model is used to explore whether results are impacted by the small proportion of initial CRS participants in the sample.

The logistic regression model is the most appropriate for analyzing CRS participation due to the binary nature of the dependent variable, which can take on the values of zero or one. Within the model that I use, zero represents CRS non-participation and one represents CRS participation. The logistic regression model, part of the broader generalized linear model (GLM), incorporates a logistic function that, in general, results in an S-shaped curve that visually represents the probability of a binary outcome (CRS participation in this case) as a function of the predictors (Cohen et al., 2003). Additionally, whereas the ordinary least squares regression model requires model residuals to be normally distributed and homoscedastic, the distribution of residuals from the logistic regression model have no such constraints.

The logistic regression model is sensitive, however, to several assumptions that must be met in order for the model to be valid. These assumptions are independence of observations, absence of multicollinearity amongst independent variables, and the appropriate selection of the logit link function describing the relationship between independent and dependent variables (Cohen et al., 2003; Hilbe, 2016).

After performing the logistic regressions comparing initial participants and non-participants, I performed a series of multinomial logistic regressions comparing early adopters to non-participants in 2020 and subsequent participants to non-participants in 2020 on past experience and triggering event windows, flood risk, external influence, and community demographics. I used the following multinomial logistic regression model to accomplish this:

CRS = *f* (past experience, triggering event windows, flood risk, external influence, demography)

CRS = 1 for non-participants; CRS = 2 for early adopters; CRS = 3 for subsequent joiners

The models that I executed were the same as those described for the standard logistic regression above. Model 9, using the Firth logit function, was not executed because the binomial logistic regression results did not indicate any issues due to a small sample size and the results from the Firth binomial logistic model were consistent with the corresponding non-Firth model. The results from these tests were used to explore whether factors predicting CRS participation for early adopters were different in 2020 compared to 1991. The use of the multinomial logistic regression also allowed me to explore factors predicting CRS participation for subsequent participants in 2020 and then compare whether those factors differed from the ones predicting CRS participation for early adopters in 2020. These results, while describing changes in early adopters from 1991 to 2020, also provide evidence of differences between early adopters and subsequent participants, as addressed in research question two.

Multinomial logistic regression, also called polytomous logistic regression, is appropriate for the analysis of a nonordered outcome that falls within one of several categories or, in this study, groups (Cohen et al., 2003). One group serves as the baseline against which the other groups are compared. For this study, I chose non-participants as the baseline group against which early adopters and subsequent participants are compared. Testing of model fit and validity is similar to that of standard logistic regression described above.

4.6.3 Initial Versus Subsequent Participation in the CRS

After analyzing participation of the initial participants in CRS in 1991 and 2020, I compared initial participants to subsequent participants on the independent variables within the domains of past experience, triggering event windows, flood risk, external influence, and community demographics.

Rather than apply a linear transformation to each variable to account for trends or changes over time, I opted for comparing CRS communities' percentiles within the population of NFIP participants in the year of joining on all variables. Although this solution prevents me from drawing conclusions about differences between early participants and subsequent joiners in relation to the value of the variables, I am able to draw conclusions about how the groups differ by their ranks of percentiles on the variables being analyzed. An alternative to using percentile to compare communities on the variables is to use standardized z-scores (Myers et al., 2010). Since z-scores tell us how many standard deviations above or below the mean a value is located within a distribution, z-scores provide more information than percentiles. Percentiles, however, are more readily understood and are thus used here to facilitate a clearer discussion.

Because percentiles are effectively ordinal data and therefore violate the assumption of normality, I perform the nonparametric Mann-Whitney U test – instead of the standard or Welch's t-test – to compare early and subsequent CRS participants. According to Myers et al. (2010), the Mann-Whitney U test compares the distribution of ranks (after ranking the pooled data) and is appropriate for comparisons of independent groups when the normality assumption is violated.

Although the use of percentiles and ranks is a crude methodology for comparing early adopters and subsequent joiners, I contend that the results from the Mann-Whitney U test, discussed in conjunction with the results of the multinomial logistic regression model and the changes in modeled variables over time displayed in Figure 3.5, provides sufficient evidence of how subsequent joiners of CRS differ from initial participants in Texas.

The rank sum presented in Table 5.6 is the summation of the pooled ranking scores for each group and provides a crude indication of which group had higher percentile scores after ranking. As a note of caution, the rank sum statistic is sensitive to sample size differences. Because the sizes of each group differ by one, the rank sum statistic may not be a good indicator of directionality in instances where the scores for each group are similar. The U statistic is an indication of how often the rankings from the first group (early adopters) exceeded those of the second group (subsequent joiners). Unlike the rank sum statistic, the U statistic is not vulnerable to sample size differences.

5 Results

5.1 Participation in the CRS

5.1.1 Summary Statistics and T-tests

Summary statistics and results from t-tests comparing initial CRS participants to non-participants on past experience and triggering event windows, flood risk, external influence, and community demographics can be found in Table 5.1. Of the 978 NFIP communities analyzed, only 33 – or 3.4% – joined the Community Rating System in the program's first three years. In general, the initial CRS participants tended to exhibit higher levels of experience with flood loss as measured by residential flood claims from 1981 through 1990. They also tended to show higher levels of flood loss in the three-year triggering event window. On average, CRS communities experienced $1,811 in claims paid per household over the preceding ten-year period and $556 in claims paid per household over the preceding three-year period. These values equate to $181 per year and $111 per year, respectively. For non-participating communities, these values were $144 and $54, respectively. These values equate to $14 per year and $11 per year, respectively. Results from one-way, two-sample Welch's t-tests indicate that, in spite of the average difference, early CRS participants are not significantly different from non-participants, albeit marginally. This may be explained by the highly right-skewed and leptokurtotic nature of the distributions of both groups. This type of distribution describes most of the non-demographic variables in the dataset. Claims paid per household from four to six years prior (1985 – 1987) were $17 for CRS participants and $13 for non-participants. These results were not significantly different. Overall, however, these results indicate that, independently, communities with higher levels of past flood experience and more recent triggering event windows were marginally more likely to participate in CRS in its early years. Measures of external influence indicate a potential clustering effect amongst early CRS communities. CRS communities tended to be, on average, 32.2 kilometers closer to each other than non-participants were to participants. Indeed, many of the early CRS participants are located in the greater Houston and Dallas-Fort Worth metropolitan areas.

On all demographic variables, early CRS participants and non-participants were significantly different with the same caveats mentioned above regarding skewness and kurtosis. CRS participants had a larger mean population and a larger mean population density than non-participants. The population and population density averages for participants were 124,258 people and 683 people per km^2. The averages for non-participants were 9,285 and 359, respectively. These differences can be attributed to the early participation of large cities like Dallas, Austin, and El Paso and to the large proportion of smaller cities that were non-participants. Of the 945 non-participants, 708 had populations of 5,000 or less. This accounts for nearly 75% of non-participating communities.

On average, participating communities also had significantly higher levels of education, home values, and income. The average percentage of residents with a bachelor's degree was 12.6 percentage points higher for CRS participants. Although not reported in Table 5.1, and not included in the models below, median home value and median income were, on average, approximately $40,000 and $18,000 higher for CRS participants. Consistent with higher income, CRS participants also had a mean poverty rate that was 6.8 percentage points lower than non-participants. Educational attainment, home value, income, and poverty rate tend to be highly correlated with each other, especially income and home value (see Table 4.1).

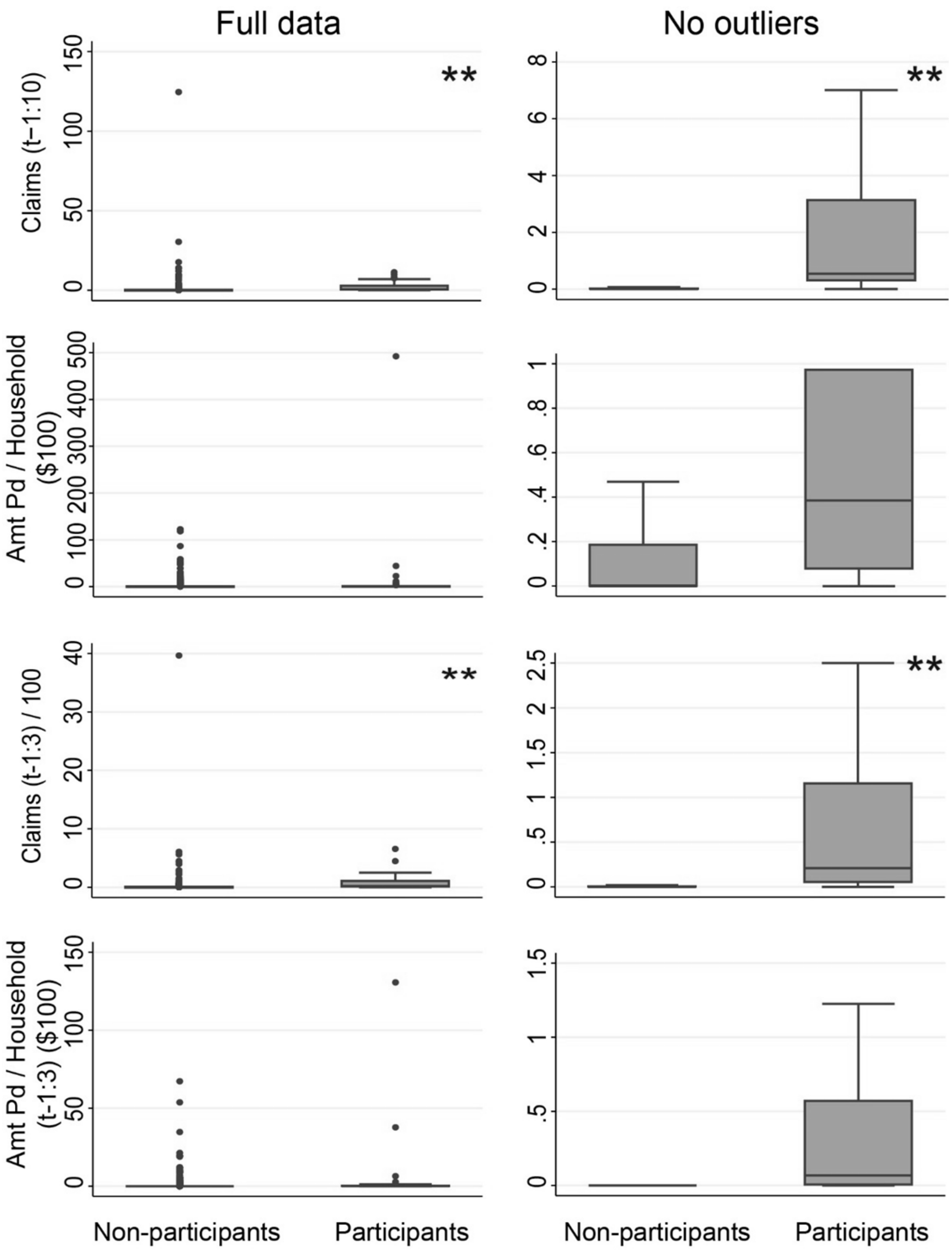
Boxplots of the variables described above for participants and non-participants can be found in Figure 5.1, Figure 5.2, and Figure 5.3. It is worth noting that due the presence of extreme outliers in most of the plots, and in order to make them more readable, I am presenting the plots with and without outliers.

