How Firms Recover after Floods: Mechanisms and Evidence *

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Abstract

Floods are among the costliest natural disasters, yet we know little about what drives business recovery. This gap matters as the incidence of flooding increases and government bailouts may become more limited under tightening fiscal budgets. Using establishment-level data that link remote sensing inundation to FEMA flood maps, I provide novel causal evidence that flood insurance is a key driver of business recovery. I combine a triple difference design around Hurricane Sandy with a spatial regression discontinuity at floodplain borders. Flooded establishments just inside floodplains, where properties with federally backed or regulated mortgages must carry flood insurance, recover more in employment and sales than otherwise similar sites just outside. Effects are larger where firms are more likely to be insured and where policy limits can cover more losses. Establishments of firms that disclosed insurance pre-flood also recover more. These patterns, including an increase in building upgrades at flooded sites inside floodplains, reflect an insurance-liquidity channel that supports rebuilding and reallocation, allowing firms to return stronger rather than merely to baseline. In equity markets, price drops around flood news are smaller for firms with prior exposure or disclosure. Overall, the evidence indicates mandated insurance coverage materially shapes business recovery.

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1 Introduction

Floods are among the most frequent and costly disasters in the U.S., causing about \$32.1 billion in annual losses under 2020 climate conditions, with losses projected to rise by more than 26% by 2050 (Wing et al., 2022). While the impacts on households and real estate have been widely studied, the consequences for businesses remain less understood. On the one hand, firms face capital damage, operational disruption, supply chain breakdowns, and local demand shocks. On the other hand, institutions exist to cushion these shocks, such as insurance and federal aid, but we have limited evidence on how effectively they restore operational performance at businesses. Understanding the path of business recovery and the role of these institutional mechanisms is increasingly urgent as climate-related flood risk intensifies, and the Federal Emergency Management Agency (FEMA) faces ongoing fiscal and administrative pressures.

Among the institutions affecting post-disaster financing, the National Flood Insurance Program (NFIP) is central. Administered by FEMA, it requires properties in mapped floodplains with federally backed or regulated mortgages to carry flood insurance, thereby increasing coverage where flood risk is highest. Mandate-induced coverage converts insured losses into cash claim payments funded by premiums, supplying liquidity when firms face financing frictions. Despite the NFIP's central role, its business recovery value has not been systematically quantified. This paper fills that gap by providing causal estimates of NFIP's effects on post-flood firm outcomes and by showing that mandate-induced coverage, which delivers liquidity via claim payments, is the institutional channel that enables stronger post-event performance.

I study how businesses recover after major floods, and how much of that recovery is driven by institutional mechanisms, especially the NFIP. To answer this, I compile a novel establishment level panel for 2000-2018 that links high-resolution remote sensing inundation maps to FEMA floodplain designations. Because the mandate increases the likelihood that establishments inside floodplains hold coverage relative to otherwise similar establishments outside, floodplain boundaries create plausibly exogenous variation in insurance take-up; I use this variation to identify the insurance channel in business recovery.

Whether mandate-induced coverage increases post-flood business recovery is not obvious ex ante. Map targeting and enforcement are imperfect: some inside-floodplain properties lack federally regulated/insured mortgages, compliance is checked mainly at origination or refinancing, and firms may carry company-wide policies that substitute for place-based mandates.

I implement two complementary designs. First, a triple difference design centered on Hurricane Sandy, one of the costliest U.S. storms, shows that flooded establishments inside floodplains recover more in employment and sales than similarly affected establishments outside. NFIP commercial policy and claim data are consistent with 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 more claim payments, particularly from required policies, consistent with greater post-event liquidity rather than simply greater damage.

Second, I implement a spatial regression discontinuity-triple-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. To further evaluate the recovery effect and role of insurance, I restrict the sample to the pre-Sandy floodplain and compare flooded to non-flooded establishments. Flooded sites outgrow peers that were not flooded, indicating that insurance-financed rebuilding offsets the damages and lifts operations above the counterfactual path, so firms return stronger rather than merely to baseline. Together, these results provide novel causal evidence that access to flood insurance induced by the NFIP mandatory purchase requirement is a key driver of business resilience and recovery after major flood events.

Floodplain targeting and mandate compliance are imperfect: FEMA maps do not perfectly align with realized risk, and the NFIP purchase requirement is only enforced at loan events. If insurance is the operative channel, the effect should be stronger where enforcement is more likely. Because lenders verify coverage at origination, increase, extension, or renewal, places with higher pre-Sandy mortgage activity should display greater compliance among inside-floodplain properties. I therefore augment the baseline triple difference specification by interacting the inside-floodplain term with pre-Sandy mortgage activities and intensity. The post-flood inside-outside recovery difference in employment is larger precisely where mortgage activity is higher, indicating that stronger lender enforcement amplifies the effect and pointing to mandate-induced coverage, rather than unobserved geography, as the driver.

Having shown on the extensive margin that the mandate binds, I also examine the intensive margin to test whether potential greater indemnification translates into larger recovery. The NFIP's $500,000 commercial building limit generates cross-sectional variation in how fully losses can be indemnified. I use this feature and extend the baseline triple difference by interacting flood exposure and floodplain status with an indicator for properties at or below the NFIP limit, and find that such establishments recover more in employment and sales than otherwise similar above-cap peers. A complementary regression-discontinuity difference-in-differences at the $500,000 threshold within floodplains, using pre-Sandy building values as the running variable, corroborates the pattern: among flooded establishments, those just below the cap recover more than those just above. These results are consistent with an insurance-depth mechanism in which greater indemnification facilitates post-disaster rebuilding.

If insurance liquidity finances rebuilding, damaged sites inside floodplains should exhibit a rise in building upgrades, such as shell and structural repairs, relocation or elevation of mechanical and electrical systems, and interior renovations that restore and expand operating capacity. To test the mechanism directly, I measure building upgrades using issued permits for major construction and core systems and re-estimate the baseline triple difference. The estimates show that flooded sites inside the pre-Sandy FEMA floodplain undertake substantially more building upgrades, especially in the first three years after Sandy. The timing and composition of this construction response are consistent with an insurance-liquidity channel in which insurance payouts, together with code-triggered flood-resilience upgrades, finance prompt rebuilding and support stronger firm recovery.

Because many establishments belong to multi-site firms, risk management often operates at the corporate rather than solely the site level. This motivates the hypothesis that, if firms are broadly exposed to mapped flood risk, they are more likely to coordinate coverage across locations, and the corporate policies will attenuate the magnitude of inside floodplain recovery. Using pre-Sandy measures of firm floodplain exposure, such as the number of a parent's establishments located in FEMA floodplain, I find that the inside floodplain advantage is smaller for parents with broader pre-Sandy exposure. This attenuation suggests the NFIP map-and-mandate channel is most salient for smaller or locally constrained firms and weakest where corporate risk management can substitute for local mandate rules.

As complementary evidence, I present two robustness exercises. First, a national-level extension applies the mandate test to all identified flood events from 2000-2018, aligning each establishment to the FEMA map in force prior to its first flood. Event study estimates show that establishments inside mapped floodplains exhibit positive, persistent post-flood employment gains relative to otherwise similar establishments outside, consistent with broader access to NFIP coverage. Second, I exploit New York City's 2007 Flood Insurance Rate Map revision as a pre-Sandy shock to mandate exposure. I document sharp, no-pretrend increases in commercial NFIP coverage in areas newly designated inside the FEMA floodplain, and, using a triple-difference around Sandy, stronger post-event employment and sales growth for flooded establishments in those newly designated areas. Together, these exercises corroborate the interpretation that mandate-induced coverage to NFIP liquidity strengthens business recovery beyond the Sandy-NYC setting.

Building on the insurance results, I next ask whether firm-level preparedness, beyond place-based mandate exposure, shapes post-flood recovery. Because I do not observe establishment-level policies and NFIP compliance is imperfect, floodplain maps indicate where coverage is more likely but not which specific sites were insured at impact. To sharpen inference and to proxy establishments' insurance coverage, I construct a pre-event parent-level disclosure measure from 10-K filings and earnings communications that signals insurance preparedness and government-spending opportunities. The classification proceeds in two steps. First, I screen earnings call transcripts and 10-K filings for flood-related keywords. Second, I apply a large language model to categorize these disclosures to classifications of risk vs opportunities. For earnings calls, I further split opportunity into insurance-related and government aid-related. Validation shows that firms with greater chronic exposure (FEMA floodplain footprint and prior floods) disclose flood risk more in earnings calls and 10-K filings.

Linking establishments to their parent firms' disclosures, I find that establishments whose parent firms disclosed insurance-related opportunities before Hurricane Sandy recover more in employment and sales after flooding. I then study investor responses to major flood events. Event study estimates show significantly negative cumulative abnormal returns that deepen over longer post-event windows. Losses are most pronounced for first-time flood firms and for firms with little mapped exposure or prior disclosure, consistent with markets penalizing unanticipated and unprepared exposure. In the cross section, floodplain exposure and prior flood experience attenuate losses, and prior government-spending opportunity disclosure also moderates reactions, whereas generic insurance-opportunity disclosure does not.

Consistent with the insurance-liquidity mechanism, I also examine whether federal programs provide complementary post-disaster financing that fills gaps where coverage is thin or NFIP policy caps bind. Two programs are central. The Small Business Administration (SBA) makes Physical Disaster Loans to repair or replace damaged real estate, machinery, and inventory, and Economic Injury Disaster Loans (EIDL) that supply working capital to eligible small businesses facing operating shortfalls after a disaster. FEMA's Public Assistance (PA) program allocates grants to local governments and eligible nonprofits for emergency response and permanent infrastructure repair (e.g., roads, utilities, public buildings, parks). Using ZIP-level SBA data, I find that greater EIDL intensity is associated with post-flood increases in employment and establishment counts, with spillovers to larger establishments. At the county level, higher PA spending following floods is linked to stronger employment growth and job creation. While these estimates are based on aggregated data and do not identify specific transmission channels, the patterns are consistent with federal aid operating alongside rules-based insurance to inject liquidity, stabilize demand, and restore essential services that support private sector recovery.

Related 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; Sastry, 2022; Sastry, Sen, and Tenekedjieva, 2023; Mulder, 2024; Issler, Stanton, Vergara-Alert, and Wallace, 2024; Ge, Johnson, and Tzur-Ilan, 2025a; Ge, Lam, and Lewis, 2025b), 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. (2024) 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 climate finance literature by linking physical risk to firms' real and financial outcomes through institutional channels. A large literature examines hazards such as sea level rise, extreme temperature shocks, and hurricanes, and their effects on investment, productivity, 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). Only a small set of papers examines flood impacts on businesses, and their effects on operational performance are mixed. Studies in international and emerging-market settings often document negative impacts (e.g., Chang and Zheng, 2023; Pankratz and Schiller, 2024); for example, Pankratz and Schiller (2024) report declines on international suppliers' operating income and their customers. By contrast, work in developed economies frequently document resilience or even post-event gains (e.g., Leiter et al., 2009; Deryugina et al., 2018; Groen et al., 2020); for example, Erda (2024) shows that U.S. manufacturing plants upgrade machinery and raise productivity after federally declared floods. The common explanation is creative destruction: damage triggers replacement and, often, upgrading with reallocation toward more productive uses. Using granular establishment-level data with high-resolution flood exposure, my paper refines flood impact estimates and shows that NFIP mandate-induced coverage supplies liquidity that enables and effectively subsidizes capital upgrading, helping explain when and where businesses rebound.

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 shape climate disclosure and ownership structure (Ilhan et al., 2023), and that shareholder activism promotes voluntary disclosure with positive valuation effects (Flammer et al., 2021); related work finds that extreme temperature shocks impair performance, but lead to little improvement in ESG metrics (Griffin et al., 2025). Building on these studies and using LLM-classified disclosures from earnings calls and 10-Ks, I show that pre-event opportunity disclosure operates as a preparedness signal: establishments linked to disclosing parents recover more after floods, and equity markets react less negatively to flood news, indicating that prices reflect both risk-sharing capacity and mapped exposure.

The paper proceeds as follows. Section 2 summarizes the institutional background. Section 3 describes the inundation, FEMA flood-map, establishment, and disclosure data. Section 4 quantifies the insurance channel in six steps: (i) a triple-difference design; (ii) a boundary-localized RD-DDD; (iii) test of mandate salience using mortgage activity; (iv) coverage depth; (v) multi-site substitution within corporate parents; and (vi) robustness, including a national extension and the 2007 NYC map revision; and a concluding subsection on federal spending that examines complementary public liquidity from SBA lending and FEMA Public Assistance. Section 5 links parent disclosures to establishment recovery and analyzes equity-market reactions, providing evidence on the information/preparedness channel on both real and financial margins. Section 6 concludes with implications for chronic flood risk.

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 Special Flood Hazard Areas (SFHAs) (the 100-year floodplains with 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 in this paper is the mandatory purchase requirement: when a loan is made, increased, extended, or renewed on collateral located in a FEMA SFHA by a covered lender, flood insurance must be in place for the collateral for the life of the loan. For commercial borrowers, this requirement binds primarily through three lender groups created by the 1994 Reform Act's amendments to 42 U.S. Code §4012a: (i) federally regulated lenders (banks, thrifts, credit unions supervised by OCC/FDIC/Federal Reserve/NCUA); (ii) federal agency lenders/guarantors such as SBA, Federal Housing Administration and United States Department of Agriculture; and, to a much smaller extent for business property, (iii) GSE channels (largely housing-focused). In practice, the mandate most often reaches small and mid-sized businesses that borrow from depository institutions or use federally guaranteed credit.

The requirement applies to any loan secured by a building (or unit) in an SFHA. If the lender also takes a security interest in contents such as equipment or inventory located in that building, contents coverage is required up to the insurable interest. For loans secured by multiple properties, only the buildings (and secured contents) in the SFHA require coverage; the lender must calculate the required amount per building and sum to meet the aggregate requirement (via one or multiple policies). The mandate does not apply to credit extended by non-regulated private lenders, debt funds, or CMBS conduits that are neither federally regulated nor selling the loan into a covered channel, and it does not apply to unsecured loans (or secured solely by collateral that is not a building/contents in an SFHA). Large commercial firms, especially those with substantial real estate holdings, frequently finance with such private/capital-markets lenders and carry manuscript or layered private flood programs, sometimes foregoing NFIP coverage except to reduce deductibles or satisfy covenants and 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).

