Trends in Flood Insurance Behavior Following Hurricanes in North Carolina

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In the past fifty years, North Carolina has experienced damage from a number of large hurricanes. The National Flood Insurance Program (NFIP) exists to offer federally backed flood insurance for at risk home owners. This study examines county level NFIP insurance uptake behavior after six major hurricanes in North Carolina to understand the relationship between experiencing a hurricane and novel insurance uptake in the following year, and finds conflicting results as to whether experiencing a hurricane is associated with a comparative increase in novel insurance uptake as compared to counties that did not experience hurricane damage. In addition, this study analyzes zip code level participation in recovery programs following Hurricane Florence as it relates to novel insurance uptake and finds that participation in disaster assistance is positively associated with insurance uptake.

Introduction

The National Flood Insurance Program (NFIP) was established in 1968 to address growing issues with flooding in the United States. The NFIP was developed after an onslaught of expensive disasters in the mid-60's (Strother 2016). These disasters were significantly damaging to communities in part due to the fact that most homeowners were not insured and that private insurance companies generally saw catastrophe insurance, like flood insurance, as bad business and refused coverage, which lead to a growing consensus that the federal government should play a role in protecting communities and individuals from flood risk (Strother 2016). The basis of the NFIP program is that risk and damage will be reduced in a number of ways. To begin, insurance coverage will reduce strain on individual households by providing support after a damaging event (Thomas and Leichenko 2011). Additionally, collective risk will be reduced because for a community to participate in the NFIP they must commit to efforts to limit new development and reduce existing development in flood-prone areas by adopting floodplain management strategies (Thomas and Leichenko 2011).

However, NFIP uptake and market infiltration has been, and remains low (Petrolia, Landry, and Coble 2013). This low uptake rate exists despite the fact that NFIP coverage is required in existing Special Flood Hazard Areas (100-yr floodplain). Many households that technically require coverage because of their location in the special flood hazard area remain without coverage due, in large part, to the fact that enforcement of this insurance purchase requirement falls to mortgage holders, which often fail to fully carry out this requirement (Huber 2012). It is also the case that low-income and minority populations uptake insurance at a lower rate than higher-income, whiter communities (Brody et al. 2017; Holladay and Schwartz 2010; Stewart and Duke 2017; Thomas and Leichenko 2011). In order to encourage participation in the NFIP, coverage has often been offered at subsidized or grandfathered rates, which combined with the increasing costs of flood damage, has resulted in the program now operating at an extreme deficit of billions of dollars to the United States Treasury Department (Wriggins 2014).

The Biggert-Waters Flood Insurance Reform Act of 2012 required significant changes to the functioning of the NFIP, focused largely on the actuarial soundness of the program (Vazquez 2015). The

Biggert-Waters Act largely focused on removing subsidies and grandfathered rates, which were originally implemented to improve the affordability of insurance in high flood-risk areas. However, the Biggert-Waters Act faced immediate backlash as communities and individuals reeled from the increase in insurance rates (Vazquez 2015). The rate increases for many communities would be devastating to individual and community financial sustainability, and low-income areas were more dramatically affected by Biggert-Waters Act than high-income areas (Frazier, Boyden, and Wood 2020). In response to the disarray caused by the Biggert-Waters Act, steps were taken towards delaying the insurance premium increases implicated in Biggert-Waters (Vazquez 2015). The Homeowner Flood Insurance Affordability Act of 2014 delayed rate increases and other parts of the Biggert-Waters Act to give the Federal Emergency Management Agency (FEMA) time to conduct an affordability study and check the accuracy of the flood maps (Vazquez 2015).

Besides uptake issues, the NFIP has suffered from inappropriate risk assessment. Analysis by both FEMA and external sources has indicated that the NFIP floodplain mapping efforts can, at times, be inaccurate in predicting flood risk (FEMA 2006; Xian, Lin, and Hatzikyriakou 2015). This, in combination with low uptake rates, results in situations where the majority of damage after extreme events exists in uncovered areas (First Street Foundation 2019; Kousky and Michel-Kerjan 2017).

