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Titel | Title

Measuring the Causal Effect of Hurricane Ian on Homeowner Insurance Premiums Across Florida

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Zusammenfassung

Hurrikane bedrohen Florida jedes Jahr mit Zerstörung. Da sich die Auswirkungen des Klimawandels verstärken, werden Hurrikane zweifellos zu einer noch größeren Bedrohung für Menschen und deren Eigentum. Die vorliegende Arbeit zielt darauf ab, eine kausale Beziehung zwischen dem Weg, den Hurrikan Ian nach seinem Auftreffen an Land nahm, und den durchschnittlichen Versicherungsprämien der betroffenen Bezirke herzustellen. Ich stelle fest, dass es keinen Effekt des Hurrikans auf die durchschnittlich gezahlte Prämie gibt. Ich schließe daraus, dass die Versicherungsbranche nicht naiv ist und versteht, dass Hurrikanpfade im Wesentlichen zufällig sind, wobei zu beachten ist, dass die Versicherungsprämien im gesamten Bundesstaat weiterhin generell steigen.

Abstract

Hurricanes threaten Florida with destruction every year. As the effects of climate change intensify, hurricanes will undoubtedly become an even bigger threat to both people and their property. This paper aims to identify a causal relationship between the path Hurricane Ian took after it made landfall, and the average insurance premiums paid by counties which it hit. I find that there is no treatment effect of the hurricane on the average premium paid. I conclude that this is because insurance industries are not naïve and understand that hurricane paths are essentially random, noting that insurance premiums have continued to see a general rise across the state.

Acknowledgements

First and foremost, I would like to thank my mom, Silvia Prieto, whose experience with Hurricane Ian was the inspiration for this thesis. I would also like to thank my advisor, Professor Alexandra Brausmann, for her patience and feedback over these past few months. Finally, I would like to thank my Economics professors from the University of Central Florida and especially my AP Economics teacher from Boone High School, Mr. Daniel. I would never have been able to succeed and make it here without their wisdom, guidance, and support.

1. Introduction

1.1 Hurricanes in Florida

Hurricanes and their weaker form, Tropical Storms, impact the U.S. state of Florida and the lives of Floridians almost yearly. Every year Floridians are warned during hurricane season (which lasts from June 1st to November 30th) to stock up on essential resources such as water, gas, and food, and to make sure they know where the nearest emergency shelter is. Since 2017 with Hurricane Irma, three other Major Hurricanes, defined as having a wind speed above category 3 (111-129mph), have made landfall in Florida, occurring the next year in 2018 (Michael), 2022 (Ian), and in 2023 (Idalia). Hurricane Ian alone caused over $109 billion in damage, the deaths of 150 in Florida, and the loss of power for over 9 million Americans.

Before Hurricane Irma, the last major Hurricane was in 2005. Notably, of the nine major hurricanes since 2004, five were category 4 (130-156mph) or above, and four of these five were just within the past seven years. What used to be considered a once in a lifetime event is now happening with alarming frequency.

Alongside these developments, there is plenty of literature to support the growing danger of climate change to Florida and its population. NASA estimates that because of climate change, Tropical Cyclones will only get stronger and cause more rainfall, increasing the risk of flooding. In addition, global sea level rises may result in freshwater ecosystems becoming flooded with salt water from the ocean. This thesis thus adds to the vast amount of literature about the consequences of climate change.

1.2 Florida

Despite these catastrophic storms and the increasing dangers of climate change, Florida's population continues to grow steadily, and currently ranks as the 3rd largest state in the United States by population. From 2018 to 2022, Florida experienced an 18% growth in population, compared to the national average growth rate of 7.7% in the same period. Of the 22 million people in Florida, 16 million live in coastal counties. Cities like Miami, Tampa, and Jacksonville are located directly on the waterfront. Even inland counties are somewhat vulnerable, as the average elevation of Florida is just 105 meters (about 344 ft), and lakes cover the state, making flood risk almost inescapable.

According to the September 2023 Florida Community Resilience Survey, 90% of Floridians believe that climate change is happening, compared to the national average of 74%. This reflects how exposed many Floridians are to the effects of climate change itself. Politically, Florida is a somewhat right-wing state. Its Republican Governor, Ron DeSantis, ran an environmentally focused campaign to win the leadership of the republican nomination in 2018. Since taking office, his actual policies towards environmentalism have however been described as "confusing and hypocritical."

1.3 Housing Insurance

Given these vulnerabilities and combined with Florida's wealth and desirability as a place to move to (or retire to), perhaps unsurprisingly, housing insurance in Florida is experiencing a rapid increase in its prices. In fact, not only do Floridians already pay the highest for Home Insurance out of any other state in the Union, according to the Insurance Information Institute, the average premium for Florida homeowners in 2023 was $6,000 per year, a 42% increase compared to 2022. This situation has been described as an insurance crisis, with 10% of Floridians lacking housing insurance completely and ranking ninth in the nation for percentage uninsured. Underinsurance is well-researched, and papers like Gallagher (2014) found that despite insurance take-up rates being highly responsive to large scale flooding events, these rates are still below the socially optimum.