On market structure, NFIP dominates residential coverage, while commercial coverage is split between NFIP and private policies. In 2017, NFIP collected roughly $3.5 billion in total premiums; NAIC filings report about $589 million in private flood premiums, approximately 64% commercial (Horn and Webel, 2018; Carrier Management, 2018). Private commercial policies are concentrated in high-value or multi-location risks and frequently serve as excess above

NFIP limits or as manuscript, multi-peril forms. A 2019 rulemaking required covered lenders to accept qualifying private flood policies as satisfying the mandate, expanding substitution possibilities but not altering the underlying obligation to maintain flood insurance on mortgaged SFHA collateral. Consistent with this, all validation exercises using NFIP policy data in this paper are restricted to 2000-2018, when NFIP was the primary mapped source of commercial flood coverage.

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). These are zones with at least a 1% annual chance of flooding and are commonly referred to 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 flood, 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.

For disclosure-based measures, I first retain a risk-opportunity split, with the opportunity side refined into the two categories. An insurance-related opportunity captures pre-event statements about preparedness, coverage, or indemnification (e.g., business-interruption policies, expected or realized claim proceeds) and also includes insurance-related services such as underwriting, brokerage, or program administration tied to flood risk. A government spending opportunity captures potential revenue from public programs and contracting, not just disaster loans or grants; for example, FEMA/HUD-funded debris removal and mitigation projects, infrastructure repair or longer-run resilience partnerships with public agencies. Appendix Tables A1-A2 show earnings-call examples with model rationales. For analyses of pre-disaster opportunity disclosure, I mainly rely on earnings calls because they are more precisely timed and more informative as the management would discuss concrete forward-looking risk and opportunities. Details of other classification categories such as physical risk and regulatory risk are in Appendix A.1.

Appendix Tables A6 and A7 validate the disclosure measures. In firm-quarter panel regressions with firm, industry-year, and year-quarter fixed effects, firms are more likely to disclose when they have a larger SFHA footprint and recent flood experience. Results are robust to alternative definitions of exposure and realized flooding, supporting the construct validity of the classification.

Figure 2 illustrates the evolution of flood-related disclosures over time. Panel (A) shows that

[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.

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

I obtain property-level market values from the NYC Department of Finance Property Valuation and Assessment, clean and geocode addresses, and link parcels to establishments (via spatial join, with remaining matches completed using tax-lot/BBL). I exclude residential and government/public facility classes, retaining commercial/industrial properties. To measure pre-Sandy mortgage intensity, I combine NYC ACRIS mortgage/deed records with the Real Property Legals to recover BBLs, drop residential property types using building-class codes, merge to PLUTO parcels, and aggregate to parcel-buffer, census block group, and neighborhood scales.

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 The Insurance Channel of Post-Disaster Recovery

Before turning to mechanism, I first document the reduced-form effects of floods on establishments nationwide. Using granular establishment data and event studies, I estimate post-flood dynamics and find that both employment and sales recover and rise significantly in the years following major floods. The analyses and results are in Appendix A.2 and motivate a mechanism-based analysis.

This section tests whether insurance operates as a key mechanism behind the recovery. As described in Section 2, properties located within FEMA's Special Flood Hazard Area (SFHA) with federally regulated or insured mortgages are subject to the National Flood Insurance Program's (NFIP) mandatory purchase requirement. This regulatory feature increases the likelihood that businesses located inside the SFHA hold flood insurance relative to otherwise similar businesses outside the SFHA during my sample period from 2000 to 2018. I use this institutional feature to identify the effect of insurance on post-disaster recovery.

4.1 Baseline and Boundary-Based Designs

I use two complementary research designs to identify the insurance channel. First, a difference-in-differences-in-differences (DDD) specification around Hurricane Sandy compares outcomes for flooded and non-flooded establishments inside versus outside the SFHA before and after the storm. Second, a boundary-localized RD-DDD restricts the sample to establishments located within a narrow distance of the SFHA boundary and estimates the same inside-outside, pre-post contrast locally. As a robustness check, I exploit the 2007 New York City flood map revision, which reclassified many parcels into the SFHA prior to Sandy, as an exogenous shift in insurance requirements and risk salience to validate the mechanism.

Triple Difference: Inside-Map Flooded Sites Recover More

The main hypothesis is that, conditional on being flooded, establishments located inside the SFHA recover more in the post-disaster period than comparable flooded establishments located outside the SFHA. I test this hypothesis using Hurricane Sandy as a quasi-experiment, focusing on New York City where I can also exploit the 2007 flood map revision. Sandy struck in October 2012 and was one of the costliest storms in U.S. history and caused over $19 billion in damages. The event provides a sharp post period and significantly heightened public awareness of climate risk, especially among local residents and businesses.

A potential concern with using FEMA floodplain designation as an instrument for insurance 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 show commercial insurance uptake was systematically lower outside floodplains before Hurricane Sandy and 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 3, 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 3 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 3 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 by showing that 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:

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times I(FloodPlain)_{i,pre} \\ &+ \theta_1 Post_t \times I(FloodPlain)_{i,pre} + FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $Flood_i$ is an indicator for whether establishment i was exposed to Hurricane Sandy flooding, and $I(FloodPlain)_{i,pre}$ 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 4. 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 4 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 triple-difference (RD-DDD) 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 RD-DDD 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:

$$
\begin{aligned}
y_{i,t} = & \beta_1 Flooded_i \times Post_t \times I(Floodplain)_{i,pre} \\
& + \gamma_1 Flooded_i \times Post_t + \gamma_2 Post_t \times I(Floodplain)_{i,pre} + \gamma_3 Flooded_i \times I(Floodplain)_{i,pre} \\
& + f(r_i) + \alpha_{nbh,t} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

where $y_{i,t}$ are establishment employment, $I(Floodplain)_{i,pre}$ 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 5 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 2 are reported in Table 5. Across multiple specifications using triangular and rectangular kernels and both constant and MSE-optimal bandwidth proposed 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 RD-DDD assumptions, I conduct two additional checks. Figure 6 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-DDD specification, another identifying assumption is parallel trends in the absence of treatment. Panel B of Figure 6 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.

Recovery Effects Among Inside Floodplain Firms

Having shown that the NFIP mandate strengthens recovery relative to otherwise similar flooded establishments outside floodplains, I also restrict attention to firms inside FEMA floodplains and ask what the recovery path looks like among establishments that all face the same insurance mandate. I focus on establishments inside the pre-Sandy FEMA floodplain and estimate a difference-in-differences that compares flooded to non-flooded establishments before and after Sandy.

Appendix Table A13 shows that the post-Sandy coefficient on flooded is positive and statistically significant. Because treated establishments bear the damage shock while controls do not, a positive post-Sandy coefficient reflects a net gain. It implies that insurance-financed rebuilding more than offsets the losses, so flooded establishments outperform comparable floodplain peers rather than merely returning to trend.

4.2 Mortgage Intensity: Where the Mandate Bites

Flood map targeting may be imperfect: maps can misclassify risk, and firms outside the floodplain may face material risk but no mandate. Enforcement of the NFIP purchase requirement is transaction-triggered: lenders check for coverage when they make, increase, extend, or renew a mortgage on SFHA property so compliance is most salient at origination and refinancing.[3] Thus, some inside SFHA businesses without federally regulated/insured mortgages may be uninsured, while some outside SFHA properties may insure voluntarily. If the insurance channel is causal, its real effects should be most visible where lender enforcement is most likely and the mandate is more likely to bind. I therefore use pre-Sandy local mortgage intensity around each establishment as a proxy for the likelihood that inside-SFHA establishments were subject to a binding lender check.

To test this mandate binding hypothesis, I extend the baseline triple-difference specification by interacting the inside floodplain term with mortgage intensity. Specifically,

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times I(FloodPlain)_{i,pre} \\ &+ \beta_3 Flooded_i \times Post_t \times I(FloodPlain)_{i,pre} \times MortgageIntensity_b \\ &+ \gamma \text{ (lower-order terms)} \\ &+ FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $y_{i,t}$ is log employment or sales, and $I(FloodPlain)_{i,pre}$ indicates whether establishment i was located in the floodplain before Sandy so map status is pre-determined with respect to the shock. $MortgageIntensity_b$ is pre-Sandy mortgage intensity measured at the spatial scale (parcel or census block group) and fixed over time in the panel. I construct three measures: i) a parcel-level indicator of whether a commercial mortgage exists on the parcel before Sandy; ii) a count-based measure, defined as the number of commercial mortgages divided by the number of commercial real properties in the area; and a dollar-based measure, defined as the total dollar amount of commercial mortgages divided by the market value of commercial real property in the area. The intensity measures are expressed in percent. The lower-order interaction

[3] Board of Governors of the Federal Reserve System, Consumer Compliance Handbook: Regulation H - Flood Disaster Protection, current version at: https://www.federalreserve.gov/boarddocs/supmanual/cch/flood.pdf (accessed September 15, 2025)

terms include $Flooded_i \times Post_t \times MortgageIntensity_b$, $Post_t \times I(FloodPlain)_{i,pre}$ and $Post_t \times MortgageIntensity_b$. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects, with standard errors two-way clustered by establishment and year. In this specification, β_3 captures mandate salience, how the inside premium varies with local mortgage prevalence.

Table 6 reports the results. Columns (1)-(2) restrict the sample to establishments located inside the floodplain, and present within-floodplain triple-difference specifications to benchmark the baseline effect. The remaining columns implement the quadruple-difference specification in the full sample using each mortgage-intensity measure and geography. Across geographies and definitions of mortgage prevalence, the quadruple interaction is positive and statistically significant. Lower-order interaction terms with mortgage intensity are small and generally insignificant, consistent with mortgage prevalence amplifying the inside-map effect rather than proxying for broader credit conditions. These results support the mandate-binding hypothesis and indicates that the post-flood inside-outside recovery differential is larger precisely where pre-Sandy mortgage activity is higher and lender enforcement is more likely.

4.3 Intensive Margin of the NFIP Coverage

The baseline analysis shows that establishments inside FEMA designated floodplains at the time of Hurricane Sandy experienced stronger post-flood recovery. That result reflects an extensive-margin effect as it captures the average recovery premium from being inside the floodplains, treating all mandated establishments as equally insured. In reality, NFIP protection for non-residential buildings is capped at \$500,000 (plus a separate contents limit). This cap means that insurance depth varies cross-sectionally: establishments with building values well below the cap can be fully indemnified for structure losses, while those above the cap face uninsured exposure unless they layer on private flood coverage. This institutional feature allows me to test the intensive margin of insurance of whether greater coverage relative to property value yields stronger recovery.

If the insurance channel operates through indemnity payouts, the post-disaster recovery premium for flooded establishments in floodplains should be increasing in the proportion of building value covered by NFIP. Specifically, fully insured establishments (at or below the cap) should recover more than partially insured ones (above the cap), with the largest gains for those far below the cap, smaller gains for those near the cap, and minimal gains for those above the cap.

To test this intensive-margin hypothesis, I extend the baseline triple-difference specification by interacting the floodplain indicator with measures of coverage depth. Specifically,

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times I(FloodPlain)_{i,pre} \\ & + \beta_3 Flooded_i \times Post_t \times I(FloodPlain)_{i,pre} \times BelowCap_{i,t} \\ & + \gamma(\text{lower-order interactions with } BelowCap_{i,t}) \\ & + FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

where $y_{i,t}$ is log employment or sales, $I(FloodPlain)_{i,pre}$ indicates whether establishment i was located in the floodplain before Sandy, and $BelowCap_{i,t}$ equals one if the property's market value is $\leq$ \$500,000 in year t. Alternatively, I also replace this with a continuous coverage ratio, calculated as NFIP cap divided by building value, capped at 1. The lower-order interactions with $BelowCap_{i,t}$ include $Flooded_i \times Post_t \times BelowCap_{i,t}$ and $Post_t \times I(FloodPlain)_{i,pre} \times BelowCap_{i,t}$. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects, with standard errors two-way clustered by the establishment and year. β_2 captures the extensive-margin NFIP mandate effect and β_3 captures the intensive-margin gain from being fully covered.

Table 7 presents the estimation results. Column (1) restricts the sample to establishments located inside the SFHA. The triple interaction $Flooded_i \times Post_t \times BelowCap_{i,t}$ is positive and statistically significant, indicating that, conditional on flooding and being inside the SFHA, establishments whose properties are at or below the NFIP limit recover more than otherwise similar above-cap peers. Columns (2)-(4) use the full sample and include the inside-SFHA indicator. The DDD term of $Flooded_i \times Post_t \times I(Floodplain)_{i,pre}$ remains positive, consistent with the mandate/salience channel at the extensive margin. The intensive-margin result is robust when depth is measured continuously: the four-way coefficient on CoverageRatio in Column (3) is positive and significant, implying that a higher covered share is associated with a larger post-Sandy rebound for flooded establishments inside the SFHA.

To further assess the monotonic coverage-recovery relationship, Column (4) splits BelowCap into FarBelowCap ($\leq$ \$250,000) and NearCap (\$250,000-\$500,000). The four-way coefficient is largest for FarBelowCap and smaller for NearCap. This pattern is consistent with a coverage gradient: the intensive-margin benefit is strongest when properties are well under the limit, weaker near the limit, and smallest above the limit. Finally, Column (5) excludes the top 5% of establishments by pre-Sandy employment to address the concern that very large firms may obtain substantial private coverage beyond the NFIP cap. The estimates are very similar, indicating that the intensive-margin findings are not driven by the largest establishments.

Figure 7 plots the quadruple-difference coefficients of the event study specification, distinguishing between those located inside and outside FEMA-designated floodplains and those property values that are below and above NFIP insurance cap. The pre-Sandy coefficients are statistically indistinguishable from zero, providing visual support for the parallel trends assumption. Beginning in 2013, businesses inside floodplains and below the NFIP insurance building coverage cap exhibit consistently higher employment growth, suggesting that deeper insurance coverage facilitates recovery and accelerates rebuilding.