The highest penetration rate of the NFIP has been, and remains, in coastal areas that have experienced frequent damaging flood events (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2011). Major events, including hurricanes, are typically associated with at least a temporary increase in policy uptake. For example, following Hurricane Katrina, Rita, and Wilma, the number of policies increased by three to four times the growth rates from years before (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2011). This has been referred to as the “Katrina Effect” (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2011). Other studies have found insurance uptake spikes in the year after a flood event with steady declines after that year (Atreya and Ferreira 2013; Gallagher 2014).

Complicating the trajectory of the “Katrina Effect” is the operation of other flood recovery programs available to uninsured individuals, including FEMA grant programs that do not require repayment. “Charity hazard” refers to the potential pattern in which expectations for disaster assistance after hazards results in individuals choosing to forgo insurance (Browne and Hoyt 2000). In this scenario, people may rely on federal recovery programs, like FEMA grants that do not require repayment and also do not require homeowners to pay insurance premiums, to assist if their home is damaged in a hurricane or other extreme event. In the event of “charity hazard” individuals and homeowners avoid personal responsibility for protective actions like insurance by focusing on the potential for recovery aid from other sources. However, examinations of the existence of charity hazards have had conflicting results in terms of the role of the expectation of disaster assistance and insurance decisions (Atreya and Ferreira 2013; Landry, Turner, and Petrolia 2021; Petrolia, Landry, and Coble 2013).

This study examines absolute and comparative novel insurance policy purchases, referred to as uptake, in counties with and without FEMA disaster declarations after six major hurricane years in North Carolina. This study finds conflicting patterns depending on the year and the storm. In addition, it explores the impact of the “charity hazard” phenomenon after Hurricane Florence in North Carolina by modeling participation in disaster assistance as it compares to insurance uptake after Florence and finds that participation in disaster assistance is positively associated with insurance uptake after Hurricane Florence.

Methodology

All NFIP policies were downloaded from FEMA’s open-source data platform (downloaded 10-22-2020). Of these policies, all policies that were purchased to cover property within North Carolina were selected from the entire policy sample. Six major storm years were selected to represent the diversity of storms experienced by North Carolina in recent history. After examining insurance uptake trends in North Carolina (see Figure 2), Hurricane Fran and Bertha were selected to be the first hurricanes examined in the study because of the extremely limited insurance uptake in the state before the 1990's. Following Bertha and Fran, flood loss by storm was examined to select a sample of hurricanes that experienced a range of losses and a temporal diversity between 1996 and present, which also represents a diversity in insurance coverage. The storm years selected were:

- 1996 – Hurricane Fran and Hurricane Bertha (4 July 1996 –10 September 1996)
- 1999 – Hurricane Dennis and Hurricane Floyd (23 August 1999 – 20 September 1999)
- 2003—Hurricane Isabel (18 September 2003 – 26 September 2003)
- 2011—Hurricane Irene (25 August 2011 – 1 September 2011)
- 2016—Hurricane Matthew (4 October 2016 – 26 October 2016)
- 2018—Hurricane Florence (7 September 2018– 29 September 2018)

Figure 1 shows the tracks of each hurricane through North Carolina. The tracks mainly involve the eastern part of the state with the exception of Hurricane Florence, which was significantly weakened when it traveled through the western part of the state.

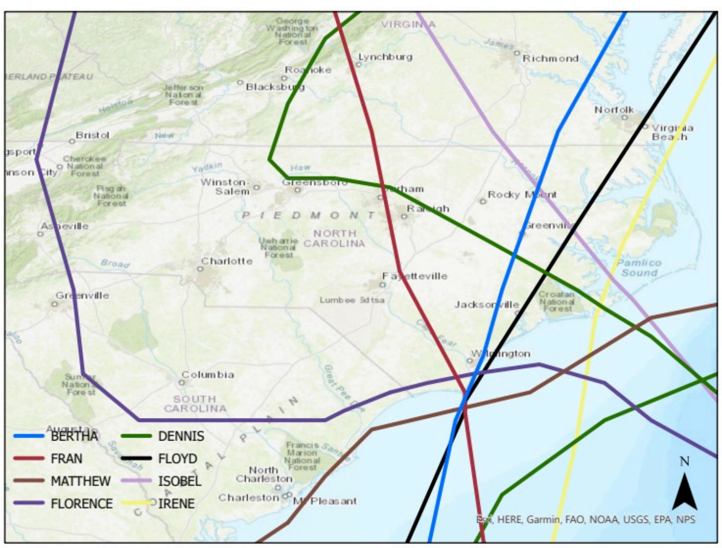

Figure 1. Tracks of all hurricanes in study (National Hurricane Center and NOAA 2020)

The dates of each storm were determined by FEMA designation for major disasters. The study focused on novel insurance uptake before and after each of these major storm event years. As such, for each storm the novel policies were isolated for a full year immediately preceding the storm, and a full year immediately following the storm.