The initial inspiration for this paper came in summer of 2023. In July 2023, Farmers Insurance, which provided coverage to 100,000 Floridians, pulled out of the state completely, citing the increasing risk of hurricanes as the motive for their departure. Other insurance companies have also withdrawn from Florida specifically since 2022, citing similar reasonings. Given these events, I wanted to investigate exactly what happens across the insurance market following such a catastrophic event (which is only predicted to become more catastrophic in the future).

In this paper, I aim to employ a difference-in-difference estimation to measure the casual effect of Hurricane Ian on average insurance premiums across Florida counties to answer the question of whether specific counties see higher premiums after they are hit by a catastrophic hurricane. This will contribute to the already existing wealth of information on Hurricanes and their causal impacts on economic aspects of societies, as well as to the pre-existing literature on risk perception following a transient shock.

2. Literature

Research on Hurricanes and their economic effects is abundant and filled with many insightful findings. Many papers that investigate hurricanes from the past look into their effect on housing prices, and draw their conclusions from there, often relating their findings to a relationship between risk perception and the value of homes in affected areas. Relating to risk perception, Kozlowski et al. (2015), concluded that even transitory events have lingering effects, as, once observed these temporary events become a permanent data point in the agent's mindset. It is with this conclusion that I expect to find that the counties impacted by Hurricane Ian will exhibit higher insurance premiums. In effect, the hurricane's temporary destruction will leave a permanent "scar" in the minds of insurance companies operating in the area, increasing risk perception permanently in those areas (which is exhibited with higher premiums).

Key to this thesis are two papers. Namely, Carbone, Hallstrom and Smith (2006), and Fang, Li, and Yavas (2023). In the first, Carbone, Hallstrom and Smith use a difference-in-difference model to investigate two counties in Florida, following the disastrous category 5

Hurricane Andrew in 1992. Lee county, located on the western coast of Florida was only lightly affected by the Hurricane, while Miami-Dade County, located on the east coast, took the full brunt of Andrew. In what we might see become relevant for this paper, both counties saw decreases in the rate of increase for housing prices (though the magnitude of this effect was noticeably higher in Miami-Dade). The second paper, published just last year, looks at the far-reaching effects of Hurricane Sandy, which devastated the mid-Atlantic region of the east coast in 2012. Although Florida managed to avoid the hurricane, Floridians were aware of the disastrous event and flood risk perception was increased, resulting in lowered premiums for normally desired waterfront areas. Importantly, the effects which were observed only persisted for around a single quarter. A similar effect was also observed in Morgan (2007), though notably, the premium for waterfront locations lingered.

Another paper which looks at Hurricane Sandy in particular, Ortega and Taspinar (2018), explored the long-term effects of the hurricane on property values, finding that while damaged properties eventually partially recovered, areas at risk of flooding saw long lasting and persistently lower values, even in areas that weren't hit. A separate paper, Murphy & Strobl (2010), find the opposite effect: that real house prices increase slightly and last for several years after a typical hurricane strike. This mixed bag of results is what encouraged me to eschew using property values as a proxy for risk perception, and instead look at the industry built around risk perception: Insurance.

Other notable findings in papers related to this one involve the lingering geographic displacement effects of hurricane Katrina, as noted in Deryugina et al. (2014), along with the risk perception changes because of transient events in general as found in McCoy and Zhao (2018).

3. Data

3.1 Insurance Cost

The dependent variable, which we will be regressing the model on, is the average premium charged for homeowners' insurance, for a county, in a given quarter of a particular year. The Florida Office of Insurance Regulation publishes semi-annual reports in July and December of each year, with a list of every county's average premium.

Though published in July and December, these reports show the data reported as of March and September, respectively, in the National Association of Insurance Commissioners financial database: the Quarterly and Supplemental Reporting System – Next Generation (QUASRng). This data is available to the public; however, it is important to note that the figures in the reports will not line up with what the public can retrieve from this database, because trade secrets are withheld from this publicly accessible database (the official reports include these trade secrets). For the purposes of the model, I will only be using the official figures reported in the 2022 and 2023 Property Insurance Stability Reports.

Because most of the other data is reported yearly, robustness checks will be done using both semi-annual reports. This should also account for any lag in the effect of hurricane Ian.