Table 5.1 Summary of Variables and T-test Results for Initial CRS Participants and Non-participants

	Non-participants						Participants						
Variable	N	Mean	Median	SD	Min	Max	N	Mean	Median	SD	Min	Max	t-test*
Past Experience (t-1:10)													
Claims /100	945	0.39	0.00	4.34	0	124.55	33	2.36	0.54	3.19	0	11.36	0.001
Amt Pd / Household ($100)	945	1.44	0.00	7.71	0	122.53	33	18.11	0.39	85.54	0	492.23	0.136
Triggering Event Window													
(t-1:3)													
Claims / 100	945	0.12	0.00	1.36	0	39.64	33	0.83	0.21	1.40	0	6.56	0.004
Amt Pd / Household ($100)	945	0.54	0.00	3.48	0	67.27	33	5.56	0.07	23.41	0	130.71	0.114
(t-4:6)													
Claims / 100	945	0.03	0.00	0.27	0	6.87	33	0.35	0.09	0.83	0	4.67	0.019
Amt Pd / Household ($100)	945	0.13	0.00	1.17	0	26.43	33	0.17	0.03	0.40	0	1.58	0.314
Flood Risk													
Digital Flood Map (2021)	945	0.75	1.00	0.43	0	1	33	0.91	1.00	0.29	0	1	0.002
External Influence													
Dist. To Nearest CRS (km)	945	68.96	53.46	64.00	0	325.62	33	37.29	1.06	78.49	0	355.87	0.014
Community Demographics													
Population Size (K)	945	9.29	1.86	64.18	0.16	1630.55	33	124.26	58.72	199.71	1.09	1006.88	0.001
Population Density (per km^2)	945	359.06	279.42	323.24	17.02	2502.12	33	682.67	606.07	374.69	152.10	1477.01	0.000
Education (% Bach)	945	14.32	11.03	11.43	0.01	0.73	33	26.91	25.95	12.09	0.10	0.51	0.000
Rent Share (%)	945	27.22	27.11	11.43	0.04	0.89	33	40.01	38.68	10.82	0.24	0.68	0.000
Poverty Rate (%)	945	19.64	18.80	11.87	0.01	0.70	33	12.76	10.01	8.81	0.03	0.37	0.000

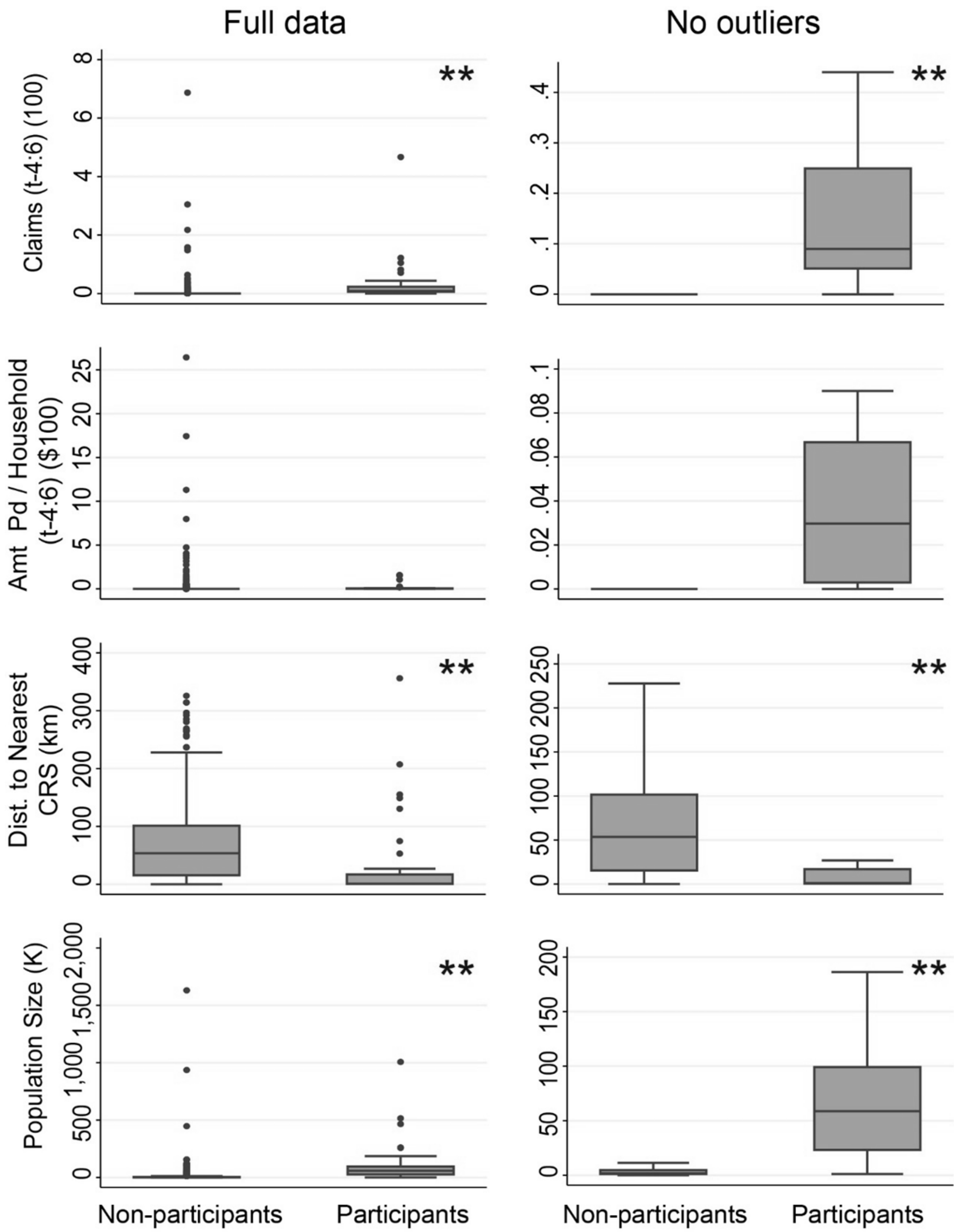
* T-test significance is based on one-tailed hypothesis testing for all variables.

Figure 5.1 Boxplots Comparing Initial CRS Participants and Non-participants on Flood Experience and Triggering Event Window (t-1:3)



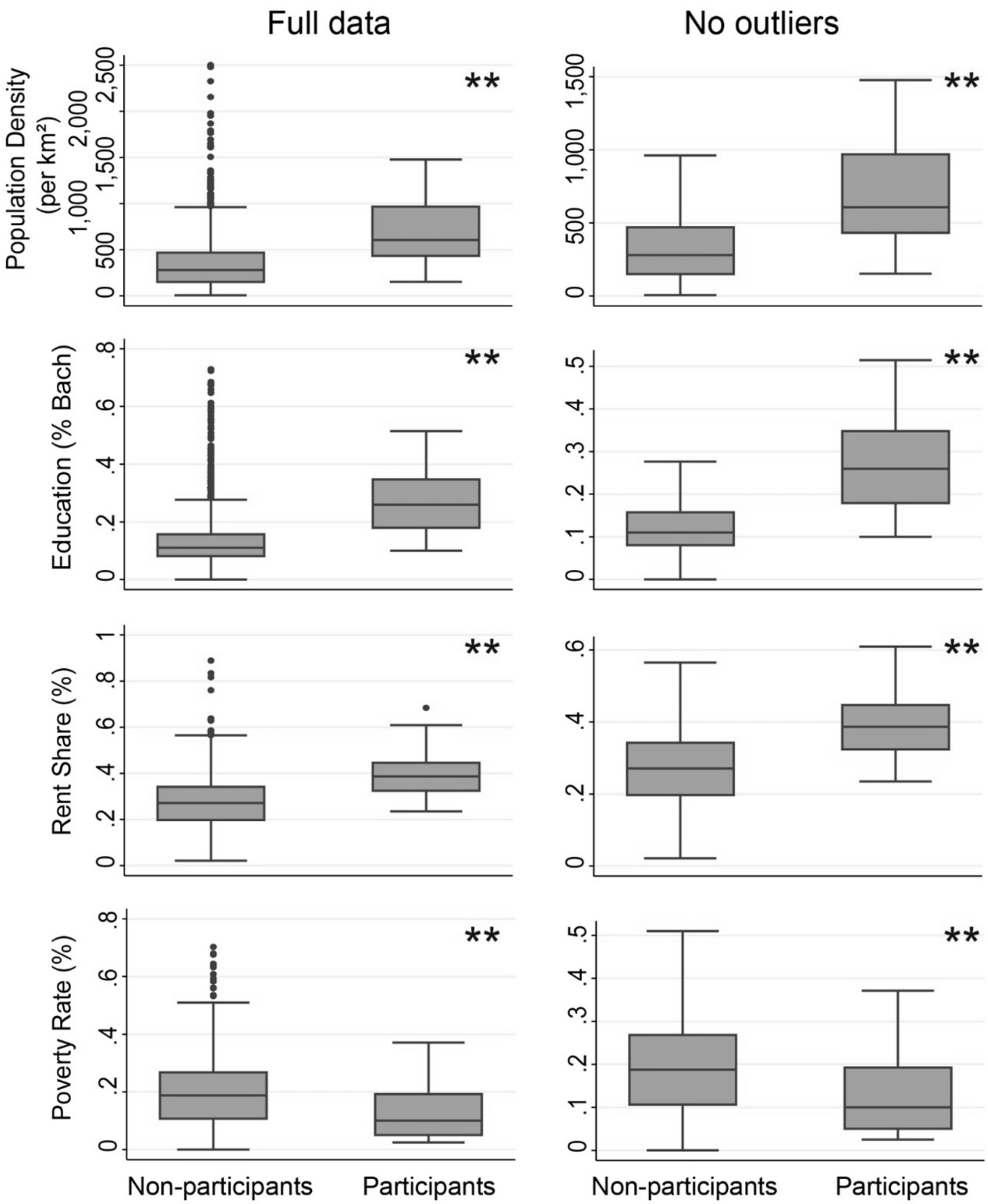
** T-test results were significant at p < .05.

Figure 5.2 Boxplots Comparing Initial CRS Participants and Non-participants on Triggering Event Window (t-4:6), External Influence, and Community Demographics (Population Size)



** T-test results were significant at p < .05.

Figure 5.3 Boxplots Comparing Initial CRS Participants and Non-participants on Community Demographics



** T-test results were significant at p < .05.

5.1.2 Logistic Regression Results

Table 5.2 and Table 5.3 present the logistic regression results – with coefficients and odds ratios, respectively – of the models for initial CRS participation. An odds ratio (OR) tells us by what amount the odds of being in the outcome group are multiplied when the independent variable is increased by one (Cohen et al., 2003). Given the directionality of the hypotheses presented in section 4.2, the p values shown are one-tailed probabilities for all coefficients. All models were statistically significant at $p < .05$ or better. The four complete models (models six through nine) were statistically significant at $p < .001$. Model 5 (community demographics domain) was also significant at $p < .001$ indicating the importance of demographic variables alone in predicting CRS participation. The results from models 5 through 9 indicated that, overall, the variables accounted for a substantial amount of the variance in predicting CRS participation. Amongst these models, the likelihood ratio χ^2 value ranged from 64.94 in Model 9 to 97.92 in Model 8. The pseudo-R^2 ranged from 25.8% to 42.2%. Predictors that were significant in models 5 through 9 were the number of claims and total amount of claims paid per household in a community in the past experience domain, the number of claims and total amount of claims paid per household in a community in the t-1:3 triggering event window subdomain, the number of claims in a community in the t-4:6 triggering event window subdomain, and population size, educational attainment, share of renters, and poverty rate in the community demographics domain.