Independent samples t-testing were run on two variables, each separated into two groups by counties with and without a FEMA disaster declaration that made a county eligible for Individual Assistance following the storm. The two variables were absolute increase by number of policies in the year following the hurricane, and percent increase from the year immediately preceding the storms. In several of the storm years, some counties were excluded from the percent increase t-testing due to having 0 policies purchased in the year before or after the storm, which precludes calculation of percent change.

To examine the effect of charity hazard on insurance uptake following Hurricane Florence, the FEMA Individual Assistance Program data (downloaded 9/2/2020) and NFIP Redacted Claims (downloaded 10/22/2020) were downloaded from FEMA's open-source data platform. FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

For the Individual Assistance (IA) Applications, only those with a payout for rental assistance, repair assistance, or replacement assistance with a Florence disaster code (NC-4393) were isolated. Those qualifying only for Other Needs Assistance (ONA; including Personal Property Assistance) were excluded because some types of this assistance (including Personal Property Assistance) are only available for those who also qualified for Small Business Association loans, and these loans were not included in this analysis. After the payouts were isolated from all the claims, only those payouts that were not made in combination with an insurance claim were further isolated so comparisons could be made between applicants who used these two programs separately. For FEMA NFIP Redacted Claims, only those in North Carolina with a date of loss during FEMA's recognized incident period (Sept 7 – Sept 29, 2018) were isolated. The claims were further isolated to identify only those claims which had a payout.

In addition, demographic data were downloaded from the American Community Survey data for 2018 by zip code to test the influence of demographic variables on insurance uptake in the model. These demographic data included two variables—per capita income and percent non-Hispanic white. The per capita income data comes from ACS Variable B19301 (2018 5-year estimates), and the percent non-Hispanic white comes from ACS Variable B03002 (2018 5-year-estimates).

A negative binomial regression was run with novel insurance uptake after Hurricane Florence as the dependent variable, and NFIP and IA participation, along with the demographic variables, as the independent variables. Three variables were recoded to increase comprehension of the standardized beta coefficient. Per capita income was recoded as per capita/10,000, and NFIP and IA participation were recoded as NFIP/100 and IA/100.

Results

Figure 2 explores the general trends in novel insurance uptake in North Carolina. The data indicate that there were general increases in novel insurance uptake until 2010, with steady decline in uptake after these years.

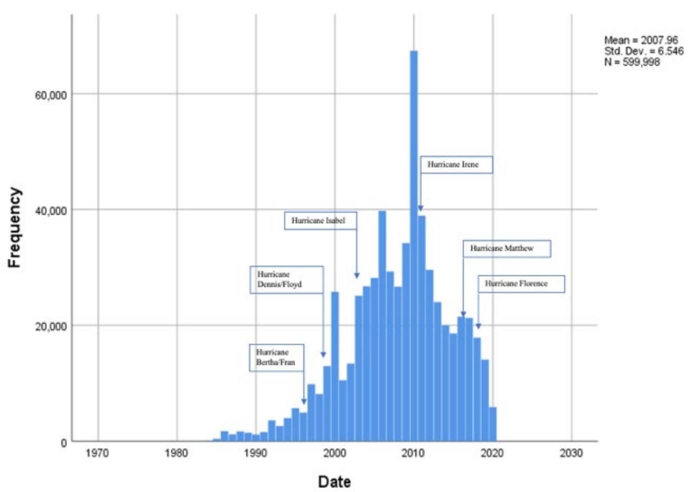

Figure 2. Frequency table of novel NFIP insurance policies

Hurricane Bertha and Hurricane Fran

Both disaster-designated counties and non-disaster counties had an average percent increase in novel insurance uptake after Hurricane Bertha and Hurricane Fran (1996). Disaster-designated counties had an average increase of approximately 144 percent, while non-disaster counties had an average increase of approximately 38 percent. However, this percent change difference is not significantly different between disaster and non-disaster counties at the $p < .05$ level ($p = .219$).