3.2 FEMA aid as a proxy for the counties hit by a hurricane

To maintain the consistency regarding the unit of observation, we must use a county-level data measurement for the treatment, hurricane Ian. Since we cannot be so granular, we will instead use the Federal Emergency Management Agency's (FEMA) Disaster Declaration, and its associated Designated Counties. After Hurricane Ian, every Florida county was designated for FEMA aid in some manner, under the Hazard Mitigation Grant Program. In counties that were eligible for public assistance (all of them), "state, local, tribal and territorial governments and certain private-non-profit organizations were eligible for assistance for emergency work and the repair or replacement of disaster-damaged facilities".

However, 26 of Florida's 67 counties were designated as being eligible for both public *and* individual assistance. In these counties, in addition to the assistance offer described above, individuals and households were eligible for financial and direct services. This assistance, depending on the individual's eligibility, included funds for temporary housing, funds repair or replacement of one's primary residence, temporary housing units, funds for hazard mitigation to rebuild strong and more durable housing, and funds for other under or uninsured disaster-related expenses. The counties that were designated in this way roughly follow the path of Hurricane Ian, and will serve as the proxy for which counties were directly hit by the Hurricane.

3.3 Median House Price and Monthly Mortgage Payment from NAR

The most likely-to-be strongest explanatory variable of insurance premiums, and the variable that most economists have used in the past to measure risk aversion, is the median house price observed in a county. The National Association of Realtors publishes quarterly reports of median house prices across the entire county. This report uses data from both the American Community Survey and the Federal Housing Finance Agency to derive home values for almost every county.

3.4 Other Data

Conveniently, the remainder of the data relevant for the model I would like to use comes from a yearly report published by the Florida Office of Economic and Demographic Research. These reports contain many county-level figures, namely, the percentage of individuals with a bachelor's degree or higher, median household income, population estimates, and crime statistics such as admissions to prison per 100,000.

3.5 Summary Stats

The summary statistics for all 67 observed counties during 2022 and 2023 are displayed in table 1. The 41 counties which were not rendered FEMA individual aid are considered the control group. The 26 counties which were in the direct path of the hurricane and thus rendered FEMA individual aid are thus the treatment group are.

	2022		2023	
	Control	Treatment	Control	Treatment
Q1 Insurance Premium	2315.2	2557.69	2738.93	3014.35
Q3 Insurance Premium	2526.78	2760.85	2998.02	3275.69
Q1 Median Home Price	235225.61	322562	279748.27	285438.44
Bachelors or Higher (%)	21.77	26.99	22.22	27.69
Median HH Income	54737.12	58920.54	59726.41	65034.62
Population Estimate	239228.78	479528.92	242599.34	488011.31
Admissions to prison per 100,000	259.47	155.3	276.77	155.73
Monthly Home Payment	1007	1292.81	1618.78	2028.62

Table 1: Summary statistics of Florida counties. Treatment columns denote counties which were rendered FEMA individual aid.

The treatment counties are, on average, more populous, more well-educated, earn more, and are safer than their control group counterparts, which were not so much in the path of the hurricane. They however pay higher insurance premiums reflecting both the higher value of their homes and mirroring their higher monthly home mortgage payments.

4. Model

4.1 Difference-in-difference estimation

For establishing a causal relationship between Hurricane Ian and insurance premiums, I will use a difference-in-difference estimator. A difference-in-difference (DiD) estimation method, when using panel data, should result in an unbiased estimate of a "treatment" (in the case Hurricane Ian), when comparing across time periods the counties that were hit by hurricane Ian and received public and individual assistance from FEMA, versus the counties that only received public assistance. To this effect, the counties receiving individual assistance are the treatment group, and the counties which did not are the control group. If we assume that the control group is valid under the parallel trends assumption, the simple equation for the DiD analysis takes the following form:

$$IC_{i,t,f} = \beta_0 + \beta_1 F_f + \beta_2 T_t + \beta_3 (T_t F_f) + \varepsilon_{i,t,f} \qquad (1)$$

Where $IC_{i,t,f}$ is a continuous dependent variable showing the average household insurance premium in county *i* from group *f* in year *t*, F_f *is* a dummy variable denoting whether the county received individual assistance from FEMA, and $\varepsilon_{i,t,f}$ is the error term. T_t is a set of time fixed effects denoting the year of observation.

The variable of interest is then β_3, which should tell us the average treatment effect (ATE) of the hurricane on insurance premiums. Generally, a DiD estimator without control variables should be sufficient to estimate the ATE. However, in the case that omitted variables play a role in the coefficient of interest, we will add a matrix of control variables, $X_{i,t,f}$. These control variables should account for other county characteristics that might have changed between the two time periods. Adding that into the equation, we get:

$$IC_{i,t,f} = \beta_0 + \beta_1 F_f + \beta_2 T_t + \beta_3 (T_t F_f) + \gamma X_{i,t,f} + \varepsilon_{i,t,f} \qquad (2)$$

All other variables are the same as in the previous equation.