Model 1 includes measures of past experience, specifically the number of NFIP claims per community and the average claim amount paid per household per community for the ten years before the start of the CRS program (1981-1990). Within the past experience subdomain, the number of claims (b = .025, p = .06) and the total amount of claims paid per household (b = .015, p = .07) were significant. For each additional 100 claims, a community was 25% less likely to join CRS (OR = 1.025). For each additional $100 in claims paid per household, a community was 1.5% more likely to join CRS (OR = 1.015).

Like Model 1, Model 2 also estimates CRS participation based on the number of NFIP claims per community and the average claim amount paid per household per community, but for two specific triggering event windows: these windows are the three years prior to the establishment of CRS (1988-1990) and the three years before that (1985-1987). Within the t-1:3 triggering event window subdomain, the number of claims (b = -.251, p = .03) and the total amount of claims paid per household (b = .071, p = .01) were both significant, but in different directions. For each additional 100 claims, a community was 23% less likely to join CRS (OR = .778). For each additional $100 in claims paid per household, a community was 7.4% more likely to join CRS (OR = 1.074). Within the t-4:6 triggering event window subdomain, only the number of claims (b = 1.875, p = .00) was significant. For each additional 100 claims in this triggering event window, a community was more than six times as likely to join CRS (OR = 6.522).

In model 3, I entered the dummy variable, risk map presence to predict CRS participation. This was the only model where this variable was significant (b = .1.203, p = .02). When used on its own, presence of digital flood map meant the community was about three times more likely to join CRS (OR = 3.329).

Model 4 only includes the single external influence variable, which is distance to the nearest CRS community, to predict CRS participation. Again, this was the only model in which this variable was significant, and it had a negative relationship (b = -.109, p = .00). For each additional ten kilometers of distance from the nearest CRS community, the community was 10% less likely to join CRS.

Model 5 estimates participation based on all demographic variables, which are population size, population density, education (percent of population with a bachelor's degree), percent of households renting their home, and percent households living below the poverty level. Within this community demographics domain, population size (b = .033, p = .01), educational attainment (b = .297, p = .02), share of renters (b = .693, p = .00), and poverty rate (b = -.788, p = .00) were all significant. For each additional 10,000 residents, a community was 3.4% more likely to join CRS (OR = 1.034). For each additional ten percent share of the population with a bachelor's degree, a community was 34.6% more likely to join (OR = 1.346). For each additional ten percent share of renting households, a community was twice as likely to join (OR = 2.000). And for each additional ten percent increase in the poverty rate, a community was 54% less likely to join (OR = .455).

Due to the fact that NFIP insurance claims data contributing to variables within the triggering event window domain are a subset of data contributing to variables within the past experience domain, I found high levels of multicollinearity between the two domains. As a result, Model 6 is a nearly full model with the triggering event window variables removed. Within the past experience subdomain, the number of claims (b = -

.093, p = .01) and the total amount of claims paid per household (b = .015, p = .04) were significant. For each additional 100 claims, a community was 9% less likely to join CRS (OR = .911). For each additional $100 in claims paid per household, a community was 1.5% more likely to join CRS (OR = 1.015).

Significant variables within the community demographics domain were population size (b = .078, p = .00), educational attainment (b = .297, p = .03), share of renters (b = .663, p = .00), and poverty rate (b = -.842, p = .00). For each addition of 10,000 residents, a community was about 8% more likely to join CRS (OR = 1.081). For each additional ten percent share of the population with a bachelor's degree, a community was 34.6% more likely to join (OR = 1.346). For each additional ten percent share of renting households, a community was nearly twice as likely to join (OR = 1.940). And for each additional ten percent increase in the poverty rate, a community was 57% less likely to join (OR = .431).

Model 7 is a nearly full model with past experience variables removed. Within the t-1:3 triggering event window subdomain, the number of claims (b = -.434, p = .01) and the total amount of claims paid per household (b = .069, p = .01) were significant. For each additional 100 claims, a community was 1.54 times less likely to join CRS (OR = .648) after controlling for the other variables in the model. For each additional $100 in claims paid per household, a community was 7.2% more likely to join CRS (OR = 1.072).

Within the t-4:6 triggering event window subdomain, the number of claims (b = 1.094, p = .02) was significant, but the total amount of claims paid per household (b = -

.429, p = .25) was not. For each additional 100 claims in this triggering event window, a community was almost three times as likely to join CRS (OR = 2.986).

Within the community demographics domain, population size (b = .067, p = .01) educational attainment (b = .291, p = .03), share of renters (b = .680, p = .00), and poverty rate (b = -.889, p = .00) were significant. For each addition of 10,000 residents, a community was almost 7% more likely to join CRS (OR = 1.069). For each additional ten percent share of the population with a bachelor's degree, a community was almost 34% more likely to join (OR = 1.338). For each additional ten percent share of renting households, a community was about 97% more likely to join (OR = 1.973). And for each additional ten percent increase in the poverty rate, a community was 2.32 times less likely to join (OR = .411).

I constructed Model 8 as a full model – ignoring multicollinearity – to observe full model fit and compare to the fit of Models 6 and 7, whose variables are more readily interpretable due to lower variance scores. Within the past experience subdomain, the number of claims (b = -.327, p = .04) was significant. For each additional 100 claims, a community was 28% less likely to join CRS (OR = .721).

In the two triggering event window subdomains, only the number of claims within t-4:6 window (b = 1.510, p = .01) was significant. For each additional 100 claims, a community was four and a half times more likely to join CRS (OR = 4.529) after controlling for the other variables in the model. Despite the collinearity, this effect is the highest effect within this model.

Significant variables within the community demographics domain were population size (b = .076, p = .00), educational attainment (b = .299, p = .03), share of renters (b = .657, p = .00), and poverty rate (b = -.845, p = .01). For each addition of 10,000 residents, a community was about 8% more likely to join CRS (OR = 1.079). For each additional ten percent share of the population with a bachelor's degree, a community was 34.9% more likely to join (OR = 1.349). For each additional ten percent share of renting households, a community was nearly twice as likely to join (OR = 1.929). And for each additional ten percent increase in the poverty rate, a community was 57% less likely to join (OR = .430). Each of these effects was nearly identical to the results of Model 7.

Model 9 is a repeat of Model 7, but run using the Firth logit method. Within the t-1:3 triggering event window subdomain, the number of claims (b = -.346, p = .00) and the total amount of claims paid per household (b = .048, p = .01) were both significant. Within the t-4:6 triggering event window subdomain, only the number of claims (b = .771, p = .01) was significant. Within the community demographics domain, population size (b = .061, p = .01) educational attainment (b = .299, p = .02), share of renters (b = .637, p = .00), and poverty rate (b = -.833, p = .00) were significant.

In further discussions, I am focusing on the results of Model 7 because the model has the best predictive ability (Pseudo-R^2 = 32.8%) while avoiding issues of collinearity.

Table 5.2 Logistic Regression Results with Coefficients: Initial CRS Participation

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9*	
Variable	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
Constant	-3.442		-3.523		-4.365		-2.799		-5.279		-5.064		-5.101		-5.043		-4.865	
Past Experience (t-1:10)																		
Claims (100)	0.025	.06									-0.093	.01			-0.327	.04		
Amt Pd / Household ($100)	0.015	.07									0.015	.04			0.006	.37		
Triggering Event Window																		
(t-1:3)																		
Claims (100)			-0.251	.03									-0.434	.00	0.464	.18	-0.346	.00
Amt Pd / Household ($100)			0.071	.01									0.069	.01	0.041	.24	0.048	.00
(t-4:6)																		
Claims (100)			1.875	.00									1.094	.02	1.510	.01	0.771	.01
Amt Pd / Household ($100)			-0.572	.23									-0.429	.25	-0.513	.24	0.021	.40
Flood Risk																		
Digital Flood Map (2021)					1.203	.02					-0.206	.38	-0.167	.41	-0.284	.34	-0.307	.32
External Influence																		
Dist. To Nearest CRS (10 km)							-0.109	.00			-0.005	.43	-0.010	.40	-0.012	.38	-0.002	.48
Community Demographics																		
Population Size (10K)									0.033	.01	0.078	.00	0.067	.01	0.076	.00	0.061	.01
Population Density (10/km^2)									0.004	.16	0.004	.18	0.004	.17	0.004	.19	0.005	.14
Education (10% Bach.)									0.297	.02	0.297	.03	0.291	.03	0.299	.03	0.299	.02
Rent Share (10%)									0.693	.00	0.663	.00	0.680	.00	0.657	.00	0.637	.00
Poverty Rate (10%)									-0.788	.00	-0.842	.00	-0.889	.00	-0.845	.01	-0.833	.00
Observations	978		978		978		978		978		978		978		978		978	
LR χ^2	9.49		23.70		5.31		9.57		74. 35		89.26		94.66		97.92		64.94	
Prob > χ^2	0.009		0.000		0.021		0.002		0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	0.033		0.082		0.018		0.033		0.258		0.309		0.328		0.339		0.422	
Log Likelihood	-139.53		-132.42		-141.62		-139.49		-107.01		-99.64		-96.95		-95.32		-67.63	

Note: p value is based on one-tailed test.
* Firth logit with penalized log likelihood

Table 5.3 Logistic Regression Results with Odds Ratios: Initial CRS Participation

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9*	
Variable	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P
Constant	0.032		0.030		0.013		0.061		0.005		0.006		0.006		0.006			
Past Experience (t-1:10)																		
Claims (100)	1.025	.06									0.911	.01			0.721	.04		
Amt Pd / Household ($100)	1.015	.07									1.015	.04			1.006	.37		
Triggering Event Window																		
(t-1:3)																		
Claims (100)			0.778	.03									0.648	.00	1.590	.18	0.708	.00
Amt Pd / Household ($100)			1.074	.01									1.072	.01	1.042	.24	1.049	.00
(t-4:6)																		
Claims (100)			6.522	.00									2.986	.02	4.529	.01	2.162	.01
Amt Pd / Household ($100)			0.564	.23									0.651	.25	0.599	.24	1.021	.40
Flood Risk																		
Digital Flood Map (2021)					3.329	.02					0.813	.38	0.846	.41	0.753	.34	0.736	.32
External Influence																		
Dist. To Nearest CRS (10 km)							0.897	.00			0.995	.43	0.990	.40	0.988	.38	0.998	.48
Community Demographics																		
Population Size (10K)									1.034	.01	1.081	.00	1.069	.01	1.079	.00	1.063	.01
Population Density (10/km^2)									1.004	.16	1.004	.18	1.004	.17	1.004	.19	1.005	.14
Education (10% Bach.)									1.346	.02	1.346	.03	1.338	.03	1.349	.03	1.349	.02
Rent Share (10%)									2.000	.00	1.940	.00	1.973	.00	1.929	.00	1.891	.00
Poverty Rate (10%)									0.455	.00	0.431	.00	0.411	.00	0.430	.01	0.435	.00
Observations	978		978		978		978		978		978		978		978		978	
LR χ^2	9.49		23.70		5.31		9.57		74.53		89.26		94.66		97.92		64.94	
Prob > χ^2	0.009		0.000		0.021		0.002		0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	0.033		0.082		0.018		0.033		0.258		0.309		0.328		0.339		0.422	
Log Likelihood	-139.53		-132.42		-141.62		-139.49		-107.01		-99.64		-96.95		-95.32		-67.63	

Note: p value is based on one-tailed test.

