Environmental Disasters and Stock Market Performance*

Ishuwar Seetharam†
Stanford University

September 2017

Abstract

Do environmental disasters affect company stock performance? The extent to which markets respond to disaster onsets depends on the extent to which stock prices incorporate key information on the firms' adaptive capacity, in the midst of increasingly calamitous disaster patterns and reduced insurability. Employing an event study methodology, I study daily stock data of publicly listed firms in the United States and their responses to the top 122 US natural disasters between 1980-2014. I find that exposed companies are associated with stock market valuations that are 0.3 to 0.7 percentage points lower relative to the returns of non-exposed companies. The estimated impact translates into US$9 million to US$22 million lost in the market valuation of exposed firms, with the larger losses occuring further away from the day of the disaster. Firms operating a large number of subsidiaries are able to mitigate these impacts to some extent, but labor market frictions play no role in explaining these negative impacts.

JEL:
Keywords:

*I'm grateful to Nicholas Bloom and Shai Bernstein for their guidance. I'm also grateful to Luigi Pistaferri, Melanie Morten and Mounu Prem for their kind feedback and support during the course of the project.
†Department of Economics, Stanford University; 579 Serra Mall, Stanford, CA 94305-6072. email: ishuwar@stanford.edu

1 Introduction

The upshot of climate change on global patterns of growth and development is a topic of much debate. The increasingly erratic patterns in the timing, location and intensity of natural disasters in the last fifteen years (see Figure 1) has given rise to many studies that explore the aggregate consequences of extreme weather on economic growth. Natural disasters are found to have an economically large causal effect on countries' long run growth, with losses from a 90th percentile event comparable to those of a banking crisis. National incomes losses are also found to be persistent, and do not recover to their pre-disaster trend within twenty years (Hsiang and Jina, 2014).

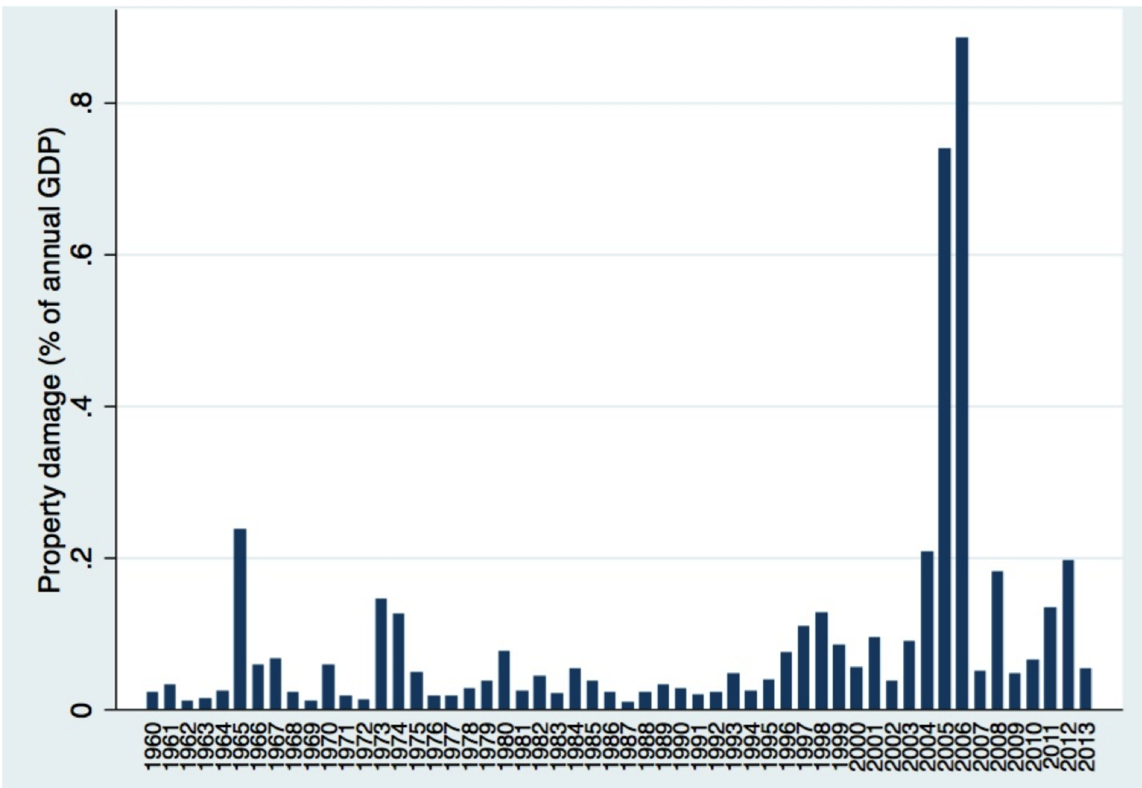

Figure 1: Annual Property Damage due to Natural Disasters (% of Annual GDP, deflated by House Price Index)

Source: Storm Events Database, National Oceanic and Atmospheric Administration

Do environmental disasters affect the performance and growth of adaptive agents like companies? It is challenging to ascertain the extent to which stock prices respond to natural disaster shocks. On the one hand, stock prices only respond to news, and otherwise fully incorporate essential information concerning the adaptive capacity of the firm -

through financial mechanisms like insurance, or by the strategic choice of plant location.[1] In this case, stock prices may not be impacted by disaster shocks. On the other hand, climate change poses novel risks often outside the range of experience; because of increasingly calamitous and uncertain trends in extreme weather patterns, as well as reduced insurability and threatened insurance schemes, even as insurance demand increases ((ABI, 2005); (Dlugolecki and Lafeld, 2005); (Mills, 2005); (Valverde Jr and Andrews, 2006)). If stock prices do not internalize unexpected hazards to firm adaptive capacity, markets may respond to disaster onsets.[2]

In this paper, I discern the impact of major catastrophic weather events in the United States, on the stock market valuations of exposed and non-exposed firms. The event study encapsulates the top 122 environmental disasters by property damage in the United States, and spans different event-day-windows; i.e. $[-5, 0]$, $[-5, 10]$, $[-5, 20]$, $[-5, 30]$, and $[-5, 40]$ days around the event[3]. An event study methodology is beneficial as company stock prices internalize key information regarding the adaptive capacity of the firm, such as the degree of insurance they possess from external financial markets or internal capital markets. Thus, it captures the effect of environmental disasters on market participants' expectation of the net present value of economic damage accruing to exposed companies relative to the net present value of non-connected firms. I estimate that exposed companies are associated with stock market valuations that are 0.3 to 0.7 percentage points lower relative to the returns of non-exposed companies. Economically this translates into US$ 9 million to US$ 22 million of market capitalization lost due to extreme weather disasters.

In the paper, I first examine the raw data of mean stock returns for the 122 natural disaster events analyzed. The graphs are presented for the event window $[-20, 40]$ around the event, with the first day normalized to 0. The graphs illustrates how the stock returns of firms exposed to natural disasters are associated with lower stock market valuations relative to non-exposed firms.

Next, I estimate the impact of natural disasters on stock returns using a cross-sectional

[1] Adaptive capacity is the ability or potential of a system to respond successfully to climate variability and change, and includes adjustments in both behaviour and in resources and technologies (Adger et al., 2007). Societies have a long record of adapting to the impacts of weather and climate through a range of practices that include crop diversification, irrigation, water management, disaster risk management, and insurance.

[2] Firms are also additionally constrained by geo-physical considerations in their choice of plant location due to the nature of the business they operate. For example, oil drilling companies have no choice but to locate on the coast. Final assembly lines may be located in important port cities to minimize time and costs associated with transportation.

[3] Day 0 is the first day of the event. Day -5 is five days before the first day, Day 40 is forty days after the first day of the event

event study methodology, along the lines of Acemoglu et al. (2014). For the 122 events, I estimate a separate impact coefficient for each event-day-window, spanning the days [-5,0], [-5,10], [-5,20], [-5,30], [-5,40] around the event's first day. The methodology relates changes in the cumulative returns on each company's stock between five days before the event and the last day ($m \in \{0, 10, 20, 30, 40\}$) of the weather event, to the exposure of the company.