4.2 Assumptions

The most important assumption when performing a difference-in-difference estimation, is that the pre-treatment trends of both the control and treatment groups, regarding the outcome of interest, are at least similar. In this case, the trends of those counties which were hit by the hurricane and rendered FEMA individual aid, are not too dissimilar to the counties which were *not* rendered this individual aid, in so far as the insurance premiums are concerned. To test the validity of this assumption in this case, I will examine the insurance premium trends for the years 2020 to 2023, using a combination of figures from the official FLOIR reports, and the figures that are available to the public (which do not include trade secrets).

Figure 1 shows the pre-and-post treatment trends of both control and treatment group counties. Though there is some jumpiness in the pre-2022 figures, I would say it is not enough to discard the assumption that the trends are similar. It is of note that these pre-2022 figures are calculated via FLOIR's publicly accessible tool and are not from their semi-annual reports. Thus, it is possible that this jumpiness is a result of omitted data not available to the public, rather than a reflection of the true average premiums.

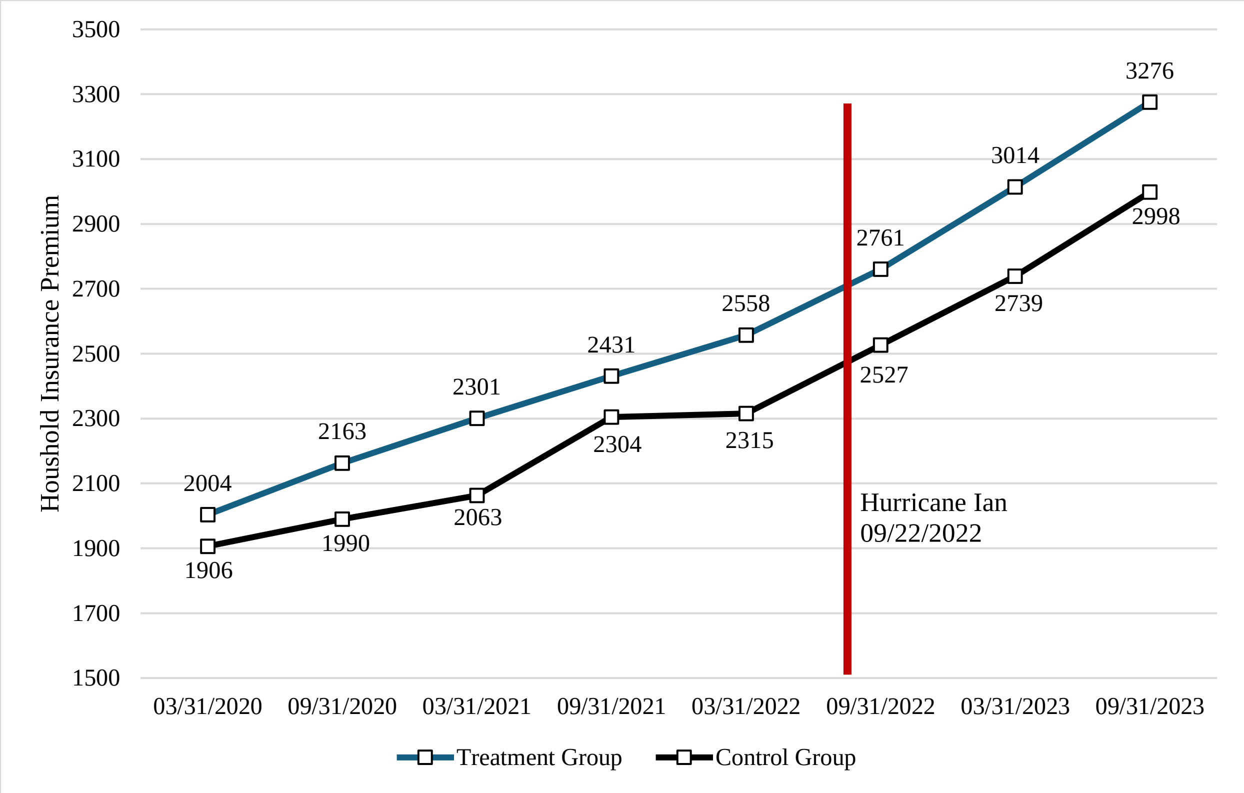

Figure 1: Semi-Annual Insurance Premium Trends (2020 – 2023). Figures before 2022 were calculated using FLOIR's publicly accessible tool, which does not include trade secrets.

In an ideal scenario, what we want to see in figure 1 is a divergence in the trends after the treatment (denoted by the red vertical line in this case). As one can conclude from briefly looking at the figure, this isn't the case. On the contrary, the trends are essentially parallel, giving us an early hint of what our results might look like. Importantly, this does not mean that there is no effect, just that it is not immediately visible to the naked eye. The purpose of the model then is to shed some light on this and see if it can find even a tiny ATE.