5.1.3 Early Adopters and Subsequent Joiners in 2020

Results of multinomial logistic regression models comparing early adopters to non-participants in 2020 and late adopters to non-participants in 2020 on past experience and triggering event windows, flood risk, external influence, and community demographics are presented in Table 5.4 and Table 5.5. To summarize, the factors that predicted participation for early adopters are different from those predicting subsequent joiner participation. Most notable are external influence and rent share. Although external influence is significant for subsequent joiners, it is not significant for early adopters. On the other hand, whereas rent share is significant for early adopters, it is not significant for subsequent joiners. Population size shows mixed results. It is marginally not significant in predicting early adopter participation and is only significant in predicting participation for subsequent joiners within Model 5; this is the model containing only the variables within community demographics domain.

Within the past experience domain in Model 1, the number of claims (early: $b = .634$, $p = .00$; late: $b = .648$, $p = .00$) and the amount of claims paid per household (early: $b = -.034$, $p = .00$, late: $b = -.035$, $p = .00$) were significant for both groups. For each additional 100 claims, the early adopter communities were nearly 89% more likely to participate in CRS (OR = 1.889) compared to non-participants, while late adopters were 91% more likely to participate (OR = 1.912) compared to non-participants. For each additional $100 in claims paid per household, early adopter communities were 3.3% less likely to participate (OR = .967) and late adopters were 3.4% less likely to participate

(OR = .966) than non-participants. From these results we can see there is little to no difference between early and late adopters in comparison to non-participants.

In Model 2, within the triggering event window t-1:3 subdomain, the number of claims (early: $b = .269$, $p = .02$; late: $b = .386$, $p = .00$) and the amount of claims paid per household (early: $b = -.014$, $p = .07$, late: $b = -.024$, $p = .00$) were significant for both groups. For each additional 100 claims, the early adopter communities were just over 30% more likely to participate in CRS (OR = 1.309) compared to non-participants, while late adopters were about 47% more likely to participate (OR = 1.471) compared to non-participants. For each additional \$100 in claims paid per household, early adopter communities were 1.4% less likely to participate (OR = .986) and late adopters were 2.4% less likely to participate (OR = .976) than non-participants.

Within the triggering event window t-4:6 subdomain in Model 2, the number of claims (early: $b = 3.405$, $p = .00$; late: $b = 3.066$, $p = .00$) and the amount of claims paid per household (early: $b = -.297$, $p = .01$, late: $b = -.189$, $p = .05$) were significant for both groups. For each additional 100 claims, the early adopter communities were just over 30 times more likely to participate in CRS (OR = 30.123) compared to non-participants, while late adopters were about 21 times more likely to participate (OR = 21.452) compared to non-participants. For each additional \$100 in claims paid per household, early adopter communities were 25.7% less likely to participate (OR = .743) and late adopters were 17.3% less likely to participate (OR = .827) than non-participants.

In Model 3, presence of digital flood map (flood risk domain) significantly predicted participation only for early adopters ($b = 1.228$, $p = .04$) relative to non-participants. When used on its own, presence of digital flood map meant the community was 3.4 times more likely to join CRS (OR = 3.413). Digital flood map presence was highly insignificant for late adopters (b = 1.93e6, p = .99). The small sample size of late adopters (n = 32) and high random error have likely led to large effect and high p-value.

Model 4, which only includes distance to the nearest CRS community as an external influence variable, indicated this was a significant predictor of participation for both early adopters (b = -.146, p = .00) and late adopters (b = -.662, p = .00) relative to non-participants. For each additional ten kilometers of distance from the nearest CRS community, early adopters were 13.6% less likely to participate (OR = .864) and late adopters were 48.4% less likely to participate (OR = .516) in CRS than non-participants. These results indicate a much stronger clustering effect for late adopters than early adopters in 2020.

The next model, Model 5 estimates participation based on community demographic variables: population size, population density, education (percent of population with a bachelor’s degree), percent of households renting their home, and percent households living below the poverty level. Within this domain, population size (b = .087, p = .00) and density (b = .013, p = .00), educational attainment (b = .260, p = .07), and share of renters (b = .550, p = .00) were all significant for early adopters. For late adopters, only population size (b = .090, p = .00) and population density (b = .011, p = .00) were significant predictors of participation relative to non-participants. For each additional 10,000 residents, an early adopter community was 9.1% more likely to participate in CRS (OR = 1.091). For each additional 10 people per km^2, an early adopter community was 1.4% more likely to participate in CRS (OR = 1.014). For each additional ten percent share of the population with a bachelor's degree, early adopter community was nearly 30% more likely to join (OR = 1.296). For each additional ten percent share of renting households, it was 73.3% as likely to join (OR = 1.733). For each additional 10,000 residents, a late adopter community was 9.5% more likely to participate in CRS (OR = 1.095). For each additional 10 people per km^2, a late adopter community was 1.1% more likely to participate in CRS (OR = 1.011).

Model 6, again, is a nearly full model with triggering event window variables removed. In this model, the number of claims (early: b = .434, p = .00; late: b = .455, p = .00) and the amount of claims paid per household (early: b = -.021, p = .00, late: b = -.022, p = .00) were significant for both groups. For each additional 100 claims, the early adopter communities were 54.3% more likely to participate in CRS (OR = 1.543) compared to non-participants, while late adopters were 57.6% more likely to participate (OR = 1.576) compared to non-participants. For each additional $100 in claims paid per household, early adopter communities were 2.1% less likely to participate (OR = .979) and late adopters were 2.2% less likely to participate (OR = .978) than non-participants.

Neither flood risk nor external influence variables were significant for early adopters, but distance to nearest CRS community (external influence) was significant for late adopters (b = -.296 p = 0.05) relative to non-participants. Late adopter communities were 25.6% less likely to participate (OR = .744) in CRS than non-participants.

Among variables within the community demographics domain, population size (b = .049, p = .03) and density (b = .015, p = .00), as well as share of renters (b = .547, p =

.00) were all significant for early adopters. For late adopters, only population density (b = .009, p = .02) was a significant predictor of participation relative to non-participants. For each additional 10,000 residents, an early adopter community was 5% more likely to participate in CRS (OR = 1.050). For each additional 10 people per km^2, an early adopter community was 1.5% more likely to participate in CRS (OR = 1.015). For each additional ten percent share of renting households, an early adopter community was 72.8% as likely to join (OR = 1.728). For each additional 10 people per km^2, an early adopter community was 0.9% more likely to participate in CRS (OR = 1.009).

In Model 7, past experience domain was replaced with triggering event window variables. In this model, within the triggering event window t-1:3 subdomain, the number of claims was significant for both groups (early: b = .285, p = .02; late: b = .399, p = .00) and the amount of claims paid per household was only significant for late adopters (b = -.022, p = .01) relative to non-participants. For each additional 100 claims, the early adopter communities were 33% more likely to participate in CRS (OR = 1.330) compared to non-participants, while late adopters were nearly 50% more likely to participate (OR = 1.491) compared to non-participants. For each additional $100 in claims paid per household, early adopter communities were 1.4% less likely to participate (OR = .986) and late adopters were 2.2% less likely to participate (OR = .978) than non-participants.

Within the triggering event window t-4:6 subdomain, the number of claims (early: b = 1.808, p = .03; late: b = 1.500, p = .06) were the only significant variable for both groups. For each additional 100 claims, the early adopter communities were just about six times more likely to participate in CRS (OR = 6.099) compared to non-participants, while late adopters were about four and a half times more likely to participate (OR = 4.483) compared to non-participants.

Again, neither flood risk nor external influence variables were significant for early adopters, but distance to nearest CRS community (external influence) was significant for late adopters (b = -.285 p = 0.07) relative to non-participants. Late adopter communities were 25.6% less likely to participate (OR = .744) in CRS than non-participants.

Among variables within the community demographics domain, population density (b = .015, p = .00) and share of renters (b = .524, p = .00) were significant for early adopters. For late adopters, only population density (b = .010, p = .01) was the only significant predictor of participation relative to non-participants. For each additional 10 people per km^2, an early adopter community was 1.5% more likely to participate in CRS (OR = 1.015). For each additional ten percent share of renting households, an early adopter community was 69% as likely to join (OR = 1.690). For each additional 10 people per km^2, a late adopter community was 1.0% more likely to participate in CRS (OR = 1.010).

Finally, for the full model, Model 8, past experience, triggering event window and flood risk domain variables did not have a significant influence on participation for either group. Distance to the nearest CRS community was only significant for late adopters (b = -.281, p = 0.07) relative to non-participants. Late adopter communities were 24.5% less likely to participate (OR = .755) in CRS than non-participants.

Among variables within the community demographics domain, as in Model 7, population density (b = .014, p = .00) and share of renters (b = .523, p = .00) were significant for early adopters. Likewise, for late adopters, only population density (b = .010, p = .01) was a significant predictor of participation relative to non-participants. For each additional 10 people per km^2, an early adopter community was 1.5% more likely to participate in CRS (OR = 1.015). For each additional ten percent share of renting households, an early adopter community was about 69% as likely to join (OR = 1.688). For each additional 10 people per km^2, a late adopter community was 1.0% more likely to participate in CRS (OR = 1.010).

Table 5.4 Multinomial Logistic Regression Results with Coefficients: Early Adopters and Late Adopters versus Non-Participants in 2020

	Model 1				Model 2				Model 3				Model 4			
	Early		Late		Early		Late		Early		Late		Early		Late	
Variable	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
Constant	-3.742		-3.847		-3.809		-3.996		-4.390		-18.984		-2.779		-2.223	
Past Experience (t-1:10)																
Claims (100)	0.634	.00	0.648	.00												
Amt Pd / Household ($100)	-0.034	.00	-0.035	.00												
Triggering Event Window																
(t-1:3)																
Claims (100)					0.269	.02	0.386	.00								
Amt Pd / Household ($100)					-0.014	.07	-0.024	.00								
(t-4:6)																
Claims (100)					3.405	.00	3.066	.00								
Amt Pd / Household ($100)					-0.297	.01	-0.189	.05								
Flood Risk																
Digital Flood Map (2021)									1.228	.04	15.886	.99				
External Influence																
Dist. To Nearest CRS (10 km)													-0.146	.00	-0.662	.00
Community Demographics																
Population Size (10K)																
Population Density (10/km^2)																
Education (10% Bach.)																
Rent Share (10%)																
Poverty Rate (10%)																
Observations			1,016				1,016				1,016				1,014	
LR χ^2			112.60				134.61				23.56				62.46	
Prob > χ^2			0.000				0.000				0.000				0.000	
Pseudo R^2			0.1964				0.235				0.041				0.109	
Log Likelihood			-230.32				-219.32				-274.84				-255.26	

Note: Early and late adopters are compared to the base outcome, which is non-participation.