The paper then tests various hypotheses of adaptive capacity. I first test if the adaptive capacity of firms depend on their single-plant or multi-plant firm structure. the damaging effects of exposure. I obtain subsidiary data from ORBIS, and the results suggest that multi-subsidiary firms mitigate the adverse impacts of disasters, suggesting the possibility that they take advantage of their internal capital markets by reallocating assets and labor across their exposed and non-exposed plants and be unaffected (Giroud and Mueller (2015)). They could alternatively mitigate these shocks by plant expansion or shut-down activity that is not easily feasible to them in normal times. Next, I explore if labour market frictions matter for firm adaptive capacity, by testing the heterogeneous impact of disasaters depending on firms operating/not-operating in states that high unionization of labour. Using state-level variation in the passage of Right to Work laws, I find no evidence that of labor market frictions impacting firm adaptive capacity.

This paper primarily contributes to a small growing literature on the impact of disasters on stock markets. Very few prior studies have looked at the stock market responses to a broad set of disasters and have documented either generally insignificant impacts (Baker and Bloom (2013), Brounrn and Derwal. (2010)), or heterogeneous impacts by the type of disaster or industry (Koerniadi et al. (2016), Worthington* and Valadkhani (2004), Wang and Kutan (2013)). This paper also contributes by studying some untested mechanisms in the literature, such as the role of the firm structure and labor market frictions in explaining the response of markets to disasters. This paper contributes a firm-sided story to the growing empirical literature on the economic impact of global climate change, which is marked by strong theoretical foundations ((Nordhaus and Yang, 1996); (Stern, 2008);(Weitzman, 2009);(Tol, 2009); (Heal, 2009)) and a growing empirical grounding (Pindyck, 2013). Prior empirical work has focussed on the economic consequences of tropical cyclones (Hsiang and Jina, 2014), impact of Hurricane Katrina on plant closures (Basker and Miranda, 2014), or temperature's effect on agriculture (Schlenker and Roberts, 2009), health (Deschênes et al., 2009), labor (Zivin and Neidell, 2014), energy (Deschenes and Greenstone, 2007), social conflict (Hsiang et al., 2013), and growth generally (Dell et al., 2012).

The data sources are provided in Section 2. It provides details about the natural disaster events, defines firm treatment or exposure, and presents graphs of the raw stock return data. In Section 3, I present the event study methodology and important specifications that are estimated in the paper. The section also puts forth the hypotheses and mechanisms considered in the analysis. The results of the event study and the important hypotheses evaluated in the paper are presented in Section 4. A discussion of the results follows in Section 4.3, where the results are qualified under certain caveats and considerations. A concluding summary of the paper, including proposed future work, is presented in Section5.

2 Data

2.1 Natural Disaster Events

The Storm Events Database provided by the National Oceanic and Atmospheric Administration of the U.S. Government provides detailed information on the top 165 weather events by property damage across the United States spanning 1960-2014. The information provided includes the name of the disaster, the start and end date, states exposed, the dollar value of property damage and the death toll associated with the disaster, and a summary description of the event.

The disaster events exhibit interesting patterns. First, events maybe both local and non-local. Droughts cover the largest geographical areas, floods and hurricanes have relatively smaller spreads depending on the path of the river or the storm respectively, while hurricanes and blizzards are extremely local events. Even within a category, the localness varies quite a bit. In the case of hurricanes, Katrina was a highly damaging event that was concentrated mainly within three states (Louisiana, Alabama and Florida); whereas Sandy, the second most damaging event, was spread out across nine states along the east coast of the United States. Second, these geographical concentrations of disaster events are not independent of each other. For example, a highly local Midwest Tornado in 2011 quarter 1 caused terrestrial and atmospheric conditions that gave rise to non-local disaster events like flooding along the Mississippi river and heavy gusts of wind and rain along the way. Third, the costliest events that cause havoc to property damage are the least frequent. As we can see in Figure 2, approximately 70% of all property damage is accrued to events such as Hurricanes, Floods and Tornadoes, but they are only a meagre 7% of all the occurrences. In contrast, Thunderstorm wind and Hail make up for more than 60% of all occurrences, but contribute to only 7% of total damages.

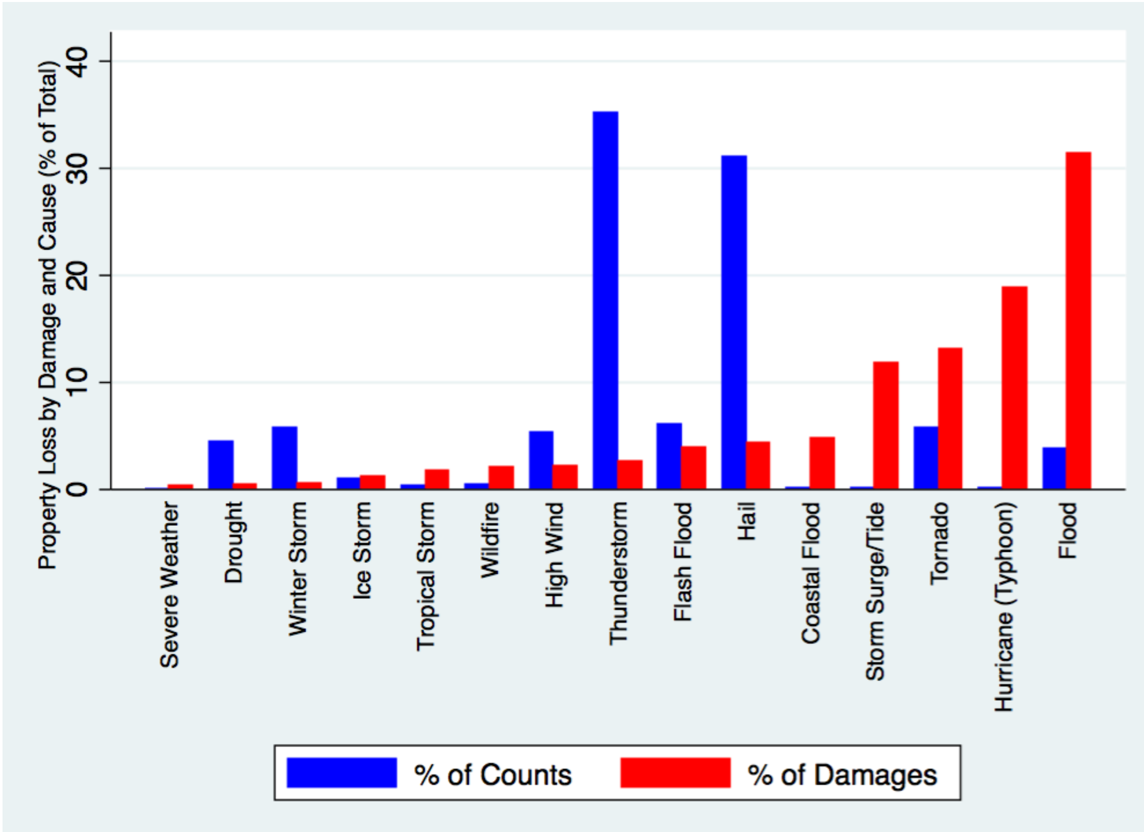

Figure 2: Natural Disasters - Frequency vs. Intensity

Source: Storm Events Database, National Oceanic and Atmospheric Administration

Of these 165 natural disasters described, I drop drought and heatwaves, and events without precise state location. I exclude droughts/heatwaves for three reasons; (i) low location accuracy, as it covers very broad geographical area; (ii) unclear on how to define day 1; (iii) extremely long horizon (spanning a whole year or more). We are left with 122 environmental disasters spanning the years 1980-2014. These disasters include 9 Fires, 30 Hurricanes, 27 Tornadoes, 6 Ice Storms (Hail, Blizzards), 18 Floods, 7 Freezes and 23 other Severe Weather events that are generally a combination of Tornado bursts accompanied by flooding.