Another key assumption that should hold is the Stable Unit Treatment Value Assumption (SUTVA). For it to hold, the treatment received by one group should not influence the outcome observed in the control. As seen in figure three, every county in Florida was designated for some category of aid by FEMA. I do not believe this violates SUTVA in a meaningful way, as the parts of Florida which received the highest rainfall, windspeeds, flooding and destruction are all mostly contained within the treatment group. Regardless, it is important to distinguish that any causal effect discovered should be correctly interpreted as the result of a FEMA individual aid designation, rather than the Hurricane itself (although I believe that the former is a very strong proxy for the later).

5. Results

5.1 The Causal Effect of Hurricanes

Table 2 shows the results of three different models used to measure the ATE of the hurricane on insurance prices. The first column represents a simple Ordinary Least Squares model, the purpose of which is to establish that the variables are in fact somewhat strong in their predictive strength. All variables are significant at the 10% level or more, so we continue onto the DiD models shown in columns two and three.

	Dependent variable:		
	2023 Insurance Premium		
	(OLS)	(DiD Simple)	(DiD Complex)
Year Dummy	210.036*	423.732*	236.516
	(124.545)	(224.271)	(153.533)
FEMA Individual Aid	−256.900*	242.497	−221.709
	(131.561)	(254.571)	(177.399)
Coastal County	251.794*		250.836*
	(142.424)		(142.987)
Median Home Price	0.008***		0.008***
	(0.001)		(0.001)
Bachelors or Higher	−36.645***		−36.753***
	(10.718)		(10.763)
Median Household Income	−0.034***		−0.034***
	(0.009)		(0.009)
Population Estimate	0.0004**		0.0004**
	(0.0001)		(0.0001)
Hurricane ATE		32.922	−71.577
		(360.017)	(240.953)
Constant	2,808.215***	2,315.195***	2,793.909***
	(341.385)	(158.583)	(346.015)
Observations	132	134	132
R^2	0.610	0.060	0.610
Adjusted R^2	0.588	0.038	0.585
Residual Std. Error	668.000 (df = 124)	1,015.429 (df = 130)	670.469 (df = 123)
F Statistic	27.665*** (df = 7; 124)	2.756** (df = 3; 130)	24.040*** (df = 8; 123)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: DiD Results using Q1 FLOIR data as the dependent variable.

The results in the column labeled *DiD Simple* represent the model specified in equation 1 in Section 4.1, and the results in the column labeled *DiD Complex* thus represent the model specified in equation 2. As one might have expected given the figure validating the parallel trends assumption, the average treatment effect for the hurricane in both DiD models is well below the threshold for being statistically significant. In essence, there is basically no measured effect of the hurricane on whether a county which was hit by the hurricane pays a higher insurance premium, in comparison to a different county in Florida which was not hit.

The next logical question to ask then, is why this is the case. Why did insurance companies not charge higher premiums in the counties that were hit, versus the counties which were not? To answer this question, I would propose a second: If the aim of insurance is to protect against risks in the future, where is a hurricane likely to hit? It is unlikely that future hurricanes will travel along the exact same route as hurricane Ian, so why would insurance companies raise premiums along that route. My interpretation of the result of the model, is that insurance companies know this. In the future, as in the past, the paths of hurricanes will be essentially random. As climate change worsens however, the frequency, strength, and magnitude of these hurricanes will also worsen. I believe this is why, despite the ATE not being statistically significant, the insurance premiums have increased year after year.

It is also possible that insurance premiums did in fact go up after the hurricane, if only for a short time, but that the semi-annual observation frequency did not allow us to pick up this increase. In this case, more frequent and granular data would be required to precisely detect the effects of the hurricane.

5.2 Robustness checks

Table 3 contains the results of the DiD model using the Quarter 3 figures published by FLOIR. The figures and significant levels are essentially identical to the figures from table 2, indicating that the lack of a significant value for the ATE is not due to the time span which was examined previously.

To reinforce my findings, I ran two more DiD models, the results of which are shown in tables 4 and 5. The first, which represents table 4, shows migration patterns to the observed counties between 2022 and 2023. The first column of table 4 uses, as the dependent variable, the percentage of residents of a county, which were a year prior to observation, living in a different state in the United States of America. Positive values can be interpreted as factors which draw migrants to an observed county. The second column represents migrants whom a year ago were residing in a different county within Florida. Interesting, migrants within Florida do not seek out coastal counties, while migrants from other parts of the county do. This may suggest that experienced Floridians know that coastal counties are potentially more dangerous and vulnerable than inland counties, and are moving appropriately, while migrants from other parts of the country are not taking this into account. In addition, Floridian migrants significantly prefer to move to counties which were not part of the treatment group. I have no explanation for this phenomenon.

