Hurricanes, Adaptation and Capital Formation*

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Abstract

A number of recent papers have investigated the impact of hurricanes on economic growth. However, there is limited understanding of the investment component of local growth after hurricanes. Using hand collected and web-scraped statutory property tax rate data in the U.S., I find that local governments respond to hurricane impact by raising tax rates. I find the hike in tax rates is persistent for 4-5 years after hurricane impact. The response is five times larger for major hurricanes compared to minor hurricanes. However, the increase in tax rates is not expected to be large enough to cause significant out-migration after the average hurricane, even though property tax revenues increase. I supplement these findings with a data set of firm facility-level hurricane impact. I find that firms initially decrease investment in the quarter following hurricane impact and increase it in the final quarters of the second year after impact. Taken together, my paper presents a novel set of stylized facts on government and firm adaptation investment response.

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1 Introduction

Hurricanes cause direct damage through the loss of life and damage to capital assets.[1] They may also cause indirect damage through impairment of the productive capability of a region. Indeed, a number of recent papers have investigated the impact of hurricanes on economic growth, with mixed evidence. For instance, Hsiang and Jina (2014) find that hurricanes lead to a loss of 3.7 years of average development over a period of two decades. In the U.S., Strobl (2011) documents a reduction in coastal county economic growth in the short term after hurricanes, and Boustan et al. (2020) study the effect of natural disasters on out-migration and house price declines concluding that the estimated effects are consistent with a decline in local productivity. On the other hand, Belasen and Polachek (2009), Groen et al. (2020), and Tran and Wilson (2020) document a positive effect on wages in the local economy after natural disasters stemming from an increase in demand for local labor. What could potentially reconcile this mixed evidence is the investment component of local economic growth after a hurricane. Adequate investment growth after a hurricane disaster may lead to stronger revival of the local economy as well as prepare it for future hurricanes. However, this investment response is less clearly documented in the literature. A study of the effect of hurricane impact on investment should be focused on the economic entities facing a destruction of infrastructure capital and their subsequent investment in repair and risk management – adaptation – to prevent future damage.

Municipalities are important entities in this respect in the U.S. They are responsible for upkeep of local infrastructure and amenities. These entities primarily raise revenues through taxes for their expenditures.[2] Therefore, documenting the short run tax response of municipalities after climate disasters is one way of obtaining a dollar value on the cost of repair and risk management of *public* infrastructure. Using a novel data set of hand-collected and web-scraped municipalities statutory property tax rates, I use quasi-experimental strategies to establish a number of stylized facts about the tax response of municipalities to hurricanes. First, municipalities raise property tax rates after getting hit by a hurricane. The tax rate increase is about 1.9% of existing rates. Second, this increase in tax rates is persistent over 4-5 years after the hurricane impact. Third, the effect size varies by the category of hurricane intensity at landfall. A category-4 hurricane leads to

[1] A quick snapshot of the extent of damage can be found here: `https://www.ncei.noaa.gov/access/billions/events/US/1980-2022?disasters[]=tropical-cyclone`.

[2] Municipalities raise revenue through taxes and user charges primarily. They also receive intergovernmental transfers from federal and state governments. They can also raise debt but the debt is typically tied to specific projects and purposes.

an increase in tax rates that is *five times* that of a category-1 hurricane. Tax rates rise by roughly 3.7% of existing tax rates for municipalities hit by category-4 hurricanes. Fourth, a municipality that gets hit by hurricanes in consecutive years shows a response that is larger than the case when the municipality does not get hit by consecutive strikes. Lastly, using census of government data, I find that property tax revenues increase in the 1-5 years after the hurricane strike.[3]

My data set consists of a balanced panel of almost 4,500 municipalities located in twelve U.S. states in the Atlantic Basin from 2012 to 2021. To my knowledge, no systematic data set of statutory municipality tax rates in the U.S. has been collected in previous studies. This exercise is necessary because of two reasons. First, statutory tax rates measure the pure decision response of municipalities after hurricane impact. A rational local government would set the tax rate with a target revenue for the purpose of post-disaster investment, taking into account the rate's effects on house prices, migration etc. Second, collecting data for these rates directly is necessary because tax amounts typically available with CoreLogic or ZTRAX include taxes imposed from other units of government, such as school districts, special districts, and county governments, leading to potential mis-measurement of municipality response. I focus on municipalities as my unit of observation, which are consistent government bodies present across the U.S. and perform similar functions such as provision and maintenance of local public infrastructure. I focus on property taxes which comprise on average 66% of the total taxes collected in coastal states. Lastly, I focus on hurricanes which are the most costly natural disasters in the U.S. (Smith and Katz (2013)).

I calculate the out-migration effect from the tax rate increase using estimates of migration elasticity to tax rates from Giesecke and Mateen (2022).[4] Using this causally identified estimate of migration elasticity, I calculate that the out-migration effect due to tax rate increase after hurricane impact will be very small for the average hurricane. This is in line with county-level population change evidence from Tran and Wilson (2020) after natural disasters. This result implies that the tax rate increase after hurricane impact, though statistically significant and persistent, is not large enough to cause out-migration. Part of the reason why the tax rate hike is not larger may be because of the well-documented subsidization of capital damage costs by the federal government, through flood insurance and FEMA aid.[5] I find evidence that suggests this: intergovernmental

[3]Census of Government is conducted every 5 years. The Annual Survey of State and Local Government Finances provides survey data (as against a census) for a core group of municipalities that are termed "certainty sample." This sample is concentrated on larger cities and as such omits many coastal towns that are the topic of research in this paper.

[4]In Giesecke and Mateen (2022), the authors study the out-migration response from municipalities in Connecticut due to tax rate increases after a fiscal shock.

[5]That the federal government is the residual holder of house flood risk is documented in Sastry (2021), upto a

transfers at the local level to municipalities hit by hurricanes increase, in the period up to 5 years after the disaster.[6] Indeed, if optimal policy dictates that residents should ultimately vacate very vulnerable regions, then they need to bear more of the local losses. This is only possible through reduced higher-government subsidization. Results on property tax revenues indicate an increase of almost a million dollars for the average municipality which is about 2.5% of its average total revenue, a sizeable increase. However, this is supplemented by an increase of almost $800,000 from intergovernmental transfers.

I supplement these results with firm level responses to hurricane impact. My motivation comes from a recent wave of general equilibrium models using disaster risk that model how firm investment gets affected after climate disasters (Pindyck and Wang (2013)), how adaptation response takes into account the frequency of climate disasters (Bretschger and Vinogradova (2014)), and how local government tax rate response and firm investment response are interlinked (Hong et al. (2023)) in the economy. Using a data set of facilities-level impact of climate disasters on U.S. firms, I document two facts on the response of firms to hurricanes. First, the investment response of firms changes dynamically over the quarters following impact. Firms whose facilities have been impacted by hurricanes reduce capital investment cash flows by 0.6 percentage points (pp) of capital assets for each standard deviation increase in impact, in the first quarter following impact. This is followed by an *increase* in capital investment of 0.5 pp and 0.6 pp of capital assets in quarters 7 and 8 after impact respectively. The estimated quarterly capital investment increase is sizeable: the quarterly increase in quarters 7 and 8 is 12% and 14% of average quarterly capital investment cash flows in my data, for each standard deviation increase in hurricane impact. Companies also increase their cash holdings in quarters 7, 8, 9 after hurricane impact.

There are two challenges to measuring hurricanes' impact on firms. First, the impact on firms depends on the impact of hurricanes on their individual facilities. I show the importance of measuring firm facility exposure. For example, the firm's headquarters can be far away from the coast, such as General Mills being headquartered in Minneapolis, Minnesota, but having facilities along the coast, for example in Florida. The distance between headquarters of a firm and its facilities is, in fact, typically in the hundreds of miles. I show that facilities getting hit by hurricanes matters

coverage limit. Deryugina (2017) documents how the total insurance against hurricane damage, including disaster aid and other sources such as unemployment insurance, is larger than that from trade and weather shocks.

[6]FEMA transfers are typically given on the basis of both emergency needs and hazard mitigation needs. The latter is often given at the county level which is then transferred to municipalities and accounted for as "local intergovernmental transfers." Indeed, for municipalities, local intergovernmental transfers are about as large as federal intergovernmental transfers, as per the Census of Governments 2017.

for firm-level outcomes, though the effect is larger if the firm facilities are clustered around the same geographical area. Second, even though many data sets and ESG scores capture the exposure to hurricanes by providing a score, these scores only describe the *exposure* of firms *on average*, and cannot link it with the magnitude of impact they faced for individual climate disasters. My scores capture direct impact to facilities, as against risk measures from text-based analysis, such as in Sautner et al. (2020) and Engle et al. (2020). I use this novel data on facilities level hurricane impact for U.S. firms from 2009 to 2020. I use precise geo-coordinates of these facilities that allows me to construct a net hurricane impact score of firms, normalized by the total number of facilities they own. I then measure the firm investment response, and the effect on other financial variables of these firms in the years after the hurricane strike, by linking these firms to Compustat.

Using this novel impact score, I find that firms decrease investments in the first quarter after hurricane impact, and increase investments in quarters 7 and 8 after hurricane impact. The capital investment cash flow decreases by 0.6 percentage points (pp) of capital assets in the first quarter after hurricane impact for each standard deviation increase in hurricane impact, followed by an increase in capital investment cash flow of 0.5 pp and 0.6 pp of capital assets in quarters 7 and 8 after hurricane impact for each standard deviation increase in hurricane impact. Given that the average firm has capital assets of $2 bn, the estimate implies a reduction in investment of $12 mn in the first quarter after impact, followed by an increase of $10mn and $12mn in quarters 7 and 8 respectively after impact. The decrease in capital investment in the first quarter after impact accounts for 16% of within-firm standard deviation of quarterly capital investment cash flow. Similarly, the increase in investment in quarters 7 and 8 accounts for 13% and 16% of within-firm standard deviation of quarterly capital investment cash flow, respectively. Cash holdings increase in quarters 7, 8, 9 after hurricane impact, by 0.4 pp, 0.6 pp, 0.6 pp respectively of total assets for each standard deviation increase in impact. In dollar terms, the increase in cash holdings in quarters 7, 8, 9 after impact is $27mn, $41mn, $41mn respectively, or 3.6%, 5.5%, 5.5% of within-firm standard deviation of cash holdings. There is no effect on sales growth. The results suggest firms opt to increase their investments along with cash holdings in quarters 7 and 8 after impact, possibly at the expense of profits. The median interval for a second hurricane impact, conditional on a first hurricane impact, for a firm in my sample is 2 years. The rise in investment may be interpreted as a form of adaptation investment done before the expected onset of the next hurricane season, two years after the first hurricane impact. This recalls the result in Bretschger and Vinogradova (2014) that shows optimal adaptation to be based on the frequency of the climate disaster.

Related literature: A number of recent papers have documented the potential and realized damage from weather events using panel regression specifications.[7] There is also increasing evidence linking anthropogenic climate change with increased frequency and intensity of tropical cyclones (Kossin et al. (2020)); an increase in land area hit by forest fires (Abatzoglou and Williams (2016)); and negative impact on agricultural yields due to temperature rise (Lobell et al. (2011)). Jerch et al. (2020) document the fiscal dynamics of local governments 1-5 and 6-10 years after a hurricane strike for the period 1982-2017, depending on availability of Census of Governments data.[8] In particular, they find a drop in revenues and expenditures 6-10 years after the hurricane. These outcome variables thus measure the net effect of economic activity and local economy health in hurricane prone municipalities in the long term. However, there is scarce evidence on the short term adaptation response of firms and governments. There is limited evidence for adaptation in the literature due to the absence of data directly measuring the adaptation response by local governments and firms. Recent papers have focused on municipal bond market responses of specific measures of adaptation. Lu and Nakhmurina (2022) use textual analysis to measure the effect of local government concern and adaptation measures on municipal bond yields. Rizzi (2022) measures natural capital losses and its effect on municipal bond yields following extreme weather events. Anecdotally, a number of adaptation measures such as creating seawalls, beach nourishment, elevated roads etc. have been taken up by vulnerable regions. Most of these investments have been made by local governments.[9] Adaptation is a function of the *perceived* exposure of a region to climate change disasters and may have an attenuating effect on the damage, both economic and of human life, caused by future disasters (Hsiang and Narita (2012)). It is part of the adaptation response to anthropogenic climate change (Bouwer et al. (2007)) and an understanding of adaptation is necessary to translate short run weather event impacts to long run climate change effects (Dell et al. (2014)).

My results on local tax rates are novel in the literature. They allow a study of both the choice of tax rates and its resulting effect on property tax revenues, during the period 2012-2021. Therefore, the results provide insight into the *short term* dynamic response of municipalities in

[7] Hsiang and Jina (2014) and Yang (2008) for losses from cyclones; Dell et al. (2012) for temperature effects on per capita income; Schlenker and Roberts (2009) find non-linear effects on crop damage with higher temperature using a panel of county level yields of different crops in the U.S.

[8] The Census of Governments is conducted every 5 years so fiscal data is collected in Jerch et al. (2020) for each municipality anywhere between 1 to 5 years after the hurricane for the first data point, with the second data point 5 years after.

[9] Florida recently passed two bills, SB 1954 and SB 2514, that earmark $100 million annually for flooding and sea level rise projects. It is foreseeable that more state level funding will be available. However, for this paper, such funding has been largely absent.

terms of a policy variable they directly control – the property tax rate. In fact, in my set-up, there is a robustly present tax rate hike that leads to an increase in tax revenues. The property tax revenues rise because of the increase in tax rates and also the important institutional detail that property re-assessments are conducted in intervals of 3 years or more in 75% of the municipalities in the coastal states in my sample. This allows any short term property price shock to not get transmitted to the property tax base, allowing governments to generate revenues for post-disaster expenditures. Importantly, this short term increase in tax rates and tax revenue can be seen as a measure of the adaptation investment response of municipalities towards necessary repair as well as risk management after hurricane disasters, supplemented by intergovernmental transfers.

Apart from the literature on damages from panel regression specifications (see Dell et al. (2014)), my paper contributes to a fast growing literature documenting the effects of climate change in asset markets, specifically housing markets.[10] These effects include increased frequency of climate disasters (hurricanes, wild fires, heat waves) as well as gradual shifts in living conditions (sea level rise and temperature increase). Several papers investigate the effect on house prices, with mixed results, see Bakkensen and Barrage (2017), Boustan et al. (2020), Ortega and Taspinar (2018), Baldauf et al. (2020), and Keys and Mulder (2020). My paper contributes to this literature because property prices depend on property tax capitalization. In a general equilibrium set-up, this capitalization depresses prices but the effect of adaptation may keep the amenity value of coastal cities high enough so that property prices do not change significantly.

Another literature focuses on the market perceived risks faced by cities exposed to climate change effects such as sea level rise. These papers use municipal bond yields to see if markets have priced in future sea level rise, see Painter (2020) and Goldsmith-Pinkham et al. (2021). My paper looks at how cities themselves are responding to climate change risks by investing in mitigation and adaptation. Tax rates are a hedge against climate change damage as per Hong et al. (2023). I find that cities choose to raise tax rates and this gives me a measure for the *perceived* risk for cities from climate change. This response is measured for a much larger sample of municipalities since not all municipalities consistently issue debt in the bond market, and municipalities are the local government looking after general public works in the city.

