Marcelo Costa Marques

Returns and Hazard Mitigation: Evidence from Tropical Cyclones

Dissertação de Mestrado

Thesis presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor: Prof. Marcelo Medeiros

Rio de Janeiro
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Abstract

Marques, Marcelo Costa; Medeiros, Marcelo (Advisor). **Returns and Hazard Mitigation: Evidence from Tropical Cyclones**. Rio de Janeiro, 2022. 69p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

In this paper, we provide evidence that information about hazard mitigation infrastructure in the United States (U.S.) during an indirect exposure to tropical cyclones and the indirect exposure to tropical cyclones per se generate anomalies in returns after considering the 5 Fama-French factors and momentum. We formulate two possible hypotheses to explain these anomalies: local investor and general market hypotheses. Both hypotheses assume that hazard mitigation investments are lower than the ideal. Their difference is based on how investors interpret the hazard mitigation programs. We focus on local investors' perceptions about them in the local investor hypothesis. More significant investments in these programs mean more local investors will acknowledge them and their flaws. On the other hand, we focus on general investors' associations between hazard mitigation investment level and disaster risk in the general market hypothesis. In the end, we give some evidence of the local investors' hypothesis, but we cannot guarantee that this is the only possible explanation. The whole point depends on how much investors know about hazard mitigation programs. Beyond that, we give evidence that an information channel is the probable path in which the anomalies are generated. Thus, in this dissertation, we shed some light on the uncertainty generated by natural disasters that prices assets, a topic that gets more attention in a warming world.

Keywords

Climate Finance; Stock Returns; Hazard Mitigation Programs; Tropical Cyclones.

Resumo

Marques, Marcelo Costa; Medeiros, Marcelo. **Retornos e Mitigação de Desastres: Evidência de Ciclones Tropicais**. Rio de Janeiro, 2022. 69p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Nesse artigo, fornecemos evidências de que as informações sobre a infraestrutura de mitigação de riscos nos Estados Unidos (EUA) durante uma exposição indireta a ciclones tropicais e a própria exposição indireta a ciclones tropicais geram anomalias nos retornos após considerar os 5 fatores Fama-French e *momentum*. Formulamos duas hipóteses possíveis para explicar essas anomalias: hipótese do investidor local e hipótese do investor geral. Ambas as hipóteses assumem que os investimentos em mitigação de riscos são inferiores ao ideal. Sua diferença é baseada em como os investidores interpretam os programas de mitigação de riscos. Na hipótese do investidor local, Nós nos concentramos nas percepções dos investidores locais sobre os programas. Investimentos mais significativos nesses programas significam que mais investidores locais irão reconhecê-los e conhecer suas falhas. Por outro lado, na hipótese do investor geral, nos concentramos nas associações que os investidores gerais fazem entre o nível de investimento em mitigação de perigos e o risco de desastres. No final, damos algumas evidências da hipótese dos investidores locais, mas não podemos garantir que essa seja a única explicação possível. A questão toda depende de quanto os investidores sabem sobre os programas de mitigação de riscos. Além disso, evidenciamos que um canal de informação é o provável caminho pelo qual as anomalias são geradas. Assim, nesta dissertação, lançamos alguma luz sobre a incerteza gerada pelos desastres naturais que precificam os ativos, um tema que recebe mais atenção em um mundo em aquecimento.

Palavras-chave

Finanças do Clima; Retorno de ações; Programas de Mitigação de Desastres; Ciclones Tropicais.

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U.S. – United States
NOAA – National Oceanic and Atmospheric Administration
NHC– National Hurricane Center
ENSO–El Niño-Southern Oscillation
FEMA– Federal Emergency Management Agency
HMGP– Hazard Mitigation Grant Program
PDM– Pre-Disaster Mitigation
FMA – Flood Mitigation Assistance
BRIC – Building Resilient Infrastructure and Communities
SEC– U.S. Securities and Exchange Comission
EDGAR – Electronic Data Gathering, Analysis and Retrieval system
CIK – Central Index Key
CRSP– Center for Research in Security Prices
WSJ – Wall Street Journal
NHS–National Household Survey
GAO – United States Government Accountability Office
HMA – Hazard Mitigation Assistance
GCS – Geographic coordinate system

1
Introduction

This dissertation provides evidence that information about hazard mitigation infrastructure and the risk of exposure to tropical cyclones affects investors' trading behavior, i.e., they generate anomalies in returns. Firstly, the evidence that tropical cyclone risks generate anomalies in returns agrees with the growing literature that evaluates the effects of natural disaster strikes on companies' operations and stock prices short-term volatility (Dessaint & Matray, 2017, Kruttli et al., 2021, respectively). Secondly, understanding how effective hazard mitigation infrastructures are is fundamental in a world where climate changes are becoming the main worldwide concern. How much the changing climate will affect natural disasters occurrences and destruction capacity is still debated. However, undoubtedly changes will happen, and adaptation to mitigate its effects is a first-order necessity (Burke & Emerick, 2016, Barreca et al., 2016, Deschênes & Greenstone, 2011).

What could explain these anomalies? We propose two different approaches: one based on local investors and the other one based on a general perspective of the market.

From the local investors' perspective of the anomalies, we argue that local investors perceive U.S. federal investments in hazard mitigation infrastructure as insufficient to reduce the effects of tropical cyclones. In other words, the more prominent presence of this kind of investment in a specific county makes the inability of these investments to deal with tropical cyclones more known by local investors.

On the other hand, the market explanation starts with acknowledging that most hazard mitigation projects happen after a natural disaster, as the hazard mitigation section shows. Thus, when a county receives a more significant amount of money in hazard mitigation projects, it probably means that more or worse disasters have happened to this county compared to others. Hence, the general investors will understand that place is more susceptible to a tropical cyclone strike, generating the anomaly.

Both explanations rely on the hypothesis that investors do not trust the hazard mitigation projects' capacity to deal with the threat of tropical cyclones. This hypothesis comes from questions left by the literature that studies the effectiveness of hazard mitigation programs. This literature usually uses cost-benefits methodology (Godschalk et al., 2009, Rose et al., 2007 and Davlasheridze et al., 2017). Beyond that, most papers show that these programs are effective, with the benefits surpassing their cost. However, in a second moment, two important questions arise with no clear answer: **Assuming the investment are effective, are they enough for a robust answer? How do people perceive them?**

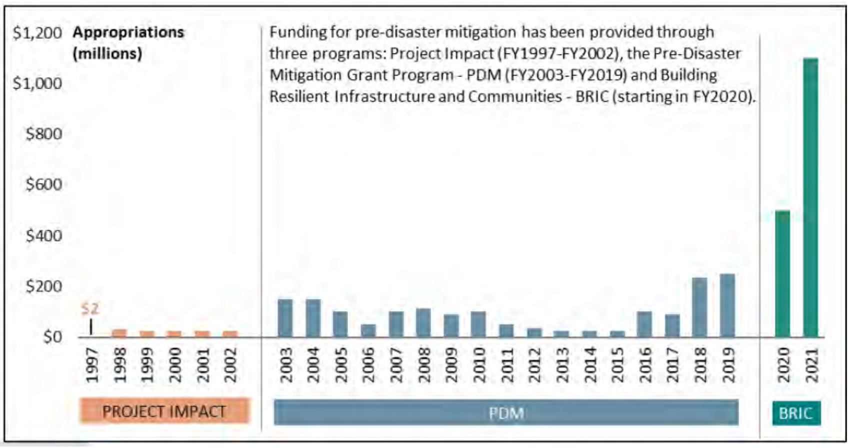
For the first question, anecdotal evidence indicates that the U.S. federal government and members of Congress understand that they are not enough. The Federal Emergency Management Agency (FEMA) is an agency created by the U.S. federal government to help people before, during, and after disasters that surpass the response capacity of local and state authorities. This agency is responsible for all the hazard mitigation programs. In its first year in charge, President Biden's administration committed $3.46 Billion in hazard mitigation funds to reduce the effects of climate change. This one-time investment represents a 23% increase in the funding made available for declared disasters since the program's inception[1]. Another critical recent legislation change that will be better discussed later was the creation of the Building Resilient Infrastructure and Communities (BRIC), which replaced the Pre-Disaster Mitigation (PDM) program. The BRIC has a funding procedure that generates larger and steadier funding streams of 6% of the estimated previous year's total disaster losses in the United States. On the other hand, the PDM had a funding procedure based on annual congressionally appropriated budgets [2] which was subject to variation from one year to another. Beyond that, the budget level significantly grew when the BRIC replaced PDM. This growth can be explained by the fact that as PDM was a competition-driven program, there were few incentives to elected members of Congress to direct large amounts of the budget to a program that would not necessarily be beneficial to their electoral districts. Figure 1.1 shows this pattern during the two years that the program has been functioning. They represent records in pre-disaster mitigation funding. Thus, recently there was a recognition that this type of program was underfunded, and to improve its funding, it was necessary to change the law.

Based on the recent changes made by the authorities in the hazard mitigation programs, we expect that these programs are not perceived as efficient by the exposed counties dwellers. This reality is stronger for the

[1]https://www.fema.gov/press-release/20210805/biden-administration-commits-historic-346-billion-hazard-mitigation-funds

[2]An appropriated budget is a law of Congress that provides an agency with budget authority

Figure 1.1: Funding for Pre-Disaster Mitigation (1997-2021).



Source: https://crsreports.congress.gov/product/pdf/IN/IN11733.

people that live in areas with tropical cyclone risks. Since 2017, FEMA has published the National Household Survey (NHS), a survey to track people's disaster preparedness in disaster-prone regions. Every year, the survey shows that people who live in hurricane areas are more likely to take some action than people from other hazard zones. Thus, it is plausible to assume that the hazard mitigation programs are not seen as adequate by the dwellers, at least for the hurricane areas. A relative measure in the NHS is how people perceive their preparation efficacy. During all the years that the survey is available, the perception of efficacy for hurricane areas has had only a slight variation, showing that people do not substantially change their efficacy perceptions.

To link the possible inefficacy of hazard mitigation programs to firm returns on the local investor's hypothesis, we explore an important empirical regularity explored in the finance literature: local bias. The local bias is a tendency of market participants (retail investors, mutual funds, hedge funds, and other investors) to give an overweight in their portfolio to companies headquartered near their residence locations. I.e., local companies receive more attention from local investors[3]. For example, Seasholes & Zhu, 2010 shows that, on average, 30% of a retail investor's portfolio was formed by companies headquartered within a 250 miles radius from the investor. However, at the same distance, the number of companies, on average, was 12% of all stocks in the market.

What can explain that? The literature proposes two explanations: Cognitive bias and access to better local information. The debate is still ongoing. Coval & Moskowitz, 2001, Coval & Moskowitz, 1999, Kang et al., 2019, Shive, 2012, Brown et al., 2015, Shen et al., 2016, Gamble & Berry, 2012, Ivković

[3]This effect is less pronounced when the investor is more sophisticated.

& Weisbenner, 2005 argue for the local bias as an information advantage. In contrast, Baltzer et al., 2013, Lindblom et al., 2018, Stukalo, 2017, Seasholes & Zhu, 2010, Bhamra et al., 2019, Pool et al., 2012 advocate for the non-information based bias. The local investor's hypothesis focuses on the rational explanation, i.e., the local bias justified by the access to better local information about hazard mitigation projects. Thus, joining together the local bias concept and the hazard mitigation programs inefficiency to generate a robust answer, we define an hypothesis based on our local investor's explanation of the anomalies: **Larger investments in hazard mitigation programs in a county make local investors more informed about them. However, they do not make investors feel safer concerning the tropical cyclones structural damage risk.**

Here, we are trying to capture the local investors' perceptions about the hazard mitigation programs. We are interested in the informational channel the mitigation programs give to investors. Suppose we put together the hypothesis above with the local bias principle. In that case, we expect that firms exposed to some disaster risk would receive a price discount promoted by the local investors. This discount would grow with the investments in hazard mitigation programs as more investors would be informed about them. This result is based on a well-explored hypothesis in the literature that firms exposed to disasters receive a discount in prices (negative return), at least in the short run. Thus, we are getting a little further from that previously explored argument in the literature. We are adding to the analysis the local investors' perceptions about hazard mitigation programs. A critical underline hypothesis that we are assuming is that the hazard mitigation programs funding is insufficient when we think about the trade-off between damage and hazard mitigation investment. Investing enough to eliminate all damages caused by natural hazards is virtually impossible, but this does not mean that not investing or low investment is enough. There is an optimal investment level that we hypothesized has not been reached based on the anecdotal pieces of evidence of recent significant increases in funding shown above.

On the other side, the general market hypothesis does not need local bias to be characterized. Beyond the investors' perception of low investment in hazard mitigation programs, this hypothesis interprets the hazard mitigation programs as a proxy for natural disaster risks. This interpretation comes directly from the fact that the U.S. does not invest enough in hazard mitigation. Because of that, the hazard mitigation programs cannot reduce the damage risks associated with tropical cyclones. Thus, the general market hypothesis can be summarized by: **Larger investments in hazard mitigation**

programs in a county are associated with larger risks of damages related to tropical cyclones.

Although the hypotheses appear to be significantly related, there is an essential difference regarding hazard mitigation programs interpretation. More significant investments in these programs mean that more investors will acknowledge them and their flaws for local investors. On the contrary, for general investors, as investors do not necessarily live near the areas that receive these programs, the investors who trade based on these programs have some knowledge about the programs' lack of investment beforehand and associate the more significant investments with larger risks of damages as the majority of hazard mitigation projects are available after a disaster.

To construct the anomalies is important to clarify how we define exposition to tropical cyclones. The literature that looks at the effects of disaster over returns usually focuses on the direct exposition, i.e., the landfall of tropical cyclones over counties (Lanfear et al., 2018). Here, we look at the indirect exposition to tropical cyclones.

Our definition of indirect exposition has three main characteristics. Firstly, we are considering just hurricanes, i.e., we are only considering the tropical cyclones that at some point in their lifetime had a wind speed sufficiently to be considered a hurricane. Moreover, the indirect exposition considers the tropical cyclones that do not affect the contiguous U.S., our considered firm universe. Finally, the tropical cyclone must be at some point in its lifetime at a maximum of one thousand kilometers from at least one county. Thus, being a hurricane at some point during its lifetime, not affecting the contiguous U.S., and being close to at least one county are the three requirements for a tropical cyclone to be indirectly exposing a county.

Disasters expected to strike but do not are ideal for studying the informational channel. Firstly, we consider just the perceived (salient) risk that triggers investors' reactions anticipating the disaster effects. However, as the disaster does not occur, the disaster effects themselves do not fulfill, making the investors' reaction exclusive based on preconceived opinions about the effects, including the investors' opinion over county capacity (hazard mitigation projects) to deal with it. Secondly, a disaster strike generates significant side effects via network effects to other no affected counties. The linkage that generates these side effects can have an economic origin, such as firm's internal linkages or relations between firms and their suppliers as seen in Barrot & Sauvagnat, 2016, Seetharam, 2017 and Giroud & Mueller, 2019. Another possible origin for that linkage can be seen in Tubaldi, 2020 where hurricane strikes generate a run for liquidity by local investors, which causes local mutual funds' fire sales and effects on firms not related to the hurricane strike. On the other hand, there are no network effects in the indirect exposition. Finally, Braun et al., 2021 shows differences between the states that have direct exposure to hurricanes (Landfall) from the states with at least one company that reported hurricane losses in U.S. Securities and Exchange Commission (SEC) 's filings. Most firms that reported hurricane losses are located in the directly exposed states. However, there are firms not located in these states characterizing the network effects.

Last but not least, direct disaster effects can affect hazard mitigation programs' perception. Turner & Landry, 2021 shows using survey data of U.S. east coast homeowners how large their misperceptions are regarding hurricane risks. The paper's findings suggest a strong tendency to overestimate the probability of a major hurricane strike and the likely damage of a major hurricane. As there is a mismatch between objective and subjective probabilities of hurricane risk, a hurricane may strike with a strength different from the expected strength. Thus, the perception of how good are the hazard mitigation projects can change. Moreover, Henriksson, 2021 shows how disasters can affect the disposition effect of impacted investors. Thus, for our purpose, the indirect exposition is a better approach to identify how the investors perceive these hazard mitigation investments.