2.2 Firm Data

The outcome variable of interest is the daily stock returns of all publicly listed companies in the United States. It is obtained from CRSP COMPUSTAT, provided by the Wharton Research Data Services. In addition to daily stock prices, COMPUSTAT also provides identifying information like the headquarter location and the industry of operation (4 digit SIC code). I also obtain other firm characteristics from quarterly balance sheet data on capital expenditures, total assets, sales, long term debts, property plant and equipment, revenue, etc.

Information on subsidiary locations of the parent COMPUSTAT companies is obtained from a dataset called ORBIS, provided by Dun & Bradstreet. ORBIS contains information on every subsidiary of both listed and unlisted companies around the world. I narrow it down to companies within the United States, and observe every company's subsidiary location. We are then left with 12,584 firms along with their subsidiary locations.

A company is defined to be **"Exposed"** to an environmental disaster if it has a headquarter or a subsidiary in the state where a natural disaster has occured. The 'state' location of a disaster was obtained from the National Oceanic and Atmospheric Administration's Storm Events Database, as well as any mention of a state in the Wikipedia descriptions of the disaster. 12,449 companies are exposed to one or more of the 122 events. Firm Exposure by Sector (2 digit SIC) to different events is presented below in Table 1. All types of firms are represented as exposed to a variety of natural disasters. Droughts show up with no observations since we excluded them from our analysis. More firms from all sectors are exposed to hurricanes, tornadoes and severe weather categories of events, which are supposed to be the most damaging of among all categories. It is difficult to read if firms in the Finance and Retail industries have very few unexposed firms just because coverage is lower in ORBIS. Throughout our analysis, we include industry (4 digit SIC) fixed effects in our regressions.

Table 1: Firm Exposure by Sector

Industry	Unexposed	Drought	Fire	Flood	Freeze	Hurricane	IceStorm	Sev'Weather	Tornado	Total
Agriculture	57	0	3	6	3	12	2	6	7	100
Construction	12	0	6	12	3	20	3	18	22	100
Finance	1	0	8	12	2	21	3	24	27	100
Govt Admin	18	0	7	10	3	21	2	17	17	100
Manufacturing	51	0	4	6	2	12	2	9	11	100
Mining	34	0	5	8	2	13	2	14	19	100
Retail	5	0	7	12	3	23	3	19	23	100
Services	52	0	4	6	2	13	1	8	10	100
Wholesale	55	0	3	6	3	11	2	7	9	100
Transportation	60	0	3	5	2	10	1	6	9	100

Notes: Firm Exposure by Sector (2 digit SIC) to different events is presented in the Table. All types of firms are represented in the "exposed" category, to a variety of natural disasters. Droughts show up with no observations since we excluded them from our analysis. More firms from all sectors are exposed to hurricanes, tornadoes and severe weather categories of events, which are supposed to be the most damaging of among all categories. It is difficult to read if firms in the Finance and Retail industries have very few unexposed firms just because coverage is lower in ORBIS. Throughout our analysis, we include industry (4 digit SIC) fixed effects in our regressions.

2.3 Stock Returns Raw Data

I present graphs of the raw data of mean stock returns across all events for the 12,584 companies in the sample, split between exposed (treated) and non-exposed. The first graph Figure 3 presents the mean cumulative stock returns of exposed and non exposed companies across the 122 events, for each relative day 20 days prior and 40 days after[4]. Figure 4 plots the mean daily stock returns for the same period.

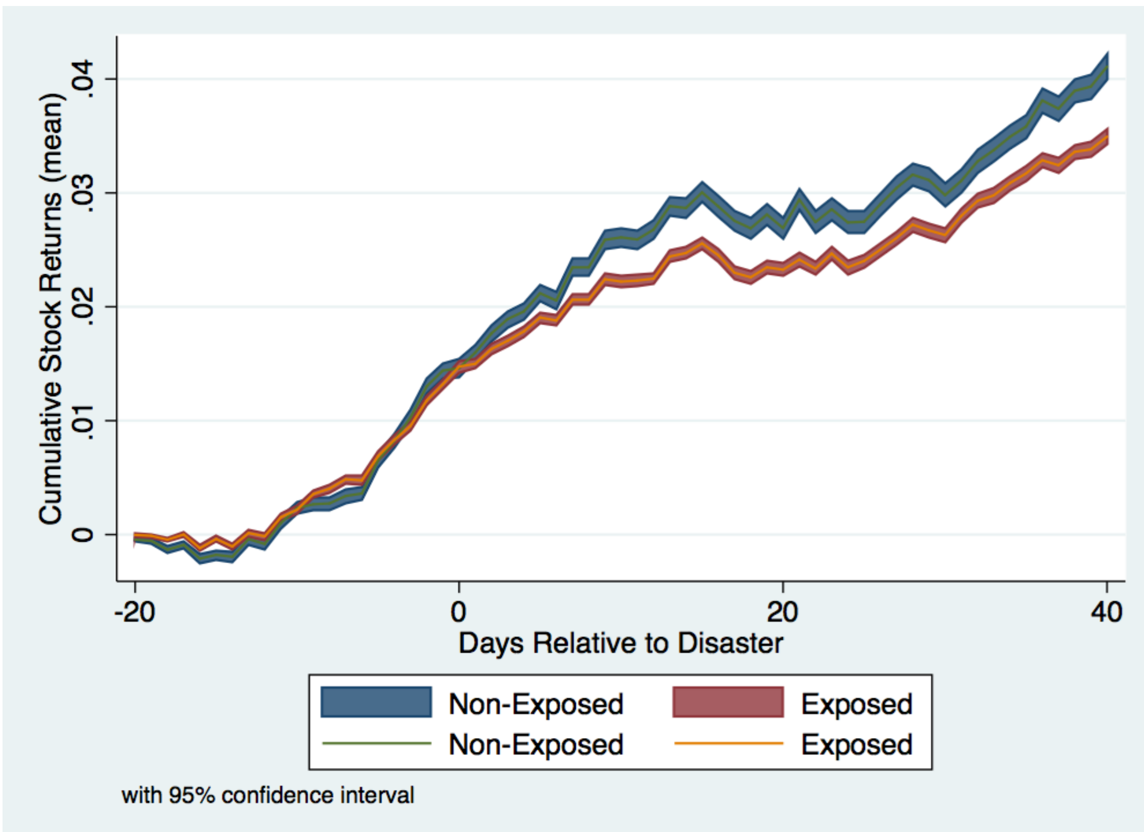

Figure 3: Cumulative Returns for all Disaster Relative Days

Source: COMPUSTAT, ORBIS and National Oceanic and Atmospheric Administration

The cumulative returns graph in Figure 3 illustrates a great deal of comovement in the pre-period $[-20, 0)$, a split-down in the returns of exposed firms beginning on day 0, and a gradual widening apart beyond day 0. All along, Figure 4 shows how daily stock returns co-move, ticking around 0.

In theory, we must expect an immediate sharp drop on day 0 in the cumulative returns of exposed firms during any event of uncertainty, and a parallel trend between the two

[4]Cumulative stock returns are the integral of daily stock returns. On any relative day $m \in [-20, 40]$, Cumulative stock return for day m relative to the disaster is defined as $\sum_{t=-20}^{m} stockreturn_t$).