Finally, I ran a model using what was previously an independent variable, median house price, as the dependent variable. According to the pre-existing literature, we expect to find that prices should be impacted (though in which direction is evidently up for debate). To the contrary, we find yet again that the ATE of the hurricane was not statistically significant, indicating that the median housing prices in the affected counties were essentially not impacted differently by the hurricane. This comes as a surprise, as I was expecting there to at least be some effect, whether positive or negative.

6. Conclusion

Although the ATE of the hurricane was not significant, the actual result of the model is. There are many different possibilities for why the model says that the hurricane had no real impact on insurance premiums. The most obvious is that there simply isn't a real impact, in other words, people move on and either forget about the event, or they internalize via something else that we can't detect. I have a hard time believing this explanation. Hurricane

Ivan caused $190 billion in damage, wiping out homes and property in the counties it hit. It may however be that these damages may be seen as just the cost of doing business in Florida.

Other explanations call into question the data and methodology used. In this model, we used county-level data, where the figures used were one year apart. To start, it may be that the county-level data is simply not granular enough. Other papers such as Carbone, Hallstrom and Smith (2006), which investigate the impact of hurricanes on housing prices, have much richer datasets which include for example each house's price within a county, along with better data for measuring the hurricane itself. My dataset for insurance premiums on the other hand looks quite crude in comparison, containing only 67 observations per year.

Speaking of hurricane data, the proxy I use, FEMA designated counties, is also somewhat crude. Like the previous point, it may be too large a scale to detect the effects which we expected to find. It also does not include other hurricane-related data which may be needed. For instance, it does not consider the damages per county from the hurricane, the take-up rate of the aid which was administered by FEMA, or the recorded wind speed of the hurricane in each county.

Regardless of the findings, climate change is going to get worse before it gets better. Among the many different challenges that climate change will throw at humanity, natural disasters will be among the hardest to overcome. Florida, sticking out into the warm Caribbean and covered in lakes and swamps, sits in the US as one of the most vulnerable states to the effects of climate change, and everyday people living and visiting there will be exposed to it in one way or another. The insurance industry knows that disasters which used to be considered "once-in-a-lifetime" events will become more frequent, and will adjust to them, either by charging more across the state, or as we've seen this past summer, leaving the market all-together.

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8. Appendices

1. Florida map figures

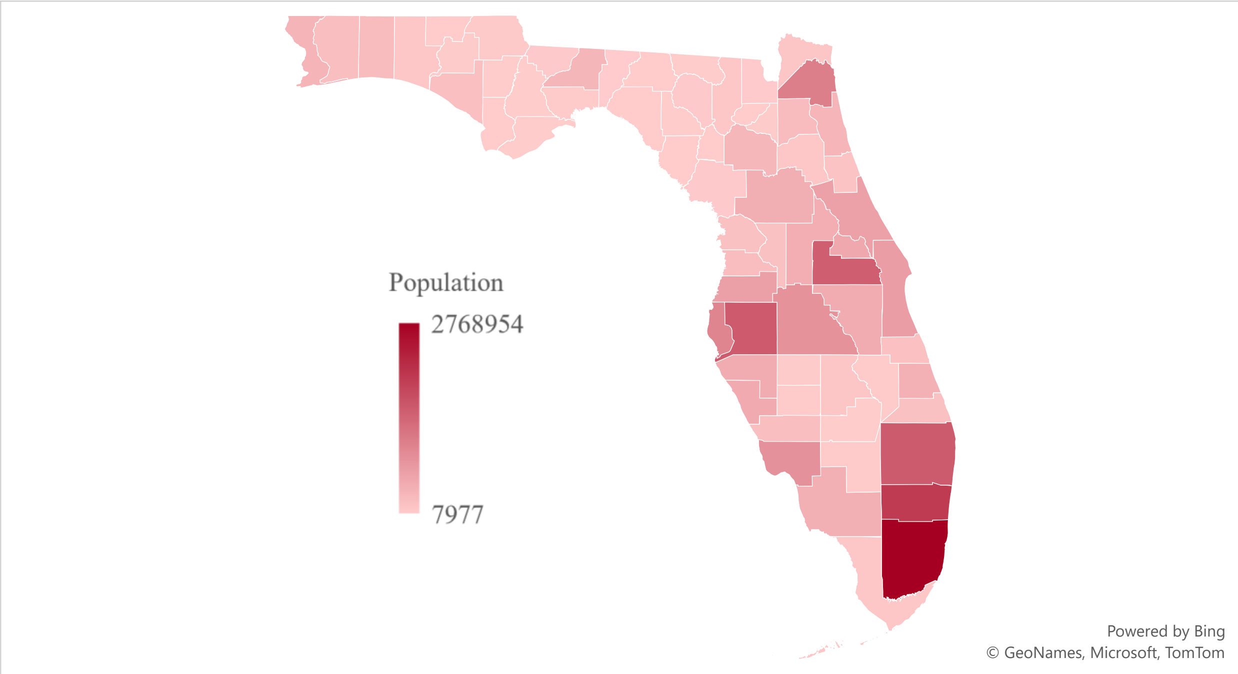

Figure 1: Population heatmap of Florida.