Disaster-designated counties added around 87 policies in the year following Hurricane Bertha and Hurricane Fran, while non-disaster counties added around 49. The policy uptake difference between the two designations was not significant at the $p < .05$ level ($p = .395$).

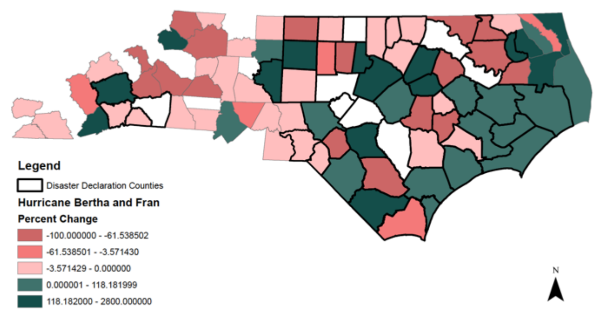

Figure 3. Percent change of novel insurance uptake one year following Hurricane Bertha and Hurricane Fran

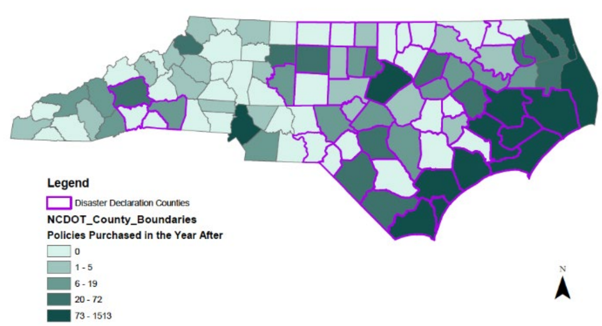

Figure 4. Number of policies purchased within a year following Hurricane Bertha and Hurricane Fran

Table 1. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Bertha and Hurricane Fran

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	46	144.631	493.53	106.08	.219
No	37	38.5502	185.4452	106.08	

Table 2. Independent samples t-test for mean difference in novel policy uptake between disaster- and non-disaster-designated counties following Hurricane Bertha and Hurricane Fran

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	54	86.70	218.533	38.117	.395
No	46	48.59	226.731	38.117	

Hurricane Dennis and Hurricane Floyd

Both disaster-designated counties and non-disaster counties had an average percent increase in novel insurance uptake after Hurricane Dennis and Hurricane Floyd (1999). Disaster-designated counties had an average increase of approximately 354 percent, while non-disaster counties had an average increase of approximately 139 percent. This percent change difference is statistically significant between disaster and non-disaster counties at the $p < .05$ level ($p = .015$).

Disaster-designated counties added about 434 policies in the year following Hurricane Dennis and Hurricane Floyd, while non-disaster counties added around 36. The policy difference between the two designations was significant at the $P < .05$ level ($p = .002$).

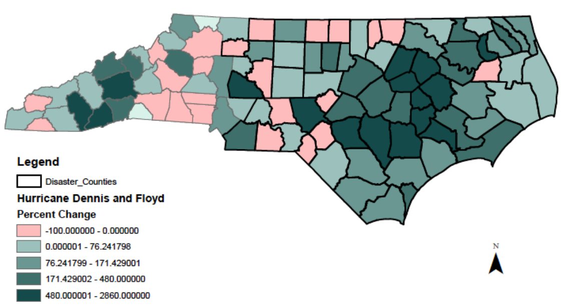

Figure 5. Percent change of novel insurance uptake one year following Hurricane Dennis and Hurricane Floyd

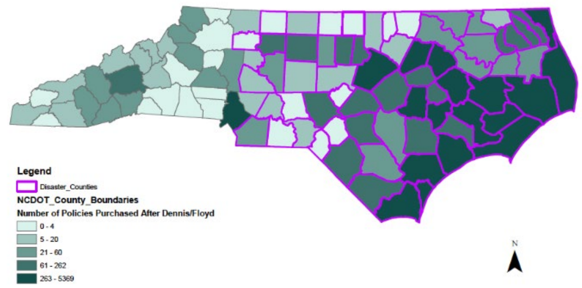

Figure 6. Number of policies purchased within a year following Hurricane Dennis and Hurricane Floyd

Table 3. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Dennis and Hurricane Floyd

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	60	354.01	543.273	214.994	**.015*** **
No	30	139.0157	276.591	214.994	