With respect to firm results, a paper that investigates similar concerns to mine is Dessaint and Matray (2017) who find that firms headquartered in counties not hit by hurricanes but neighboring a county that got hit by a hurricane differentially increase their cash holdings compared to firms

[10] See Giglio et al. (2021) for a survey of recent work in climate finance.

headquartered far from affected counties. The result is possibly because of the salience effect of future hurricane damage leading to a desire for cash holding flexibility. My paper differs from Dessaint and Matray (2017) in several important respects. First, I do not investigate the salience story but look at the *direct* effect of actual hurricane strikes on firm level decision making. Second, I look at firm facility hurricane impact rather than firm headquarters hurricane impact. This is important because a number of firms have headquarters that are far removed from actual hurricane impact but have facilities that are hit by hurricanes, as I explain in Section 3.3. Therefore, there are levels of treatment to hurricane disasters for firms, even if their headquarters are not hit by the disaster. Third, and as a result of the previous point, I look at the effect of this intensive measure of impact – less affected firms compared to more affected firms – along with firms that have no impact from the hurricane, i.e. they have no facilities hit by hurricanes.

Finally, my paper connects more broadly with the theme of urban resilience (Glaeser (2021)) in the face of climate change. The general equilibrium effects of climate change on cities include the endogenous response of agents which can be political (voting out unfavorable policies), mobility-based (out-migration if location becomes unfavorable), investment based (firms supplementing public with private goods), or related to social justice (sorting, gentrification). This connects with the literature started by Tiebout (1956) and on fiscal unions (Oates (1999)), more broadly connected to local public goods (see Stiglitz (1977)). However, any model that incorporates these effects must begin with measuring the actual response of local governments, in terms of tax rates, and that of firms, in terms of investment. My paper is among the first tentative steps in this direction.

The rest of the paper is organized as follows: Section 2 describes the data and its construction. Section 3 provides a number of descriptive facts about municipalities and firms hit by hurricanes. Section 4 provides the main natural experiment regression results for municipalities. Section 5 provides the main natural experiment regression results for firms. Section 6 provides an interpretation of the results obtained in Sections 4 and 5. Section 7 presents robustness tests. Section 8 concludes.

2 Data and Summary Statistics

2.1 Municipality Tax Rates

I hand-collect and web-scrape property tax rates at the municipality level. Different states have different levels of tax autonomy and taxation structures. Yet, every state allows municipalities to collect property taxes, and they form 66% of total tax revenue, as per the Census of Government, and reported in Table 5. I collect statutory tax rates for 4,699 municipalities across 13 states. The coverage varies across states and format. I harmonize the data, and set it to its corresponding municipality fiscal year. Municipality fiscal years typically end on June 30, with some exceptions.[11] Depending on the municipality, preparation of the new budget starts well before June 30 (larger cities or cities with better fiscal controls start earlier). In most cases the budget must be passed by the municipality council and approved prior to June 30 (with a cushion of maybe a month) so that the municipality is authorized to make debt payments for the month of July. Therefore, when classifying the year of hurricane impact I make sure that it is aligned with the particular state's fiscal year. Data coverage for tax rates falls substantially before 2012. Therefore, I restrict myself to a balanced panel of municipalities from 2012 to 2021.[12] This leaves me with 4,432 municipalities across 12 states along the East Coast and the Gulf of Mexico.[13]

2.2 Municipalities Hit By Hurricanes

The list of municipalities hit by hurricanes is collected from First Street Foundation. The data gives the name of the event ("Hurricane Irma Storm Surge"), its calendar year, and its type. This gives me 1,697 affected municipalities across 12 states. The data gives a flood score for the static flood risk of the properties in a municipality. First Street data set also provides the number of properties inundated by a given disaster along with a measure of damage based on the level of flooding. I can construct hurricane damage measures based on the damage to the buildings as a proportion of all buildings, or alternatively as a proportion of all exposed buildings. Finally, I can also observe levels of adaptation for each city, through a normalized score from First Street Foundation. Table 1 provides a list of hurricanes studied. My main analysis is restricted to hurricanes but I run robustness checks by including nor-easters and tropical storms as well with similar results.

2.3 Firm Facilities

Firm data is obtained from Moody's Analytics. It comprises of two data sets. The primary data set contains 4,097 firms with 976,231 facilities in the U.S. To get better intuition, I zoom in to the state of Florida. Figure 1 gives a snapshot of the coverage within the state. The red dots represent manufacturing facilities located in the state of Florida. Some of these are within municipality

[11] 46/50 states end their fiscal year on June 30. Alabama and Michigan end their year on September 30; New York on March 31; Texas on August 31.

[12] Results remain the same for an unbalanced panel qualitatively and in statistical significance.

[13] The states are Connecticut, Florida, Georgia, Maryland, Massachusetts, New Jersey, New York North Carolina, Rhode Island, South Carolina, Texas, and Virginia.

boundaries. Others are outside these boundaries. For each of these firm facilities, I additionally have SIC codes for the facility – manufacturing, wholesale etc. The data set provides the location of establishments at the start of the sample period. I assume that movement of firm establishments in and out of an area is limited through my sample period. All outcomes variables are measured at the firm level. The quasi-experimental analyses in Section 5 are based on the firm facilities data set. When tracking hurricane impact on firm facilities, I exclude non-contiguous U.S. states and focus on the states with a coastline in the Atlantic Basin: Alabama, Connecticut, Florida, Georgia, Louisiana, Massachusetts, Maryland, Mississippi, New Jersey, New York, North Carolina, Rhode Island, South Carolina, Texas, Virginia.

2.4 Facilities Hit By Hurricanes

Data for firm facilities hit by hurricanes is obtained using First Street Foundation data. First Street has precise geocoordinates for properties located across all states of interest. For each of these properties, it tracks if the property was hit by a flooding event, in particular providing us the name of the event ("Hurricane Katrina Storm Surge"), its calendar year, and its type (hurricanes, river floods etc). For each facility, I find the closest building in the FirstStreet database and assign its hurricane impact status for the firm facility. The median distance from this exercise is about half a mile (see Table 2). I exclude any facility that has a distance of more than 2.5 miles from a FirstStreet property.[14] The hurricane impact for any facility then follows from the hurricane impact of the nearest building. I choose the time period 2009 - 2020 to collect the hurricane impact for each facility. The time frame gives me a broader panel of firms and zero treatment in years 2009 and 2010 when no hurricanes hit the Atlantic Basin.[15]

2.5 Firm Financial Data

I measure investment response of the firms by linking Moody's data to Compustat. I primarily use the Compustat Fundamentals Quarterly data set. I am able to match a total of 3,366 firms from Compustat with the Moody's sample between the years 2009 – 2020. Panel A of Table 3 provides descriptive statistics of this full sample. Further sample selection – dropping utility and financial sector firms – leads to a total sample size of 2,689. Panel B of Table 3 gives descriptive statistics for these firms. Finally, running the regression analysis with the full set of fixed effects, leads and

[14]This exercise only drops 541 out of 408,898 facilities, i.e. about 0.1% of all observations, used in the main regression. Results are robust to changing the cutoff.

[15]Results, are robust if the time frame is shortened or lengthened.

lags utilizes a sample of 1,934 unique firms. Panel C of Table 3 gives descriptive statistics for these firms. We see that the regression sub-sample selects firms that have similar capital assets to the original sample, measured by net plant, property and equipment. The regression sample firms are slightly bigger in terms of total assets.

2.6 Other Variables

Controls for population, per capita income, median house value, share below poverty level, share of less than high school above the age of 25, share of white residents, share of black residents, share above age 65, are obtained from NHGIS for the year 2010 (Manson et al. (2021)). I also calculate the distance to the coast for each city using shape files provided from TIGER, U.S. Census. Municipalities are identified by unique city codes from the Census. Basic summary statistics for the municipalities are discussed in Section 3. Data for property tax share and debt share is calculated from the Annual Survey of State and Local Finances, also called the Census of Governments. I take data from the full census year before the start of my analysis, in 2007.[16]

For robustness checks, I construct hurricane paths. Hurricane paths are obtained from the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC) HURRDAT2 dataset. This dataset contains storm position and wind speeds for all hurricanes from 1851. The positions are given at 6 hour frequencies. I construct hurricane paths for all hurricanes from 1851 to 2021. As an example, Figure 2 plots the paths of all hurricanes in the year 2019. Figure 3 plots the path of Hurricane Sandy in 2012. I also create a heatmap of the historical hurricane experience for Atlantic basin geographies in terms of wind speed, in Section 7.4.

3 Descriptive Results

3.1 Treated vs Control Municipalities

It is instructive to see the general differences between treated and control municipalities. These differences do not affect my causal results because I use unit level fixed effects but they help document important facts about the differences between the two groups. I start by looking at the property tax rates in these two groups. Table 4 tabulates the mean and median tax rates at the beginning of my sample in 2012 to the end in 2021. I find that control municipalities

[16]The Census of Governments carries out a full census of local U.S. governments every 5 years in years ending with '2' and '7'.

typically have higher property tax rates than treated municipalities. The mean tax rate in control municipalities is 0.58% of house assessment value while it is 0.48% of house assessment value in treated municipalities. By the end of the sample period, both treated and control municipalities see an increase in property taxes. Therefore, there is a general trend of increasing property taxes in my sample. Back of the envelope calculations, however, tell us that the percentage increase in property taxes in treated municipalities is higher than in control municipalities, something I will rigorously estimate in Section 4.

Next, I look at the differences between the control group and treatment group across a number of demographic and economics variables. These time varying variables are collected before the analysis period through the 2010 U.S. Census. I find that control municipalities are significantly less populous compared to treated municipalities. Control group municipalities have higher home ownership than treated municipalities. However, there is no statistically significant difference in per capita income or median house values. They have a higher share of white residents and a lower share of older residents. However, control municipalities have fewer below poverty line individuals and fewer share of less than high school education individuals. Therefore, regions more vulnerable to hurricanes are poorer and are less white. This mirrors the findings in other papers such as that by Jerch et al. (2020) and Boustan et al. (2020). This is also related to the idea of "climate gentrification" put forward by recent papers such Keenan et al. (2018) and Bakkensen and Ma (2020), the idea being that hurricanes induce property appreciation in coastal areas that are less exposed to these disasters, causing gentrification.

Using Census of Government (CoG) Data from 2007, I find that property taxes constitute more than 50% of net taxes for both control and treatment but control municipalities receive more income from property taxes. The high share of property taxes in both treated and control municipalities motivates this paper's attention on property tax rates. I also use CoG data to calculate the debt share defined as the long term debt outstanding for a municipality divided by its total revenue. I find no significant difference in this variable indicating that municipalities hit by hurricanes do not have a higher debt burden on their local economies. I also use my firm facilities data to calculate the density of facilities within each municipality boundary. I do this by dividing the total number of facilities within a municipality by the municipality's area. This gives me a measure of the industrial concentration in each municipality. I find from Table 5 that the density of facilities is lower in the control group than the treated group. This result corroborates the cross-country findings in Kocornik-Mina et al. (2020) who find that more flooded cities have more economic activity per square kilometer. Lastly, I calculate the distance to the coast for each municipality by calculating the distance from the municipality's centroid to the nearest coast. As expected, control municipalities are farther away from the coastline. Treated municipalities are significantly closer to the coast.

In my main regression specification, I use unit fixed effects and state-year fixed effects. I also use control variables interacted with year fixed effects to capture differential linear time trends in the effect of each control on the outcome variable. This allows me to absorb the static differences and time varying trends at the regional level.

3.2 Relationship of Firm Facility Density with Municipalities Characteristics

In this sub-section, I present several interesting facts about the relationship of firm facilities within a municipality boundary with several characteristics of the municipality. I split these facts across control and treated municipalities in Table 6. First, I find that more prosperous municipalities across control and treated groups, where prosperity is measured by the median home value and the per capita income, are more likely to have higher firm facilities per square area of municipality. This is possibly because areas with firm facility presence are associated with healthier local economies. Next, I see that higher home ownership is likely to reduce the presence of firm facilities in the municipality in both control and treatment groups, possibly because higher home ownership is associated with more residential areas.

I find that more populous municipalities are more likely to have higher firm facility density. This could be because more prosperous local economies have more people in the municipality. A higher presence of above 65 residents is associated with fewer firm facilities in both control and treated municipalities, although the relationship is weaker in treated municipalities in terms of statistical significance. Most likely this is because there are fewer individuals who are available to work in these facilities. Interestingly, in the control group, the relationship between firm facility density and the share of white residents is negative – as the municipality has more white residents it is associated with fewer firm facilities in that municipality. No such relationship exists for the treated group. Note that the mean share of white residents in the treated group is lower than the control group.

Next, I find that a higher share of less than high school educated residents is associated with a lower firm facility density in the municipality, whether in the control or treated group. Interestingly, the share of below poverty line residents has no effect on the firm facility density in control municipalities. It has a negative relationship in treated municipalities; the relationship is highly significant. Finally, there is a small but statistically significant relationship between distance from the coast and the firm facility density for both control and treated municipalities. The firm facility density falls with distance from the coast.

3.3 The Importance of Measuring Hurricane Impact on Facilities

A number of studies, such as Chaney et al. (2012) and Dessaint and Matray (2017), assume that the firm's production facilities are clustered around its headquarters, in the same state, county, or MSA. However, my data set shows this is not true. Firm facilities are in fact geographically dispersed, often in a different state, and hundreds of miles away. Taking treatment and control assignment on the basis of firm headquarters is likely to be imprecise.

Consider a few examples. General Mills is a famous Fast Moving Consumer Goods (FMCG) company headquartered in Minneapolis, Minnesota. The headquarters is comfortably away from the coast line. However, a look at its facilities shows that it has significant exposure to possible hurricanes. Figure 4 shows that identification based on headquarters alone would classify the firm in the control group when some of its facilities, particularly in Florida and New Jersey are getting treated in my sample. On the other hand, take the example of Tupperware Brands Corp. The company is headquartered in Orlando, Florida. It is clearly in a hurricane prone state and it has facilities in the state of Florida as seen in Figure 5. However, it has even more facilities outside Florida, away from the Atlantic Basin. Therefore, its exposure to hurricanes and subsequent capital loss is attenuated by the many facilities not being exposed to any such event. Lastly, National Beverage Corporation (makers of La Croix selzer) is located in a hurricane prone state and has most of its facilities in the state, as seen in Figure 6. Therefore, its exposure is concentrated.

The above anecdotes are also confirmed by some simple statistics. First, out of 932,403 facilities, 85%, or 796,961 facilities, are located in a state that is not the state of headquarters. Second, I look at the distribution of the distance between firm facilities to their respective headquarters, in Table 7. The median distance between firm headquarters and its facilities for all firms in my facility dataset, consisting of 932,403 facilities, is 665 miles. Excluding islands such as Hawaii makes little difference to the distribution except in the very right tail. We can further restrict the sample to only those facilities that are present in hurricane exposed states in the Atlantic Basin. The distribution shifts left but the median distance is still 641 miles.

4 Quasi-Experimental Results for Municipalities

4.1 Identification strategy

The dynamics of a municipality's tax response to hurricanes can be tracked on an annual basis. Typically, the municipality is unable to change tax rates within the same fiscal year as the hurricane strike because tax rate changes have to be approved in the budgetary process, and this can take time. I track whether a municipality is hit by a hurricane or not, i.e. a dummy indicator. Figure 7 shows the simple identification strategy here. Municipality A does not get hit by the hurricane while Municipality B gets hit by a hurricane. I will include unit fixed effects and state-time fixed effects in the main specification to compare municipalities within the same state and to control for state specific time trends.