Besides the two possible interpretations for the hazard mitigation program anomaly, there is an anomaly related to the indirect exposition to tropical cyclones. This return anomaly is associated with the susceptibility to tropical cyclones.

This anomaly emerges from the use of indirect exposition. The indirect exposition allows us to map counties exposed to a structural risk of hurricanes. For example, a recent study by Braun et al., 2021 analyses hurricane exposure as a systematic risk factor in the U.S. stock market. The authors theoretically show that a systematic risk factor associated with hurricane strikes could exist and show empirical evidence using aggregate hurricane loss growth. Thus, the authors were interested in constructing a factor related to hurricane strikes. On the other hand, we are simply interested in capturing anomalies in alpha during an indirect exposition to hurricanes. In that sense, other studies are more related to our goals. For example, Kruttli et al., 2021 shows that stock options of firms exposed to hurricane landfall exhibit large increases in implied volatility, which was not priced in terms of expected volatility, generating abnormal returns.

Based on these perceptions about hazard mitigation programs and indirect exposition, our results show how these anomalies behave. Considering our favorite specification, an additional dollar, in real per capita terms, spent on hazard mitigation programs related with hurricanes represents, on average, a discount on firm stock's excess returns of 3.4 percentage points on firms headquartered in counties with an indirect exposition to hurricanes located at a maximum 300 kilometers distance from the county, during the exposition month. This value decreases when we consider ranges that include more distant hurricanes from the counties. When we consider all hurricanes at 500 kilometers, 700 kilometers, 900 kilometers, and 1000 kilometers maximum distances, the excess returns fall, on average, 0.38, 0.17, 0.11, and 0.09 percentage points, respectively. For the indirect exposure to tropical cyclones, the results are less significant. When we consider all hurricanes at 300 kilometers, 500 kilometers and 700 kilometers maximum distances, the anomaly associated with hurricane risk makes the excess returns, on average, increase 5.14, 8.98 and 6.88 percentage points, respectively. The coefficients are not significant for the 900 kilometers and 1000 kilometers maximum distances.

Our dissertation is related to several streams of the literature. Firstly, it may contribute to the policy evaluation literature of hazard mitigation programs. The literature main focus is on cost-benefit analysis of the hazard mitigation programs such as Godschalk et al., 2009, Rose et al., 2007 and Davlasheridze et al., 2017. Here, instead of evaluating the program itself, we want to capture the investors' perceptions of the programs via the flow between information and market prices.

Next, our dissertation may contribute to the literature on disaster shocks in financial markets. The literature on this topic is vast and addresses different aspects of the phenomenon, and our dissertation does the same. Firstly, part of the literature focuses on event study analysis of the impact of disasters on returns. Brounen & Derwall, 2010, Koerniadi et al., 2011, Worthington & Valadkhani, 2004, Wang & Kutan, 2013, Seetharam, 2017 and Bourdeau-Brien & Kryzanowski, 2017 are some researches that deal with these impacts in a more general way. On the other hand, Lanfear et al., 2018 focuses on the short-run effects of hurricanes over returns, as we do in our dissertation.

Moreover, our study explores the salient or indirect natural disaster effects on firms. The finance literature explores salient exposition, usually using neighborhood exposition, i.e., if the firm is near an area that suffered a natural disaster strike. Dessaint & Matray, 2017 explores this idea by looking at managers' reaction to a hurricane landfall near the firm's headquarters via corporate cash holdings and expressed concerns about hurricane risk in 10-Ks/10-Q, they show that both measures increase after the nearby strike. On the contrary, our dissertation definition of indirect exposition is different. We define the indirect exposition based on the proximity of hurricanes to the coast, i.e., considering just the hurricanes that do not affect the contiguous U.S. but pass close to it.

Our dissertation may contribute to the local bias literature too. As discussed above, there is an ongoing debate about what explains local bias: information advantage or cognitive bias. Our work sheds some light on this discussion and may contribute to the information advantage explanation for the local bias phenomenon.

Last but not least, our dissertation may contribute more broadly to the climate finance literature. Climate change affects the occurrence of natural disasters worldwide, the effects that this phenomenon will have on the world economy is not completely understood (Stern, 2007). The finance literature tries to understand how the uncertainty generated by the changing climate affects firms' decisions (Kovacs et al., 2021, Dessaint & Matray, 2017, Ginglinger & Moreau, 2019), investors' decisions (Henriksson, 2021, Huynh & Xia, 2021) and, in the end, market efficiency (Ilhan et al., 2021, Hong et al., 2019, Engle et al., 2020), i.e., how well all this uncertainty is priced. This research is part of this effort as we relate information about government investments on mitigating tropical cyclones with market prices.

The rest of the dissertation is organized as follows. Section 2 gives an introduction to the hazard mitigation programs. Section 3 summarizes information about tropical cyclones. Section 4 presents all the databases used in this dissertation, our empirical strategy, and the methodology. Section 5 and 6 describe the results and the robustness checks, respectively. Last but not least, section 7 concludes our dissertation.

2
Hazard Mitigation Programs

Natural disasters frequently happen in the U.S., costing many lives and assets. The Federal Emergency Management Agency (FEMA) is an agency created by the U.S. federal government to help people before, during, and after disasters when the disaster that has stroke overwhelms the response capacity of local and state authorities. To receive FEMA's resources, the governor of a state hit by a disaster (natural or not) must declare a state of emergency and request the President to declare that the federal government will help the disaster response via FEMA. The federal response help procedure was defined by the Robert T. Stafford Disaster Relief and Emergency Assistance Act of 1988.

When the President declares that federal resources can be used for fighting the emergency declared by the state, FEMA starts to work via three types of programs. Individual assistance focused on individuals and households, public assistance focused on public facilities and private non-profit organizations, and hazard mitigation assistance for investments to reduce future losses related to disasters.

Individual and public assistance programs are focused on during and post-disaster investments, i.e., their focus is to repair and reconstruct private and public facilities hit by a disaster. On the other hand, hazard mitigation assistance programs are focused on a pre-disaster approach. They are interested in mitigating the long-run risks of disasters, fundamentally the natural ones, to people and properties. As seen before, our dissertation focuses on these hazard mitigation programs.

Hazard mitigation assistance programs can be of two different types: disaster-driven assistance or competition-driven assistance. Firstly, the disaster-driven assistance projects are related to the Hazard Mitigation Grant Program (HMGP). HMGP is a program that provides funds to states and local authorities when the President declares a major disaster. For each approved project under HMGP's umbrella, the federal government can provide up to 75% of its cost. The competition-driven assistance projects are related to hazard mitigation programs that do not need a major disaster declaration to be triggered. This kind of program is meant to foment competition between different proposed projects from different states as just the best ones according to FEMA's criteria are chosen. This second criterion includes the PDM program, which BRIC recently replaced, and the Flood Mitigation Assistance (FMA) program focusing on flood-prone regions.

In terms of presidential declarations, the President can make two different declarations: emergency declarations and major disaster declarations. Both declarations activate federal government assistance to affected locations. However, the type and the amount of assistance that each declaration enables are different.

Emergency declarations do not exceed the amount of $ 5 million dollar in assistance, and for this type of declaration, just public assistance and individual assistance programs are available, the HMGP program is not. An important application for this type of declaration is the pre-disaster emergency declaration. In that scenario, states could ask for an anticipated emergency declaration when a potential threat has an imminent impact that could generate destruction in the magnitude that a major disaster could be declared. The resources are anticipated to better prepare for the imminent disaster.

On the other side, a major disaster declaration provides the affected locations with a broader range of individual assistance and public assistance programs when compared with an emergency declaration. HMGP program is available.

Table 2.2 shows summary statistics for the three most important hazard mitigation programs from 1989 to 2021. We can see that the HMGP program has the most significant number of projects, mean and median, i.e., it is the program with the largest budget. When we look to the max column, the budget disparity is more evident. The maximum project under HMGP's umbrella is close to 730 million dollars. On the other hand, the maximum projects associated with FMA and PDM are close to 35 million dollars. Although large projects exist at least related to HMGP, most projects are low budget, as the median shows. Again, HMGP is the program with the largest median value of $123,813. The larger share of the HMGP disaster-driven program, when compared with others, shows us that the general market hypothesis that higher investments are associated with higher disaster risks is a good proxy.

As we know, HMGP projects need a major disaster declaration to be available. In table 2.2, we present the five disasters that have more HMGP projects related to them. Hurricanes are the second most important disaster, getting behind of severe storms. Tropical cyclones generate storms that can be severe but not necessarily reach the threshold to be considered a hurricane. Thus, it is probable that some of the severe storm projects are related to the

Table 2.1: Summary statistics for Hazard Mitigation Assistance Programs from 1989 to 2019.

Program	mean	median	standard deviation	count	max	min
FMA	$552,349	$93,254	$1,637,020	2,659	$31,476,299	$0
HMGP	$977,274	$123,813	$10,205,000	23,085	$729,000,000	$0
PDM	$460,578	$85,000	$1,522,164	3,928	$35,475,000	$0

Source: FEMA OpenDatabase.

Table 2.2: HMGP projects according to the natural disaster that generated them from 1989 to 2019.

Natural Disaster	Number of HMGP project grants	Percentage of Total
Fire	980	4.3%
Severe Ice Storm	1200	5.2%
Flood	3168	13.7%
Hurricane	6121	26.5%
Severe Storm(s)	9432	40.9%

Source: FEMA OpenDatabase.

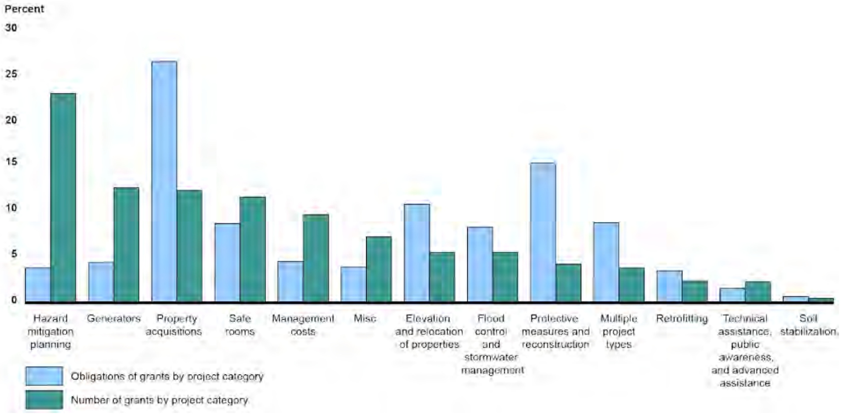
tropical cyclone phenomenon.

The low value associated with projects of hazard mitigation programs reflects in the types of projects financed by these programs. Figure 2.1 shows the categories of projects that the HGMP, FMA, and PDM programs financed in terms of the number of grants and total obligations. Firstly, although the planning category has a small cost, the number of grants associated with it is almost 25% or one-quarter of all grants. The other three categories highlighted in terms of the number of grants are: generators, property acquisition, and safe rooms.

Looking for the expenditure part of the figure 2.1, we can see property acquisition being the largest expenditure among all categories. The other categories that have some highlights are related to protective measures and reconstruction, multiple project types (more than one category), and elevation and relocation of properties. Thus, the projects are generally associated with local interventions.

Finally, an exciting topic that is related to the use of hazard mitigation programs can be found at Petkov, 2021 paper. This research shows that culture homogeneity matters for the expenditure in hazard mitigation. More specifically, the author shows that more homogeneous counties spend more local funds to mitigate disasters and, thus, they need a smaller amount of federal funds. Furthermore, as seen above, the principal instrument to finance hazard

Figure 2.1: HMGP, FMA and PDM project categories by percent of total obligations and total number of grants (2010-2018).



Source: United States Government Accountability Office (GAO) analysis of FEMA data.

mitigation is associated with post-disaster investments (HMGP). Hence, more fractionalized places are more vulnerable to natural disaster damages.

3
Tropical Cyclones

According to the National Oceanic and Atmospheric Administration (NOAA), tropical cyclones are the deadliest and costliest natural disaster that hit the U.S. annually. Table 3.1 shows us that among all natural disasters that reached the one billion dollar cost threshold, Tropical Cyclones are the most costly by event ($20.3B) and by year ($26.6B).

Table 3.1: Billion-dollar events that affect the United States from 1980 to 2021 (CPI-Adjusted).

Disaster Type	Events	Events/Year	Percent Frequency	Total Costs	Percent of Total Costs	Cost/Event	Cost/Year	Deaths	Deaths/Year
Drought	29	0.7	9.4%	$272.3B	13.1%	$9.7B	$6.5B	4,139	99
Flooding	35	0.8	11.4%	$161.9B	7.8%	$4.6B	$3.9B	624	15
Freeze	9	0.2	2.9%	$32.3B	1.5%	$3.6B	$0.8B	162	4
Severe Storm	141	3.4	45.8%	$320.0B	15.3%	$2.3B	$7.6B	1,786	43
Tropical Cyclone	56	1.3	18.2%	$1,117.7B	53.6%	$20.3B	$26.6B	6,697	159
Wildfire	19	0.5	6.2%	$107.9B	5.2%	$6.0B	$2.6B	399	10
Winter Storm	19	0.5	6.2%	$74.1B	3.6%	$3.9B	$1.8B	1,223	29
All Disasters	308	7.3	100.0%	$2,086.2B	100.0%	$6.8B	$49.7B	15,030	358

Source: NOAA - https://www.ncdc.noaa.gov/billions/summary-stats.

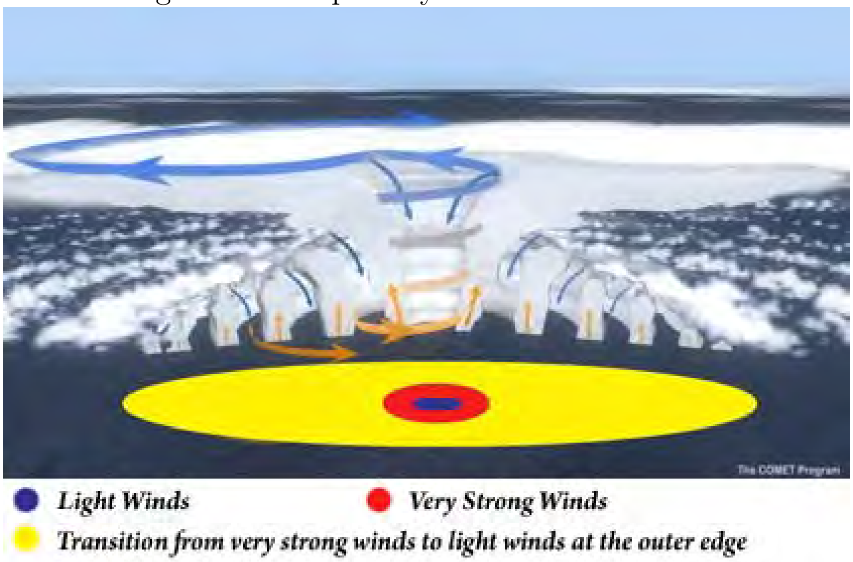
The tropical cyclone leadership is reflected in firm managers' climate risk perceptions. Li et al., 2020 analyze earnings conference calls and found out that hurricane is the most important and cited word related to severe climate events, showing that tropical cyclones are an important matter of concern to companies.

According to the National Hurricane Center of the United States (NHC), tropical cyclones are:

"a warm-core non-frontal synoptic-scale cyclone, originating over tropical or subtropical waters, with organized deep convection and a closed surface wind circulation about a well-defined center. Once formed, a tropical cyclone is maintained by the extraction of heat energy from the ocean at high temperature and heat export at the low temperatures of the upper troposphere."

Figure 3.1 shows the basic circular structure of a tropical cyclone. The blue region is the cyclone eye, the red region is the eyewall, and the yellow region is the rain bands. It is evident by the figure that the worse part is located at the eyewall, and the winds get weaker as we go further away from the eyewall.

Figure 3.1: Tropical cyclone basic structure.



Source: http://www.hurricanescience.org/science/science/hurricanestructure.