Table 4. Independent samples t-test for mean difference in novel policy uptake between disaster and non-disaster-designated counties following Hurricane Dennis and Hurricane Floyd

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	65	434.11	984.233	397.765	**.002*** **
No	35	36.24	81.693	397.765	

Hurricane Isabel

Both disaster-designated counties and non-disaster counties had an average percent increase in novel insurance uptake after Hurricane Isabel (2003). Disaster-designated counties had an average increase of approximately 26 percent, while non-disaster counties had an average increase of approximately 92 percent. In this case, non-disaster counties had a higher percent increase, however this percent increase difference is not statistically significant between disaster and non-disaster counties at the $p < .05$ level ($p = .226$).

Disaster-designated counties added around 536 policies in the year following Isabel, while non-disaster counties added around 30. The policy difference between the two designations was significant at the $p < .05$ level ($p = .007$).

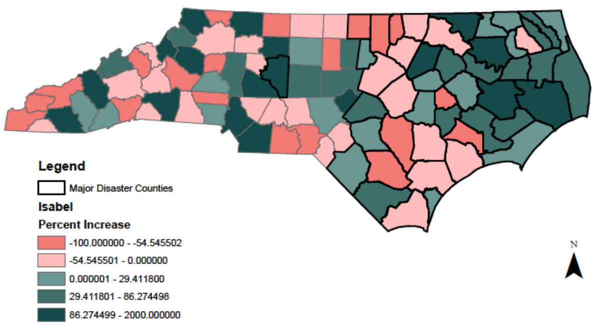

Figure 7. Percent change of novel insurance uptake one year following Hurricane Isabel

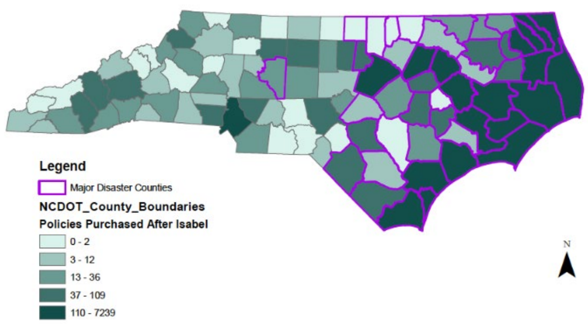

Figure 8. Number of policies purchased within a year following Hurricane Isabel

Table 5. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Isabel

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	45	26.239	84.525	-66.111	.226
No	35	92.35	275.19	-66.111	

Table 6. Independent samples t-test for mean difference in novel policy uptake between disaster- and non-disaster-designated counties following Hurricane Isabel

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	47	536.09	1228.19	506.047	**.007*** **
No	53	30.04	74.347	506.047	

Hurricane Irene

Following Hurricane Irene (2011), disaster-designated counties had an average decrease in policy uptake, whereas non-disaster-designated counties had an average increase. Disaster-designated counties had an average decrease of approximately 31 percent, while non-disaster counties had an average increase of approximately 2 percent. This percent change difference is significantly different between disaster and non-disaster counties at the $p < .05$ level ($p = .016$).

Disaster-designated counties added around 642 policies in the year following Irene, while non-disaster counties added around 106. The policy difference between the two designations was significant at the $p < .05$ level ($p = .003$).

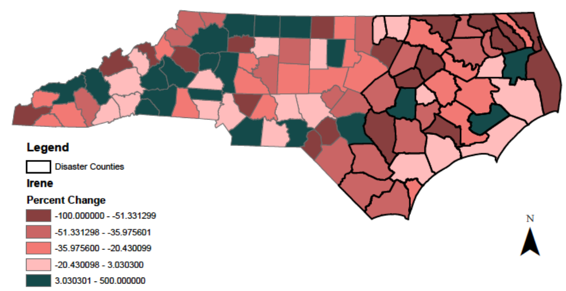

Figure 9. Percent change of novel insurance uptake one year following Hurricane Irene