My main specification for municipalities is a panel regression of the following form:[17]

$$Y_{ist} = \sum_{n=1}^{4} \beta_{t-n} H_{i,t-n} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \epsilon_{ist} \tag{1}$$

where Y_{ist} is the tax rate in municipal government i in state s and year t, $H_{i,t-n}$ is a dummy that is one if there is a hurricane in lag year $t-n$, α_i is an individual fixed effect, α_{st} is state $\times$ time fixed effect, $\mathbf{X}_i \alpha_t$ is a time varying differential trend for each control including distance from coast. The municipality fixed effects account for differences in taxation structures and base rates. They also remove static differences between municipalities, such as those associated with demographic and geographic differences. The state-time fixed effect takes into account state trends over time like the state's political representation in Congress, fiscal shocks etc. They also capture state level aid over time. The time varying differential trends for the controls interacts an initial vector of characteristics with year fixed effects. This allows for differences through time for municipalities based on the vector of their characteristics. Standard errors are clustered at the city level. I omit the fiscal year of the hurricane shock and it acts as the base year for my analysis. The identifying assumption is that the hurricane regressors are strictly exogenous conditional on the unobserved unit level characteristic. The identifying assumption therefore assumes that there is no time varying unit level change. I am effectively assuming that climate change, to the extent that it occurs between 2012 and 2021, is captured by state-time fixed effects, or captured by the differential trends based on variables such as distance from coast. If there are more local changes,

[17] Later in this section, I will run an event study by each hurricane cohort separately, obtaining the same results and no pre-trends.

then this specification will not capture the intended causal effect.

4.2 Main Results

Table 8 presents the results of this regression. Column (2) is my preferred specification. I find that the tax rate increases after hurricane impact. The rate increase is by 1.66 dollars for every 100 dollars of assessment value in the 4th year after the hurricane strike. Since the average tax rate in the sample is 0.88, this is roughly a 1.9% increase in tax rates. This result can also be seen visually in Figure 9. The rate hike is persistent and statistically significant for all four years after impact. Column (3) adds another lag to the regression. This changes the sample size of the panel since there are fewer observations with 5 lags of hurricane impact. However, I find that the effect size is similar across the three year horizon. In fact, the 5 year horizon suggests that the rate hike is actually larger in the 4th year at the 1% level. Column (4) redoes the regression in Column (3) but keeps the dependent variable as the logarithm of $\tau_{ist} + 1$.[18] This allows us to interpret the coefficients in percentages. The coefficients are very similar to that in Column (4) given that the average tax rate in the sample is close to 1. Column (5) runs the same specification but here the treated group consists of municipalities that have only been hit once by a hurricane through the sample period. The coefficients obtained are very similar. Finally, Column (1) shows the importance of adding differential trends on the controls. The effect size is the close to that in Column (2) but we obtain a clearer picture of the effect of hurricane impact on tax rates in the years immediately after hurricane impact.

A possible question in the regressions of this section is the endogenous movement of residents. There is a rich literature both theoretical and empirical that investigates the out-migration of residents in response to higher taxes.[19] The question here is: does the tax rate response of municipalities change according to the migration patterns they are experiencing? I split my sample into two groups: above median net percentage population change between 2020 and 2010, and below median net percentage population change between the same two periods. The results are plotted in Figure 11 and 12 and show that the effect size is the same, and significant, 3 years after the hurricane, and in line with our main results, at the 90% confidence level. These results tell us that irrespective of net migration, the tax rate response of municipalities is very similar.

[18] The added 1 adjusts for municipalities with zero property tax rate observations. Results are robust to using inverse hyperbolic sine function.

[19] See Giesecke and Mateen (2022) for a recent analysis and related literature.

4.3 Does Hurricane Storm Intensity Matter?

Hurricanes can be of different intensities, measured by their wind speeds. They are typically classified into one of five categories with category-5 being the most intense.[20] I use wind speed data from NOAA to classify the hurricanes in my sample into different categories *when they make landfall*. This distinction is important because hurricanes generally achieve maximum wind speeds off the U.S. coast. For example, Hurricane Matthew was a category 5 hurricane in 2016 that caused widespread destruction in Haiti. It also caused damage in the U.S. but by the time it made landfall in the U.S. it was a category-1 hurricane. To capture the effect of the category of hurricane I run the following regression:

$$Y_{ist} = \sum_{n=1}^{4} \beta_{t-n} H_{i,t-n} + \sum_{n=1}^{4} \gamma_{t-n} H_{i,t-n} \times C^{k}_{i,t-n} + \sum_{n=1}^{4} \theta_{t-n} C^{k}_{i,t-n} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \epsilon_{ist} \quad (2)$$

where I added an interaction of the hurricane dummy with the category of hurricane $C^{k}_{i,t-n}$ when a category-k hurricane makes landfall at event time $t-n$. The coefficient of interest is γ_{t-n}. I use categorical variables for each category because I do not want to impose a continuous linear relationship in treatment effect of categories. In my sample, the category of hurricanes when they make landfall is either category-1, category-4 or category-5. I use category-4 as my reference group and omit it. The effect size that I will estimate will be compared to the effect in a category-4 hurricane.

Table 9 presents the result of this regression. The coefficients for lagged hurricane dummies, $H_{i,t-n}$, display the general shape and persistence as in my main specification. What is very interesting is that the coefficient size, which is for impact from category-4 hurricanes, is roughly double that the main specification. This tells us that more powerful hurricanes lead to a much higher tax rate response, presumably because of greater damage from the hurricane. Next, I move to the interaction coefficients. I find that the coefficients for category-1 are negative and statistically significant at the 5% level for the second and third year after hurricane impact. This suggests that the tax rate response after a category-1 hurricane is smaller than that of a category-4 hurricane. For each category-1 hurricane, the net tax rate increase is about 0.7% over existing rates ((0.0329 − 0.027)/0.88) by the third year after impact. The tax rate increase is therefore less than 1/5th for the least powerful hurricanes as compared to the more powerful (major) hurricanes. Lastly, the coefficient for category-5 hurricanes is not statistically significant though the

[20] This is called the Saffir-Simpson scale. See https://www.nhc.noaa.gov/aboutsshws.php.

size of the coefficient is in the direction of a greater response for a category-5 hurricane compared to a category-4 hurricane. Note that the number of available lags for category-4 and category-5 hurricanes in the regression table is limited by the fact that they all take place in or after fiscal year 2018.[21] These results are in line with the fact that major hurricanes (category 3 and above) account for 80% of all damage from hurricanes even while being only 33% of all hurricanes that make landfall, in the period 1900-2017 in the U.S. (Weinkle et al. (2018)).

4.4 Do Hurricanes in Consecutive Years Matter?

An interesting question of interest is measuring the effect on tax rates from hurricanes in consecutive years. For example, if a municipality is hit by a hurricane at year t and then gets hit by another hurricane at year $t+1$, do tax rates increase further? The following model is along the lines of what has been suggested by Dell et al. (2014).[22]

$$Y_{ist} = \beta H_{it} + \sum_{j=1}^{4} \beta_j H_{i,t-j} + \sum_{j=1}^{4} \omega_{t-j} H_{i,t} \times H_{i,t-j} + \alpha_i + \alpha_{st} + +\delta'(\mathbf{X}_i \alpha_t) + \epsilon_{ist} \quad (3)$$

The key coefficient of interest is ω_{t-j} which measures if the impact of a given shock depends on the particular configuration of previous shocks. For example, ω_{t-2} measures the effect of having hurricanes in years t and $t-2$, with a gap of one year. Column (2) of Table 12 shows the results of this regression. The coefficients on the lagged variables are very close to those in my main specification. Interestingly, among the two interaction terms, I find a significant coefficient on the term for hurricanes in consecutive years. The size of the coefficient is of the same order as the coefficient on the first lagged term, $H_{i,t-1}$. This implies a higher response in tax rates if hurricanes hit in consecutive years. However, this effect is not present if the gap between the two hurricanes becomes two years. The coefficient ω_{t-2} is small and statistically insignificant. Tax rate changes in our setting are in response to hurricane impact. The increased tax rate would be used to fund repair and clean-up as well as future adaptation. The fact that hurricane strikes in consecutive years leads to a higher tax rate response implies that the local government decides to invest more in post-disaster repair work if hurricanes hit one after the other. This may in fact also imply

[21] In fact, Hurricane Michael in fiscal year 2019 was the first category-5 hurricane to make landfall in the contiguous U.S. since Hurricane Andrew in 1992.

[22] Section 4.1.2 of the paper, pp - 777. I omit the use of a time varying covariates since they may be an outcome variable, thus potentially introducing endogeneity and over-controlling. I also omit a lagged term of tax rates to ensure comparability with my main specification. Adding back the lag of tax rate does not affect the significance or qualitative nature of the results.

that there is added learning with consecutive hurricanes about the probability of future strikes and consequent damage, leading to much higher tax rate hikes.

4.5 Stacked Difference-in-Difference by Cohort

My main specification involves a staggered design with different units getting treated at different points of time by different hurricanes. The staggered design involves a control group that includes never-treated municipalities as well as municipalities that get treated later or earlier in the study period. If there is heterogeneity in effects across cohorts and over time, then my estimated effect may not be correct. A number of papers have recently explored this problem and offered possible solutions such as in Borusyak and Jaravel (2017), Goodman-Bacon (2018), Cengiz et al. (2019), De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), Callaway and Sant'Anna (2021); most recently summarized in Baker et al. (2022).

In this section, I use the method in Cengiz et al. (2019) where I transform my data set into a set of "clean" 2×2 difference-in-difference cohorts where the control group is not treated throughout the sample period. My cohorts are defined by each hurricane, giving me 10 cohorts in all. I estimate the difference-in-difference coefficients for each of these 10 hurricane cohorts and then stack them to estimate the average coefficient estimate. Effectively, this eliminates the problem associated with negative weighting of some events, as explained in Sun and Abraham (2021). It also helps prevent bias associated with heterogeneous treatment effects. I run this design as a dynamic difference-in-difference with three leads and three lags. The regression specification is:

$$Y_{ist} = \sum_{k=-3, k\neq -1}^{3} \beta_k H_{i,t+k} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \epsilon_{ist} \tag{4}$$

Table 10 presents the results of this regression. We can see that there are no pre-trends – the estimates are small and statistically insignificant. The shape of the response is like we obtained in our main specification – the tax rate increases with time. The coefficients are highly statistically significant (p-value ≈ 0.000). The size of the coefficients are also very similar to that in the main specification. The r-squared value is very high. The results can also be visually inspected in Figure 10.

4.6 Property Tax Revenues and Intergovernmental Revenues

The increase in property tax rates by municipalities is of great interest by itself. However, it is interesting to note the effects of hurricane impact on property tax revenues, debt issuance, and intergovernmental revenues as well. For property taxes, we can understand if any added money is raised through the hiked tax rates. Intergovernmental revenues are also important sources for support for local governments after natural disasters. Therefore, in this subsection we study the effect of hurricane impact on property tax revenues, intergovernmental revenues, and debt issuance.

In Table 11, we regress the logarithm of property tax revenues, intergovernmental revenues at the local, state, and federal level, using the following specification:

$$Y_{ist} = \beta_t H_{i,t}^{1-5} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \epsilon_{ist} \tag{5}$$

where $H_{i,t}^{1-5}$ is a dummy that is 1 if there is a hurricane in the last 5 years from t. Given that data for revenues and debt is obtained from the Census of Governments 2012 and 2017, this regression essentially looks at the effect of any hurricane in the period 2012-2016 on revenues and debt in 2017.[23]

Column (1) provides results on property tax revenues. We find that the coefficient suggests an increase in tax revenues of almost 7%. Since the mean property tax revenue is about \$14 million, the estimate implies an increase in revenues of almost \$1 million in the period after the hurricane strike, a sizeable increase. This revenue increase takes advantage of two important points. First, there is the direct effect of tax rate increase that would increase revenues keeping house prices constant. Second, there is the effect of re-assessment intervals that lock in property prices in the immediate aftermath of the disaster. Indeed, almost 75% of the municipalities in my sample only see a property reassessment after 3 years or more. Therefore, the positive effect comes from both factors — a rise in tax rates and potential house price declines not translating to tax base property assessments.

Column (2) has local intergovernmental revenues as the dependent variable. We find a significant 70% increase in local intergovernmental transfers, translating to about \$800,000 for the average municipality. This accords well with the idea that significant amounts of money disbursed by FEMA

[23]The 2022 Census of Governments is still awaited as of writing this draft. The Annual Survey of State and Local Government Finances provides survey data (as against a census) for a core group of municipalities that are termed "certainty sample." This sample is concentrated on larger cities and as such omits many coastal towns that are the topic of research in this paper.

are directed to counties and states with the former typically receiving funds for non-emergency disaster related expenses, so called Public Assistance and Hazard Mitigation.[24] Importantly, the amounts raised are comparable to that from property tax revenues, indicating a significant amount of support from higher governments post-disaster, with important welfare implications. We do not find statistically significant amounts coming from state or federal governments in comparison, nor is there any added debt issuance.

5 Quasi-Experimental Results for Firms

5.1 Identification strategy

The identification strategy is explained with the help of Figure 8. Consider three companies A, B, C. Each of these companies has two facilities each. In a given year, Company A's facilities do not experience a hurricane (marked by yellow suns); Company B has one facility, B1, that experiences a hurricane (marked by cloud and lightning); finally, both facilities of Company C, i.e. C1 and C2, experience hurricanes.

I use the richness of the data to measure the impact of hurricanes on a given company by constructing a normalized score that divides the number of facilities of a given company that experiences a hurricane by the total number of company facilities. This intensive score allows me to compare companies that do not get hit at all (Company A), with companies that get hit in different intensities (Company B and C).

My main specification is a difference-in-difference regression of the following form:

$$Y_{iyqs} = \sum_{n=1}^{12} \beta_{t-n} NS_{i,t-n} + \sum_{n=1}^{4} \beta_{t+n} NS_{i,t-n} + \alpha_{iq} + \alpha_{yq} + \alpha_s + \epsilon_{iyqs} \tag{6}$$

where Y_{iyqs} is the outcome of interest of firm i in year y, quarter q, and headquartered in state s. Continuous Normalized Score for damage $NS_{i,k}$ is tracked from 4 quarters before the hurricane to 12 quarters after the hurricane. I add firm quarter fixed effects α_{iq} to control for non-time varying quarterly variation for each firms; year-quarter fixed effects α_{yq} for time varying trends; and state of headquarters fixed effects α_s. I cluster standard errors by firms to control for unit-level serially correlated errors in the panel. To review our identification example above, company A, in the

[24] In fact, generally speaking, municipalities receive most revenues (about \$6 million on average) from state governments, followed by local transfers from counties, and then finally from federal governments directly (about \$900,000 on average).

above example, will have $NS_A = 0$, while company C will have a bigger score than company B: $NS_C > NS_B$.

The main outcome of interest is the investment rate – the capital expenditure in a quarter divided by the net plant, property, and equipment of the company. This measures the cash flow capital expenditure response of a firm in a given quarter normalized by its capital assets. I will run equation 1 with other dependent variables as well. The key parameters β_k show the relative response of the outcome variable to the baseline at $t = 0$.[25]

5.2 Main Results

Companies react flexibly through the year, unlike municipal governments. Therefore, I can get a deeper dive into the dynamics of investment behavior by looking at quarterly data. I use Compustat quarterly data to get a data set of 3,366 firms whose facilities' hurricane impact I track from 2009 to 2020. I run the regression given by equation 8. I drop utility and financial firms (NAICS codes 22 and 52). I also drop SIC codes above 9000 which are public administration entities. All financial variables are winsorized at the 1 and 99 percentile levels.

Table 13 presents the results of the regression. Column (3) is the specification of interest. I find that there is an immediate decline in investment in the very next quarter after impact. The effect statistically significant at 5% level and implies a reduction of investment of 0.6 percentage points (pp) for every standard deviation increase in impact. Since the mean net plant, property and equipment in our sample is \$2 bn, this translates to an effect size of \$12 mn in the first quarter after impact. There is no other change then for several quarters until quarters 7 and 8, i.e. in the second year after impact, when there is an increase in investments by 0.5 pp and 0.6 pp respectively for each standard deviation increase in impact, for a total investment flow of \$22mn. Given the average quarterly capital expenditure of \$86 mn in the data, the net quarterly increase is an increase of 13% per quarter. The quarterly decrease in investments in the first quarter after impact accounts for 16% of the within-firm standard deviation of quarterly capital investment cash flow. The increase in quarters 7 and 8 after impact, similarly, account for 13% and 16% of within-firm standard deviation of quarterly capital investment cash flow. This effect size would be larger for the largest hurricanes – the 95th percentile of impact scores is 0.27. The R^2 is almost 50% indicating a good fit. The results can also be seen visually in Figure 13. Interestingly, adding time-fixed effects makes a difference to the coefficients as we move from Column (1) to Column (2).