This structure is fundamental for our empirical strategy, which consists in getting all the tropical cyclones' effects over the contiguous U.S. As figure 3.1 shows, the most critical factor to define a tropical cyclone strength is the maximum sustained wind speed: Less than 62km/h (tropical depression), 63km/h to 118 km/h (tropical storm) and more than 119 km/h (hurricane). Thus, hurricanes are the most potent form of tropical cyclones.

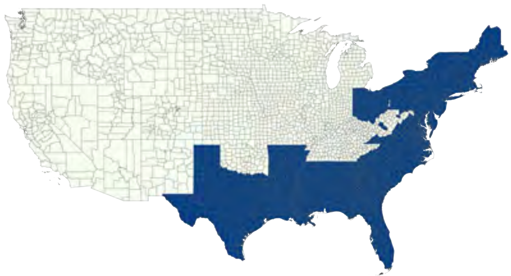
In addition, two tropical cyclones seasons can affect the U.S.: the Pacific season and the Atlantic season. Although both seasons happen simultaneously, between May and November, they have different consequences for the contiguous U.S. While the Pacific cyclone system generates rare landfalls and effects over the contiguous U.S., affecting mainly Hawaii and some small Pacific islands, the Atlantic season generates frequent landfalls and damages over the contiguous U.S.

That difference relies on two factors: tropical cyclones in the northern hemisphere move in the west-northwest direction. Therefore, on the west coast (Pacific ocean), tropical cyclones tend to move away from the U.S. coast. On the contrary, on the east coast, it tends to move into the vicinity of the coast. The second reason is related to the water temperature of the ocean. The west coast water is colder when compared to the southeast coast water. As seen in the tropical cyclone definition, a tropical cyclone is maintained by the heat energy of hot ocean water. Thus, the west coast's low water temperature protects the land against tropical cyclones. Figure 3.2 shows all tropical cyclones tracks since 1949 in the Pacific and since 1851 in the Atlantic. It is clear from the pattern exposed above that the Atlantic season generates

Figure 3.2: All tropical cyclones tracks from both seasons.

Source: NOAA.

Figure 3.3: Counties that received HMGP investments related with hurricane at some point in time since 1990.



Source: OpenFEMA.

much more damage for the U.S. than the Pacific season[1]. As we are interested in the indirect effect of hurricanes in our analysis, we will consider just the Atlantic season in this dissertation because the indirect effect only makes sense if it represents a real threat for investors.

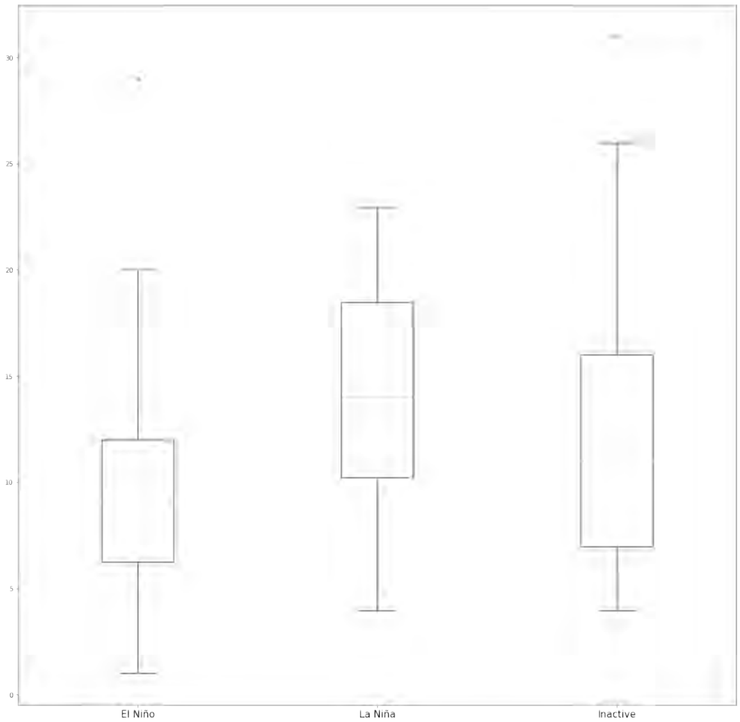
Beyond that, when considering the covering area of HMGP projects related to hurricanes, we get support for excluding the Pacific season. Figure 3.3 shows how this program is distributed in the contiguous U.S. It is distributed just to the states affected by the Atlantic season.

Two characteristics make tropical cyclones a useful natural disaster to analyze: exogeneity and occurrence in a specific area.

When we talk about tropical cyclones, we are interested in two different types of forecasting: season forecast and hurricane path forecast. The season forecast depends on complex factors such as the El Niño-Southern Oscillation

[1]https://www.scientificamerican.com/article/why-do-hurricanes-hit-the-east-coast-of-the-u-s-but-never-the-west-coast/

Figure 3.4: Distribution of the number of tropical cyclones that occured by year for each ENSO phase (1871-2020).



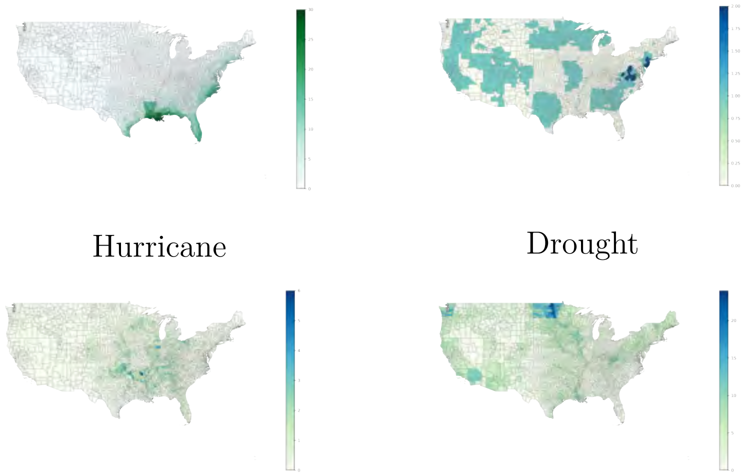
Source: HURDAT 2.

(ENSO) phase (El Niño and La Niña)[2]. The importance of the ENSO phase for the season forecast can be seen in figure 3.4. It is clear that depending on the ENSO phase, the expected number of tropical cyclones and their distribution change from one year to another. Beyond that, ENSO tends to develop between March-June. As the tropical cyclone season starts to form in June, the season forecast depends on the forecast of other climate phenomena. This lack of forecasting capacity reflects the probabilities that the NOAA's hurricane season outlooks give to each season. For example, in the 2021 Atlantic hurricane season, the forecast was 60% above-normal season, 30% near-normal season, and 10% below-normal season.

When we talk about hurricane path forecasts, the scenario is better, but much work still needs to be done. On average, a tropical cyclone lasts for ten days, and it can move more than 500 km per day. Thus, it is very unpredictable when a hurricane starts where it will end. Following the National Hurricane Center:

[2]The ENSO cycle refers to the variations in sea- surface temperatures, convective rainfall, surface air pressure, and atmospheric circulation that occur across the equatorial Pacific Ocean. El Niño refers to the above-average sea-surface temperatures that periodically develop across the east-central equatorial Pacific. La Niña refers to the periodic cooling of sea-surface temperatures across the east-central equatorial Pacific. El Niño occurs more frequently than La Niña. Episodes of El Niño and La Niña typically last nine to 12 months but can sometimes last for years.

Figure 3.5: Emergency and major disaster declarations since 1964 by disaster type.



Hurricane Drought

Tornado Flood

Source: OpenFEMA.

"Today a 3-day forecast is as accurate as those issued for a 2-day prediction in the late 1980s. However, much work remains to better understand and predict wind intensity changes in tropical storms and hurricanes."

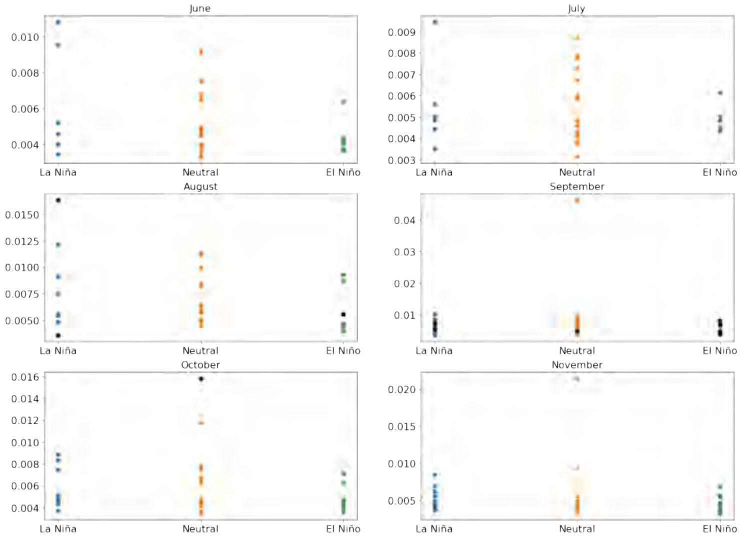
Another essential characteristic of tropical cyclones is that it is a local phenomenon. When we say that, we mean that tropical cyclones affect just the east/southeast part of the U.S. because it only hits that area. Firstly, figure 3.5 shows us the distribution over contiguous U.S. counties of emergency and major disaster declarations for four different natural hazards: hurricane, drought, tornado, and flood. It is clear how, compared to the others, hurricanes are concentrated in a specific region. The graph scale reinforces that point. We can observe that the darker colors for the hurricane graph were associated with a much larger number of occurrences than the other natural hazards, only flood occurrences get close. This fact means that hurricane occurrence generates enough damage to justify emergency and major disaster declarations and that people who live in hurricane areas are aware of the possibility of recurrence.

The local aspect of tropical cyclones can be recognized too using the natural disaster index constructed by Bybee et al., 2021 based on the Wall Street Journal.[3] The authors used full-text content of 800,000 Wall Street Journal (WSJ) articles from 1984 to 2017 to estimate monthly news attention indexes for different topics, including natural disasters.

With that in mind, we construct two measures based on the WSJ natural

[3]http://structureofnews.com

Figure 3.6: Wall Street Journal index (1984–2017) distribution for natural disaster divided by month and ENSO phase. The black dots represent months in which an outlier number of tropical cyclones happened.



Source: Bybee et al., 2021 and HURDAT 2.

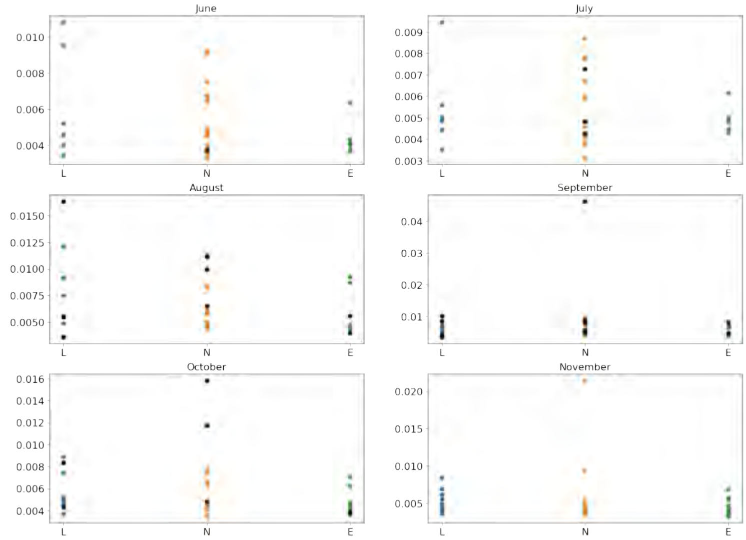
disaster index of how much attention tropical cyclones receive in a U.S. general newspaper. The measures are based on the intensity and quantity of tropical cyclones.

Firstly, we get all the months in which an outlier amount of tropical cyclones happened based on the distribution of tropical cyclones on each ENSO phase.[4]. If tropical cyclones are an important U.S. occurrence, at least for investors, we would expect that all the months, or at least the majority, that we selected would get a high score in the natural disaster index based on WSJ. I.e., months with a considerable amount of tropical cyclones would get attention to this topic from the WSJ and, hence, receive a relatively high score in the WSJ natural disaster index. In figure 3.6 the black dots represent these year/months with the highest number of tropical cyclones. Only two of them are highlighted in the distribution: October/2005 (hurricane Katrina) and August/2011 (hurricane Irene). Hence, the extensive margin of tropical cyclones does not appear to get a lot of WSJ's attention.

Secondly, we get all the months when a billion-dollar cost tropical cyclone event happened. As seen in figure 3.6, the extensive margin of a tropical cyclone does not generate enough salience to get more importance for the WSJ. Here, we want to discover if the intensive margin of tropical cyclones is relevant to the natural disaster index of the WSJ. In figure 3.7 the black dots represent these year/months with the billion-dollar cost tropical cyclones. The intensive

[4] Here, the outlier amount was based on all months that surpass the threshold calculated by the 75^{th} percentile of the distribution plus 1.5 multiplied by the interquartile range.

Figure 3.7: Wall Street Journal index (1984–2017) distribution for natural disaster divided by month and ENSO phase. The black dots represent months in which a high-cost tropical cyclone happened.



Source: Bybee et al., 2021 and OpenFEMA.

margin has a larger appeal for the WSJ than the extensive margin. This result was expected as many tropical cyclones formed do not make landfall in the U.S. but stay in the ocean, affecting just oil extraction in the Gulf of Mexico. However, the appeal is not automatic. As we can see in figure 3.7, some black dots are not highlighted in the distribution. Thus, even the most costly tropical cyclones that made landfall in the U.S. do not necessarily receive more attention from the WSJ than other natural disasters.

4
Empirical Design

4.1
Data Description

4.1.1
Center for Research in Security Prices database

The Center for Research in Security Prices (CRSP) is a historical stock market database. This dissertation used the monthly returns data from all companies between 2004 and 2017. We exclude from the database companies that had since 1996 less than two years of data. We exclude these companies traded during a short period to reduce the number of companies less known by the investors. Beyond that, we used 1996 year as a reference because if we considered 2004 as a reference, companies publicly listed during a long period, i.e., known by investors, but that were delisted during 2004 or 2005 would be excluded from the database.

4.1.2
Factors

We use Fama/French 5 Factors and Momentum as controls in our empirical strategy. The five factors are: Market Premium, SMB, HML, RMW, and CMA. Firstly, the market premium is constructed as the difference between the value-weight average return of all firms in the CRSP database and the one-month Treasury bill rate. SMB is the factor related to the market capitalization of the firm. It is constructed as the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios of firms. HML is related to the B/M ratio (value vs. growth stocks). It is constructed as the average return on the two value portfolios minus the average return on the two growth portfolios. RMW is the factor related to the firm profitability. It is constructed as the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. CMA is the factor related to the investment policies by the firms (high vs. low). It is constructed as the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.[1]

4.1.3
Firm headquarters database

The firm headquarters database used in this study was constructed using the Augmented 10-X Header Data from the Software Repository for Accounting and Finance of the University of Notre Dame[2] that gives us historical firm headquarters based on the SEC 10-K/Qs files stored on EDGAR.[3] We used the Central Index Key (CIK) number to match my monthly returns database with this historical headquarters database. However, this merger was not enough to capture all firms' headquarters. Thus, we construct a web scraping code to match company names between the stock prices database and EDGAR to complete the missing headquarters information. The use of firm headquarters information as a proxy for firm activity location is based on an empirical regularity that firms are usually close to their primary activity. Barrot & Sauvagnat, 2016 show that the median firm has over 67 percent of its employees located at the headquarters. The data of this paper was obtained considering listed and not listed firms. We could think that as listed firms tend to be larger, on average, this percentage would be lower for them as their production is possibly more decentralized. Thus, we should not worry about it because this is going against and not in favor of our estimated effects as firms more decentralized are less affected when a disaster hits its headquarters.