As a robustness, I implement a regression-discontinuity difference-in-differences (RD-DiD) around the NFIP \$500,000 building-coverage cap within SFHAs. Using pre-Sandy property market value as the running variable and the cap as the cutoff, the design compares the post- versus pre-Sandy discontinuity at the threshold for flooded establishments relative to non-flooded ones. I estimate local linear specifications with triangular kernel weights and MSE-optimal bandwidths, including establishment, neighborhood-by-year, and industry-by-year fixed effects; results are stable to alternative kernels, bandwidths, and a quadratic polynomial. Consistent with the insurance-depth mechanism, flooded firms just below the cap recover more than those just above; estimates are economically meaningful and robust. See Appendix A.3 (Table A14 and Figures A5) for the specification and full results.

4.4 From Liquidity to Rebuilding: Capital Upgrades

If insurance relaxes financing frictions after a disaster, an early and observable margin of adjustment should be physical investment in premises. This includes shell repairs, upgrades to mechanical, plumbing, and life-safety systems, and interior renovations that restore and expand operating capacity. Such activity should arrive quickly and be concentrated where mapped flood risk and realized inundation coincide. This subsection provides direct evidence consistent with that mechanism.

I re-estimate Equation (1) using outcomes constructed from New York City Department of Buildings (DOB) issued, initial permits aggregated to the parcel (tax-lot)-year level.[4] I retain New Building and Alteration I/II jobs and core systems work, and I exclude signage, equipment-only, and curb-cut permits, as well as renewals and revoked records. One- to three-family houses are dropped, and mixed-use and commercial parcels are kept. Larger multi-tenant parcels tend to file more permits. To avoid overweighting such locations, I also normalize permit counts by the parcel's pre-Sandy establishment count, which yields an upgrading-intensity measure per initial tenant base.

Table 8 reports triple-difference estimates. Columns (1) to (3) use the full post-Sandy period. The interaction terms imply that flooded locations inside the pre-Sandy FEMA floodplain exhibit higher construction intensity than otherwise similar flooded locations outside the floodplain. Columns (4) and (5) split the post period into Early (2012-2015) and Later (2016-2018) windows. The windowed specifications indicate a clear increase in upgrade activity in the Early window for parcels that were both inside the floodplain and inundated, with smaller and statistically weaker effects in Later years. Estimates using contemporaneous establishment counts are similar in sign and magnitude but mechanically larger. Because the denominator can change with post-Sandy exits and entries, I view these as per-survivor intensities and present the pre-Sandy denominator in the main analysis.

Figure 8 presents an event study with event time relative to 2012 that includes the corresponding lower-order terms. There is no economically large pre-trend, and we can see a modest uptick in 2012, which is consistent with emergency stabilization and make-safe work issued in late 2012 following Sandy. The main increase appears in 2013 to 2015, followed by attenuation thereafter. Dropping 2012 leaves the 2013 to 2015 surge unchanged.

The timing and composition of permits are consistent with an insurance-liquidity channel that finances near-term rebuilding. The evidence provides a direct physical counterpart to the

[4]Parcels are identified by NYC's Borough-Block-Lot (BBL). Building identifiers (BINs) can change when a structure is demolished and rebuilt, whereas the BBL remains stable. Accordingly, I aggregate to parcel-year. Because the establishment data do not contain suite or unit identifiers, I interpret permits as premises-level investment at the parcel.

establishment-level recovery results and links insurance to capital upgrading, which in turn supports improvements in operating performance.

4.5 Enterprise vs. local: firm floodplain footprint

The baseline and intensive margin results show that place-based access to insurance through FEMA maps, the lender mandate, and coverage depth raises post-flood recovery. Many establishments, however, belong to multi-site firms that manage risk at the enterprise level (e.g., blanket or portfolio policies, centralized liquidity, standardized continuity plans). If such firm-wide arrangements are material, they should compress location-specific differences generated by the local mandate: when a parent carries broader exposure to mapped flood risk across its network, an establishment just inside the SFHA should look more like one just outside because preparedness and coverage are coordinated at the firm rather than dictated solely by the site's regulatory status. The resulting prediction is that the inside-floodplain recovery attenuates as the parent's SFHA footprint grows.

To test this prediction, I augment the baseline triple-difference with a firm-level floodplain exposure interaction:

$$\begin{aligned}
y_{i,t} =& \beta_1 Flooded_i \times Post_t \times I(Floodplain)_{i,pre} \\
&+ \beta_2 Flooded_i \times Post_t \times I(Floodplain)_{i,pre} \times FloodplainExposure_{firm} \\
&+ \gamma \text{ (lower-order terms)} \\
&+ FloodRisk_{i,t} + \alpha_i + \alpha_{firm,t} + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t}
\end{aligned}$$

where $y_{i,t}$ is log employment or sales. $FloodplainExposure_{firm}$ captures the parent firm's ex-ante pre-Sandy floodplain footprint using three measures: (i) a dummy for whether the parent has any establishment in the SFHA before Sandy; (ii) a risk exposure dummy equal to one if the parent's pre-Sandy count of establishments in FEMA floodplain is at or above the 5th percentile across firms; and (iii) the log count of establishments in FEMA floodplain before Sandy. $I(FloodPlain)_{i,pre}$ indicates whether establishment i was located in the floodplain before Sandy so map status is pre-determined with respect to the shock. The lower-order interaction terms include $Flooded_i \times Post_t$, $Flooded_i \times Post_t \times FloodplainExposure_{firm}$, $Post_t \times I(FloodPlain)_{i,pre}$

and $Post_t \times FloodplainExposure_{firm}$. All specifications include establishment, firm-by-year, neighborhood-by-year, and industry-by-year fixed effects, with standard errors two-way clustered by establishment and year. The coefficient of interest β_2 measures how the inside floodplain treatment effect varies with the firm's footprint.

Table 9 presents the results. In columns (1) and (4), where the footprint is a dummy for whether the parent has any establishment in the SFHA pre-Sandy, the quadruple interaction is statistically significant for both employment and sales, suggesting the inside-map recovery is smaller when the parent has pre-existing mapped exposure elsewhere. Similarly, when I use risk exposure binary variable in Columns (2) and (5) and number of establishments in FEMA floodplain in Columns (3) and (6), the four way interaction term is negative and generally significant for both employment and sales. These results indicate that enterprise risk management substitutes for the local map-and-mandate channel: the place-based premium is largest for small-footprint, locally constrained firms and smallest for parents with broad mapped exposure whose coverage and liquidity are coordinated at the corporate level.

4.6 Robustness Checks

National level analysis

To complement the Hurricane Sandy analyses, I extend the baseline NFIP flood insurance mandate 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:

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

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^* 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 A4 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.

FEMA Map Revision as a Shock to Flood Insurance Mandates

In 2007, FEMA implemented a major revision of New York City's Flood Insurance Rate Map (FIRM), reclassifying a collection of areas into the FEMA floodplain without contemporaneous changes in hydrological conditions. The remapping expanded the set of properties subject to the NFIP lender-enforced mandatory purchase requirement and likely heightened risk salience through increased lender scrutiny and regulatory compliance checks. Because the boundary changes were driven by updated modeling and administrative review rather than short-run shifts in underlying flood risk, the map revision provides plausibly exogenous variation in insurance requirements that is orthogonal to unobserved factors affecting near-term economic performance.

I use this institutional shock to evaluate the insurance channel from a complementary perspective. If NFIP coverage facilitates recovery, then flooded establishments newly designated inside the floodplain in 2007 should experience greater post-Sandy recovery than otherwise similar flooded establishments that remained outside the floodplain without the mandate.

Before testing this hypothesis, as the first stage, I examine whether the 2007 revision increased commercial NFIP coverage in Newly-In areas. Using NFIP insurance policy data at the census block group level from 2000 to 2011, I estimate:

$$\begin{aligned} Coverage_{i,t} =& \delta_1 postRevision_t \times NewlyIn_b + \delta_2 postRevision_t \times NewlyOut_b \\ &+ X_{b,t} + \alpha_b + \alpha_{nbh,t} + \epsilon_{b,t} \end{aligned}$$

where $newlyIn_b$ and $newlyOut_b$ measure the percentage of census block group land newly added to or removed from the FEMA floodplain. Outcomes include policy count, log total policy cost, and log total building and content coverage. Table 10 shows that census block groups with larger Newly-In shares experienced statistically significant increases in all coverage measures after the map revision, controlling for Newly-Out shares. The event-study evidence in Figure 9 confirms that these differences emerge sharply after 2007, with no discernible pre-trends, consistent with a discrete and persistent shock to insurance access and salience.

To estimate the effect of map-induced insurance access on post-Sandy performance, I use the following triple-difference specification:

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times NewlyIn_i \\ &+ \theta_1 Post_t \times NewlyIn_i + FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned}$$

where $Flood_i$ is an indicator for whether establishment i was exposed to Hurricane Sandy flooding, and $NewlyIn_i$ identifies establishments located in parcels added to the FEMA floodplain in 2007. $y_{i,t}$ is log employment or log 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. Establishment fixed effects absorb time-invariant heterogeneity, while industry-by-year and neighborhood-by-year fixed effects capture time-varying sectoral and local shocks.

Table 11 reports positive and statistically significant estimates of β_2: flooded establishments in Newly-In areas experienced 5.7-8.1% greater employment growth and 8.4-12.2% greater sales growth post-Sandy than comparable flooded establishments outside the SFHA. These effects are robust to restricting the control group to always-outside parcels in Columns 2 & 5, and to excluding the largest 5% of pre-Sandy employers to address potential influence from very large employers in Columns 3 & 6. The event study in Figure 10 shows no evidence of differential pre-Sandy trends, with the recovery advantage for Newly-In flooded establishments emerging only after 2012. Together with the first-stage results, these findings provide additional evidence that NFIP insurance access, enhanced by the 2007 map revision, significantly improved post-disaster firm recovery.

4.7 Government spending

The insurance results indicate that relaxing post-disaster financing frictions improves recovery. A natural question is whether federal programs supply additional liquidity that complements insurance filling gaps where coverage is thin or caps constrain indemnification.

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). Two programs are particularly relevant: SBA disaster loans, which inject working capital and repair funding directly to firms, and FEMA's Public Assistance (PA), which finances emergency response and infrastructure repair through local governments and nonprofits. I use these programs to test whether public funds operate as complementary liquidity consistent with the insurance mechanism.

4.7.1 SBA Disaster Loans

The SBA provides two main post-disaster loan programs. Physical Disaster Loans finance repair or replacement of damaged real estate, machinery, and inventory and are broadly available to firms of all sizes and most nonprofits. Economic Injury Disaster Loans (EIDL) supply working capital to small businesses unable to meet ordinary expenses due to a disaster.[5] EIDL eligibility is limited by industry-specific size standards and location within declared disaster areas. Public firms are generally ineligible for EIDL; thus, any effects of EIDL loans in my public firm sample

[5]EIDL funds cover regular and necessary operating expenses for eligible small businesses; they do not compensate for lost profits or expected sales.

are likely to reflect improvements among local small businesses.

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, the sample is restricted to ZIP codes with non-missing SBA loan values. I estimate:

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

where $y_{zip,t}$ is log employment or log establishments and $AfterFirstFlood_t$ is an indicator of whether year t is after the first flooding event. To focus on the first disaster experience and for identification, I exclude zip codes that experienced subsequent flood events later in the sample period. $SBALoanIntensity_{zip,t}$ is approved SBA loan dollars divided by the number of establishments, and its interaction with $AfterFirstFlood_t$ captures the variation in the intensity of disaster assistance conditional on experiencing a flood. Controls $X_{zip,t}$ include FEMA floodplain share, historical flood counts, SBA-verified losses, and demographics; fixed effects absorb time-invariant local factors and state-year shocks.

Table 12 Panel A shows that a \$1,000 increase in EIDL disbursement per establishment is associated with a 4.26% increase in employment and a 0.8% increase in the number of establishments in Columns (1)-(5), consistent with EIDL's design to support small business operations. Effects are also evident for larger establishments (≥ 50 employees): both EIDL and total SBA loan intensity predict increases in the count of large establishments in Columns (7)-(8), suggesting spillovers from small business recovery to the broader local economy. Estimates remain statistically significant under alternative scaling by population in Appendix Table A15.

4.7.2 FEMA Public Assistance Spending

Beyond firm-targeted loans, the federal government supports community recovery through FEMA's Public Assistance (PA) program, which finances emergency response and permanent infrastructure repair. Emergency work covers debris removal and protective measures, while permanent work funds roads, utilities, public buildings, and parks, with typical completion targets of 18 months.

Table 12 Panel B links county-level PA intensity to local labor market outcomes. 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 in Columns (1) and (2), suggesting that infrastructure investment supports labor market recovery. Appendix Table A15 focuses on permanent-work categories and shows broadly similar patterns, with PA-funded reconstruction associated with continued gains in job creation.

Taken together with the SBA results, these estimates indicate that federal disaster spending provides complementary post-disaster liquidity: direct firm support (EIDL) coincides with higher employment and establishment counts, and community-scale PA investments are associated with stronger local job growth. Because both sets of results are estimated from aggregated data, they do not identify precise mechanisms, but they provide suggestive evidence that federal aid supports local business recovery through both firm-level financing and public-funded rebuilding.

5 Firm Preparedness and Post-Flood Outcomes: Real and Financial

This section examines the information/preparedness channel that operates alongside place-based insurance rules. Because establishment-level insurance data are unavailable and NFIP compliance is imperfect, floodplain maps indicate where coverage is more likely but not which sites were actually insured at impact. I proxy firm preparedness using pre-event parent disclosures in 10-K filings and earnings calls that signal insurance capacity (and, separately, government-spending opportunities). I first bring this proxy into the establishment design to test whether disclosed parents' sites recover more after flooding, complementing the map-and-mandate indicators by identifying which firms likely pre-positioned liquidity. I then study how investors price major flood shocks, asking whether prior exposure and preparedness disclosures attenuate equity-market losses. For clarity, the real-side analysis includes all establishments linked to public parents, whereas the market tests are restricted to public firms; in both cases, disclosures are measured prior to the flood.