[25] Results are robust to setting the baseline at $t = -1$.

This suggests that there is a secular decline in the investment rate during this period.

I investigate if other financial variables are also affected by hurricane impact. Table 14 presents results when the dependent variables are quarterly cash and cash equivalents over quarterly total assets, quarterly net income over quarterly revenues, and quarter over quarter sales growth. Column (1) shows a persistent increase in cash holdings in quarters 7, 8 and 9 after the hurricane impact. The effect size is by 0.4 pp, 0.6 pp, 0.6 pp respectively of total assets for each standard deviation increase in impact. In dollar terms, the increase in cash holdings in quarters 7, 8, 9 after impact is $27mn, $41mn, $41mn respectively, or 3.6%, 5.5%, 5.5% of within-firm standard deviation of cash holdings. There is no effect on sales growth in Column (2). Finally, there is a persistent negative effect on profits all through the second year of impact although the coefficient is statistically significant only in quarter 6.

I can also run the same regression by taking the impact score to be binary: 1 if *any* facility of a firm is hit by a hurricane and 0 otherwise. Naturally, such a score has to be treated with caution for a firm because it overweighs the less impacted firms and underweighs the more impacted firms.[26] Nonetheless, I run a similar regression as in equation 8 by replacing the impact scores with impact dummies. Figure 14 presents the result of this regression. I see a similar and more persistent increase in investment in the second year after impact. I also see a small increase in investment in the second quarter after impact.

5.3 Do Hurricanes in Consecutive Years Matter?

As with municipalities I measure the effect on investment rates from hurricanes in consecutive years. For example, if a firm is hit by a hurricane at time t and then gets hit by another hurricane at time $t+1$, do investment rates increase further? To investigate this question requires us to zoom out to the yearly level.[27] Therefore, I use annual data from Compustat to conduct this analysis. I run the following model

$$Y_{isys} = \beta NS_{iy} + \sum_{j=1}^{K} \beta_{y-j} NS_{i,y-j} + \sum_{j=1}^{K} \omega_{y-j} NS_{iy} \times NS_{i,y-j} + \alpha_i + \alpha_y + \alpha_s + \epsilon_{isys} \tag{7}$$

where NS_{iy} measures the impact of the hurricane in year y. The key coefficient of interest

[26] This is unlike the case with municipal governments, in Section 4, where a city getting hit by a hurricane means that all individual units of the city are getting hit.

[27] Practically speaking, hurricanes hitting the same region in consecutive quarters are very rare.

is ω_{y-j} which measures if the impact of a given shock depends on the particular configuration of previous shocks. Column (1) of Table 12 shows the results of this regression where I take K to be 3 years. The first thing to note is that the financial data regression on an annual level captures the increase in investment two years after impact. The effect size is roughly the sum of the effects in quarters 7 and 8 in Table 13. With respect to intensification, I see that there is an increase in investment rates if there are hurricanes in consecutive years. In other words, the result suggests firms respond sooner to hurricanes if a firm is hit by hurricanes in consecutive years. The effect is quite large and twice that of the effect coming from one impact alone.

5.4 Heterogeneous Effects by Firm Facility Spatial Clustering

An interesting question is whether there is heterogeneity in firm response based on its spatial distribution. If a firm's facilities are hit by a hurricane, it will have to bear the costs of repairing the facility as well as possibly investing in risk mitigation. However, a more spatially diffused firm will have other facilities where it can continue production and investment activities. In contrast, a firm that is spatially concentrated will be more affected by the hurricane impact and will have less "internal insurance." The question then is how highly clustered firms may experience the additional effect of their internal network getting hit by the hurricane.

To analyze this, I first define a measure for the spatial clustering for each firm. I calculate the matrix of facility to facility and facility to headquarters distance for each of the 2,500 firms. I then sort these firms in order of the average distance between their facilities. There is wide heterogeneity here. Some firms are tightly clustered in one location, such as those in pharmaceuticals and technology, with inter-facility distance below 100 miles. Others such as many manufacturing firms have spread out facilities with inter-facility distance being more than 1,500 miles. I divide the firms into four quartiles, Q_1, Q_2, Q_3, Q_4. I carry out the following regression:

$$Y_{iyqs} = \sum_{n=-4}^{12} \beta_{t-n} NS_{i,t-n} + \sum_{n=-4}^{12} \gamma_{t-n} NS_{i,t-n} \times Q_1 + \alpha_{iq} + \alpha_{yq} + \alpha_s + \epsilon_{iyqs} \tag{8}$$

where the dependent variable is the investment rate as before. The idea of the regression above is to capture the heterogeneous effect of being a spatially clustered firm, i.e. being in the first quartile of inter-facility distance, compared to the rest of the distribution. The coefficients of interest here are γ_{t-n}. Table 15 presents the results from this regression, where I have placed the interaction coefficients side-by-side with the non-interacted coefficients for better interpretation. We can see that firms that are most spatially clustered generally see a point estimate that is relatively more negative throughout the quarters after the hurricane, but the interaction effect becomes statistically significant from the second year. In fact, the rebound in investment seen in our main specification in quarters 7, 8, 9 after the hurricane is muted and sometimes negative for these set of firms, once the main coefficient and the interaction coefficient are added. This suggests that firms that are more spatially clustered and hit by hurricanes see a more persistent decline in investments. The same results can be obtained by interacting the hurricane impact with dummies for each quartile. However, there is no such persistent negative effect on investment for firms in the higher quartiles of spatial clustering.

6 Interpretation of Results

6.1 Implications for Out-Migration

Boustan et al. (2020) have documented the out-migration effect from natural disasters at the county level. This effect is strongly present for severe disasters but also mildly present for less severe disasters. On the other hand, Tran and Wilson (2020) find no negative population change after natural disasters except for severe disasters. Similarly, Deryugina (2017) too does not find a change in population effect after the average hurricane strike. All the above evidence is from county level studies. The conflicting evidence may have a partial explanation in the response of local governments to these disasters. The response in terms of tax rates depends on the magnitude of the disaster, which as this paper documents, leads to a greater hike in tax rates with greater intensity of hurricane impact. But how to translate tax rate hikes to migration responses? More recently, Giesecke and Mateen (2022) use a natural experiment set-up to document the out-migration from tax rate hikes in municipalities (rather than counties) in Connecticut. Concretely, they find that a 10% increase in tax rates leads to a 0.28% decline in population over a horizon of 5 years. The fiscal shock that Giesecke and Mateen (2022) use is a revenue shock coming from the Great Financial Crisis. In my setting, hurricanes primarily constitute an expenditure shock, since there is repair and reconstruction work required after the hurricane. However, it does constitute a fiscal shock requiring municipalities to manage revenues. If I use the results from Giesecke and Mateen (2022), the average tax rate increase of 1.9% would lead to out-migration of 0.053% in population at a horizon of 5 years. Given the average size of a treated municipality in my sample is 20,000 people, this implies a loss of only 10 people. This is a small response. This would be more in line with the evidence in Tran and Wilson (2020) and Deryugina (2017), and the out-migration effect will be stronger as the intensity of the hurricane increases.[28]

A municipality tax rate hike is aimed at managing municipal revenues after the hurricane. The hike leads to an increase in revenue in the short run. This extra revenue is arguably used for repair and risk management expenditures borne at the local level after the hurricane. The fact that the magnitude of the tax rate hike, though persistent and strongly statistically significant, does not lead to out-migration suggests that the tax rate hike is small. A likely reason for this is the relatively large magnitude of support received by residents and municipalities after hurricane impact from the federal government in the form of insurance and FEMA aid. In fact, this paper documents that as much as $800,000 is transferred to municipalities through local intergovernmental transfers, which is about 80% of the revenues directly raised from property tax rate hikes. As Deryugina (2017) notes, the total magnitude of insurance received by local governments after hurricanes is much larger than those from trade or weather shocks. This insurance would reduce the burden faced by municipalities after hurricanes, thereby distorting local residents' incentives to migrate. Thus, if optimal policy dictates that residents should move out of municipalities vulnerable to hurricanes, the local burden of repair and risk management borne by residents has to increase. Future research should aim to understand the optimal distribution of risk between local and federal governments. Finally, note that there is a caveat in the interpretation offered in this sub-section. Unlike the setting in Giesecke and Mateen (2022) with the Great Financial Crisis shock, when hurricanes strike a municipality they have a transitory direct fiscal shock (like with a financial crisis) but they also lead to belief updating about future likelihood of hurricane disasters. How this latter channel affects residents' decision-making is a worthy topic for future research.

6.2 Interpreting Firm Investment Response

I find two main results with respect to firm response from hurricanes. First, I find a reduction in investment right after the disaster. Second, I find an increase in investment in quarters 7 and 8 after the disaster. The reduction in investment result is consistent with two possible theories. First, models with belief updating would suggest that there is an increase in uncertainty about the return on investment since the belief that there may be future disasters has increased. This is the mechanism found in Hong et al. (2023). Second, damage to the factory makes investment difficult.

[28] See also Deryugina et al. (2018) who find sizeable out-migration after the damage from Hurricane Katrina in the case of New Orleans.

It is also made difficult because they may have to wait for insurance payouts for the damage and so they are temporarily constrained. The increase in investment may be interpreted as preparatory investments for the next hurricane. Conditional on a first hurricane, the median time to a second hurricane for a firm is two years. The rise in investment happens just before the start of hurricane season two years after the first strike. This is accompanied by an increase in cash holdings as well as a decline in profits. All of this is compatible in a world where firms anticipate future hurricanes and they make adaptation investments, along with increasing their cash holdings, at the expense of profits. Proactive adaptation efforts to reduce climate risk exposure have been found to have a positive effect on firm value in Pérez-González and Yun (2013). However, this explanation can only be validated by more granular level data on firm investment at the facility level.

7 Robustness and Supplementary Results

7.1 Municipalities – Looking at Effect of First Strike Only

In this sub-section, I look at the first instance of hurricane strike between 2012 and 2021 to measure effect on tax rate outcome for any municipality in an event-study design. In other words, I ignore any hurricane strike that hits a municipality if the municipality has already experienced a hurricane strike during the period 2012 and 2021. Since the hurricane strikes can be assumed to be random conditional on municipality fixed effects, I should not see any bias in my estimates. The regression specification is on the lines of that used by Deryugina (2017):

$$Y_{ist} = \sum_{k=-3, k\neq -1}^{2} \beta_k H_{i,t+k} + \alpha_i + \alpha_{st} + \delta'(\mathbf{X}_i \alpha_t) + \beta_3 H_{i,3} + \beta_{-4} H_{i,-4} + \epsilon_{ist} \tag{9}$$

where the outcome variable Y_{ist} is the tax rate of municipality i in state s in year t, we use 2 leads and 3 lags for hurricane dummies $H_{i,k}$, and where we have an indicator $H_{i,-3}$ if there is any hurricane 3 years or before for municipality i and an indicator $H_{i,-4}$ if there is any hurricane 4 years or after for municipality i.[29] The last two indicators control for a hurricane strike outside the time window of interest in this specification. Standard errors are clustered by municipality.

Table 16 presents the results of this regression. We find that the coefficient on the first, second and third year after hurricane strike is statistically significant. Importantly, the coefficient size on the third year after hurricane strike is 1.4% of tax rates, which is comparable to the estimate in

[29] Results are statistically significant and qualitatively similar if $k = 0$ is used as the omitted year.

our main specification.

7.2 Restricting Distance of Municipalities from Coastline

A concern may be that municipalities far from the coastline within a state may not be an adequate control for comparison. To mitigate this concern, I restrict attention to a sample of municipalities that are close to the coastline. I measure this distance from the centroid of the municipality to the closest coastline. The distances I take are municipalities that are less than 100, 75, 50, 25, and 15 miles from the coast. The idea is that municipalities closer to the coast have similar observables and unobservables. Moreover, I will continue to use the same set of state x year and unit fixed effects so that comparisons continue to be for municipalities within the same state. The results are presented in Table 17. Restricting the distance from the coast leads to a similar response as in the full sample. The tax rate response has a similar shape and is statistically significant. At 15 miles and less, I am restricted to only 862 municipalities, yet I see a similar effect. In fact, the effect size becomes larger as we get closer to the coastline which makes sense since the treated municipalities would be expected to experience more damage.

7.3 Local Projections

7.3.1 Municipalities

I run local projection regressions of the following form:

$$Y_{is,t+h} = \beta_t H_t + \alpha_i + \alpha_{st} + \epsilon_{ist} \tag{10}$$

I regress the tax rate at different horizons on the impulse from a hurricane impact h periods before, following Jordà (2005). Figure 15 shows the result of this regression. Once again, I find an increase in tax rates that persists and is significant 5 years into the future. The coefficient becomes as large as an increase 2 dollars on 100 dollars of assessment. The closeness of the coefficient size to the panel specification and its statistical significance gives strong support to the results in the panel specification. In the same plot, I conduct a "placebo" projection where I regress tax rates on future hurricane impacts. Reassuringly, the estimated coefficients are statistically insignificant.

7.3.2 Firms

Instead of running a panel regression, I run local projection regressions of the following form:

$$Y_{is,yq+h} = \beta_{yq} D_{yq} + \alpha_{iq} + \alpha_{yq} + \alpha_s + \epsilon_{iyq} \tag{11}$$

In other words, I regress the investment rate at different horizons on the impulse from a hurricane impact D_{yq} that hits h periods before. Figure 16 plots the result of this exercise. I see similar dynamics of a fall in investment in the next quarter, which is significant at the 10% level, and a persistent statistically significant increase in investment in quarters 7, 8, 9, 10. The magnitude of the increase in investment, if anything, has increased. In the same plot, I conduct a "placebo" projection where I regress tax rates on future hurricane impacts. The estimated coefficients are statistically insignificant.

7.4 Hurricane Alleys?

There may be a concern that there are only some locations that get hit by hurricanes. In other words, there may be an analogue to tornado alleys. The problem would then be that affected areas are systematically exposed to hurricanes and therefore have a very different response pattern than non-affected areas. I plot a heat map for historical hurricane experience for the Atlantic basin for all hurricanes between 2000 – 2021. Figures 17 shows the result of this exercise. The heatmap is more yellow for cells that have experienced more storms with hurricane force winds and above. Bluer cells experience fewer hurricane force winds in the 20 year period. A cell is white when a region has not experienced a hurricane force wind. Figure 17 shows that hurricane force winds are more typically experienced off-shore, as is well documented. On-shore, all coastal regions in the U.S. have experienced hurricane force winds in the past 20 years. There is even more homogeneity within states. Figure 18 extends the heatmap to cover all tropical storms and above wind speed events. If anything the homogeneity in previous storm experience increases.

8 Conclusion

I use novel hand-collected and web-scraped tax rate data to document a number of facts about the tax rate response of municipalities after hurricanes. Municipalities raise tax rates after a hurricane and the size of the response depends on the intensity of the hurricane and its frequency. This hike is persistent. I argue that the tax rate response in the years immediately after a hurricane constitute a municipality's attempt to manage revenues for repair and risk management, thereby being a measure of *local* investment response to hurricanes. I further argue that the average tax rate response after the hurricane is not sufficient to cause out-migration unless the hurricane is of high severity. I supplement these findings by bringing in firm facilities data. I document why facilities data is crucial in understanding a firm's response to hurricane strike. I find that firms decrease investment in the immediate quarter after the hurricane possibly because of uncertainty and budgetary constraints. I also find that firms increase investment two years after the strike and I argue that the timing of the investment, along with other facts such as an increase in cash holdings and a drop in profit, suggest that firms may be engaging in preparatory adaptation investment before hurricane season.