4.1.4
HURDAT 2

The HURDAT 2 is a historical database constructed by the NHC using a post-storm analysis of each tropical cyclone's area of responsibility to determine the official assessment of the cyclone's track history. For each cyclone, the eye position is given on a 6-hour base (00h-06h-12h-18h), in that case, we get the precise path that the tropical cyclone has made. From 2004 onwards, the database was improved. Nowadays, we can get wind strength radii beyond the eye position in every ordinal direction: Northeast, southeast,

[1]The data can be found in the following link: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data$_{l}$*ibrary.html*

[2]The data can be found in the following link: https://sraf.nd.edu/data/augmented-10-x-header-data/

[3]EDGAR is is the primary system for companies and others submitting documents under the Securities Act of 1933, the Securities Exchange Act of 1934, the Trust Indenture Act of 1939, and the Investment Company Act of 1940. Contains millions of company and individual filings.

southwest, and northwest, with more precision. As seen before, a tropical cyclone loses strength when it gets far away from its eye. Moreover, the tropical cyclone has three possible states according to its wind speed: hurricane, tropical storm, and tropical depression. Thus, the database defines three radii from the eye where the cyclone behaves as a hurricane, tropical storm, or tropical depression.

We can construct the tropical cyclone influence area with these wind strength radii data. This measure gives us a more precise definition than using just the eye position data into how far away from its eye the tropical cyclone can still influence the weather. However, measuring distances using geographic position data can be tricky. Our approach was based on the NAD83 geographic coordinate system (GCS). This system is the most widely used by federal U.S. agencies as it was built to better fit U.S. territory. For distance measures between two coordinate points, we used the haversine formula. Beyond that, we construct the hurricane size to capture its influence area. For that task, we again needed to use the haversine formula to get the most distant point that the tropical cyclones have some influence. Figure 4.1 represents this construction effort of hurricane size for the Katrina Hurricane. The red figures represent the influence area of the hurricane that varies throughout its existence period.

4.1.5
WSJ Natural disaster index

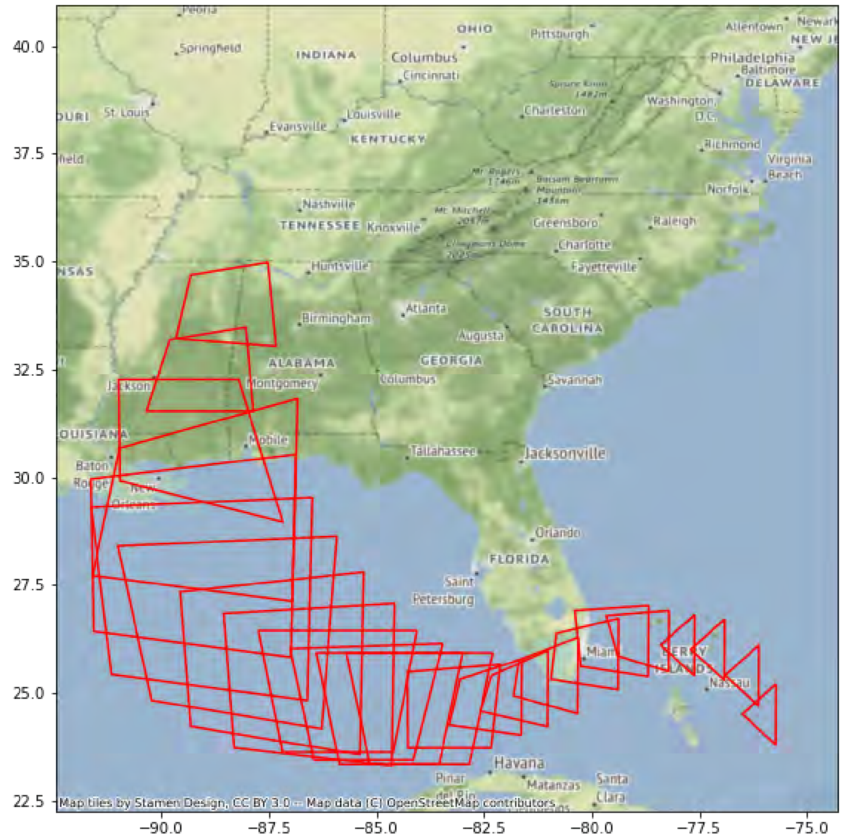
The WSJ natural disaster index was constructed by Bybee et al., 2021. The authors estimate a topic model based on 800,000 WSJ articles from 1984 to 2017.[4] The estimation allows us to construct time series of news attention on each topic and compare the topic evolution through time. For example, we use the natural disasters topic time series in our estimation to control the evolution of attention to this topic on the financial market when a tropical cyclone strikes in a county, as WSJ is one of the most influential media sources for financial market participants.

4.1.6
Historical state Governor and President political parties

We construct a historical database for each U.S. state to know in what years of our analyses the state governor was in the same party as the President. Here, the idea is to capture possible political reasoning for the President's approval of emergency and major disaster declaration. As declarations come

[4]http://structureofnews.com/

Figure 4.1: Hurricane Katrina path using hurricane size information.



Source: HURDAT 2.

with federal resources, we could expect that Presidents are more inclined to declare for states with an allied governor.

4.1.7 Hazard Mitigation Programs

The hazard mitigation programs database is part of the OpenFEMA Data Sets[5] repository that has several databases related to FEMA's operation in disaster situations. Here, we use the database related to projects under the Hazard Mitigation Programs umbrella. Our interest relies on the counties primarily affected by each project and the amount of money each project received.[6]

[5] https://www.fema.gov/about/openfema/data-sets

[6] In some projects, beyond the primary counties, some other counties are secondary beneficiaries of the project. As we cannot find how much each of these secondary counties receives from the project, we ignore them and focus just on the primary counties.

4.1.8
State and Local Finance Data

The state and local finance data came from the Urban-Brookings Tax Policy Center's State and Local Finance Initiative project. The researchers of this project processed data from the U.S. Census Bureau's Census of Governments and Annual Survey of State and Local Government Finances to aggregate information about the states. Our interest here is in the investment part. We get nominal per capita total capital outlays made by local and state governments for each state.

4.2
Identification strategy

Our identification relies on the exogeneity of tropical cyclones, as described in section 3. The tropical cyclone's exogeneity is clear and generates few debates. However, to test the significance of the anomalies estimations, we need exogeneity for the variable related to the hazard mitigation programs and the interaction between this variable and indirect exposition. Firstly, we need to understand how the investment process works for this kind of program. Figure 4.2 shows how hazard mitigation programs' application and funding processes work. The application process follows the opposite path of the funding process. It starts with local authorities receiving community demands and conveying them to the state authorities. In the end, the state authorities must organize the requests to the federal government via FEMA.

It is important to emphasize that the process order is the same for disaster-driven assistance or competition-driven assistance, the differences between programs are in the requirements and budget. This decentralized infrastructure has advantages as the local authorities are better prepared to know the more urgent necessities of their communities. However, Smith & Vila, 2020 argues that this process may hinder the capacity of communities with less internal capacity to fight for resources, fundamentally in the competition-driven programs.

What could generate endogeneity problems between excess returns and investment in hazard mitigation programs or between excess returns and indirect tropical cyclone exposition?

Firstly, as seen in the introduction, direct natural disasters can impact investors' behavior (Henriksson, 2021). I.e., direct disaster exposition can affect stock returns not only through the physical impact over firms but changing investors' behavior too. Moreover, tropical cyclones can affect a specific county directly and indirectly at the same time as they have a seasonal occurrence;

they are correlated. Thus, we can have an endogeneity problem associated with investors' behavior change correlated with direct exposition that, in its turn, is correlated with indirect exposition, making our estimation biased. To tackle this endogeneity problem, we exclude from the database firms' observations in months that a tropical cyclone direct exposition and an indirect exposition happened to the county where the firm is headquartered. We cut the thread between investors' behavior change and indirect exposition when we do this. This database exclusion is also valid for all the aspects discussed in the introduction concerning why indirect exposition is better for our identification effort.

Secondly, Pirinsky & Wang, 2006 shows how returns are correlated between firms with headquarters located closely. Following the authors, this happens because of the co-movement of the local trading pattern. Suppose there is a difference between local trading patterns based on county characteristics, and these characteristics are related to the capacity of receiving resources from FEMA hazard mitigation programs. In that case, we could expect that endogeneity is a problem. How could we solve that? Using a fixed-effects model with county-level fixed effects could help solve that because we exclude from the analysis all idiosyncratic county characteristics that do not change over time.

Thirdly, there is a political component, as seen in section 2 in the hazard mitigation programs processes, essentially, for the HMGP projects that need major disaster declarations by the President to be available. Lee Helms, a former Alabama Emergency Management Agency chief, said: **"Politics always plays a part in that, if it is a borderline call, the ultimate decision is made by the President."**. This emphasizes the idea that politics matter for FEMA declarations. As the final process happens between the state governor and President, we used a dummy variable that represents if the governor was at the same party as the President or not.

Furthermore, another important point to worry about endogeneity is related to investments per capita. It is clear that general state and local investments and federal hazard mitigation investments are related as more investments by local authorities could reduce the necessity of federal funds (Petkov, 2021). Beyond that, investments are possibly related to returns as better infrastructure helps businesses thrive. Thus, it is important in our identification effort to control for local investments.

The cultural importance for the HMGP investment decision shown by Petkov, 2021 is a concerning point in our analysis as Grinblatt & Keloharju, 2001 showed that culture matters for trading behavior too. We used county fixed effects to deal with this cultural problem because we are dealing with just 14 years of data, and we thought it was reasonable to assume that this is not enough to change a county's cultural roots. Beyond that, the infrastructure variable can help us proxy for this cultural heritage as Petkov, 2021 showed us that culture matters for the infrastructure expenditure.

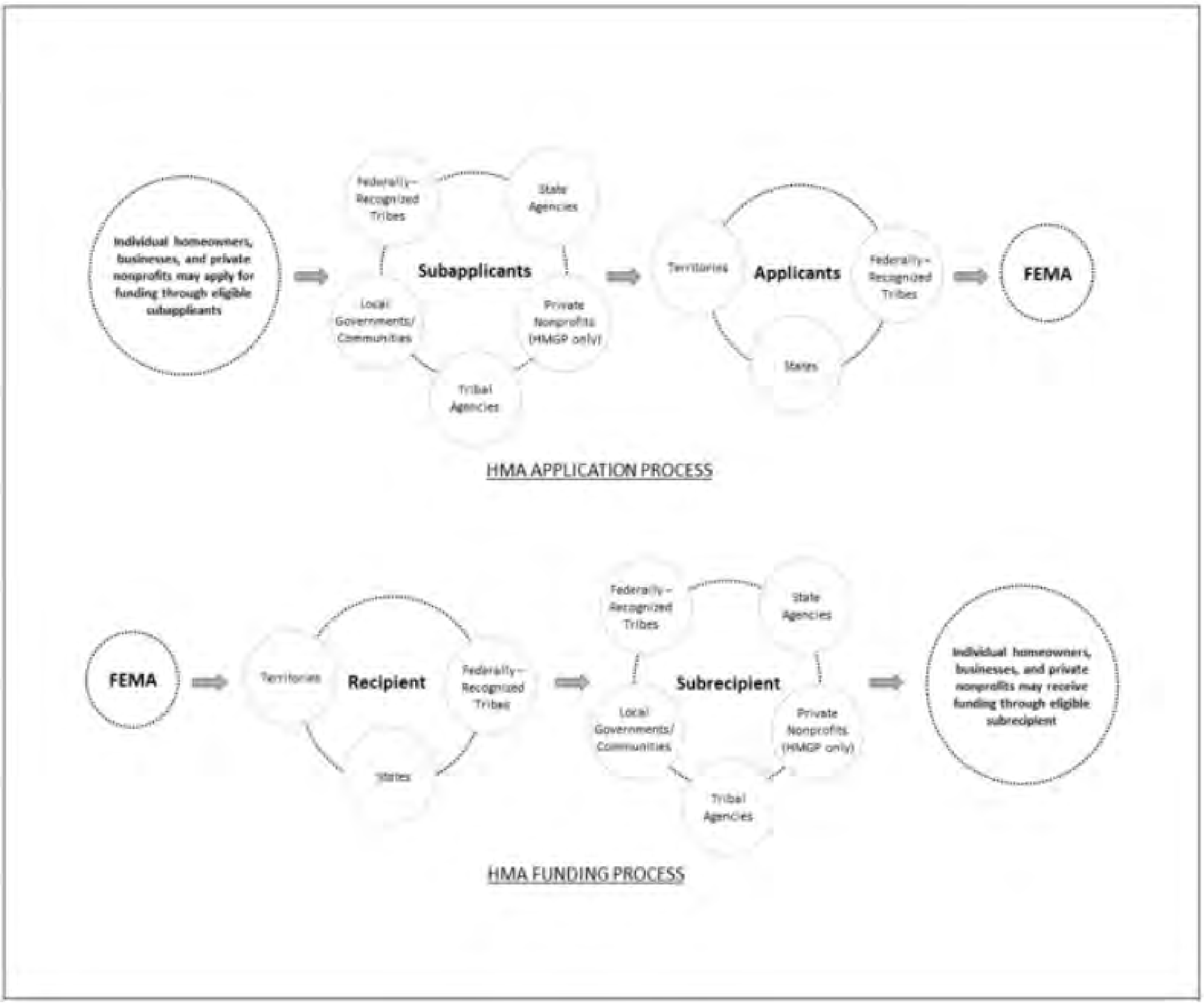
In addition, firms are differently exposed to tropical cyclones, and hazard mitigation measures have different effects on them. An important example is firms in the oil sector that explore Gulf of Mexico wells. Although the production over there is affected by tropical cyclones, hazard mitigation measures do not reach them. Moreover, as we saw before, HMGP depends on hazards to be available. This can generate endogeneity when we regress excess returns in hazard mitigation investment. Hence, we use firm-level fixed effects, dummies for hurricane season months, and tropical cyclones exposure to overcome firm-level problems.

Finally, a concern is the real influence of local investors on firms. The weight of local investors on firms varies according to some firms' characteristics. The literature shows that some characteristics are associated with a larger presence of local investors in a firm's ownership. Small firms (Coval & Moskowitz, 1999, Ivković & Weisbenner, 2005, and Jacobs & Weber, 2012) is the characteristic that is most correlated with a high local investment. Shive, 2012 explores other characteristics correlated with local firms, such as lower log market to book ratio, lower log Tobin's Q, and larger bid-ask spread. However, in this dissertation, we do not split between firms with big local influence and firms with low local influence. However, this should not be a problem because we expect that the hazard mitigation programs' perceptions do not influence firms with low local influence as much as they influence firms with high local influence. In that case, the inclusion of all firms could reduce the significance of our results, making our significant results even more robust. Despite all of that, we make a local firm exercise in the robustness chapter. At each month, in our database, we exclude all firms' observations that have a market value lower than the average and the median market value at that specific month. I.e., we used the principal characteristic (firm size) of a local company to split between a local and non-local company database.

4.3 Methodology

We estimate the effects of the salient exposition to hurricanes over $\widehat{\alpha}_{i,t,c}$. We are considering just hurricanes that do not affect the contiguous U.S. For county indirect (salient) exposition, we consider five range definitions: 300km,

Figure 4.2: FEMA application and funding process for all hazard mitigation programs.



Source: Smith et all. (2020).