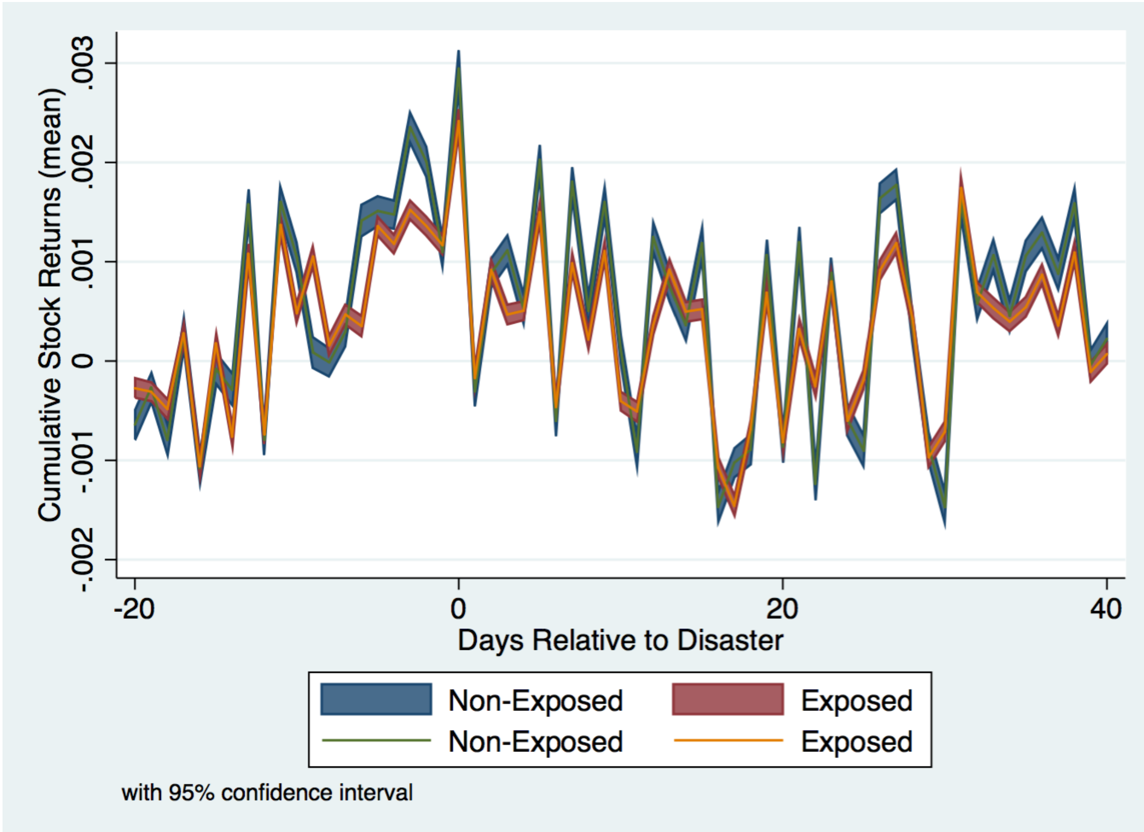

Figure 4: Daily Returns

groups in the post-period. This pattern in cumulative stock returns is expected because of movements in the daily stock returns. The daily stock returns of exposed vulnerable firms momentarily drops on day 0 (or a day or two prior) and quickly gets back to its normal path. The instantaneous return to trend, independent to the duration of the event, is a characteristic distinctive of stock prices. Stock markets only respond to news, and the average disaster's magnitude as well as the company's ability to mitigate itself is already internalized in the stock price.

Instead, Figure 3 illustrates a gradual widening in the post period, and then an eventual parallel trend once again. This gradual disunity occurs due to an end selection issue; i.e. the event study encompasses the top 122 disaster events in the United States. Each one of these events recorded property damages of USD 1bn or more. Inevitably, markets may under-estimate magnitude of the disaster in the pre-period and update its information after the event actually occurs. Analogously in the data, the gradual divergence of exposed cumulative returns reflect that the firms learn over time that these 122 disasters are of a large economic magnitude. However, this end selection is not a problem. At the time that these events hit, firms cannot distinguish between the "bigs" or the "smalls", but learn the actual magnitude of the event over the following days.

Visually, Figure 3 clearly illustrates that exposed firms are associated with lower market capitalizations in comparison to unexposed firms. To discern the impact of natural disaster exposure on firms' stock market valuations, the next two sections present the details of the event study estimation methodologies and results.

3 Methodology

3.1 Cross Sectional Methodology

I employ the standard cross-sectional event study methodology[5] to describe the impact of major catastrophic weather events in the United States on the daily stock returns of publicly listed companies, captured by their differential geographical exposure across the United States in the event of the weather shock. The methodology relates changes in the cumulative returns on each firm's stock between the opening of trade on trading day n and the closing of trade on the end trading day m (all trading days are counted relative to the first day, "Day 0", of each event).

A unit of observation is a company, event. That is, the dataset has a single observation for every firm per event, with 122 events overall. $CR(n,m)_{i,e}$ is the cumulative returns for company i in event e between start day n and end day m. Cumulative returns are calculated as the sum of firm i's returns on trading day t, at the time of event e. $\sum_{t=n}^{m} log(1 + return_{i,e,t})$. The methodology relates changes in cumulative returns on each company's stock between the first day (n) and the last day (m) of the weather event, to the exposure of the company. The empirical model I estimate is:

$$CR(n,m)_{i,e} = \gamma Treat_{i,e} + X'_{i,e}\mu + \eta_s + \psi_e + \epsilon_{i,e} \tag{1}$$

$Treat_{i,e}$ is an exposure dummy for firm i during event e, which takes the value 1 if a firm has a headquarter or subsidiary in the location of natural disaster. η_s is a full set of industry fixed effects that controls for time invariant differences between the firms. ψ_e is a full set of event fixed effects. $X_{i,e}$ is a vector of controls which includes firm charac-

[5]The methodology is borrowed from Acemoglu et al. (2014) and related recent papers that employ an event study analysis. Given the numerous methods in the literature, I resorted to the latest method that is now standard in the literature.

teristics from the previous year such as Revenues, Assets, Debts and Sales; as well as World-market Betas β_i^{world} and US-market Betas β_i^{US}. These betas are obtained, for each firm i, by running a separate regression of the daily stock returns of each company i on the returns on the MSCI-US and MSCI-World indices, respectively:

$$\log(1 + ret)_{i,t} = \alpha_i^x + \beta_i^x R_t^x + v_{i,t}$$

where $x = \{US, World\}$. $log(1 + ret)_{i,t}$ is the return on firm i on trading day t and R_t^x denotes the return on the respective MSCI index, i.e. either the MSCI US or MSCI World index.

The coefficient γ measures how the cumulative stock market returns of a group of exposed companies changed relative to the returns of non-exposed companies. In other words, γ captures the effect of natural disaster exposure on market participants' expectation of the net present value of economic damage accruing to exposed companies relative to the net present value of non-exposed firms. This strategy is valid if, absent the natural disasters taking place during the event window, no systematic differences exist between the returns of exposed firms and the non-exposed firms. In other words, we require the standard identification assumption $Cov(Treat_{i,e}, \epsilon_{i,e} | X_{i,e} \eta_s) = 0$.

The plausibility of this assumption depends on the controls included in the regression. The fixed effects for industry and event control for the potential differential impacts of weather on firms due to non-weather reasons. Controls for firm characteristics from the previous year include total assets, sales, revenues, capital expenditures and long-term debts, as non-exposed firms are found to be significantly bigger on all these fronts in a t-test of means between these two groups of firms in the year before the disaster, except assets and total debts (see Table 2). These differences between the two groups shed light on a predictive bit and non-predictive bit. Larger firms are mechanically more likely to be affected than smaller firms, because they have more subsidiaries. However, larger firms may have more leeway to efficiently allocate their assets across their many plants, and mitigate themselves.

Betas for the world market β_i^{world} and the US market β_i^{US} controls for omitted factors in a more flexible manner, as they allow for partial diversification between U.S. and world markets. This is a slight deviation from the earlier event study methodologies in that, instead of constructing abnormal returns relative to a U.S. Capital Asset Pricing Model, the regression rather includes various controls for each firm, including the U.S. and World market betas.

Table 2: t-test of Firm Characteristics, 1 Year before Disaster

	Means (in USD million)		
	Unexposed	Exposed	p
Sales	2,451	922	0
Revenues	2,549	886	0
CapEx	379	118	0
Assets	3,536	3,141	7.05e-29
Capital	1,422	627	0
Debts	1,169	1,074	.0153

All the standard errors reported throughout the paper are robust against heteroscedasticity. The standard errors are clustered at the firm level to account for potential cross-firm correlation of residual returns.

3.2 Assessing the Channels: Firm Structure & the Labour Market

Adaptive Capacity through Firm Structure?

Do multi-plant businesses mitigate adverse consequences due to extreme events? Firms face increasingly volatile patterns in the incidence of property damage from natural disasters, reduced insurability, and geo-physical restrictions to location. Consequently, multi-plant firms may weather weather the storm better because of access to internal capital markets that help them allocate resources more efficiently across plants.

This question on resource allocation and plant level investment dynamics finds its base in the “efficient internal capital markets" hypothesis, as articulated in Stein (1997). Headquarters of multi-plant businesses have the potential to create value by actively reallocating scarce resources across projects. Prior work by Giroud and Mueller (2015) finds evidence that supports the hypothesis – that an investment opportunity in one plant spills over to other plants within the same firm. Weather disasters, in our case, exogenously either decrease or increase a company’s appeal to invest in its affected plants, thus creating the possibility of both positive (expansion) or negative (shut-down) adjustments due to weather disasters.

I test for this hypothesis by estimating the differential impact of weather disasters on single standalone plants vs. multi-plant firms. If internal capital markets of multi-plant firms are valuable insurance mechanisms in addition to existing mechanisms, we must see an insignificant impact on multi-plant firms. If weather disasters provide an opportunity to these firms to optimally expand or shut down plants, which is otherwise difficult to execute in normal times, we must see a positive coefficient for multi-plant firms conditional on weather disasters being detrimental to all exposed firms.

Do Labour Market Frictions determine Adaptive Capacity?

Do labour market frictions matter for firms? One major constraint that inhibits firms from shutting down plants and efficiently re-allocating resources is labour market frictions. Highly unionized labour markets hamper the optimal management of firm resources and hurts firm value. Accordingly, in the event of a natural disaster, we must expect firms with operations in locations of highly fricional labour markets to perform worse than firms with operations in low friction areas.

One indicator of the extent of labour market frictions in a state is whether the state has passed the Right-to-Work legislation. According to Shermer (2009)

> A "Right-to-Work" law is a statute in the United States that prohibits union security agreements, or agreements between labor unions and employers, that govern the extent to which an established union can require employees' membership, payment of union dues, or fees as a condition of employment, either before or after hiring.

The law monitors contractual agreements between employers and labor unions, preventing any exclusion of non-union workers and prohibiting employees to pay fees to unions that negotiate the labor contracts that the employees work under.

The law finds its roots in the revisions to the National Labor Relations Act of 1935, popularly called the Wagner Act, passed as part of President Franklin D. Roosevelt's "Second New Deal". The Wagner Act (1935) laid down the foundations for the different types of labor unions that exist today across the United States. The Taft-Harley Act of 1947 repealed some of the provisions of the Wagner Act, particularly outlawing any exclusive unionization of the workplace. In addition, the Taft-Hartley Act also authorizes individual states to choose to lift any other less extreme forms of unionization that require fees or membership. This provision is what has come to be, the Right-to-Work law.

Right-to-Work significantly lifts labor market frictions in the states that passed the legislation. By effectively freezing the monopoly power of unions, the law has aided businesses by lowering wages, insurance premiums and pension payments. Not only are firms insulated from the bargaining costs associated with unions, the legislation also protects the interests of a dissenting minority in the labour market against the opposing majoritarian collective bargain. The law exists today in 25 U.S. states, mostly in southern and western United States, but also including the midwestern states of Michigan, Indiana, and Wisconsin.

To test the hypothesis that labour market frictions may explain the loss of market value for exposed firms, I estimate the differential impact of weather disasters on firms located in states with Right-to-Work law vs. those that are located elsewhere. If lower labour market frictions help firms manage their resources and plants more efficiently, we must see a positive coefficient on firms located in Right-to-Work states, conditional on weather disasters being detrimental to all exposed firms.

4 Results

4.1 Results - Cross Sectional Model

Summary Statistics for all the firms are presented in Table **??**, by exposure category. On an average across events, half the firms are found to be exposed to a natural disaster. Table **??** also reflects that Unexposed firms are bigger in time pre-characteristics from a year before, such as Sales, Assets, Revenues, Capital, etc (as seen in Table 2).

I first present the results of estimating (1) in Table 3, for every single event window considered. The outcome variable is the Cumulative Returns for the event window specified in the columns of Table 3. Column 1 has the shortest event window, spanning the first five days before the disaster. Column 5 has the longest horizon, spanning the interval from five days prior to 40 days after the first day of the disaster. I control for time varying characteristics from the previous year such as Sales, Revenues, Capital, Debts, Capital Expenditures, and Assets; as well as 4 digit SIC and event fixed effects.

The estimates suggest a sizable decline in the value of exposed firms relative to non-exposed firms. The immediate effect in column 1 is small and only significant at the 10% level, but the effect in longer horizons are all larger and significant at the 1% level. The coefficients suggest that the fall in market valuation is between 0.3 (in the fifteen day horizon of column 2) and 0.7 percentage points (in the 45 day horizon of column 5). The mean market capitalization of the treated firms in the pre-period is USD 3,148 million. So a 0.5 percentage point fall in cumulative stock returns would translate into a monetary cost of approximately US$16 million for exposed firms. Therefore, a 0.3-0.7 percentage point estimated loss translates into dollar costs of US$9.4 million to US$ 22 million lost in the market valuation of exposed firms.

Table 3: Event Study Cross-Section Results: All Event Windows

	(1) [-5,0] b/se	(2) [-5,10] b/se	(3) [-5,20] b/se	(4) [-5,30] b/se	(5) [-5,40] b/se
Treat	-0.0006*	-0.0026***	-0.0035***	-0.0043***	-0.0067***
	(0.0003)	(0.0005)	(0.0008)	(0.0010)	(0.0012)
Beta US	0.0159	0.0428	0.0100	-0.0115	-0.0094
	(0.0124)	(0.0249)	(0.0385)	(0.0553)	(0.0728)
Beta World	0.0132	-0.0076	-0.0322	-0.0760	-0.1018
	(0.0134)	(0.0264)	(0.0405)	(0.0578)	(0.0765)
Sales	0.0031***	0.0047***	0.0056**	0.0094***	0.0167***
	(0.0006)	(0.0012)	(0.0021)	(0.0027)	(0.0032)
Revenue	-0.0023***	-0.0018	-0.0008	-0.0027	-0.0086**
	(0.0006)	(0.0012)	(0.0020)	(0.0027)	(0.0032)
Assets	-0.0004	-0.0013*	-0.0020**	-0.0027**	-0.0037**
	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0012)
Debt	0.0002	-0.0001	-0.0005*	-0.0006*	-0.0009*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
CapEx	0.0002	-0.0001	0.0004	0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0008)
Capital	0.0001	0.0002	-0.0001	0.0003	0.0017
	(0.0002)	(0.0004)	(0.0006)	(0.0008)	(0.0010)
Event FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.123	0.152	0.239	0.295	0.298
N	227908	228330	228632	228931	229148

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

For each event window horizon presented in columns 1-5, I present a triangular table of regressions in the Appendix 5 to illustrate the robustness of the estimates to inclusion of fixed effects and controls. Table 7 to Table 11 in the Appendix unanimously indicate that the level of significance is independent of including fixed effects or adding controls. The inclusion of industry and event fixed effects increases the estimated negative impact of weather disasters relative to the OLS, and the further inclusion of MSCI world and US betas, as well as time varying controls, reduces the impact of weather disasters relative to the OLS coefficient. Thus, the OLS coefficient over-estimates the impact of weather disasters without accounting for time varying firm characteristics that systematically explain the differences in the stock returns between exposed and the non-exposed firms, absent the natural disasters

The long horizon event window in column 5 of Table 3, $[-5, 40]$ around the event, is most likely the right size of event window. This is because of the end-selection of events here, as discussed in Section 2 when we analyzed the gradual disunity in the pattern of cumulative stock returns (Figure 3) between exposed and non-exposed firms. The end selection is the analysis studies the top 122 events in the history of U.S. natural disasters. Conditional on the event being this big, column 5's 0.7 percentage points is the eventual negative impact. Why don't the markets capitalize these magnitudes earlier? For the average event, markets would be aware of the details and will react or over-react immediately. However, the 122 events in my study are end selected by property damage and the markets under-react intially and capitalize the rest eventually due to learning. Hence, the total cost to market valuations of exposed firms is US$ 22 million against the valuation of non-exposed firms.

4.2 Hypotheses: Adaptive Capacity & Labour Market Frictions

Given the non-trivial consequences of natural disaster exposure, this section presents results from testing the hypotheses that firms either operating multiple plants or located in Right to Work states, are better placed among exposed firms.

Table 4 presents estimation results of the differential impact of weather disasters on single standalone plants vs. multi-plant firms. Multi is an indicator that a firm owns multiple subsidiaries, and is not a single plant firm. The coefficient on *Treat* is now the exposure impact for single standalone plants. The coefficient on the interaction $Treat * Multi$ is the differential impact of exposure on multi-plant firms.

The estimates suggest that multi-plant firms possess higher adaptive capacity to natural disasters than single-plant firms. The coefficient for single-plant firms are negative and significant across all event windows including the initial window in column 1, and are slightly bigger in magnitude, compared to the initial exposure estimates in Table 3. However, the coefficient on the impact of exposure for multi-plant firms is positive always, but insignificant except at the 10% level for the shortest and longest horizons of columns 1 and 5. The positive effect and the low level of significance confirms the hypothesis of adaptive capacity being tied to the internal capital markets both the stories contained in the hypothesis that the internal capital markets of multi-plant firms are important for the adaptive capacity of firms. The first story justifies the positive coefficient - weather disasters may help multi-plant firms to expand or shut down plants, which they find hard to do in normal times, and thus improves their profitability. The second story justifies the small degree of significance to the positive coefficients - multi-plant firms may use their internal capital markets to reallocate resources across plants, to insulate themselves from the detrimental impact of natural disaster exposure. Both these channels of exposure mitigation are unavailable to single-plant standalone firms, and hence the large negative impact is concentrated on them.

Next we test if firms located in states with fewer labour market frictions may perform better, conditional on disasters being bad for everyone. Table 5 presents estimates that test this hypothesis. The coefficient on *Treat* now measures the impact of weather disasters on companies not located in Right-to-Work (RTW) states, whereas the coefficient on the interaction $Treat * RTW$ measures the treatment effect on companies , both single and multiplant, located in Right to Work states.

The coefficients on Treatment in Table 5 are similar in magnitude and significance level across event windows like those in the base specification in Table 3. The coefficient on the interaction is insignificant across all event windows, and shows no evidence of any positive advantage that firms operating in Right-to-Work states possess against weather disaster exposure.

Perhaps the lack of evidence to support that firms facing lesser labour market frictions are better off in facing natural disasters, is because the hypothesis being tested for both single and multi-plant firms combined. Does labour market frictions differentially affect single and multi-plant firms? The results of testing this hypothesis are presented in Table 6. The coefficient on *Treat* now measures the impact of natural disasters for single-plant firms that do not operate in Right-to-Work states. $Treat * Multi$ reports the coefficient for affected multiplant firms, that do not operate in Right-to-Work states. The hypothesis is separately tested for single and multi-plant firms as follows - the coefficient on $Treat * RTW$ measures the impact of operating with lower labour frictions for single-plant firms, and $Treat * Multi * RTW$ measures the same for multi-plant firms alone.

The results testing the Internal Capital Markets story in Table 4 still holds, as the coefficient on $Treat * Multi$ is still positive, and additionally significant for more event-day horizons. The results testing labour market frictions hypothesis in Table 5 still holds for single plant

Table 4: Internal Capital Markets - Single vs. Multi-plant

	(1)	(2)	(3)	(4)	(5)
	[-5,0]	[-5,10]	[-5,20]	[-5,30]	[-5,40]
	b/se	b/se	b/se	b/se	b/se
Treat	-0.0010**	-0.0030***	-0.0037***	-0.0050***	-0.0080***
	(0.0003)	(0.0007)	(0.0010)	(0.0013)	(0.0015)
Treat*Multi	0.0012*	0.0014	0.0007	0.0024	0.0043*
	(0.0005)	(0.0009)	(0.0013)	(0.0016)	(0.0019)
Beta US	0.0161	0.0430	0.0102	-0.0111	-0.0087
	(0.0124)	(0.0249)	(0.0385)	(0.0553)	(0.0728)
Beta World	0.0133	-0.0076	-0.0322	-0.0759	-0.1017
	(0.0134)	(0.0264)	(0.0405)	(0.0578)	(0.0764)
Sales	0.0030***	0.0046***	0.0056**	0.0093***	0.0165***
	(0.0006)	(0.0012)	(0.0021)	(0.0027)	(0.0032)
Revenue	-0.0023***	-0.0018	-0.0007	-0.0026	-0.0085**
	(0.0006)	(0.0012)	(0.0020)	(0.0027)	(0.0031)
Assets	-0.0004	-0.0012*	-0.0020**	-0.0026**	-0.0036**
	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0012)
Debt	0.0002	-0.0001	-0.0005*	-0.0006*	-0.0009*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
CapEx	0.0002	-0.0000	0.0004	0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0008)
Capital	0.0001	0.0001	-0.0001	0.0003	0.0017
	(0.0002)	(0.0004)	(0.0006)	(0.0008)	(0.0010)
Event FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.123	0.152	0.239	0.295	0.298
N	227908	228330	228632	228931	229148

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Multi is an indicator that equals 1 if a company has multiple subsidiaries. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 5: Labor Market Frictions - Right-to-Work

	(1) [-5,0] b/se	(2) [-5,10] b/se	(3) [-5,20] b/se	(4) [-5,30] b/se	(5) [-5,40] b/se
Treat	-0.0009*	-0.0023***	-0.0032***	-0.0041***	-0.0066***
	(0.0003)	(0.0007)	(0.0009)	(0.0012)	(0.0015)
Treat*RTW	0.0005	-0.0006	-0.0009	-0.0006	-0.0002
	(0.0004)	(0.0007)	(0.0010)	(0.0013)	(0.0016)
Beta US	0.0159	0.0428	0.0101	-0.0115	-0.0094
	(0.0124)	(0.0249)	(0.0385)	(0.0553)	(0.0728)
Beta World	0.0135	-0.0079	-0.0327	-0.0763	-0.1019
	(0.0135)	(0.0264)	(0.0405)	(0.0578)	(0.0765)
Sales	0.0031***	0.0047***	0.0056**	0.0095***	0.0167***
	(0.0006)	(0.0012)	(0.0021)	(0.0027)	(0.0032)
Revenue	-0.0023***	-0.0018	-0.0008	-0.0027	-0.0086**
	(0.0006)	(0.0012)	(0.0020)	(0.0027)	(0.0032)
Assets	-0.0004	-0.0013*	-0.0020**	-0.0027**	-0.0037**
	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0012)
Debt	0.0002	-0.0001	-0.0005*	-0.0006*	-0.0009*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
CapEx	0.0002	-0.0001	0.0004	0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0008)
Capital	0.0001	0.0002	-0.0000	0.0003	0.0018
	(0.0002)	(0.0004)	(0.0006)	(0.0008)	(0.0010)
Event FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.123	0.152	0.239	0.295	0.298
N	227908	228330	228632	228931	229148

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. RTW is an indicator that equals 1 if a company is located in a state that has passed the Right-to-Work legislation. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * p<0.05, ** p<0.01, *** p<0.001.

firms, as we find no significant effect of operating in Right-to-Work states. For multi-plant firms however, we find either no effect or a negative significant effect at the event-day windows $[-5, 10]$ and $[-5, 20]$. We defined a multi-plant firm to be operating in a Right-to-Work (RTW) state if it had atleast one subsidiary in a state that passed the RTW legislation. This result in Table 6 may come from multi-plant firms that have most of their subsidiaries in non-RTW states. Overall, we still do not find any evidence in favor of the hypothesis that labour market frictions matter for firms, in the context of natural disaster exposure.

4.3 Discussion of Results

Is the estimated monetary cost of US$ 22 million to firms exposed to natural disasters an over-estimate or an under-estimate? The results need to be qualified under certain caveats, and this section discusses some of the problems and considerations that must be accounted for, to answer the question at hand.

A first caveat is the veracity of assumption that the Unexposed group of firms are actually untreated. Our definition of exposure largely hinges on firm location information provided for headquarters by COMPUSTAT and subsidiaries by ORBIS. While the COMPUSTAT information is pretty complete and accurate, there are certain drawbacks in the coverage of ORBIS. First, there are many missing observations in the locational information of subsidiaries in ORBIS. Second, among those recorded in ORBIS, the subsidiaries may not necessarily represent the establishment of economic activity, but an office location of the subsidiary that reports its balance sheet information. This is quite a difficult problem to account for, since there are no other publicly available external datasets on firm subsidiary locations other than ORBIS.

Secondly, stock returns reflect the present value of discounted future profits. Thus, our outcome variable is essentially a discounted profit variable. Discounting is probably good as it provides a lower-estimate when measuring adverse impact of an event.

A third important point is that we are measuring profits, and not GDP. While it is an important economic variable that previous studies focus on, GDP alone need not necessarily be the right variable to consider. Profits really matter because a firm's margins shift around. Shifting margins make it unclear if a disaster has a positive or negative impact on profit. Thus, our estimates of the impact of natural disasters on exposed firms internalize both the positive and negative effects.

Table 6: Labor Market Frictions - Right-to-Work, Single vs Multi-plant

	(1)	(2)	(3)	(4)	(5)
	[-5,0]	[-5,10]	[-5,20]	[-5,30]	[-5,40]
	b/se	b/se	b/se	b/se	b/se
Treat	-0.0011**	-0.0029***	-0.0037***	-0.0047***	-0.0077***
	(0.0004)	(0.0007)	(0.0010)	(0.0013)	(0.0016)
Treat*RTW	0.0004	-0.0005	-0.0002	-0.0010	-0.0013
	(0.0005)	(0.0009)	(0.0012)	(0.0017)	(0.0020)
Treat*Multi	0.0019	0.0054***	0.0064**	0.0058*	0.0076*
	(0.0010)	(0.0016)	(0.0023)	(0.0028)	(0.0032)
Treat*Multi*RTW	-0.0011	-0.0048*	-0.0070**	-0.0036	-0.0034
	(0.0011)	(0.0019)	(0.0026)	(0.0033)	(0.0038)
Beta US	0.0160	0.0429	0.0098	-0.0111	-0.0086
	(0.0124)	(0.0249)	(0.0385)	(0.0553)	(0.0728)
Beta World	0.0134	-0.0078	-0.0323	-0.0764	-0.1023
	(0.0135)	(0.0264)	(0.0404)	(0.0578)	(0.0764)
Sales	0.0030***	0.0046***	0.0056**	0.0093***	0.0165***
	(0.0006)	(0.0012)	(0.0021)	(0.0027)	(0.0032)
Revenue	-0.0023***	-0.0018	-0.0007	-0.0026	-0.0085**
	(0.0006)	(0.0012)	(0.0020)	(0.0027)	(0.0031)
Assets	-0.0004	-0.0013*	-0.0020**	-0.0026**	-0.0036**
	(0.0003)	(0.0005)	(0.0007)	(0.0010)	(0.0012)
Debt	0.0002	-0.0001	-0.0005*	-0.0006*	-0.0009*
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
CapEx	0.0002	-0.0000	0.0004	0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0005)	(0.0007)	(0.0008)
Capital	0.0001	0.0001	-0.0001	0.0003	0.0017
	(0.0002)	(0.0004)	(0.0006)	(0.0008)	(0.0010)
Event FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.123	0.152	0.239	0.295	0.298
N	227908	228330	228632	228931	229148

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. RTW is an indicator that equals 1 if a company is located in a state that has passed the Right-to-Work legislation. Multi is an indicator that equals 1 if a company has multiple subsidiaries. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * p<0.05, ** p<0.01, *** p<0.001.

While we quite understand how damaging natural disasters can be, here is an example of the positive impacts of environmental disasters on firm profitability. Price gouging can happen as a result of a natural disaster, both unintentionally as well as intentionally. Price gouging in a non-explicit way happens for example, when a disaster wipes out a chunk of retail superstores. The surviving ones may mechanically be hurt by the disaster. Nevertheless the survivors also enjoy a profit opportunity as their low margin line of commodities sell out, and the people are then forced to buy the high margin commodities. Deliberate price gouging also happens, for example, if an airline or agricultural cartel concomitantly experience half their volume getting wiped out. The price they charge on their remaining capacity can be astronomically high. Any cartel with highly elastic prices is consequently being aided by disasters to enjoy profitability by restricting supply.

A fourth piece of information, that informs the magnitude of the US$ 22 million estimated as the dollar cost of disaster exposure, is that we study big COMPUSTAT firms. The North American sample consists of some of the biggest listed firms recorded by Standard and Poor's, of which many are multinational companies. In this light, it is safe to contend that the estimated cost is on the lower side.

Lastly, the fact that the event study is end selecting natural disasters is not a problem. Firms learn the actual magnitude of these events immediately over the days following the first day, even though the initial magnitude is uncertain. Given that stock prices completely internalize all adaptive information on the firms and only respond to news, the negative impact measured in the paper is an under-estimate if stock prices are used as an outcome variable.

5 Conclusion

The increasingly erratic patterns in the timing, location and intensity of natural disasters pose novel risks on the adaptive capacity of firms to environmental disaster exposure. In this paper, I provide evidence using an event study methodology, that firms exposed to environmental disasters are associated with lower market valuations in comparison to non-exposed firms. The *negative* impact of exposure on stock returns ranges from 0.3 percentage points for the event-day window $[-5, 0]$ to 0.7 percentage points for the longest event-day window $[-5, 40]$. This translates into a maximum US$ 22 million of market capitalization lost to firms due to natural disaster exposure. Examining the impact exclusively for each day in the window of $[-20, 40]$ days around the event, the largest negative impact is concentrated around 6 days prior and 20 days post the event.

Moreover, the adverse impact is mainly centered on single-plant standalone firms, and only multi-plant firms retain their adaptive capacity to counter the adverse costs of extreme weather. The small positive effect on multi-plant firms,due to exposure, reflects a combination of two stories regarding their internal capital markets. Firstly, natural disasters may facilitate multi-plant firms to shut down low performance plants or expand high performance plants, which is difficult to do in normal times. This reflects the positive effect on stock returns, a measure of firm profitability. Second, the small degree of significance on this result is a result of multi-plant firms utilizing their internal capital markets to reallocate resources across plants and mitigate the deleterious effects of inclement weather. Neither of these two possibilities are available for single plant firms, and they suffer a large negative impact. Moreover, I find no support to the hypothesis that the degree of labour market frictions in the location of firm exposure has any sway on the extent of the harmful impact of weather. This is true even when I investigate the impact for both single and multi-plant firms.

References

ABI (2005). Financial risks of climate change.

Acemoglu, D., Hassan, T. A., and Tahoun, A. (2014). The power of the street: Evidence from egypt's arab spring. Technical report, National Bureau of Economic Research.

Adger, W. N., Agrawala, S., Mirza, M. M. Q., Conde, C., O'Brien, K., Pulhin, J., Pulwarty, R., Smit, B., and Takahashi, K. (2007). Assessment of adaptation practices, options, constraints and capacity. *Climate change*, pages 717–743.

Baker, S. R. and Bloom, N. (2013). Does uncertainty reduce growth? using disasters as natural experiments. Technical report, National Bureau of Economic Research.

Basker, E. and Miranda, J. (2014). Taken by storm: Business survival in the aftermath of hurricane katrina. *Available at SSRN 2417911*.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2011). Weather and death in india. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript*.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth:

Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Deschenes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *The American Economic Review*, pages 354–385.

Deschênes, O., Greenstone, M., and Guryan, J. (2009). Climate change and birth weight. *The American Economic Review*, pages 211–217.

Dlugolecki, A. and Lafeld, S. (2005). Climate change and the financial sector. an agenda for action.

Giroud, X. and Mueller, H. M. (2014). Capital and labor reallocation within firms. *Journal of Finance, Forthcoming*.

Heal, G. (2009). Climate economics: a meta-review and some suggestions for future research. *Review of Environmental Economics and Policy*, 3(1):4–21.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367.

Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.

Jarmin, R. S. and Miranda, J. (2009). The impact of hurricanes katrina, rita and wilma on business establishments. *Journal of Business Valuation and Economic Loss Analysis*, 4(2).

Koerniadi, H., Krishnamurti, C., and Tourani-Rad, A. (2016). Natural disasters—blessings in disguise? *The Singapore Economic Review*, 61(01):1640004.

Lamont, O. A. and Polk, C. (2002). Does diversification destroy value? evidence from the industry shocks. *Journal of Financial Economics*, 63(1):51–77.

Luo, N. (2012). The impact of natural disasters on global stock market: the case of the japanese 2011 earthquake.

Maksimovic, V. and Phillips, G. (2002). Do conglomerate firms allocate resources inefficiently across industries? theory and evidence. *The Journal of Finance*, 57(2):721–767.

Mills, E. (2005). Insurance in a climate of change. *Science*, 309(5737):1040–1044.

Nordhaus, W. D. (2007). A review of the" stern review on the economics of climate change". *Journal of economic literature*, pages 686–702.

Nordhaus, W. D. and Yang, Z. (1996). A regional dynamic general-equilibrium model of alternative climate-change strategies. *The American Economic Review*, pages 741–765.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? Technical report, National Bureau of Economic Research.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Schoar, A. (2002). Effects of corporate diversification on productivity. *The Journal of Finance*, 57(6):2379–2403.

Shermer, E. T. (2009). Counter-organizing the sunbelt: right-to-work campaigns and anti-union conservatism, 1943–1958.

Shin, H.-H. and Stulz, R. M. (1998). Are internal capital markets efficient? *Quarterly Journal of Economics*, pages 531–552.

Stein, J. C. (1997). Internal capital markets and the competition for corporate resources. *The Journal of Finance*, 52(1):111–133.

Stern, N. (2008). The economics of climate change. *The American Economic Review*, pages 1–37.

Tol, R. S. (2009). The economic effects of climate change. *The Journal of Economic Perspectives*, pages 29–51.

Valverde Jr, L. J. and Andrews, M. W. (2006). Global climate change and extreme weather: An exploration of scientific uncertainty and the economics of insurance. *Insurance Information Institute*.

Wang, L. and Kutan, A. M. (2013). The impact of natural disasters on stock markets: Evidence from japan and the us. *Comparative Economic Studies*, 55(4):672–686.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, 91(1):1–19.

Worthington*, A. and Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: an empirical application using intervention analysis. *Applied Economics*, 36(19):2177–2186.

Zivin, J. G. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Appendix

Table 7: Event Study Cross-Section Regression: WINDOW [-5,0]

	(1) OLS b/se	(2) FE b/se	(3) FE b/se	(4) FE b/se
Treat	-0.0021***	-0.0019***	-0.0020***	-0.0006*
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Beta US			0.0320**	0.0159
			(0.0098)	(0.0124)
Beta World			0.0190	0.0132
			(0.0105)	(0.0134)
Sales				0.0031***
				(0.0006)
Revenue				-0.0023***
				(0.0006)
Assets				-0.0004
				(0.0003)
Debt				0.0002
				(0.0001)
CapEx				0.0002
				(0.0002)
Capital				0.0001
				(0.0002)
Event FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
R-squared	0.000	0.103	0.104	0.123
N	511947	511947	511932	227908

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 8: Event Study Cross-Section Regression: WINDOW [-5,10]

	(1)	(2)	(3)	(4)
	OLS	FE	FE	FE
	b/se	b/se	b/se	b/se
Treat	-0.0051***	-0.0050***	-0.0051***	-0.0026***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Beta US			0.0628***	0.0428
			(0.0180)	(0.0249)
Beta World			-0.0261	-0.0076
			(0.0190)	(0.0264)
Sales				0.0047***
				(0.0012)
Revenue				-0.0018
				(0.0012)
Assets				-0.0013*
				(0.0005)
Debt				-0.0001
				(0.0002)
CapEx				-0.0001
				(0.0003)
Capital				0.0002
				(0.0004)
Event FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
R-squared	0.001	0.133	0.133	0.152
N	513929	513929	513910	228330

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 9: Event Study Cross-Section Regression: WINDOW [-5,20]

	(1)	(2)	(3)	(4)
	OLS	FE	FE	FE
	b/se	b/se	b/se	b/se
Treat	-0.0060***	-0.0072***	-0.0072***	-0.0035***
	(0.0005)	(0.0007)	(0.0007)	(0.0008)
Beta US			0.0116	0.0100
			(0.0310)	(0.0385)
Beta World			-0.0505	-0.0322
			(0.0326)	(0.0405)
Sales				0.0056**
				(0.0021)
Revenue				-0.0008
				(0.0020)
Assets				-0.0020**
				(0.0007)
Debt				-0.0005*
				(0.0002)
CapEx				0.0004
				(0.0005)
Capital				-0.0001
				(0.0006)
Event FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
R-squared	0.000	0.214	0.215	0.239
N	515893	515893	515872	228632

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * p<0.05, ** p<0.01, *** p<0.001.

Table 10: Event Study Cross-Section Regression: WINDOW [-5,30]

	(1)	(2)	(3)	(4)
	OLS	FE	FE	FE
	b/se	b/se	b/se	b/se
Treat	-0.0057***	-0.0098***	-0.0097***	-0.0043***
	(0.0007)	(0.0009)	(0.0008)	(0.0010)
Beta US			-0.0094	-0.0115
			(0.0415)	(0.0553)
Beta World			-0.0711	-0.0760
			(0.0434)	(0.0578)
Sales				0.0094***
				(0.0027)
Revenue				-0.0027
				(0.0027)
Assets				-0.0027**
				(0.0010)
Debt				-0.0006*
				(0.0003)
CapEx				0.0002
				(0.0007)
Capital				0.0003
				(0.0008)
Event FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
R-squared	0.000	0.265	0.265	0.295
N	517832	517832	517811	228931

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 11: Event Study Cross-Section Regression: WINDOW [-5,40]

	(1) OLS b/se	(2) FE b/se	(3) FE b/se	(4) FE b/se
Treat	-0.0081***	-0.0143***	-0.0142***	-0.0067***
	(0.0008)	(0.0010)	(0.0010)	(0.0012)
Beta US			-0.0006	-0.0094
			(0.0504)	(0.0728)
Beta World			-0.0744	-0.1018
			(0.0529)	(0.0765)
Sales				0.0167***
				(0.0032)
Revenue				-0.0086**
				(0.0032)
Assets				-0.0037**
				(0.0012)
Debt				-0.0009*
				(0.0004)
CapEx				-0.0002
				(0.0008)
Capital				0.0017
				(0.0010)
Event FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
R-squared	0.000	0.256	0.256	0.298
N	519738	519738	519715	229148

Notes: Treat is an indicator that equals 1 if a company is exposed to a weather disaster. Exposure is defined by the presence of a firm's headquarters or subsidiary in the state where a natural disaster occurs. Standard Errors are clustered at the firm level. World & US-market betas for each firm is estimated by regressing the daily stock returns of each firm on the returns on the MSCI-US and MSCI-world indices, respectively. Stars indicate level of significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.