Taken together, my paper is the first step in bringing more rigorous evidence about the investment response of agents after a climate disaster. A number of interesting directions emerge after this exercise. My firm facility data offers the potential to construct a network of within-firm supply chains. It would be interesting to see the effect of climate shocks hitting a few facilities of a firm and to trace its spillover effects through the firm's supply chain network. Separately, better facility level investment data would help pinpoint the exact dollar expenditure made by firms at the local level. On the municipalities side, Giesecke et al. (2022) document a troubling secular decline in financial health of municipalities in the U.S. With increased frequency of climate disasters, it is an open question if municipalities can continue to raise revenues to increase their investment in adaptation, taking into account their financial constraints and the endogenous response of economic agents. This is especially so if the federal government decides to make local governments bear more of the capital damage cost.

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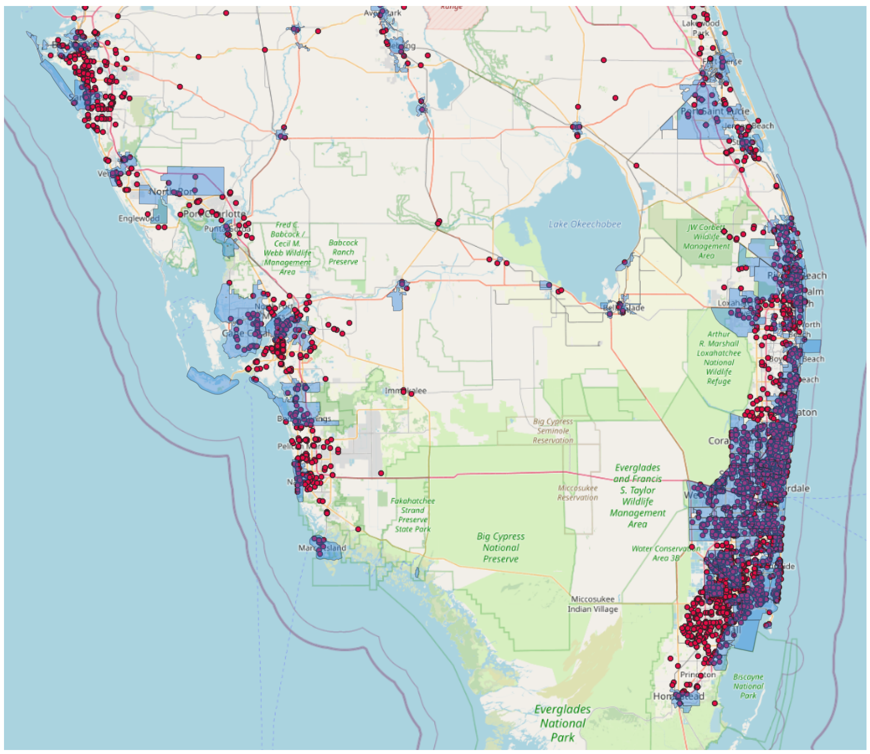


Figure 1: Florida Facilities and Municipal Boundaries

Notes: The figure plots the location of manufacturing facilities, dots in red, in a part of Florida, as an example. The blue outlines are municipal boundaries. Data is from 2021.

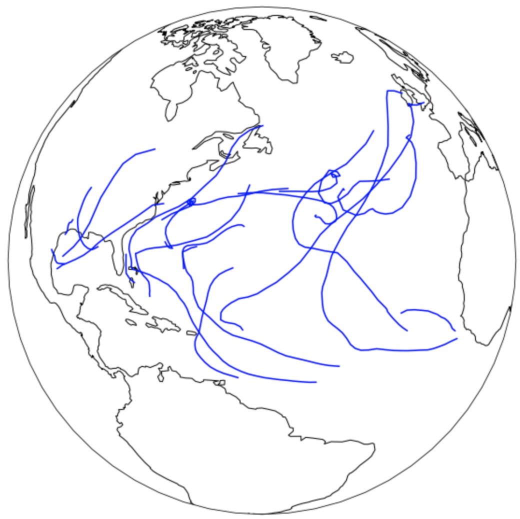


Figure 2: Atlantic Basin Hurricanes in 2019

Notes: The figure traces out hurricane paths in the Atlantic Basin in the year 2019. Data from HURRDAT2. I extrapolate based on the positions provided at 6 hours frequencies.

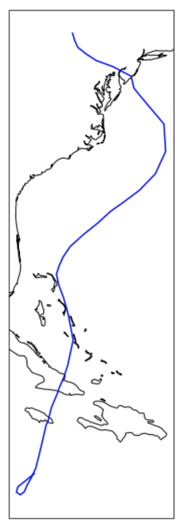
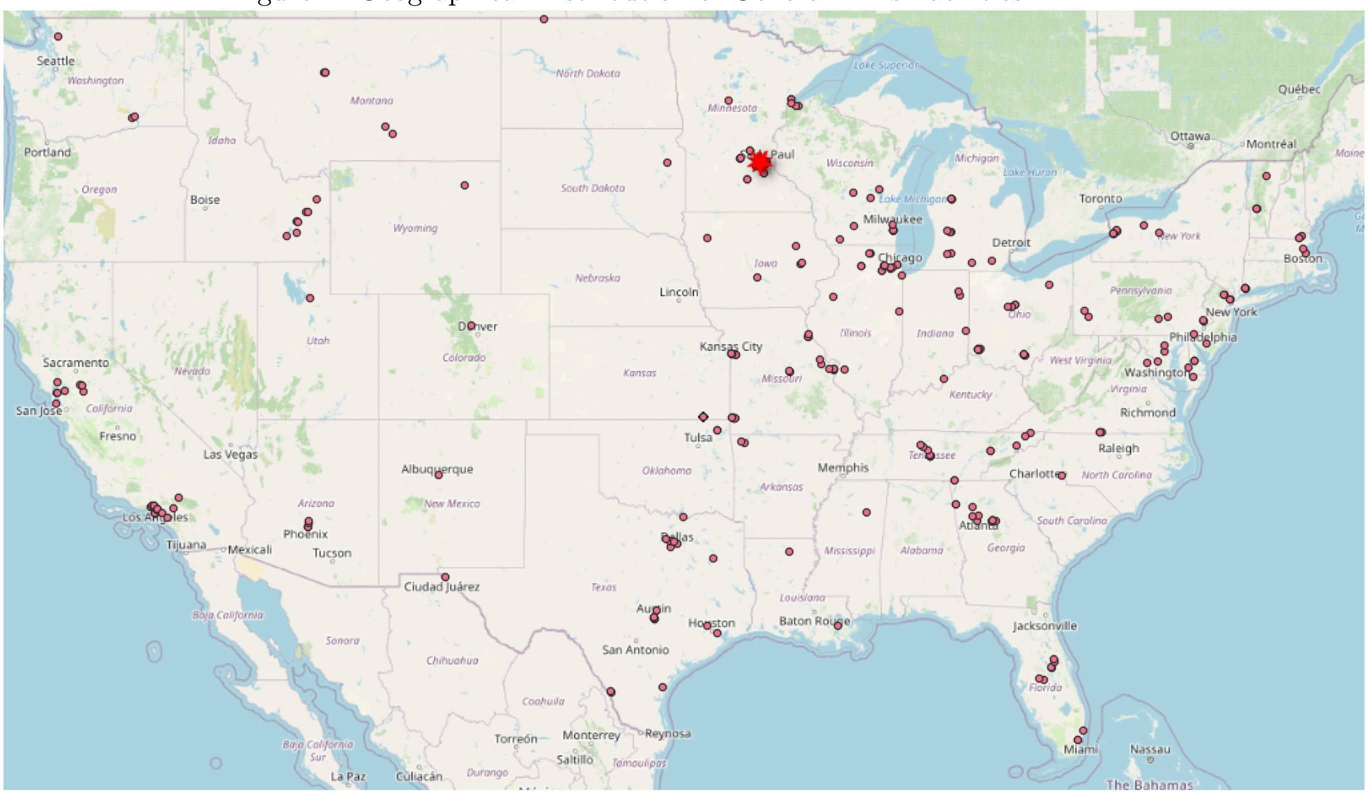


Figure 3: Path of Hurricane Sandy 2012

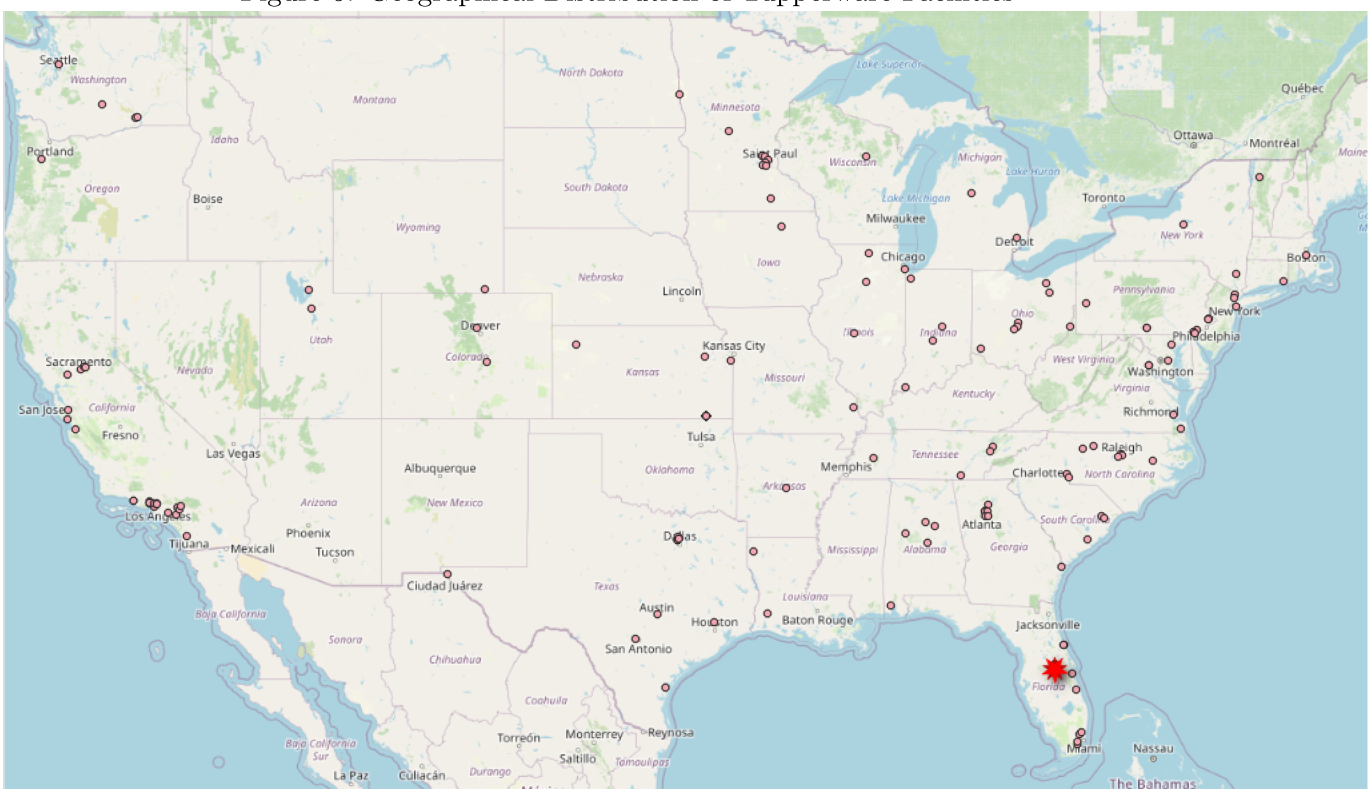
Notes: The figure traces the path taken by Hurricane Sandy in the year 2012. Data from HURRDAT2. I extrapolate based on the positions provided at 6 hours frequencies.

Figure 4: Geographical Distribution of General Mills Facilities



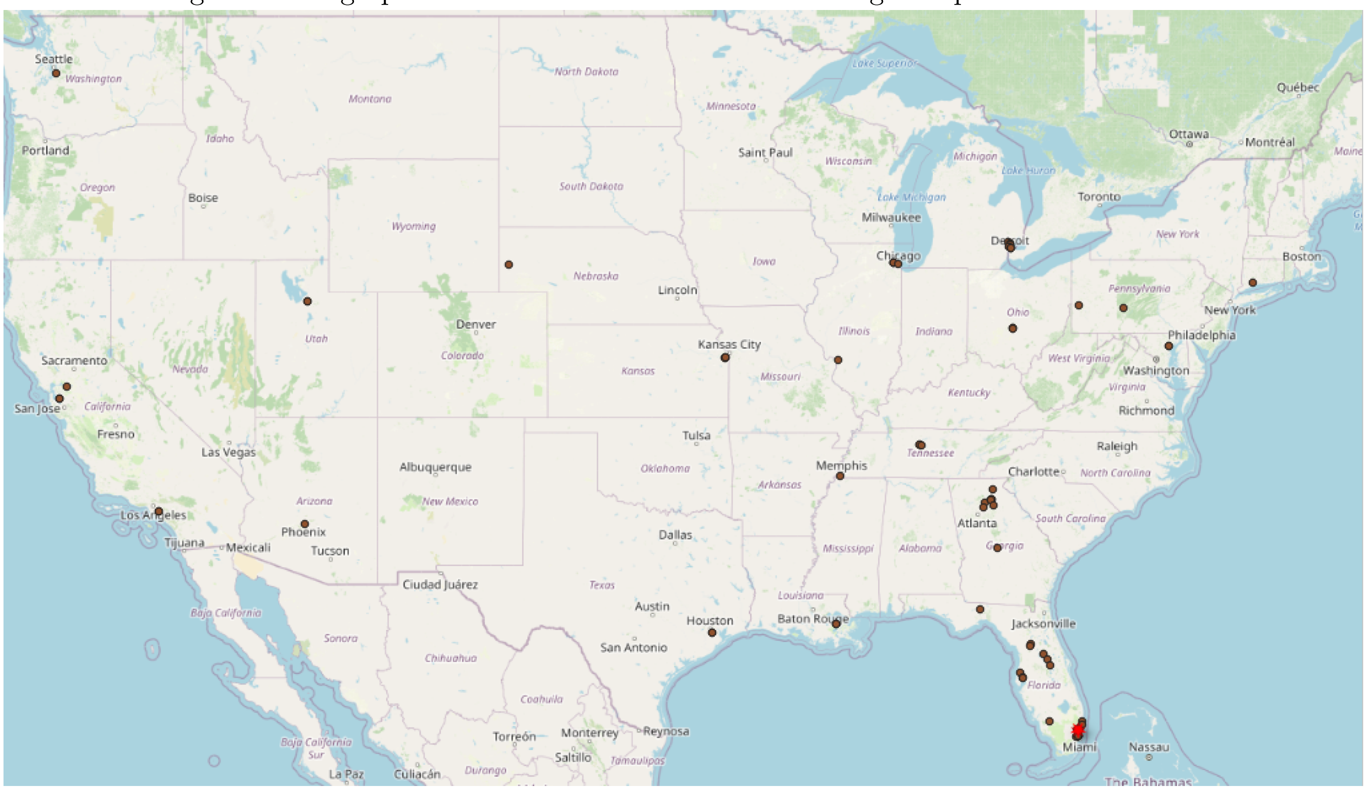
Notes: The map displays the geographical locations of facilities of General Mills. The headquarters of the firm are marked by a red star.

Figure 5: Geographical Distribution of Tupperware Facilities



Notes: The map displays the geographical locations of facilities of Tupperware Brands Corp. The headquarters of the firm are marked by a red star.