500km, 700km, 900km, and 1000km distances from hurricanes and estimate each one separately. We estimate a fixed-effect model with county-level and time-level clustering, and county-level and firm-level fixed effects. Abadie et al., 2017 shows why we need to consider clustering and fixed effect when dealing with county-level heterogeneous shocks. Beyond that, the time-level clustering is necessary for the well-known high cross-section correlation between stock returns even when we consider the 5 Fama-French factors (Petersen, 2009). The subscripts represent: i stock level, t month/year, y year, c county level, and s state level.

$$R_{i,t,c} - Rf_t = \alpha_{i,t,c} + \beta_{1,i} Market\_Premium_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} RMW_t + \beta_{5,i} CMA_t + \beta_{6,i} Momentum_t \quad (4\text{-}1)$$

Firstly, to construct $\widehat{\alpha}_{i,t,c}$, we estimate equation 4-1 regressing on the time series each stock excess return against the five Fama-French factors and momentum. With that estimation, we get the residuals $\widehat{\alpha}_{i,t,c}$ which are used in our principal estimation.

$$\widehat{\alpha}_{i,t,c}{=}\alpha_c{+}\alpha_i{+}\lambda Hurricane_{t,c}{+}\iota Tropical\_Depression_{t,c}{+}\omega Tropical\_Storm_{t,c}{+}$$
$$\theta ProximityHurricane_{t,c} * Project\_per\_capita_{t,c} + \delta Projectpercapita_{t,c}+$$
$$\psi Proximity\_Hurricane_{t,c}{+}\sum_{j=1}^{5}\kappa_j HurricaneSeason_t{*}PastHurricane_{j,y,c}{+}\Lambda GovernorParty_{t,s}{+}$$
$$\sum_{k=1}^{5}\zeta_k PastHurricane_{k,y,c} + \gamma HurricaneSeason_t + \varphi Total\_cap\_out_{s,y}+$$
$$\upsilon NaturalDisasterINDEX_t{*}Hurricane_{t,c}{+}\Upsilon NaturalDisasterINDEX_t{*}Tropical\_Storm_{t,c}$$
$$+ \varrho NaturalDisasterINDEX_t * Tropical\_Depression_{t,c} + \varepsilon_{i,t,c} \quad (4\text{-}2)$$

$R_{i,t,c}$ is the monthly return of the stock i at month t and firm located at county c. Rf_t is the risk-free (1-month T bill rate) at month t. $MarketPremium_t$, SMB_t, HML_t, RMW_t and CMA_t represent the 5 Fama/French factors and momentum factor. $Hurricane_{t,c}$ is a dummy variable that assumes 1 if the county c at month t was exposed to a hurricane. $Tropical\_Storm_{t,c}$ is a dummy variable that assumes 1 if the county c at month t was exposed to a tropical storm. $Tropical\_Depression_{t,c}$ is a dummy variable that assumes 1 if the county c at month t was exposed to a tropical depression[7]. $Projectpercapita_{t,c}$ is a variable that defines how much money per capita in real terms[8] had been invested on hazard mitigation projects at the county c in the month t. $Proximity\_Hurricane_{t,c}$ is a dummy variable that assumes 1 if the county c at month t had a salient hurricane affecting it. I.e., following some range definition, there was at least one hurricane sufficiently close to the county that did not affect the county and no other contiguous U.S. counties. $NaturalDisasterINDEX_t$ is the value of the WSJ Natural Disaster index for the month t. $GovernorParty_{t,s}$ is a dummy variable that assumes 1

[7]We capture exposition to tropical cyclones getting the intersection between tropical cyclone area of influence and the U.S. territory. Beyond that, tropical cyclones lose strength when it gets away from its eye. Thus, when using the size construction method, weaker tropical cyclones have a larger area than stronger ones. Hence, we get a dummy variable equal to 1 for hurricanes, and by size construction, we probably get a dummy equal to 1 for tropical storms and tropical depressions. To tackle this, we assume that when a county is exposed to a stronger tropical cyclone, this status is the only one that prevails. For example, if a county is exposed to a hurricane, it is exposed only by it and not by the other tropical cyclone status.

[8]The $Projectpercapita_{t,c}$ variable was deflated to be in 1996 U.S. dollars value.

if at the month t and state s the state governor is at the same political party as the U.S. President. $PastHurricane_{k,y,c}$ is a dummy variable that assumes 1 if at year y and county c, there were in k[9] years ago a hurricane strike in the county. $HurricaneSeason_t$ is a dummy variable that assumes 1 if t is one of the hurricane season months[10]. $Total\_cap\_out_{s,y}$ is the variable that defines the total capital outlay per capita in real terms [11] spent during a year by local and state governments for each state.

The most important estimated parameters are red: θ and ψ. The θ refers to the interaction between investments per capita in hazard mitigation programs and indirect exposure to hurricanes. On the other side, ψ is related to the indirect exposure to hurricanes only.

The first part of our methodology estimates each equation separately as different ranges represent different model specifications. In the second part, we estimated the exposure by part, i.e., we estimate a single equation with the following ranges: 0-300, 300-500, 500-700, 700-900, and 900-1000. The idea here is to get how each range contributes to the total salient effect of hurricanes. The methodology used is the same as the one shown above, with the only difference that $ProximityHurricane_{t,c}$ and $ProximityHurricane_{t,c} * Project\_per\_capita_{t,c}$ repeats itself five times, one for each range.

[9]where k is 1,2,3,4 and 5
[10]from June until November
[11]The $Total\_cap\_out_{s,y}$ variable was deflated to be in 1996 U.S. dollars value.

5
Results

The main results were presented in tables 5.1, 5.2 and 5.3. In the table 5.1, we consider just the 300km range with two different specifications for the project per capita variable. The total mitigation column considers all hazard mitigation programs except the HMGP projects not associated with hurricanes in the project per capita variable. On the other hand, the HMGP column considers just the HMGP projects associated with hurricanes. The only difference between table 5.1 to tables 5.2 and 5.3 is the number of considered ranges. Table 5.2 considers 500 km and 700 km ranges and table 5.3 considers 900 km and 1000 km ranges. The total mitigation and HMGP columns in tables 5.2 and 5.3 have the same specification particularities of table 5.1. Thus, the difference between the tables is on the range specification considered, as described in the methodology section.

Going from the 300 km to 1000 km range, we expand the number of hurricanes considered, i.e., all hurricanes in the 300 km range are in the 1000 km range. However, the hurricanes that pass between 300km and 1000 km are not in the 300 km range, but they are in the 1000 km range.

In our favorite specification, we look at the HMGP column that reflects HMGP related to hurricanes. For the iteration term between project per capita and hurricane close (distance[1])), we find a negative and significant parameter estimation. Beyond that, the estimations get smaller when we change the hurricane range specification. For example, it goes from -0.034 with the 300km range specification to -0.0009 with the 1000km range specification. This result was expected because adding hurricanes far away from the coast reduce the general risk of a strike. Therefore, one dollar in project per capita investment for a 300km range exposition to hurricanes is equivalent to an average reduction of $-1 * -0.0340 * 1 * 1 = 0.034$ in the realized return alpha during the month of exposition. This is the first anomaly that our estimation captures.

The total mitigation columns in tables 5.1, 5.2 and 5.3 show that the effect is less pronounced and even insignificant for some specifications when we include other hazard mitigation programs. We understand this fact as a capacity of investors to differentiate the HMGP projects related to hurricanes

[1]distance is equal to 300 km, 500 km, 700 km, 900 km or 1000 km.

that have a higher probability of combatting hurricanes effects from other hazard mitigation projects without the same goal. Our robustness analyses give evidence in this direction too.

Moreover, the indirect exposition to hurricanes generates anomalies in returns too. We find that Hurricane close (distance[2]) has positive and significant effects, however the results are less significant than the ones observed for the iteration term above. The estimated parameters go from 0.0514 for the 300km range specification to 0.0688 for the 700km range specification. The results are not significant for the 900km and 1000km specifications. The total mitigation columns show little variation compared with the HMGP columns.

What could explain these estimated coefficients? As described in the introduction section, there are two possible explanations for these anomalies. Firstly, the local investor's hypothesis is that hazard mitigation programs do not make local investors feel safer concerning a tropical cyclone strike. On the contrary, more hazard mitigation programs investments in a county make local investors more aware of their failure to relieve the effects of the tropical cyclone. As a result, firms in counties indirectly exposed to hurricanes will have, on average, a reduction in their realized returns during the exposition month. This reduction grows with the investment per capita in hazard mitigation programs. I.e., supposing that local investors are more aware of this type of program and its lack of capacity to mitigate risks with more investment per capita. That is why, the discount on realized returns would grow with the investment per capita in hazard mitigation programs. To explain the positive estimated coefficients for the indirect exposition dummy, we rely on Alok et al., 2020. In this study, the authors show that local investors sell more local firms affected by a disaster when compared with distant investors. In our case, as the disaster does not strike, the positive anomaly in returns could be associated with compensation for the over-sell of local investors when the disaster does not materialize.

On the other hand, the general market perspective can explain these results too. The hazard mitigation section showed that most hazard mitigation projects are available after a natural disaster strike. Beyond that, anecdotal evidence indicates that the investments in hazard mitigation programs are lower than necessary. With that information in mind, investors may interpret that larger per capita investments in a county mean that this county is more vulnerable than others to tropical cyclone strikes. Hence, investors will sell stocks of companies exposed to tropical cyclone threats (indirect exposition). This sell will grow with investments per capita as more investments per capita

[2]distance is equal to 300 km, 500 km, 700 km, 900 km or 1000 km

are associated with larger risk, generating a negative and significant coefficient estimation. The positive coefficient estimated again can be a reduction in the discount as tropical cyclones do not strike.

In addition, when we look at the dummy variables related to being hit by a tropical cyclone (hurricane, tropical depression, or tropical storm dummies), we observe an interesting pattern: all tropical storm and hurricane coefficients are not statistically different from zero, the tropical depression exposition coefficient is significant and negative, i.e., it has a negative effect over returns of firms headquartered in a county that they hit. A possible explanation for that pattern can be associated with tropical cyclones' dynamics. As seen before, tropical cyclones become stronger when we get close to its eye. Hence, the first impacts of tropical cyclones on land are less pronounced than the impact when the eye gets closer to the coast. Thus, the tropical depression impact, even without a posterior hurricane impact, can be interpreted as a messenger to a possible worst-case scenario of future hurricane landfall. In that case, its first and less damaging land impacts are associated with the first significant and negative effects on firm returns. Thus, this dissertation confirms well-known literature findings of the short-term impacts of tropical cyclone strikes over returns.

A significant result for all hurricane range specifications is that the parameters related to project per capita are statistically non-different from zero. This result reinforces the idea of the irrelevance for investors of the project per capita variable when there is no exposition to a hazard. I.e., investors are only interested in the project per capita variable when evaluating the real risks using the informational channel is necessary.

Another result worth noting is related to the total capital outlays variable. The state and local investments per capita level variable is significant and equal to negative 0.0002 in all regressions. This result was expected as total investments are in a magnitude level of spending much higher than hazard mitigation program. That is why the project per capita coefficients are not statistically different from zero and only matter when we consider the informational channel. Here, on the other hand, as the investment level is higher than hazard mitigation federal funds, the investment by itself impacts returns. This impact can be related to a better infrastructure acquired with more significant investments.

Beyond that, some secondary results are found. First, we interact the natural disaster index constructed using WSJ news with tropical cyclones occurrence. We do not find any effects for the three stages of tropical cyclones. The idea here was to capture if the WSJ natural disaster index would be more associated with tropical cyclones during an exposition to tropical cyclones. I.e., when a disaster strikes, if the media's attention to tropical cyclones is larger, we should expect that investors would pay more attention to tropical cyclones, generating anomalies, which was not the case. Although the estimated coefficients are not significant, this result can be related to the fact that tropical cyclones are a local phenomenon and do not raise a lot of the attention of the WSJ, as seen previously. Moreover, the memory associated with past hurricanes is irrelevant until three years after the strike, when it gets too old, there is a reversal. Moreover, we capture no effects of being in the hurricane season or being in the hurricane season and with a past hurricane occurrence. Finally, a governor at the same party as the president does not seem to make any difference for alpha.

Secondly, table 5.4 is the single equation estimation by a range of our interest parameters. The results are similar to those obtained in the analyses by different ranges. It is important to highlight that the results here are by a range which can generate problems of lack of hurricanes in some ranges making the results less straightforward. Besides this fact, the results are very similar to those obtained when we consider separate range specifications.

Thus, our results show evidence that our two stories can be true. Local investors' lack of trust in hazard mitigation programs or investors in general risk perceptions can be the two ways driving these anomalies results. The conclusion for both stories, in policy terms, means that better and more robust investment by the U.S. federal government into hazard mitigation programs are necessary as investors do not see them as enough to fight hazard associated with tropical cyclones. As seen in the introduction, the U.S. government appears to agree with this story as recent changes have boosted hazard mitigation programs.

Table 5.1: Results for 300km range.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0130	-0.0129
	(0.0202)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0020	0.0020
	(0.0205)	(0.0205)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0203	0.0202
	(0.0171)	(0.0171)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0136	0.0139
	(0.0181)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0070	0.0073
	(0.0182)	(0.0182)
Tropical Cyclones Season	-0.0103	-0.0103
	(0.0189)	(0.0189)
Hurricane	-0.0256	-0.0246
	(0.0321)	(0.0319)
Tropical Depression	-0.0798*	-0.0799*
	(0.0425)	(0.0426)
Tropical Storm	-0.1152	-0.1154
	(0.1149)	(0.1149)
Project per capita*Hurricane close (300km)	-0.0115	-0.0340***
	(0.0075)	(0.0074)
Hurricane close (300km)	0.0463**	0.0514***
	(0.0189)	(0.0191)
Project per capita	0.0007	0.0003
	(0.0010)	(0.0005)
Hurricane 1 Year Ago	-0.0494	-0.0493
	(0.0435)	(0.0434)
Hurricane 2 Years Ago	-0.0719	-0.0717
	(0.0467)	(0.0466)
Hurricane 3 Years Ago	0.0006	0.0008
	(0.0341)	(0.0341)
Hurricane 4 Years Ago	0.0585***	0.0587***
	(0.0166)	(0.0166)
Hurricane 5 Years Ago	0.0721***	0.0724***
	(0.0141)	(0.0141)
Governor Party	-0.0080	-0.0081
	(0.0152)	(0.0152)
Total Cap outlays	-0.0002***	-0.0002***
	(6.56×10^{-5})	(6.56×10^{-5})
Natural disaster index*Hurricane	-1.128	-1.218
	(2.402)	(2.395)
Natural disaster index* Tropical Depression	1.907	1.907
	(2.502)	(2.504)
Natural disaster index* Tropical Storm	11.69	11.70
	(8.174)	(8.171)
Fit statistics		
Observations	606,261	606,261
R^2	0.02562	0.02556
Within R^2	0.01514	0.01507

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.2: Results for 500km and 700km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0128	-0.0127	-0.0123	-0.0122
	(0.0202)	(0.0202)	(0.0202)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0021	0.0020	0.0024	0.0024
	(0.0205)	(0.0205)	(0.0204)	(0.0204)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0182	0.0181	0.0184	0.0182
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0124	0.0124	0.0134	0.0135
	(0.0181)	(0.0181)	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0058	0.0058	0.0037	0.0037
	(0.0182)	(0.0182)	(0.0177)	(0.0177)
Tropical Cyclones Season	-0.0106	-0.0106	-0.0112	-0.0112
	(0.0189)	(0.0189)	(0.0189)	(0.0189)
Hurricane	-0.0251	-0.0241	-0.0245	-0.0236
	(0.0321)	(0.0320)	(0.0321)	(0.0320)
Tropical Depression	-0.0790*	-0.0791*	-0.0780*	-0.0781*
	(0.0425)	(0.0426)	(0.0425)	(0.0425)
Tropical Storm	-0.1141	-0.1143	-0.1135	-0.1136
	(0.1148)	(0.1148)	(0.1152)	(0.1152)
Project per capita*Hurricane close (500km)	-0.0030**	-0.0038***		
	(0.0014)	(0.0014)		
Hurricane close (500km)	0.0908***	0.0898***		
	(0.0184)	(0.0184)		
Project per capita	0.0007	0.0003	0.0007	0.0003
	(0.0010)	(0.0004)	(0.0010)	(0.0005)
Hurricane 1 Year Ago	-0.0491	-0.0491	-0.0491	-0.0490
	(0.0434)	(0.0434)	(0.0433)	(0.0432)
Hurricane 2 Years Ago	-0.0717	-0.0715	-0.0717	-0.0715
	(0.0466)	(0.0465)	(0.0465)	(0.0464)
Hurricane 3 Years Ago	0.0009	0.0010	0.0009	0.0011
	(0.0341)	(0.0340)	(0.0340)	(0.0339)
Hurricane 4 Years Ago	0.0587***	0.0589***	0.0587***	0.0590***
	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Hurricane 5 Years Ago	0.0723***	0.0726***	0.0724***	0.0727***
	(0.0141)	(0.0140)	(0.0140)	(0.0140)
Governor Party	-0.0081	-0.0082	-0.0084	-0.0085
	(0.0152)	(0.0152)	(0.0151)	(0.0151)
Total Cap outlays	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(6.56×10^{-5})	(6.56×10^{-5})	(6.54×10^{-5})	(6.55×10^{-5})
Natural disaster index*Hurricane	-1.124	-1.215	-1.116	-1.205
	(2.411)	(2.405)	(2.413)	(2.407)
Natural disaster index* Tropical Depression	1.898	1.898	1.893	1.894
	(2.504)	(2.505)	(2.506)	(2.508)
Natural disaster index* Tropical Storm	11.66	11.67	11.70	11.71
	(8.177)	(8.174)	(8.199)	(8.196)
Project per capita*Hurricane close (700km)			-0.0015**	-0.0017**
			(0.0007)	(0.0008)
Hurricane close (700km)			0.0692***	0.0688***
			(0.0207)	(0.0206)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02602	0.02595	0.02650	0.02642
Within R^2	0.01554	0.01547	0.01602	0.01594