	Model 5				Model 6				Model 7				Model 8			
	Early		Late		Early		Late		Early		Late		Early		Late	
Variable	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P	Coef.	P
Constant	-6.578		-4.875		-7.126		-19.532		-6.796		-21.871		-6.739		-21.305	
Past Experience (t-1:10)																
Claims (100)					0.434	.00	0.455	.00					-0.056	.95	0.231	.73
Amt Pd / Household ($100)					-0.021	.00	-0.022	.00					-0.367	.61	0.006	.90
Triggering Event Window																
(t-1:3)																
Claims (100)									0.285	.02	0.399	.00	0.333	.69	0.178	.79
Amt Pd / Household ($100)									-0.013	.12	-0.022	.01	0.355	.62	-0.029	.59
(t-4:6)																
Claims (100)									1.808	.03	1.500	.06	1.905	.17	1.228	.32
Amt Pd / Household ($100)									0.160	.13	-0.076	.37	0.206	.78	-0.077	.45
Flood Risk																
Digital Flood Map (2021)					0.692	.43	15.555	.98	0.639	.47	17.94	.99	0.630	.47	17.373	.99
External Influence																
Dist. To Nearest CRS (10 km)					-0.007	.87	-0.296	.05	-0.013	.78	-0.285	.07	-0.016	.73	-0.281	.07
Community Demographics																
Population Size (10K)	0.087	.00	0.090	.00	0.049	.03	0.034	.16	0.037	.12	0.029	.26	0.038	.12	0.026	.34
Population Density (10/km^2)	0.013	.00	0.011	.00	0.015	.00	0.009	.02	0.015	.00	0.010	.01	0.014	.00	0.010	.01
Education (10% Bach.)	0.260	.07	0.226	.10	0.191	.23	0.110	.47	0.168	.29	0.102	.51	0.169	.28	0.100	.52
Rent Share (10%)	0.550	.00	0.210	.16	0.547	.00	0.104	.54	0.524	.00	0.079	.66	0.523	.00	0.071	.70
Poverty Rate (10%)	-0.410	.19	-0.575	.11	-0.600	.13	-0.267	.56	-0.657	.10	-0.337	.49	-0.640	.11	-0.337	.50
Observations			1,014				1,014				1,014				1,014	
LR χ^2			135.63				224.25				230.35				231.52	
Prob > χ^2			0.000				0.000				0.000				0.000	
Pseudo R^2			0.237				0.391				0.402				0.404	
Log Likelihood			-218.68				-174.37				-171.32				-170.73	

Note: Early and late adopters are compared to the base outcome, which is non-participation.

Table 5.5 Multinomial Logistic Regression Results with Odds Ratios: Early Adopters and Late Adopters versus Non-Participants in 2020

	Model 1				Model 2				Model 3				Model 4			
	Early		Late		Early		Late		Early		Late		Early		Late	
Variable	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P
Constant	0.024		0.021		0.022		0.018		0.012		-0.000		0.062		0.108	
Past Experience (t-1:10)																
Claims (100)	1.886	.00	1.912	.00												
Amt Pd / Household ($100)	0.967	.00	.966	.00												
Triggering Event Window																
(t-1:3)																
Claims (100)					1.309	.02	1.471	.00								
Amt Pd / Household ($100)					0.986	.07	0.976	.00								
(t-4:6)																
Claims (100)					30.123	.00	21.452	.00								
Amt Pd / Household ($100)					0.743	.01	0.827	.05								
Flood Risk																
Digital Flood Map (2021)									3.413	.04	7.93e6	.99				
External Influence																
Dist. To Nearest CRS (10 km)													0.864	.00	0.516	.00
Community Demographics																
Population Size (10K)																
Population Density (10/km^2)																
Education (10% Bach.)																
Rent Share (10%)																
Poverty Rate (10%)																
Observations			1,016				1,016				1,016				1,014	
LR χ^2			112.60				134.61				23.56				62.46	
Prob > χ^2			0.000				0.000				0.000				0.000	
Pseudo R^2			0.1964				0.235				0.041				0.109	
Log Likelihood			-230.32				-219.32				-274.84				-255.26	

Note: Early and late adopters are compared to the base outcome, which is non-participation.

	Model 5				Model 6				Model 7				Model 8			
	Early		Late		Early		Late		Early		Late		Early		Late	
Variable	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P	Odds	P
Constant	0.001		0.007		0.001		0.000		0.001		0.000		0.001		0.000	
Past Experience (t-1:10)																
Claims (100)					1.543	.00	1.576	.00					0.946	.95	1.260	.73
Amt Pd / Household ($100)					0.979	.00	0.978	.00					0.693	.61	1.006	.90
Triggering Event Window																
(t-1:3)																
Claims (100)									1.330	.02	1.491	.00	1.396	.69	1.195	.79
Amt Pd / Household ($100)									0.987	.12	0.978	.01	1.426	.62	0.971	.59
(t-4:6)																
Claims (100)									6.099	.03	4.483	.06	6.717	.17	3.415	.32
Amt Pd / Household ($100)									0.852	.13	0.927	.37	1.229	.78	0.925	.45
Flood Risk																
Digital Flood Map (2021)					1.997	.43	5.69e6	.98	1.894	.47	6.19e7	.99	1.878	.47	5.51e7	.99
External Influence																
Dist. To Nearest CRS (10 km)					0.993	.87	0.744	.05	0.987	.78	0.752	.07	0.984	.73	0.755	.07
Community Demographics																
Population Size (10K)	1.091	.00	1.095	.00	1.050	.03	1.035	.16	1.038	.12	1.029	.26	1.039	.12	1.026	.34
Population Density (10/km^2)	1.014	.00	1.011	.00	1.015	.00	1.009	.02	1.015	.00	1.010	.01	1.015	.00	1.010	.01
Education (10% Bach.)	1.296	.07	1.254	.10	1.211	.23	1.116	.47	1.183	.29	1.108	.51	1.184	.28	1.105	.52
Rent Share (10%)	1.733	.00	1.234	.16	1.728	.00	1.110	.54	1.690	.00	1.083	.66	1.688	.00	1.074	.70
Poverty Rate (10%)	0.664	.19	0.563	.11	0.549	.13	0.766	.56	0.519	.10	0.714	.49	0.527	.11	0.714	.50
Observations			1,014				1,014				1,014				1,014	
LR χ^2			135.63				224.25				230.35				231.52	
Prob > χ^2			0.000				0.000				0.000				0.000	
Pseudo R^2			0.237				0.391				0.402				0.404	
Log Likelihood			-218.68				-174.37				-171.32				-170.73	

Note: Early and late adopters are compared to the base outcome, which is non-participation.

5.2 Initial Versus Subsequent Participation in the CRS

Results of Mann-Whitney U tests comparing initial and subsequent CRS participants on past experience and triggering event windows, flood risk, external influence, and community demographics are presented in Table 5.6. Of the 65 CRS participants in the sample, there was a nearly even split with 33 participants joining in the first three years (early adopters), and the remaining 32 participants joining in the years following (subsequent joiners). Overall, results indicate that the two groups differed on presence of a digital flood map in 2021, population size, and rent share.

Within the past experience domain, the groups were not significantly different on claims ($U = 510.0$, $p = .813$) or amount paid per household ($U = 470.0$, $p = .447$). Nonetheless, the rank sums and U statistic suggest lower rankings for the early adopter on both variables. Interestingly – although also not significantly different – rank sums and U statistics within the triggering event window domain suggest higher rankings for early adopters on all variables (claims (t-1:3): $U = 485.0$, $p = .573$; amt pd / household (t-1:3): $U = 478.5$, $p = .516$; claims (t-4:6): $U = 493.0$, $p = .646$; amt pd / household (t-4:6): $U = 488.0$, $p = .600$).

Early adopters were significantly different from subsequent joiners on the presence of a digital flood map in 2021 ($U = 118.0$; .000). This result suggests that the subsequent joiners were more likely to have a digital flood map by the year 2021. Distance to nearest CRS community in the external influence domain was not significant ($U = 511.0$, $p = .823$). This result suggests that the joining communities (both early adopters and subsequent joiners) maintain the same general rankings amongst non-participating communities at the time of joining. Coupled with evidence from the t-tests above that early adopters were located closer to CRS communities than non-participants were (Table 5.1), this points to potential clustering of CRS communities amongst both early adopters and subsequent joiners.

Within the community demographics domain, tests on both population size ($U = 372.0$, $p = .041$) and rent share ($U = 335.0$, $p = .011$) were significant. In general, subsequent joiners had lower rankings within the distribution of population sizes at the time of joining. In addition, subsequent joiners had lower rankings on the distribution of rent share percentages. Early adopters and subsequent joiners were not significantly different on rankings of population density ($U = 521.0$, $p = .927$), education ($U = 492.5$, $p = .641$) or poverty rate ($U = 488.5$, $p = .604$). The contradictory rank sum and U statistics for population density and education prevent me from being able to state anything about possible changes in rankings, but the consistent rank sum and U statistics for poverty rate indicate higher poverty rate rankings overall for subsequent joiners.

Table 5.6 Mann-Whitney U Test Results: Initial Versus Subsequent Participation

	Early Adopters		Subsequent Joiners				
Variable	N	Rank Sum	N	Rank Sum	U	z	p
Past Experience (t-1:10)							
Claims /100	33	1071	32	1074	510.0	-0.24	0.813
Amt Pd / Household ($100)	33	1031	32	1114	470.0	-0.76	0.447
Triggering Event Window							
(t-1:3)							
Claims / 100	33	1132	32	1013	485.0	0.56	0.573
Amt Pd / Household ($100)	33	1138.5	32	1006.5	478.5	0.65	0.516
(t-4:6)							
Claims / 100	33	1124	32	1021	493.0	0.46	0.646
Amt Pd / Household ($100)	33	1129	32	1016	488.0	0.53	0.600
Flood Risk							
Digital Flood Map (2021)	33	678	32	1466	118.0	-5.45	0.000
External Influence							
Dist. To Nearest CRS (km)	33	1072	32	1073	511.0	-0.22	0.823
Community Demographics							
Population Size (K)	33	1245	32	900	372.0	2.05	0.041
Population Density (per km^2)	33	1082	32	1063	521.0	-0.92	0.927
Education (% Bach)	33	1124.5	32	1020.5	492.5	0.47	0.641
Rent Share (%)	33	1282	32	863	335.0	2.53	0.011
Poverty Rate (%)	33	1049.5	32	1095.5	488.5	-0.52	0.604

6 Discussion and conclusion

Through this research, I contribute to the literature on CRS participation in several ways. First, and perhaps most important given the results, I introduce the concept of early adopters and subsequent joiners and establish that there are, indeed, differences between the two groups on several predictors of CRS participation. Second, I extend the analysis of CRS participation as a binary outcome to the case of Texas. And third, I limit the unit of analysis to incorporated communities on the assumption that the locus of decision-making matters in analyzing CRS participation. In the sections below, I first discuss findings from my analysis on initial participation and participation in 2020. I then discuss the findings of my comparisons between in initial and subsequent participants. This is followed by a summary of the important contributions of this study and concludes with the discussion of study limitations and directions for further research.