Figure 6: Geographical Distribution of National Beverage Corp Facilities

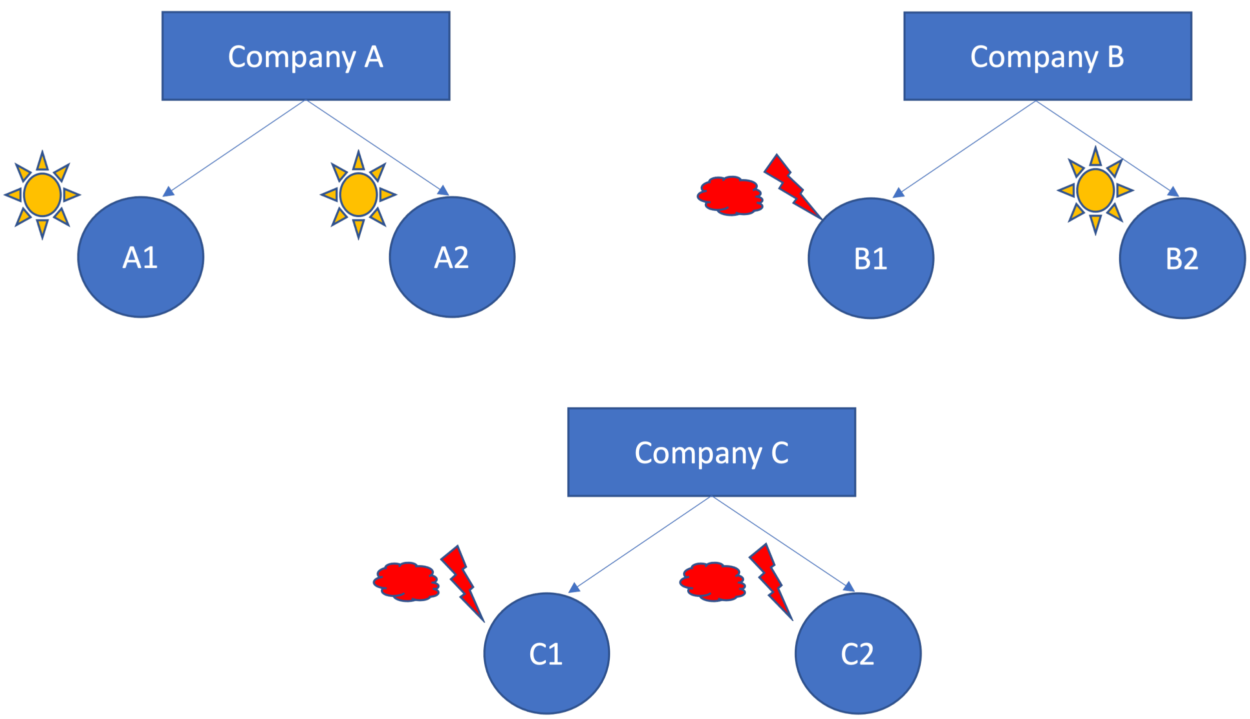


Notes: The map displays the geographical locations of facilities of National Beverage Corp. The headquarters of the firm are marked by a red star.

Figure 7: Municipalities Identification

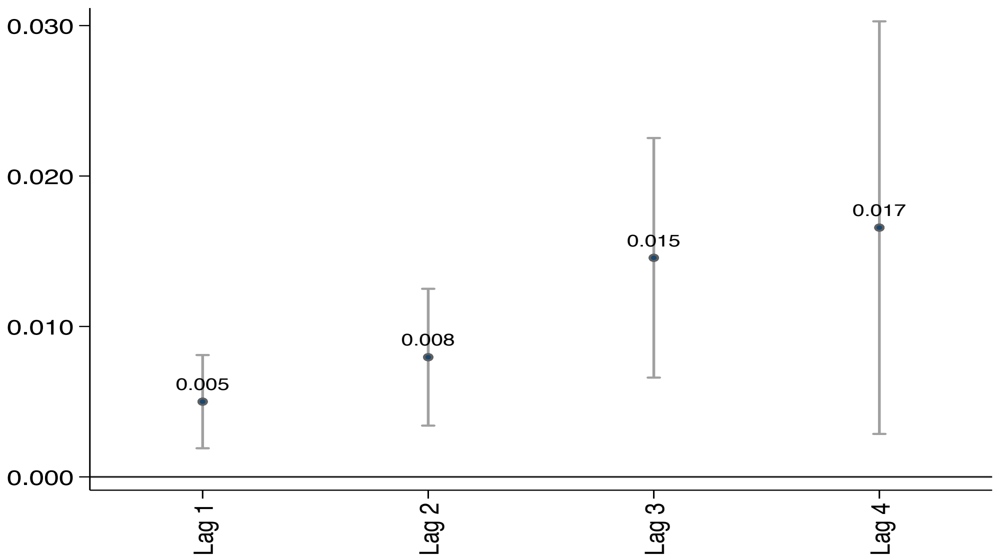
Notes: A simple representation of identification for municipalities. Municipality B is hit by a hurricane and is treated. Municipality A is the control.

Figure 8: Firm Identification



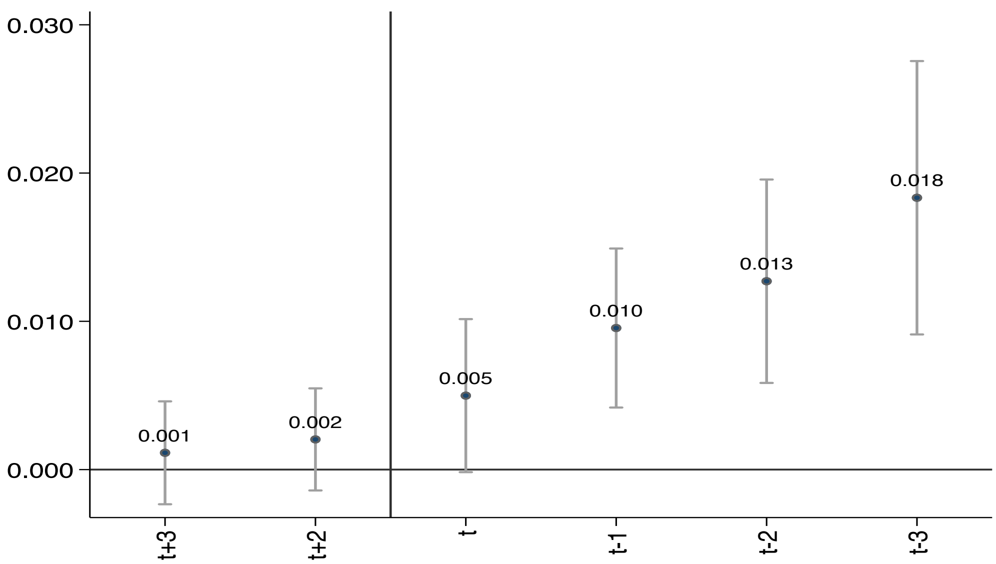
Notes: A simple representation of identification for firms. Firm C has the largest impact from hurricane strike. Firm B has less impact than firm C. Firm A has no impact.

Figure 9: Impact of Hurricanes on Municipality Property Tax Rates



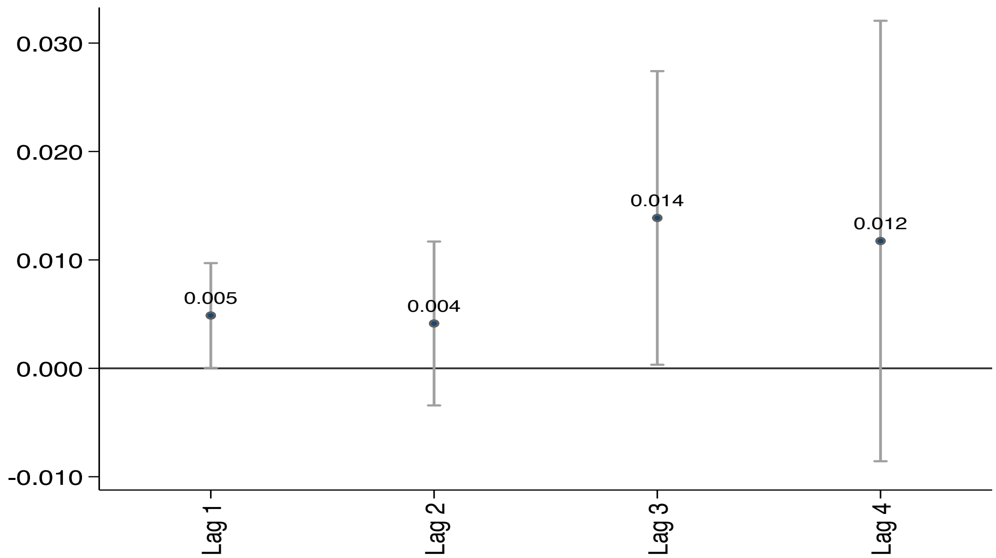
Notes: The figure plots the coefficients from a regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 1. 90% confidence intervals.

Figure 10: Impact of Hurricanes on Municipality Property Tax Rates – Stacked DiD by Hurricane Cohort



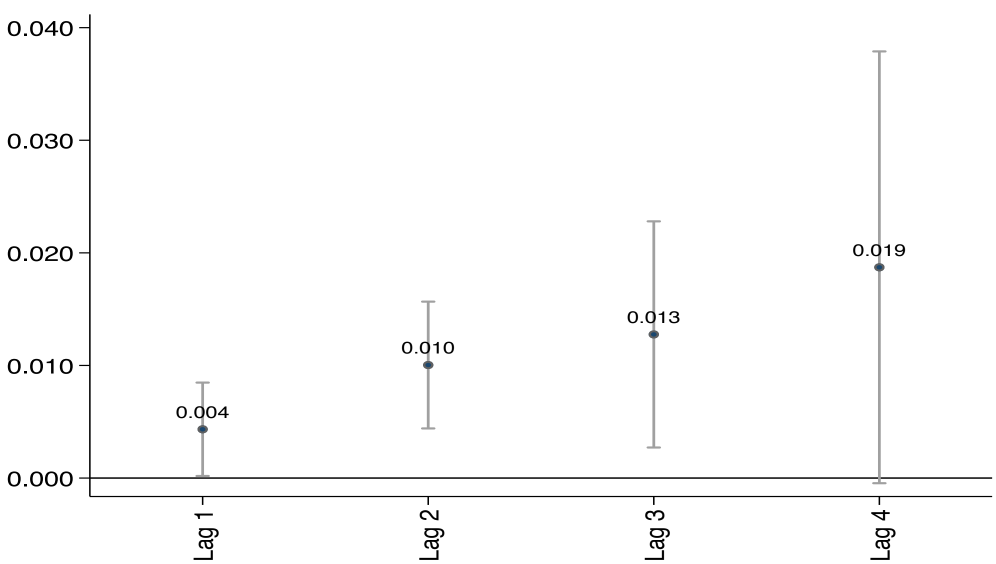
Notes: The figure plots the coefficients from a stacked difference-in-difference regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, after running each DiD separately by hurricane cohort as given in equation 4. 95% confidence intervals.

Figure 11: Impact of Hurricanes on Municipality Property Tax Rates – Below Median Population Change



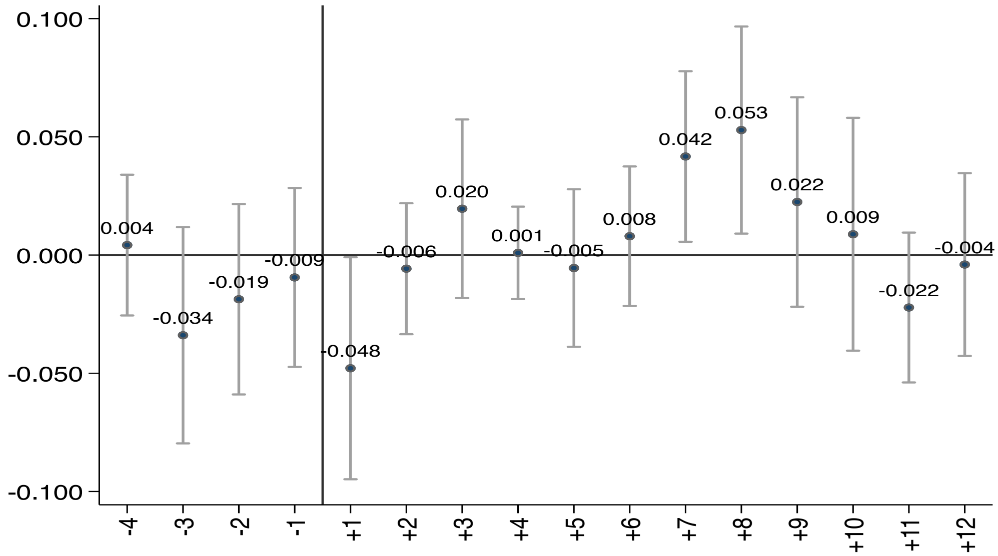
Notes: The figure plots the coefficients from a regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 1, for lower than median percentage population change between 2020 and 2010 as given by the Census Bureau. 90% confidence intervals.

Figure 12: Impact of Hurricanes on Municipality Property Tax Rates – Above Median Population Change



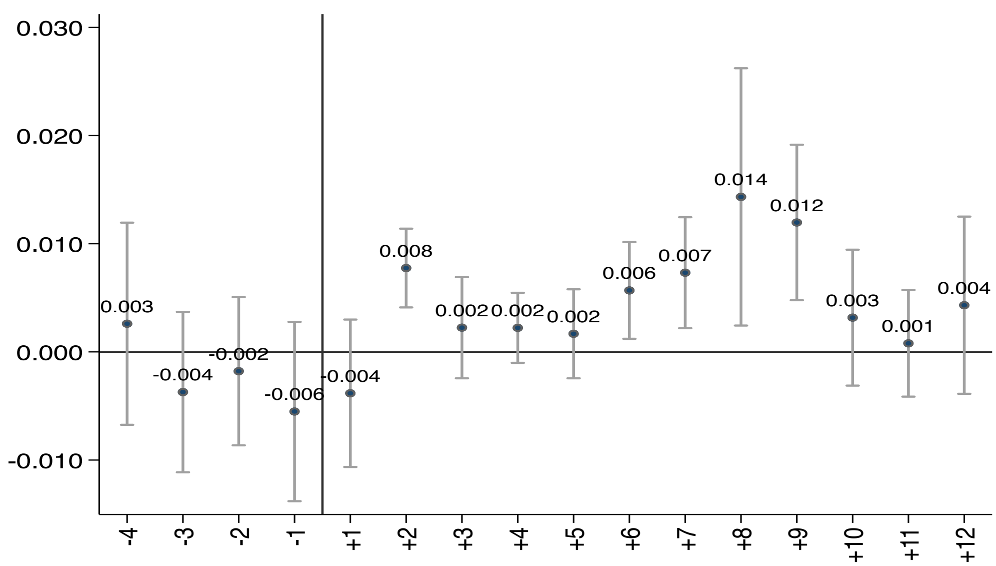
Notes: The figure plots the coefficients from a regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 1, for higher than median percentage population change between 2020 and 2010 as given by the Census Bureau. 90% confidence intervals.