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.3: Results for 900km and 1000km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0125	-0.0124	-0.0125	-0.0124
	(0.0203)	(0.0202)	(0.0202)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0020	0.0019	0.0021	0.0020
	(0.0206)	(0.0207)	(0.0206)	(0.0206)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0195	0.0193	0.0198	0.0196
	(0.0170)	(0.0170)	(0.0170)	(0.0170)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0138	0.0138	0.0138	0.0138
	(0.0182)	(0.0182)	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0056	0.0055	0.0054	0.0053
	(0.0180)	(0.0180)	(0.0182)	(0.0182)
Tropical Cyclones Season	-0.0110	-0.0110	-0.0110	-0.0110
	(0.0190)	(0.0190)	(0.0190)	(0.0190)
Hurricane	-0.0249	-0.0239	-0.0248	-0.0239
	(0.0322)	(0.0321)	(0.0324)	(0.0323)
Tropical Depression	-0.0787*	-0.0788*	-0.0787*	-0.0788*
	(0.0426)	(0.0426)	(0.0426)	(0.0427)
Tropical Storm	-0.1139	-0.1141	-0.1140	-0.1141
	(0.1150)	(0.1150)	(0.1150)	(0.1150)
Project per capita*Hurricane close (900km)	-0.0011	-0.0011*		
	(0.0008)	(0.0006)		
Hurricane close (900km)	0.0243	0.0240		
	(0.0300)	(0.0298)		
Project per capita	0.0007	0.0003	0.0007	0.0003
	(0.0010)	(0.0005)	(0.0010)	(0.0005)
Hurricane 1 Year Ago	-0.0493	-0.0492	-0.0492	-0.0491
	(0.0434)	(0.0434)	(0.0435)	(0.0434)
Hurricane 2 Years Ago	-0.0719	-0.0716	-0.0718	-0.0715
	(0.0466)	(0.0466)	(0.0467)	(0.0466)
Hurricane 3 Years Ago	0.0007	0.0009	0.0008	0.0010
	(0.0341)	(0.0340)	(0.0341)	(0.0340)
Hurricane 4 Years Ago	0.0584***	0.0587***	0.0585***	0.0587***
	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Hurricane 5 Years Ago	0.0722***	0.0725***	0.0722***	0.0725***
	(0.0141)	(0.0140)	(0.0141)	(0.0140)
Governor Party	-0.0082	-0.0083	-0.0082	-0.0083
	(0.0151)	(0.0152)	(0.0151)	(0.0151)
Total Cap outlays	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(6.56×10^{-5})	(6.56×10^{-5})	(6.55×10^{-5})	(6.56×10^{-5})
Natural disaster index*Hurricane	-1.123	-1.213	-1.121	-1.211
	(2.407)	(2.401)	(2.407)	(2.401)
Natural disaster index* Tropical Depression	1.901	1.901	1.906	1.906
	(2.504)	(2.505)	(2.502)	(2.504)
Natural disaster index* Tropical Storm	11.69	11.70	11.69	11.70
	(8.180)	(8.178)	(8.183)	(8.180)
Project per capita*Hurricane close (1000km)			-0.0008	-0.0009*
			(0.0006)	(0.0005)
Hurricane close (1000km)			0.0183	0.0181
			(0.0258)	(0.0257)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02584	0.02576	0.02578	0.02571
Within R^2	0.01535	0.01527	0.01530	0.01522

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.4: Regression results when considering each individual range separately.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0123	-0.0123
	(0.0202)	(0.0208)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0027	0.0025
	(0.0204)	(0.0210)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0181	0.0179
	(0.0167)	(0.0170)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0137	0.0139
	(0.0183)	(0.0183)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0045	0.0046
	(0.0178)	(0.0179)
Tropical Cyclones Season	-0.0110	-0.0110
	(0.0190)	(0.0192)
Hurricane	-0.0248	-0.0238
	(0.0323)	(0.0323)
Tropical Depression	-0.0784*	-0.0784*
	(0.0426)	(0.0430)
Tropical Storm	-0.1138	-0.1140
	(0.1153)	(0.1160)
Hurricane close (0-300km)	0.0472**	0.0524***
	(0.0188)	(0.0196)
Hurricane close (300-500km)	0.0950***	0.0945***
	(0.0186)	(0.0185)
Hurricane close (500-700km)	0.0609***	0.0606***
	(0.0225)	(0.0227)
Hurricane close (700-900km)	-0.0185	-0.0188
	(0.0354)	(0.0356)
Hurricane close (900-1000km)	0.0024	0.0024
	(0.0239)	(0.0240)
Project per capita*Hurricane close (0-300km)	-0.0112	-0.0333***
	(0.0074)	(0.0085)
Project per capita*Hurricane close (300-500km)	-0.0026**	-0.0035***
	(0.0010)	(0.0011)
Project per capita*Hurricane close (500-700km)	-0.0012**	-0.0012**
	(0.0006)	(0.0005)
Project per capita*Hurricane close (700-900km)	-0.0009	-0.0005
	(0.0012)	(0.0010)
Project per capita*Hurricane close (900-1000km)	-0.0001	-0.0002
	(0.0002)	(0.0007)
Project per capita	0.0007	0.0003
	(0.0010)	(0.0005)
Hurricane 1 Year Ago	-0.0491	-0.0490
	(0.0433)	(0.0491)
Hurricane 2 Years Ago	-0.0717	-0.0715
	(0.0465)	(0.0535)
Hurricane 3 Years Ago	0.0009	0.0011
	(0.0340)	(0.0361)
Hurricane 4 Years Ago	0.0588***	0.0590***
	(0.0166)	(0.0167)
Hurricane 5 Years Ago	0.0724***	0.0727***
	(0.0140)	(0.0140)
Governor Party	-0.0083	-0.0084
	(0.0151)	(0.0160)
Total Cap outlays	-0.0002***	-0.0002**
	(6.54×10^{-5})	(7.79×10^{-5})
Natural disaster index*Hurricane	-1.119	-1.208
	(2.414)	(2.407)
Natural disaster index* Tropical Depression	1.894	1.894
	(2.506)	(2.508)
Natural disaster index* Tropical Storm	11.70	11.71
	(8.201)	(8.198)
Fit statistics		
Observations	606,261	606,261
R^2	0.02662	0.02656
Within R^2	0.01614	0.01608

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6
Robustness

Our robustness analysis help to better understand and support the results seen in the prior section. Our analysis will focus on different ways to define the project per capita variable. Our idea here is to support the vision that the informational channel is the responsible for the existence of the anomalies. The informational channel is not limited to one story, both stories argue for the existence of an informational channel between investors' (locals or not) perceptions about the hazard mitigation programs and the market. The total mitigation column in the results section gave us a preview of the robustness results. There, when we considered all the hazard mitigation programs, the results were less precise than those in the HMGP column considering only the HMGP generated by hurricane disasters. This fact means that when we construct the variable project per capita, what type of programs are considered is essential for a precise result. Thus, the informational channel, what and how information is used, is fundamental for our analysis.

In that sense, we explore two different ways to choose programs and construct the project per capita variable here. Firstly, we consider all HMGP projects that are not related to hurricanes. This estimation is the opposite of what we have done in the results section, where we considered just the HMGP projects related to hurricanes.

Tables 6.1, 6.2, 6.3 and 6.4 show the same tables of results section with the different definition for the project per capita variable. While the total mitigation column is composed of HMGP projects unrelated to hurricanes and other hazard mitigation programs, the HMGP projects column is composed of HMGP projects unrelated to hurricanes. When we look at the results that try to answer our hypotheses, we can see that the results, in general, are not significant, fundamentally, when we look at the interaction term between project per capita and the Hurricane close (distance) variable. This result shows that when we consider HMGP projects without relation to mitigating tropical cyclones, investors do not consider this information when looking at the risk of indirect exposition to hurricanes. Thus, the evidence points to the importance of the informational channel and the investors' capacity to understand what information is important to consider.

Secondly, we consider all HMGP projects, including those related to tropical cyclones and those unrelated. Tables 6.5, 6.6, 6.7 and 6.8 show the same tables of results section with the different definition for the project per capita variable. The total mitigation column includes all total mitigation programs. Otherwise, the HMGP column includes all HMGP projects. When we look at the interaction term between hazard mitigation program and indirect exposition, the results are less clear than the original HMGP specification. However, they are clearer than the specification that does not consider HMGP projects related to tropical cyclones.

In general, the interaction term between project per capita and Hurricane close (distance) variable is significant when the Hurricane close (distance) is significant too, reinforcing that the interaction term and Hurricane close (distance) variable are complementary effects.

Finally, we make an exercise to give some evidence for local firms. As seen before, the most important characteristic of a local firm is the firm size. Smaller firms tend to be more local than larger firms. With that in mind, we find the mean and median firm value for each month and exclude the firms' observations above these measures at the specific month from the database. With the local firm database, we estimated the same model of the results section with the project per capita, considering just the HMGP projects associated with hurricanes. Tables 6.9, 6.10, 6.11 and 6.12 show the results of this exercise. We can observe that the results in most ranges stay the same in signal and size terms, though some results are not significant (range 900km and 1000km). Thus, the exercise shows us that when we do a simple exercise to capture local firms better, the results stay the same, indicating possible importance for local investors in our analysis.

Thus, the robustness section improves the understanding of our results. Firstly, the results support the information channel. When we consider different project specifications, different results arise depending on how valuable the projects are to mitigate the impacts of tropical cyclones. Therefore, we can conclude that investors use information to formulate perceptions. I.e., they can split between useful and useless information. Secondly, to give some evidence for our local investors' hypothesis, our local firm specification shows us that when we restrict the database to firms with more local influence (small market value), the results are still present, which indicates that local investor's story is a possible important path to consider.

Table 6.1: Results for 300km range.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0128	-0.0128
	(0.0203)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0019	0.0020
	(0.0206)	(0.0206)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0203	0.0203
	(0.0171)	(0.0171)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0137	0.0136
	(0.0181)	(0.0181)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0068	0.0067
	(0.0182)	(0.0182)
Tropical Cyclones Season	-0.0103	-0.0103
	(0.0189)	(0.0189)
Hurricane	-0.0242	-0.0241
	(0.0320)	(0.0320)
Tropical Depression	-0.0799*	-0.0799*
	(0.0426)	(0.0426)
Tropical Storm	-0.1152	-0.1156
	(0.1150)	(0.1148)
Project per capita*Hurricane close (300km)	-0.0047	-0.0391
	(0.0095)	(0.0456)
Hurricane close (300km)	0.0234	0.0147
	(0.0159)	(0.0424)
Project per capita	0.0002	-0.0002
	(0.0012)	(0.0012)
Hurricane 1 Year Ago	-0.0494	-0.0493
	(0.0434)	(0.0434)
Hurricane 2 Years Ago	-0.0719	-0.0716
	(0.0465)	(0.0465)
Hurricane 3 Years Ago	0.0001	0.0012
	(0.0340)	(0.0344)
Hurricane 4 Years Ago	0.0582***	0.0591***
	(0.0169)	(0.0170)
Hurricane 5 Years Ago	0.0719***	0.0728***
	(0.0143)	(0.0144)
Governor Party	-0.0082	-0.0081
	(0.0151)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**
	(6.82×10^{-5})	(6.77×10^{-5})
Natural disaster index*Hurricane	-1.283	-1.275
	(2.392)	(2.393)
Natural disaster index* Tropical Depression	1.911	1.901
	(2.504)	(2.502)
Natural disaster index* Tropical Storm	11.70	11.70
	(8.175)	(8.166)
Fit statistics		
Observations	606,261	606,261
R^2	0.02556	0.02555
Within R^2	0.01507	0.01506

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.2: Results for 500km and 700km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0126	-0.0126	-0.0122	-0.0122
	(0.0202)	(0.0202)	(0.0203)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0018	0.0020	0.0023	0.0024
	(0.0206)	(0.0205)	(0.0205)	(0.0204)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0179	0.0179	0.0183	0.0181
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0122	0.0122	0.0134	0.0131
	(0.0181)	(0.0181)	(0.0182)	(0.0181)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0057	0.0057	0.0047	0.0057
	(0.0182)	(0.0182)	(0.0180)	(0.0181)
Tropical Cyclones Season	-0.0106	-0.0106	-0.0113	-0.0112
	(0.0189)	(0.0189)	(0.0189)	(0.0189)
Hurricane	-0.0236	-0.0236	-0.0230	-0.0229
	(0.0321)	(0.0320)	(0.0321)	(0.0320)
Tropical Depression	-0.0790*	-0.0791*	-0.0780*	-0.0780*
	(0.0427)	(0.0426)	(0.0426)	(0.0426)
Tropical Storm	-0.1141	-0.1145	-0.1134	-0.1137
	(0.1149)	(0.1147)	(0.1153)	(0.1151)
Project per capita*Hurricane close (500km)	-5.29×10^{-5}	-0.0015		
	(0.0017)	(0.0033)		
Hurricane close (500km)	0.0870***	0.0874***		
	(0.0202)	(0.0196)		
Project per capita	0.0002	-0.0002	0.0002	-0.0001
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Hurricane 1 Year Ago	-0.0491	-0.0490	-0.0491	-0.0490
	(0.0433)	(0.0433)	(0.0432)	(0.0432)
Hurricane 2 Years Ago	-0.0717	-0.0714	-0.0717	-0.0713
	(0.0465)	(0.0465)	(0.0464)	(0.0464)
Hurricane 3 Years Ago	0.0004	0.0015	0.0004	0.0015
	(0.0340)	(0.0343)	(0.0339)	(0.0342)
Hurricane 4 Years Ago	0.0585***	0.0594***	0.0585***	0.0594***
	(0.0169)	(0.0170)	(0.0169)	(0.0170)
Hurricane 5 Years Ago	0.0722***	0.0731***	0.0723***	0.0732***
	(0.0143)	(0.0143)	(0.0142)	(0.0143)
Governor Party	-0.0083	-0.0082	-0.0086	-0.0084
	(0.0151)	(0.0151)	(0.0150)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(6.82×10^{-5})	(6.77×10^{-5})	(6.81×10^{-5})	(6.76×10^{-5})
Natural disaster index*Hurricane	-1.280	-1.272	-1.274	-1.266
	(2.401)	(2.402)	(2.404)	(2.405)
Natural disaster index* Tropical Depression	1.901	1.891	1.895	1.885
	(2.506)	(2.503)	(2.508)	(2.505)
Natural disaster index* Tropical Storm	11.68	11.67	11.71	11.71
	(8.176)	(8.168)	(8.200)	(8.192)
Project per capita*Hurricane close (700km)			-0.0022	-0.0042**
			(0.0024)	(0.0019)
Hurricane close (700km)			0.0707***	0.0707***
			(0.0217)	(0.0212)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02595	0.02593	0.02644	0.02643
Within R^2	0.01546	0.01545	0.01596	0.01595