5.1 Firm Insurance Disclosure and Establishment Recovery

Because enforcement of the NFIP purchase requirement occurs at loan events, map-and-mandate indicators are an informative prior about coverage but cannot identify insurance in force at a specific site when the flood hits. To sharpen inference on the insurance channel and to capture corporate decisions made above the site level, I construct a pre-event, parent-level disclosure measure from 10-Ks and earnings communications that signals insurance preparedness (Section 3). These statements are made before the flood, so they proxy for corporate-level coverage and claims capacity rather than ex-post reactions.

I bring this proxy into the establishment design by interacting it with the baseline treatment. I test if disclosure captures insurance in force or related claims capacity, then flooded establishments whose parents disclosed insurance preparedness ex ante should exhibit larger post-flood recoveries than otherwise similar flooded establishments whose parents did not. In this interpretation, disclosure does not replace the map-and-mandate variables; it complements them by identifying which firms actually pre-positioned liquidity despite imperfect enforcement.

I estimate the following baseline specification:

$$\begin{aligned} y_{i,t} =& \beta_1 Flooded_i \times Post_t + \beta_2 Flooded_i \times Post_t \times PreInsuranceDisclosure_i \\ &+ FloodRisk_{i,t} + \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned} \tag{5}$$

where $y_{i,t}$is log employment (or sales) at establishment i in year t, $Flood_i$ indicates Sandy inundation, $Post_t$ indicates the post-Sandy period, and $PreInsuranceDisclosure_i$ is the percentage of pre-Sandy calls in which the parent firm discussed insurance coverage, payouts, or related opportunities. $FloodRisk_{i,t}$ indicates whether establishment i is currently located within the FEMA floodplain. The dependent variables $y_{i,t}$ include measures of establishment employment and sales. Establishment, industry-by-year, and neighborhood-by-year fixed effects are included to account for unobserved heterogeneity and time-varying local or sectoral trends. To align with the inside flood risk mechanism, I also estimate a specification that adds the inside-floodplain margin and the corresponding four-way interaction to the above baseline specification.

Table 14 shows that establishments whose parents had disclosed insurance preparedness before the event recover more after flooding. In Columns (1)-(3), the coefficient on $Flooded_i \times Post_t \times PreInsuranceDisclosure$ is positive and statistically significant for employment. Columns (4)-(6) report analogous estimates for sales with the same pattern. When I add the floodplain margin, the four-way interaction term is positive and significant, indicating that the disclosure-recovery differential is stronger for establishments inside mapped high-risk areas where the mandate and salience are most relevant. These estimates indicate that pre-event insurance disclosure behaves like a preparedness signal that aligns with faster post-flood operational recovery, especially in locations where mapped rules make indemnification more likely.

5.2 Investor Reactions and Cross-Sectional Pricing

Flood announcements convey information about expected cash-flow disruptions such as physical damage, downtime, and supply-chain frictions, and about how preparedness can buffer these shocks through pre-positioned liquidity from insurance or access to post-disaster public programs. If this information/preparedness channel is economically meaningful and partly unanticipated, equity prices should adjust on impact. Accordingly, I expect exposed firms to experience negative abnormal returns around flood news; I further expect losses to be larger when exposure is a surprise (for firms without prior flood experience, with little mapped footprint, or lacking prior flood disclosure) and smaller when exposure is anticipated.

I implement an event-study around the onset of major flood events and estimate cumulative abnormal returns (CAARs) using the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. Expected returns are fit over the window $[-275, -20]$ trading days prior to the event; CAARs cumulate from five trading days before landfall to windows ending +1, +5, +10, and +20 days after landfall to account for weather forecast. The equity sample is restricted to public firms, and all disclosure measures are constructed strictly prior to the event.

The event study results in Table 15 indicate that market reactions are negative and increase in magnitude with the horizon. Under the Fama-French three-factor model, for example, CAAR equals -0.078% over $[-5, +5]$ and -0.277% over $[-5, +20]$, consistent with gradual incorporation of information about damage severity and operating disruption. As shown in

Figure 11, losses are sharper for first-time flood firms, for firms with little mapped exposure, as proxied by the share or number of establishments in the floodplains, and for firms lacking prior 10-K flood disclosure, consistent with markets penalizing unanticipated exposure and limited preparedness.

To formalize these gradients, I regress firm-level CARs on exposure and disclosure measures:

$$\begin{aligned} CAR_{i,j,[0,T_2]} =& \beta_1 I(PreviouslyFlooded)_i + \beta_2 NumEstbsInFP_i + \beta_3 PriorDisclosure_i \\ &+ \gamma FloodSeverity_j + X_{i,t} + \alpha_t + \alpha_{industry} + \epsilon_{i,j} \end{aligned}$$

where $I(PreviouslyFlooded)_i$ is a dummy variable of whether the firm has been flooded before, and $NumEstbsInFP_I$ captures the firm's log number of establishments in the floodplain. $PriorDisclosure_i$ distinguishes insurance-opportunity vs government-spending-opportunity disclosures made before the event. The outcome variable is the cumulative abnormal returns for firm i of flood j. $FloodSeverity_j$ includes event-level log number of death and displacement. $X_{i,t}$ is the list of firm characteristics including size, log assets, cash, debt, capex, and intangible asset ratio at the firm by year-quarter level. For conciseness, I estimate the specifications separately using event windows with $T_2 = 2$, 5, 10, and 20, respectively.

Table 16 presents the cross-sectional results. Panel A shows that prior government-spending opportunity disclosure is associated with attenuated losses: the coefficient is positive and statistically significant in all windows and grows with horizon, from 3.0 bps over [-5,0] to 15.9 bps over [-5,20]. The indicator for previously flooded firms is significantly positive in short windows. Event severity loads as expected: displacement is negative and significant across windows, while deaths are negative but insignificant. Panel B replaces government-spending disclosure with insurance-opportunity disclosure but the coefficients are insignificant across the event windows. Overall, prices reward floodplain-and-realized exposure and pre-event signals of access to government-linked reconstruction opportunities, but they do not systematically reprice on generic insurance-opportunity language. These cross-sectional estimates accord with the interpretation that investors place greater weight on scalable, externally funded reconstruction opportunities than on generic insurance references.

6 Conclusion and Discussion

This paper asks whether NFIP flood insurance helps businesses not only recover but recover stronger after major floods, and through what mechanism. Linking high-resolution inundation to FEMA flood maps at the establishment level, I show that mandate-induced coverage delivers liquidity via claims at the time of loss, materially strengthening post-event performance; reduced-form evidence in Appendix A.2 documents that recoveries can exceed pre-flood baselines.

A triple-difference design around Hurricane Sandy shows that flooded establishments inside Special Flood Hazard Areas (SFHAs) recover more in employment and sales than otherwise similar flooded peers just outside. A boundary-localized RD-DDD at floodplain borders confirms the same pattern within narrow geographic bands. Robustness exercises reach beyond the Sandy setting: a national extension (2000-2018) finds positive, persistent post-flood gains for establishments inside mapped floodplains relative to those outside, and New York City's 2007 flood map revision, which moved parcels into the FEMA floodplains prior to Sandy, yields additional evidence consistent with increased mandate exposure.

Mechanism tests point to insurance-provided liquidity. Recovery differentials are larger where pre-event mortgage activity is higher, indicating that effects are strongest where lender enforcement makes the mandate more likely to bind. On the intensive margin, establishments for which a greater share of losses can be indemnified recover more, and an RD-DiD at the \$500,000 NFIP commercial building cap corroborates this insurance-depth mechanism. The inside-floodplain advantage is attenuated for multi-site parents with broader mapped exposure, consistent with corporate risk management substituting for local mandate salience.

Preparedness at the parent level aligns with these establishment results. Using pre-event insurance-opportunity disclosure to proxy coverage or claims capacity, affiliated establishments recover more after flooding, regardless of whether they are located inside or outside floodplains. In equity markets, event studies show significantly negative reactions to flood news that deepen over longer windows; cross-sectionally, losses are smaller for firms with prior exposure and for those that disclosed government-spending opportunities ex ante, consistent with investors partially recognizing preparedness signals.

Federal disaster programs appear complementary to the insurance channel: ZIP-level SBA disaster loans coincides with post-flood gains in employment and establishment counts, and county-level FEMA Public Assistance spending is associated with stronger employment growth. These aggregate results do not identify specific channels but suggest that public funds supplement rules-based insurance where coverage is thin or limits bind.

While these results concern recovery after shocks, chronic exposure operates differently and is a different margin. Reduced-form evidence in Appendix A.4 shows that persistently higher flood risk is associated with weaker long-run growth at the establishment and county levels, with patterns consistent with population decline, higher job destruction and exit, and reduced industry diversity. Higher NFIP commercial premiums are also associated with weaker local activity, suggesting that the cost of coverage can weigh on growth even as insurance speeds rebuilding when shocks occur.

Taken together, by combining new granular data with complementary identification designs, the paper documents a causal insurance-liquidity channel for business recovery: mandate-induced coverage converts losses into cash at impact, allowing firms to rebuild and reallocate so that recovery exceeds baseline. Policy implications follow directly: the recovery premium depends on the functioning of floodplain-based rules: accurate maps, enforceable lender checks, adequate limits, and timely claims. Weakening these institutions would slow rebounds for already-exposed firms, as chronic flood risk continues to weigh on long-run growth.

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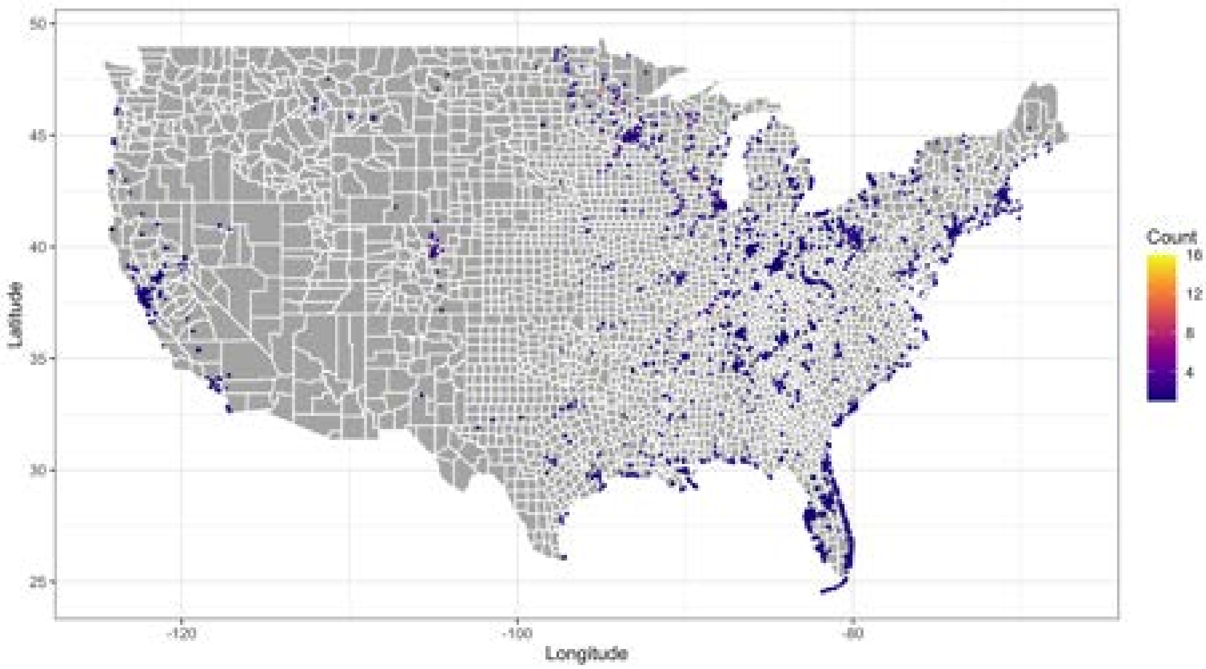
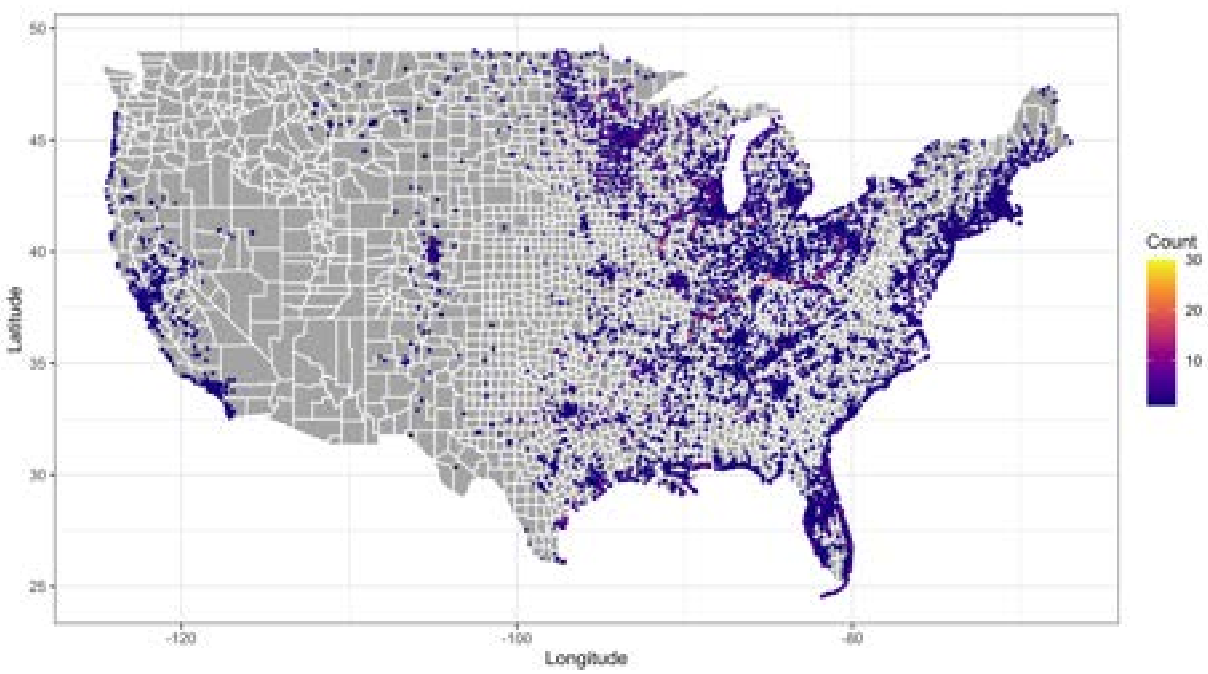
Figure