6.1 Participation in the CRS

6.1.1 Early Adopters in 1991

Overall, results showed that, within Texas, CRS participants in the first three years of the program differed from non-participants on the number of flood insurance claims, claims paid per household, population size, educational attainment, share of renters, and poverty rate. Although limited to the early adopters of the CRS program, my findings regarding CRS participation in Texas are, with a few exceptions described below, generally consistent with previous studies on CRS participation (Asche, 2013; Fan & Davlasheridze, 2014; Landry & Li, 2012; Li, 2012; Li & Landry, 2018; Posey, 2008, 2009; Sadiq & Noonan, 2015b).

The significant impact of past experience on CRS participation tends to agree with results from Asche (2013), Landry and Li (2012), and Posey (2008, 2009), although with important and sometimes contradictory caveats. Similar to the number of claims and the amount of claims paid per household variables under the past experience domain in my models, Asche (2013) also operationalizes a variable – which she calls flood risk – as the average of insured losses from ten years before the year of observation. She finds that for every $1 million increase in insured losses to a community in the previous ten years, there is a .00048 higher probability of CRS participation. Although they are not directly comparable due to the way I adjusted for number of households in a community, this seems to be a substantially smaller effect than the one I found with the amount of claims paid per household variable: for each additional $100 of claims per household, there is a 1.5% higher chance – or .50 higher probability – of joining CRS. Contradicting these results, however, is the number of claims variable in Model 6, which has a negative and significant coefficient value. Given that this variable's coefficient was positive and significant in Model 1 (the past experience domain alone predicting CRS participation), and given that the variable was highly correlated with population size (r = .70), I suspect that the inclusion of both population size and number of claims in the same model may attenuate and, indeed, change the direction of the effect of the number of claims on its own.

Posey (2009) operationalized historical flood loss as the number of insurance claims from 1978 to 2007. This period is substantially longer than the ten-year windows used by Asche and in my research. As a result, his variable potentially attenuates the assumption that losses within the past ten years impact CRS participation. Nonetheless, Posey found this variable to be positive and significant ($b = .00021$, $p < .01$) in his model.

In general, the number of claims and amount paid per household in three years prior to joining CRS were significant but contradictory. Unexpectedly, and with the exception of full model, the number of claims was associated with a decrease in CRS participation. Conversely, the number of claims in four to six years prior to joining, was positively and significantly associated with CRS participation across all models. These seemingly contradictory findings can be explained by the fact that disaster losses are characterized as spiky, where lulls in flood losses and flood claims are interrupted by spikes of extreme loss (Bradt & Kousky, 2020). Figure 3.1 and Figure 3.2 tend to support this claim. At the same time, the review of regional participation trends described in section 3.1 suggests that many communities seem to join CRS within six years of an event impacting a local region.

Li and Landry (2018) found that their one-year lagged variable representing the number of floods was a significant positive predictor of CRS points. Their lagged risk index variable operationalized as annual precipitation, on the other hand, was a significant negative predictor. In their 2012 study, the lagged variables for floods and damage were not significant. An important point of difference is that my analyses considered CRS participation at the time of joining. The other studies consider CRS participation at a point in time not related to joining and therefore do not take into account the effect of joining. These differences in approach could be part of the explanation for the differing results. I recommend that short term lag predictions of CRS participation be used only when time of joining and regional flood impacts are considered because, otherwise, they are likely to be strongly influenced by individual community circumstances that may drown out other trends.

Presence of a digital flood map and distance to nearest CRS community were not significant predictors when considered in models with additional independent variables. Although significant on their own, the pseudo-R^2 statistics indicated very poor explanatory effects. One challenge with the external influence domain in this context is the fact that there are no leaders and followers in the logistic regression model; communities all join at the same time. Hence the external influence variable may not be the best indicator of a leader-laggard or imitation theory, which assumes that a government is influenced by another that has already adopted the policy in question. (Berry & Berry, 2018). The external influence effect variable does, however, seem to be an important variable in the model of subsequent joiners – discussed later – and therefore is appropriate for future studies.

Within the community demographics domain, the results were remarkably consistent across all models. All variables except population density were significant. Furthermore, population size, education level, and rent share had a positive relationship to CRS participation. On the other hand, the relationship between CRS participation and poverty rate was negative. The results regarding population size were consistent with Asche (2013). Among the population of NFIP communities, CRS participants appear on average to have larger population sizes. This could be explained in part by the early participation of large cities like Austin, Dallas, and El Paso.

Population density, the only community demographics variable found not to be significant, was a significant variable in Li and Landry (2018). I expected similar findings in Texas to those from North Carolina. Although t-test results show that participants and non-participants are significantly different on population density (Table 5.1), the effect size in the logistic regression models, irrespective of significance, was small. This suggests that although the groups may differ on population density, the impact of this factor when controlling for other variables is minimal.

Education as a measured by percent of population with a Bachelor's degree significantly predicted CRS participation. This finding is consistent with Fan and Davlasheridze (2014) and Sadiq and Noonan (2015a) but contradicts findings by Landry and Li (2012). Sadiq and Noonan (2015a) used both the share of population with Bachelor's degree and the share of population without a high school diploma and, not surprisingly, found opposite effects of those two variables. In each case, the higher level of education was linked to a higher CRS participation, as was the case in this study. Inconsistent results with the Landry and Li study can be explained by their assertion that their research design may have masked true effect of education (Landry & Li, 2012).

Similar to Asche (2013), I predicted that a higher rent share would be a significant predictor for CRS participation due to a landlord's interest in protecting their capital assets. In her study, there was a negative relationship between owner occupancy, which is consistent with my finding of a positive relationship with rent share. These results are also consistent with Sadiq and Noonan (2015a) and Noonan et al. (2020).

The negative relationship between CRS participation and poverty rate indicates that wealth is a significant predictor of CRS participation. This is consistent with other studies that examined other predictors of wealth, such as income and housing value (Noonan et al., 2020; Posey, 2008, 2009; Sadiq & Noonan, 2015a). In these other studies, higher median incomes and home values significantly and positively predicted CRS participation.

In summary, there is general agreement across my models and with existing literature regarding the significant factors that influence initial CRS participation for early adopters. Overall, communities with larger populations that were more highly educated, had higher shares of renters, and had lower levels of poverty were more likely to participate in the CRS in the program's early years.

6.1.2 Early Adopters and Subsequent Joiners in 2020

Notably, several factors that predicted participation for early adopters in 1991 are different from factors that predicted participation for early adopters in 2020. Although not a significant factor in 1991, population density becomes a significant factor for early adopters in 2020 in comparison to non-participants. Conversely, poverty rate, which was a significant factor in 1991, becomes nonsignificant in 2020. Population size shows mixed results. Although population size is unquestionably significant in predicting early adopter participation in 1991, it is marginally not significant in predicting early adopter participation in 2020. Given that Figure 3.5 shows that average population size for CRS participants is increasing each year while population size for non-participants remains relatively flat, it seems that higher variance in 2020 may play a role in population size no longer being significant.

The steady increase in population density for CRS participants over time and the shift in significance of population density in predicting CRS participation suggests, in agreement with Brody et al. (2014); Brody, Zahran, Highfield, et al. (2007); Brody, Zahran, Maghelal, et al. (2007), that characteristics of urbanization, may be nudging communities towards flood mitigation and, therefore, CRS participation. The converging of CRS participants and non-participants on poverty rate over the years might explain why poverty rate is no longer significant. Poverty rate shows a lower effect size and a higher p-value in predicting participation for subsequent joiners supporting the decreasing importance of poverty rate and wealth over time.

When comparing the results of early adopter participation and subsequent joiner participation in 2020, recent claims paid per household and external influence significantly predict participation only for subsequent joiners. Rent share is significant only for early adopters. Given the spiky nature of claims (Bradt & Kousky, 2020), I do not read too much into the differing significance of recent claims paid per household. In reference to Figure 3.5, the converging of CRS participants and non-participants on rent share over the years might explain why rent share is significant for early adopters, but not for subsequent joiners.

The difference between early adopter and subsequent joiner participation as explained by external influence is convincing. External influence did not predict early adopter participation in either the early participation or 2020 participation models.

Subsequent joiner participation, however, is significantly predicted by external influence. These results indicate a much stronger clustering effect for late adopters than early adopters in 2020. This is also consistent with results from the t-test on the external influence variable and Figure 3.5 showing the change in the external influence variable over time. The t-tests above suggest that early adopters were, on average, located closer to CRS communities than non-participants were (Table 5.1). Figure 3.5 shows that although both CRS participants non-participants are, on average, getting closer to other CRS communities, CRS participants are doing so at a faster rate. On the whole, this evidence points to continued clustering of CRS communities over time and, quite likely, to greater levels of clustering for subsequent joiners.

6.2 Initial Versus Subsequent Participation in the CRS

This research brings new findings to the literature by showing that initial CRS participants – or early adopters – differed significantly from subsequent joiners in several ways. The first major finding is that the ranks of population sizes of initial participants in their year of joining appear to be different from those of subsequent joiners in their year of joining relative to non-participants. Although the significance test performed was two-tailed, results indicate that, in comparison to early adopters, subsequent joiners rank lower in population size relative to non-participants in the year of joining. Interestingly, when considered in relation to the diverging population slopes presented in Figure 3.5, it seems that although the populations of subsequent joiners rank lower than early adopters, the average population size of CRS participants is growing over time. In comparison, the average population size of non-participants remains relatively flat. This could indicate several things. First, it could be that, irrespective of population size, population growth may be an indicator CRS participation. Hypothetically, yet consistent with research by Brody, Zahran, et al. (2009), Landry and Li (2012), Li and Landry (2018), and Sadiq and Noonan (2015a), as communities grow and gain resources and capacity, they seem to be more willing to join CRS. Brody, Zahran, et al. (2009) show that CRS scores in several activities are significantly and positively related to non-profit assets in a community. Results from Landry and Li (2012) and from Li and Landry (2018) suggest that communities with higher tax revenues are associated with higher levels of flood mitigation. Sadiq and Noonan (2015a) find that factors associated with local governing capacity and political economy are positively and significantly related to CRS participation. In a qualitative study of CRS participation Sadiq, Tyler, and Noonan (2020) similarly found in interviews with community floodplain managers (and others with similar positions) that a lack of government resources was a common reason why communities did not join CRS.

Second, when considering the populations slopes, the inclusion of large cities like Austin, Dallas, and El Paso in the initial cohort may mask the effect of smaller cities joining later. This would be consistent with my finding that subsequent joiners rank lower on population size. In general, however, the trend of smaller population sizes amongst CRS participants (albeit at later times) runs contrary to my own results presented in section 5.1 and the results of Asche (2013) who also a found positive and significant association between CRS participation and population. At best, these results regarding population size suggest that future studies on CRS participation would benefit by accounting for time of joining in their research design and analysis. At worst, testing the association between CRS participation and population growth may be worthwhile.

The second major finding is that the ranks of initial participants on rent share appear to be different from ranks of subsequent joiners relative to non-participants in their respective years of joining. Again, with respect to the two-tailed significance test, results indicate that subsequent joiners rank lower in rent share relative to non-participants in the year of joining. From Figure 3.5, slopes of rent share percentages across time for participants and non-participants are converging. Whereas the average rent share is decreasing over time for participants, it is increasing for non-participants.