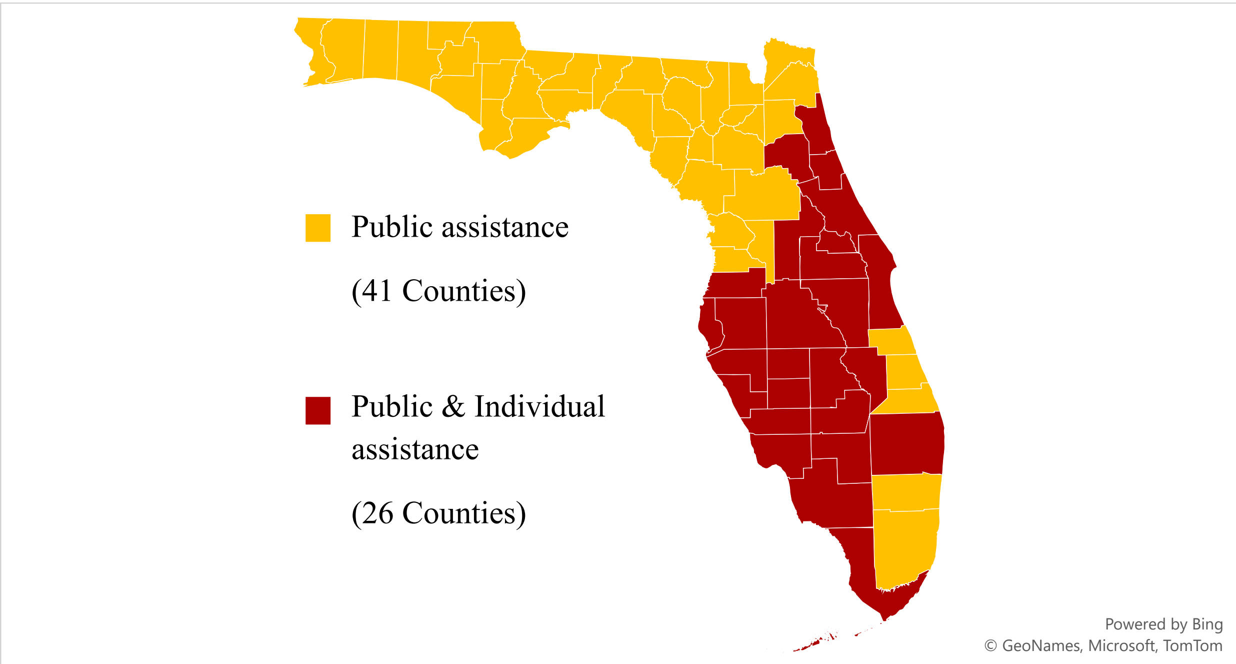

Figure 2: Map of Florida showing which counties were rendered FEMA individual aid