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

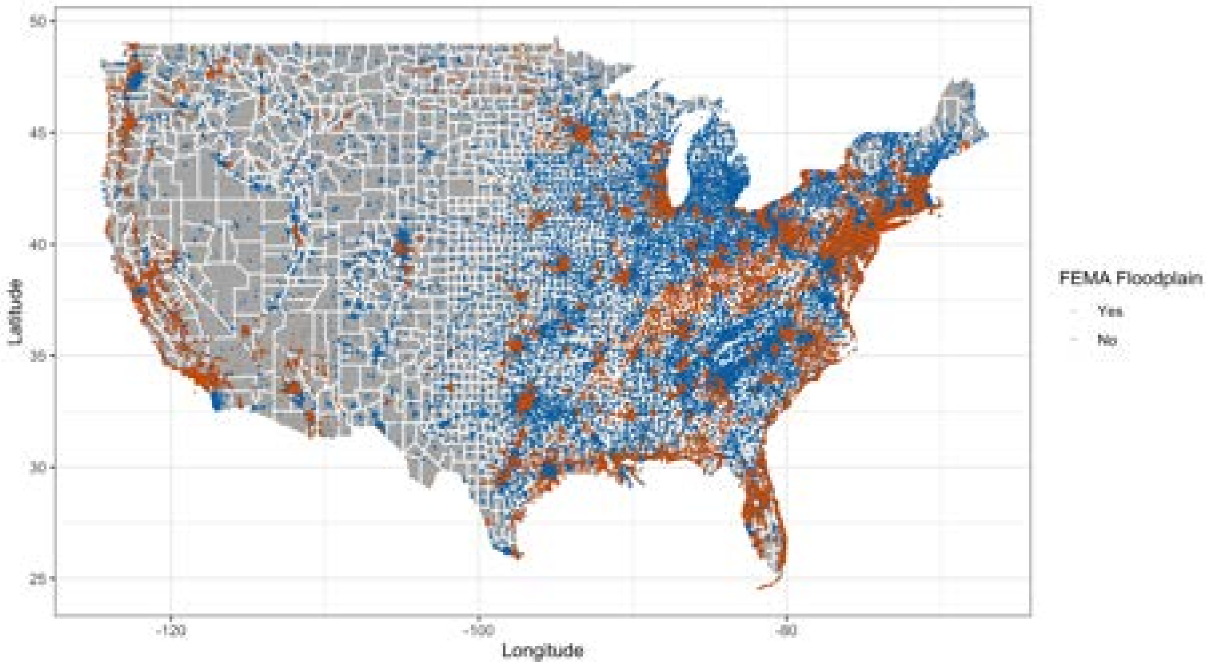


(A) Flooded Establishments



(B) Flooded Establishments w/ 1km Spatial Buffer

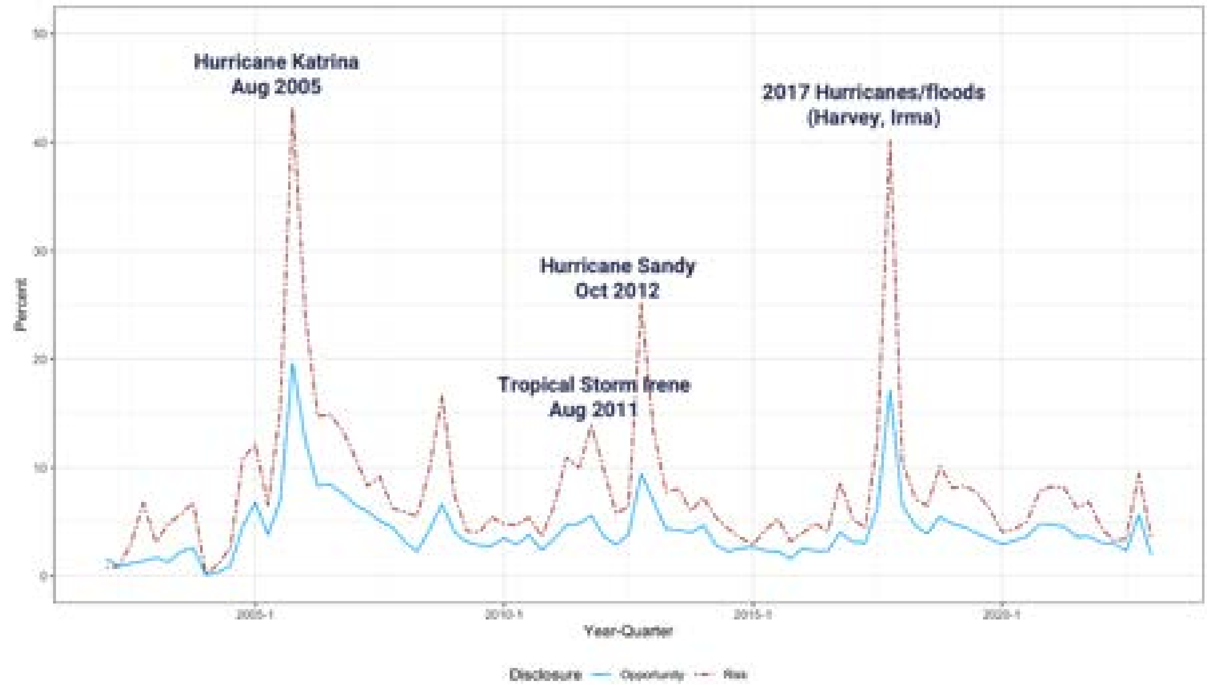
Figure 1: Geographic Distribution of Flooded Establishments and High-Risk Zones (Continued)