The interpretation of these results is complicated. Although rent share predicts CRS participation in my results (section 5.1) and, arguably, those of Asche (2013) – whose dataset is nationwide and from 2004 to 2009 – the effect of rent share appears to be lower in more recent years than it was when the CRS program was established. Consistent with my data from Figure 3.5 and Table 5.6 suggesting that the effect of rent share is decreasing over time, my logistic regression results show a larger impact for rent share than Asche's results. Whereas each 10% increase in rent share nearly doubles the chances of a community participation my model, a 1% increase in owner occupied homes results in a .008 lower probability of participation in her model, which is based on later data. Complicating this interpretation, however, are the contradictory findings from Asche (2013), Sadiq and Noonan (2015a), and myself. Whereas Asche found a negative and significant relationship between owner occupancy and CRS participation (confirming her assumption, consistent with mine, that landlords would want to protect their incomeearning assets), Sadiq and Noonan found the near opposite (confirming their assumption that resident-owners would be more likely to advocate for flood protection). Sadiq and Noonan generally found that CRS participation was associated with lower rent shares (as opposed to lower owner occupancy). It should be noted that Sadiq and Noonan use nationwide demographic data from 1990, the same as year as my demographic data for early adopters. Given the strong evidence of the changing effect of rent share over time, and given the contradictory results amongst the studies described, I can only recommend further study into the impact of owners and renters on CRS participation.

To summarize, considering the evidence presented, these findings suggests that early adopters are, indeed, qualitatively different from subsequent joiners. They are also consistent with the concern from Sadiq and Noonan (2015a) that a program's operation has an impact on participant characteristics. Although these findings are generally limited to the significant variables of population size and rent share, evidence from the difference in slopes between CRS participants and non-participants on modeled variables (Figure 3.5), and from the multinomial logistic regression model, suggests that there may be meaningful changes occurring over time within and between the groups of CRS participants and non-participants. I suspect, however, that the crude nature of the Mann-Whitney U test – with its transformation of the underlying data structure into a series of ranks – and my conversion of variable values to percentiles in order to standardize the data across time, may be masking some of these changes.

6.3 Additional Considerations

Although I do not directly measure governing capacity through variables of financial capabilities, like taxation and city budgets, or staffing levels (Brody, Kang, & Bernhardt, 2010), several variables that I analyze are indirect indicators of governing capacity. These variables are education level and poverty rate, which are both indicators of wealth (Ashenfelter & Rouse, 1999). Amongst NFIP communities within my study, for example, education and median income were highly correlated (r = .797). The same was true for poverty rate and income (r = -.698). Governing capacity has been tied to measures of wealth and economic development, including per capita income (Berry & Berry, 2018). With these connections in mind, and in consideration of the studies mentioned above connecting capacity with CRS participation, I expected education and poverty rate to consistently predict CRS participation across models. As described, however, this was not the case. Education and poverty rate were significant only for early adopters in 1991. These findings suggest, consistent with descriptions by Berry (2018), that intuitional capacity, while important at times, may be overshadowed by the perception of problem severity. With the substantial increase in flood losses in Texas over the past 20 years, this may, in fact, be the case.

In general, these results could have implications for a number of policy areas beyond flood mitigation. Policy areas characterized by high public losses and insufficient private protections come to mind. Within the area of disaster management, this includes wildfire management, particularly in places that lack sufficient insurance uptake or mitigation measures. Another policy area is public health, where the health needs on uninsured residents may be covered by public funds. If results from this study are applicable, we might expect early adopting communities to be wealthier, perhaps less sensitive to the problem threat, more educated, and have larger populations. As the programs matured, or alternatively, as the problem threat increased, less wealthy communities with a higher perception of problem threat may be expected to join. The larger takeaway, however, is the importance of paying attention to policy adoption trends over time to better understand if incentives are appropriately targeted to the communities that are expected to join.

In spite of these observations, it is important to recognize that policy decision-making is also a qualitative process. In order for us to understand if the factors described above are, in fact, important for community decision-makers, we should ask the decision-makers directly (Sadiq, Tyler, & Noonan, 2020). There is currently a shortage of qualitative CRS participation studies to confirm or refute the quantitative studies (Sadiq, Tyler, Noonan, et al., 2020). Future studies on CRS participation should fill this gap, particularly at the sub-national levels in order to address the nuances of local and statewide governance.

6.4 Contribution of This Study

The major contribution of this study is the finding that early adopters significantly differ from subsequent joiners, especially in terms of external influence, rent share, and possibly, population size. In general, I argue that subsequent joiners in Texas have smaller populations than initial joining cohort in relation to the year when they joined. In addition, subsequent joiners had a lower percentage of renters relative to early adopters in relation to the year when they joined. Qualitatively, when considering the entire period of study, the two groups of communities are converging in relation to percentage of renters. On the other hand, they are diverging when it comes to population trends. Regarding external influence, consistent findings amongst participation models for early adopters and subsequent joiners convincingly shows a much stronger clustering effect for late adopters than early adopters in 2020.

These findings demonstrate the importance of including a factor representing the time of joining, or an equivalent longitudinal consideration, in CRS participation models. Most studies, in selecting an arbitrary year to determine CRS participation of the sample, analyze CRS participation without considering the impact of program implementation or policy changes over time. Including a temporal component in future modelling studies will provide better understanding of how newly joining communities are changing over time.

This could help policy makers in identifying candidates for CRS participation with increased success, especially given that CRS adopters in more recent years seem to be qualitatively different from early adopters.

6.5 Limitations and Areas for Future Research

The first limitation of this study is its limited geographic and temporal scope. In general, my findings are limited to the state of Texas. While it is encouraging that the findings are similar to those of other studies of CRS participation, all of the studies suffer from similar limitations. Landry and Li (2012), for example, is limited to the case of North Carolina. Asche (2013), on the other hand, as a nationwide study, does not capture the nuance of local- and state-level impacts, which could be particularly relevant from the decision-making and policy perspective.

The second limitation revolves around the crude methodology I used for comparing initial adopters to subsequent joiners. In order to compare joiners across time, and in relation to the non-joiners in the year of joining, I needed to standardize the variables so they would be comparable across both dimensions. This standardization – through the use of percentiles – likely masks important information about the joiners. Furthermore, the analytical methodology underlying the Mann-Whitney U-test – ranking the cases – adds another level of masking. Given this crude methodology, I am not able to draw any conclusions about the effect of changes, only the directionality. There is qualitative evidence from Figure 3.5 and quantitative evidence from the multinomial logistic regression model that suggests early adopters and subsequent joiners may be more different than demonstrated with the Mann-Whitney tests that I used. In general, I believe that all of the evidence I presented, when viewed together, supports the likelihood of important differences between early adopters and subsequent joiners on the factors described.

The third limitation is the fact that my models did not account for policy changes at specific points in time. As an indicator of this limitation, I point to the shift in the rate of CRS adoption after 2008 (see Figure 3.3). Although there is an increase in the rate of CRS adoption following Hurricane Ike in 2008, the continued growth in adoption could also be related to the passage of the Biggert-Waters Flood Insurance Reform Act of 2012 which effectively raises the flood insurance premiums for policy holders nationwide.

The fourth limitation is due to the linear interpolation of the census data that I performed between 1990 and 2000, as well as between 2000 and 2010. Because interpolation results in data that is an estimation of reality, we cannot be certain that the interpolated data or subsequent analysis of the data is entirely accurate.

With these results and limitations in mind, future studies on CRS participation should incorporate a temporal variable or longitudinal methodology that accounts for differences in CRS adoption and participation over time. My findings that early adopters and subsequent joiners are different on external influence, population size, percent of renters suggests that CRS participation studies that focus on one point in time without accounting for time of joining may not be adequately capturing participation trends. Such a longitudinal approach would also provide information to policy-makers on how the program participation changes over time and could allow optimization of efforts to encourage joining.

Additionally, given the localized nature of the CRS program in terms of scoring, incentives, and impacts of policy, I recommend that researchers attempt to confirm statistical findings on CRS participation with qualitative interviews or surveys. Sadiq, Tyler, and Noonan (2020) provide an excellent example of how qualitative research can meaningfully contribute to the literature on CRS participation. They use earlier findings on CRS participation and ask floodplain managers directly about which factors influence their city's participation in CRS. Although these results can also be criticized for their lack of generalizability, they paint a more complete picture of the CRS participation by conveying exactly what motivated participation rather than guessing through statistical methods. Unfortunately, this is the only study of its kind on the subject at the moment.

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Appendix A Texas CRS Communities and Class by Year (1998-2020)

Table A.1 Texas CRS Communities and Class by Year (1998-2009)

Community	Year of entry	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
ARLINGTON, CITY OF	1991	9	9	9	9	9	9	9	8	8	8	8	8	7
AUSTIN, CITY OF	1991	7	8	8	8	8	8	8	8	7	7	7	7	6
BASTROP COUNTY*	2004							8	8	8	8	8	8	8
BAYTOWN, CITY OF	1991	8	8	8	8	7	7	7	7	6	6	6	6	6
BEAUMONT, CITY OF	2008												8	8
BELLAIRE, CITY OF	1993	9	9	9	9	9	9	9	9	9	9	9	8	8
BENBROOK, CITY OF	1991	8	8	8	8	7	7	7	7	6	6	6	6	6
BEVIL OAKS, CITY OF	2010													8
BRYAN, CITY OF	1995	9	9	9	9	9	9	9	9	9	9	7	7	7
BURLESON, CITY OF	1991	9	9	9	9	9	9	9	9	9	8	8	8	8
BURNET COUNTY*	2014													
CARROLLTON, CITY OF	1991	9	9	9	9	7	7	7	7	7	7	7	7	7
CLEBURNE, CITY OF	1992	9	9	9	9	9	9	9	9	9	9	9	9	9
COLLEGE STATION, CITY OF	2010													7
CONROE, CITY OF	1992	8	8	8	8	7	7	7	7	7	7	7	7	7
COPPELL, CITY OF	1993	9	9	9	9	9	8	8	8	8	8	8	7	7
COPPERAS COVE, CITY OF	2018													
CORPUS CHRISTI, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9	9	9
DALLAS, CITY OF	1991	8	8	8	8	7	7	7	7	7	7	7	7	7
DEER PARK, CITY OF	2000			9	9	9	9	9	9	9	9	9	9	9
DENTON, CITY OF	1991	9	9	9	9	8	8	8	8	8	6	6	6	6
DICKINSON, CITY OF	2912													
DUNCANVILLE, CITY OF	1991	9	9	9	9	8	8	8	8	8	8	8	8	8
EL PASO, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9	9	9
FLOWER MOUND, TOWN OF	2019													
FORT WORTH, CITY OF	2012													
FRIENDSWOOD, CITY OF	1991	8	8			8	5	5	5	5	5	5	5	5
GALVESTON, CITY OF	2014													
GARLAND, CITY OF	1991	7	7	7	7	7	7	7	7	7	7	7	7	7
GRAND PRAIRIE, CITY OF	1991	8	8	8	8	8	8	8	7	7	7	7	7	6
GUADALUPE COUNTY*	2009												8	8
HALTOM CITY, CITY OF	2012													