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.3: Results for 900km and 1000km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0125	-0.0125	-0.0125	-0.0125
	(0.0203)	(0.0202)	(0.0203)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0017	0.0019	0.0017	0.0020
	(0.0207)	(0.0207)	(0.0207)	(0.0207)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0192	0.0192	0.0195	0.0194
	(0.0170)	(0.0171)	(0.0170)	(0.0170)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0138	0.0138	0.0138	0.0138
	(0.0182)	(0.0182)	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0052	0.0051	0.0050	0.0049
	(0.0179)	(0.0179)	(0.0181)	(0.0181)
Tropical Cyclones Season	-0.0110	-0.0110	-0.0110	-0.0110
	(0.0190)	(0.0190)	(0.0190)	(0.0190)
Hurricane	-0.0234	-0.0234	-0.0233	-0.0233
	(0.0322)	(0.0321)	(0.0323)	(0.0323)
Tropical Depression	-0.0787*	-0.0788*	-0.0788*	-0.0788*
	(0.0427)	(0.0427)	(0.0428)	(0.0427)
Tropical Storm	-0.1139	-0.1143	-0.1140	-0.1144
	(0.1151)	(0.1149)	(0.1151)	(0.1149)
Project per capita*Hurricane close (900km)	0.0003	0.0006		
	(0.0012)	(0.0012)		
Hurricane close (900km)	0.0230	0.0228		
	(0.0311)	(0.0306)		
Project per capita	0.0002	-0.0002	0.0002	-0.0002
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Hurricane 1 Year Ago	-0.0493	-0.0492	-0.0492	-0.0491
	(0.0434)	(0.0433)	(0.0434)	(0.0433)
Hurricane 2 Years Ago	-0.0718	-0.0715	-0.0717	-0.0714
	(0.0465)	(0.0465)	(0.0465)	(0.0465)
Hurricane 3 Years Ago	0.0003	0.0014	0.0004	0.0015
	(0.0340)	(0.0343)	(0.0340)	(0.0344)
Hurricane 4 Years Ago	0.0583***	0.0592***	0.0583***	0.0592***
	(0.0169)	(0.0170)	(0.0169)	(0.0170)
Hurricane 5 Years Ago	0.0721***	0.0730***	0.0722***	0.0731***
	(0.0143)	(0.0143)	(0.0143)	(0.0144)
Governor Party	-0.0083	-0.0082	-0.0083	-0.0082
	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(6.82×10^{-5})	(6.76×10^{-5})	(6.81×10^{-5})	(6.75×10^{-5})
Natural disaster index*Hurricane	-1.277	-1.268	-1.276	-1.267
	(2.398)	(2.399)	(2.399)	(2.400)
Natural disaster index* Tropical Depression	1.904	1.894	1.908	1.898
	(2.506)	(2.503)	(2.504)	(2.502)
Natural disaster index* Tropical Storm	11.70	11.70	11.70	11.70
	(8.179)	(8.170)	(8.180)	(8.171)
Project per capita*Hurricane close (1000km)			0.0004	0.0006
			(0.0011)	(0.0011)
Hurricane close (1000km)			0.0168	0.0167
			(0.0269)	(0.0266)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02577	0.02576	0.02572	0.02572
Within R^2	0.01528	0.01527	0.01523	0.01523

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.4: Regression results when considering each individual range separately.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0122	-0.0122
	(0.0202)	(0.0201)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0023	0.0026
	(0.0205)	(0.0204)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0176	0.0178
	(0.0167)	(0.0168)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0133	0.0132
	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0057	0.0065
	(0.0182)	(0.0184)
Tropical Cyclones Season	-0.0110	-0.0110
	(0.0190)	(0.0190)
Hurricane	-0.0232	-0.0232
	(0.0323)	(0.0323)
Tropical Depression	-0.0784*	-0.0785*
	(0.0428)	(0.0427)
Tropical Storm	-0.1138	-0.1141
	(0.1154)	(0.1152)
Hurricane close (0-300km)	0.0247	0.0162
	(0.0163)	(0.0426)
Hurricane close (300-500km)	0.0911***	0.0925***
	(0.0201)	(0.0194)
Hurricane close (500-700km)	0.0637***	0.0635***
	(0.0239)	(0.0235)
Hurricane close (700-900km)	-0.0225	-0.0226
	(0.0354)	(0.0352)
Hurricane close (900-1000km)	-0.0001	-0.0002
	(0.0253)	(0.0251)
Project per capita*Hurricane close (0-300km)	-0.0046	-0.0391
	(0.0093)	(0.0452)
Project per capita*Hurricane close (300-500km)	0.0008	-0.0016
	(0.0013)	(0.0034)
Project per capita*Hurricane close (500-700km)	-0.0029	-0.0044**
	(0.0024)	(0.0019)
Project per capita*Hurricane close (700-900km)	0.0013	0.0017
	(0.0012)	(0.0012)
Project per capita*Hurricane close (900-1000km)	0.0006	0.0009
	(0.0011)	(0.0011)
Project per capita	0.0002	-0.0002
	(0.0012)	(0.0012)
Hurricane 1 Year Ago	-0.0491	-0.0489
	(0.0432)	(0.0432)
Hurricane 2 Years Ago	-0.0716	-0.0713
	(0.0463)	(0.0463)
Hurricane 3 Years Ago	0.0005	0.0017
	(0.0339)	(0.0343)
Hurricane 4 Years Ago	0.0586***	0.0596***
	(0.0169)	(0.0170)
Hurricane 5 Years Ago	0.0724***	0.0733***
	(0.0143)	(0.0143)
Governor Party	-0.0085	-0.0084
	(0.0150)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**
	(6.8×10^{-5})	(6.74×10^{-5})
Natural disaster index*Hurricane	-1.276	-1.265
	(2.405)	(2.406)
Natural disaster index* Tropical Depression	1.895	1.885
	(2.508)	(2.504)
Natural disaster index* Tropical Storm	11.71	11.71
	(8.202)	(8.194)
Fit statistics		
Observations	606,261	606,261
R^2	0.02660	0.02661
Within R^2	0.01612	0.01614

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.5: Results for 300km range.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0129	-0.0129
	(0.0203)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0019	0.0020
	(0.0205)	(0.0206)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0203	0.0202
	(0.0171)	(0.0171)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0137	0.0140
	(0.0181)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0070	0.0073
	(0.0182)	(0.0182)
Tropical Cyclones Season	-0.0103	-0.0103
	(0.0189)	(0.0189)
Hurricane	-0.0248	-0.0241
	(0.0321)	(0.0320)
Tropical Depression	-0.0798*	-0.0799*
	(0.0426)	(0.0426)
Tropical Storm	-0.1152	-0.1155
	(0.1150)	(0.1149)
Project per capita*Hurricane close (300km)	-0.0087*	-0.0259***
	(0.0051)	(0.0054)
Hurricane close (300km)	0.0503**	0.0581***
	(0.0193)	(0.0198)
Project per capita	0.0002	-1.93×10^{-5}
	(0.0009)	(0.0009)
Hurricane 1 Year Ago	-0.0493	-0.0493
	(0.0435)	(0.0434)
Hurricane 2 Years Ago	-0.0719	-0.0717
	(0.0466)	(0.0466)
Hurricane 3 Years Ago	6.28×10^{-5}	0.0008
	(0.0338)	(0.0341)
Hurricane 4 Years Ago	0.0580***	0.0588***
	(0.0168)	(0.0168)
Hurricane 5 Years Ago	0.0717***	0.0725***
	(0.0142)	(0.0142)
Governor Party	-0.0081	-0.0081
	(0.0151)	(0.0152)
Total Cap outlays	-0.0002**	-0.0002**
	(6.77×10^{-5})	(6.72×10^{-5})
Natural disaster index*Hurricane	-1.214	-1.285
	(2.402)	(2.403)
Natural disaster index* Tropical Depression	1.914	1.904
	(2.502)	(2.502)
Natural disaster index* Tropical Storm	11.70	11.70
	(8.176)	(8.170)
Fit statistics		
Observations	606,261	606,261
R^2	0.02559	0.02554
Within R^2	0.01510	0.01505

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.6: Results for 500km and 700km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0127	-0.0126	-0.0122	-0.0122
	(0.0202)	(0.0202)	(0.0202)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0019	0.0019	0.0023	0.0023
	(0.0205)	(0.0205)	(0.0204)	(0.0205)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0182	0.0181	0.0184	0.0182
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0124	0.0124	0.0135	0.0135
	(0.0181)	(0.0181)	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0058	0.0057	0.0045	0.0045
	(0.0182)	(0.0182)	(0.0178)	(0.0178)
Tropical Cyclones Season	-0.0106	-0.0106	-0.0113	-0.0112
	(0.0189)	(0.0189)	(0.0189)	(0.0189)
Hurricane	-0.0243	-0.0236	-0.0237	-0.0230
	(0.0321)	(0.0321)	(0.0321)	(0.0321)
Tropical Depression	-0.0790*	-0.0791*	-0.0780*	-0.0781*
	(0.0426)	(0.0426)	(0.0426)	(0.0426)
Tropical Storm	-0.1140	-0.1143	-0.1133	-0.1136
	(0.1149)	(0.1148)	(0.1153)	(0.1152)
Project per capita*Hurricane close (500km)	-0.0020**	-0.0023***		
	(0.0008)	(0.0008)		
Hurricane close (500km)	0.0913***	0.0904***		
	(0.0184)	(0.0185)		
Project per capita	0.0002	-1.83×10^{-5}	0.0003	1.28×10^{-6}
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Hurricane 1 Year Ago	-0.0491	-0.0491	-0.0491	-0.0491
	(0.0434)	(0.0434)	(0.0433)	(0.0432)
Hurricane 2 Years Ago	-0.0717	-0.0715	-0.0717	-0.0715
	(0.0465)	(0.0465)	(0.0464)	(0.0464)
Hurricane 3 Years Ago	0.0003	0.0010	0.0002	0.0010
	(0.0338)	(0.0340)	(0.0337)	(0.0339)
Hurricane 4 Years Ago	0.0583***	0.0590***	0.0583***	0.0590***
	(0.0167)	(0.0168)	(0.0167)	(0.0168)
Hurricane 5 Years Ago	0.0720***	0.0728***	0.0720***	0.0728***
	(0.0141)	(0.0142)	(0.0141)	(0.0141)
Governor Party	-0.0082	-0.0082	-0.0085	-0.0085
	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(6.77×10^{-5})	(6.72×10^{-5})	(6.76×10^{-5})	(6.71×10^{-5})
Natural disaster index*Hurricane	-1.209	-1.280	-1.200	-1.271
	(2.411)	(2.412)	(2.414)	(2.415)
Natural disaster index* Tropical Depression	1.905	1.895	1.900	1.891
	(2.504)	(2.503)	(2.506)	(2.506)
Natural disaster index* Tropical Storm	11.68	11.67	11.72	11.71
	(8.179)	(8.173)	(8.202)	(8.196)
Project per capita*Hurricane close (700km)			-0.0015*	-0.0016*
			(0.0009)	(0.0010)
Hurricane close (700km)			0.0709***	0.0702***
			(0.0211)	(0.0210)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02599	0.02594	0.02648	0.02642
Within R^2	0.01550	0.01545	0.01600	0.01594

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.7: Results for 900km and 1000km ranges.

Dependent Variable:	Excess return alpha			
Model:	Total Mitigation	HMGP	Total Mitigation	HMGP
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0125	-0.0125	-0.0125	-0.0125
	(0.0203)	(0.0203)	(0.0203)	(0.0203)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0017	0.0018	0.0018	0.0019
	(0.0207)	(0.0207)	(0.0207)	(0.0207)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0193	0.0192	0.0195	0.0194
	(0.0170)	(0.0170)	(0.0169)	(0.0170)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0137	0.0137	0.0138	0.0138
	(0.0182)	(0.0182)	(0.0182)	(0.0182)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0055	0.0054	0.0051	0.0050
	(0.0180)	(0.0180)	(0.0181)	(0.0181)
Tropical Cyclones Season	-0.0110	-0.0110	-0.0110	-0.0110
	(0.0190)	(0.0190)	(0.0190)	(0.0190)
Hurricane	-0.0240	-0.0233	-0.0239	-0.0232
	(0.0322)	(0.0322)	(0.0323)	(0.0323)
Tropical Depression	-0.0787*	-0.0788*	-0.0788*	-0.0788*
	(0.0427)	(0.0427)	(0.0427)	(0.0427)
Tropical Storm	-0.1139	-0.1142	-0.1139	-0.1142
	(0.1151)	(0.1149)	(0.1151)	(0.1149)
Project per capita*Hurricane close (900km)	-0.0002	-6.83×10^{-5}		
	(0.0007)	(0.0007)		
Hurricane close (900km)	0.0240	0.0238		
	(0.0308)	(0.0305)		
Project per capita	0.0002	-1.99×10^{-5}	0.0002	-2.97×10^{-5}
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Hurricane 1 Year Ago	-0.0492	-0.0492	-0.0491	-0.0491
	(0.0434)	(0.0434)	(0.0434)	(0.0434)
Hurricane 2 Years Ago	-0.0718	-0.0716	-0.0717	-0.0715
	(0.0465)	(0.0465)	(0.0465)	(0.0465)
Hurricane 3 Years Ago	0.0002	0.0010	0.0003	0.0011
	(0.0338)	(0.0340)	(0.0338)	(0.0341)
Hurricane 4 Years Ago	0.0581***	0.0588***	0.0582***	0.0589***
	(0.0167)	(0.0168)	(0.0168)	(0.0168)
Hurricane 5 Years Ago	0.0719***	0.0727***	0.0719***	0.0728***
	(0.0142)	(0.0142)	(0.0142)	(0.0142)
Governor Party	-0.0083	-0.0083	-0.0083	-0.0083
	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(6.76×10^{-5})	(6.72×10^{-5})	(6.76×10^{-5})	(6.71×10^{-5})
Natural disaster index*Hurricane	-1.208	-1.279	-1.209	-1.280
	(2.408)	(2.409)	(2.409)	(2.410)
Natural disaster index* Tropical Depression	1.907	1.898	1.911	1.902
	(2.503)	(2.503)	(2.502)	(2.502)
Natural disaster index* Tropical Storm	11.70	11.70	11.70	11.70
	(8.181)	(8.174)	(8.182)	(8.175)
Project per capita*Hurricane close (1000km)			1.76×10^{-5}	0.0001
			(0.0006)	(0.0006)
Hurricane close (1000km)			0.0176	0.0175
			(0.0267)	(0.0265)
Fit statistics				
Observations	606,261	606,261	606,261	606,261
R^2	0.02579	0.02574	0.02574	0.02569
Within R^2	0.01530	0.01525	0.01525	0.01520

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.8: Regression results when considering each individual range separately.

Dependent Variable:	Excess return alpha	
Model:	Total Mitigation	HMGP
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0124	-0.0124
	(0.0202)	(0.0202)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0023	0.0024
	(0.0204)	(0.0204)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0178	0.0177
	(0.0167)	(0.0168)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0137	0.0139
	(0.0182)	(0.0183)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0050	0.0053
	(0.0179)	(0.0179)
Tropical Cyclones Season	-0.0110	-0.0110
	(0.0190)	(0.0190)
Hurricane	-0.0239	-0.0232
	(0.0323)	(0.0323)
Tropical Depression	-0.0784*	-0.0785*
	(0.0427)	(0.0427)
Tropical Storm	-0.1137	-0.1140
	(0.1154)	(0.1152)
Hurricane close (0-300km)	0.0512***	0.0590***
	(0.0192)	(0.0198)
Hurricane close (300-500km)	0.0955***	0.0951***
	(0.0187)	(0.0185)
Hurricane close (500-700km)	0.0626***	0.0620***
	(0.0232)	(0.0231)
Hurricane close (700-900km)	-0.0218	-0.0218
	(0.0355)	(0.0353)
Hurricane close (900-1000km)	0.0003	0.0004
	(0.0247)	(0.0246)
Project per capita*Hurricane close (0-300km)	-0.0086*	-0.0254***
	(0.0050)	(0.0053)
Project per capita*Hurricane close (300-500km)	-0.0017***	-0.0022***
	(0.0006)	(0.0006)
Project per capita*Hurricane close (500-700km)	-0.0013	-0.0014
	(0.0011)	(0.0012)
Project per capita*Hurricane close (700-900km)	0.0009	0.0011
	(0.0008)	(0.0008)
Project per capita*Hurricane close (900-1000km)	0.0004	0.0006
	(0.0006)	(0.0005)
Project per capita	0.0002	-2.45×10^{-5}
	(0.0009)	(0.0009)
Hurricane 1 Year Ago	-0.0491	-0.0490
	(0.0432)	(0.0432)
Hurricane 2 Years Ago	-0.0716	-0.0714
	(0.0464)	(0.0464)
Hurricane 3 Years Ago	0.0004	0.0012
	(0.0337)	(0.0339)
Hurricane 4 Years Ago	0.0584***	0.0592***
	(0.0167)	(0.0168)
Hurricane 5 Years Ago	0.0721***	0.0729***
	(0.0141)	(0.0142)
Governor Party	-0.0085	-0.0085
	(0.0151)	(0.0151)
Total Cap outlays	-0.0002**	-0.0002**
	(6.74×10^{-5})	(6.7×10^{-5})
Natural disaster index*Hurricane	-1.201	-1.272
	(2.414)	(2.414)
Natural disaster index* Tropical Depression	1.901	1.890
	(2.506)	(2.506)
Natural disaster index* Tropical Storm	11.72	11.71
	(8.202)	(8.195)
Fit statistics		
Observations	606,261	606,261
R^2	0.02662	0.02659
Within R^2	0.01614	0.01611

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.9: Results for 300km range - Local Firms.