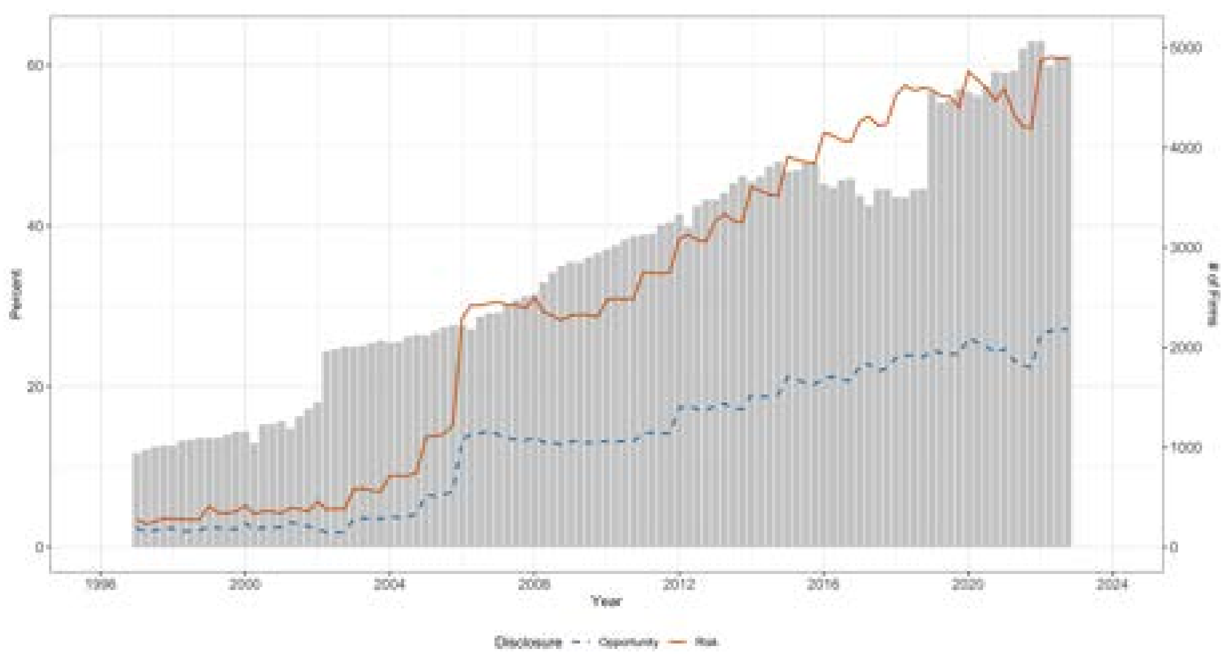
(C) Establishments in FEMA Flood plain

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



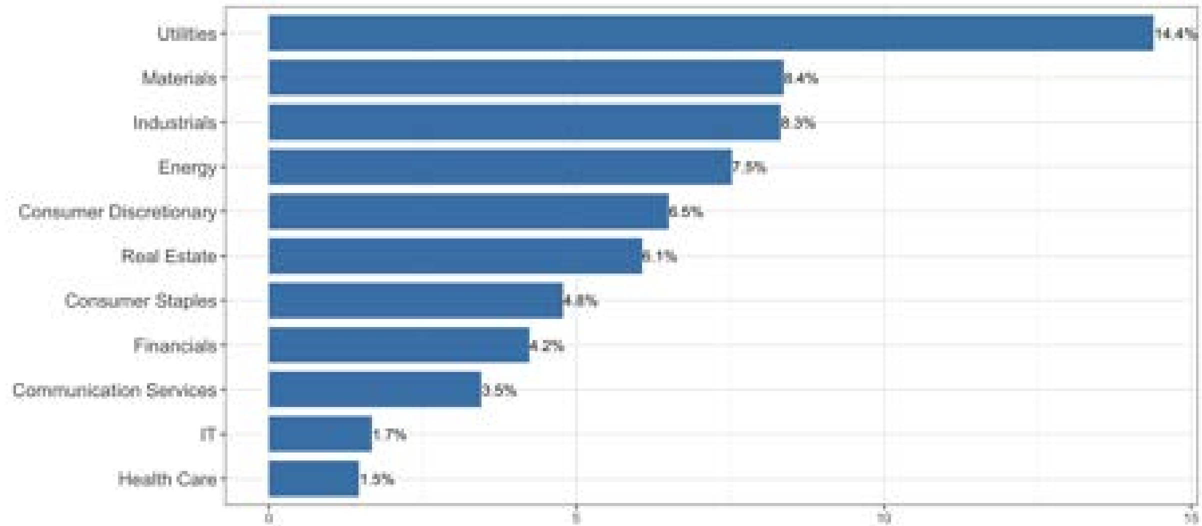
(A) Earning Calls



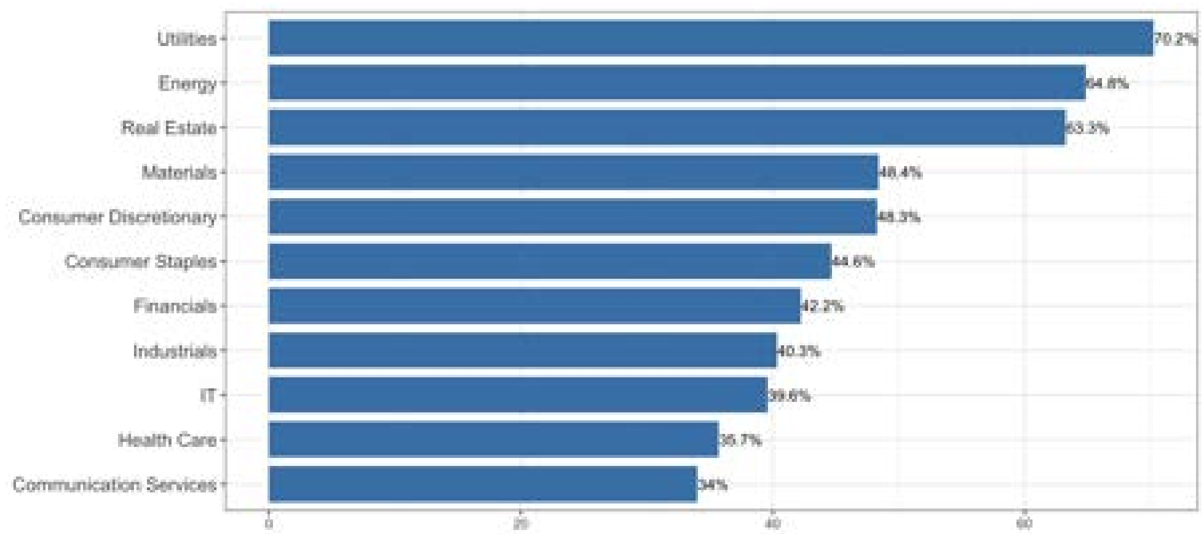
(B) 10-Ks

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



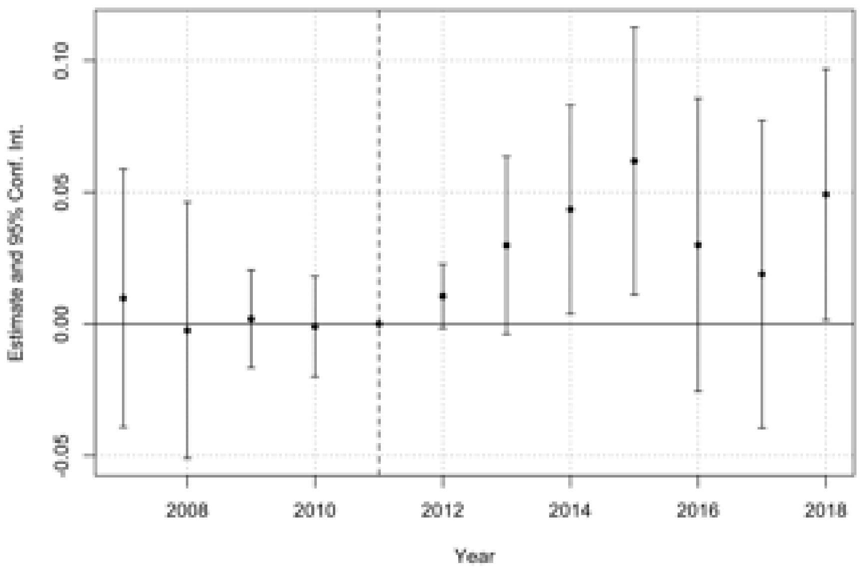
(A) Earning Calls



(B) 10-Ks

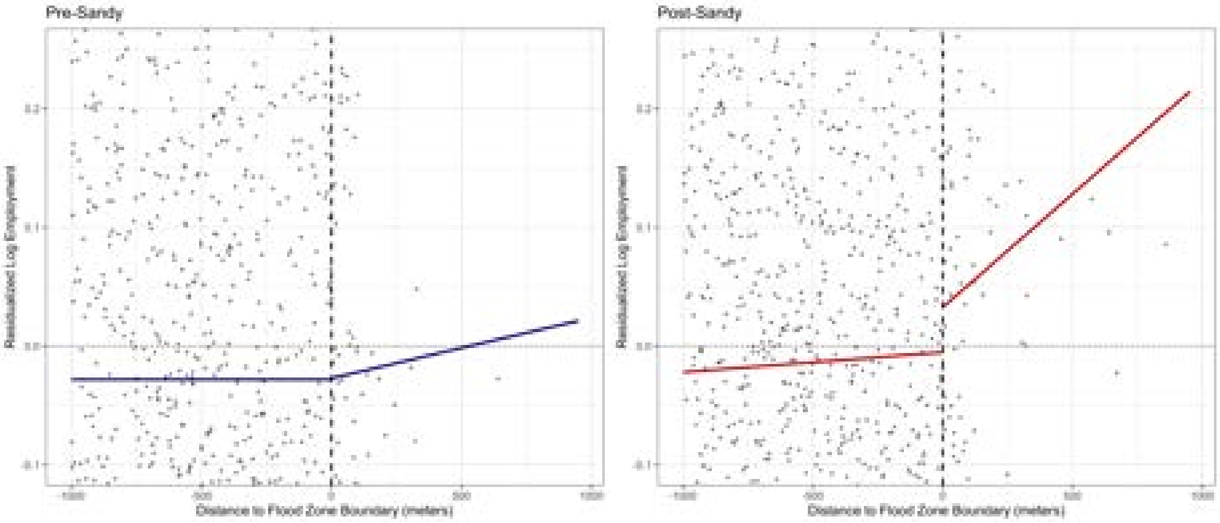
Notes: This figure reports the average percentage of firms within each GICS sector that disclosed flood-related risks or opportunities during the sample period. Disclosure percentages are calculated as the number of firms in a sector with at least one flood-related disclosure divided by the total number 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: Employment Recovery for Flooded Establishments Inside vs. Outside FEMA Floodplains



Notes: This figure plots event-time coefficients from a triple-difference specification examining employment recovery for establishments affected by Hurricane Sandy in New York City. Each coefficient shows the dynamic treatment effect for the interaction term $Flood_i \times I(Sandy - t = \tau) \times I(Floodplain)_i$, measuring the differential change in log employment for flooded establishments located inside FEMA-designated floodplains relative to similarly flooded establishments outside the floodplain. The omitted category is $\tau = -1$, the year before Hurricane Sandy. The vertical dashed line marks the year before Hurricane Sandy. The model includes all lower-order terms, establishment fixed effects, industry-by-year fixed effects, neighborhood-by-year fixed effects, and controls for flood risk. Error bars represent 95% confidence intervals.

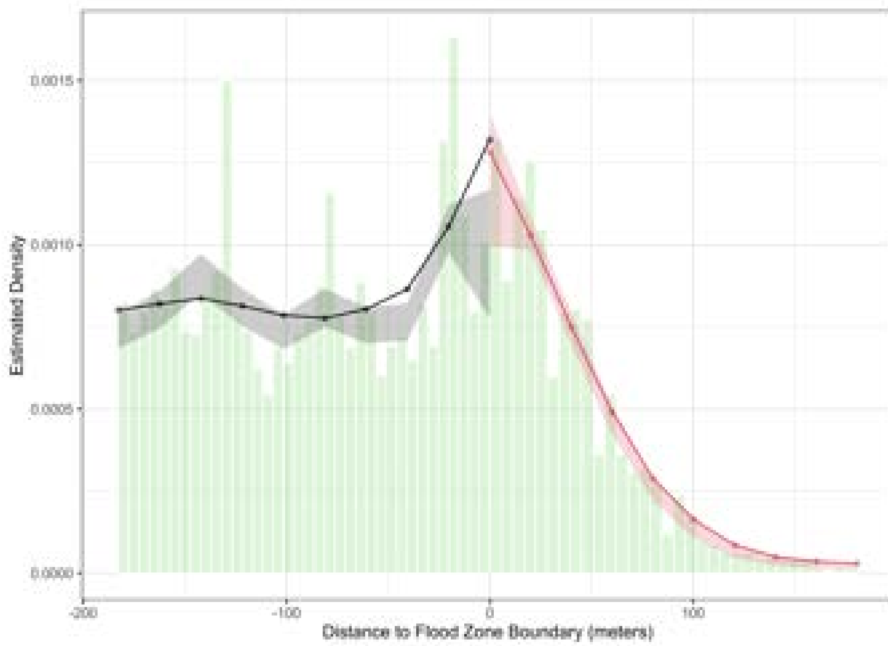
Figure 5: Spatial Regression Discontinuity: Insurance



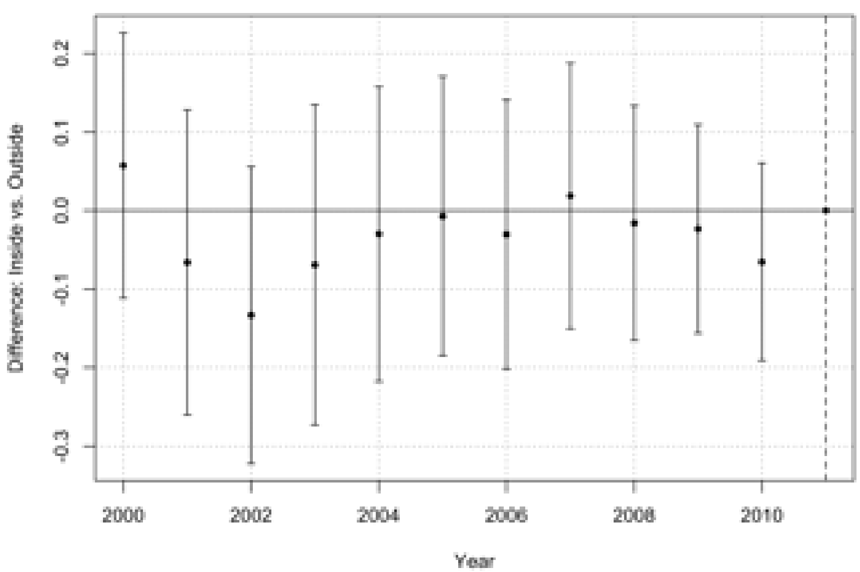
(A) Pre-Sandy: 2000-2011 **(B)** Post-Sandy: 2012-2018

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 6: Spatial RDD-DiD Checks at the Floodplain Boundary



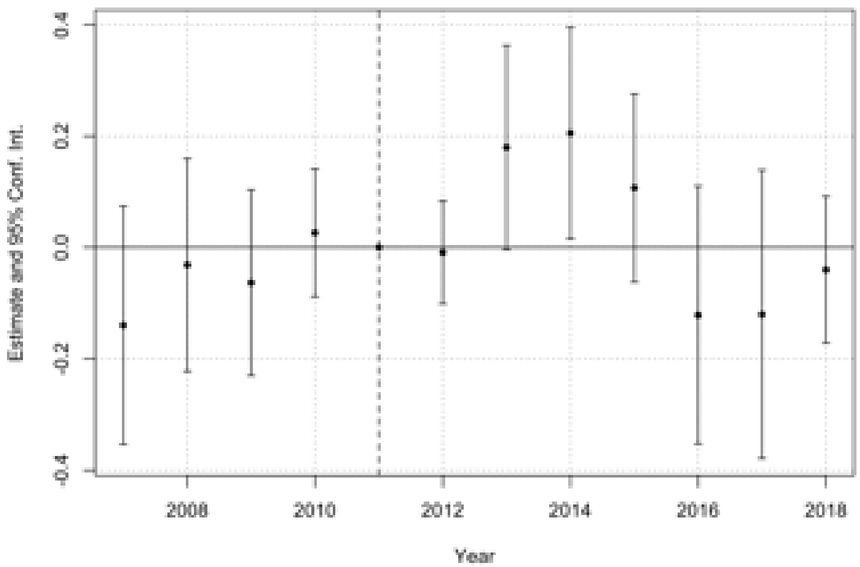
(A) Density Plot of Establishments



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

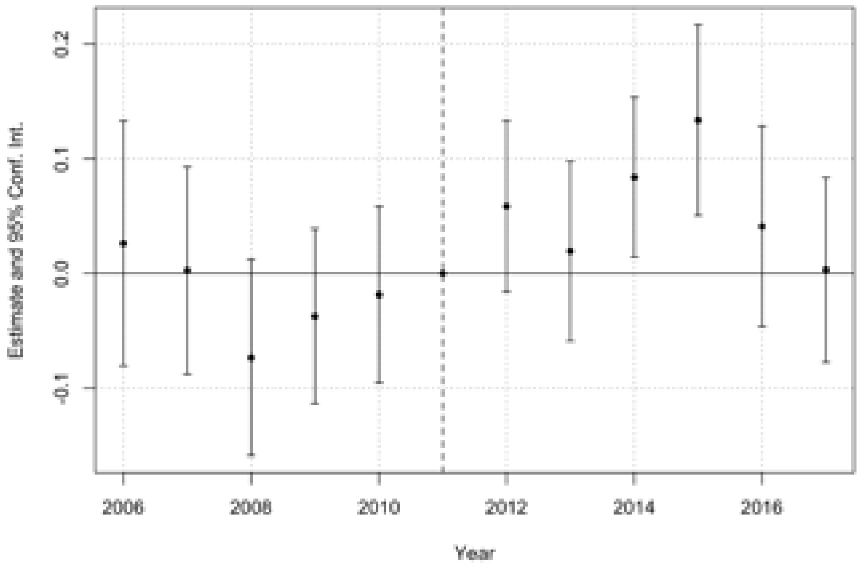
Notes: Panel A uses the McCrary density discontinuity test to assess sorting at the floodplain boundary, with the x-axis denoting distance (in meters) from the boundary and positive values representing locations inside the flood zone. Panel B estimates the differences in residualized log employment between 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 two-way clustered by establishment and year levels.

Figure 7: Event Study: Intensive Margin of NFIP Coverage for Floodplain × Below-Cap Among Flooded Establishments



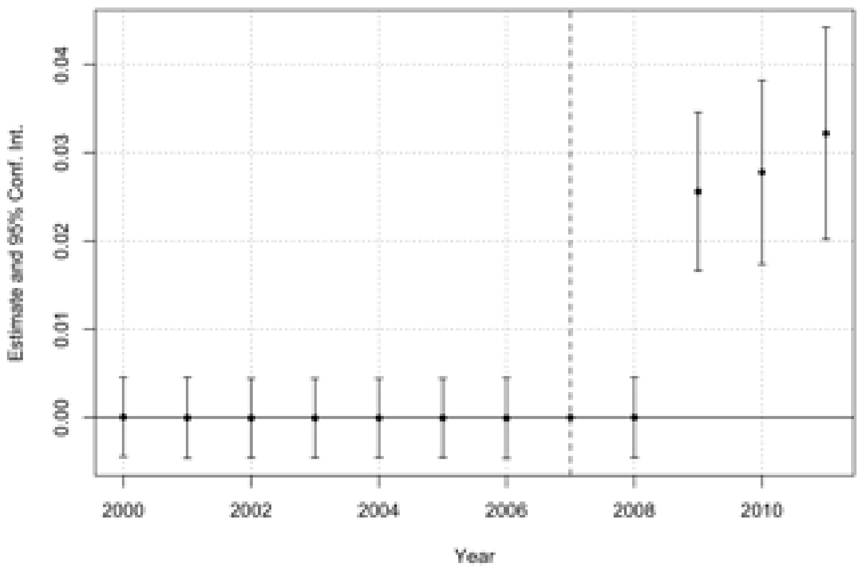
Notes: The figure plots event-time coefficients from a quadruple-difference event-study of employment around Hurricane Sandy. Each point is the estimate for $Flooded_i \times I(Sandy - t = \tau)\times$ I(Floodplain)$_{i,pre}\times$ BelowCap$_i$, measuring the incremental change in log employment for flooded establishments that are inside the FEMA floodplain before hurricane Sandy and valued below the NFIP commercial cap, relative to the omitted groups, with $\tau = -1$ as the reference year. All lower-order interactions with the event-time dummies (Flooded×year, SFHA×year, BelowCap×year, and the three 3-way terms) are included, along with establishment fixed effects, neighborhood-by-year fixed effects, industry-by-year fixed effects, and a time-varying flood-risk control. The vertical dashed line marks the year before Sandy. Error bars show 95% confidence intervals.

Figure 8: Event Study: Parcel-Level Upgrade Permits for Flooded Establishments Inside vs. Outside FEMA Floodplains



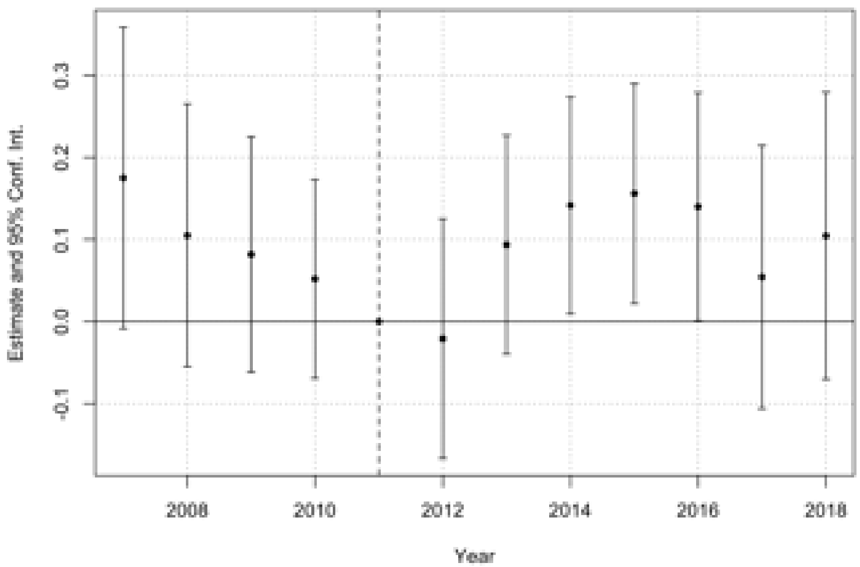
Notes: The figure plots event-time coefficients from a triple-difference event-study of NYC Department of Buildings permit issuances around Hurricane Sandy. Each point is the estimate for $Flooded_i \times I(Sandy - t = \tau) \times$ I(Floodplain)$_{i,pre}$, measuring the incremental change in log permits for parcels that were both inundated by Sandy and inside the FEMA floodplain prior to Sandy, relative to other parcels, with $\tau = -1$ as the reference year. All lower-order interactions with the event-time dummies (Flooded×year and SFHA×year) are included, along with establishment fixed effects, neighborhood-by-year fixed effects, industry-by-year fixed effects, and a time-varying flood-risk control. The vertical dashed line marks the year before Sandy and bars denote 95% confidence intervals.