Figure 13: Impact of Hurricane on Firm Investment - Continuous Measure of Hurricane Impact



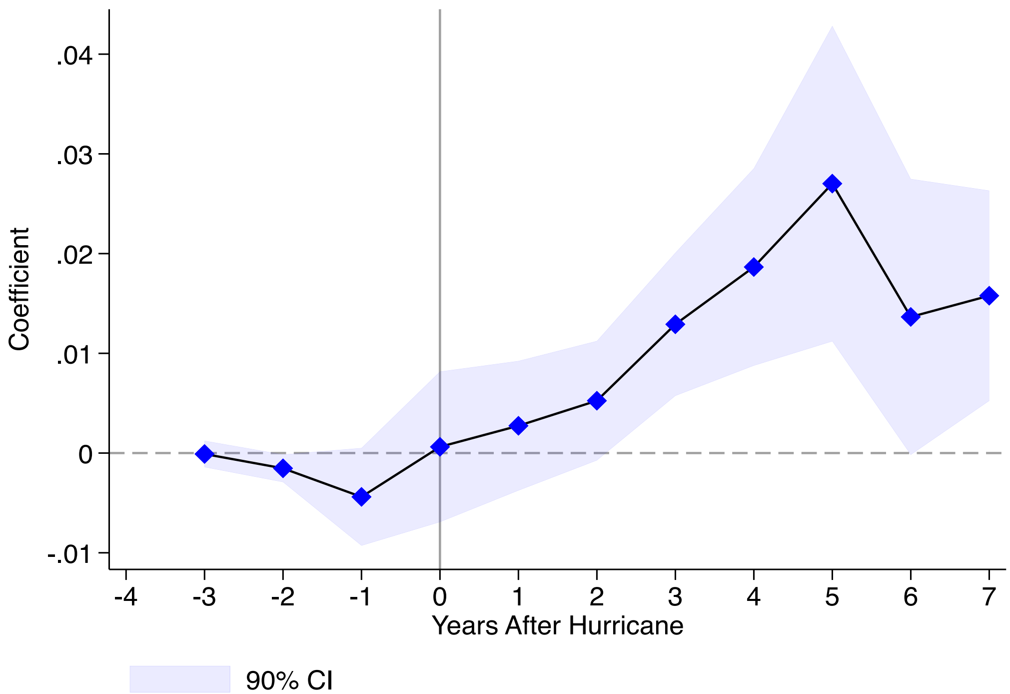
Notes: Regression of firm investment rate on hurricane impact as in equation 8. Impact is measured by the number of facilities hit by a hurricane divided by total facilities of the firm. Investment rate is the capital expenditure cash flow in the quarter divided by the net plant, property, equipment in that quarter's balance sheet. 95% confidence intervals.

Figure 14: Impact of Hurricane on Firm Investment - Dummy Measure of Hurricane Impact



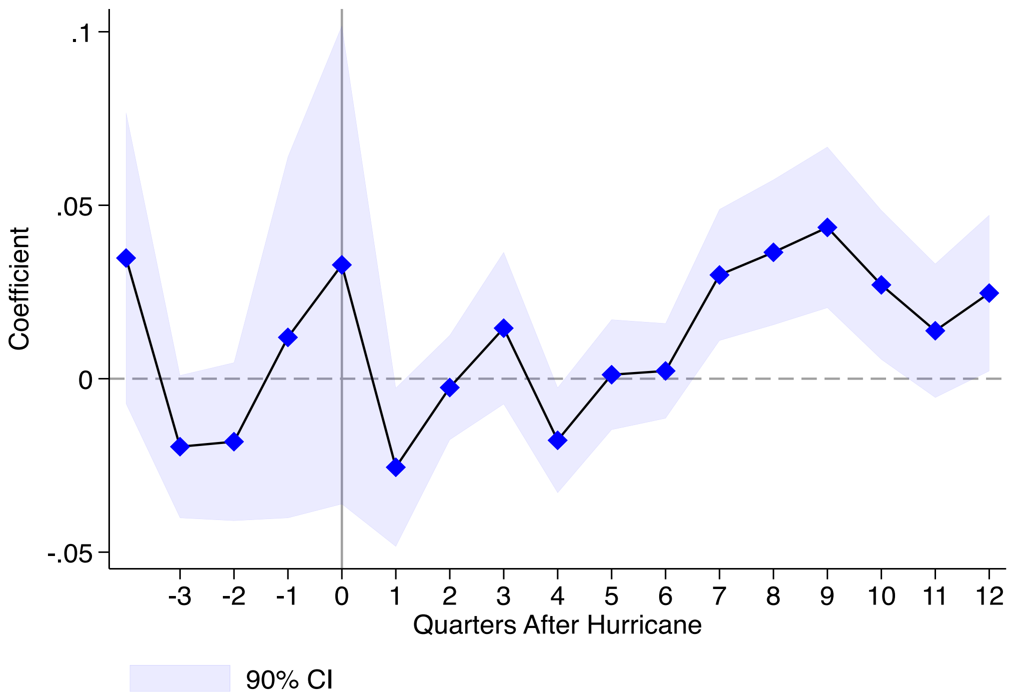
Notes: Regression of firm investment rate on hurricane dummy impact as in equation 8. Impact is 1 if any facility of a firm is hit by a hurricane in that quarter and 0 otherwise. Investment rate is the capital expenditure cash flow in the quarter divided by the net plant, property, equipment in that quarter's balance sheet. 95% confidence intervals.

Figure 15: Local Projections: Impact of Hurricanes on Municipality Property Tax Rates



Notes: Local projection of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 10. 90% confidence intervals.

Figure 16: Local Projections: Impact of Hurricanes on Firm Investment



Notes: Local projection of firm impact rate on hurricane impact. Impact is measured by the number of facilities hit by a hurricane divided by total facilities of the firm. Investment rate is the capital expenditure cash flow in the quarter divided by the net plant, property, equipment in that quarter's balance sheet, as in equation 11. 90% confidence intervals.

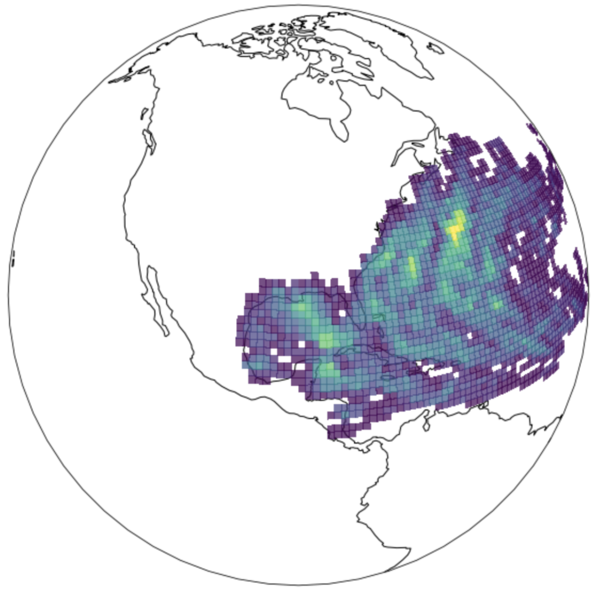


Figure 17: Historical Atlantic Hurricane Windspeed Heatmap

Notes: The figure plots a heatmap for all hurricanes in the Atlantic Basin between 2000 - 2021. Data from HURRDAT2. More yellow regions have experienced more hurricane level wind speeds historically. Dark blue regions have experienced fewer hurricane level wind speeds.

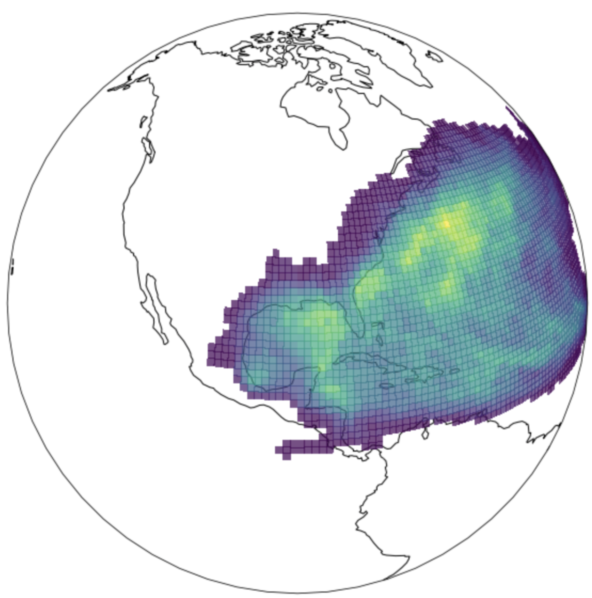


Figure 18: Historical Atlantic Storm Windspeed Heatmap

Notes: The figure plots a heatmap for all hurricanes and tropical storms in the Atlantic Basin between 2000 - 2021. Data from HURRDAT2. More yellow regions have experienced more hurricanes and tropical storms level wind speeds historically. Dark blue regions have experienced fewer hurricanes and tropical storms wind speeds.

Table 1: List of hurricanes used in analyses

Name	Begin	End	Damage (bn USD)	Deaths	Year
Hurricane Irene	20110826	20110828	17.4	45	2011
Hurricane Isaac	20120826	20120831	3.5	9	2012
Hurricane Sandy	20121030	20121031	81.9	159	2012
Hurricane Hermine	20160828	20160903	0.5	2	2016
Hurricane Matthew	20161008	20161012	12.1	49	2016
Hurricane Harvey	20170825	20170831	148.7	89	2017
Hurricane Irma	20170906	20170912	59.5	97	2017
Hurricane Florence	20180913	20180916	27.8	53	2018
Hurricane Michael	20181010	20181011	28.9	49	2018

Notes: The table provides details of the Atlantic Basin hurricanes that are used in the analyses for both firms and municipalities. Data is gathered from NOAA. For municipalities analyses the year of disaster is adjusted to match the fiscal year for the local government.

Table 2: Distance of Firm Facility to Nearest Property

	mean	p25	p50	p75	count
Distance to Nearest Building	0.04	0.02	0.03	0.04	408,357
Distance to Nearest Building (hurricane hit)	0.04	0.02	0.03	0.04	218,802
Hurricane Irene (August 2011)	0.03	0.02	0.02	0.03	15,072
Hurricane Sandy (October 2012)	0.03	0.02	0.02	0.03	11,642
Hurricane Isaac (August 2012)	0.05	0.02	0.03	0.04	3,886
Hurricane Matthew (October 2016)	0.04	0.02	0.03	0.04	28,860
Hurricane Harvey (August 2017)	0.04	0.02	0.03	0.05	19,727
Hurricane Irma (September 2017)	0.04	0.02	0.03	0.04	30,621
Hurricane Florence (September 2018)	0.04	0.02	0.03	0.04	26,569
Hurricane Michael (October 2018)	0.04	0.02	0.03	0.04	540

Notes: The table provides the distance in miles from each firm facility location to the nearest building in First Street data. The 99th percentile, not reported here, is 0.17 miles.

Table 3: Summary Statistics for Matched Sample

	mean	p25	p50	p75	count
Panel A: Full Matched Sample					
Total Assets	6946	331	1247	4643	165,062
Cash and Cash Equivalent	604	26	102	353	165,062
Long Term Debt	1821	8	247	1257	165,062
Net Income(Loss)	79	-2	9	52	165,062
Plant, Property and Equipment (Net)	2202	39	241	1255	165,062
Revenues	1160	60	252	877	165,062
Working Capital	450	22	134	439	165,062
Panel B: Dropping Utility and Financial Firms					
Total Assets	6952	351	1316	4548	91,137
Cash and Cash Equivalent	664	35	119	390	91,137
Long Term Debt	1807	7	254	1301	91,137
Net Income(Loss)	78	-4	9	51	91,137
Plant, Property and Equipment (Net)	1969	35	232	1118	91,137
Revenues	1199	63	260	874	91,137
Working Capital	526	35	163	517	91,137
Panel C: Sample Used For Regression					
Total Assets	7627	391	1427	4936	51,407
Cash and Cash Equivalent	743	41	132	415	51,407
Long Term Debt	1997	9	289	1500	51,407
Net Income(Loss)	92	-2	11	59	51,407
Plant, Property and Equipment (Net)	1972	41	230	1060	51,407
Revenues	1328	78	307	992	51,407
Working Capital	580	47	190	586	51,407

Notes: Panel A provides summary statistics for the matched sample between Moody's and Compustat. There are 3,366 unique firms. Panel B provides summary statistics for the matched sample between Moody's and Compustat after dropping utility and financial firms. There are 2,689 unique firms. Panel C provides summary statistics for the main sample used in the main specification in firm level regressions. There are 1,934 unique firms. All financial data is from Compustat Quarterly. The sample period is 2009 – 2020. All data is winsorized at the 1 and 99 percentile levels. All amounts in millions of USD.

Table 4: Summary Statistics for Tax Rates

	Control 2012		Treated 2012	
	mean	p50	mean	p50
Tax Rate	0.93	0.58	0.61	0.48

	Control 2021		Treated 2021	
	mean	p50	mean	p50
Tax Rate	1.02	0.60	0.68	0.49

Notes: The table provides mean and median data for control and treated municipalities. Data is included for 2012 which is the start of the analysis period and 2021 which is final year of the analysis. All data is in percentage of house assessment value in dollars.

Table 5: Summary Statistics for Municipalities

	Control		Treated		Difference	
	Mean	SD	Mean	SD		t-stat
Population Census 2010	12588	42021	20847	86603	-8259**	(-3.18)
Median Home Value Census 2010 (mn)	0.20	0.17	0.20	0.19	0.01	(0.85)
Per Capita Income Census 2010	27348	13871	26402	17282	945	(1.71)
Share above 65 Census 2010	0.15	0.05	0.17	0.08	-0.02***	(-7.39)
Share White Census 2010	0.82	0.18	0.69	0.22	0.13***	(18.56)
Share of Home Ownership Census 2010	0.72	0.14	0.66	0.14	0.06***	(13.16)
Share Less than High School Census 2010	0.16	0.11	0.18	0.11	-0.02***	(-4.88)
Share Below Poverty Line Census 2010	0.13	0.10	0.17	0.11	-0.04***	(-10.39)
Property Taxes/Total Taxes in 2007	0.70	0.29	0.55	0.23	0.15***	(17.33)
Debt Outstanding/Total Revenue in 2007	0.68	2.03	0.68	1.18	-0.01	(-0.13)
No of Firms/Sq Km Area	1.50	2.49	1.91	2.59	-0.41***	(-4.47)
Distance to Coast	120	122	56	53	64***	(24.17)
Observations	3221		1211		4432	

Notes: The table provides summary statistics for the main sample used in municipalites analysis. Data is obtained from the decennial Census of 2010, from the Census of Governments 2007, and from GIS calculations using Moody's data for firm facilities and Census TIGER shape files for municipalities. The sample period is 2012 – 2020. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia.

Table 6: Correlation of Firm Facility Density with Municipality Level Variables

	Control	Treated
Median Home Value Census 2010 (mn)	1.79***	2.66***
	(5.97)	(4.93)
Per Capita Income Census 2010	0.156***	0.213**
	(4.76)	(3.03)
Share of Home Ownership Census 2010	-6.427***	-6.048***
	(-11.32)	(-9.43)
Population Census 2010	0.145***	0.065**
	(4.10)	(3.13)
Share above 65 Census 2010	-4.163***	-2.057*
	(-4.24)	(-2.51)
Share White Census 2010	-2.500***	-0.039
	(-9.22)	(-0.12)
Share Less than High School Census 2010	-1.082**	-3.608***
	(-2.96)	(-5.48)
Share Below Poverty Line Census 2010	-0.442	-2.745***
	(-1.33)	(-4.80)
Distance to Coast	-0.00158***	-0.00801***
	(-4.46)	(-6.15)
N	2426	1180

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table provides the coefficient from a regression of the firm facility density on different characteristics for each municipality. The regressions are run with robust standard errors. Rows for Population Census 2010 and Per Capita Income are multiplied by 10,000 for better readability.

Table 7: Distance of Firm Facility to Headquarters

	mean	p25	p50	p75	count
Distance to HQ	835	264	665	1201	932,403
Distance to HQ ex-islands	828	264	664	1197	930,142
Distance to HQ Exposed	747	238	641	1050	744,726

Notes: The table provides the distance in miles from each firm facility location to the its headquarters. "Distance to HQ" measures this distance for the entire sample used in the main regression analysis. "Distance to HQ ex-islands" removes facilities located in Hawaii, Guam or Virgin Islands. "Distance to HQ Exposed" confines the sample to facilities located in hurricane exposed states.