Dependent Variable:	valor.residuals	
Model:	(Mean)	(Median)
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0114	-0.0093
	(0.0171)	(0.0173)
Tropical Cyclones Season*Hurricane 2 Years Ago	-0.0001	-0.0008
	(0.0188)	(0.0190)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0196	0.0201
	(0.0174)	(0.0177)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0191	0.0182
	(0.0186)	(0.0185)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0075	0.0071
	(0.0181)	(0.0180)
Tropical Cyclones Season	-0.0143	-0.0144
	(0.0177)	(0.0174)
Hurricane	-0.0428	-0.0421
	(0.0438)	(0.0425)
Tropical Depression	-0.0922**	-0.0922**
	(0.0437)	(0.0442)
Tropical Storm	-0.1269	-0.1323
	(0.1120)	(0.1099)
Project per capita*Hurricane close (300km)	-0.0363***	-0.0358***
	(0.0082)	(0.0080)
Hurricane close (300km)	0.0550*	0.0549**
	(0.0279)	(0.0276)
Project per capita	3.69×10^{-6}	-8.03×10^{-6}
	(0.0002)	(0.0002)
Hurricane 1 Year Ago	-0.0559	-0.0559
	(0.0391)	(0.0392)
Hurricane 2 Years Ago	-0.0780*	-0.0770*
	(0.0401)	(0.0400)
Hurricane 3 Years Ago	-0.0077	-0.0074
	(0.0284)	(0.0289)
Hurricane 4 Years Ago	0.0509***	0.0511***
	(0.0153)	(0.0153)
Hurricane 5 Years Ago	0.0716***	0.0707***
	(0.0140)	(0.0138)
Governor Party	-0.0077	-0.0080
	(0.0140)	(0.0137)
Total Cap outlays	-0.0002***	-0.0002***
	(6.36×10^{-5})	(6.27×10^{-5})
Natural disaster index*Hurricane	0.1505	0.1445
	(4.027)	(3.978)
Natural disaster index* Tropical Depression	2.784	2.797
	(3.080)	(3.166)
Natural disaster index* Tropical Storm	11.83	12.32
	(7.853)	(7.686)
Fit statistics		
Observations	308,492	301,614
R^2	0.04152	0.04190
Within R^2	0.01245	0.01228

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.10: Results for 500km and 700km ranges - Local Firms.

Dependent Variable:	valor.residuals			
Model:	(Mean)	(Median)	(Mean)	(Median)
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0111	-0.0091	-0.0107	-0.0087
	(0.0169)	(0.0172)	(0.0171)	(0.0173)
Tropical Cyclones Season*Hurricane 2 Years Ago	-8.39×10^{-5}	-0.0008	0.0002	-0.0005
	(0.0188)	(0.0190)	(0.0188)	(0.0190)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0172	0.0179	0.0175	0.0180
	(0.0173)	(0.0176)	(0.0173)	(0.0175)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0177	0.0167	0.0186	0.0176
	(0.0186)	(0.0185)	(0.0186)	(0.0185)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0056	0.0053	0.0042	0.0038
	(0.0180)	(0.0179)	(0.0175)	(0.0174)
Tropical Cyclones Season	-0.0146	-0.0147	-0.0152	-0.0153
	(0.0177)	(0.0174)	(0.0178)	(0.0175)
Hurricane	-0.0425	-0.0417	-0.0419	-0.0411
	(0.0439)	(0.0426)	(0.0439)	(0.0426)
Tropical Depression	-0.0914**	-0.0914**	-0.0906**	-0.0906**
	(0.0437)	(0.0442)	(0.0437)	(0.0442)
Tropical Storm	-0.1257	-0.1312	-0.1252	-0.1308
	(0.1119)	(0.1099)	(0.1123)	(0.1102)
Project per capita*Hurricane close (500km)	-0.0057***	-0.0059***		
	(0.0016)	(0.0017)		
Hurricane close (500km)	0.0954***	0.0922***		
	(0.0229)	(0.0232)		
Project per capita	1.92×10^{-6}	-9.5×10^{-6}	2.88×10^{-5}	1.76×10^{-5}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Hurricane 1 Year Ago	-0.0558	-0.0558	-0.0557	-0.0557
	(0.0390)	(0.0392)	(0.0389)	(0.0390)
Hurricane 2 Years Ago	-0.0779*	-0.0768*	-0.0779*	-0.0768*
	(0.0401)	(0.0400)	(0.0400)	(0.0399)
Hurricane 3 Years Ago	-0.0074	-0.0072	-0.0074	-0.0071
	(0.0284)	(0.0288)	(0.0284)	(0.0288)
Hurricane 4 Years Ago	0.0511***	0.0512***	0.0513***	0.0514***
	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Hurricane 5 Years Ago	0.0718***	0.0709***	0.0720***	0.0711***
	(0.0140)	(0.0138)	(0.0140)	(0.0138)
Governor Party	-0.0079	-0.0081	-0.0081	-0.0083
	(0.0139)	(0.0137)	(0.0139)	(0.0137)
Total Cap outlays	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(6.36×10^{-5})	(6.26×10^{-5})	(6.35×10^{-5})	(6.26×10^{-5})
Natural disaster index*Hurricane	0.1651	0.1580	0.1716	0.1657
	(4.041)	(3.991)	(4.048)	(3.999)
Natural disaster index* Tropical Depression	2.776	2.790	2.775	2.789
	(3.083)	(3.170)	(3.087)	(3.173)
Natural disaster index* Tropical Storm	11.81	12.30	11.85	12.34
	(7.858)	(7.691)	(7.879)	(7.711)
Project per capita*Hurricane close (700km)			-0.0015*	-0.0015*
			(0.0008)	(0.0008)
Hurricane close (700km)			0.0643***	0.0622***
			(0.0236)	(0.0234)
Fit statistics				
Observations	308,492	301,614	308,492	301,614
R^2	0.04193	0.04229	0.04217	0.04251
Within R^2	0.01287	0.01268	0.01312	0.01291

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.11: Results for 900km and 1000km ranges - Local Firms.

Dependent Variable:	valor.residuals			
Model:	(Mean)	(Median)	(Mean)	(Median)
Variables				
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0109	-0.0088	-0.0109	-0.0089
	(0.0171)	(0.0174)	(0.0171)	(0.0174)
Tropical Cyclones Season*Hurricane 2 Years Ago	-0.0003	-0.0010	-0.0002	-0.0009
	(0.0190)	(0.0192)	(0.0189)	(0.0191)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0188	0.0193	0.0191	0.0196
	(0.0174)	(0.0177)	(0.0174)	(0.0177)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0189	0.0180	0.0190	0.0180
	(0.0186)	(0.0185)	(0.0186)	(0.0185)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0060	0.0056	0.0059	0.0055
	(0.0178)	(0.0177)	(0.0180)	(0.0179)
Tropical Cyclones Season	-0.0149	-0.0150	-0.0148	-0.0149
	(0.0178)	(0.0175)	(0.0178)	(0.0175)
Hurricane	-0.0423	-0.0415	-0.0423	-0.0416
	(0.0439)	(0.0427)	(0.0440)	(0.0428)
Tropical Depression	-0.0913**	-0.0913**	-0.0915**	-0.0915**
	(0.0438)	(0.0443)	(0.0438)	(0.0443)
Tropical Storm	-0.1257	-0.1313	-0.1259	-0.1314
	(0.1121)	(0.1100)	(0.1120)	(0.1099)
Project per capita*Hurricane close (900km)	-0.0010*	-0.0012		
	(0.0006)	(0.0007)		
Hurricane close (900km)	0.0206	0.0197		
	(0.0289)	(0.0285)		
Project per capita	2.1×10^{-5}	1.28×10^{-5}	1.41×10^{-5}	5.31×10^{-6}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Hurricane 1 Year Ago	-0.0559	-0.0558	-0.0558	-0.0558
	(0.0390)	(0.0392)	(0.0391)	(0.0392)
Hurricane 2 Years Ago	-0.0780*	-0.0769*	-0.0779*	-0.0769*
	(0.0401)	(0.0400)	(0.0401)	(0.0400)
Hurricane 3 Years Ago	-0.0076	-0.0073	-0.0076	-0.0073
	(0.0284)	(0.0288)	(0.0284)	(0.0289)
Hurricane 4 Years Ago	0.0509***	0.0511***	0.0510***	0.0511***
	(0.0153)	(0.0153)	(0.0153)	(0.0153)
Hurricane 5 Years Ago	0.0717***	0.0708***	0.0717***	0.0708***
	(0.0140)	(0.0138)	(0.0140)	(0.0138)
Governor Party	-0.0079	-0.0081	-0.0078	-0.0081
	(0.0139)	(0.0137)	(0.0139)	(0.0137)
Total Cap outlays	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(6.36×10^{-5})	(6.26×10^{-5})	(6.35×10^{-5})	(6.26×10^{-5})
Natural disaster index*Hurricane	0.1623	0.1569	0.1633	0.1574
	(4.034)	(3.985)	(4.033)	(3.984)
Natural disaster index* Tropical Depression	2.780	2.794	2.783	2.797
	(3.082)	(3.169)	(3.081)	(3.168)
Natural disaster index* Tropical Storm	11.83	12.32	11.83	12.32
	(7.860)	(7.691)	(7.860)	(7.691)
Project per capita*Hurricane close (1000km)			-0.0005	-0.0007
			(0.0005)	(0.0005)
Hurricane close (1000km)			0.0133	0.0128
			(0.0250)	(0.0246)
Fit statistics				
Observations	308,492	301,614	308,492	301,614
R^2	0.04165	0.04202	0.04159	0.04196
Within R^2	0.01258	0.01240	0.01252	0.01234

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.12: Regression results when considering each individual range separately - Local Firms.

Dependent Variable:	valor.residuals	
Model:	(Mean)	(Median)
Variables		
Tropical Cyclones Season*Hurricane 1 Year Ago	-0.0109	-0.0088
	(0.0170)	(0.0172)
Tropical Cyclones Season*Hurricane 2 Years Ago	0.0004	-0.0003
	(0.0187)	(0.0189)
Tropical Cyclones Season*Hurricane 3 Years Ago	0.0170	0.0176
	(0.0173)	(0.0175)
Tropical Cyclones Season*Hurricane 4 Years Ago	0.0190	0.0181
	(0.0187)	(0.0186)
Tropical Cyclones Season*Hurricane 5 Years Ago	0.0053	0.0050
	(0.0177)	(0.0176)
Tropical Cyclones Season	-0.0148	-0.0149
	(0.0178)	(0.0175)
Hurricane	-0.0424	-0.0416
	(0.0441)	(0.0428)
Tropical Depression	-0.0911**	-0.0911**
	(0.0439)	(0.0443)
Tropical Storm	-0.1258	-0.1313
	(0.1122)	(0.1102)
Hurricane close (0-300km)	0.0557**	0.0556**
	(0.0278)	(0.0276)
Hurricane close (300-500km)	0.0996***	0.0962***
	(0.0240)	(0.0244)
Hurricane close (500-700km)	0.0518**	0.0502**
	(0.0239)	(0.0234)
Hurricane close (700-900km)	-0.0217	-0.0214
	(0.0314)	(0.0313)
Hurricane close (900-1000km)	-0.0062	-0.0058
	(0.0224)	(0.0217)
Project per capita*Hurricane close (0-300km)	-0.0357***	-0.0353***
	(0.0081)	(0.0079)
Project per capita*Hurricane close (300-500km)	-0.0055***	-0.0056***
	(0.0014)	(0.0015)
Project per capita*Hurricane close (500-700km)	-0.0009***	-0.0009***
	(0.0002)	(0.0002)
Project per capita*Hurricane close (700-900km)	-0.0002	-0.0008
	(0.0010)	(0.0010)
Project per capita*Hurricane close (900-1000km)	0.0010***	0.0009***
	(0.0003)	(0.0003)
Project per capita	1.75×10^{-5}	6.1×10^{-6}
	(0.0002)	(0.0002)
Hurricane 1 Year Ago	-0.0558	-0.0558
	(0.0389)	(0.0390)
Hurricane 2 Years Ago	-0.0779*	-0.0769*
	(0.0399)	(0.0398)
Hurricane 3 Years Ago	-0.0074	-0.0072
	(0.0283)	(0.0288)
Hurricane 4 Years Ago	0.0513***	0.0514***
	(0.0153)	(0.0153)
Hurricane 5 Years Ago	0.0719***	0.0710***
	(0.0140)	(0.0138)
Governor Party	-0.0081	-0.0083
	(0.0139)	(0.0137)
Total Cap outlays	-0.0002***	-0.0002***
	(6.35×10^{-5})	(6.26×10^{-5})
Natural disaster index*Hurricane	0.1683	0.1609
	(4.046)	(3.998)
Natural disaster index* Tropical Depression	2.772	2.786
	(3.087)	(3.173)
Natural disaster index* Tropical Storm	11.84	12.34
	(7.875)	(7.709)
Fit statistics		
Observations	308,492	301,614
R^2	0.04235	0.04269
Within R^2	0.01331	0.01309

Note: All models are fixed effects estimates controlling for county-level and stock-level fixed effects.
Robust standard errors are clustered at the county and year/month levels.
Numbers between parentheses are the coefficient standard deviations.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

7
Conclusions

My dissertation may contribute to the climate finance literature. Our contributions emphasize the tropical cyclones' capacity to generate uncertainty, as Kruttli et al., 2021 shows, to firms' operations and market prices. In the future, with a warmer world, this uncertainty could grow, making it even more important to investors, in general, to take into account this risk. For example, one of the most debated aspects of climate change is the sea level rise, Hauer et al., 2016 discuss this aspect for the U.S. Tropical cyclones are formed and sustained in warm waters and dissipate when they move over land or cooler waters. Thus, with the sea level rise, the hurricanes could reach more often interior counties that nowadays are not significantly affected by them. Another important climate finance aspect that we studied is the perceived efficacy of hazard mitigation projects that are getting much more attention recently and will in the future when mitigating natural disaster effects will be much more crucial.

We showed evidence of the presence of anomalies. Firstly, there is evidence that hurricane strike risk generates anomalies in returns. Secondly, the small investments in hazard mitigation programs do not seem enough to convince investors of their power to face the threat of hurricanes strikes and their effects on the counties. Our methodology captures information pricing assets. We argue that this information flows from investors to the market as they know the insufficiency of mitigation programs in protecting firms and their production. The robustness checks give more evidence that investors use information advantages to price assets, as specific hazard mitigation projects related to hurricanes are more meaningful to firms exposed to hurricanes. Beyond that, we explain two possible mechanisms behind the anomalies, both mechanisms are possible, and further study is needed to address which one is probably correct. The whole point depends on how much investors know about hazard mitigation in general. The local investor's argument is probably more accurate if they are more locally known. On the other hand, if the knowledge about them is widespread, the general investor's argument better suits the anomalies found.

Our dissertation leaves several open questions that could be addressed in the future. Some questions are: Is this phenomenon exclusive of tropical cyclones? Are the new BRIC program and the larger HMGP budget enough to change the investors' perceptions about hazard mitigation programs?

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