Figure 9: Event Study: Commercial Policy Uptake After Map Revision

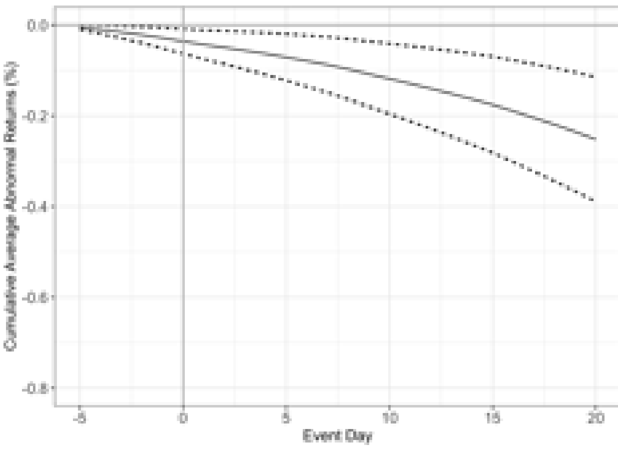


Notes: This figure plots event-time coefficients from a difference in difference specification examining whether the New York City's 2007 FEMA Flood Insurance Rate Map update increase commercial NFIP policy uptake. Each point shows the dynamic treatment effect for the interaction term $I(Sandy - t = \tau) \times NewlyIn(\%)$ measuring the incremental change in commercial policy count for each census block group with each addition percent increase in newly in area after Map revision. The omitted category is $\tau = -1$, the year before Hurricane Sandy. Census block group and neighborhoods-by-year fixed effects are included. The vertical dashed line marks the year before Sandy. Error bars represent 95% confidence intervals.

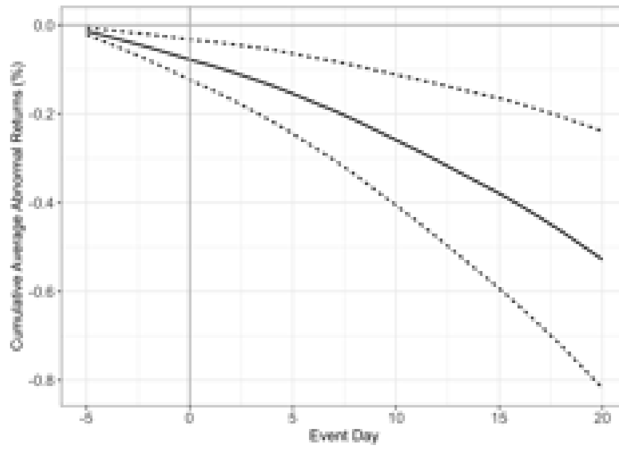
Figure 10: Event Study: Employment Recovery for Flooded Establishments Newly inside after 2007 Map Revision



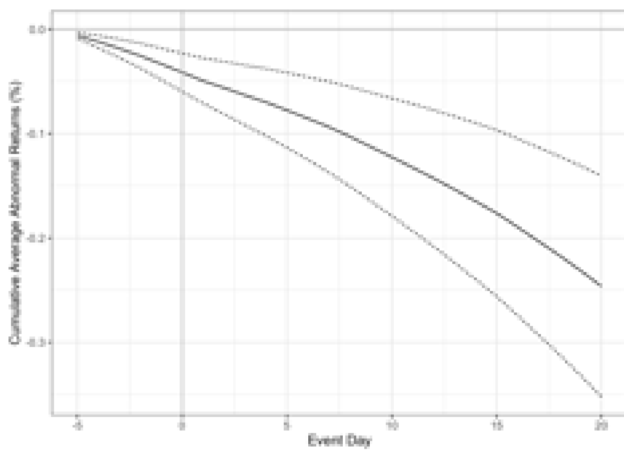
Notes: This figure plots event-time coefficients from a triple-difference specification examining the insurance channel using New York City's 2007 FEMA Flood Insurance Rate Map update. Each point shows the dynamic treatment effect for the interaction term $Flooded_i \times I(Sandy - t = \tau) \times NewlyIn_i$ measuring the incremental change in log employment for flooded establishments newly placed inside the FEMA-designated floodplain in 2007, relative to other similarly flooded establishments. The omitted category is $\tau = -1$, the year before Hurricane Sandy. All lower-order terms and fixed effects for establishments, industries-by-year, and neighborhoods-by-year are included, along with controls for flood risk. The vertical dashed line marks the year before Sandy. Error bars represent 95% confidence intervals.



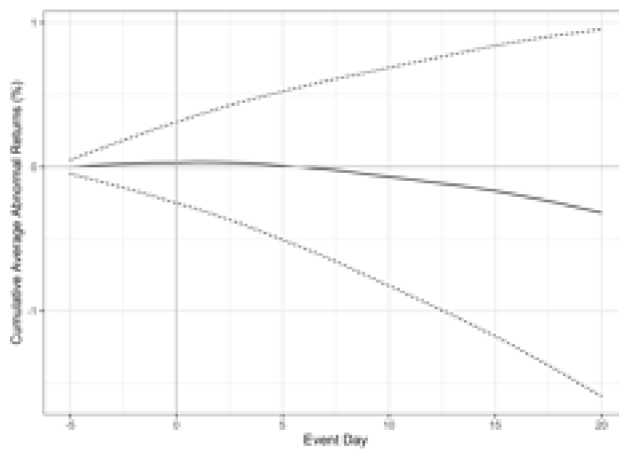
(A) All stocks



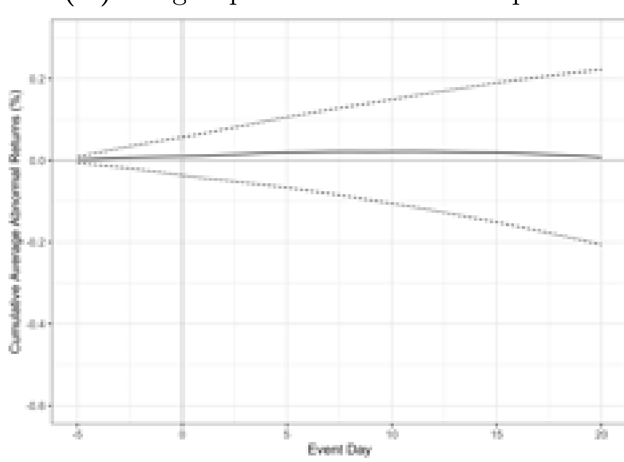
(B) Subgroup: firstly experienced



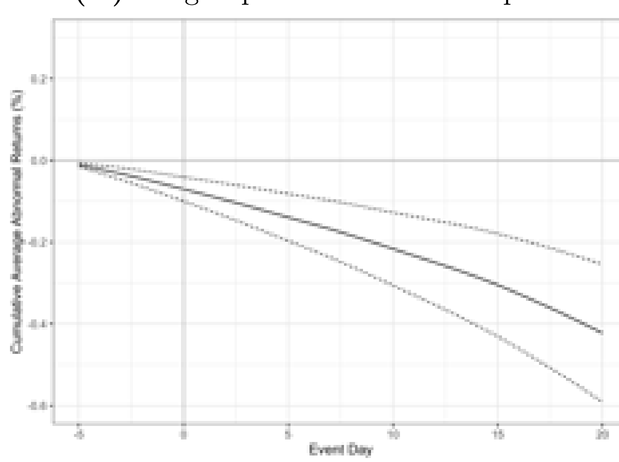
(C) Subgroup: not in FEMA floodplain



(D) Subgroup with estbs in floodplain



(E) Subgroup with prior 10-K disclosure



(F) Subgroup without 10-K disclosure

Figure 11: Market reactions to flooding news. 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), stocks that do not have any establishments in the FEMA floodplains in Panel (C), stocks with at least one establishment in floodplain in Panel (D), and stocks with and without 10-K flood disclosure respectively in Panels (E) and (F). Abnormal returns are calculated using the Fama-French five-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 5.2

	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: 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

	Claim Count	Building Claims	Contents Claim	Building Claims	Contents Claim	Required Claim Count		Voluntary Claim Count	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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 4: 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. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment			Sales		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Flooded}_i \times \text{AfterSandy}_t$	0.0129**	0.0083	0.0083	0.0150	0.0085	0.0085
	(2.010)	(1.265)	(1.266)	(1.553)	(0.8659)	(0.8631)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre}$		0.0498**	0.0500**		0.0923**	0.0924**
		(2.051)	(2.060)		(2.239)	(2.241)
$\text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre}$		0.0028	0.0029		-0.0108	-0.0108
		(0.1379)	(0.1430)		(-0.2895)	(-0.2901)
$\text{Flood Risk}_{i,t}$			-0.0368**			0.0271
			(-2.055)			(1.141)
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 5: Spatial Regression Discontinuity Design: Before and After Hurricane Sandy in NYC

This table reports estimates from the spatial regression discontinuity design described in Equation 2, 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)
$\text{Flood}_i \times \text{AfterSandy}_t \times \text{I(FP)}_{i,pre}$	0.2511***	0.2253***	0.3644***	0.1361***
	(25.72)	(69.74)	(43.11)	(30.29)
$\text{Flood}_i \times \text{AfterSandy}_t$	-0.0173	0.0176	-0.0900	0.0125
	(-0.2996)	(0.7512)	(-1.709)	(0.3462)
$\text{AfterSandy}_t \times \text{I(FP)}_{i,pre}$	-0.0158	-0.0193	0.0249	0.1116
	(-0.0846)	(-0.1167)	(0.1198)	(0.5016)
$\text{Flood}_i \times \text{I(FP)}_{i,pre}$	-0.1690**	-0.1564***	-0.2195***	-0.1047***
	(-2.142)	(-3.489)	(-3.085)	(-3.245)
$f(r_i)$	Local linear	Local linear	Local linear	4th-order polynomial
Nbh×Year FEs	Yes	Yes	Yes	Yes
Observations	13,077	13,053	10,296	28,687
R^2	0.17340	0.15893	0.16696	0.14360

Table 6: Mandate Binding: Mortgage Intensity and the Inside-Map Premium

This table reports estimates from triple- and quadruple-difference specifications with establishment-level data from 2000 to 2018. Column (1) and (2) restrict the sample to establishments located inside the SFHA and Column (3)-(7) use the full sample. $I(mortgage)_{parcel}$ is a parcel-level indicator of whether a commercial mortgage exist on the parcel level before Sandy. $MorgageItensity_{parcel}$ or $MorgageItensity_{CBG}$ is the number of commercial mortgages divided by the number of commercial real properties in the parcel or census block group level (in %). $MorgageItensity(\$)$ is dollar-based intensity defined as the total dollar amount of commercial mortgages divided by the market value of commercial real property (in %). All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Flooded}_i \times \text{Post}_t \times \text{I(mortgage)}_{parcel}$	0.2367***		-0.0477***				
	(2.948)		(-2.589)				
$\text{I(mortgage)}_{parcel} \times \text{Post}_t$	-0.0958		0.0159				
	(-1.407)		(1.465)				
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre} \times \text{I(mortgage)}_{parcel}$			0.1302**				
			(2.358)				
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre} \times \text{MortgageIntensity}_{parcel}$				0.0132**			
				(2.362)			
$\text{Flooded}_i \times \text{Post}_t \times \text{MortgageIntensity}_{parcel}$		0.0184**		-0.0019			
		(2.425)		(-1.260)			
$\text{MortgageIntensity}_{parcel} \times \text{Post}_t$		-0.0044		-0.0005			
		(-0.6970)		(-0.4587)			
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre} \times \text{MortgageIntensity}_{CBG}$					0.0284**		
					(2.497)		
$\text{Flooded}_i \times \text{Post}_t \times \text{MortgageIntensity}_{CBG}$					-0.0060		
					(-1.389)		
$\text{MortgageIntensity}_{CBG} \times \text{Post}_t$					0.0011		
					(0.4911)		
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre} \times \text{MortgageIntensity(\$)}_{parcel}$						0.0001*	
						(1.871)	
$\text{Flooded}_i \times \text{Post}_t \times \text{MortgageIntensity(\$)}_{parcel}$						0.0000	
						(1.516)	
$\text{MortgageIntensity(\$)}_{parcel} \times \text{Post}_t$						0.0000**	
						(-2.051)	
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre} \times \text{MortgageIntensity(\$)}_{CBG}$							0.0002***
							(2.587)
$\text{Flooded}_i \times \text{Post}_t \times \text{MortgageIntensity(\$)}_{CBG}$							0.0000***
							(-2.885)
$\text{MortgageIntensity(\$)}_{CBG} \times \text{Post}_t$							0.0000
							(0.7670)
$\text{Flooded}_i \times \text{Post}_t \times \text{I(FP)}_{i,pre}$			0.0337	0.0357	0.0290	0.0109	0.0106
			(1.325)	(1.423)	(1.147)	(0.4392)	(0.4235)
$\text{I(FP)}_{i,pre} \times \text{Post}_t$			0.0069	0.0084	0.0076	0.0226	0.0214
			(0.3258)	(0.3980)	(0.3601)	(1.034)	(0.9777)
$\text{Flooded}_i \times \text{Post}_t$	0.0214	0.0402	0.0242***	0.0200***	0.0216***	0.0216***	0.0238***
	(0.6604)	(1.288)	(3.537)	(2.934)	(3.100)	(3.236)	(3.568)
$\text{Flood Risk}_{i,t}$	0.0215	0.0222	-0.0161	-0.0160	-0.0160	-0.0415**	-0.0419**
	(0.6712)	(0.6967)	(-0.9094)	(-0.9026)	(-0.9025)	(-2.228)	(-2.247)
Establishment, Nbh×Year, Industry×Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,561	10,561	180,421	180,421	180,421	175,956	175,956
R^2	0.94408	0.94407	0.91765	0.91765	0.91765	0.91814	0.91814