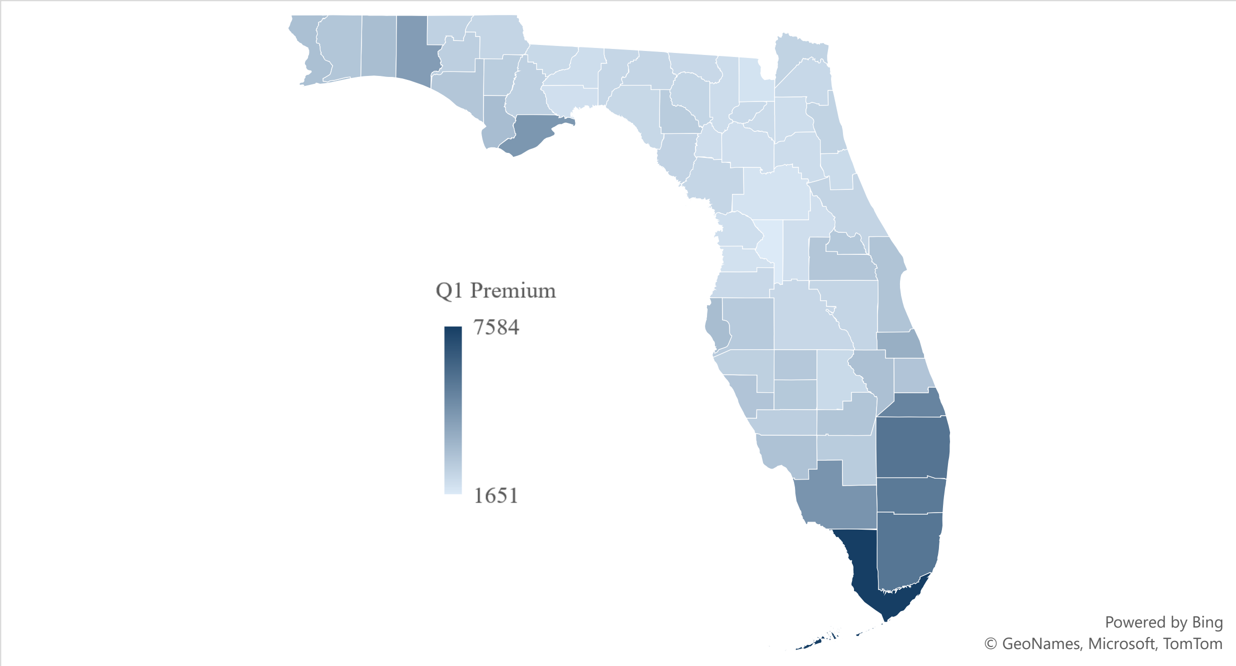

Figure 3: Map of Florida showing the average insurance premiums per county, according to the March 2023 FLOIR report

2. Models with different variables

	Dependent variable:		
	2023 Insurance Premium		
	(OLS)	(DiD Simple)	(DiD Complex)
Year Dummy	250.134*	471.244*	274.135
	(136.406)	(240.056)	(168.175)
FEMA Individual Aid	−278.935*	234.066	−247.038
	(144.090)	(272.489)	(194.317)
Coastal County	288.202*		287.334*
	(155.989)		(156.623)
Median Home Price	0.009***		0.009***
	(0.001)		(0.001)
Bachelors or Higher	−39.207***		−39.305***
	(11.738)		(11.790)
Median Household Income	−0.036***		−0.036***
	(0.010)		(0.010)
Population Estimate	0.0003**		0.0003**
	(0.0001)		(0.0001)
Hurricane ATE		43.602	−64.877
		(385.358)	(263.932)
Constant	3,055.683***	2,526.780***	3,042.716***
	(373.898)	(169.745)	(379.012)
Observations	132	134	132
R^2	0.592	0.062	0.592
Adjusted R^2	0.569	0.040	0.566
Residual Std. Error	731.620 (df = 124)	1,086.901 (df = 130)	734.408 (df = 123)
F Statistic	25.702*** (df = 7; 124)	2.845** (df = 3; 130)	22.326*** (df = 8; 123)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: DiD Results using Q3 FLOIR data as the dependent variable

	Dependent variable:	
	Migrant From Other State	Migrant From Florida
	(1)	(2)
Year Dummy	−0.094	−0.220
	(0.243)	(0.604)
FEMA Individual Aid	0.230	−2.068***
	(0.281)	(0.698)
Coastal County	0.714***	−1.334**
	(0.226)	(0.562)
Median Home Price	0.00000	−0.00001**
	(0.00000)	(0.00000)
Bachelors or Higher	0.064***	−0.054
	(0.017)	(0.042)
Median Household Income	0.00002	0.0001
	(0.00001)	(0.00004)
Population Estimate	−0.00000***	−0.00000**
	(0.00000)	(0.00000)
Hurricane ATE	−0.076	0.438
	(0.381)	(0.947)
Constant	−0.572	7.431***
	(0.548)	(1.360)
Observations	132	132
R^2	0.564	0.441
Adjusted R^2	0.536	0.405
Residual Std. Error (df = 123)	1.061	2.636
F Statistic (df = 8; 123)	19.883***	12.134***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: DiD results using migration figures as dependent variables. Migrant from Other States and Migrant from Florida refer to the percentage of people in an observed county who were migrants from another state in the United States, or were migrants from another county within Florida, respectively.

	Dependent variable:	
	Median Home Price	
	(DiD Simple)	(DiD Complex)
Year Dummy	44,522.660	19,104.120
	(30,468.150)	(15,422.950)
FEMA Individual Aid	87,336.390**	36,332.220**
	(35,005.240)	(17,630.910)
Coastal County		43,622.010***
		(13,911.080)
Median Household Income		4.629***
		(0.806)
Bachelors or Higher		4,972.855***
		(991.988)
Population Estimate		0.024*
		(0.014)
Hurricane ATE	18,353.780	12,020.750
	(49,504.890)	(24,329.930)
Constant	235,225.600***	−154,434.000***
	(21,544.240)	(32,105.370)
Observations	132	132
R^2	0.135	0.798
Adjusted R^2	0.114	0.786
Residual Std. Error	137,950.400 (df = 128)	67,766.310 (df = 124)
F Statistic	6.645*** (df = 3; 128)	69.863*** (df = 7; 124)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: DiD results using Median Home Price as the dependent variable.