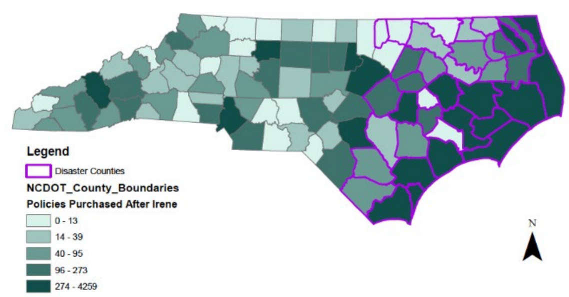

Figure 10. Number of policies purchased within a year following Hurricane Irene

Table 7. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Irene

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	38	-31.01	28.543	-32.699	**.016*** **
No	60	1.69	96.051	-32.699	

Table 8. Independent samples t-test for mean difference in novel policy uptake between disaster- and non-disaster-designated counties following Hurricane Irene

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	38	642.84	1045.23	536.16	**.003*** **
No	62	106.68	186.764	536.16	

Hurricane Matthew

Following Hurricane Matthew (2016), both disaster and non-disaster counties had an increase in novel insurance policy uptake. Disaster-designated counties had an average increase of approximately 105 percent, while non-disaster counties had an average increase of approximately 2 percent. This percent change difference is significantly different between disaster and non-disaster counties at the $p < .05$ level ($p = .001$).

Disaster-designated counties added around 391 policies in the year following Irene, while non-disaster counties added of around 102. The policy difference between the two designations was significant at the $p < .05$ level ($p = .003$).

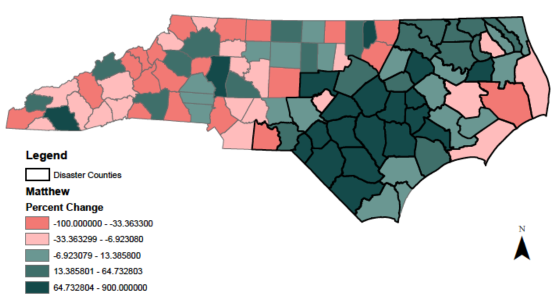

Figure 11. Percent change of novel insurance uptake one year following Hurricane Matthew

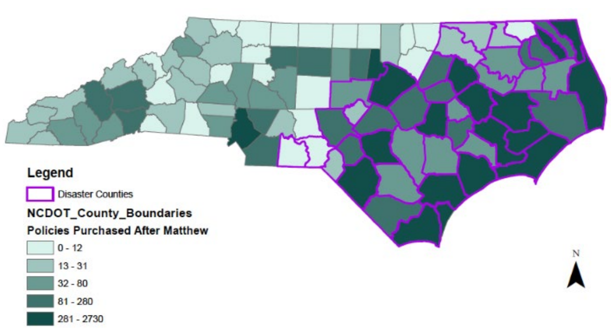

Figure 12. Number of policies purchased within a year following Hurricane Matthew

Table 9. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Matthew

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	45	104.74	150.317	102.43	**.001*** **
No	54	2.302	133.56	102.43	

Table 10. Independent samples t-test for mean difference in novel policy uptake between disaster- and non-disaster-designated counties following Hurricane Matthew

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	45	391.07	572.281	288.685	**.003*** **
No	55	102.38	310.089	288.685	

Hurricane Florence

Following Hurricane Florence (2018), both disaster and non-disaster counties had an increase in novel insurance uptake. Disaster-designated counties had an average increase of approximately 103 percent, while non-disaster counties had an average increase of approximately 13 percent. This percent change difference is not significantly different between disaster and non-disaster counties at the $p < .05$ level, but is significant at the $p < .10$ level ($p = .066$).

Disaster-designated counties added around 469 policies in the year following Irene, while non-disaster counties added around 66. The policy difference between the two designations was significant at the $p < .05$ level ($p = .007$).

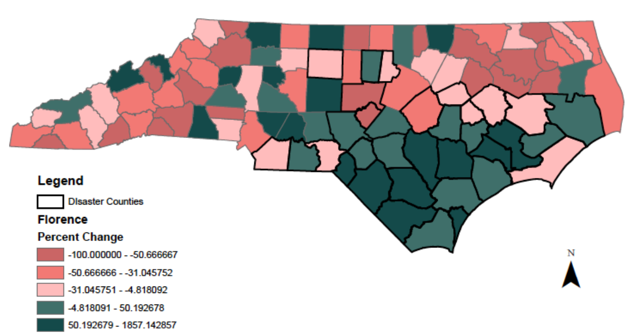

Figure 13. Percent change of novel insurance uptake one year following Hurricane Florence