Table 8: Regression of Tax Rate on Hurricane Dummy – Main Specification

	(1) Tax Rate	(2) Tax Rate	(3) Tax Rate	(4) log(Tax Rate)	(5) Tax Rate
$H_{i,t-1}$	0.00101	0.00500***	0.00565***	0.0000487***	0.00389
	(0.00176)	(0.00188)	(0.00173)	(0.0000185)	(0.00256)
$H_{i,t-2}$	0.00212	0.00796***	0.00805***	0.0000785***	0.00901**
	(0.00236)	(0.00276)	(0.00268)	(0.0000273)	(0.00385)
$H_{i,t-3}$	0.0107**	0.0146***	0.0133***	0.000143***	0.0136**
	(0.00431)	(0.00484)	(0.00378)	(0.0000473)	(0.00594)
$H_{i,t-4}$	0.0183**	0.0166**	0.0192***	0.000160**	0.0152***
	(0.00772)	(0.00834)	(0.00675)	(0.0000808)	(0.00763)
$H_{i,t-5}$			0.0172		
			(0.0119)		
Observations	4432	4432	4432	4432	3988
Unit FE	Yes	Yes	Yes	Yes	Yes
State × Time FE	Yes	Yes	Yes	Yes	Yes
Linear trend controls	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.994	0.995	0.995	0.994	0.994

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 1. $H_{i,t-n}$ is the nth lag after hurricane strike in municipality i. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia.

Table 9: Regression of Tax Rate on Hurricane Dummy – Interaction with Hurricane Intensity

	(1)
	Tax Rate
$H_{i,t-1}$	0.00682*
	(0.00372)
$H_{i,t-2}$	0.0191***
	(0.00629)
$H_{i,t-3}$	0.0329***
	(0.00872)
$H_{i,t-4}$	0.0164*
	(0.00842)
$H_{i,t-1} \times C^1_{i,t-1}$	-0.00216
	(0.00430)
$H_{i,t-2} \times C^1_{i,t-2}$	-0.0166**
	(0.00662)
$H_{i,t-3} \times C^1_{i,t-3}$	-0.0270***
	(0.0101)
$H_{i,t-1} \times C^5_{i,t-1}$	0.0307
	(0.0255)
$H_{i,t-2} \times C^5_{i,t-2}$	0.0335
	(0.0307)
Observations	4432
Unit FE	Yes
State × Time FE	Yes
Linear trend controls	Yes
Adjusted R^2	0.995

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 2. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia. $H_{i,t-n}$ is the nth lag after hurricane strike in municipality i. $C^k_{i,t-n}$ is a hurricane of category-k in the nth lag after hurricane strike in municipality i. Category-4 hurricanes are the omitted category in this regression. Three lags available for category-1 hurricanes because the omitted category only has a maximum of three lags. Two lags available for category-5 hurricane because the only hurricane at category-5, Michael, occurred in 2019.

Table 10: Regression of Tax Rate on Hurricane Dummy: Stacked Event-by-Event Estimates

	(1)
	Tax Rate
$H_{i,t+4}$	-0.00188
	(0.00337)
$H_{i,t+3}$	0.000265
	(0.00262)
$H_{i,t+2}$	0.00116
	(0.00210)
$H_{i,t}$	0.00420*
	(0.00243)
$H_{i,t-1}$	0.00877***
	(0.00261)
$H_{i,t-2}$	0.0119***
	(0.00337)
$H_{i,t-3}$	0.0175***
	(0.00458)
Observations	4432
Unit FE	Yes
State × Time FE	Yes
Linear trend controls	Yes
Adjusted R^2	0.991

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 4. The estimates are produced by stacking separate event study cohorts defined by each hurricane. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia. $H_{i,t\pm n}$ is the nth lead/lag of hurricane strike in municipality i.

Table 11: Regression of Fiscal Variables on Hurricane Occurrence

	(1)	(2)	(3)	(4)	(5)
		Intergovernmental Revenue			
	Property Tax Revenue	Local	State	Federal	Debt
Hurricane in last 1-5 years	0.0699**	0.709***	0.188	-0.170	0.174
	(0.026)	(0.239)	(0.128)	(0.185)	(0.136)
Observations	4018	3626	3626	3626	3626
State × Time FE	Yes	Yes	Yes	Yes	Yes
Linear trend controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.944	0.746	0.826	0.729	0.870

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of logarithm of property tax revenues, local, state, federal intergovernmental revenue and debt on a dummy for whether there was a hurricane strike in the last 1-5 years. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia.

Table 12: Regression of Tax Rate on Hurricane Dummy – Configuration of Previous Hurricanes

	(1) Investment Rate	(2) Tax Rate
$H_{i,t}$	-0.107	0.00265
	(0.0670)	(0.00240)
$H_{i,t-1}$	0.0114	0.00448*
	(0.0235)	(0.00240)
$H_{i,t-2}$	0.102**	0.00908*
	(0.0434)	(0.00471)
$H_{i,t-3}$	0.0291	0.0146**
	(0.0315)	(0.00621)
$H_{i,t} \times H_{i,t-1}$	0.199**	0.00821***
	(0.0879)	(0.00294)
$H_{i,t} \times H_{i,t-2}$	0.121	0.000452
	(0.124)	(0.00341)
Observations	15879	30554
Adjusted R^2	0.579	0.994

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table runs equation 7 and equation 3. Both regressions are run on an yearly level. For the municipality regression, the following states are included – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia. Investment rates are in annual capital expenditure cash flows divided by net plant, property and equipment. Tax rates are in \$ per \$100 property assessed value. ω_3, ω_4 coefficients are omitted because there are no observations with hurricanes hitting the same unit after a gap of 2 and 3 years respectively.

Table 13: Regression of Firm Investment Rate on Hurricane Impact

	Investment Rate		
	(1)	(2)	(3)
-4	-0.0104	0.00545	0.00421
	(0.0108)	(0.0144)	(0.0152)
-3	-0.0296**	-0.0374*	-0.0339
	(0.0145)	(0.0221)	(0.0233)
-2	-0.0169	-0.0192	-0.0187
	(0.0139)	(0.0194)	(0.0205)
-1	-0.0138	-0.00885	-0.00946
	(0.0129)	(0.0182)	(0.0193)
+1	-0.0326**	-0.0509**	-0.0479**
	(0.0140)	(0.0223)	(0.0239)
+2	-0.0207*	-0.00771	-0.00578
	(0.0115)	(0.0137)	(0.0141)
+3	0.00423	0.0178	0.0196
	(0.0146)	(0.0185)	(0.0193)
+4	-0.00495	-0.00139	0.000927
	(0.00823)	(0.00993)	(0.00997)
+5	-0.0185	-0.00812	-0.00549
	(0.0132)	(0.0168)	(0.0170)
+6	-0.0372***	0.00504	0.00797
	(0.0117)	(0.0145)	(0.0150)
+7	-0.0194	0.0365**	0.0417**
	(0.0143)	(0.0177)	(0.0184)
+8	-0.0155	0.0463**	0.0529**
	(0.0130)	(0.0206)	(0.0223)
+9	-0.0614***	0.0185	0.0224
	(0.0170)	(0.0217)	(0.0226)
+10	-0.0354*	0.00871	0.00880
	(0.0210)	(0.0243)	(0.0251)
+11	-0.0512***	-0.0251	-0.0222
	(0.0152)	(0.0158)	(0.0162)
+12	-0.0339**	-0.00398	-0.00402
	(0.0145)	(0.0187)	(0.0197)
Observations	59932	59932	53759
Adjusted R^2	0.482	0.485	0.494
Unit-Quarter FE	Yes	Yes	Yes
Year-Quarter FE	No	Yes	Yes
State-HQ FE	No	No	Yes

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Impact is measured by the number of facilities hit by a hurricane divided by total facilities of the firm. Investment rate is the capital expenditure cash flow in the quarter divided by the net plant, property, equipment in that quarter's balance sheet. Column (3) is our preferred specification.

Table 14: Regression of Financial Variables on Hurricane Impact

	Cash/Assets (1)	Sales Growth (2)	Profits (3)
-4	0.0296*	-0.0340	0.110
	(0.0167)	(2.283)	(0.388)
-3	0.0200	1.032	0.0639
	(0.0196)	(1.543)	(0.259)
-2	0.0200	-3.293	0.300
	(0.0184)	(5.689)	(0.307)
-1	0.00782	-0.546	0.356
	(0.0210)	(4.992)	(0.449)
+1	0.000384	-0.406	0.192
	(0.0209)	(2.456)	(0.509)
+2	-0.00598	-0.617	-0.0220
	(0.0185)	(2.064)	(0.287)
+3	-0.00535	-8.648	0.0816
	(0.0205)	(8.086)	(0.417)
+4	-0.00278	-2.095	-0.539
	(0.0178)	(2.099)	(0.343)
+5	0.0147	2.192	-0.407
	(0.0237)	(1.746)	(0.377)
+6	0.0265	-3.006	-0.448*
	(0.0196)	(3.271)	(0.263)
+7	0.0324*	0.00339	-0.325
	(0.0195)	(1.144)	(0.424)
+8	0.0502***	0.406	-0.430
	(0.0189)	(1.346)	(0.373)
+9	0.0515**	0.632	0.00269
	(0.0213)	(1.889)	(0.388)
+10	0.0276	2.146	-0.705
	(0.0218)	(3.854)	(0.489)
+11	0.0165	-1.774	-0.143
	(0.0242)	(1.838)	(0.569)
+12	0.0265	-1.194	-1.014
	(0.0248)	(1.585)	(0.892)
Observations	57678	55878	56153
Adjusted R^2	0.874	0.037	0.697
Year-Quarter FE	Yes	Yes	Yes
Unit-Quarter FE	Yes	Yes	Yes
State-HQ FE	Yes	Yes	Yes

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Impact is measured by the number of facilities hit by a hurricane divided by total facilities of the firm.

Table 15: Regression of Firm Investment Rate on Hurricane Impact – Heterogeneity by Firm Facility Clustering

	Investment Rate		Investment Rate
$NS_{i,t+4}$	-0.00195 (0.0202)	$NS_{i,t+4} \times Q_1$	0.0140 (0.0278)
$NS_{i,t+3}$	-0.0204 (0.0283)	$NS_{i,t+3} \times Q_1$	-0.0297 (0.0410)
$NS_{i,t+2}$	-0.00620 (0.0236)	$NS_{i,t+2} \times Q_1$	-0.0282 (0.0368)
$NS_{i,t+1}$	-0.0193 (0.0199)	$NS_{i,t+1} \times Q_1$	0.0230 (0.0331)
$NS_{i,t-1}$	-0.0457* (0.0285)	$NS_{i,t-1} \times Q_1$	-0.00596 (0.0415)
$NS_{i,t-2}$	0.0114 (0.0152)	$NS_{i,t-2} \times Q_1$	-0.0396 (0.0294)
$NS_{i,t-3}$	0.0169 (0.0197)	$NS_{i,t-3} \times Q_1$	0.00683 (0.0364)
$NS_{i,t-4}$	0.000350 (0.0128)	$NS_{i,t-4} \times Q_1$	-0.00255 (0.0190)
$NS_{i,t-5}$	0.0214 (0.0156)	$NS_{i,t-5} \times Q_1$	-0.0618* (0.0325)
$NS_{i,t-6}$	0.0449*** (0.0151)	$NS_{i,t-6} \times Q_1$	-0.0845*** (0.0285)
$NS_{i,t-7}$	0.0705*** (0.0199)	$NS_{i,t-7} \times Q_1$	-0.0617* (0.0346)
$NS_{i,t-8}$	0.0693** (0.0295)	$NS_{i,t-8} \times Q_1$	-0.0421 (0.0346)
$NS_{i,t-9}$	0.0531** (0.0239)	$NS_{i,t-9} \times Q_1$	-0.0719* (0.0423)
$NS_{i,t-10}$	0.00386 (0.0254)	$NS_{i,t-10} \times Q_1$	0.00373 (0.0442)
$NS_{i,t-11}$	-0.00895 (0.0229)	$NS_{i,t-11} \times Q_1$	-0.0228 (0.0311)
$NS_{i,t-12}$	-0.0181 (0.0311)	$NS_{i,t-12} \times Q_1$	0.0247 (0.0338)

Observations	49228
Adjusted R^2	0.499
Unit-Quarter FE	Yes
Year-Quarter FE	Yes
State-HQ FE	Yes

Notes: Impact is measured by the number of facilities hit by a hurricane divided by total facilities of the firm. Investment rate is the capital expenditure cash flow in the quarter divided by the net plant, property, equipment in that quarter's balance sheet. Q_1 is a dummy that is 1 if the firm belongs to the first quartile of firm size by spatial clustering, that is the most clustered of firms.

Table 16: Regression of Tax Rate on Hurricane Dummy using First Hurricane Strike Only

	(1)
	Tax Rate
$H_{i,3}$	0.00562
	(0.00343)
$H_{i,t+2}$	0.00334
	(0.00235)
$H_{i,t}$	0.00395
	(0.00343)
$H_{i,t-1}$	0.00955**
	(0.00382)
$H_{i,t-2}$	0.0129***
	(0.00440)
$H_{i,t-3}$	0.0137**
	(0.00568)
$H_{i,-4}$	0.000521
	(0.0135)
Observations	4432
Adjusted R^2	0.987

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of property tax rates ($ for every $100 of assessment value) in a municipality on hurricane impact dummies as per equation 9. Importantly, the hurricane dummy is equal to 1 if an only if it is the first hurricane strike for municipality i between 2012-2021. $H_{i,t-n}$ is the nth lag after hurricane strike in municipality i. $H_{i,t+n}$ is the nth lead after hurricane strike in municipality i. $H_{i,3}$ is a dummy that is one if hurricane strike takes place before the time window of interest. $H_{i,-4}$ is a dummy that is one if hurricane strike takes place after the time window of interest.

Table 17: Regression of Tax Rate on Hurricane Dummy for Municipalities at Different Distance from Coast

	(1) Tax Rate	(2) Tax Rate	(3) Tax Rate	(4) Tax Rate	(5) Tax Rate
$H_{i,t-1}$	0.00247	0.00493*	0.00333	0.00344	0.00462
	(0.91)	(1.67)	(0.97)	(0.76)	(1.51)
$H_{i,t-2}$	0.00565	0.00736	0.00713	0.00455	0.00257
	(1.33)	(1.54)	(1.24)	(0.98)	(0.54)
$H_{i,t-3}$	0.0275***	0.0252***	0.0124	0.00427	0.0107
	(3.05)	(2.68)	(1.36)	(0.45)	(1.06)
$H_{i,t-4}$	0.0220*	0.0250*	0.0304*	0.0405**	0.0435**
	(1.70)	(1.73)	(1.80)	(2.07)	(2.04)
Observations	2794	2421	1958	1226	862
Unit FE	Yes	Yes	Yes	Yes	Yes
State × Time FE	Yes	Yes	Yes	Yes	Yes
Linear trend controls	Yes	Yes	Yes	Yes	Yes
Distance from coast (miles)	< 100	< 75	< 50	< 25	< 15
Adjusted R^2	0.995	0.995	0.995	0.996	0.997

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Regression of property tax rates ($ for every $100 of assessment value) in a municipality on an indicator for hurricane impact in a given year, as given in equation 1. $H_{i,t-n}$ is the nth lag after hurricane strike in municipality i. Each column restricts municipalities below a certain distance from the coast. States – Connecticut, Florida, Georgia, Massachusetts, Maryland, North Carolina, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia.