Cornell
SC Johnson College of Business

August 7, 2025

Sijia Fan, Ph.D. candidate
SC Johnson College of Business
Cornell University
Ithaca, NY 14853
Phone: (973) 668-3687
Email: sf395@cornell.edu

Workshop Organizers
Climate Finance
National Bureau of Economic Research

Dear Professors Flammer and Giglio,

I am writing to apply for the PhD Student Workshop on Climate Finance to be held on October 9, 2025. I am a sixth-year Ph.D. candidate in Applied Economics and Management with a concentration in Finance, expecting to complete my degree in May 2026. My research focuses on climate finance and sustainable investing, with particular emphasis on how market participants respond to physical and transition risks, and how financial mechanisms shape adaptation and resilience. The workshop would offer a valuable opportunity to present my work, receive feedback from leading scholars in the field, and strengthen my academic network as I prepare for the job market.

My job market paper, *Flooded but Thriving? The Uneven Economic Effects of Floods and Flood Risk*, studies how businesses respond to flood shocks and chronic flood risk, and how institutional mechanisms, such as insurance, affect their recovery. Combining remote sensing flood data, FEMA flood maps, and establishment-level outcomes, I provide novel causal evidence that firms located in zones subject to mandatory flood insurance requirements recover more robustly after flood events. In contrast, chronic flood risk is associated with declines in employment and business diversity, likely due to rising insurance costs. These findings illustrate how risk-sharing institutions can enhance climate resilience, while also revealing the persistent distortions that climate risk can impose on local economic activity.

Beyond my job market paper, I explore how climate risks and investor expectations influence firm behavior and capital allocation. In one project, I estimate heterogeneous institutional demand for ESG by constructing a revealed-preference measure of corporate sustainability. Using international institutional holdings data, I find substantial variation in how investors allocate capital to greener firms: European investors exhibit strong positive preference for greener firms, while investors in China respond negatively. In another paper with Miao Liu, Yao Lu, and David Ng, we examine how firms disclose biodiversity risk in 10-K filings, classifying disclosures as direct (explicit) or indirect (implied). We find that managers are more likely to provide direct disclosures when institutional ownership and stakeholder pressure rise, yet investors respond more strongly to indirect disclosures. This pattern reflects a tension between managerial preferences for reliable disclosures and investor demand for timely signals of emerging risks.

Together, these projects contribute to understanding how climate- and nature-related risks become financially material, and how market participants and institutions navigate evolving expectations and information gaps in the climate transition. My future research will continue to explore how markets and institutions jointly shape the economic and financial consequences of climate and environmental risk, with a focus on the mechanisms through which capital is allocated and risks are communicated. In an ongoing project with Kelly Posenau and Ana-Maria Tenekedjieva, we examine how institutional

investors influence the allocation of local climate infrastructure in New York City following Hurricane Sandy. Using a neighborhood-year dataset that links geo-located climate infrastructure investments to building ownership histories and lobbying expenditures, we find that neighborhoods with greater pre-Sandy institutional investor concentration, particularly private equity, received significantly more climate investment after Sandy. Our results suggest a novel political channel through which investors can shape local public goods provision in the face of emerging risks.

I am genuinely excited about the opportunity to participate in the workshop, connect with peers who share similar research interests, and engage in discussions that will help strengthen both my job market paper and broader research agenda. I have enclosed my CV and job market paper. My advisor, Professor David Ng, would be happy to serve as a reference. I look forward to the opportunity to contribute to and learn from this valuable event.

Sincerely,

Sijia Fan

SIJIA FAN

Warren 442, Cornell University ⋄ Ithaca, NY
Email: sf395@cornell.edu
Website: sijiafan.org

EDUCATION

Cornell University 2020 - 2026
Ph.D. in Applied Economics and Management, Concentration: Finance

Cornell University 2018 - 2019
M.Eng., Operations Research and Information Engineering

Skidmore College 2014 - 2018
B.A. in (Hons) Economics and Mathematics. *Summa Cum Laude*
Undergrad Thesis: "Stock Market Reactions to Industrial Disasters: Evidence from Incident Firms and Their Competitors"; 2018 Periclean Scholar Thesis Award

RESEARCH PAPERS

Publication

Fan, Sijia, Qi Ge, Benjamin Ho, and Lirong Ma. "Sorry Doesn't Cut It, or Does It? Insights from Stock Market Responses to Corporate Apologies." *Journal of Economic Behavior & Organization* 205 (2023): 68-86.

· Featured in Business Scholarship Podcast.

Working Papers

"Flooded but Thriving? The Uneven Economic Effects of Floods and Flood Risk" (JMP)

· **Abstract:** I study how floods and chronic flood risk affect U.S. establishments and firms by combining high-resolution remote sensing flood data, FEMA flood maps, and establishment-level data. After floods, I find that establishments show growth in employment and sales, with recovery supported by insurance payouts and federal aid. Using a triple-difference and spatial regression discontinuity design around regulatory boundaries, I provide novel causal evidence that flood insurance plays a critical role in enhancing recovery, particularly for establishments subject to the mandatory National Flood Insurance Program purchase requirement. Federal aid, notably SBA disaster loans, also strengthens recovery by supporting small businesses and generating local spillovers. In contrast, chronic flood risk is associated with persistent declines in employment and business diversity, likely driven by higher insurance expenses and increased business exits. At the firm level, these patterns persist and the dynamics aggregate: firms with greater flood risk disclose these risks more proactively and reduce investment in physical assets, while markets react more negatively to floods for firms lacking prior exposure or disclosure. Overall, my findings highlight how insurance and risk communication enhance resilience to climate shocks, while underscoring the need for policies that mitigate long-term vulnerability without encouraging unsustainable development.

"International ESG Equity Investing and Heterogeneous Asset Demand"

· **Abstract:** I study how sustainable investing impacts cross-sectional equity prices and valuation with institutional investors' heterogeneous demand and tastes internationally. To obtain a sustainability measure for companies around the world and to capture the ESG tilt in portfolios of institutional investors, I construct a reveal-preference sustainability measure for each firm instead of using a third-party ESG score. With Factset international institutional holding data from 2010

to 2021, I apply an equilibrium asset pricing framework to empirically estimate heterogeneous preference, allowing for investment portfolio choices within and across countries. I find that separately estimated investor demands are sensitive to the sustainability of firms. The demand of investors on average increases by 26% following a one standard deviation increase in the perceived greenness, but there exists huge investor heterogeneity across countries; for example, investors from mainland China would decrease their demand by 21%. With the estimated coefficients, I conduct counterfactual analyses that consider the implications when the ESG coefficient increases following realized climate risk and when a subset of ESG investors switch to holding a market-weighted portfolio to understand the significance of different groups of institutional investors.

- ***Presentations***: NFA 2024; Cornell Sustainable Environment, Energy, and Resource Economics Seminar.

"Biodiversity Risk Disclosure" with Miao Liu, Yao Lu, and David Ng

- **Abstract:** Biodiversity risk is an emerging challenge for firms and a growing concern for investors. We develop a method to evaluate how companies disclose biodiversity risk exposure in their 10-K filings and how these disclosures shape investor perceptions. Using a two-step approach that combines natural language processing and large language models, we identify and classify voluntary disclosure of exposure to biodiversity risk as either direct (explicit acknowledgments of exposure) or indirect (implied exposure embedded in business discussions). We find that firms are more likely to disclose biodiversity risk exposure, particularly through direct disclosure, when institutional ownership is higher and when local stakeholder pressure intensifies, as proxied by Google search interest and biodiversity-related protests. While managers tend to issue direct disclosures in response to information demand, investors react more strongly to indirect disclosures, especially when these appear for the first time. This divergence underscores a tension in disclosure preferences for exposure to emerging and rapidly evolving risk such as biodiversity: managers prioritize "reliability" and disclose only when confident, whereas investors value "relevance" and respond more strongly to timely, even if less definitive, signals.
- ***Presentations***: CICF (China International Conference in Finance) 2025; SMU SOAR Accounting Symposium 2024*; 2024 HKUST Conference Accounting Research Symposium*; Cornell Accounting Brown bag*.

"Do Donors of Donor-Advised Funds Respond to Natural Disasters?" with Yipiao Cai, David Ng, and Jie Ying (Under Review)

- **Abstract:** Donor Advised Funds (DAFs) have grown significantly over the past decade as a popular tool for charitable giving. Despite their popularity, concerns remain about their efficiency in meeting charitable goals, especially during times of increased need. These concerns stem from the government subsidizing the tax treatment of DAFs, which provides donors with favorable tax deductions. Using data from Form 990 e-filings, this study examines how DAFs respond to natural disasters, which typically encourage charitable donations. We find that contributions to DAFs rise significantly during years with frequent natural disasters compared to other nonprofits. However, DAFs do not proportionally increase their grant payouts following these events. This trend persists even when comparing DAFs to private foundations and focusing on local disasters. Although total grants remain limited, DAF donors show increased engagement in reallocating funds to health- and food-related organizations and nonprofits with greater media coverage after disasters. This selective distribution pattern indicates that while DAF donors respond to disasters, they are hesitant to significantly increase total grant payouts, possibly due to factors like mental accounting.

Work in Progress

"Investors and the City: The Role of Institutional Ownership in the Allocation of Climate Infrastructure" with Kelly Posenau and Ana-Maria Tenekedjieva

- ***Presentations***: 2024 WAPFIN at Stern*; 2024 Oxford Sustainable Private Markets Conference*.

TEACHING EXPERIENCE

TA for Undergraduate Courses

AEM 4230/5230 Behavioral Finance (Lawrence Jin, Fall 2024 & Fall 2025)
AEM 4280 Valuation of Capital Investment (David Ng, Spring 2024)
AEM 4060/6061 Risk Simulation and Monte Carlo Methods (Calum Turvey, Spring 2022 & 2023)
AEM 2600 Managerial Economics (Ben Leyden, Fall 2022)
ORIE 4741 Learning with Big Messy Data (Madeleine Udell, Fall 2019)

TA for Graduate Courses

NBA 5980 Behavioral Finance (Lawrence Jin, Spring 2023)
NRE 5280 PhD Seminar in Empirical Asset Pricing (David Ng, Fall 2022)
AEM 6140 Behavioral Economics and Managerial Decisions (David Just, Fall 2021)

Average TA rating: 4.76/5 in student course evaluations for courses with TA sessions

AWARDS, FELLOWSHIP, AND GRANTS

Cornell University
Richard D. Aplin Teaching Excellence Fund, 2024 & 2025
NFA PhD Student Travel Grant, 2024
Morgenthau Henry & Marcelle Fellowship Award, 2021-2023
Cornell PhD TA/GRA Fellowship, 2020-2026
Silent Hoist and Crane Award, Third Place, 2019

Skidmore College
Mathematical/Interdisciplinary Contest in Modeling, 2018

- Outstanding Paper Award, INFORMS Award, and International COMAP Scholarship Award
- Fan, Sijia, Ran Tao, and Kaifeng Yang. "How Does Climate Change Influence Regional Instability?", *UMAP (Undergraduate Mathematics and Its Application) Journal* Vol.39 Issue 2 (2018): p165-186
    - *Presentation*: MAA MathFest 2018

William E. Weiss Memorial Award in Economics, 2018
Phi Beta Kappa, 2017

OTHER EMPLOYMENT

Block Renovation, NYC
Data Science Intern, February 2020 - July 2020

OTHERS

Programming Languages	R, Python, Julia, Java, SQL
Passed PhD qualifying Exams	Finance in Jan. 2023; Dyson Economics in June 2021.
Languages	Mandarin (native), English (fluent), Spanish (basic)

Flooded but Thriving?

The Uneven Economic Effects of Floods and Flood Risk*

Sijia Fan†

July, 2025

Abstract

I study how floods and chronic flood risk affect U.S. establishments and firms by combining high-resolution remote sensing flood data, FEMA flood maps, and establishment-level data. After floods, I find that establishments show growth in employment and sales, with recovery supported by insurance payouts and federal aid. Using a triple-difference and spatial regression discontinuity design around regulatory boundaries, I provide novel causal evidence that flood insurance plays a critical role in enhancing recovery, particularly for establishments subject to the mandatory National Flood Insurance Program purchase requirement. Federal aid, notably SBA disaster loans, also strengthens recovery by supporting small businesses and generating local spillovers. In contrast, chronic flood risk is associated with persistent declines in employment and business diversity, likely driven by higher insurance expenses and increased business exits. At the firm level, these patterns persist and the dynamics aggregate: firms with greater flood risk disclose these risks more proactively and reduce investment in physical assets, while markets react more negatively to floods for firms lacking prior exposure or disclosure. Overall, my findings highlight how insurance and risk communication enhance resilience to climate shocks, while underscoring the need for policies that mitigate long-term vulnerability without encouraging unsustainable development.

*I am deeply grateful to my advisors David Ng, Kelly Posenau, and Andrew Karolyi for their continuous guidance and encouragement. I also thank Chuqiao Bi, Pietro Bini, Yipiao Cai, Feng Chi, Jihye Jang, Taehoon Lim, Yiding Ma, and seminar participants at Cornell for helpful comments and suggestions. I welcome any comments, and any errors are my own.

†SC Johnson College of Business, Cornell University: sf395@cornell.edu

1 Introduction

Floods are among the most frequent and economically damaging natural disasters in the United States, causing an estimated $32.1 billion in annual losses under 2020 climate conditions, with projected increases of over 26% by 2050 due to climate change (Wing et al., 2022). As sea levels rise, storm surges intensify, and extreme precipitation becomes more common, flooding poses an increasing challenge to businesses and investors. Understanding how both acute flood events and chronic flood exposure affect economic outcomes is essential for designing adaptation strategies and guiding market responses. While the economic effects of flooding have been widely studied in the context of housing markets and household insurance decisions, much less is known about how businesses respond to floods and how institutional mechanisms, particularly insurance, shape their recovery. This paper fills that gap by providing the novel causal evidence on the role of flood insurance in supporting business resilience.

The economic consequences of floods are not straightforward. Flooding is a negative shock to capital and productivity, yet institutional features in the United States, such as the National Flood Insurance Program (NFIP) and federal recovery aid, may alleviate losses or even foster rebuilding that enhances productivity. Prior research documents mixed findings: some studies report negative effects on economic activity and firm performance (e.g., Pankratz and Schiller, 2024; Kocornik-Mina et al., 2020), while others find find evidence of resilience or post-disaster gains (e.g., Leiter et al., 2009; Erda, 2024; Deryugina et al., 2018). These conflicting results raise two key questions: (1) How do floods affect business outcomes, and through what mechanisms do these effects arise? (2) How does chronic flood risk, even in the absence of disasters, shape long-term business performance and investor perceptions?

While prior studies have examined the financial effects of chronic climate risk, less is known about how chronic flood exposure influences business operations. Flood-prone regions may still attract businesses due to advantages such as tourism, trade access, or infrastructure investment. However, persistent exposure can also increase insurance costs, impose regulatory constraints, and create uncertainty that discourages hiring and investment. These contrasting forces make it unclear whether flood risk ultimately supports or undermines local economic activity, underscoring the need to understand this relationship to assess the long-term costs of climate exposure and explain the persistence of economic activity in vulnerable yet strategic areas.

To address these questions, I compile a novel establishment-level panel dataset that combines high-resolution remote sensing flood inundation maps with FEMA-designated floodplains for the period 2000–2018. Using the inherently unpredictable timing of flood events, I implement an event study design centered and show that flooded establishments experience notable increases in employment and sales in the years following the event. These findings contrast with the common perception of natural disasters as purely destructive shocks and instead suggest that, under certain institutional conditions, flooding can trigger recovery dynamics that support business growth.

A key mechanism in my paper is the role of flood insurance in business recovery. In the U.S., the National Flood Insurance Program (NFIP) mandates businesses located in FEMA-designated floodplains to purchase flood insurance if they hold federally backed mortgages. This regulatory requirement creates a clear source of variation in insurance coverage that I use to evaluate its effects. Using a triple-difference design around Hurricane Sandy, one of the costliest U.S. storms with damages exceeding $19 billion, I find that flooded establishments inside floodplains recover more strongly in employment and sales than similarly affected establishments outside. Analysis of NFIP commercial policy and claims data further supports this mechanism: before Sandy, coverage was much lower for businesses outside floodplains, but these areas saw a sharper increase in voluntary policies after the storm. Moreover, areas with greater floodplain exposure received larger payouts, particularly from required policies, aligning with the stronger recovery observed in the main analysis.

To strengthen these findings, I implement a spatial regression discontinuity difference-in-difference design that compares establishments located just inside and just outside FEMA floodplain boundaries before and after Hurricane Sandy. This approach controls for unobserved geographic and economic factors, such as coastal access or differences in local infrastructure, that could confound the results. The findings show that establishments just inside the regulatory boundary experienced stronger post-flood employment recovery than those just outside, despite being otherwise similar. Together, these results provide novel causal evidence that flood insurance access is a key driver of business resilience and recovery after major flood events.

Beyond insurance, federal disaster spending represents another mechanism that can influence post-flood business recovery. Previous research and surveys identify federal aid as a major

source of support for local economies after disasters (e.g., Collier, Howell, and Rendell, 2024; Erda, 2024). Two programs are particularly relevant. The Small Business Administration (SBA) provides disaster loans directly to firms, including physical disaster loans for repairing damaged property and Economic Injury Disaster Loans (EIDL) for working capital needs of small businesses. Separately, FEMA's Public Assistance (PA) program allocates grants to local governments and nonprofit organizations to fund emergency response and the reconstruction of damaged infrastructure. These programs provide liquidity, help stabilize local demand, and facilitate the rebuilding of essential services that support economic activity.

Using a panel of SBA loan disbursements at the zip code level, I find that EIDL loans, which are designed primarily for small businesses, are significantly associated with post-flood increases in employment and establishment counts. Interestingly, the positive effects also extend to larger establishments, suggesting that support for small businesses can generate beneficial spillovers for the broader local economy. At the county level, my analysis of FEMA PA funding shows that higher spending on recovery projects is linked to greater employment growth and job creation following floods. Although these results rely on aggregated data and do not directly capture establishment-level responses, they underscore that federal investments in both private businesses and community infrastructure play an important role in strengthening local resilience and accelerating economic recovery.

While insurance payouts and federal assistance can support recovery and growth in employment and sales after floods, chronic flood risk shows a very different pattern. Using establishment-level data linked to FEMA floodplain designations, I find that businesses located in high-risk zones are associated with lower employment and sales, even when actual flooding is taken into account. This contrast suggests that while acute events can trigger support that helps businesses recover, persistent risk gradually reduces business performance over time.

To understand why chronic risk undermines local economies, I examine potential mechanisms. Prior studies have shown that population movement and economic disinvestment are common responses to persistent climate risk, particularly in areas facing repeated or projected hazards (e.g., Desmet et al., 2021; Jia et al., 2022). Consistent with this, I find that high-risk counties experience lower employment and fewer establishments, largely due to higher business

exit rates and job destruction rather than slower growth. These areas also exhibit reduced industry diversity with fewer active sectors.

Another contributing factor is the cost of insurance. While the NFIP provides essential coverage, rising premiums increase operating costs and may discourage long-term investment. I find that higher premiums are associated with lower employment and fewer establishments. However, the negative impact of premiums is less severe in high-risk areas, possibly because businesses there are more likely to hold insurance, receive government support, or value coverage more highly. Overall, these findings show that chronic flood risk increases operational costs and contributes to structural changes in local economies. They suggest the importance of policies that reduce unnecessary financial burdens while still encouraging firms to invest in resilience, helping communities adapt without fostering unsustainable patterns of development.

Beyond establishment-level outcomes, it is crucial to understand how floods and flood risk affect firms operating across multiple locations. Publicly traded companies have the capacity to strategically reallocate resources among establishments, adjust their capital structures, and communicate climate-related risks to investors. Linking granular establishment-level flood exposure to firm-level financial data and corporate disclosures enables me to examine how climate risks shape firm performance, strategic decisions, and investor perceptions.

Extending the establishment-level findings to firms, I find that companies affected by flooding events experience increases in employment and sales, likely driven by recovery support mechanisms such as insurance payouts and government aid. In contrast, firms with substantial exposure to chronic flood risk exhibit persistent declines in employment and sales. These contrasting outcomes indicate that long-term operational costs associated with chronic flood exposure can outweigh the benefits from short-term post-disaster support. Further, firms with higher chronic flood risk tend to strategically shift away from investments in tangible, asset-intensive operations.

To better understand how firms manage and communicate flood-related risks, I use a two-step classification approach. First, I screen 10-K filings and earnings call transcripts for flood-related keywords. Second, I apply a large language model (LLM) to categorize these disclosures as physical risk, regulatory risk, and/or opportunities. The results show that firms with greater chronic flood risk are more likely to communicate regulatory concerns, while firms with prior

flood experience tend to emphasize physical risks. These disclosure patterns underscore how both ongoing risk exposure and past disaster experiences shape firms' communication strategies and operational decisions.

Finally, I examine investor responses to flooding events through event study analyses. I document significant negative abnormal stock returns following major floods, particularly over longer post-event horizons. The adverse reaction is strongest for firms lacking prior flood exposure, suggesting that markets penalize companies perceived as inadequately prepared for climate shocks. Additionally, investor reactions are more severe when floods cause fatalities without significant population displacement, reflecting market sensitivity to unanticipated climate risks lacking a clear recovery narrative. Taken together, these firm-level findings provide new insights into how physical climate risk affects corporate operations, disclosure practices, and investor perceptions as firms face increasing flood exposure.

1.1 Literature

This paper primarily contributes to the growing literature on climate risk and insurance by providing new causal evidence on the role of flood insurance in facilitating business recovery and adaptation. While prior research has largely focused on household flood insurance decisions—including uptake, pricing, and behavioral responses (e.g., Kousky, 2018; Oh, Sen, and Tenekedjieva, 2021; Mulder, 2024; Ge, Johnson, and Tzur-Ilan, 2025), much less is known about the insurance channel in a firm context. For example, studies such as Wagner (2022), Bradt et al. (2021), and Hu (2022) document underinsurance and adverse selection in the National Flood Insurance Program (NFIP). Recent papers by Billings et al. (2022) and Issler et al. (2020) show that insurance payouts and disaster aid can help households reduce mortgage delinquency and financial distress in the aftermath of disasters. However, to the best of my knowledge, business-perspective evidence remains limited. My paper extends this literature by showing that NFIP coverage materially strengthens post-disaster business recovery, highlighting how institutional risk-sharing mechanisms shape economic resilience in the face of climate shocks.

This paper also contributes to the broader climate finance literature examining the effects of physical climate risk on firm outcomes. Prior studies have assessed the real and financial effects of hazards like sea level rise, extreme temperature, and hurricane, including on investment, pro-

ductivity, and valuation (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020; Choi et al., 2020; Addoum et al., 2023; Kruttli et al., 2025). Some papers focus specifically on flood events or flood risk—such as Pankratz and Schiller (2024) document significant negative effect of flood on supplier operating income and their customers. Erda (2024) find positive impact of floods on US manufacturing plants because of upgraded machinery and relocation of used capital. Overall, findings in the literature remain mixed: some discover recovery and resilience in labor income and wages and firms' capital accumulation (e.g., Leiter et al., 2009; Belasen and Polachek, 2009; Deryugina et al., 2018; Groen et al., 2020), while others document negative effects of floods and risk exposure on firm growth, labor dynamics and local economies (e.g., Kocornik-Mina et al., 2020; Jia et al., 2022). My paper enhances the precision of flood impact assessments by using granular establishment-level data with high-resolution flood exposure, helping to reconcile previously conflicting findings in the literature.

Lastly, this paper contributes to the literature on firm behavior and financial market responses to climate risk by providing new evidence on how firms and investors react to flooding events. Prior studies show that institutional investors influence firms' climate disclosures and ownership structure (Ilhan et al., 2023), and that shareholder activism promotes voluntary disclosure with positive valuation effects (Flammer et al., 2021). Griffin, Lont, and Lubberink (2025) find extreme temperature shocks significant affect firm performance but lead to little improvement in ESG scores or carbon emissions. Building on these studies, I show that firms with higher flood exposure are more likely to disclose relevant climate risks and reduce investment in tangible assets, while financial markets react negatively to flooding events, particularly when firms lack prior disclosure or experience.

The remainder of the paper is organized as follows. Section 2 provides institutional background. Section 3 describes the data sources on floods, flood risk, and establishments, along with relevant summary statistics. Section 4 examines the direct effects of flooding on establishments, focusing on mechanisms such as insurance and federal disaster spending. Section 5 analyzes the effects of chronic flood risk on establishment outcomes and explores potential mechanisms, including population decline, business exits, reduced industry diversity, and elevated insurance costs. Section 6 examines how firms respond to flood events and chronic flood risk through changes in employment, capital allocation, voluntary risk disclosures, and investor

reactions. Section 7 concludes.

2 Institutional Background

This section describes the institutional context underlying the empirical strategies of my paper, focusing on FEMA's flood maps, the National Flood Insurance Program (NFIP), and the regulations governing mandatory flood insurance purchases. These institutional features generate the variation in insurance coverage and flood risk exposure that is central to the identification strategy.

2.1 Flood Maps and National Flood Insurance Program

The National Flood Insurance Program (NFIP) was established by Congress in 1968 to address the lack of private market flood insurance and to reduce the economic losses of flood-related disasters. NFIP has since been the dominant provider of flood insurance for both homeowners and businesses, particularly in high-risk areas where private coverage has historically been sparse or expensive.

To administer the program and set premiums, FEMA produces Flood Insurance Rate Maps (FIRMs), which delineate areas of varying flood risk based on engineering studies that incorporate hydrological models, base maps and detailed elevation data. Properties located in the highest-risk zones—Special Flood Hazard Areas (SFHAs), also known as 100-year floodplains where there is at least a 1% annual chance of flooding—are subject to higher insurance premiums, and flood insurance is mandatory if the property is financed with a federally backed or regulated mortgage.

The production of FIRMs is costly and time-intensive. In the early 2000s, most FIRMs were paper-based. Between 1996 and 2000, FEMA digitized flood zones for over 1,300 counties and created the Q3 maps. To further improve accuracy and accessibility, a federal initiative known as Map Modernization allocated $1.4 billion beginning in 2005 to convert paper FIRMs into digital flood insurance rate maps, prioritizing densely populated and flood-prone areas (Morrissey, 2008). This effort led to the creation of the National Flood Hazard Layer (NFHL), a geospatial database integrating updated digital flood maps.

FEMA is required to update flood maps every five years because there are new topography, infrastructure development, and changing flood risks. However, in practice, updates have been slow and uneven. Funding constraints and slow revision processes have left most maps older than five years, with few communities ever receiving a second digital map (Weill, 2022). For those that did, updates typically took three to five years (Wilson and Kousky, 2019; Horn and Webel, 2018). As of 2019, fewer than 20% of census tracts had undergone multiple updates, and approximately 16 million residential properties—about 12% of the U.S. housing stock—remained uncovered by a digital map (Weill, 2022).

Other measures of flood risk have emerged in recent years. For example, commercial providers such as the First Street Foundation use advanced risk classification techniques that incorporate more granular data on topography, climate projections, and building characteristics. However, these measures also rely on information and modeling methods that are only available after my sample period. In addition, beginning in 2021 FEMA introduced Risk Rating 2.0, a new initiative that shifts from traditional map-based classifications toward property-specific risk assessments. Since my study focuses on the 2000–2018 period, prior to these developments, I rely on the NFHL and Q3 maps, which were the operative risk measures during the sample period and shaped business and policy decisions at the time.

2.2 Insurance Mandate and Business Coverage

A key institutional feature used in this paper is the NFIP insurance mandate: businesses with federally regulated or insured mortgages and located within SFHAs are required to purchase flood insurance. This rule provides a quasi-exogenous source of variation in insurance access between businesses just inside and just outside of FEMA-designated floodplains—an identification strategy employed in both the triple-difference and spatial regression discontinuity design analyses.

While NFIP dominates the residential market, the commercial flood insurance market has historically included both public and private options. In 2017, NFIP collected $3.5 billion in total premiums. In contrast, $589 million in private flood insurance premiums are reported to the National Association of Insurance Commissioners (NAIC), and roughly 64% of them was commercial (Horn and Webel, 2018; Carrier Management, 2018). However, the private market

tends to focus on high-value properties and is often used by large firms as excess coverage beyond NFIP limits or as manuscript policies that bundle multiple perils.

Most large commercial firms, especially those with substantial real estate holdings, tend to hold private manuscript policies, sometimes foregoing NFIP coverage unless required to reduce deductibles or meet federal loan conditions. Nonetheless, for small and mid-sized firms operating in regulated lending markets, NFIP remains the primary or only source of flood insurance (Dixon et al., 2013).

In 2019, federal regulations were revised to require lenders to accept private flood insurance policies that meet NFIP-equivalent standards to satisfy the mandatory purchase requirement for properties in SFHAs. This change increased the potential for substitution away from NFIP toward private coverage, particularly for businesses that could meet the regulatory standard through alternative policies. Such substitution would weaken the link between FEMA floodplain designation and NFIP insurance uptake, which is central to my identification strategy. By restricting the analysis to the 2000–2018 period before this rule took effect, I ensure that the NFIP mandate remained the primary determinant of insurance coverage in floodplains, making this sample period well-suited for studying the role of insurance in post-disaster recovery.

3 Data

3.1 Flooding data

The high-resolution inundation maps used in this paper are obtained from the Global Flood Database (GFD), which identifies large flooding events recorded by the Dartmouth Flood Observatory (DFO) from 2000 onward using NASA's MODIS satellite imagery. Many prior studies (e.g., Kocornik-Mina et al., 2020; Jia et al., 2022; Pankratz and Schiller, 2024) have relied on the DFO dataset, which combines remote sensing sources and hand-mapped polygons based on government alerts and news reports to document global floods. While the DFO has been widely used, the GFD improves upon it by applying advanced inundation detection algorithms to twice-daily MODIS imagery, distinguishing temporary floodwaters from permanent water bodies, and offering raster data at a 250-meter spatial resolution (Tellman et al., 2021). For each mapped flood event, there are pixel-level information on whether an area was inundated

and for how many days. I focus on U.S. flood events from 2000 to 2018, during which 98 events were successfully mapped using mostly cloud-free observations. As summarized in Table 1, the median flood duration is approximately 10 days, and the dataset also records annual totals for displacement and mortality associated with these events.

To link flooding events to establishment outcomes, I merge each inundation map from the Global Flood Database (GFD) with the geocoded locations of establishments. Figure 1 maps the spatial distribution and frequency of flooded establishments between 2000 and 2018. Using the original 250-meter resolution (Panel A), more than 13,000 establishments experienced at least one flood during the sample period, with an average of 1.5 flood events and a maximum of 16 events per establishment. Panel B applies a 1 km spatial buffer to account for possible spillover effects and under-detection in the GFD's composite classification, resulting in a broader footprint: over 140,000 establishments were affected by flooding at least once, with the average and maximum number of events rising to 2.5 and 29, respectively. Panels A and B of Table 2 present summary statistics for the flood exposure variables, where Panel A reports the establishment-level flood indicator and Panel B summarizes the firm-level measure based on the number of flooded establishments.

3.2 Flood risk data

My primary measure of flood risk is based on FEMA flood maps, which delineate Special Flood Hazard Areas (SFHAs)—zones with at least a 1% annual chance of flooding, also known as 100-year floodplains. These maps are the official benchmarks used to determine mandatory insurance requirements under the NFIP. As discussed in Section 2, FEMA maps have undergone several modernization efforts, transitioning from paper-based FIRMs to digital formats under the National Flood Hazard Layer (NFHL).

For this paper, I systematically downloaded and compiled the full set of digitized NFHL maps available from FEMA's Map Service Center as of October 2023. Because updated NFHL maps overwrite prior versions on FEMA's platform, I supplement them with historical Q3 Flood Data, which represent polygon-level designations based on FEMA's 1999 Flood Insurance Rate Maps. The Q3 data are available for over 1,300 U.S. counties and were obtained from the Princeton University geospatial data library. These two sources allow me to construct

a consistent panel of flood risk over time. For each establishment-year observation, I assign flood risk status by spatially merging establishment geolocations with the appropriate flood map version, using the NFHL map's publication date to determine the applicable map. For example, if a county's NFHL map was updated in 2011, I use the Q3 map for 1997–2010 and the updated NFHL map for 2011 onward.

This approach captures significant variation in flood risk exposure across both time and space. As summarized in Table 1, nearly half of the firms in my dataset have at least one establishment located in a FEMA-designated SFHA during the study period, underscoring the widespread exposure of U.S. businesses to flood risk. Panel C of Figure 1 shows the geographic distribution of spatial distribution of establishments in FEMA's SFHAs in 2018, based on NFHL and Q3 maps.

As a robustness check, I also use flood risk measures from FEMA's National Risk Index (NRI), first released in late 2020. The NRI provides census tract-level risk scores for eighteen natural hazards; I focus specifically on coastal and riverine flooding. These scores are derived primarily from NFHL data, supplemented by CoreLogic data in areas lacking digital flood maps. The NRI also has community resilience measures developed by the University of South Carolina's Hazards and Vulnerability Research Institute. This index is on the county and consists of six broad categories of community disaster resilience including social, economic, community capital, institutional capacity, housing/infrastructure, and environmental. The higher the score a county has, the more resilient the community is. The data is available in three time periods, 2010, 2015, and 2020 respectively.

3.3 Firm and establishment data

The establishment-level data come from Your-economy Time Series (YTS) from 1997 to 2018. An establishment is defined as a single physical business location where economic activity occurs (e.g., a store, plant, or office) and is linked to a parent company when applicable. The YTS dataset provides annual establishment-level information on employment, sales, geographic coordinates, and headquarters location. YTS contains annual establishment data on sales and employment as well as the coordinates and headquarters information. I focus on all the establishments of publicly traded companies in the US. To link establishments with firm-level

financials, I use ticker information for headquarters in YTS and apply a combination of spatial matching and fuzzy name matching to merge YTS with CRSP/Compustat. Panel B of Table 2 reports summary statistics of firm characteristics, such as employee size, firm size, log assets and PP&E from 2000 to 2018.

To analyze how firms perceive and communicate flood risk, I use 10-K filings from the SEC's EDGAR database and earnings call transcripts from Refinitiv Transcripts and Briefs with over 7,200 companies since 2001. I track whether firms disclose flood-related risks in these communications using a two-step classification approach. In the first step, I apply a traditional natural language processing algorithm to search for flood-related keywords in 10-K filings and earnings calls.[1] The keyword list includes food, heavy precipitation, sea level rise, water inundation, national flood insurance program, NFIP, National Flood Hazard Layer, NFHL, extreme weather events, hurricane, storm, cyclone, and natural disaster.[2] Any firm-year with at least one flood-related sentence is retained for the second step. In the second step, I extract the flood-related sentence along with its surrounding context (three sentences before and after for 10-K filings and four sentences for conference calls). The extracted disclosure is then processed using ChatGPT-4o, which classifies the disclosure based on predefined risk categories. For each category, the model outputs a binary classification, a probability score between 0 and 1, and an explanation for its decision.

I classify firm disclosures into three main dimensions. For 10-K filings, I distinguishes between physical risk and/or regulatory risk. Physical risk captures negative effects on a company's operations, assets, or supply chains resulting directly from flood events, such as facility damage, operational shutdowns, or disrupted logistics. In contrast, regulatory risk refers to risks arising from changes in policies or standards aimed at managing or mitigating flood risk. For example, a manufacturer might disclose concerns about rising costs due to new FEMA floodplain regulations requiring facility elevation, or a real estate company might highlight the impact of stricter zoning policies limiting development in coastal areas.

I also identify whether disclosures mention opportunities related to flood risk, including strategic positioning, market expansion, or product innovation. For example, a real estate firm

[1]For 10-Ks, the search is restricted to Items 1 (Business), 1A (Risk Factors), 2 (Properties), and 7 (Management's Discussion and Analysis).

[2]The list intentionally includes broader climate-related terms to capture implied discussions of flood risk. In later classification, I prompt the LLM to identify whether the risk specifically pertains to flooding.

may highlight the value of properties in low-risk areas, while a construction materials company may report growing demand for flood-resistant products.

For earnings calls, I apply a similar risk-versus-opportunity classification and add an additional layer by distinguishing whether the disclosure was initiated by the firm (e.g., during management's prepared remarks) or prompted by analysts (e.g., during the Q&A). This distinction allows me to capture differences between proactive communication and reactive responses to investor concerns. Appendix Tables A9–A12 provide examples of both 10-K and earnings calls disclosure classification with the model's explanations.

Figure 2 illustrates the evolution of flood-related disclosures over time. Panel (A) shows that disclosures in earnings calls often spike following major disasters, such as Hurricane Katrina in 2005, Hurricane Sandy in 2012, and the 2017 hurricanes, reflecting firms' immediate communication of risk during periods of heightened investor attention. In contrast, Panel (B) indicates that 10-K disclosures exhibit a steady upward trend over the sample period, with a noticeable jump around 2005—potentially linked to regulatory or risk management shifts following the catastrophic impacts of Hurricane Katrina. The overall rise in disclosures is consistent with growing awareness of flood risk and potential legal or reputational concerns.

Figure 3 further breaks down the average disclosure rates by industry. Panel (A) shows that utilities, materials, and industrials are the most likely to mention flood risk in earnings calls, consistent with their high exposure to physical assets and regulatory oversight. Panel (B) reveals that utilities, energy, and real estate sectors also dominate in 10-K disclosures. These patterns underscore the sectoral heterogeneity in how firms perceive and report flood-related risks, with asset-intensive and infrastructure-dependent sectors showing the highest rates of disclosure.

3.4 Insurance, federal spending and other data

To analyze insurance uptake, payouts, and their role in post-disaster recovery, I use NFIP policy and claims data from the OpenFEMA Redacted Policies and Redacted Claims databases. These datasets cover the universe of policies and claims since 2009 and provide information on coverage amounts, policy effective dates, claims paid, date of loss, building and occupancy type, small business indicator, and location at the census block group level. I identify com-

mercial policies and claims by classifying any record where the occupancy type indicates a non-residential use or where the small business indicator is true.

To examine the role of federal disaster aid, I obtain zip-code-level disaster loan data from the Small Business Administration (SBA) Disaster Loan Program starting from 2001, which includes information on total approved loan amounts, verified losses, and approved amount of Economic Injury Disaster Loans (EIDLs). These records are linked to FEMA-declared disasters and allow me to focus specifically on flood-related events. Additionally, I use the FEMA Public Assistance Funded Projects database from OpenFEMA, which provides county-level information on project spending linked to FEMA disasters. This data distinguishes between emergency and permanent recovery work funded under the program.

For local economic outcomes, I use data from the County Business Dynamics (CBD) and Zip Code Business Dynamics (ZBD) datasets obtained through the Census Bureau API. These provide annual measures of employment, establishments, job creation, job destruction, and the number of active firms at both the county and zip code levels. To control for demographic factors, I include county-level data from the National Institutes of Health (NIH), including total population as well as population by race, gender, and age group. At the zip code level, population data are obtained from the 2000 and 2010 U.S. Censuses. Panels D to F of Table 2 present summary statistics of key variables generated using these data.

4 Flood Shocks and Establishment Impact

Following the literature on studying the impacts of natural disasters such as Deryugina (2017), I use an event study setup to examine the dynamic impact of flooding events on establishments' operational performance.

$$Y_{i,t} = \sum_{\tau=-4,\tau\neq-1}^{10} \beta_\tau Flood_{i,\tau} + X_{i,t} + FloodRisk_{i,t} + \alpha_{s,t} + \alpha_{ind,t} + \alpha_i + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is sales or employment in a given year t of establishment i. The main variable of interest $Flood_{i,\tau}$ equals 1 if and only if $t - \tau_i^* = \tau$, where τ_i^* is the year a flood-affected establishment i. I normalize the effect in the year before the flooding ($\tau = -1$) to zero. $FloodRisk_{i,t}$ is whether

i is located in a FEMA high flood risk zone, and $Flood_{i,t}$ is the actual occurrence of flooding at the establishment i in year t. $X_{i,t}$ is the list of control variables including the previous number of floods and community infrastructure on the county level. Establishment, industry-by-year, and state-by-year fixed effects are included to absorb time-invariant establishment-level characteristics and any aggregate trends in specific states in a given year. The standard errors are spatially clustered following Conley (1999), allowing spatial correlation of up to 150 kilometers around each establishment's coordinate and for autocorrelation of order 5.

The identification relies on two primary assumptions. First, given the inherently unpredictable nature of weather-related disasters, the timing of flooding events is plausibly exogenous and should be typically satisfied. Second, no other contemporaneous confounding events should occur in the event window of floodings. This second assumption may also be satisfied because the event window is relatively narrow, and other confounders related to business-cycle fluctuations, state-level regulatory changes, or industry trends would be orthogonal to the timing of floods. Thus, given these identifying assumptions, the changes in establishments' outcomes in post-flood periods could be attributed to the impact of flooding events.

Using flooding data derived from remote sensing data during 2000–2018, I focus on the first flooding event experienced by each establishment within this timeframe. Specifically, I exclude any observations involving establishments that experienced prior flooding during this period and omit flooding events occurring before the year 2000. Given that flooding is difficult to predict, and after controlling for establishment-specific and state-year fixed effects, this methodological choice should not systematically bias the estimated impacts.

The event study plots are in Figure 4. There are significant patterns in the left-hand-side plot where the employee numbers declined significantly in the year that flooding occurred and then increased in the subsequent years in the long term. In terms of sales revenue, the pattern is less clear and we would only be able to observe some significant increases from year 2 to year 5. The estimation results are in Appendix Table A3. As I further included community resilience and the number of flooding days that an establishment experienced as well as industry sector by year fixed effects, the results are similar. Various spacial buffers to inundated areas are included and their respective event study plots and tables are in Appendix. As I include buffers to inundated areas, the negative impact of floods in the year 0 on employee numbers

dissipate, which on the other hand suggest the accuracy of the flooding data from GFD.

To further understand the heterogeneity across establishments, I separated the data sample into various GIC sector groups and I presented the event study plots with the employee number as the outcome variable in Figure **??**. I selected six industries that have interesting relations in the baseline analyses. We could observe that the negative impact on employee numbers in the year when flooding occurs is driven by establishments in the consumer discretionary and IT sectors. Interestingly, in contrast to the other sectors, establishments in the utilities sector consistently experience negative impacts 5 years after the occurrence of flooding.

4.1 Flood insurance

To examine whether insurance serves as a channel through which flood events positively affect establishments' operational performance, I use an institutional feature of the National Flood Insurance Program (NFIP). As explained in Section 2, businesses located in FEMA-designated floodplains with federally regulated or insured mortgages are required to purchase NFIP flood insurance. As a result, similar to the homeowners, these businesses located in floodplains are inherently more likely to hold NFIP coverage, particularly during my data sample period from 2000 to 2018.

Triple Difference in Difference

This institutional feature motivates the main hypothesis: if an establishment is located within a floodplain, it is more likely to recover and rebuild more effectively after a flood event than a comparable establishment located outside the floodplain but also affected by flooding.

I test this hypothesis using Hurricane Sandy as a quasi-experiment, focusing on New York City due to the availability of additional data from FEMA's 2007 flood risk map update. Hurricane Sandy, which struck in October 2012, was one of the costliest storms in U.S. history and caused over $19 billion in damages. This event significantly heightened public awareness of climate risk and flood risk in particular, especially among local residents and businesses.[3]

A potential concern with using FEMA floodplain designation as an instrument for insurance

[3]Evidence on the long-run positive impact of Hurricane Sandy on establishment employment in NYC is presented in the appendix.

access is that, unlike households, businesses may behave more rationally, purchasing insurance based on their perceived actual flood risk rather than regulatory requirements. If firms outside the floodplain anticipate high flood risk, they may voluntarily obtain coverage, which could undermine the exogeneity of floodplain designation. To address this concern, I first examine whether commercial insurance uptake was systematically lower outside floodplains prior to Hurricane Sandy and whether coverage expanded disproportionately in these areas after the storm.

Using a difference-in-differences approach with NFIP commercial policy data at the census block group level, I find that post-Sandy, flood insurance coverage grew more substantially outside of floodplains. As shown in Column 1 of Panel A in Table 4, a 1% increase in high-risk flood area within a block group is associated with 17.12 increase in voluntary policy counts after Sandy. In contrast, Column (2) shows a much smaller increase in total policies, only 2.25, suggesting that the rise in coverage was largely driven by voluntary uptake. This pattern implies that pre-Sandy, businesses outside floodplains were less likely to hold flood insurance, consistent with the institutional feature of mandatory coverage within FEMA-designated zones.

Beyond policy counts, the results in Columns (3) through (10) of Panel A of Table 4 provide additional evidence that commercial insurance expanded significantly after Hurricane Sandy, particularly in areas outside FEMA-designated flood zones: insurance policy costs and coverage amounts increased significantly along both the building and content dimensions post-Sandy. A similar pattern remains, although smaller, when expanding the analysis to include medium-risk areas, indicating that the rise in coverage was not limited to policy counts but also extended to the value and types of coverage. These findings suggest a broad-based expansion of commercial flood insurance uptake after Sandy.

To validate that these patterns translate into actual financial mitigation and further support the institutional feature underlying my identification strategy, I turn to NFIP commercial claims data to examine whether businesses in floodplains were more likely to receive payouts. Panel B of Table 4 shows that flood exposure is strongly associated with both the frequency and size of insurance claims. Columns (1)–(3) indicate that a 1% increase in flooded area within a block group is associated with more claims and higher building and content payouts, confirming that heavily flooded areas received more financial support from the NFIP. Importantly, Columns (4)

and (5) show that these effects are significantly stronger in high-risk flood zones: the interaction between flooded area and high-risk designation is positively and significantly associated with larger building and content payouts. This supports the institutional mechanism—businesses in FEMA-designated floodplains are not only more likely to hold coverage but also more likely to receive meaningful payouts after disasters.

Columns (6) through (9) distinguish between required and voluntary policies. Required claims increase significantly in response to flood exposure in high-risk zones, validating the role of the mandate in driving insurance use and payout. While voluntary claims also rise with flooding, the interaction term is not statistically significant, suggesting that firms in high-risk areas are more reliant on required policies for post-disaster support. Taken together, these results strengthen the credibility of my identification strategy: FEMA floodplain designation reliably predicts greater access to and use of insurance in the wake of disaster, justifying its use as a quasi-exogenous source of variation in insurance exposure.

Building on this, I formally test whether greater insurance access in floodplain areas translates into better recovery outcomes using a triple-difference framework. If insurance is indeed an important mitigating channel, then establishments located inside FEMA-designated floodplains and impacted by Hurricane Sandy should recover more effectively relative to similarly affected firms outside the floodplain. To test this, I estimate the following specification:

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times I(FloodPlain)_{i,2007} \\ &+ FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Flood_i$ is an indicator for whether establishment i was exposed to Hurricane Sandy flooding, and $I(FloodPlain)_{i,2097}$ denotes whether the establishment was located in the FEMA-designated floodplain prior to the storm. $FloodRisk_{i,t}$ indicates whether establishment i is currently located within the FEMA floodplain. The dependent variables $y_{i,t}$ include measures of establishment employment and sales. $FloodRisk_{i,t}$ captures the current FEMA floodplain designation for each establishment to control for any direct effects of being in a flood-risk zone. The model includes establishment fixed effects, industry-by-year, and neighborhood-by-year fixed effects to account for unobserved heterogeneity and time-varying local or sectoral trends.

The results are presented in Table 5. The positive and significant coefficients on the triple interaction terms suggest that establishments located within FEMA-designated floodplains prior to Hurricane Sandy recovered better in terms of employment and sales compared to similarly flooded businesses outside the floodplain. This differential recovery pattern is consistent with the institutional feature of the NFIP, where businesses in floodplains are more likely to hold insurance due to the mandatory purchase requirement. Coupled with earlier findings showing increased insurance uptake and higher insurance payouts among floodplain businesses, these results reinforce the insurance channel as a key mechanism of post-disaster recovery.

Figure 5 plots the extended difference-in-differences estimates of employment for flooded establishments, distinguishing between those located inside and outside FEMA-designated floodplains. Before Sandy, employment trajectories between the two groups were largely parallel, providing visual support for the parallel trends assumption. After the storm, however, firms inside floodplains exhibit consistently higher employment growth, suggesting that access to insurance played a meaningful role in facilitating recovery.

The triple-difference framework provides a flexible and general approach for estimating post-disaster recovery effects across the full sample, controlling for both time-invariant establishment characteristics and differential trends at the neighborhood and industry levels. However, a potential concern is that floodplain designation may be correlated with unobserved geographic or economic characteristics—such as coastal access, infrastructure resilience, or historical development patterns—that are not fully captured by fixed effects. These confounders could bias the estimated effect of insurance access. To address this, I turn to a complementary spatial regression discontinuity design that offers a more localized but potentially cleaner identification strategy.

Spatial Regression Discontinuity Design

To provide a more targeted test of the insurance channel and further strengthen causal identification, I implement a spatial regression discontinuity difference-in-difference (RD-DiD) design that exploits the sharp boundary of the FEMA-designated floodplain. This approach uses the institutional feature of the NFIP that applies only to establishments within the SFHA. Establishments located just inside and just outside this boundary are likely to be similar in

their exposure to flood risk, local infrastructure, and economic context, yet differ in a critical institutional feature: those inside the boundary are subject to mandatory flood insurance requirements under the NFIP. This policy discontinuity provides a quasi-experimental setting to isolate the effect of insurance availability on recovery following Hurricane Sandy.

The design combines spatial regression discontinuity with a pre/post comparison around Hurricane Sandy, effectively creating an RDD-DiD framework. The key identifying assumption is that, within a narrow window around the flood zone boundary, the assignment of floodplain status is effectively random once we account for smooth differences in distance to the boundary. This approach helps control for potential confounding factors, such as unobserved amenities or neighborhood characteristics, that might otherwise bias the comparison. By comparing changes in employment for firms just inside versus just outside the boundary before and after Sandy, I can thus isolate the effect of insurance eligibility on recovery.

Formally, I estimate the following specification:

$$y_{i,t} = \beta_1 Floodplain_i + \beta_2 Floodplain_i \times Post_t + f(r_i) + \alpha_{nbh,t} + \epsilon_{i,t} \tag{3}$$

where $y_{i,t}$ are establishment employment, $Floodplain_i$ is a dummy variable which equals 1 if the establishment i is located inside the flood zone before Hurricane Sandy, and 0 otherwise, and r_i is the perpendicular distance from the establishment to the nearest floodplain boundary. $f(r_i)$ is modeled as local linear functions in the baseline models and higher-order polynomials as robustness checks. The coefficient of interest, β_2, captures the differential change in employment after Sandy for businesses inside the floodplain relative to those just outside, holding constant smooth spatial trends and neighborhood-by-year fixed effects.

To validate the key identifying assumption, I check the smoothness through the regulatory boundaries prior to Sandy. Panel A of Figure 6 provides visual support for the design and shows no visible jump in pre-Sandy residualized employment across the boundary. In contrast, panel B displays a positive discontinuity in the post-Sandy period. These average linear visual patterns are consistent with the hypothesized mechanism: establishments with greater access to insurance—due to mandatory NFIP coverage—experienced stronger employment recoveries.

The estimates following Equation 3 are reported in Table 6. Across multiple specifications using triangular and rectangular kernels and both constant and MSE-optimal bandwidth pro-

posed by Calonico et al. (2014), the interaction term β_2 is consistently positive and statistically significant. This implies that, conditional on geography, firms inside the floodplain recovered more robustly after Sandy than similar firms just outside the boundary. These results align closely with the findings from the triple-difference framework and provide additional support for the insurance channel as a key mechanism in post-disaster recovery.

To further assess the validity of the RDD-DiD assumptions, I conduct two additional checks. Figure 7 presents two validations. Another key identification assumption for RDD is that establishments are assumed to be as good as randomly assigned to just inside or just outside the FEMA-designated flood zone, conditional on location. In the spatial context, this assumes that the boundary is exogenously drawn and not subject to manipulation by firms or regulators in anticipation of treatment. Panel A shows the McCrary density test, and there is no statistically significant discontinuity in the number of establishments around the floodplain boundary ($p = 0.125$). Therefore, we cannot reject the hypothesis that there is no perfect manipulation at the 5% level.

For the RD-DiD specification, another identifying assumption is parallel trends in the absence of treatment. Panel B of Figure 7 runs the event study regression and tests for differential pre-trends in employment between inside and outside establishments prior to Hurricane Sandy. The year-by-year coefficients fluctuate around zero and are statistically indistinguishable from it, potentially supporting the parallel trends assumption required for the DiD component of the design. Together, the graphical and statistical evidence strengthens the credibility of the identification strategy and indicates the plausibility of the insurance channel in post-disaster recovery.

4.2 Robustness Checks

Survivorship Bias

A potential concern in interpreting establishment-level results is survivorship bias. If the positive post-flood impacts documented earlier are driven primarily by the exit of weaker establishments, then observed improvements could simply reflect the selective survival of stronger businesses rather than genuine recovery effects. This is particularly relevant because my establishment-level analysis focuses on continuing units and may not fully capture dynam-

ics of entry and exit, especially when floods cause broader regional disruptions beyond directly inundated sites.

To address this, I conduct a robustness check at the county level using an event study design, examining how flooding influences aggregate establishment entry and exit. Unlike the establishment-level approach, which focuses on surviving businesses, this county-level specification incorporates both new entrants and exiting firms, allowing me to test whether the observed patterns in employment and operations reflect a cleansing mechanism (where low-performing firms exit) or broader economic adjustment.

Appendix Figure A4 plots the dynamic effects. Panel (A) shows that while establishment entry remains relatively stable in the years following a flood, there is no strong evidence of a sustained increase. Panel (B), in contrast, reveals that establishment exit rises noticeably after flooding events, with the effect persisting over several years. This pattern suggests that post-flood dynamics at the county level are characterized by a high-turnover environment where increased exits dominate, leading to net declines in the total number of establishments.

These findings provide important context for the main results. The positive effects on surviving establishments should not be interpreted as evidence that floods unambiguously strengthen local economies. Rather, they likely reflect a combination of recovery support for survivors (e.g., through insurance or aid) and the attrition of weaker businesses, which raises the average performance of those that remain. This robustness check underscores that while some establishments thrive post-flood, many others exit, leading to mixed aggregate outcomes at the county level.

National level analysis

To complement the Hurricane Sandy analyses, I extend the insurance channel test to the national level using all identified flood events between 2000 and 2018. Although historical updates of FEMA's NFHL maps are not fully available, I take advantage of the effective dates listed on the FEMA Flood Map Service Center to match each establishment to the appropriate floodplain designation for the year of its flooding event. Specifically, for each establishment, I use the floodplain status based on the map in effect prior to the event year, ensuring that the classification reflects the information available to businesses at the time. This setup allows me

to test whether the post-flood recovery advantage observed for insured establishments in the Sandy analysis generalizes across the United States.

The empirical specification follows the event-study framework:

$$Y_{i,t} = \sum_{\tau=-4,\tau\neq-1}^{10} \left(\beta_\tau Flood_{i,\tau} + \delta_\tau Flood_{i,\tau} \times Floodplain_{\tau_i^*-1}\right) + FloodRisk_{i,t} + X_{i,t} + \alpha_{s,t} + \alpha_{ind,t} + \alpha_i + \epsilon_{i,t}$$

where $Y_{i,t}$ is employment for establishment i in year t. $Flood_{i,\tau}$ equals 1 if year t is τ years relative to the first flood year τ_i^*m and $Floodplain_{\tau_i^*-1}$ indicates whether the establishment was outside a FEMA floodplain prior to the flood. The interaction coefficients δ_τ capture differences in recovery between establishments outside versus inside floodplains. Control variables $X_{i,t}$ include the number of previous floods and county-level community infrastructure.

Appendix Figure A3 plots the dynamic coefficients from this specification. Panel (A) shows that establishments located inside floodplains exhibit positive and persistent post-flood gains in employment, consistent with the availability of NFIP insurance. Panel (B) shows the interaction term, where establishments outside floodplains experience weaker recovery following floods, supporting the interpretation that lacking NFIP coverage limits their ability to rebound. While the confidence intervals widen in later years, the patterns remain broadly consistent with the earlier Hurricane Sandy findings: insurance access enhances recovery capacity even in a broader national context.

4.3 Government spending

Prior research and business surveys have highlighted the importance of federal spending as one of the key sources supporting local economic recovery after natural disasters for businesses (Collier et al., 2024; Erda, 2024). Federal disaster assistance may promote post-disaster economic recovery through two main channels: (i) direct capital injections to affected businesses, and (ii) public investments in local infrastructure and services. The Small Business Administration (SBA) provides loans directly to businesses following major disasters or emergencies declared by the President, while FEMA's Public Assistance (PA) program is the largest grant

program that funds local governments and nonprofits to undertake recovery and rebuilding projects after disasters. Both types of aid can boost the local economy by providing cash, helping businesses recover, and supporting community rebuilding.

4.3.1 SBA Disaster Loans

The SBA offers two primary types of post-disaster recovery loans for businesses. Physical disaster loans are intended to repair or replace disaster-damaged real estate, machinery, or inventory. These are broadly accessible to firms of all sizes and most nonprofit organizations. In contrast, Economic Injury Disaster Loans (EIDLs) provide working capital to small businesses unable to meet operating expenses due to the disaster.[4] Eligibility for EIDL is restricted to small firms based on industry-specific size standards and geographic location relative to the declared disaster area. Publicly traded companies are generally ineligible for EIDLs; thus, any observed effect of EIDL loans on outcomes in my sample of public firms would suggest direct improvements of local small businesses.

To examine the role of direct federal funding in affecting local economic recovery following flooding events, I use zip-code-level panel data from the SBA, focusing specifically on loans tied to FEMA-declared flood-related disasters, including floods, hurricanes, tornadoes, tropical storms, severe storms, and coastal storms. To avoid including ineligible regions or imputing zeros where no loan applications were possible, I restrict the sample to ZIP codes with non-missing SBA loan values. The following empirical specification is used to estimate the effect of SBA loan intensity on local economic recovery:

$$\begin{aligned} y_{zip,t} =& \beta_1 SBALoanIntensity_{zip,t} \times AfterFirstFlood_t + \beta_2 Flooded_{zip} \times AfterFirstFlood_t \\ &+ X_{zip,t} + \alpha_{zip} + \alpha_{t,state} + \epsilon_{zip,t} \end{aligned}$$

where $y_{zip,t}$ is a local economic outcome such as log employment or log establishments in zip code zip and year t, and $AfterFirstFlood_t$ is an indicator for years following the first flooding event in a zip code. To focus on the first disaster experience and for identification, I exclude zip codes that experienced subsequent flood events later in the sample period. $SBALoanIntensity_{zip,t}$

[4] Those loans are for small businesses who are unable to meet its financial obligations and pay its regular and necessary operating expenses, but not loss of expected profits or a decline in sales.

is the dollar value of approved SBA loans divided by the number of establishments in a zip code in a given year, and its interaction with $AfterFirstFlood_t$ captures the variation in the intensity of disaster assistance conditional on experiencing a flood.

To isolate the effects of SBA loan intensity from the underlying shock of flooding itself, I also include an interaction term between the flooding indicator $Flood_{zip}$ and the post-disaster period $AfterFirstFlood_t$. Control variables $X_{i,t}$ include the percentage of each ZIP code designated as high flood risk according to FEMA flood maps, the female population share, the number of historical flooding events, and verified disaster losses recorded by the SBA. These controls are included to mitigate concerns that more severely impacted areas simply receive more SBA aid.

Table 7 Panel A presents OLS estimates of this specification. Columns (1) and (5) show that a $1,000 increase in EIDL loan disbursement per establishment is associated with a 4.26% increase in employment and a 0.8% increase in total number of establishments. These findings are consistent with the intention of EIDL to support small businesses during disasters. If we focus on establishments with at least 50 employees, interestingly, as shown in Column (7)-(8), we could see significant positive effects of both EIDL and total loan intensity on the number of large establishments, suggesting that SBA disaster assistance may benefit not only small businesses but also larger firms. These effects are statistically significant and robust to alternative scaling of loan intensity by population, as shown in Appendix Table A5. These results suggest that small business recovery can generate broader economic benefits through local linkages that may enhance the recovery of larger establishments operating in the same region after a disaster.

4.3.2 FEMA Public Assistance Spending

In addition to business-targeted loans, the federal government also supports community recovery through FEMA's Public Assistance (PA) program, which funds emergency response and permanent infrastructure reconstruction. Emergency categories include debris removal and protective measures, while permanent categories cover roads, utilities, public buildings, and parks that need to be completed within 18 months.

Table 7, Panel B presents results linking county-level FEMA PA spending intensity to local economic outcomes. As shown in Columns (1) and (2), a $1,000 increase in total PA funding per capita is associated with a 0.27% increase in overall employment and a 0.5% increase in

job creation following a flood event. These findings indicate that federal investment in local infrastructure plays a meaningful role in supporting labor market recovery. Appendix Table A5 provides additional results focusing specifically on permanent work categories. The patterns are generally consistent, with permanent FEMA-funded projects continuing to show positive effects on job creation, suggesting a positive spillover effect on the local economy.

Taken together, the results show that federal disaster spending plays an important role in promoting local economic resilience following flood-related disasters. On the business side, the significant effects of EIDL loans on employment and the number of establishments suggest that direct liquidity support helps small firms recover and continue operating in the aftermath of disaster shocks. Importantly, the results also show the positive effects on larger establishments, suggesting potential spillover benefits from small business recovery or broader market revitalization. On the community side, the positive association between FEMA PA funding and job creation suggests that rebuilding efforts can support labor market recovery. While my analyses do not identify the exact mechanisms through which these spillover effects occur, they provide suggestive evidence that federal disaster aid can help support local business recovery through both private businesses and public funding.

5 Chronic Flood Risk

While establishments increase employment and sales following unexpected flooding events, a natural question arises: how does the chronic presence of flood risk, even when no actual flooding occurs, affect business operations in the long run? Acute disasters may trigger short-term insurance and recovery aid, but the persistent designation of a location as high flood risk may shape business decisions in a fundamentally different way. Elevated flood risk can influence business behavior through several channels, including increased insurance premiums, more restrictive lending terms, or a decline in local consumer and investor confidence. Over time, such pressures may reduce firms' willingness to invest, hire, or expand operations in high-risk areas.

To explore these longer-term consequences, I examine how flood risk affects employment and sales at the establishment level using a fixed effects panel specification that uses FEMA

flood zone designations from 2000 to 2018. This analysis complements the prior findings by shifting the focus from post-disaster recovery to the broader economic costs of chronic exposure to climate-related hazards.

$$Y_{i,t} = \beta_1 FloodRisk_{i,t} + \beta_2 Flood_{i,t} + X_{i,t} + \alpha_{s,t} + \alpha_i + \epsilon_{i,t} \tag{4}$$

where the outcome variable $Y_{i,t}$ denotes either log employment or log sales at establishment i in year t. $FloodRisk_{i,t}$ is an indicator equal to one if the establishment is located in a FEMA-designated high flood risk zone, and $Flood_{i,t}$ is an indicator for whether the establishment experienced an actual flood event in year t. $X_{i,t}$ are control variables, including the cumulative number of historical flood events at the establishment level and a county-level measure of community infrastructure. I include state-by-year and establishment fixed effects, and, in robustness specifications, industry-by-year fixed effects to account for time-varying unobservables.

The estimates are in Table 8. Columns (1)-(2) and (3)-(4) show that being located in a high flood risk zone is associated with a 1% reduction in employment and a 2.4-2.7% decrease in sales. To validate the findings, I use an alternative flood risk measure that combines riverine and coastal flood hazard scores from FEMA's National Risk Index (NRI) at the census tract level. Results using the NRI measure are in Columns 3 and 6 and show the adverse effects of flood risk on both employment and sales. As a further robustness check, Appendix Table A6 presents specifications using flood exposure defined by geospatial buffers (250m, 500m, and 1km) around inundation map of the flooding events. As buffer sizes increase, the positive effect of previous flood experience on employment and sales becomes smaller and less significant.The results show an interesting asymmetry: disasters may trigger insurance payouts and federal aid that support growth, but the mere presence of flood risk may deter private sector investment and hiring. This contrast helps reconcile the seemingly positive effects of the acute physical climate risk with the negative long-run consequences of flood risk exposure.

5.1 Potential Mechanisms

What mechanisms can explain the negative relation between flood risk and establishments' operations? Prior empirical and theoretical papers have shown population relocation as a

response to chronic climate risk, particularly for regions facing repeated or projected hazards (e.g., Desmet et al., 2021; Jia et al., 2022). Businesses in these regions may face shrinking local demand, rising operational costs, and declining labor availability. For instance, persistent flood risk may discourage new business formation, increase firm exit, and reduce sectoral diversity. Additionally, as firms evaluate the costs and benefits of continuing operations in high-risk areas, some may choose to downsize or relocate altogether.

To explore these potential mechanisms, I estimate fixed-effects regressions with flood risk exposure and county-level business outcomes using the following specification:

$$Y_{a,t} = \beta_1 FloodRisk_{a,t} + X_{i,t} + \alpha_{s,t} + \alpha_a + \epsilon_{a,t} \tag{5}$$

where the outcome variable $Y_{i,t}$ includes a broad range of county-level outcomes: population, number of employees (in thousands), job creation and destruction (in thousands), number of establishments, entry and exit rates, and counts of distinct industries based on 4-digit and 6-digit NAICS codes. The key variable $FloodRisk_{a,t}$ measures the percentage of land in each county a designated as high flood risk by FEMA in a given year. Controls $X_{i,t}$ include county demographics and lagged economic indicators. I include county and state-by-year fixed effects to absorb unobserved time-invariant heterogeneity and time-varying state-level shocks.

Panel A of Table 9 presents the results. Columns (1) and (2) show that higher flood risk is associated with lower population and reduced employment at the county level. These declines do not appear to stem from a lack of economic activity; rather, Columns (3) through (7) indicate that while job creation and establishment entry do increase slightly in high-risk areas, they are more than offset by increases in job destruction and establishment exit. The net effect is a decline in overall employment and no significant result in establishment counts, reflecting a high-turnover environment where maintaining operations becomes increasingly difficult. Furthermore, Columns (8) and (9) show that flood risk is associated with a decline in the number of active industries at both the 4-digit and 6-digit NAICS levels, suggesting a loss of business diversity in high-risk areas.

Another plausible channel is the rising cost of insurance in flood-prone areas. While federal programs like the NFIP offer coverage, premiums can still be prohibitively expensive and may increase as FEMA remaps flood zones or adjusts risk models. Recent studies, such as Ge

et al. (2025), have shown that rising flood insurance costs affect household decisions, leading to relocations or prepayment of their mortgages to avoid the required insurance. For businesses, higher insurance premiums may reduce operating margins, deter expansion, and increase the financial burden of compliance.

To assess the role of insurance cost, I include the NFIP commercial insurance premium costs and also interact them with local flood risk measure. Including the interaction term allows me to test whether the economic impact of insurance costs depends on the degree of flood exposure in a given area. Conceptually, while flood risk captures the physical or regulatory exposure to flooding, insurance premiums represent the financial burden that businesses and households bear in response to that risk. The interaction term helps determine whether this burden has more severe effects in flood-prone areas or whether its impact is mitigated where flood coverage is more valued or commonly adopted.

Panel B of Table 9 presents the results. Columns (1) and (4) show that higher NFIP insurance premiums are significantly associated with lower employment and fewer establishments. This suggests that rising insurance costs can place financial pressure on businesses, making it harder for them to maintain or expand operations. Interestingly, the interaction between insurance premiums and flood risk is positive and statistically significant. This means that the negative effects of higher insurance costs are smaller in areas with higher flood risk. One possible explanation is that in high-risk areas, insurance coverage is more widespread, more heavily subsidized, or more essential to continued business operation. In other words, although high insurance costs can be a burden overall, they may be less harmful—or even helpful—for firms in areas that are more exposed to flood risk and have adapted accordingly. I replace insurance premium sums with counts of commercial and total policies Appendix Table A7 and the results are generally similar.

In sum, the negative effects of long-run flood risk on business operations can be potentially explained by three interrelated mechanisms: (1) declining local population, which reduces labor supply and consumer demand; (2) increased firm exit and reduced industrial diversity; and (3) elevated insurance costs that raise the cost of doing business in high-risk zones. They highlight the need for targeted adaptation strategies and coordinated policy to mitigate the long-run economic consequences of climate-driven hazards.

6 Firm-level Performance and Disclosure

So far, the establishment-level analyses show an asymmetry in how businesses respond to actual flood events versus chronic flood risk. On one hand, flooded establishments tend to experience growth in employment and sales, consistent with the stabilizing role of federal flood insurance and possibly post-disaster reconstruction activity. On the other hand, establishments located in high-risk flood zones show persistent declines in these same metrics, likely due to longer-term disincentives such as higher insurance costs, increased uncertainty, or depressed local investment.

But how do these patterns scale up to the firm level? Firms typically operate across multiple establishments—some of which may be exposed to flood risk or flooding while others are not. It is therefore unclear whether the benefits of post-disaster aid dominate at the firm level, or whether the long-run drag of flood risk translates into broader operational constraints. This section investigates that question by analyzing how floods and flood risk affect firms' employment, disclosure, and asset composition.

I begin by comparing the effects of flood exposure and long-term flood risk on firm performance. I then explore how firms respond operationally through adjustments in property, plant, and equipment (PP&E) and intangible assets, as well as through their public communication of risk in financial disclosures. As described in the Data section, these analyses combine establishment-level geospatial data with annual and quarterly financial data from Compustat. I further incorporate text-based measures of voluntary flood risk disclosure using natural language processing and large language models applied to earnings calls and 10-K filings.

6.1 Flood Exposure vs. Flood Risk: Firm-Level Effects

A natural question that arises is whether the establishment-level asymmetry between flood events and flood risk persists at the firm level—or whether it dissipates once we aggregate across a firm's broader footprint. In particular, do firms increase employment and sales when affected by floods, but reduce them when exposed to long-term risk? To examine this, I construct firm-year measures of flood exposure and flood risk based on the geographic distribution of establishments.

Flood exposure is measured by the number of a firm's establishments that experienced inundation in a given year, using high-resolution satellite-based flood maps. Flood risk is proxied by the number of establishments located within FEMA-designated SFHAs, both with and without employment-based weighting. I estimate panel OLS regressions on the annual level with firm and industry-year fixed effects to absorb time-invariant firm characteristics and common industry shocks in a given time period. In the regressions, I also control for other firm accounting variables in the previous period, including size, total assets, debt, cash, CAPEX, and EBIT.

Table 10 presents the results. Columns (1) and (2) show that firms experiencing a flood event in a given year exhibit significant increases in employment and sales. These effects are consistent with the earlier establishment-level results and likely reflect insurance payouts, federal business aid, or local reconstruction spending. However, when I impose spatial buffers from 250 meters to 500 meters to 1 km around the remote sensing flooded area to allow for possible imprecision or spillover, the coefficients shrink, and significance weakens, suggesting that the positive impacts are highly localized and highlighting the plausibility of the insurance channel to the post-disaster recovery.

In contrast, Columns (7) and (8) show that firms with greater exposure to chronic flood risk experience significant and negative effects on employment and sales. These effects persist even after controlling for historical flood experience, as shown in Columns (9) and (10), suggesting that it is not just past damages but the anticipation of risk that drives these outcomes. These negative effects might be because flood risk imposes structural costs on firms, possibly through higher insurance premiums, reduced investment incentives, or declines in the economic vitality of high-risk regions.

Overall, the contrast between the flood and flood risk coefficients suggests an asymmetry: while publicly traded firms may benefit from disaster-related aid and reconstruction following a flood event, chronic exposure to flood risk appears to reduce long-run growth and employment. This divergence echoes broader concerns about the economic drag of climate risk and suggests that market responses to acute shocks differ sharply from those to chronic vulnerabilities.

6.2 Firm Disclosure and Operational Adjustment

Next, I explore how firms respond to flood-related risks through disclosure and changes in operations. These responses reflect the firm's forward-looking risk management behavior, with implications for how capital markets and stakeholders interpret and respond to climate risk.

To do this, I estimate panel regressions using quarterly financial data, controlling for firm fixed effects, year-quarter fixed effects, and industry-by-year fixed effects. Table 11 presents the main results, examining two sources of flood exposure: (i) flood risk, defined as the number of a firm's establishments located in FEMA-designated flood zones, and (ii) cumulative flood experience, defined as the log number of flood events that affected the firm's establishments since 2002.

Panel A of Table 11 shows that firms with greater exposure to flood risk are significantly more likely to voluntarily disclose flood-related risks in both earnings calls and 10-K filings. Column (3) shows that such disclosures are more likely to be initiated by the firm itself during earnings calls, suggesting that firms with high flood risk proactively manage communication with investors. In terms of operations, Columns (8) and (9) show that high-risk firms tend to reduce their holdings of tangible assets and potentially PP&E, suggesting that firms appear to internalize physical climate risks not only in their communications but also in how they allocate capital.

Panel B turns to cumulative flood experience. Results are largely consistent. Firms that have experienced more flood events are more likely to disclose flood-related risks and also reduce physical capital investment. This suggests that both forward-looking (floodplain exposure) and backward-looking (past floods) measures of flood exposure shape firm behavior.

Interestingly, when decomposing 10-K flood disclosures into physical and regulatory risk, I find that cumulative flood experience is strongly associated with disclosures of physical risk as shown in Column 6 of Panel B, while exposure to flood risk is more closely tied to regulatory risk disclosure, as shown in Column 7 of Panel A. This distinction implies that firms interpret chronic risk and past experience through different lenses—anticipating regulatory scrutiny when floodplain exposure is high, while reacting to damage when floods have already occurred.

To assess robustness, I adopt two alternative definitions. First, I redefine high flood risk as having more than 1% of total firm employees located in flood zones. Second, I modify the

cumulative flood measure by incorporating a 1-km spatial buffer around the original inundation maps. Appendix Table A8 reports the results. The key patterns remain: firms facing higher flood risk continue to show significantly higher disclosure propensities, particularly in earnings calls, and reduced PP&E and intangible assets.

6.3 Stock Market Reaction to Flooding

To complement the analysis of firm operations and disclosures, I examine how investors perceive and price flood risk by analyzing the stock market reaction to flooding events. Using a standard event study framework, I compute abnormal stock returns around the occurrence of floods to assess whether investors react to these climate shocks and whether the reaction differs across firm characteristics. The analysis focuses on cumulative abnormal returns (CARs) measured over event windows ranging from 1 to 20 trading days after the flood start date. Expected returns are estimated using Fama–French three-factor, Carhart four-factor, and Fama–French five-factor models, with the main specification relying on the FF3 model and an estimation window of [-275, -20] trading days.

Figure 8 Panel (a) shows the cumulative average abnormal returns (CAARs) for all flooded firms. The results reveal that market reactions are initially muted but turn significantly negative after about 15 trading days, suggesting that investors gradually incorporate flood-related information into stock prices. This delayed response may reflect the time required to assess the operational and financial implications of flooding events.

I further investigate heterogeneity in market reactions by separating firms based on their prior exposure to flood risk and experience. As illustrated in Panel (b), firms experiencing a flood for the first time face more severe negative abnormal returns, consistent with markets penalizing firms perceived to be less prepared for climate shocks. Similarly, Panels (c) and (d) show that firms without establishments in FEMA high-risk floodplains experience more negative reactions, highlighting that unexpected events drive stronger investor responses.

7 Conclusion

This paper provides new evidence on the uneven economic effects of floods and chronic flood risk on U.S. establishments and firms, contributing to the broader literature on climate finance, disaster recovery, and insurance. By combining establishment-level geospatial data with high-resolution satellite flood maps, FEMA flood risk designations, and firm-level financials, I document an important difference in how businesses respond: measurable improvement in employment and sales are found in years following acute flood events, while persistent exposure to flood risk is associated with gradual declines in these same outcomes.

I identify insurance access under the National Flood Insurance Program (NFIP) as a key recovery mechanism driving the positive post-disaster effects. Exploiting the institutional mandate requiring businesses in FEMA-designated floodplains with federally backed mortgages to purchase insurance, I show that establishments inside the floodplain recover more robustly after disasters. Results from a triple-difference framework centered on Hurricane Sandy and a spatial regression discontinuity design reinforce the causal role of insurance in facilitating recovery. In addition, federal disaster spending, including SBA loans and FEMA Public Assistance, supports local resilience by boosting employment and encouraging the survival and growth of establishments, particularly small businesses.

In contrast, chronic flood risk negatively affects local economies by reducing employment, establishments, and industry diversity. Analyses at the county level reveal that these declines are driven by higher business exits and job destruction, while rising insurance costs further exacerbate operational challenges. These patterns suggest that persistent risk imposes long-run economic burdens that are not offset by the adaptive benefits observed after acute events.

At the firm level, I show that the variation between acute floods and chronic risk also holds. Firms exposed to floods experience operational improvements, while those with higher exposure to chronic risk reduce employment, sales, and tangible asset holdings. Firms respond to these risks by adjusting their disclosure behavior—those with higher risk or flood experience are more likely to communicate flood-related risks in 10-K filings and earnings calls, with risk type (physical vs. regulatory) shaping disclosure content. Finally, stock market analyses reveal that investors react negatively to floods, particularly when they occur at firms with no prior flood risk disclosure or exposure, indicating that markets penalize perceived unpreparedness.

Overall, my findings carry several important policy implications. Businesses, particularly medium-sized and smaller firms located outside FEMA flood risk zones, are less likely to hold flood insurance and, as a result, recover less effectively after disasters. This highlights the need for policies that encourage greater voluntary participation in flood insurance programs in areas where coverage is available but underutilized. Measures such as premium subsidies targeted at small businesses, streamlined enrollment procedures, and bundled coverage options could increase uptake without undermining risk-based pricing.

My paper also finds that chronic flood risk, even in the absence of actual flood events, gradually weakens long-term economic activity by increasing business exits and reducing industrial diversity. This highlights the need for policies that lower the structural costs of operating in high-risk areas while avoiding incentives that encourage harmful or unsustainable development. For example, targeted tax credits or grants could offset the elevated insurance and compliance costs faced by firms that invest in physical resilience, such as elevating facilities or installing flood barriers. At the same time, local governments could adopt zoning and infrastructure policies that guide new investment toward safer areas without abruptly disrupting existing economic hubs. Together, these policies would help reduce the negative economic impact of chronic risk while supporting adaptive business behavior rather than sustaining continued vulnerability.

References

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2023). "Temperature shocks and industry earnings news." *Journal of Financial Economics*, *150*(1), 1–45.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). "Does climate change affect real estate prices? only if you believe in it." *The Review of Financial Studies*, *33*(3), 1256–1295.

Belasen, A. R., and Polachek, S. W. (2009). "How disasters affect local labor markets: The effects of hurricanes in Florida." *Journal of Human Resources*, *44*(1), 251–276.

Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). "Disaster on the horizon: The price effect of sea level rise." *Journal of Financial Economics*, *134*(2), 253–272.

Billings, S. B., Gallagher, E. A., and Ricketts, L. (2022). "Let the rich be flooded: the distribution of financial aid and distress after Hurricane Harvey." *Journal of Financial Economics*, *146*(2), 797–819.

Bradt, J. T., Kousky, C., and Wing, O. E. (2021). "Voluntary purchases and adverse selection in the market for flood insurance." *Journal of Environmental Economics and Management*, *110*, 102515.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). "Robust nonparametric confidence intervals for regression-discontinuity designs." *Econometrica*, *82*(6), 2295–2326.

Carrier Management (2018). "Top private flood insurers: 2017 market study." Tech. rep., Insurance Journal Research & Trends.

Choi, D., Gao, Z., and Jiang, W. (2020). "Attention to global warming." *The Review of Financial Studies*, *33*(3), 1112–1145.

Collier, B. L., Howell, S. T., and Rendell, L. (2024). "After the storm: How emergency liquidity helps small businesses following natural disasters." Tech. rep., National Bureau of Economic Research.

Conley, T. G. (1999). "Gmm estimation with cross sectional dependence." *Journal of econometrics*, *92*(1), 1–45.

Deryugina, T. (2017). "The fiscal cost of hurricanes: Disaster aid versus social insurance." *American Economic Journal: Economic Policy*, *9*(3), 168–198.

Deryugina, T., Kawano, L., and Levitt, S. (2018). "The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns." *American Economic Journal: Applied*

Economics, *10*(2), 202–233.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2021). "Evaluating the economic cost of coastal flooding." *American Economic Journal: Macroeconomics*, *13*(2), 444–486.

Dixon, L. S., Clancy, N., Bender, B., Kofner, A., Manheim, D., and Zakaras, L. (2013). *Flood Insurance in New York City Following Hurricane Sandy*. RAND Santa Monica, CA.

Erda, T. (2024). "Disasters, capital, and productivity." In *2024 APPAM Fall Research Conference, APPAM*.

Flammer, C., Toffel, M. W., and Viswanathan, K. (2021). "Shareholder activism and firms' voluntary disclosure of climate change risks." *Strategic Management Journal*, *42*(10), 1850–1879.

Ge, S., Johnson, S., and Tzur-Ilan, N. (2025). "The hidden cost of climate risk: How rising insurance premiums affect mortgage, relocation, and credit." *Working paper*.

Griffin, P. A., Lont, D. H., and Lubberink, M. J. (2025). "The effects of extreme high temperature spells on financial performance." *The British Accounting Review*, *57*(2), 101383.

Groen, J. A., Kutzbach, M. J., and Polivka, A. E. (2020). "Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term." *Journal of Labor Economics*, *38*(3), 653–685.

Horn, D. P., and Webel, B. (2018). "Private flood insurance and the National Flood Insurance Program." *Washington, DC: Congressional Research Service*.

Hu, Z. (2022). "Social interactions and households' flood insurance decisions." *Journal of Financial Economics*, *144*(2), 414–432.

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2023). "Climate risk disclosure and institutional investors." *The Review of Financial Studies*, *36*(7), 2617–2650.

Issler, P., Stanton, R., Vergara-Alert, C., and Wallace, N. E. (2020). "Mortgage markets with climate-change risk: Evidence from wildfires in California."

Jia, R., Ma, X., and Xie, V. W. (2022). "Expecting floods: Firm entry, employment, and aggregate implications." Tech. rep., National Bureau of Economic Research.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., and Rauch, F. (2020). "Flooded cities." *American Economic Journal: Applied Economics*, *12*(2), 35–66.

Kousky, C. (2018). "Financing flood losses: A discussion of the National Flood Insurance Program." *Risk Management and Insurance Review*, *21*(1), 11–32.

Kruttli, M. S., Tran, B. R., and Watugala, S. W. (2025). "Pricing Poseidon: Extreme weather uncertainty and firm return dynamics." *The Journal of Finance*.

Leiter, A. M., Oberhofer, H., and Raschky, P. A. (2009). "Creative disasters? flooding effects on capital, labour and productivity within European firms." *Environmental and Resource Economics*, *43*, 333–350.

Morrissey, W. A. (2008). *FEMA Funding for Flood Map Modernization*. Congressional Research Service.

Mulder, P. (2024). "Mismeasuring risk: The welfare effects of flood risk information." *Available at SSRN 4966795*.

Murfin, J., and Spiegel, M. (2020). "Is the risk of sea level rise capitalized in residential real estate?" *The Review of Financial Studies*, *33*(3), 1217–1255.

Oh, S., Sen, I., and Tenekedjieva, A.-M. (2021). "Pricing of climate risk insurance: Regulation and cross-subsidies." *Journal of Finance, Forthcoming*.

Pankratz, N. M., and Schiller, C. M. (2024). "Climate change and adaptation in global supply-chain networks." *The Review of Financial Studies*, *37*(6), 1729–1777.

Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A. (2021). "Satellite imaging reveals increased proportion of population exposed to floods." *Nature*, *596*(7870), 80–86.

Wagner, K. R. (2022). "Adaptation and adverse selection in markets for natural disaster insurance." *American Economic Journal: Economic Policy*, *14*(3), 380–421.

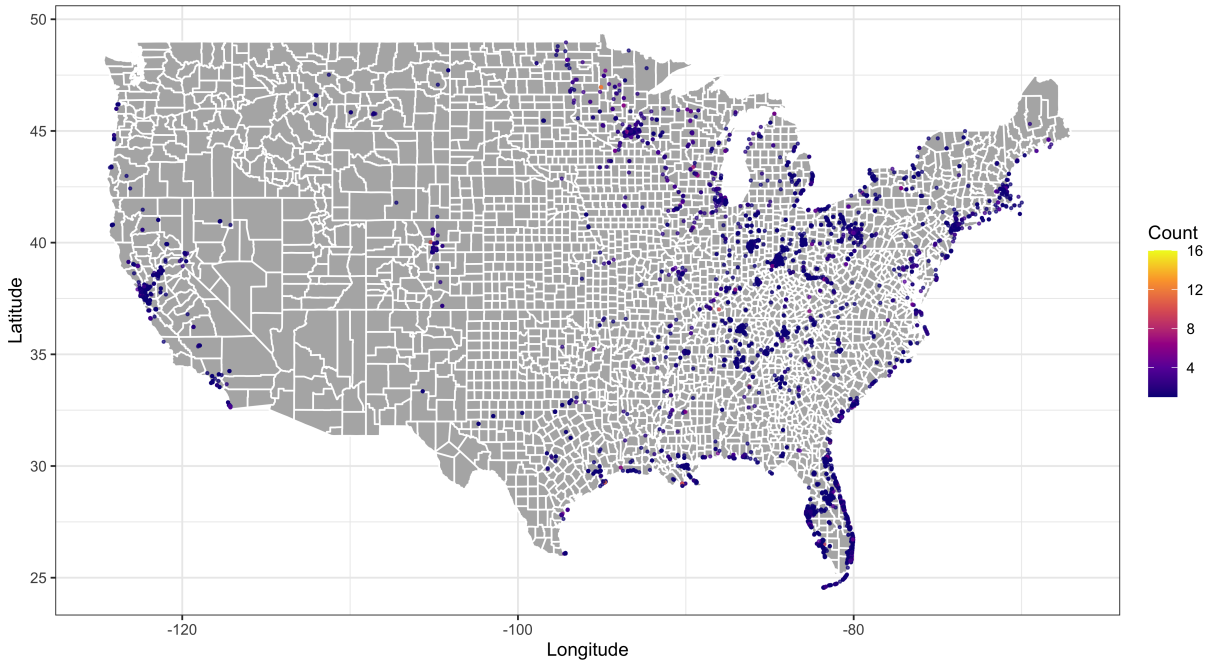
Weill, J. (2022). "Perilous flood risk assessments." *Available at SSRN 4143914*.

Wilson, M. T., and Kousky, C. (2019). "The long road to adoption: how long does it take to adopt updated county-level flood insurance rate maps?" *Risk, Hazards & Crisis in Public Policy*, *10*(4), 403–421.

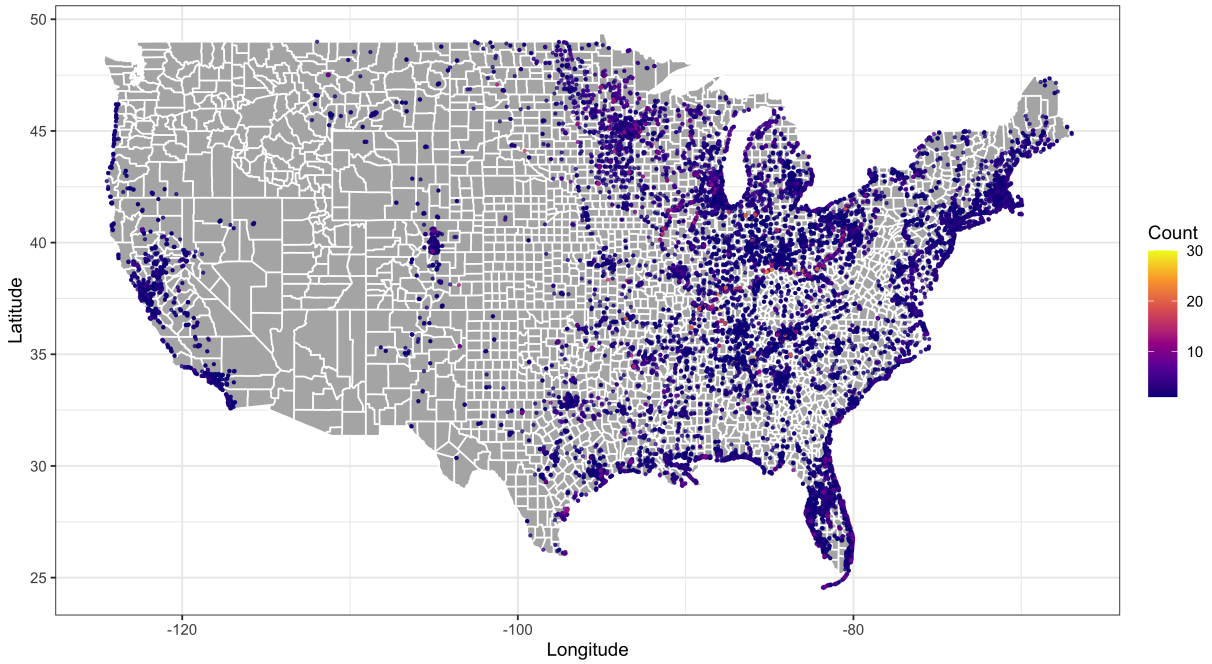
Wing, O. E., Lehman, W., Bates, P. D., Sampson, C. C., Quinn, N., Smith, A. M., Neal, J. C., Porter, J. R., and Kousky, C. (2022). "Inequitable patterns of us flood risk in the anthropocene." *Nature Climate Change*, *12*(2), 156–162.

Figure

Figure 1: Geographic Distribution of Flooded Establishments and High-Risk Zones

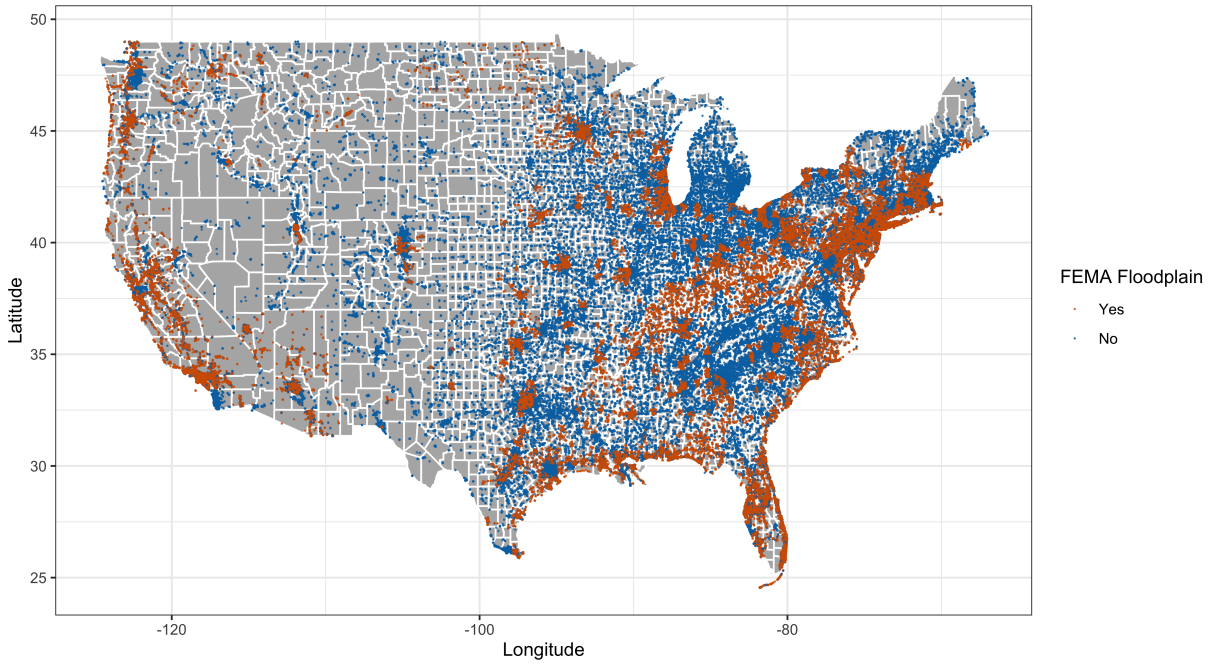


(A) Flooded Establishments



(B) Flooded Establishments w/ 1km Spatial Buffer

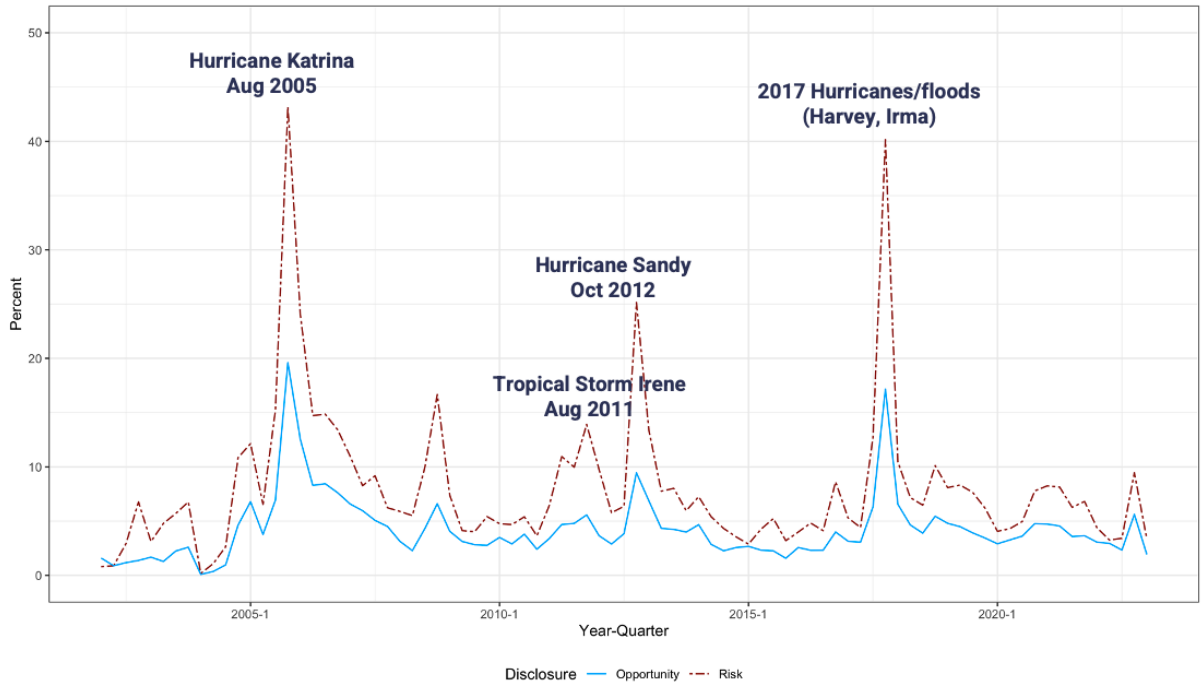
Figure 1: Geographic Distribution of Flooded Establishments and High-Risk Zones (Continued)



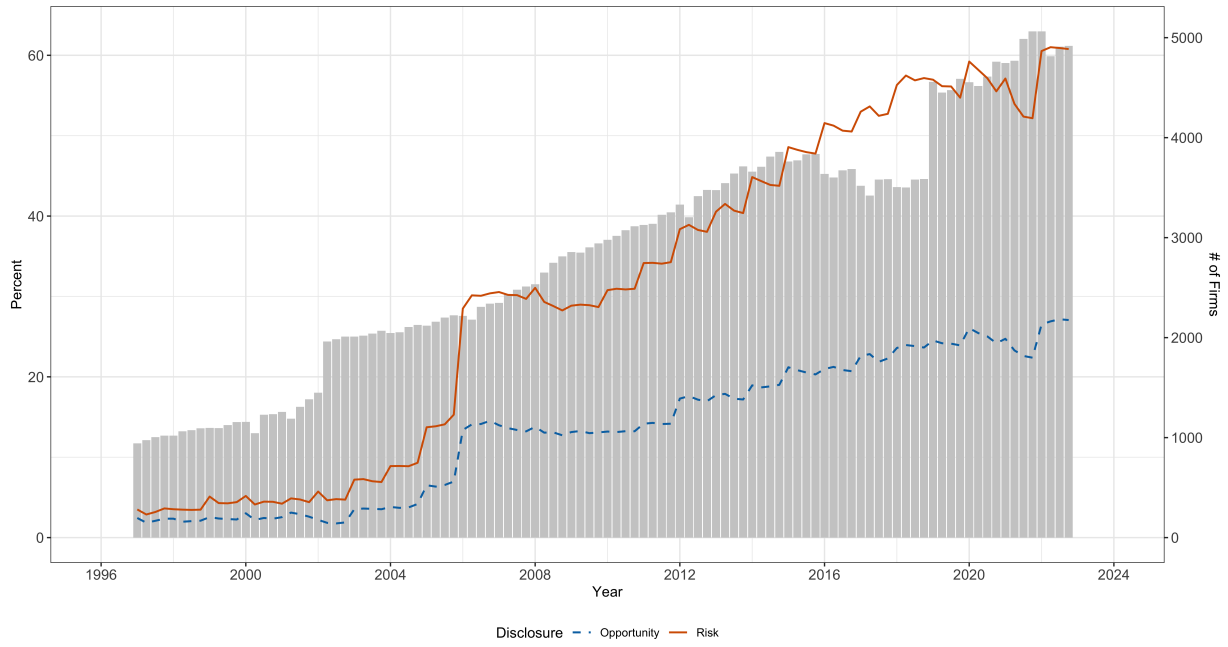
(C) Establishments in FEMA Flood plain

Notes: This figure shows the spatial distribution of U.S. establishments affected by flooding events from 2000 to 2018 and those located in FEMA-designated high-risk flood zones. Panel (A) maps flooded establishments identified using inundation data from the Global Flood Database (GFD). Panel (B) shows the same distribution applying a 1 km spatial buffer to capture nearby exposures. Panel (C) illustrates the locations of establishments inside and outside Special Flood Hazard Areas (SFHAs) in 2018, based on FEMA's National Flood Hazard Layer (NFHL) and historical Q3 maps.

Figure 2: Trends in Flood-Related Disclosures in Earnings Calls and 10-K Filings



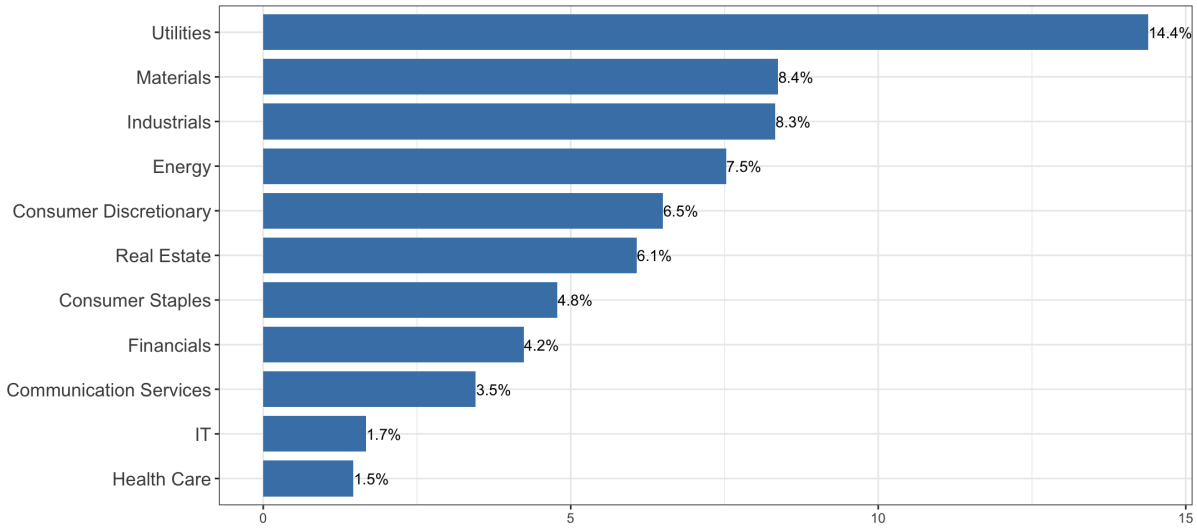
(A) Earning Calls



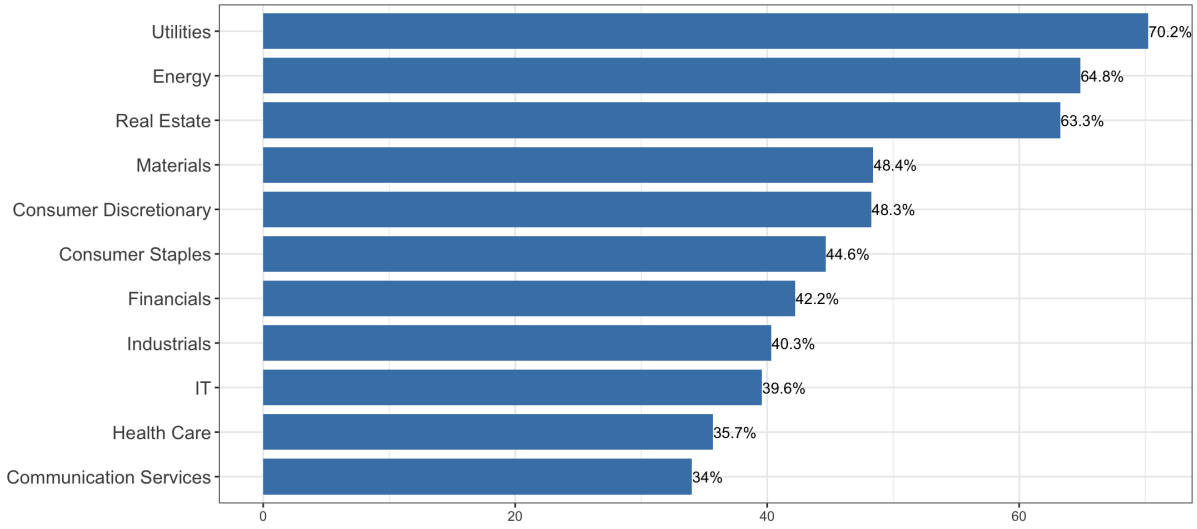
(B) 10-Ks

Notes: This figure plots the time series of flood-related disclosures identified using a two-step classification approach combining keyword-based natural language processing and large language models. Panel (A) shows the quarterly share of earnings calls that mention flood-related risks (red dashed line) or opportunities (blue solid line), with major flood events labeled. Panel (B) displays the annual share of 10-K filings disclosing flood-related risks (red line) and opportunities (blue dashed line), overlaid with bars indicating the total number of 10-K filings each year.

Figure 3: Industry Averages of Flood-Related Disclosures in Earnings Calls and 10-K Filings



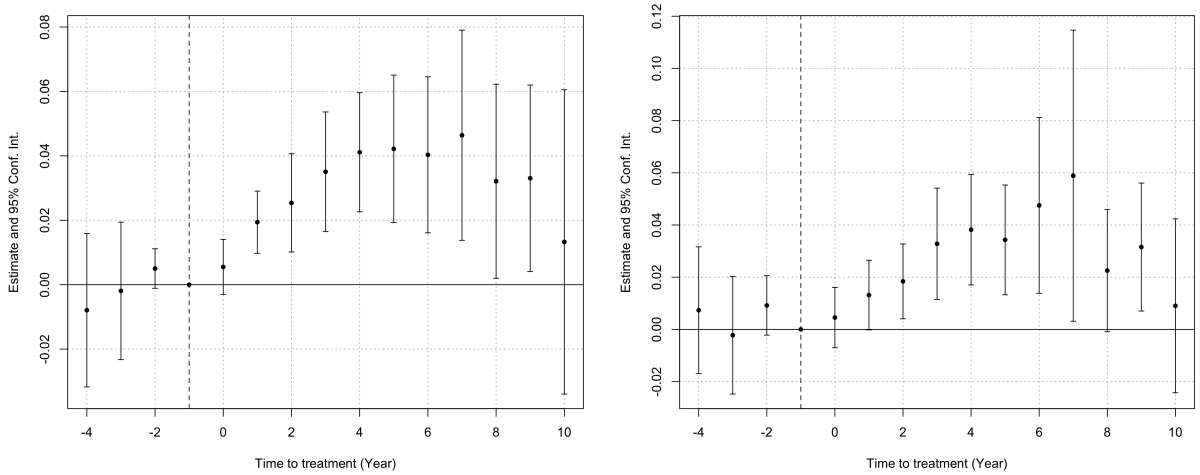
(A) Earning Calls



(B) 10-Ks

Notes: This figure reports the average percentage of firms within each GICS sector that disclosed flood-related risks or opportunities during the sample period. Disclosure percentages are calculated as the number of firms in a sector with at least one flood-related disclosure divided by the total number of firms in that sector, averaged across all years in the sample. Panel (A) shows the industry breakdown for earnings call disclosures, while Panel (B) shows the corresponding breakdown for 10-K filings. Flood-related disclosures were identified and classified using a two-step approach that combines keyword-based searches with large language model (LLM) screening.

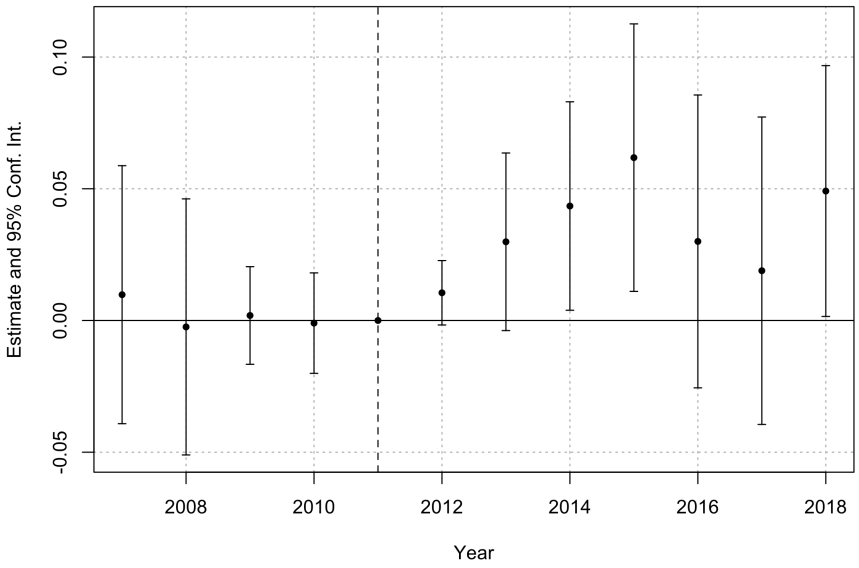
Figure 4: Event Study: The Impact of Flooding on Establishment



(A) Employment **(B)** Sales

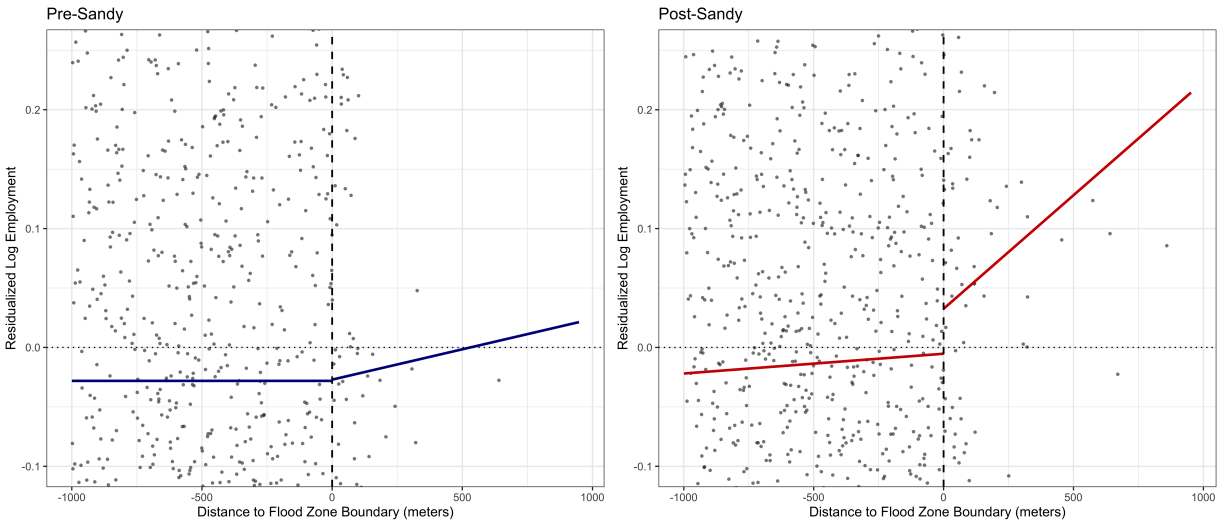
Notes: This figure plots the dynamic effects of flooding on establishment outcomes using an event study specification. The dependent variables are log employment (Panel A) and log sales (Panel B). Coefficients represent the estimated impact for each year relative to the year before the first flood event (t=-1), which is normalized to zero. The model controls for establishment fixed effects, state-by-year fixed effects, and industry-by-year fixed effects, flood risk, and county-level community infrastructure. Standard errors are clustered spatially following Conley (1999) with a 150 km cutoff. Vertical bars indicate 95% confidence intervals.

Figure 5: Extended Difference-in-Differences: Employment Recovery for Flooded Establishments Inside vs. Outside FEMA Floodplains



Notes: This figure shows the dynamic treatment effects from an extended difference-in-differences (DiD) specification examining employment recovery for establishments affected by Hurricane Sandy in New York City. The coefficients plot the differential change in log employment for flooded establishments located inside FEMA-designated floodplains relative to similarly flooded establishments outside the floodplain. The vertical dashed line marks the year before Hurricane Sandy. The model includes establishment fixed effects, neighborhood-by-year fixed effects, and controls for pre-existing flood risk. Error bars represent 95% confidence intervals.

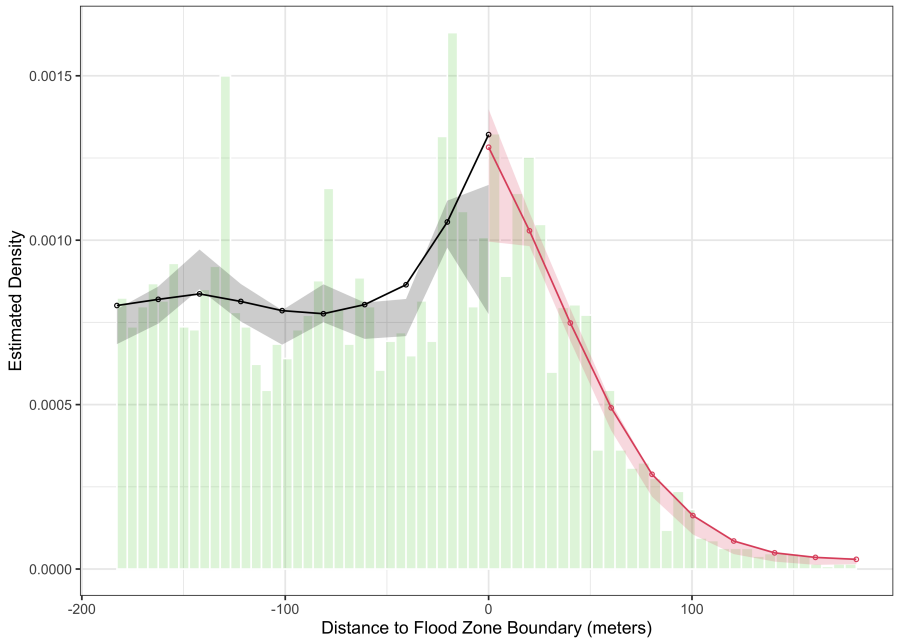
Figure 6: Spatial Regression Discontinuity: Insurance



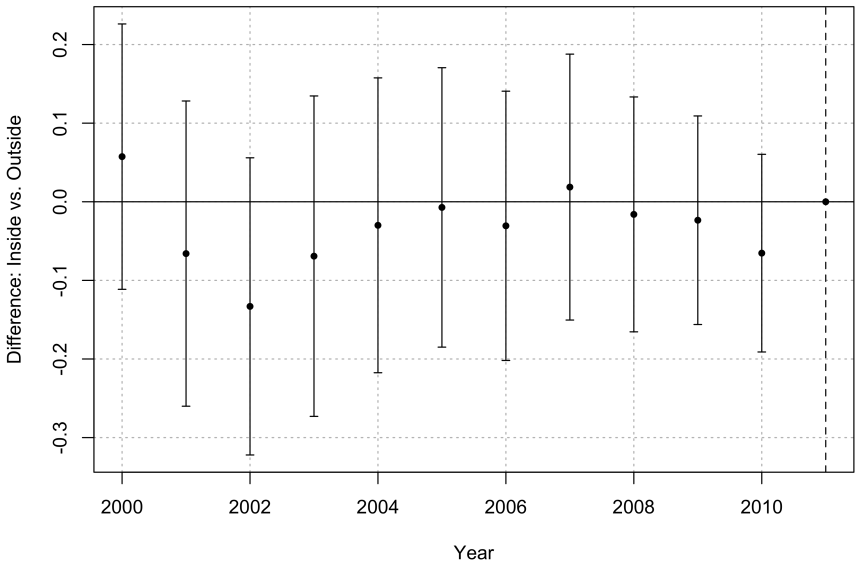
(A) Pre-Sandy: 2000-2011 **(B)** Post-Sandy: 2012-2018

Notes: Figures present spatial regression discontinuity plots with a local linear fit on either side of the flood zone boundary. Distance to boundary is measured in meters, with positive distance indicating being inside the flood zone. Plotted points are binned averages of observations. Estimates are residualized of neighborhood, industry, and year fixed effects.

Figure 7: Spatial RDD-DiD Checks at the Floodplain Boundary

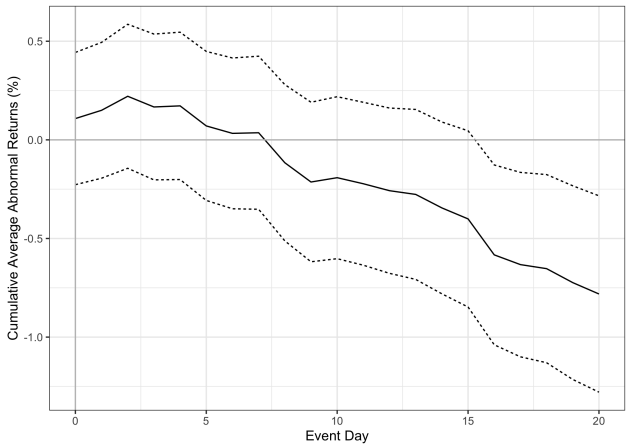


(A) Density Plot of Establishments

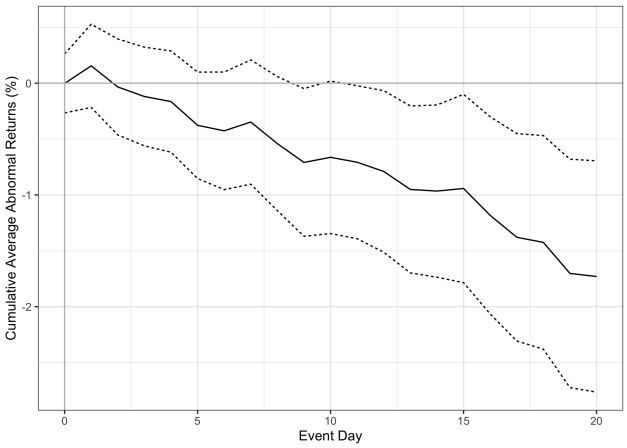


(B) Event Study: Pre-Trend Test for Employment

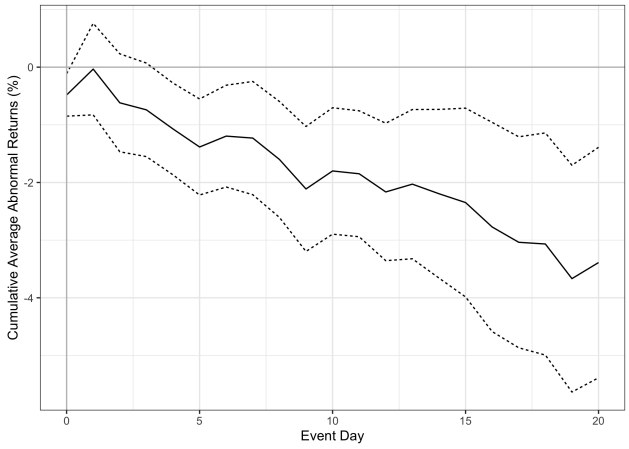
Notes: Panel A uses the McCrary density discontinuity test to assess sorting at the floodplain boundary, with the x-axis denoting distance (in meters) from the boundary and positive values representing locations inside the flood zone. Panel B estimates the differences in residualized log employment between inside and outside floodplain establishments using pre-Sandy data with 95% confidence intervals. Residuals are obtained from regressions including neighborhood, industry, and year fixed effects. Standard errors are clustered at the establishment and year levels.



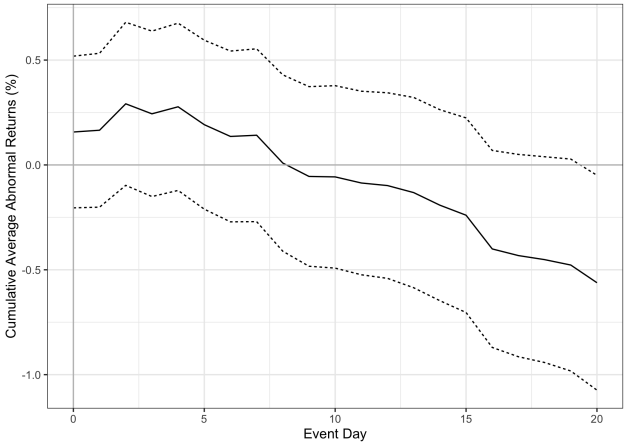
(A) All stocks



(B) Subgroup: firstly experienced



(C) Subgroup: not in FEMA high flood risk zone risk



(D) Subgroup: ≥ 1 establishment with high flood

Figure 8: Market reactions to Floodings. The figures indicate the cumulative average abnormal returns within 20 trading days of all stocks in Panel (a), stocks that firstly experienced a flood in Panel (b), and stocks that do not have any establishments in the FEMA floodplains in Panel (c). Abnormal returns are calculated using the Fama-French three-factor model and an estimation window of [-275, -20].

Table

Table 1: Summary Statistics of US Flooding Events and Firms

This table presents summary statistics of floods, the number of affected establishments, and median statistics of all firms in my sample from 2000 to 2017 by year. The flooding data is obtained from the Global Flood Database (GFD) where I report the total number of floods, total deaths and people displaced, and median number of the flood duration if there are multiple floods in a year. % of firms with flood risk shows the proportion of firms that have at least one establishment in the FEMA high flood risk area (100-year floodplains or so-called Special Flood Hazard Zones). The capitalization is in the units of million dollars and the number of employees is in the units of thousand.

					Flooded Establishments			Median Stats of All Firms			
Year	Num of Floods	Deaths	Num of Displaced	Flood Duration	No buffer	1km buffer	% of firms with flood risk	Num of establishments per firm	Return (%)	Employee	Cap
2001	2	4	500	8.5	10	718	46.094	10	5.875	64.550	212.922
2002	12	38	323,675	11.5	1065	10,652	46.466	10	-10.393	66.950	180.148
2003	11	17	11,250	9	3725	69,286	45.984	10	36.979	67	295.535
2004	11	3,016	282,740	12	699	23,041	45.585	10	9.795	67.300	360.976
2005	5	1,080	608,000	18	2688	27,373	45.923	10	-3.279	71.600	379.057
2006	6	10	780	11.5	107	5,133	46.561	11	9.224	74.100	440.748
2007	5	42	9,400	11		13,551	46.913	11	-10.445	70.700	394.127
2008	7	31	4,230	8	1520	26,017	47.365	11	-44.284	75	214.393
2009	5	48	428,550	7	806	23,267	47.021	10	25	67.750	285.766
2010	10	32	54,100	5.5	4117	58,698	46.329	10	15.480	64.250	350.322
2011	3	20	375,900	36	1584	17,774	45.438	9	-8.165	61.500	286.020
2012	2	1	60,100	6.5	39	2,507	44.400	8	9.778	56.500	297.657
2013	3	9	4,800	10	378	9,203	44.641	7	28.407	53.150	420.312
2014	1	3	0	3	82	2,404	45.762	8	1.383	56.100	455.456
2015	3	34	4,000	13	2534	39,169	47.018	9	-5.967	60.350	411.390
2016	4	31	43,500	14.5	112	4,445	47.518	9	14.610	64.750	532.726
2017	3	89	17,000	11	887	18,871	49.740	9	9.474	74	645.822

Table 2: Summary Statistics of Key Data Sample

This table presents descriptive statistics for the variables used in estimations. The definitions and constructions of the variable are described in Sections 3 to 6

	Obs.	Mean	Std.Dev	p10	p25	median	p75	p90
Panel A: Establishment level								
Flood	9276777	0.002	0.046	0.000	0.000	0.000	0.000	0.000
Flood (1km Buffer)	9276777	0.029	0.216	0.000	0.000	0.000	0.000	0.000
Flood Duration	9276777	0.005	0.266	0.000	0.000	0.000	0.000	0.000
Flood Risk	9276777	0.099	0.298	0.000	0.000	0.000	0.000	0.000
NRI - Flood	7239158	8.337	8.171	0.000	1.816	6.752	12.145	18.624
Employment	9276777	34.521	197.659	3.000	5.000	10.000	22.000	55.000
Sales	8839411	9517.950	683965.952	360	690	1468	3456	10430
Panel B: Firm level (Annual)								
Flood	45664	0.310	2.350	0.000	0.000	0.000	0.000	0.000
Flood (250m Buffer)	45664	1.135	8.598	0.000	0.000	0.000	0.000	2.000
Flood (1km Buffer)	45664	5.369	37.079	0.000	0.000	0.000	1.000	7.000
Flood Risk	45664	14.096	76.518	0.000	0.000	1.000	4.000	20.000
Employment	45664	11.431	54.333	0.026	0.161	1.079	5.930	22.412
Sales	45664	3908.351	16499.340	6.020	48.822	352.779	1892.625	7421.93
Size	45654	6.162	2.383	2.994	4.465	6.259	7.811	9.229
Assets	45664	6.321	2.530	2.892	4.714	6.513	8.003	9.431
PP&E	45664	1763.620	8221.631	0.582	7.350	57.844	448.995	2578.95
Debt	45601	195.173	917.910	0.268	1.638	13.130	76.285	325.8
Cash	45525	435.748	2926.849	1.044	7.310	37.568	169.508	671.196
Capex	45580	257.711	1201.407	0.077	1.087	10.930	77.931	388.01
EBIT	45658	537.037	3131.030	-14.711	-0.310	29.899	204.560	898
Panel C: Firm level (Quarterly)								
CC Disclose	156647	0.056	0.229	0.000	0.000	0.000	0.000	0.000
CC Risk	156647	0.047	0.211	0.000	0.000	0.000	0.000	0.000
CC Firm Initiated	156647	0.046	0.210	0.000	0.000	0.000	0.000	0.000
10-K Disclose	156647	0.384	0.486	0.000	0.000	0.000	1.000	1.000
10-K Risk	156647	0.359	0.480	0.000	0.000	0.000	1.000	1.000
10-K Physical Risk	156647	0.354	0.478	0.000	0.000	0.000	1.000	1.000
10-K Regulatory Risk	156647	0.099	0.298	0.000	0.000	0.000	0.000	0.000
Intangible Assets	156647	1041.581	5827.438	0.000	0.000	21.105	298.559	1605.048
PP&E	156647	1457.044	7223.656	0.227	4.333	56.889	439.572	2352.000

Table 2: Summary Statistics of Key Data Sample (Continued)

	Obs.	Mean	Std.Dev	p10	p25	median	p75	p90
Panel D: Census Block Group level (NYC)								
Voluntary Policy Count	63621	3.147	20.251	0	0	0	1	3
Commercial Policy Count	63621	0.251	1.566	0	0	0	0	0
Required Claim Count	63621	0.003	0.111	0	0	0	0	0
Voluntary Claim Count	63621	0.405	12.558	0	0	0	0	0
Panel E: County level								
Public Assistance (PA) Intensity	57259	0.034	0.375	0	0	0	0.004	0.041
PA Permanent Work Intensity	57259	0.024	0.323	0	0	0	0.001	0.025
Population	57259	41606.636	138514.226	2381	4929.500	10951	27611.5	80926
Employment	57259	38179.637	136560.463	1090	2568.500	7186	21228	72999.8
Job creation	57259	5539.821	21353.454	135	321	924	2811.5	10168.8
Job Destruction	57259	5171.953	20073.358	133	322	902	2680	9223.4
Establishments	57259	2194.070	7109.922	118	239	551	1430.5	4405.4
Establishments Entry	57259	234.173	844.908	10	21	50	137	456
Establishments Exit	57259	218.440	774.250	11	22	50	131	419
Population Density	57259	28.698	94.426	0.870	3.032	7.141	18.130	56.118
4-digit NAICS	57259	38.954	37.842	6	13	26	50	91
Insurance Policy Count	24616	1377.332	9879.782	0	14	93	355	1371.5
Comm Insurance Cost Sum	24616	212930.220	1030754.686	0	3523.750	23500	93416	339323.5
Comm Insurance Policy Count	24616	96.905	488.520	0	3	15	51	158
Panel F: Zip code level								
SBA EIDL Intensity	10886	0.396	3.307	0	0	0	0.114	0.606
SBA All Loan Intensity	10886	2.712	21.561	0	0	0.105	0.798	3.763
Employment	10886	6394.988	8557.679	94	615	3260	8864	17148.5
Establishments	10886	422.082	452.853	21	76	271	623	1047
Small Estb	10886	316.172	349.589	17	56	197	462	790.5
Large Estb	10886	55.691	168.033	0	1	6	21	121
Total Disaster Loss	10886	0.770	8.035	-0.010	-0.003	0.026	0.161	0.743

Table 3: The Effect of Floods on Establishments' Employment and Sales

This table presents the regression results on the impact of flooding on establishment outcomes with establishment-level data from Your Economy Time Series (YTS) from 2000 to 2018. Columns (1)-(2)'s dependent variable is log employee numbers in establishment i. Columns (3)-(4)'s dependent variable is log sales. Flood risk$_{i,t}$ is a dummy variable indicating whether an establishment is located in a FEMA-designated floodplain. Flood$_{i,t}$ is whether an establishment was flooded in year t with various buffers. I include the community infrastructure on the county level from the University of South Carolina as an additional control variable. Flood Duration is the number of days that an establishment has been flooded that is captured by the remote sensing. Standard errors are clustered by establishment & year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment$_{i,t}$		Sales$_{i,t}$	
Model:	(1)	(2)	(3)	(4)
Post × Flood	0.0268***	0.0259***	0.0202**	0.0232**
	(4.056)	(4.055)	(2.237)	(2.629)
Flood Risk$_{i,t}$	-0.0100***	-0.0099***	-0.0274	-0.0264*
	(-3.401)	(-3.349)	(-1.432)	(-1.873)
Community Infrastructure$_{c,t}$		0.00007		-0.0019
		(-0.3839)		(-0.8938)
Flood Duration$_{i,t}$		-0.0034***		-0.0036*
		(-3.008)		(-1.787)
Establishment, State-Year FEs	Yes	Yes	Yes	Yes
Industry-Year FEs		Yes		Yes
Observations	9,245,212	9,245,212	8,811,389	8,811,389
R^2	0.92535	0.92584	0.90795	0.91580

Table 4: Commercial Insurance Take-Up and Payouts Around Hurricane Sandy

This table reports OLS regression estimates examining the relationship between FEMA-designated flood risk areas and commercial flood insurance uptake and claims in New York City. Panel A uses NFIP policy data from 2009 to 2018 at the census block group level to measure changes in policy counts, coverage amounts, and costs before and after Hurricane Sandy. Panel B uses NFIP claims data from the Hurricane Sandy season to assess whether flood exposure and floodplain status are associated with insurance payouts. The standard errors are clustered at the census block group and year level in panel A and are clustered on the census block group level in panel B and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Insurance Policies Before and After Hurricane Sandy

Model:	Voluntary Policy Count (1)	Policy Count (2)	Policy Cost (3)	Voluntary Policy Count (4)	Policy Count (5)	Policy Cost (6)	Building Coverage (7)	Content Coverage (8)	Building Coverage (9)	Content Coverage (10)
High Risk Area(%)	0.2749***	0.0132***	0.0551***				0.0721***	0.0265**		
	(4.810)	(3.695)	(7.284)				(8.245)	(3.089)		
After Sandy × High Risk Area(%)	0.1712***	0.0225***	0.0270***				0.0256***	0.0447***		
	(9.830)	(5.796)	(7.067)				(6.966)	(6.834)		
High & Medium Risk Area(%)				0.1593***	0.0088***	0.0426***			0.0544***	0.0236***
				(5.011)	(3.933)	(8.811)			(9.685)	(4.065)
After Sandy × High&Medium Risk Area(%)				0.1279***	0.0156***	0.0233***			0.0245***	0.0348***
				(13.42)	(6.084)	(6.478)			(6.430)	(6.621)
Nbh, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,621	63,621	63,621	63,621	63,621	63,621	63,621	63,621	63,621	63,621
R^2	0.33328	0.21971	0.23702	0.32316	0.21596	0.24764	0.22426	0.18882	0.23631	0.19696

Panel B: Insurance Claims During Hurricane Sandy Season

Model:	Claim Count (1)	Building Claims (2)	Contents Claim (3)	Building Claims (4)	Contents Claim (5)	Required Claim Count (6)	Required Claim Count (7)	Voluntary Claim Count (8)	Voluntary Claim Count (9)
Flooded Area(%)	0.2634***	0.0484***	0.0208***	0.0228***	0.0091*	0.0020***	-0.0016	0.2614***	0.1688
	(3.456)	(7.539)	(4.721)	(3.138)	(1.803)	(2.714)	(-1.125)	(3.447)	(1.439)
Flooded Area(%) × High Risk Area(%)				0.0006***	0.0003**		8.35×10^{-5}***		0.0021
				(3.934)	(2.297)		(2.888)		(0.9114)
Nbh FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,367	6,367	6,367	6,367	6,367	6,367	6,367	6,367	6,367
R^2	0.16133	0.24694	0.17735	0.26123	0.18376	0.15844	0.18395	0.16049	0.16174

Table 5: Triple-Difference: Floodplain Insurance Access and Post-Sandy Outcomes

This table presents the estimates of triple difference in difference specification with establishment-level data from 2000 to 2018. The standard errors are clustered at the establishment by year level, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment			Sales		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flooded × AfterSandy_t	0.0205*	0.0165	0.0164	0.0150	0.0091	0.0090
	(1.778)	(1.434)	(1.430)	(0.8500)	(0.5113)	(0.5101)
Flooded × AfterSandy_t × $\text{I(Floodplain)}_{i,2007}$		0.0444*	0.0451*		0.0821*	0.0822*
		(1.778)	(1.804)		(1.897)	(1.898)
$\text{Flood Risk}_{i,t}$			-0.0374			0.0271
			(-1.241)			(0.7070)
Establishment, Nbh×Year, Industry×Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193,167	193,167	193,167	164,333	164,333	164,333
R^2	0.91697	0.91698	0.91698	0.91713	0.91714	0.91714

Table 6: Spatial Regression Discontinuity Design: Before and After Hurricane Sandy in NYC

This table reports estimates from the spatial regression discontinuity design described in Equation 3, examining the differential impact of Hurricane Sandy on employment for establishments located just inside versus just outside FEMA-designated floodplains in New York City. Column (1), (3) and (4) use MSE-optimal bandwidth proposed by Calonico et al. (2014). The specifications use a combination of triangular and rectangular kernels as well as local linear and polynomial specifications for the running variable $f(r_i)$. Standard errors are clustered at the census block group × year level. The standard errors are clustered at the census block group and year level, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment			
Model:	Triangular kernel, optimal bandwidth (1)	Rectangular kernel, constant bandwidth (2)	Rectangular kernel, optimal bandwidth (3)	Triangular kernel, optimal bandwidth (4)
Floodplain × Post	0.3106**	0.2919**	0.3241*	0.1319**
	(2.145)	(2.404)	(2.072)	(2.155)
Floodplain	-0.3071	-0.2923	-0.2839	-0.1132
	(-1.259)	(-1.332)	(-1.059)	(-0.4336)
$f(r_i)$	Local linear	Local linear	Local linear	4th-order polynomial
Nbh×Year FEs	Yes	Yes	Yes	Yes
Observations	13,077	13,053	10,296	28,700
R^2	0.17458	0.15977	0.16747	0.14310

Table 7: Federal Spending and Local Economy Following Flood-related Disasters

This table presents OLS regression estimates examining the relationship between federal disaster assistance programs and local economic conditions following flood-related disasters. Panel A focuses on SBA Economic Injury Disaster Loan (EIDL) and total SBA disaster loan intensity, defined as the thousand dollar value of approved loans per establishment in a ZIP code. Panel B examines FEMA Public Assistance (PA) project spending intensity, defined as the thousand dollar per capita in a county. The outcomes include log employment, log annual payroll, and the log number of establishments at the ZIP code level (Panel A) and county level (Panel B), based on ZIP Code Business Patterns and County Business Patterns data from Census Bureau. The main variables of interest are interactions between disaster assistance intensity and a post-flood indicator. Control variables include the percentage of high flood risk areas, log female population, population density, the number of flooding events, and verified disaster losses from the SBA. All regressions include ZIP or county, and state-by-year fixed effects. Standard errors are clustered at the ZIP or county, and year level, with t-statistics in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Small Business Administration Disaster Loan

			Establishments$_{z,t}$					
	Employment$_{z,t}$		All		<20 ppl		≥ 50 ppl	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AfterFirstFlood$_t$ × SBA EIDL Intensity$_{z,t}$	0.0426*		0.0080***		0.0091***		0.0730**	
	(1.927)		(3.353)		(3.662)		(2.795)	
AfterFirstFlood$_t$ × SBA Loan Intensity$_{z,t}$		0.0017		0.0003		0.0004		0.0060**
		(0.7985)		(0.6468)		(0.9212)		(2.232)
Flooded$_z$ × AfterFirstFlood$_t$	-0.0587	-0.0486	0.0220	0.0241	0.0199	0.0219	0.0939	0.1020
	(-0.2540)	(-0.2099)	(0.8422)	(0.9104)	(0.7318)	(0.7937)	(0.6132)	(0.6667)
Total Disaster Loss$_{z,t}$	-0.0041**	-0.0022	-0.0010**	-0.0006	-0.0009*	-0.0005	-0.0073**	-0.0057**
	(-2.717)	(-1.687)	(-2.846)	(-1.473)	(-2.016)	(-0.9706)	(-2.524)	(-2.222)
Number of Floodings$_{a,t}$	-0.0096	-0.0110	-0.0097	-0.0099	-0.0114	-0.0116	-0.0623	-0.0629
	(-0.1288)	(-0.1478)	(-1.051)	(-1.129)	(-1.174)	(-1.256)	(-0.9433)	(-0.9087)
High Flood Risk Area %$_{z,t}$	-0.0083	-0.0075	0.0031	0.0032	0.0038	0.0039	0.0145	0.0157
	(-0.8363)	(-0.7896)	(1.135)	(1.225)	(1.365)	(1.473)	(0.5450)	(0.6014)
Female Population$_{z,t}$	0.0128	0.0109	0.0059	0.0056	0.0047	0.0043	0.0562**	0.0530*
	(0.4977)	(0.4130)	(1.708)	(1.554)	(1.262)	(1.124)	(2.165)	(1.990)
Zip, State×Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,103	8,103	8,103	8,103	8,103	8,103	8,103	8,103
R^2	0.96022	0.96017	0.99844	0.99843	0.99815	0.99814	0.98289	0.98283
Within R^2	0.00177	0.00059	0.01287	0.00873	0.01173	0.00742	0.01718	0.01373

Panel B: FEMA Public Assistance Funded Projects

Model:	Emp$_{a,t}$ (1)	Job Creation$_{a,t}$ (2)	Estb$_{a,t}$ (3)	Estab Entry$_{a,t}$ (4)	Estab Exit$_{a,t}$ (5)
AfterFirstFlood$_t$ × Public Assistance Intensity$_{a,t}$	0.0027*	0.0059**	0.0003	0.0194***	0.0119**
	(1.962)	(2.098)	(0.6015)	(3.610)	(2.505)
Flooded$_i$ × AfterFirstFlood$_t$	0.0017	0.0116	0.00001	-0.0137	0.0010
	(0.2255)	(0.9416)	(0.0090)	(-0.6849)	(0.0406)
Controls	Yes	Yes	Yes	Yes	Yes
County, State×Year	Yes	Yes	Yes	Yes	Yes
Observations	53,213	53,213	53,213	53,213	53,213
R^2	0.99492	0.97238	0.99862	0.89932	0.91071
Within R^2	0.32318	0.06570	0.67360	0.01880	0.08640

Table 8: Impact of Long-Run Flood Risk: Fixed Effect Estimates

This table presents the regression results on the impact of flooding on establishment outcomes in Equation 4 with establishment-level data from Your Economy Time Series (YTS) for the years 2000-2018. Columns (1)–(3) use the log number of employees at establishment i as the dependent variable, and Columns (4)–(6) use log sales. The key explanatory variables are: Flood risk$_{i,t}$, a dummy indicating whether establishment i is located in a FEMA-designated high-risk flood zone; and Flood$_{i,t}$ which captures whether establishment i experienced a flood in year t. An alternative measure of flood risk is obtained from FEMA's 2021 National Risk Index (NRI) on the census tract level. Additional control variables include a county-level measure of community infrastructure from the University of South Carolina and the cumulative number of floods previously experienced by the establishment. Standard errors are clustered to allow for spatial correlation within a 100-kilometer radius around each establishment's centroid and for autocorrelation of order 5. T-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment$_{i,t}$			Sales$_{i,t}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk$_{i,t}$	-0.0101***	-0.0102***		-0.0237***	-0.0268***	
	(-3.102)	(-3.124)		(-4.520)	(-5.500)	
Flood$_{i,t}$	0.0049*	-0.0053	-0.0704***	0.0003	-0.0089	-0.0635***
	(1.897)	(-1.505)	(-7.066)	(0.0510)	(-1.165)	(-6.445)
Community Infrastructure$_{c,t}$	-0.0002	-0.0001	0.0054***	-0.0020***	-0.0019***	0.0054***
	(-0.8959)	(-0.5468)	(12.38)	(-6.906)	(-6.730)	(11.80)
Previous Num of Flood$_{i,t}$		0.0233**	0.1095***		0.0151*	0.0869***
		(2.281)	(4.742)		(1.801)	(5.641)
NRI - Flood$_{ct}$			-0.0008**			-0.0010**
			(-2.521)			(-2.557)
Establishment	Yes	Yes		Yes	Yes	
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year		Yes	Yes		Yes	Yes
Company-Year			Yes			Yes
Observations	9,276,777	9,276,777	7,239,158	8,839,411	8,839,411	6,894,771
R^2	0.92516	0.92565	0.43887	0.90778	0.91563	0.52295

Table 9: Flood Risk, Insurance Costs, and Local Business Dynamics

This table presents OLS regression estimates examining how flood risk and insurance costs are associated with county-level economic outcomes. Panel A evaluates the relationship between FEMA-designated flood risk exposure and measures of local business activity from 2001 to 2018. Panel B incorporates data from the National Flood Insurance Program (NFIP) between 2009 and 2018 to examine associations between insurance policy costs and business dynamics, including an interaction with flood risk exposure. Flood Risk$_{a,t}$ and Flooded area$_{a,t}$ represent the share of a county's land area classified as high-risk for flooding or that was flooded in a given year, respectively. The dependent variables include population, employment, establishment counts, and business metrics from the Census' County Business Patterns. All models include county and year-by-state fixed effects. The standard errors are clustered at the county and state-by-year level, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Flood Risk

	Popu$_{a,t}$	Emp$_{a,t}$	Job Creation$_{a,t}$	Job Destruction$_{a,t}$	Estb$_{a,t}$	Estb Entry$_{a,t}$	Estb Exit$_{a,t}$	4-digit NAICS	6-digit NAICS
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Flood Risk$_{a,t}$	-0.0010**	-0.0139**	0.0083*	0.0229***	-0.1026	0.4659**	0.5859***	-0.0547***	-0.1219***
	(-2.883)	(-2.361)	(1.823)	(3.310)	(-0.5109)	(2.864)	(3.229)	(-3.427)	(-3.629)
Flooded area$_{a,t}$	0.0003	-0.0196	-0.0087	0.0060	-0.3236	-0.1590	0.1811	0.0108	0.0008
	(1.004)	(-1.387)	(-1.237)	(0.9627)	(-1.020)	(-0.8151)	(0.6967)	(1.625)	(0.0773)
Number of Floodings$_{a,t}$	-1.56×10^{-5}	-0.0520	-0.0074	0.0411**	-1.865	-0.3555	1.500***	-0.1061*	-0.1706*
	(-0.0228)	(-1.192)	(-0.2669)	(2.586)	(-1.141)	(-0.2523)	(2.942)	(-1.882)	(-1.861)
Female Population Share$_{a,t}$	-0.0072***	-0.0381**	0.0112	0.0527***	-0.7507	0.3382	1.131***	-0.0573**	-0.1123**
	(-13.85)	(-2.498)	(1.410)	(4.234)	(-1.715)	(1.249)	(3.549)	(-2.328)	(-2.637)
Population Density$_{a,t}$	0.0020***	0.0483	0.0273	-0.0175	0.8702	0.3405	-0.5525	0.0470**	0.1011**
	(3.075)	(1.728)	(1.370)	(-0.8457)	(1.409)	(0.8533)	(-1.018)	(2.468)	(2.405)
Employment$_{a,t-1}$	2.85×10^{-5}	0.8633***	0.2005***	0.3241***	2.071	2.367*	0.4598	0.0053	0.0322
	(0.0982)	(11.07)	(5.372)	(3.874)	(1.292)	(2.066)	(0.3211)	(0.2885)	(0.7530)
Establishments$_{a,t-1}$	2.08×10^{-5}*	0.0012	-0.0043***	-0.0056***	0.9415***	0.0052	0.0601*	0.0010*	0.0027*
	(2.050)	(0.6206)	(-5.510)	(-3.030)	(22.22)	(0.1793)	(1.872)	(1.972)	(1.965)
County, Year × State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,156	49,156	49,156	49,156	49,156	49,156	49,156	49,156	49,156
R^2	0.99899	0.99923	0.98803	0.97799	0.99983	0.99412	0.99272	0.99219	0.99357
Within R^2	0.31939	0.79047	0.19764	0.24473	0.94325	0.09642	0.13173	0.03310	0.09213

Panel B: Insurance Cost

	Employment$_{a,t}$	Job Creation$_{a,t}$	Job Destruction$_{a,t}$	Establishments$_{a,t}$	Estab Entry$_{a,t}$	Estab Exit$_{a,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Insurance Policy Cost Sum$_{a,t}$	-0.0563*	-0.0196**	0.0394*	-1.227*	-0.3589**	0.9748*
	(-2.077)	(-2.294)	(1.942)	(-2.148)	(-2.392)	(1.862)
Insurance Policy Cost Sum$_{a,t}$ × Flood Risk$_{a,t}$	0.0032*	0.0009*	-0.0026*	0.0668*	0.0065	-0.0698*
	(1.971)	(1.893)	(-2.012)	(1.870)	(0.7182)	(-2.001)
Flood Risk$_{a,t}$	-0.0574*	-0.0160*	0.0436*	-1.134	-0.1103	1.185*
	(-1.987)	(-2.010)	(1.953)	(-1.720)	(-0.6633)	(1.931)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County, Year × State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,645	27,645	27,645	27,645	27,645	27,645
R^2	0.99922	0.99085	0.97909	0.99984	0.99733	0.99230
Within R^2	0.78778	0.15890	0.08984	0.89339	0.26446	0.01161

Table 10: Effects of Flood Exposure and Flood Risk on Firm Employment and Sales

This table presents the panel fixed effects regression estimates regressing firm outcomes on annual flood exposure and flood risk with establishment location and financial data from Your Economy Time Series (YTS) and Compustat from 1997 to 2018. The outcome variables are log employment and log sales. $\text{Flood}_{i,t}$ is the number of flooded establishments in a year of a firm i with flooding data obtained from the Global Flood Database (GFD) using twice-daily 250-meter-resolution satellite data. From Column (3) to (6), for robustness, various spatial buffers are added when identifying whether an establishment was flooded. High flood risk estb $_{i,t}$ is the number of establishments that are located in the FEMA-designated floodplain. Previous Num of $\text{Floods}_{i,t}$ is the cumulative number of flooding events that a firm has experienced up to year t as long as one of its establishments was flooded. Standard errors are clustered by firm & year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Model:	$\text{Emp}_{i,t}$ (1)	$\text{Sales}_{i,t}$ (2)	$\text{Emp}_{i,t}$ (3)	$\text{Sales}_{i,t}$ (4)	$\text{Emp}_{i,t}$ (5)	$\text{Sales}_{i,t}$ (6)	$\text{Emp}_{i,t}$ (7)	$\text{Sales}_{i,t}$ (8)	$\text{Emp}_{i,t}$ (9)	$\text{Sales}_{i,t}$ (10)
$\text{Flood}_{i,t}$	0.0033***	0.0015***								
	(3.566)	(3.207)								
$\text{Flood}_{i,t}$ (250m Buffer)			0.0010***	0.0005***						
			(3.082)	(3.402)						
$\text{Flood}_{i,t}$ (1km Buffer)					0.0003**	0.0002**				
					(2.592)	(2.725)				
High Flood Risk $\text{Estb}_{i,t}$							-0.0008***	-0.0006***	-0.0009***	-0.0006***
							(-3.233)	(-3.208)	(-3.516)	(-3.042)
Previous Num of $\text{Floods}_{i,t}$									0.0069*	0.0010
									(1.969)	(0.2775)
$\text{Size}_{i,t-1}$	0.0422***	0.1316***	0.0422***	0.1316***	0.0422***	0.1316***	0.0418***	0.1316***	0.0420***	0.1316***
	(12.50)	(13.74)	(12.50)	(13.74)	(12.52)	(13.75)	(12.47)	(13.73)	(12.52)	(13.74)
$\text{Asset}_{i,t-1}$	0.0606***	0.3132***	0.0605***	0.3132***	0.0603***	0.3130***	0.0588***	0.3125***	0.0590***	0.3125***
	(5.690)	(11.35)	(5.674)	(11.35)	(5.659)	(11.34)	(5.583)	(11.34)	(5.607)	(11.34)
$\text{PP\&E}_{i,t-1}$	0.0330***	0.1018***	0.0330***	0.1018***	0.0330***	0.1018***	0.0332***	0.1017***	0.0337***	0.1018***
	(3.381)	(3.960)	(3.382)	(3.961)	(3.378)	(3.960)	(3.420)	(3.959)	(3.486)	(3.952)
$\text{Debt}_{i,t-1}$	0.1537***	0.2058***	0.1536***	0.2057***	0.1536***	0.2057***	0.1516***	0.2052***	0.1507***	0.2051***
	(13.40)	(8.171)	(13.39)	(8.168)	(13.37)	(8.168)	(13.33)	(8.144)	(13.46)	(8.117)
$\text{Cash}_{i,t-1}$	0.0099***	-0.0136**	0.0100***	-0.0136**	0.0100***	-0.0135**	0.0099***	-0.0136**	0.0096***	-0.0136**
	(3.293)	(-2.336)	(3.316)	(-2.331)	(3.345)	(-2.325)	(3.340)	(-2.339)	(3.260)	(-2.360)
$\text{Capex}_{i,t-1}$	0.0484***	0.0314***	0.0484***	0.0314***	0.0484***	0.0314***	0.0477***	0.0311***	0.0476***	0.0311***
	(10.39)	(3.665)	(10.37)	(3.661)	(10.38)	(3.662)	(10.13)	(3.625)	(10.18)	(3.619)
$\text{EBIT}_{i,t-1}$	-0.0110**	0.0250**	-0.0110**	0.0250**	-0.0109**	0.0250**	-0.0105**	0.0251**	-0.0106**	0.0251**
	(-2.191)	(2.149)	(-2.188)	(2.150)	(-2.189)	(2.151)	(-2.169)	(2.161)	(-2.162)	(2.160)
Firm, Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,664	45,664	45,664	45,664	45,664	45,664	45,664	45,664	45,664	45,664
R^2	0.98206	0.98023	0.98206	0.98023	0.98208	0.98024	0.98234	0.98025	0.98236	0.98025
Within R^2	0.37719	0.41793	0.37733	0.41794	0.37788	0.41799	0.38705	0.41835	0.38775	0.41835

Table 11: Flood Risk and Firm Disclosure and Operations

This table presents the estimates on the relationship between flood risk and firms' disclosure and operations. High Flood Risk$_{i,t}$ is a dummy variable that equals one if a firm has at least five establishments located in a FEMA-designated floodplain. Cumulative Floods$_{i,t}$ is the log cumulative number of establishments that have been flooded using the flood data from the Global Flood Database (GFD) with twice-daily 25-meter-resolution satellite images. Standard errors are clustered by firm & year-quarter, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A:	Earnings Calls			10-K					
	Disclose$_{i,t}$	Risk$_{i,t}$	Firm Initiated$_{i,t}$	Disclose$_{i,t}$	Risk$_{i,t}$	Physical Risk$_{i,t}$	Regulatory Risk$_{i,t}$	Intangible Assets$_{i,t}$	PP&E$_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Flood Risk$_{i,t}$	0.0143**	0.0118**	0.0153***	0.0238*	0.0252*	0.0210	0.0188*	0.1992***	-0.0013
	(2.604)	(2.321)	(2.821)	(1.695)	(1.859)	(1.563)	(1.899)	(3.282)	(-0.5192)
Asset$_{i,t-1}$	-0.0027	-0.0024	-0.0013	0.0178**	0.0147*	0.0153**	0.0040	0.6862***	0.0105***
	(-1.660)	(-1.600)	(-0.8739)	(2.264)	(1.964)	(2.055)	(1.027)	(18.33)	(2.759)
Size$_{i,t-1}$	0.0029*	0.0022	0.0014	0.0040	0.0031	0.0039	0.0012	0.0234	0.0302***
	(1.935)	(1.659)	(1.132)	(0.9721)	(0.7832)	(0.9957)	(0.5836)	(1.497)	(16.49)
Revenue$_{i,t-1}$	0.0046**	0.0039**	0.0033*	0.0122**	0.0110*	0.0113*	-0.0023	0.2238***	0.0135***
	(2.557)	(2.433)	(1.993)	(2.019)	(1.886)	(1.966)	(-0.6811)	(7.895)	(4.609)
PP&E$_{i,t-1}$	0.0034*	0.0034**	0.0033**	0.0250***	0.0261***	0.0251***	0.0144***	-0.0119	0.9109***
	(1.894)	(2.150)	(2.082)	(3.439)	(3.725)	(3.583)	(3.704)	(-0.3426)	(175.6)
Capex$_{i,t-1}$	0.0047***	0.0049***	0.0034**	0.0036	0.0024	0.0028	0.0047**	0.0498***	0.0207***
	(2.819)	(3.035)	(2.209)	(1.136)	(0.7868)	(0.8922)	(2.160)	(4.189)	(12.62)
R&D$_{i,t-1}$	0.0002	-0.0002	0.0003	0.0056**	0.0055**	0.0056**	0.0012	0.1090***	-0.0011*
	(0.3303)	(-0.3912)	(0.4660)	(2.421)	(2.444)	(2.461)	(1.110)	(11.94)	(-1.796)
Firm, Industry-Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647
R^2	0.27311	0.24228	0.24742	0.61892	0.60300	0.59965	0.50572	0.91342	0.99719
Within R^2	0.00113	0.00106	0.00091	0.01010	0.00876	0.00885	0.00308	0.24562	0.91727

Panel B:	Earnings Calls			10-K					
	Disclose$_{i,t}$	Risk$_{i,t}$	Firm Initiated$_{i,t}$	Disclose$_{i,t}$	Risk$_{i,t}$	Physical Risk$_{i,t}$	Regulatory Risk$_{i,t}$	Intangible Assets$_{i,t}$	PP&E$_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative Floods$_{i,t}$	0.0123***	0.0106**	0.0132***	0.0384***	0.0344***	0.0333***	0.0034	0.0500	-0.0028*
	(2.718)	(2.375)	(3.026)	(4.192)	(3.884)	(3.752)	(0.6394)	(1.505)	(-1.771)
Asset$_{i,t-1}$	-0.0027	-0.0023	-0.0012	0.0177**	0.0148*	0.0153**	0.0042	0.6884***	0.0105***
	(-1.616)	(-1.559)	(-0.8198)	(2.269)	(1.974)	(2.059)	(1.081)	(18.35)	(2.766)
Size$_{i,t-1}$	0.0029*	0.0023*	0.0015	0.0042	0.0033	0.0041	0.0012	0.0236	0.0302***
	(1.960)	(1.685)	(1.171)	(1.026)	(0.8309)	(1.044)	(0.5876)	(1.504)	(16.50)
Revenue$_{i,t-1}$	0.0050***	0.0043***	0.0037**	0.0130**	0.0117**	0.0120**	-0.0020	0.2280***	0.0134***
	(2.797)	(2.656)	(2.256)	(2.144)	(2.012)	(2.078)	(-0.5664)	(7.990)	(4.605)
PP&E$_{i,t-1}$	0.0035*	0.0035**	0.0034**	0.0249***	0.0262***	0.0251***	0.0146***	-0.0098	0.9109***
	(1.932)	(2.183)	(2.128)	(3.450)	(3.744)	(3.592)	(3.770)	(-0.2823)	(175.8)
Capex$_{i,t-1}$	0.0046***	0.0049***	0.0033**	0.0034	0.0022	0.0026	0.0047**	0.0501***	0.0207***
	(2.814)	(3.039)	(2.197)	(1.077)	(0.7320)	(0.8368)	(2.172)	(4.217)	(12.65)
R&D$_{i,t-1}$	0.0002	-0.0003	0.0002	0.0053**	0.0053**	0.0053**	0.0012	0.1089***	-0.0011*
	(0.2192)	(-0.5152)	(0.3449)	(2.291)	(2.324)	(2.344)	(1.114)	(11.93)	(-1.766)
Firm, Industry-Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647
R^2	0.27324	0.24240	0.24760	0.61938	0.60336	0.60001	0.50562	0.91331	0.99719
Within R^2	0.00132	0.00123	0.00116	0.01130	0.00966	0.00973	0.00288	0.24471	0.91727

Table 12: Cumulative Abnormal Returns After Flooding

This table presents cumulative average abnormal returns across different event windows with data from 2000 to 2017. t=0 is the day that flooding began. Abnormal returns are calculated using the Fama-French Three Factor Model, Fama-French-Carhart Four Factor Model, and the Fama-French Five Factor Model with an estimation window of $[-275, -20]$.

	Fama French 3 Factor			FFC 4 Factors			FF 5 Factors		
Event Window	$CAAR_t(\%)$	t-stats	$CAR_{i,t} > 0(\%)$	$CAAR_t(\%)$	t-stats	$CAR_{i,t} > 0(\%)$	$CAAR_t(\%)$	t-stats	$CAR_{i,t} > 0(\%)$
$[0, 1]$	0.150	0.853	47.678	0.195	1.112	48.632	-0.008	-0.033	48.560
$[0, 2]$	0.221	1.186	48.272	0.261	1.404	48.722	0.114	0.507	49.316
$[0, 3]$	0.167	0.884	48.128	0.184	0.976	48.884	0.131	0.660	48.740
$[0, 4]$	0.172	0.904	48.992	0.206	1.080	49.982	-0.046	-0.147	49.856
$[0, 5]$	0.071	0.367	47.858	0.138	0.715	49.388	-0.166	-0.516	48.758
$[0, 6]$	0.033	0.169	47.966	0.126	0.646	49.748	-0.167	-0.559	48.632
$[0, 7]$	0.036	0.182	47.930	0.128	0.646	50.126	-0.153	-0.559	48.524
$[0, 8]$	-0.116	-0.574	47.516	0.027	0.134	49.586	-0.422	-1.119	48.434
$[0, 9]$	-0.214	-1.036	47.840	-0.074	-0.356	49.802	-0.709	-1.280	48.452
$[0, 10]$	-0.192	-0.916	47.876	-0.080	-0.383	49.388	-0.709	-1.230	48.650
$[0, 15]$	-0.401	-1.758	46.544	-0.263	-1.138	48.560	-0.872	-1.577	47.480
$[0, 20]$	-0.781	-3.077	46.472	-0.508	-1.980	48.542	-1.469	-2.016	47.084

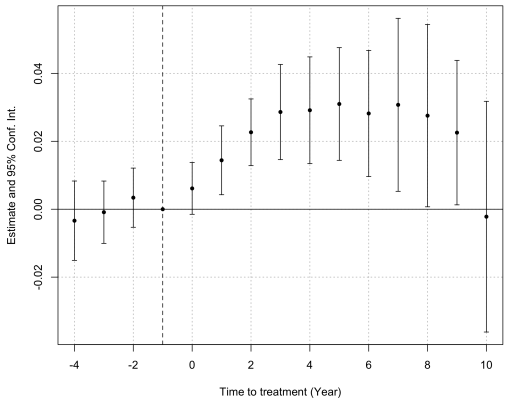
A Appendix

Appendix Table of Contents

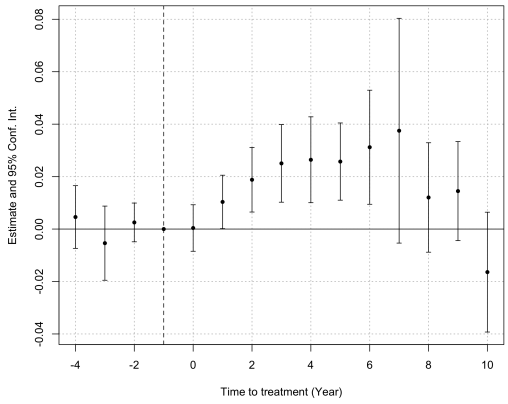
A.1 Figures ii
A.2 Tables vii
A.3 Data xxi

A.1 Figures

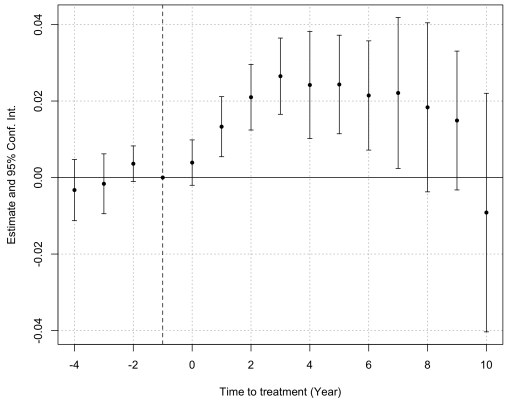
Figure A1: Event Study: The Impact of Flooding on Establishment with Spatial Buffers



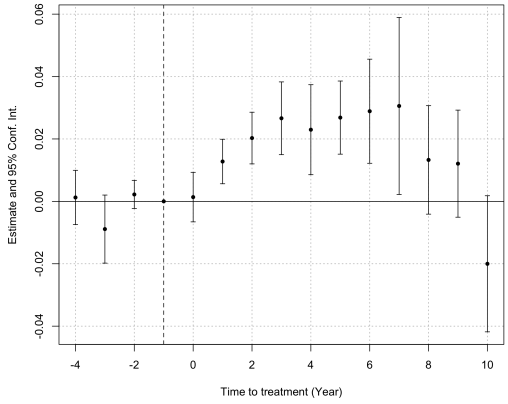
(A) Employment: 250-meter Buffer



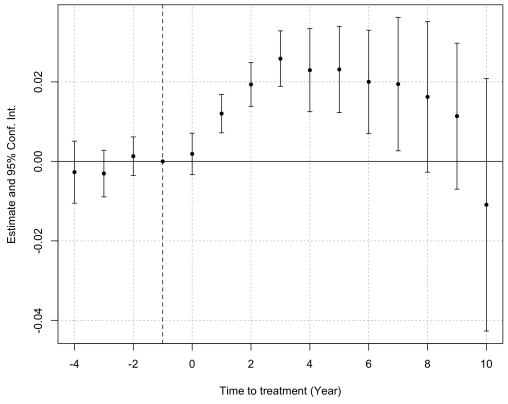
(B) Sales: 250-meter Buffer



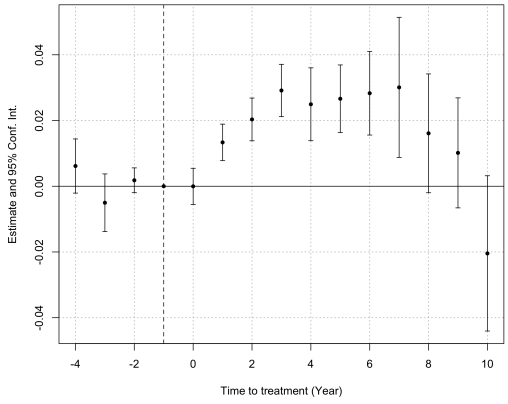
(C) Employment: 500-meter Buffer



(D) Sales: 500-meter Buffer



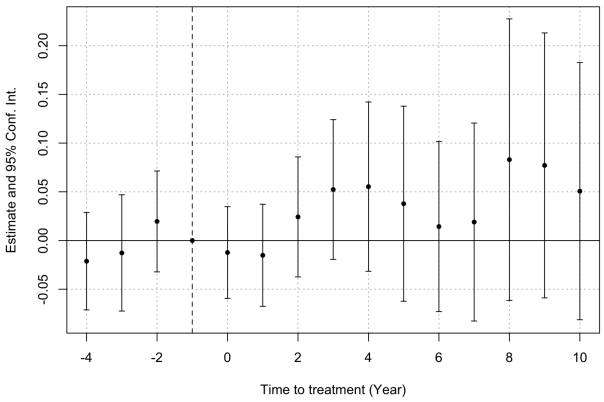
(E) Employment: 1km-meter Buffer



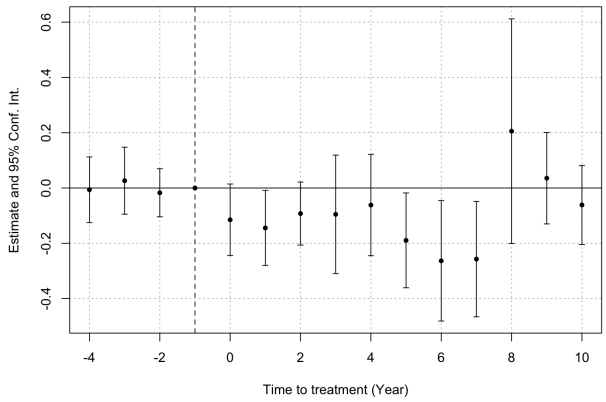
(F) Sales: 1km-meter Buffer

Notes: Figures present the event study regression plots

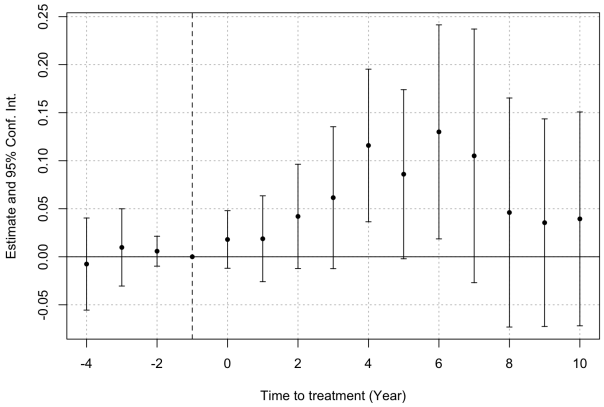
Figure A2: The Effects of Floods on Establishment Employment



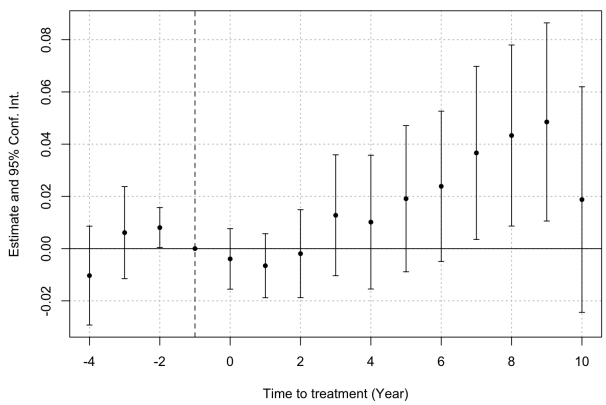
(A) Manufacturing



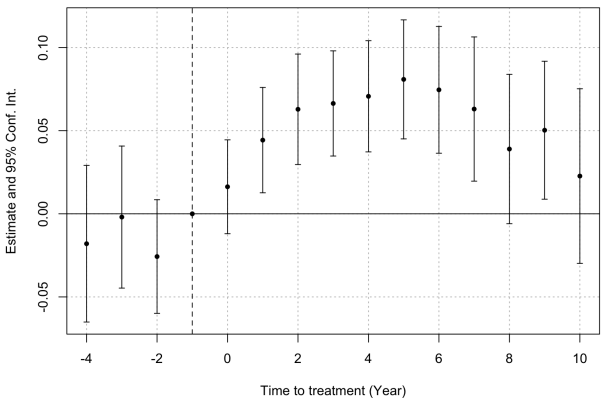
(B) Utilities



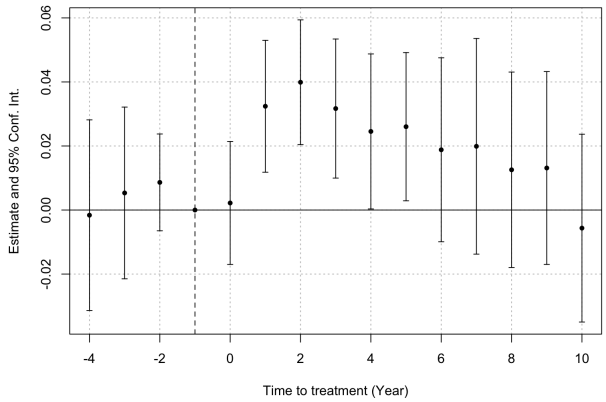
(C) Wholesale Trade



(D) Retail Trade



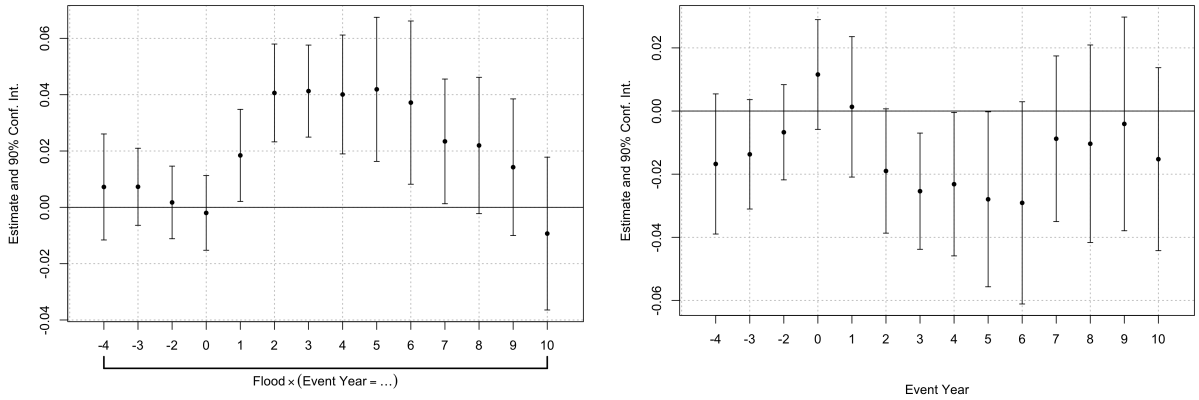
(E) Real Estate



(F) Accommodation and Food Services

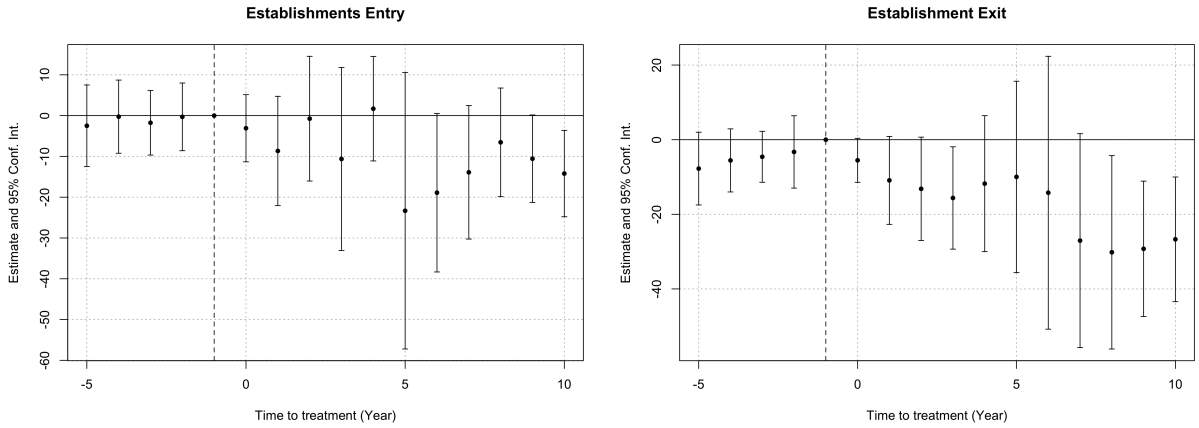
Notes: Figures present the event study regression plots

Figure A3: Event Study: Insurance - National



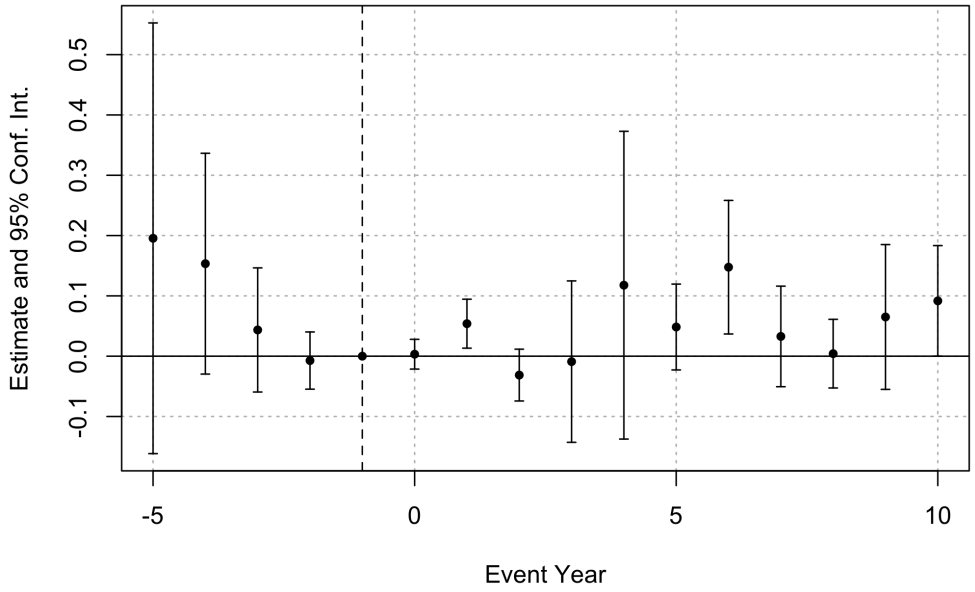
(A) Flooding **(B)** Interaction: I(Outside Floodplain)

Figure A4: County-level Survivor Bias: Flood effects

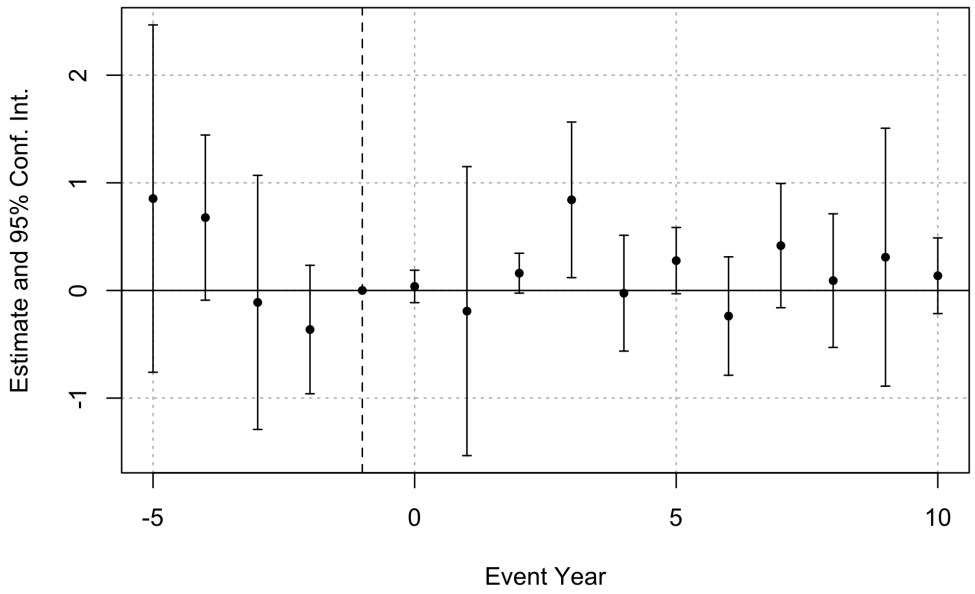


(A) Establishments Entry **(B)** Establishment Exit

Figure A5: Extended Diff-in-Diff: Small Business Administration (SBA) Total Disaster Loans

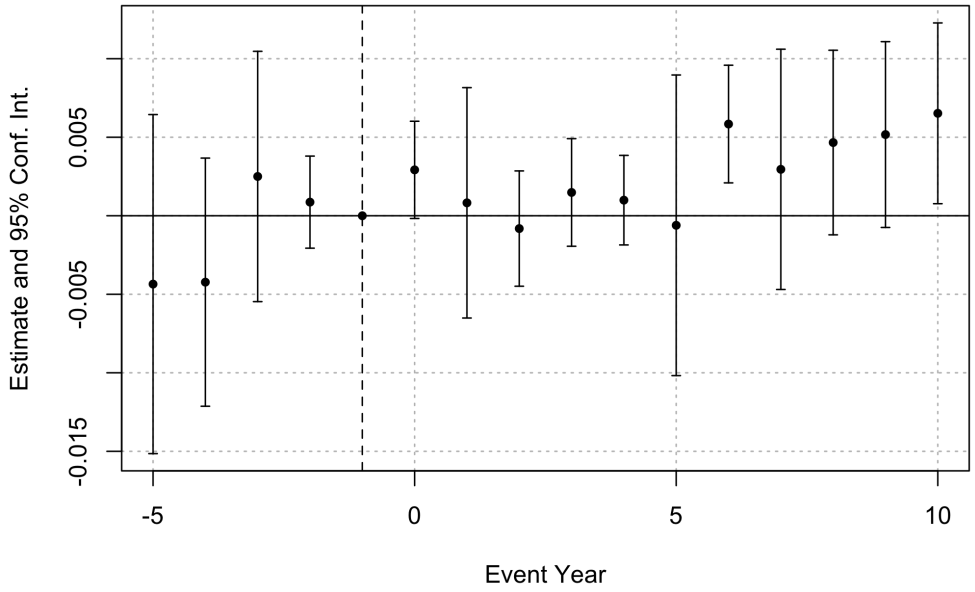


(A) Local Establishments

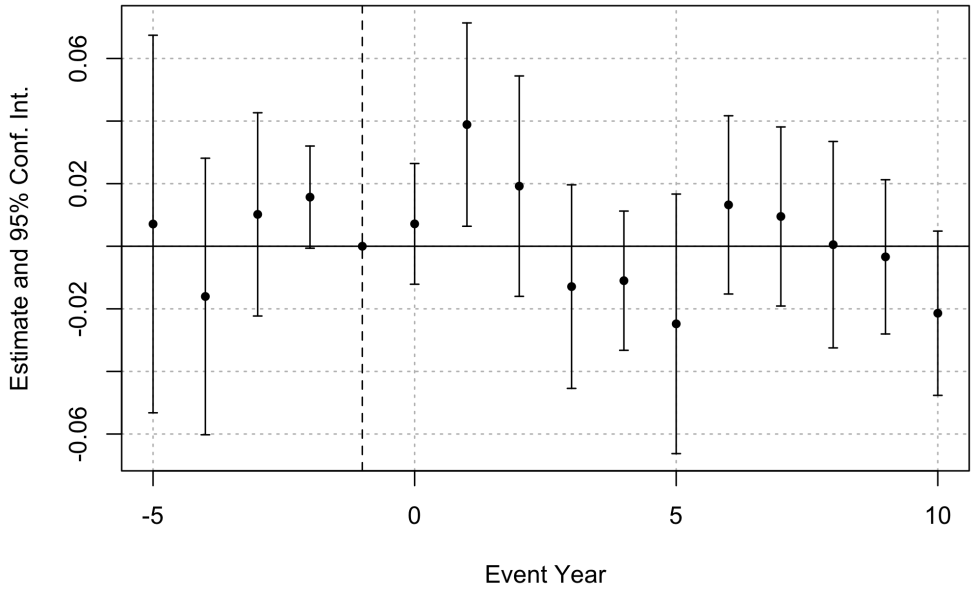


(B) Local Employment

Figure A6: Extended Diff-in-Diff: FEMA Public Assistance Funded Projects



(A) Local Establishments



(B) Local Job Creation

A.2 Tables

Table A1: The Effect of Floods on Establishments' Employment and Sales

This table presents the regression results on the impact of flooding on establishment outcomes in Equation 1 with establishment-level data from Your Economy Time Series (YTS) from 2000 to 2018. Columns (1)-(2)'s dependent variable is log employee numbers in establishment i. Columns (3)-(4)'s dependent variable is log sales. Flood risk$_{i,t}$ is a dummy variable indicating whether an establishment is located in the high-risk flood zone by FEMA. Flood$_{i,t}$ is whether an establishment was flooded in year t with various buffers. I include the community infrastructure on the county level from the University of South Carolina as an additional control variable. Standard errors allow for spatial correlation of up to 100 kilometers around the establishment's centroid and for autocorrelation of order 5. T-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment$_{i,t}$		Sales$_{i,t}$	
Model:	(1)	(2)	(3)	(4)
Post × Flood	0.0268***	0.0259***	0.0202*	0.0232**
	(2.899)	(3.009)	(1.654)	(2.061)
Flood Risk$_{i,t}$	-0.0100***	-0.0099***	-0.0274***	-0.0264***
	(-3.096)	(-3.033)	(-5.179)	(-5.380)
Community Infrastructure$_{c,t}$		-0.0001		-0.0019***
		(-0.3838)		(-6.725)
Flood Duration$_{i,t}$		-0.0034***		-0.0036*
		(-2.788)		(-1.860)
Establishment, State-Year FEs	Yes	Yes	Yes	Yes
Industry-Year FEs		Yes		Yes
Observations	9,245,212	9,245,212	8,811,389	8,811,389
R^2	0.92535	0.92584	0.90795	0.91580

Table A2: Robustness: the Effect of Floods on Establishments' Employment and Sales

This table presents the regression results on the impact of flooding on establishments' log employment and log sales with data from Your Economy Time Series (YTS) from 2000 to 2018. In columns (1) and (2), a 250-meter spatial buffer is added to the inundation map of flooding events. 500-meter buffer and 1-km buffer are added in column (3)-(4) and (5)-(6) respectively. Flood risk$_{i,t}$ is a dummy variable indicating whether an establishment is located in the high-risk flood zone by FEMA. Flood$_{i,t}$ is whether an establishment was flooded in year t with various buffers. I include the community infrastructure on the county level from the University of South Carolina as an additional control variable. Flood Duration is the number of days that an establishment has been flooded that is captured by the remote sensing. Standard errors are clustered by establishment & year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	250 meter		500 meter		1 km	
	Employment$_{i,t}$	Sales$_{i,t}$	Employment$_{i,t}$	Sales$_{i,t}$	Employment$_{i,t}$	Sales$_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Post × Flood	0.0260***	0.0233**	0.0140***	0.0166***	0.0127***	0.0145***
	(2.900)	(1.962)	(3.912)	(3.895)	(5.789)	(5.136)
Flood Risk$_{i,t}$	-0.0099***	-0.0266***	-0.0102***	-0.0266***	-0.0099***	-0.0260***
	(-2.998)	(-5.460)	(-3.135)	(-5.627)	(-3.026)	(-5.377)
Community Infrastructure$_{c,t}$	-8.33×10^{-5}	-0.0019***	-5.84×10^{-5}	-0.0019***	-8.3×10^{-5}	-0.0020***
	(-0.4652)	(-6.842)	(-0.3434)	(-6.783)	(-0.4556)	(-6.850)
Flood Duration$_{i,t}$	-0.0032***	-0.0036*	-0.0025**	-0.0032*	-0.0025**	-0.0030*
	(-2.691)	(-1.760)	(-2.441)	(-1.752)	(-2.575)	(-1.700)
Establishment, State-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,216,192	8,784,009	9,103,901	8,678,436	8,933,268	8,517,106
R^2	0.92587	0.91587	0.92640	0.91646	0.92702	0.91711
Within R^2	1.8×10^{-5}	0.00011	2.26×10^{-5}	0.00012	2.99×10^{-5}	0.00013

Table A3: Impact of Flooding On US Establishments: Event Study

This table presents the regression results on the impact of flooding on establishment outcomes in Equation 1 with establishment-level data from Your Economy Time Series (YTS) 2000-2018. Column (1)-(2)'s dependent variable is log employee numbers in establishment i. Column (3)-(4)'s dependent variable is log sales. Flood risk$_{i,t}$ is a dummy variable indicating whether an establishment is located in the high-risk flood zone by FEMA. Flood$_{i,\tau} = 1$ if $t - \tau_i^* = \tau$, where τ_i^* is the year that the establishment i was flooded. Standard errors allow for spatial correlation of up to 100 kilometers around the establishment's centroid and for autocorrelation of order 5, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment$_{i,t}$		Sales$_{i,t}$	
Model:	(1)	(2)	(3)	(4)
Flood$_{i,\tau}$ -4	-0.0079	-0.0071	0.0082	0.0074
	(-0.7404)	(-0.6828)	(0.8327)	(0.7517)
Flood$_{i,\tau}$ -3	-0.0019	-0.0011	-0.0022	-0.0022
	(-0.1957)	(-0.1191)	(-0.2351)	(-0.2257)
Flood$_{i,\tau}$ -2	0.0050	0.0053	0.0076	0.0092
	(1.002)	(1.257)	(1.141)	(1.462)
Flood$_{i,\tau}$ 0	0.0055*	0.0047*	0.0045	0.0045
	(1.877)	(1.668)	(1.052)	(0.9969)
Flood$_{i,\tau}$ 1	0.0194***	0.0180***	0.0124**	0.0132**
	(3.433)	(3.384)	(1.975)	(2.221)
Flood$_{i,\tau}$ 2	0.0254***	0.0234***	0.0182**	0.0184**
	(3.842)	(4.103)	(2.110)	(2.397)
Flood$_{i,\tau}$ 3	0.0351***	0.0338***	0.0278**	0.0328***
	(4.238)	(5.085)	(2.090)	(2.852)
Flood$_{i,\tau}$ 4	0.0411***	0.0390***	0.0351**	0.0382***
	(5.163)	(5.856)	(2.392)	(3.223)
Flood$_{i,\tau}$ 5	0.0422***	0.0391***	0.0328**	0.0343***
	(3.967)	(4.714)	(2.336)	(3.681)
Flood$_{i,\tau}$ 6	0.0403***	0.0374***	0.0443**	0.0475***
	(3.878)	(4.127)	(1.992)	(2.995)
Flood$_{i,\tau}$ 7	0.0464***	0.0377***	0.0535*	0.0589**
	(3.326)	(3.918)	(1.959)	(2.296)
Flood$_{i,\tau}$ 8	0.0321***	0.0204**	0.0226*	0.0225*
	(2.888)	(2.470)	(1.646)	(1.800)
Flood$_{i,\tau}$ 9	0.0330***	0.0262***	0.0302**	0.0316**
	(2.898)	(2.618)	(2.208)	(2.496)
Flood$_{i,\tau}$ 10	0.0133	-0.0020	0.0113	0.0090
	(0.8451)	(-0.1613)	(0.6245)	(0.5296)
Flood Risk$_{i,t}$	-0.0100***	-0.0099***	-0.0274***	-0.0264***
	(-3.422)	(-3.035)	(-5.138)	(-5.376)
Community Infrastructure$_{c,t}$		-5.97×10^{-5}		-0.0019***
		(-0.3434)		(-6.767)
Establishment	Yes	Yes	Yes	Yes
State-Year	Yes	Yes	Yes	Yes
Industry-Year		Yes		Yes
Fit statistics				
Observations	9,663,906	9,245,212	8,823,086	8,811,389
R^2	0.92435	0.92584	0.90787	0.91580

Table A4: National Insurance Channel: Inside FEMA Floodplain

This table reports OLS regression estimates examining the relationship between FEMA-designated flood risk areas and commercial flood insurance uptake and claims. The standard errors are clustered at the census block group and year level in panel A and are clustered on the census block group level in panel B, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment					
		No Buffer			1km Buffer	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Flooded}_i \times \text{Post}_t$	0.0302***	0.0292***	0.0257***	0.0205***	0.0201***	0.0177***
	(5.313)	(5.038)	(4.668)	(5.928)	(5.820)	(5.185)
$\text{Flooded}_i \times \text{Post}_t \times \text{I(Outside FP)}_{i,\tau^*-1}$	-0.0148*	-0.0184**	-0.0178**	-0.0082*	-0.0103**	-0.0094*
	(-1.888)	(-2.455)	(-2.146)	(-2.058)	(-2.290)	(-2.083)
$\text{Flood Risk}_{i,t}$	0.0074	0.0091	0.0045	0.0062	0.0073	0.0071
	(0.8179)	(0.9126)	(0.5244)	(0.7770)	(0.7823)	(0.8319)
$\text{Community Infrastructure}_{c,t}$	-0.0119			-0.0098		
	(-0.4011)			(-0.3331)		
Establishment, NAICS×Year	Yes	Yes	Yes	Yes	Yes	Yes
State×year	Yes			Yes		
County×year		Yes	Yes		Yes	Yes
Headquarter×year			Yes			Yes
Observations	2,897,122	2,897,122	2,897,122	2,865,602	2,865,602	2,865,602
R^2	0.94448	0.94507	0.95004	0.94539	0.94601	0.95142

Table A5: SBA Disaster Loans and Local Economy Following Flood-related Disasters

This table presents OLS regression estimates examining the relationship between federal disaster assistance programs and local economic conditions following flood-related disasters. Panel A focuses on SBA Economic Injury Disaster Loan (EIDL) and total SBA disaster loan intensity, defined as the dollar value of approved loans per establishment in a ZIP code. Panel B examines FEMA Public Assistance (PA) project spending intensity, defined as the thousand dollar per capita in a county. The outcomes include log employment, log annual payroll, and the log number of establishments at the ZIP code level (Panel A) and county level (Panel B), based on ZIP Code Business Patterns and County Business Patterns from Census Bureau. The main variables of interest are interactions between disaster assistance intensity and a post-flood indicator. Control variables include the percentage of high flood risk areas, log female population, population density, the number of flooding events, and verified disaster losses from the SBA. All regressions include ZIP or county, and state-by-year fixed effects. Standard errors are clustered at the ZIP or county, and year level, with t-statistics in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Small Business Administration Disaster Loan

			Establishments$_{z,t}$					
	Employment$_{z,t}$		All		<20 ppl		$\geq$ 50 ppl	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AfterFirstFlood$_t$ × SBA EIDL Intensity$_{z,t}$	0.2462		0.0646**		0.0779***		1.250***	
	(1.368)		(2.918)		(3.082)		(3.822)	
AfterFirstFlood$_t$ × SBA Loan Intensity$_{z,t}$		0.0629		0.0041		0.0187		0.3383**
		(0.6854)		(0.2694)		(1.130)		(2.812)
Flooded$_z$ × AfterFirstFlood$_t$	-0.0444	-0.0457	0.0247	0.0247	0.0229	0.0225	0.1161	0.1089
	(-0.1912)	(-0.1968)	(0.9343)	(0.9327)	(0.8256)	(0.8143)	(0.7358)	(0.6958)
Total Disaster Loss$_{z,t}$	-0.0019**	-0.0024	-0.0006**	-0.0005	-0.0005	-0.0006	-0.0058**	-0.0083**
	(-2.293)	(-1.446)	(-2.154)	(-1.166)	(-1.267)	(-1.101)	(-2.691)	(-2.472)
Number of Floodings$_{a,t}$	-0.0122	-0.0111	-0.0102	-0.0100	-0.0120	-0.0116	-0.0679	-0.0621
	(-0.1644)	(-0.1498)	(-1.135)	(-1.134)	(-1.266)	(-1.249)	(-0.9949)	(-0.9075)
High Flood Risk Area %$_{i,t}$	-0.0075	-0.0075	0.0032	0.0032	0.0039	0.0040	0.0155	0.0159
	(-0.7942)	(-0.7867)	(1.221)	(1.234)	(1.471)	(1.484)	(0.5954)	(0.6119)
Female Population$_{z,t}$	0.0113	0.0110	0.0057	0.0056	0.0044	0.0044	0.0551**	0.0540*
	(0.4300)	(0.4217)	(1.604)	(1.571)	(1.168)	(1.152)	(2.139)	(2.082)
Zip, State×Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,103	8,103	8,103	8,103	8,103	8,103	8,103	8,103
R^2	0.96017	0.96017	0.99843	0.99843	0.99814	0.99814	0.98291	0.98289
Within R^2	0.00058	0.00055	0.00946	0.00838	0.00799	0.00752	0.01809	0.01692

Panel B: FEMA Public Assistance Funded Projects

Model:	Emp$_{a,t}$ (1)	Job Creation$_{a,t}$ (2)	Estb$_{a,t}$ (3)	Estab Entry$_{a,t}$ (4)	Estab Exit$_{a,t}$ (5)
AfterFirstFlood$_t$ × PA Permanent Work Intensity$_{a,t}$	0.0023	0.0080*	0.0003	0.0243***	0.0145***
	(1.623)	(1.822)	(0.6200)	(4.359)	(11.98)
Flooded$_i$ × AfterFirstFlood$_t$	0.0018	0.0115	1.29×10^{-5}	-0.0138	0.0009
	(0.2207)	(0.9011)	(0.0087)	(-0.6622)	(0.0374)
Controls	Yes	Yes	Yes	Yes	Yes
County, State×Year	Yes	Yes	Yes	Yes	Yes
Observations	53,213	53,213	53,213	53,213	53,213
R^2	0.99492	0.97238	0.99862	0.89932	0.91071
Within R^2	0.32316	0.06572	0.67360	0.01883	0.08641

Table A6: Impact of Long-Run Flood Risk: Fixed Effect Estimates

This table presents the regression results on the impact of flooding on establishment outcomes in Equation 4 with establishment-level data from Your Economy Time Series (YTS) for the years 2000-2018. Columns (1)–(3) use the log number of employees at establishment i as the dependent variable, and Columns (4)–(6) use log sales. The key explanatory variables are: Flood risk$_{i,t}$, a dummy indicating whether establishment i is located in a FEMA-designated high-risk flood zone; and Flood$_{i,t}$ which captures whether establishment i experienced a flood in year t. An alternative measure of flood risk is obtained from FEMA's 2021 National Risk Index (NRI) on the census tract level. Additional control variables include a county-level measure of community infrastructure from the University of South Carolina and the cumulative number of floods previously experienced by the establishment. Standard errors are clustered to allow for spatial correlation within a 100-kilometer radius around each establishment's centroid and for autocorrelation of order 5. T-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A: 250 Meters

	Employment$_{i,t}$			Sales$_{i,t}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk$_{i,t}$	-0.0101***	-0.0103***		-0.0237***	-0.0268***	
	(-3.101)	(-3.136)		(-4.520)	(-5.504)	
Flood$_{i,t}$	0.0041***	0.0014	-0.0606***	-0.0009	-0.0029	-0.0592***
	(2.745)	(0.6374)	(-11.19)	(-0.3045)	(-0.7573)	(-8.974)
Community Infrastructure$_{c,t}$	-0.0002	-0.0001	0.0053***	-0.0020***	-0.0019***	0.0054***
	(-0.8982)	(-0.5850)	(12.49)	(-6.910)	(-6.727)	(11.83)
Previous Num of Flood$_{i,t}$		0.0077	0.0701***		0.0030	0.0556***
		(1.449)	(5.074)		(0.7039)	(5.571)
NRI - Flood$_{ct}$			-0.0009***			-0.0010***
			(-2.658)			(-2.640)
Establishment	Yes	Yes		Yes	Yes	
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year		Yes	Yes		Yes	Yes
Company-Year			Yes			Yes
Observations	9,276,777	9,276,777	7,239,158	8,839,411	8,839,411	6,894,771
R^2	0.92516	0.92565	0.43897	0.90778	0.91563	0.52298
Within R^2	8.92×10^{-6}	2.11×10^{-5}	0.00255	9.46×10^{-5}	0.00011	0.00190

Table A6: Impact of Long-Run Flood Risk: Fixed Effect Estimates (Continued)

Panel B: 500 Meters

	Employment$_{i,t}$			Sales$_{i,t}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk$_{i,t}$	-0.0101***	-0.0103***		-0.0237***	-0.0268***	
	(-3.102)	(-3.144)		(-4.520)	(-5.502)	
Flood$_{i,t}$	0.0013	0.0002	-0.0544***	-0.0004	-0.0019	-0.0545***
	(1.061)	(0.1285)	(-12.68)	(-0.2055)	(-0.7917)	(-10.53)
Community Infrastructure$_{c,t}$	-0.0002	-0.0001	0.0053***	-0.0020***	-0.0019***	0.0054***
	(-0.8960)	(-0.6100)	(12.49)	(-6.911)	(-6.703)	(11.87)
Previous Num of Flood$_{i,t}$		0.0029	0.0480***		0.0010	0.0404***
		(0.9593)	(6.487)		(0.3766)	(7.068)
NRI - Flood$_{ct}$			-0.0009***			-0.0010***
			(-2.673)			(-2.657)
Establishment	Yes	Yes		Yes	Yes	
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year		Yes	Yes		Yes	Yes
Company-Year			Yes			Yes
Observations	9,276,777	9,276,777	7,239,158	8,839,411	8,839,411	6,894,771
R^2	0.92516	0.92565	0.43898	0.90778	0.91563	0.52300
Within R^2	8.04×10^{-6}	1.15×10^{-5}	0.00258	9.45×10^{-5}	0.00011	0.00194

Panel C: 1km Meters

	Employment$_{i,t}$			Sales$_{i,t}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk$_{i,t}$	-0.0101***	-0.0103***		-0.0237***	-0.0268***	
	(-3.102)	(-3.152)		(-4.521)	(-5.499)	
Flood$_{i,t}$	0.0006	0.0002	-0.0488***	-0.0025	-0.0028	-0.0490***
	(0.7102)	(0.2280)	(-12.79)	(-1.600)	(-1.633)	(-12.23)
Community Infrastructure$_{c,t}$	-0.0002	-0.0001	0.0053***	-0.0020***	-0.0019***	0.0053***
	(-0.8954)	(-0.6310)	(12.56)	(-6.909)	(-6.685)	(11.94)
Previous Num of Flood$_{i,t}$		0.0004	0.0410***		-0.0013	0.0367***
		(0.2012)	(9.899)		(-0.7185)	(10.07)
NRI - Flood$_{ct}$			-0.0009***			-0.0011***
			(-2.686)			(-2.688)
Establishment	Yes	Yes		Yes	Yes	
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year		Yes	Yes		Yes	Yes
Company-Year			Yes			Yes
Observations	9,276,777	9,276,777	7,239,158	8,839,411	8,839,411	6,894,771
R^2	0.92516	0.92565	0.43915	0.90778	0.91563	0.52311
Within R^2	7.91×10^{-6}	7.39×10^{-6}	0.00288	9.55×10^{-5}	0.00011	0.00216

Table A7: Flood Risk, Insurance Costs, and Local Business Dynamics

This table presents OLS regression estimates examining how flood risk and insurance costs are associated with county-level economic outcomes. Panel A evaluates the relationship between FEMA-designated flood risk exposure and measures of local business activity from 2001 to 2018. Panel B incorporates data from the National Flood Insurance Program (NFIP) between 2009 and 2018 to examine associations between insurance policy costs and business dynamics, including an interaction with flood risk exposure. Flood Risk$_{a,t}$ and Flooded area$_{a,t}$ represent the share of a county's land area classified as high-risk for flooding or that was flooded in a given year, respectively. The dependent variables include population, employment, establishment counts, and business metrics from the Census' County Business Patterns. All models include county and year-by-state fixed effects. The standard errors are clustered at the county and state-by-year level, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A: Commercial Policies

	Employment$_{a,t}$	Job Creation$_{a,t}$	Job Destruction$_{a,t}$	Establishments$_{a,t}$	Estab Entry$_{a,t}$	Estab Exit$_{a,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Policy Count$_{a,t}$	-0.2392*	-0.0870*	0.1704*	-4.512	-1.607*	3.270
	(-1.912)	(-2.104)	(1.933)	(-1.712)	(-1.947)	(1.502)
Policy Count × High Flood Risk Area %$_{a,t}$	0.0062*	0.0018*	-0.0048*	0.0998	0.0037	-0.1121
	(1.890)	(1.975)	(-1.951)	(1.536)	(0.1957)	(-1.826)
High Flood Risk Area %$_{a,t}$	-0.0478*	-0.0140*	0.0353*	-0.8068	-0.0493	0.8793
	(-1.904)	(-1.987)	(1.872)	(-1.485)	(-0.3375)	(1.778)
Number of Floodings$_{a,t}$	0.0027	-0.0336	-0.0154	0.0605	0.7084	0.4409
	(0.0611)	(-1.272)	(-0.5612)	(0.0603)	(1.178)	(0.8159)
Flooded area$_{a,t}$	-0.0422	-0.0107	0.0191	-0.9958	-0.3793	0.7230
	(-1.218)	(-1.000)	(1.014)	(-1.166)	(-1.089)	(1.132)
Female Population Share$_{a,t}$	-0.1121*	-0.0394**	0.0729	-2.254*	-0.7021	1.786
	(-2.121)	(-2.344)	(1.827)	(-1.846)	(-1.828)	(1.790)
Population Density$_{a,t}$	0.0763	0.0256	-0.0510	0.9520	0.7010	-0.2285
	(1.743)	(1.464)	(-1.806)	(1.096)	(1.271)	(-0.4073)
Population$_{a,t-1}$	0.8686***	0.0856**	0.1918*	0.4771	-0.9638	-1.006
	(6.514)	(2.564)	(1.962)	(0.1318)	(-0.7496)	(-0.3746)
Establishments$_{a,t-1}$	0.0042	0.0005	-0.0034	1.065***	0.1209**	0.0390
	(1.589)	(0.5912)	(-1.642)	(10.63)	(2.942)	(0.5746)
County, Year × State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,645	27,645	27,645	27,645	27,645	27,645
R^2	0.99922	0.99085	0.97909	0.99984	0.99733	0.99230
Within R^2	0.78780	0.15895	0.08995	0.89339	0.26447	0.01158

Panel B: Total Policies

	Employment$_{a,t}$	Job Creation$_{a,t}$	Job Destruction$_{a,t}$	Establishments$_{a,t}$	Estab Entry$_{a,t}$	Estab Exit$_{a,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Total Policy Count$_{a,t}$	-0.3844*	-0.0996	0.3058*	-7.700*	-1.930	6.522*
	(-2.101)	(-1.781)	(2.175)	(-2.104)	(-1.702)	(2.017)
Total Policy Count × High Flood Risk Area %$_{a,t}$	0.0043*	0.0015*	-0.0030	0.0815*	0.0117	-0.0803*
	(1.933)	(2.210)	(-1.823)	(1.988)	(1.008)	(-1.932)
High Flood Risk Area %$_{a,t}$	-0.0480*	-0.0157*	0.0334	-0.8922	-0.1117	0.8986*
	(-1.943)	(-2.122)	(1.812)	(-1.721)	(-0.8547)	(1.850)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County, Year × State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,645	27,645	27,645	27,645	27,645	27,645
R^2	0.99922	0.99085	0.97909	0.99984	0.99733	0.99230
Within R^2	0.78780	0.15895	0.08995	0.89339	0.26447	0.01158

Table A8: Flood Risk and Firm Disclosure and Operations

This table presents the estimates on the relationship between flood risk and firms' disclosure and operations. High Flood Risk$_{i,t}$ is alternatively classified based on whether a firm has more than 1% of employees working in establishments in a FEMA-designated floodplain. Cumulative Floods$_{i,t}$ is the log cumulative number of establishments that have been flooded with a 1-km spatial buffer using the flood data from the Global Flood Database (GFD) with twice-daily 25-meter-resolution satellite images. Standard errors are clustered by firm & year-quarter, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Panel A:	Earnings Calls			10-K					
	Disclose$_{i,t}$	Risk$_{i,t}$	Firm Initiated$_{i,t}$	Disclose$_{i,t}$	Risk$_{i,t}$	Physical Risk$_{i,t}$	Regulatory Risk$_{i,t}$	Intangible Assets$_{i,t}$	PP&E$_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Flood Risk$_{i,t}$	0.0091***	0.0064**	0.0066**	0.0129	0.0080	0.0094	0.0040	0.1755***	0.0022
	(2.667)	(2.109)	(2.088)	(1.126)	(0.7087)	(0.8406)	(0.6043)	(4.132)	(0.9821)
Asset$_{i,t-1}$	-0.0028*	-0.0024	-0.0013	0.0178**	0.0149*	0.0154**	0.0041	0.6846***	0.0104***
	(-1.685)	(-1.598)	(-0.8481)	(2.262)	(1.980)	(2.061)	(1.062)	(18.30)	(2.742)
Size$_{i,t-1}$	0.0029*	0.0023*	0.0014	0.0040	0.0031	0.0039	0.0012	0.0243	0.0303***
	(1.959)	(1.679)	(1.154)	(0.9862)	(0.7906)	(1.005)	(0.5891)	(1.550)	(16.49)
Revenue$_{i,t-1}$	0.0048**	0.0041**	0.0035**	0.0125**	0.0113*	0.0116**	-0.0020	0.2247***	0.0134***
	(2.648)	(2.528)	(2.117)	(2.057)	(1.944)	(2.006)	(-0.5939)	(7.926)	(4.587)
PP&E$_{i,t-1}$	0.0035*	0.0035**	0.0035**	0.0251***	0.0264***	0.0253***	0.0146***	-0.0113	0.9108***
	(1.922)	(2.181)	(2.141)	(3.463)	(3.759)	(3.606)	(3.759)	(-0.3258)	(175.5)
Capex$_{i,t-1}$	0.0047***	0.0049***	0.0034**	0.0037	0.0025	0.0028	0.0047**	0.0501***	0.0207***
	(2.834)	(3.049)	(2.230)	(1.149)	(0.8070)	(0.9068)	(2.178)	(4.215)	(12.63)
R&D$_{i,t-1}$	0.0002	-0.0003	0.0003	0.0056**	0.0055**	0.0056**	0.0012	0.1085***	-0.0011*
	(0.3022)	(-0.4043)	(0.4585)	(2.413)	(2.447)	(2.458)	(1.123)	(11.88)	(-1.821)
Firm, Industry-Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647
R^2	0.27308	0.24223	0.24732	0.61889	0.60294	0.59961	0.50562	0.91346	0.99719
Within R^2	0.00109	0.00101	0.00078	0.01001	0.00860	0.00876	0.00287	0.24604	0.91727

Panel B:	Earnings Calls			10-K					
	Disclose$_{i,t}$	Risk$_{i,t}$	Firm Initiated$_{i,t}$	Disclose$_{i,t}$	Risk$_{i,t}$	Physical Risk$_{i,t}$	Regulatory Risk$_{i,t}$	Intangible Assets$_{i,t}$	PP&E$_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative Floods$_{i,t}$	0.0106***	0.0096***	0.0107***	0.0368***	0.0345***	0.0344***	0.0087**	0.0475**	-0.0015
	(3.121)	(2.875)	(3.390)	(6.653)	(6.376)	(6.417)	(2.485)	(2.291)	(-1.175)
Asset$_{i,t-1}$	-0.0029*	-0.0025*	-0.0015	0.0168**	0.0139*	0.0144*	0.0039	0.6873***	0.0105***
	(-1.770)	(-1.718)	(-0.9830)	(2.159)	(1.864)	(1.949)	(1.015)	(18.35)	(2.773)
Size$_{i,t-1}$	0.0031**	0.0024*	0.0016	0.0046	0.0037	0.0045	0.0014	0.0242	0.0302***
	(2.022)	(1.751)	(1.256)	(1.145)	(0.9477)	(1.164)	(0.6526)	(1.544)	(16.46)
Revenue$_{i,t-1}$	0.0049***	0.0042**	0.0036**	0.0126**	0.0114*	0.0117**	-0.0020	0.2276***	0.0134***
	(2.730)	(2.589)	(2.180)	(2.082)	(1.952)	(2.018)	(-0.5781)	(7.973)	(4.615)
PP&E$_{i,t-1}$	0.0030*	0.0031*	0.0030*	0.0233***	0.0246***	0.0236***	0.0142***	-0.0119	0.9110***
	(1.703)	(1.962)	(1.855)	(3.233)	(3.535)	(3.380)	(3.653)	(-0.3424)	(175.3)
Capex$_{i,t-1}$	0.0045***	0.0048***	0.0032**	0.0030	0.0018	0.0022	0.0046**	0.0495***	0.0207***
	(2.763)	(2.994)	(2.148)	(0.9551)	(0.6061)	(0.7121)	(2.125)	(4.183)	(12.67)
R&D$_{i,t-1}$	4.21×10^{-7}	-0.0005	8.63×10^{-5}	0.0048**	0.0047**	0.0048**	0.0010	0.1082***	-0.0010*
	(0.0006)	(-0.7591)	(0.1280)	(2.045)	(2.084)	(2.101)	(0.9437)	(11.85)	(-1.760)
Firm, Industry-Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647	156,647
R^2	0.27340	0.24257	0.24776	0.61992	0.60389	0.60057	0.50577	0.91334	0.99719
Within R^2	0.00154	0.00145	0.00136	0.01271	0.01099	0.01112	0.00317	0.24492	0.91727

Table A9: Earnings Call Classification Examples I

Earnings Call	GPT Explanation:
Churchill Downs Inc (2013-02-28) Harlow's revenues increased by $3.4 million, which was closed for 25 days during 2011, as a result of the historic Mississippi River **flood**. The renovations, following the **flood**, are now complete, with a January 25th grand opening. We are excited to see if these renovations will help us attract customers farther distant from our facility. ... Insurance recoveries, net of losses, increased by $6 million reflecting the final settlement of insurance claims related to the **flood** damage sustained at Harlows in 2011.	*Flood Risk*: True The disclosure explicitly mentions flood risk through the historic Mississippi River flood, which impacted Harlow's revenues by closing it for 25 days in 2011. *Flood Opportunity*: True The renovations following the flood at Harlow's resulted in a complete facility overhaul and reopening in 2012, indicating an opportunity to attract customers due to improved infrastructure.
Xenia Hotels & **Resorts Inc (2017-11-07)** Harvey caused severe **flooding** in the Houston area making transportation throughout the city a challenge, and this negatively impacted results in late August and early September. Each of our hotels remained open during the **storm** and benefited during the balance of September from increased post **hurricane** demand in the city. ... The shift in the timing of the holidays and the increased demand in Houston after American Harvey is expected to positively impact our fourth quarter results.	*Flood Risk*: True *Flood Opportunity*: True The company benefitted from increased demand in the aftermath of Hurricane Harvey, indicating a flood-related opportunity, as they experienced increased RevPAR due to post-hurricane demand.
Capstone Turbine Corp (2013-02-11) This is due to the impact of **Hurricane** Sandy and fiscal cliff concerns that curbed spending during the last three months of the calendar year, and this is not inconsistent with what companies across many industries faced during the period. ... We definitely see that as an opportunity, and even the recent snowstorm we had. Anything that knocks out power lines for any period of time helps waken up our customers on the reality of how fragile the grid is... all of our units, except for one, ran through Sandy.	*Flood Risk*: True *Flood Opportunity*: True The discussion highlights Hurricane Sandy and a snowstorm as events that underscore the fragility of power grids, positioning the company's products as a solution and opportunity to capture market share.

Table A10: Earnings Call Classification Examples II

Earnings Call	GPT Explanation:
Denbury Resources Inc (2010-04-13) We first started an EOR **flood** in 1999. ... We now have producing properties in Phases 1 through 5. I guess a week or two ago, we announced the first production at Delhi which is phase five. We just started **flooding** that in the fall in the fourth quarter. And that one is actually a couple months ahead of time. We were actually expecting production around midyear. So it's always good to be a little bit ahead. Other little updates, most of the other **floods** are kind of ongoing.	*Flood Risk*: False The term 'flood' in this context refers to enhanced oil recovery (EOR) processes using CO2 to extract oil from fields, not physical flood risk from weather. No mention of impacts from natural flooding events on operations or assets.
Fidelity National Financial Inc (2009-06-03) Our specialty insurance has three pieces, **flood**, homeowners and home warranty. First on the **flood** side it's about $150 million in revenue. We believe that we are one of the largest if not the largest writer of **flood** insurance in the US. You can see at the end of March about 650,000 policies in force. I think the most important thing in this business is the federal Government underwrites all flood insurance through the National Flood Insurance Program. We are simply a processor, we get about $0.30 for new and renewal policies and then the upside comes in processing claims. So I guess I'm not very excited right now.	*Flood Risk*: False The mention of flood insurance relates more to the provision of services rather than exposure to flood risk. There is no explicit mention of exposure to or negative impacts from floods on the company's operations or financial performance. *Flood Opportunity*: True The company highlights its significant role in the U.S. flood insurance market, with substantial revenue and a large policy base. Its position as a major processor of flood insurance claims indicates a business opportunity tied to flood-related events.
Ulta Beauty Inc (2018-05-31) About half can be attributed to better-than-expected sales, both from comparable stores and new stores. The remainder is a combination of some planned expenses shifting into later quarters and a bit more favorability than usual from a number of smaller line items, such as a modest benefit from insurance recoveries from last year's **hurricane**-related losses. Moving on to the balance sheet and cash flow. Total inventory grew 8.4% but was down 3% on a per-store basis, well below comparable sales growth.	*Flood Risk*: True *Flood Opportunity*: True The mention of 'insurance recoveries from last year's hurricane-related losses' provides a modest benefit, indicating a financial opportunity linked to past flooding events. However, the opportunity is minor, indirect, and not explicitly stated as flood-related, leading to moderate confidence.

Table A11: 10-K Disclosure Classification Examples I

Statement	ChatGPT Explanation:
HCI Grou (2014) The fact that our business is concentrated in the state of Florida subjects it to increased exposure to certain catastrophic events and destructive weather patterns such as **hurricanes**, **tropical storms**, and **tornados**. ... we plan to seek opportunities to expand and to provide new product offerings such as our **flood** product, which we began offering in January 2014.	*Flood Physical Risk*: True *Flood Regulatory Risk*: False There is moderate mention of regulatory changes affecting the insurance landscape in Florida and other states, but specific flood-related regulations are not directly referenced. *Flood Opportunity*: True The introduction of flood coverage products and expansion into the homeowners insurance market suggests a strategic approach to capitalize on flood-related market needs in Florida.
EAGLE FINANCIAL SERVICES INC (2021) On July 21, 2015, five federal regulatory agencies announced the approval of a joint final rule that modifies regulations that apply to loans secured by properties located in **special flood hazard area**s. ... On February 20, 2019, an Interagency Final Rule was issued amending regulations regarding loans in areas having special flood hazards to implement the private **flood** insurance provisions of the Biggert-Waters Act. Specifically, the final rule requires regulated lending institutions to accept policies that meet the statutory definition of 'private **flood** insurance' and permits them to exercise discretion to accept other private **flood** insurance policies, subject to certain restrictions. We are also at risk of the impact of natural disasters, terrorism and international hostilities on our systems or for the effects of outages or other failures involving power or communications systems operated by others. ... In connection with residential real estate loans, the Bank requires title insurance, hazard insurance and, if applicable, flood insurance.	*Flood Physical Risk*: False The disclosure incorporates a general mention of risks associated with natural disasters, which could imply flood risk given the nature of physical disruptions such as outages and failures affecting business operations. However, it does not explicitly link these risks to flooding specifically. *Flood Regulatory Risk*: True The company discusses regulations affecting loans in special flood hazard areas, including the requirement to accept private flood insurance, and changes to flood insurance payment escrows. This indicates a high relevance to regulatory risk connected to flood-related legislation. *Flood Opportunity*: True The company highlights its involvement in handling loans subject to flood insurance requirements. This could reflect an opportunity, as facilitating these loans might position the company advantageously due to increasing demand or requirements for flood insurance.

Table A12: 10-K Disclosure Classification Examples II

Statement	ChatGPT Explanation:
PAR TECHNOLOGY CORP (2003) In particular, the Company's **Flood***WareTM software tool and methodology is being employed in New York State in support of Federal Emergency Management Agency's Map Modernization Program. ... Also contributing to the growth was a **floodplain**-mapping contract with the New York State Department of Environment Conservation.	*Flood Physical Risk*: False *Flood Regulatory Risk*: False Although the company is involved in floodplain mapping, there is no indication of compliance costs or restrictions associated with flood-related regulations mentioned in the disclosure. *Flood Opportunity*: True The company's involvement in floodplain mapping and its Flood WareTM software tool, which supports FEMA's Map Modernization Program, highlights a proactive initiative to capture business opportunities associated with flood mapping and flood-related services.
EAGLE FINANCIAL SERVICES INC (2021) We expect to provide top-line data from the expanded cohort for the **STORM** study at the end of April 2018 ... We are also establishing the commercial infrastructure to support a potential launch of selinexor in the United States and we intend to work with existing and potential partners to establish such commercial infrastructure outside the United States. ... Although our operations are based in the United States, ... any business that we conduct outside the United States will be subject to additional risks... including ... business interruptions resulting from geo-political actions, including war and terrorism, or **natural disasters**, including earthquakes, **hurricanes**, typhoons, **floods** and fires.	*Flood Physical Risk*: False There is no indication of potential or actual physical damage to assets, infrastructure, or supply chain due to flood events. The disclosure is focused on clinical development and regulatory strategies for selinexor, with no mention of flood risk or physical threats to the company's operations. *Flood Regulatory Risk*: False The disclosure does not address compliance costs or restrictions associated with flood-related regulations. The focus is on regulatory approvals for drug development with no reference to flood-specific regulatory obligations or anticipated costs related to compliance. *Flood Opportunity*: False The disclosure does not discuss flood-related market opportunities or advantages. The focus is entirely on the development and commercialization of selinexor and other drug candidates, with no reference to flood dynamics that could impact market positioning.

Table A13: Earnings Call Examples - Mechanism

Newtek Business Services Corp (2017-11-02)

I really appreciate the question because it's interesting. 45 days ago everybody was freaked out about Houston, Puerto Rico and Florida ... We were fortunate that, number one, although we do have a reasonable amount of Florida business most of it does tend to be in southern Florida and on the East Coast and the storm did most of its damage on the West Coast. Although clearly there was significant impact given the size of the storm on the East Coast as well. We're very well protected. I shouldn't say I don't think, there was no material changes in our portfolio or in the performance of these loans due to the effect of the storm. I would also say to you that **if a storm did affect one of our clients it is highly likely that they would immediately go to the SBA for disaster loan, get capital on a 20 to 25 year term with a 1%, 2% or 3% interest rate with a lien that will be subordinated to all of our other liens.**
So it's almost like instant equity. So in a perverse way, as you're aware, sometimes these storms are actually good for businesses and good for GDP. But we really have not seen any impact for the storms that hit in Houston and in Florida.

Mammoth Energy Services Inc (2022-07-28)

Looking at our Infrastructure Services segment, we continue to grow and build upon our positive momentum in the first half of 2022 after becoming cash flow positive exiting 2021. Since the first quarter, we've been adding crews. Currently, we have more than 100 crews, and we expect to add additional crews in the coming weeks in preparation for the seasonal storm restoration services anticipated in the third and fourth quarters. **The overall infrastructure backdrop remains strong, and we believe the passage of the federal infrastructure bill last fall will provide opportunities in the infrastructure space for years to come.** As we have said previously, we anticipate the federal spending to begin stimulating project lettings across the sector later this year and into 2023. I'm proud of our infrastructure team's commitment and hard work to mitigate the myriad of headwinds in today's challenging economic environment as we remain disciplined with our capital spending to continue to improve Mammoth's cost structure.

ICF International Inc (2021-05-04)

Last week, we announced a first quarter $46 million award from the government of Puerto Rico's Public-Private Partnership Authority, that includes elements of ICF's previous work **to provide FEMA-funded project formulation services to support long-term disaster recovery from hurricanes Irma and Maria and hazard mitigation efforts to protect against future disasters**. ...
I think we've also talked about more generally, but with disaster recovery. I mean, obviously it's partially dependent on the frequency and severity of storms each year, which I think the data shows are certainly increasing. But the mitigation funding, is a new bucket. And I think that will continue to be funded by the Biden administration and for both under HUD programs and FEMA programs, and we're a market leader there. Well, I think we've talked about we've won 4 or 5 state-level contracts on mitigation in the last year. And so again, **I think we see disaster recovery as a long-term growth driver here. That said, it's certainly going to be a double-digit growth driver for us this year. We have long-term confidence in the growth of that business.**

A.3 Data

Flooding Data

Many studies such as Kocornik-Mina et al. (2020); Pankratz and Schiller (2024); Jia et al. (2022) used the Emergency Events Database (EM-DAT) and the flooding events in Dartmouth Flood Observatory (DFO) which archives flooding events primarily from news and government announcements, and other instrumental and remote sensing sources. They either report the administration locations or GIS polygons as the units of flooded areas. However, if one administrative geographical location is identified as flooded but only a small proportion of the area is affected, then the estimation results could be biased. Using high-resolution satellite data could reduce the measurement error and help identify flooded areas more precisely.

The GFD was developed by Tellman et al. (2021) and uses daily and twice-daily MODIS observations from the Aqua and Terra satellites. These instruments provide consistent global coverage and have been widely used in environmental and hydrological applications. The flooding maps are identified by applying sophisticated inundation detection algorithms that distinguish between floodwater and permanent water bodies using Landsat imagery, and employing multiday composites to flag inundation when more than half of the satellite observations indicate water. To improve the accuracy, I implement the dataset with the Hurricane Sandy inundation zones provided by FEMA Modeling Task Force using Storm Surge Sensor data from the USGS and field-verified High-Water Marks.

Each identified flood event is provided as a GeoTIFF raster in the WGS 84 coordinate system, with four data bands. This paper primarily uses the first two: one indicating inundation and the other recording the number of inundated days. Compared to the Dartmouth Flood Observatory (DFO) data, which estimates total flooded areas nearly 20 times larger, the GFD offers a more conservative and likely more accurate estimate. DFO's event polygons are sometimes hand-drawn or derived from news sources, leading to possible overestimation and measurement error. As Pankratz and Schiller (2024) notes, some DFO polygons are unrealistically large and may not reflect true physical exposure, motivating the preference for GFD in this study.

Each raster flood map is overlaid with establishment coordinates to determine whether

a facility was flooded. To address possible underdetection from cloud cover or conservative classification in the GFD, I apply spatial buffers of up to 1km when merging. The significant increase in exposed establishments with larger buffers (see Table 1) confirms the value of this adjustment and supports robustness in the exposure classification.