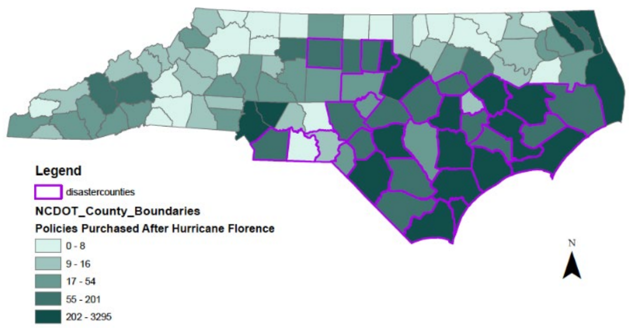

Figure 14. Number of policies purchased within a year following Hurricane Florence

Table 11. Independent samples t-test for mean difference in percent change between disaster- and non-disaster-designated counties following Hurricane Florence

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	33	102.57	346.824	89.53	**.066****
No	67	13.038	133.55	89.53	

Table 12. Independent samples t-test for mean difference in novel policy uptake between disaster- and non-disaster-designated counties following Hurricane Florence

Disaster County	N	Mean	St. Dev	Mean Diff	Sig
Yes	33	468.97	803.891	403.089	**.007*****
No	67	65.88	151.652	403.089	

Modeling Influence of Participation in Recovery Programs on Insurance Uptake

A statistically significant negative binomial distribution model indicates that three of the independent variables were significant—per capita income, IA participation, and NFIP participation, with per capita income being the biggest contributor to the model, followed by IA participation, and NFIP participation. For per capita income, a $10,000 increase in per capita income was associated with a 90 percent increase in NFIP uptake after Florence. For IA participation, an increase of 100 participants per zip code was associated with a 64 percent increase in NFIP uptake after Florence. For NFIP participation, an increase of 100 participants per zip code was associated with a 55 percent increase in NFIP uptake. Percent white was not a significant variable in the model.

Table 13. Negative Binomial Distribution Model Omnibus Test

Likelihood Ratio Chi-Square	Df	Sig.
431.822	4	**.000*****

Table 14. Negative Binomial Distribution Model Parameter Estimates

Parameter	B	Std. Error	Wald Chi Square	Sig	Exp(B)
Intercept	1.219	.2375	26.354	**.000*****	3.385
Per Capita	.644	.0957	45.284	**.000*****	1.903
Individual Assistance Participation	.485	.0588	71.060	**.000*****	1.641
NFIP Participation	.436	.1046	17.372	**.000*****	1.547
White Percent	.003	.0034	.802	.371	1.003

Discussion

Looking at overall trends in insurance policy purchasing behavior in North Carolina, there was a general increase in novel policies until 2010, followed by an average decrease in policies year after year. This is likely not due to market saturation because of continued low uptake of NFIP policies (Petrolia, Landry, and Coble 2013), and because each policy purchased is maintained for only two to four years on average (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2011). While in the history of NFIP participation in North Carolina there have been over 600,000 unique policies, the amount of people covered by a policy at any given time is much lower considering the low overall tenure of policies.

This study specifically examines the influence of hurricanes in NFIP uptake in the context of these general trends by examining novel purchasing behavior in the year immediately preceding and the year following major hurricane events in affected and non-affected counties following these events. Affected counties were represented by counties that obtained a FEMA disaster declaration that qualified the county for IA from FEMA, whereas non-affected counties did not obtain a declaration. The results indicate that there is not an overarching pattern in purchasing behavior following storms. Three of the six storm events resulted in a statistically significant difference in percent change in the year after the storm (Hurricane Dennis and Hurricane Floyd, Hurricane Matthew, and Hurricane Florence). Hurricane Bertha and Hurricane Fran, and Hurricane Isabel were both associated with higher percent change in affected counties, but not at the statistically significant level. Hurricane Irene was associated with a statistically significant negative increase in affected counties as compared with non-affected counties.

The absence of an overarching pattern works contrary to studies indicating a more universal "Katrina Effect" following any storm. However, of particular note in this study are the three storms events that were associated with significant differences. These three storm events were some of the costliest storms, which indicates that hurricanes with more associated costs may conform more to this "Katrina Effect".