Community	Year of entry	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
HARRIS COUNTY*	2004							8	8	8	8	8	8	8
HOUSTON, CITY OF	2002					8	8	8	8	7	6	6	6	5
HURST, CITY OF	1992	9	9	9	9	8	8	8	8	8	8	8	8	8
JAMAICA BEACH, CITY OF	2018													
JERSEY VILLAGE, CITY OF	2020													
KEMAH, CITY OF	1992	7	7	5	5	5	5	5	5	5	5	5	5	5
LA PORTE, CITY OF	1999		8	8	8	8	8	8	8	8	8	8	8	8
LEAGUE CITY, CITY OF	1992	9	9	9	9	9	9	9	9	9	9	9	9	9
LEON VALLEY, CITY OF	2017													
LEWISVILLE, CITY OF	1991	7	7	7	7	7	7	7	7	7	7	7	7	7
LIVE OAK, CITY OF	2010													7
LUBBOCK, CITY OF	1992	8	8	8	8	8	8	8	8	8	8	8	8	8
MIDLAND, CITY OF	1992	8	8	8	8	8	8	8	8	8	8	8	8	8
MISSOURI CITY, CITY OF	2010													7
NASSAU BAY, CITY OF	1992	8	8	8	8	8	8	8	8	8	8	8	7	7
NEW BRAUNFELS, CITY OF	2013													
NORTH RICHLAND HILLS, CITY OF	1991	8	7	7	7	7	7	7	7	7	7	7	6	6
ODESSA, CITY OF	1992	9	9	9	9	8	8	8	8	8	8	8	7	7
PASADENA, CITY OF	2010													7
PEARLAND, CITY OF	2005								8	8	8	8	8	7
PFLUGERVILLE, CITY OF	2011													
PLANO, CITY OF	1992	7	7	7	7	7	6	6	6	6	6	6	5	5
PORT ARTHUR, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9	9	9
RICHARDSON, CITY OF	1991	8	8	8	8	8	8	8	8	8	8	8	8	8
RICHLAND HILLS, CITY OF	2014													
ROCKPORT, CITY OF	2019													
SAN MARCOS, CITY OF	1992	8	8	8	8	7	7	7	7	7	7	7	7	7
SEABROOK, CITY OF	2002					9	9	9	9	9	9	9	9	9
SHOREACRES, CITY OF	2014													
SUGAR LAND, CITY OF	2010													7
SUNSET VALLEY, CITY OF	2010													8
SWEETWATER, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9	9	9
TAYLOR LAKE VILLAGE, CITY OF	2014	9	9	9	9	8	8	8	8	8	8	8	8	8
TIKI ISLAND, VILLAGE OF	2001					9	9	9	9	8	8	8	8	8

Community	Year of entry	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
WEST UNIVERSITY PLACE, CITY OF	2019													
WHARTON, CITY OF	2011													
WICHITA FALLS, CITY OF	1991	9	9	9	9	9	9	9	9	9	8	8	8	8
Number of communities		**35**	**36**	**36**	**36**	**40**	**40**	**42**	**43**	**43**	**43**	**43**	**45**	**52**

Table A.2 Communities and Class by Year (2010-2020)

Community	Year of entry	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ARLINGTON, CITY OF	1991	7	7	7	7	7	7	7	7	6	6	6
AUSTIN, CITY OF	1991	6	6	6	6	6	6	6	6	6	6	6
BASTROP COUNTY*	2004	8	8	8	8	8	8	8	8	8	8	8
BAYTOWN, CITY OF	1991	6	6	6	6	6	6	6	6	6	6	6
BEAUMONT, CITY OF	2008	8	8	8	7	7	7	7	7	7	7	7
BELLAIRE, CITY OF	1993	8	8	8	8	7	7	7	7	7	7	7
BENBROOK, CITY OF	1991	6	6	6	6	6	6	6	7	7	7	7
BEVIL OAKS, CITY OF	2010	8	7	7	7	7	7	7	7	7	7	8
BRYAN, CITY OF	1995	7	6	6	6	6	6	6	6	6	8	8
BURLESON, CITY OF	1991	8	8	7	7	7	7	7	9	9	9	9
BURNET COUNTY*	2014					9	9	9	9	9	9	9
CARROLLTON, CITY OF	1991	7	7	6	6	6	6	6	6	6	6	6
CLEBURNE, CITY OF	1992	9	9	9	8	8	8	8	8	8	8	8
COLLEGE STATION, CITY OF	2010	7	7	7	7	7	7	7	7	7	7	7
CONROE, CITY OF	1992	7	7	7	7	7	7	7	7	7	7	7
COPPELL, CITY OF	1993	7	7	7	7	7	7	8	8	8	8	8
COPPERAS COVE, CITY OF	2018									8	8	8
CORPUS CHRISTI, CITY OF	1991	9	9	9	7	7	7	7	7	7	7	7
DALLAS, CITY OF	1991	7	5	5	5	5	5	5	5	5	5	5
DEER PARK, CITY OF	2000	9	9	8	8	8	8	8	7	7	7	7
DENTON, CITY OF	1991	6	6	6	6	6	6	6	6	8	8	8
DICKINSON, CITY OF	2912			8	8	8	8	8	8	8	8	8
DUNCANVILLE, CITY OF	1991	8	8	7	7	7	7	7	8	8	8	8
EL PASO, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9
FLOWER MOUND, TOWN OF	2019										8	8
FORT WORTH, CITY OF	2012			8	8	8	8	8	8	8	8	8
FRIENDSWOOD, CITY OF	1991	5	5	5	5	5	7	7	7	7	7	7
GALVESTON, CITY OF	2014					7	7	7	7	7	6	6
GARLAND, CITY OF	1991	7	7	7	7	7	7	7	7	7	7	7
GRAND PRAIRIE, CITY OF	1991	6	6	5	5	5	5	5	5	5	5	5
GUADALUPE COUNTY*	2009	8	8	8	8	8	8	8	8	8	8	8
HALTOM CITY, CITY OF	2012			7	7	7	7	7	7	8	8	8

Community	Year of entry	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
HARRIS COUNTY*	2004	8	8	8	8	7	7	7	7	7	7	7
HOUSTON, CITY OF	2002	5	5	5	5	5	5	5	5	5	5	5
HURST, CITY OF	1992	8	8	8	7	7	7	7	8	8	8	8
JAMAICA BEACH, CITY OF	2018									8	8	8
JERSEY VILLAGE, CITY OF	2020											7
KEMAH, CITY OF	1992	5	5	5	5	5	8	8	8	8	8	8
LA PORTE, CITY OF	1999	8	8	8	7	7	7	7	7	7	7	7
LEAGUE CITY, CITY OF	1992	9	8	6	6	6	6	6	6	6	6	6
LEON VALLEY, CITY OF	2017								7	7	7	7
LEWISVILLE, CITY OF	1991	7	7	7	7	7	7	7	9	9	9	9
LIVE OAK, CITY OF	2010	7	7	7	7	7	7	7	7	7	7	7
LUBBOCK, CITY OF	1992	8	8	8	8	7	7	7	7	7	7	7
MIDLAND, CITY OF	1992	8	8	8	8	8	8	8	8	8	8	8
MISSOURI CITY, CITY OF	2010	7	7	7	7	7	7	7	7	7	7	7
NASSAU BAY, CITY OF	1992	7	7	7	7	7	7	7	7	7	7	7
NEW BRAUNFELS, CITY OF	2013				6	6	6	6	6	6	8	8
NORTH RICHLAND HILLS, CITY OF	1991	6	6	6	6	6	6	7	7	7	7	7
ODESSA, CITY OF	1992	7	7	7	7	7	7	7	7	7	7	8
PASADENA, CITY OF	2010	7	7	7	7	5	5	5	5	5	8	8
PEARLAND, CITY OF	2005	7	7	7	7	6	6	6	6	6	6	6
PFLUGERVILLE, CITY OF	2011		7	7	7	7	7	9	9	9	9	9
PLANO, CITY OF	1992	5	5	5	5	5	5	5	5	8	8	8
PORT ARTHUR, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9
RICHARDSON, CITY OF	1991	8	7	7	7	7	7	7	7	8	8	8
RICHLAND HILLS, CITY OF	2014					8	8	8	8	8	8	8
ROCKPORT, CITY OF	2019										7	7
SAN MARCOS, CITY OF	1992	7	7	7	7	7	7	7	7	7	7	7
SEABROOK, CITY OF	2002	9	7	7	7	7	7	7	7	7	7	7
SHOREACRES, CITY OF	2014					9	9	9	9	9	9	8
SUGAR LAND, CITY OF	2010	7	7	7	7	7	7	7	7	7	7	7
SUNSET VALLEY, CITY OF	2010	8	8	8	8	8	8	7	7	7	7	7
SWEETWATER, CITY OF	1991	9	9	9	9	9	9	9	9	9	9	9
TAYLOR LAKE VILLAGE, CITY OF	2014	8	8			8	8	8	8	8	8	8
TIKI ISLAND, VILLAGE OF	2001	8	8	8	8	8	8	8	7	7	7	7

Community	Year of entry	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
WEST UNIVERSITY PLACE, CITY OF	2019										7	7
WHARTON, CITY OF	2011		8	8	8	8	8	9	9	9	9	9
WICHITA FALLS, CITY OF	1991	8	8	8	8	8	8	8	8	8	8	8
Number of communities		**52**	**54**	**56**	**57**	**62**	**62**	**62**	**63**	**65**	**68**	**69**

Appendix B Levene's Test of Equal Variance

In order to examine whether independent variables within the logistic regression models comparing initial CRS participants and non-participants exhibit signs of unequal variance between groups, I ran Levene's test of equal variance for each variable. A significant result supports rejecting the null hypothesis that the variance between groups is equal and, therefore, justifies the use of robust methods in subsequent t-tests (Myers et al., 2010). Results indicate significance for five of the twelve continuous variables in the model (Table C.2). As a result of these findings, I opted to perform Welch's t-test – instead of the standard t-test – to compare groups on the independent variables. Welch's t-test is more appropriate when variances are not equal across groups (Myers et al., 2010).

Table B.1 Results of Levene's Test of Equal Variance

Variable	n	W50	df1	df2	p-value
Past Experience					
Claims Paid/Household (10 yrs 1981-1990)	978	29.419	1	976	0.000
Triggering Event Window					
$\text{Claims}_{y-1:3}$	978	26.932	1	976	0.000
$\text{Claims}_{y-4:6}$	978	0.026	1	976	0.872
Flood Risk					
% Land in SFHA	739	0.001	1	737	0.973
External Influence					
Distance to Nearest CRS	978	2.426	1	976	0.120
Community Demographics					
Population Size	978	52.150	1	976	0.000
Population Density	978	3.781	1	976	0.052
Education	978	2.855	1	976	0.091
Rent Share	978	0.236	1	976	0.627
Median Home Value	978	0.104	1	976	0.747
Median Income	978	0.267	1	976	0.606
Poverty Rate	978	1.959	1	976	0.162

Notes: Statistically significant results ($p<0.10$) indicate that the assumption of equal variances among independent variables is violated, i.e., that the variances are unequal. W50 represents the test statistic for Levene's Test centered at the median.