Table 15. Costs of Hurricanes

Hurricane Name	Associated Costs in North Carolina
Hurricane Fran and Hurricane Bertha (1996)	7.2 billion (in 2009 inflation-adjusted dollars) (RENCI at East Carolina University 2009b)
Hurricane Dennis and Hurricane Floyd (1999)	7.8 billion (in 2009 inflation-adjusted dollars) (RENCI at East Carolina University 2009a)
Hurricane Isabel (2003)	562 million (in 2013 inflation-adjusted dollars)(NOAA n.d.)
Hurricane Irene (2011)	686 million (in 2012 inflation-adjusted dollars) (NCDPS 2012)
Hurricane Matthew (2016)	1.5 billion (Associated Press 2016)
Hurricane Florence (2018)	17 billion (Porter 2018)

A notable exception to this is Hurricane Fran and Hurricane Bertha, which caused an estimated 7.2 billion dollars in damage, close to the damage caused by Hurricane Dennis and Hurricane Floyd, and more than the damage caused by Hurricane Matthew. However, as noted in Figure 2 insurance uptake in 1996 and 1997 was very low generally as compared to following years, which could explain a non-significant uptake after the event. Overall, this data adds to literature examining the potential effects of hurricanes on insurance uptake and finds that there is not an overarching pattern indicating a percent increase in novel insurance uptakes, but that more major storms (that cause more damage) are more associated with a positive pattern of novel insurance uptake.

All but one of the storm events were significant (besides Hurricane Bertha and Hurricane Fran) in the associated raw number of policies purchased in the year after the storm in disaster-designated counties as opposed to non-disaster-designated counties. However, this difference can also be explained by the fact that coastal counties, in general, have higher uptake due to increased risk (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2011). Thus, the percent difference might have more comparative predictive power.

An analysis of the impact of participation in recovery programs and NFIP uptake after Hurricane Florence indicated that participation in both programs (FEMA Individual Assistance, and NFIP participation) were both significant on the zip code, with the IA program contributing more to the model. In other words, after Hurricane Florence, both zip code participation in the IA program (uninsured individuals obtaining federal aid) and the NFIP program were associated with increased novel policy uptake. In this instance, the "charity hazard" actually had the opposite effect on the zip code level, in that participating in non-insurance programs (FEMA's Individual Assistance Program) was associated positively with insurance uptake. Because FEMA removes personal identification information, this pattern cannot be tested at the household level, which may provide more insight on the impact of disaster aid on the individual level. Of particular note in regards to the IA program is the stipulation that approved applicants living in a Special Flood Hazard Area are required to obtain and maintain flood insurance as a condition of receiving future assistance through the IA program (FEMA 2019). This may be a contributor to limiting the impact of "charity hazard" by creating circumstances in which participation in federal programs may be disallowed if insurance is not purchased.

In this model, per capita income also had significant power when examining insurance uptake after Hurricane Florence specifically. This shows agreement with other studies that indicate that lower-income areas, in general, have lower insurance uptake, which puts low-income communities at greater risk (Brody et al. 2017). The social justice ramifications of this are significant, especially considering that currently most rates are subsidized, but are still not affordable for low-income individuals. There are limited studies that examine the role of social variables in understanding the existence, or absence of, a "Katrina Effect" after hurricanes or other extreme events. This study shows that social variables may be significant, at least relating to one storm (Hurricane Florence). Because of this, more work should be done to understand trends in insurance uptake while considering social variables, especially as it relates specifically to uptake after hurricanes and other extreme events.

Conclusion

This study analyzes insurance behavior after six hurricane years in North Carolina, spanning from 1996 to 2018. The results indicate that there is not a widespread existence of a "Katrina Effect", in which insurance uptake spikes after hurricanes, for all hurricanes with damage in North Carolina. However, there were several storms that were associated with significant differences in percent uptake in non-affected versus affected counties. These results indicate that there may be features of particular storms, for example financial damage, that result in increased uptake in damaged counties.

This study also analyzes the existence of a "charity hazard" for Hurricane Florence. This model indicates that participation in federal grants (in this case the FEMA IA program) is actually associated with an increase in insurance uptake in the following year after a storm. This works contrary to a "charity hazard" scenario. This model also found that per capita income was a significant predictor in uptake, meaning that higher income individuals were more likely to uptake insurance in the year after a storm. The results of this model indicate that social variables should be considered more regularly when analyzing questions of insurance uptake, especially in relationship to harmful events.

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