Table 7: Intensive Margin of NFIP Coverage: Below-Cap vs. Above-Cap

This table presents triple-difference and quadruple-difference estimates of the effect of the NFIP building coverage cap on post–Hurricane Sandy recovery with establishment-level data from 2000 to 2018. The dependent variable is log employment plus one. BelowCap indicates establishments with estimated property values at or below the NFIP commercial building coverage cap ($500,000). Column (1) restricts the sample to establishments located in FEMA-designated floodplains. Columns (2)–(4) use the full sample. CoverageRatio is the ratio of the NFIP cap to the estimated property market value, capped at 1. FarBelowCap (property value $\leq 0.5\times$ cap) and NearCap ($0.5 \times$ cap $<$ property value $\leq$ cap) split the BelowCap group into two categories. Column (5) excludes the top 5% of establishments by pre-Sandy employment to ensure results are not driven by very large firms. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment				
Model:	(1)	(2)	(3)	(4)	(5)
$\text{Flooded}_i \times \text{AfterSandy}_t$	0.0738**	0.0283***	0.0335***	0.0282***	0.0321***
	(2.533)	(4.158)	(4.006)	(4.150)	(5.012)
$\text{Flooded} \times \text{AfterSandy}_t \times \text{BelowCap}_i$	0.1502***	-0.0035			-0.0077
	(2.643)	(-0.2634)			(-0.5854)
$\text{Flooded} \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre} \times \text{BelowCap}_i$		0.1629***			0.1851***
		(3.133)			(3.545)
$\text{Flooded} \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre}$		0.0421**	0.0321	0.0420**	0.0280**
		(2.549)	(1.589)	(2.541)	(2.005)
$\text{AfterSandy}_t \times \text{BelowCap}_i$		-0.0156**			-0.0135*
		(-2.079)			(-1.847)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre} \times \text{CoverageRatio}$			0.0009**		
			(1.978)		
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{CoverageRatio}$			-0.0002		
			(-1.476)		
$\text{AfterSandy}_t \times \text{CoverageRatio}$			-0.0001		
			(-1.231)		
$\text{Flooded} \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre} \times \text{FarBelowCap}_i$				0.2248***	
				(2.641)	
$\text{Flooded} \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre} \times \text{NearCap}_i$				0.1119*	
				(1.875)	
$\text{Flooded} \times \text{AfterSandy}_t \times \text{FarBelowCap}_i$				0.0083	
				(0.4014)	
$\text{Flooded} \times \text{AfterSandy}_t \times \text{NearCap}_i$				-0.0057	
				(-0.3603)	
$\text{AfterSandy}_t \times \text{FarBelowCap}_i$				-0.0352***	
				(-2.714)	
$\text{AfterSandy}_t \times \text{NearCap}_i$				-0.0089	
				(-1.057)	
$\text{Flood Risk}_{i,t}$	-0.0086	-0.0288	-0.0296	-0.0278	-0.0070
	(-0.2553)	(-1.462)	(-1.509)	(-1.406)	(-0.4020)
Establishment, Nbh×Year, Industry×Year	Yes	Yes	Yes	Yes	Yes
Observations	8,604	125,418	125,418	125,418	119,568
R^2	0.94178	0.91498	0.91498	0.91498	0.89363

Table 8: Mechanism: Building-Level Capital Upgrades per Establishment

This table presents the triple-difference estimates of building-level capital upgrade intensity using NYC DOB permit issuances and establishment data from 2000 to 2018. The outcome variable is log number of initial, issued construction permits scaled by pre-Sandy number of establishments on the parcel. Columns (4)–(5) split the post period into Early (2012–2015) and Later (2016–2018). All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Construction Permits$_{b,t}$/ Estab$_{b,pre}$				
Model:	(1)	(2)	(3)	(4)	(5)
Post$_t$ × Flooded$_i$	-0.0195	-0.0250**	-0.0250**		
	(-1.631)	(-1.987)	(-1.987)		
Post$_t$ × I(FloodPlain)$_{i,pre}$		-0.0463	-0.0463		
		(-1.479)	(-1.479)		
Post$_t$ × Flooded$_i$ × I(FloodPlain)$_{i,pre}$		0.0601*	0.0601*		
		(1.760)	(1.759)		
Flood Risk$_{i,t}$			35.92		35.90
			(0.5688)		(0.5676)
Early$_t$ × Flooded$_i$ × I(FloodPlain)$_{i,pre}$				0.0771**	0.0771**
				(2.138)	(2.138)
Late$_t$ × Flooded$_i$ × I(FloodPlain)$_{i,pre}$				0.0244	0.0244
				(0.5258)	(0.5253)
Flooded$_i$ × Early$_t$				-0.0351***	-0.0351***
				(-2.599)	(-2.599)
Flooded$_i$ × Late$_t$				-0.0027	-0.0027
				(-0.1547)	(-0.1548)
I(FloodPlain)$_{i,pre}$ × Early$_t$				-0.0451	-0.0451
				(-1.366)	(-1.366)
I(FloodPlain)$_{i,pre}$ × Late$_t$				-0.0488	-0.0487
				(-1.145)	(-1.145)
Estb, Nbh×Yr, Industry×Yr FEs	Yes	Yes	Yes	Yes	Yes
Observations	95,093	95,093	95,093	95,093	95,093
R^2	0.72218	0.72219	0.72219	0.72221	0.72222

Table 9: Firm Floodplain Risk Exposure

This table presents the estimates of quadruple difference in difference specification with establishment-level data from 2000 to 2018. $I(FP)_{firm}$ equals 1 if the parent has any SFHA establishment pre-Sandy. $RiskExposurefirm$ equals 1 if the parent's pre-Sandy SFHA-establishment count is $\geq$ the 5th percentile across firms. log(FP estb)$_{firm}$ is log number of establishments in FEMA floodplain before Sandy. All specifications include establishment fixed effects, firm-by-year fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, 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$_i$ × Post$_t$ × I(FP)$_{firm}$ × I(FP)$_{i,pre}$	-0.9425***			-1.126***		
	(-4.383)			(-6.268)		
Flooded$_i$ × Post$_t$ × I(FP)$_{firm}$	0.0945			0.1141		
	(1.267)			(1.110)		
I(FP)$_{firm}$ × I(FP)$_{i,pre}$	-0.0042			-0.1972		
	(-0.0403)			(-1.314)		
I(FP)$_{firm}$ × I(FP)$_{i,pre}$ × Post$_t$	-0.0250			-0.0493		
	(-1.257)			(-1.377)		
Flooded$_i$ × Post$_t$ × RiskExposure$_{firm}$ × I(FP)$_{i,pre}$		-0.0918*			-0.1654*	
		(-1.707)			(-1.890)	
Flooded$_i$ × Post$_t$ × RiskExposure$_{firm}$		-0.0104			0.0146	
		(-0.2870)			(0.3012)	
RiskExposure$_{firm}$ × I(FP)$_{i,pre}$		0.0661			0.0239	
		(0.8144)			(0.2701)	
RiskExposure$_{firm}$ × I(FP)$_{i,pre}$ × Post$_t$		-0.0270			-0.0515	
		(-1.350)			(-1.445)	
Flooded$_i$ × Post$_t$ × log(FP estb)$_{firm}$ × I(FP)$_{i,pre}$			-0.0160*			0.0103
			(-1.760)			(0.8664)
Flooded$_i$ × Post$_t$ × log(FP estb)$_{firm}$			-0.0064*			-0.0061
			(-1.793)			(-1.274)
log(FP estb)$_{firm}$ × I(FP)$_{i,pre}$			0.0069			0.0358**
			(0.5234)			(2.356)
log(FP estb)$_{firm}$ × I(FP)$_{i,pre}$ × Post$_t$			-0.0041			-0.0135**
			(-1.293)			(-2.185)
Flooded$_i$ × Post$_t$	-0.1002	0.0035	0.0312	-0.1155	-0.0163	0.0341
	(-1.343)	(0.0981)	(1.342)	(-1.125)	(-0.3407)	(1.081)
Flooded$_i$ × Post$_t$ × I(FP)$_{i,pre}$	0.9929***	0.1424***	0.1374**	1.195***	0.2354***	0.0304
	(4.635)	(2.925)	(2.500)	(6.808)	(2.967)	(0.4659)
Flood Risk$_{i,t}$	-0.0180	-0.0184	-0.0155	0.0369	0.0367	0.0374
	(-0.9071)	(-0.9237)	(-0.7983)	(1.395)	(1.385)	(1.410)
Establishment, Firm×Year, 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	0.94025	0.94024	0.94101	0.94435	0.94434	0.94435

Table 10: Commercial Flood Insurance Uptake and Coverage Changes Around the 2007 FEMA Map Revision

This table reports OLS estimates of how the 2007 FEMA Flood Insurance Rate Map (FIRM) update for New York City affected commercial flood insurance uptake and coverage at the census block group level between 2000 and 2011. The dependent variables (in logs) are: number of NFIP commercial policies (Policy Count), total policy cost, total building coverage, and total content coverage. *newlyIn*(%) is the percentage of the census block group's land area newly designated as Special Flood Hazard Area (SFHA) in the 2007 map revision, relative to the Q3 map. *newlyOut*(%) is the percentage of land area that was designated SFHA under the Q3 map but removed from SFHA after the revision. *postRevision* is an indicator that equals one for years after the 2007 revision became effective. The interaction terms capture how changes in SFHA designation affect commercial NFIP policy counts and coverage after the revision. All regressions include census block group fixed effects and neighborhood-by-year fixed effects. Standard errors are clustered at the census block group and year levels, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Dependent Variables:	Policy Count		Policy Cost		Building Coverage		Content Coverage	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{postRevision}_t \times \text{newlyIn}(\%)$	0.0172***	0.0171***	0.0834**	0.0820**	0.1058**	0.1041**	0.0403*	0.0390*
	(9.223)	(9.202)	(2.414)	(2.409)	(2.424)	(2.419)	(2.073)	(2.053)
$\text{Estb Count}_{i,t}$	0.0439***	0.0438***	0.1180*	0.1160*	0.1398*	0.1374*	0.0663	0.0644
	(5.130)	(5.131)	(1.963)	(1.949)	(1.977)	(1.964)	(1.264)	(1.239)
$\text{postRevision}_t \times \text{newlyOut}(\%)$		0.0004		0.0281		0.0327		0.0258
		(0.1973)		(1.768)		(1.721)		(1.779)
Census Block Group, Nbh-Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,833	76,833	76,833	76,833	76,833	76,833	76,833	76,833
R^2	0.38061	0.38062	0.39727	0.39800	0.38826	0.38899	0.33885	0.33945

Table 11: Triple-Difference: FEMA Map Revision and Post-Sandy Outcomes

This table reports triple-difference estimates of the effect of NFIP insurance access, induced by New York City's 2007 FEMA Flood Insurance Rate Map (FIRM) update, on post–Hurricane Sandy recovery. $NewlyIn_i$ indicates establishments reclassified into the Special Flood Hazard Area (SFHA) in 2007, making them newly subject to the NFIP's mandatory purchase requirement if they have federally backed mortgages. The dependent variables are log employment (columns 1–3) and log sales (columns 4–6). Column (1) and (4) use the full sample of establishments. Column (2) and (5) restrict the control group to establishments always outside the SFHA (dropping establishments that were newly outside or always inside after the 2007 revision). Column (3) and (6) drop the top 5% of establishments by 2011 employment to ensure results are not driven by very large firms. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment			Sales		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{NewlyIn}_i$	0.0567*	0.0649**	0.0810**	0.0835*	0.1019**	0.1220***
	(1.780)	(2.022)	(2.545)	(1.754)	(2.124)	(2.715)
$\text{Flooded}_i \times \text{AfterSandy}_t$	0.0100	0.0070	0.0062	0.0115	0.0106	0.0150
	(1.531)	(1.060)	(0.9819)	(1.171)	(1.077)	(1.616)
$\text{NewlyIn}_i \times \text{AfterSandy}_t$	0.0035	0.0087	-0.0237	0.0081	0.0141	-0.0513
	(0.1385)	(0.3416)	(-0.9349)	(0.1935)	(0.3353)	(-1.312)
$\text{Flood Risk}_{i,t}$	-0.0409**	-0.0570*	-0.0328*	0.0267	0.0247	0.0371
	(-2.278)	(-1.943)	(-1.860)	(1.120)	(0.6580)	(1.590)
Estb, Nbh×Yr, Industry×Yr FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193,167	186,099	184,823	164,333	158,515	156,312
R^2	0.91698	0.91653	0.91307	0.91714	0.91767	0.90775

Table 12: 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		$\geq$ 50 ppl	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AfterFirstFlood$_t$ $\times$ SBA EIDL Intensity$_{z,t}$	0.0426*		0.0080***		0.0091***		0.0730**	
	(1.927)		(3.353)		(3.662)		(2.795)	
AfterFirstFlood$_t$ $\times$ SBA Loan Intensity$_{z,t}$		0.0017		0.0003		0.0004		0.0060**
		(0.7985)		(0.6468)		(0.9212)		(2.232)
Flooded$_z$ $\times$ 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$\times$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

	Emp$_{a,t}$	Job Creation$_{a,t}$	Estb$_{a,t}$	Estab Entry$_{a,t}$	Estab Exit$_{a,t}$
Model:	(1)	(2)	(3)	(4)	(5)
AfterFirstFlood$_t$ $\times$ 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$_i$ $\times$ 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$\times$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 13: NFIP Insurance and Local Economy Following Flood-related Disasters

This table presents OLS regression estimates examining the relationship between NFIP Insurance coverage and local economic conditions following flood-related disasters. The outcomes include log employment, log annual payroll, and the log number of establishments at the ZIP code level, based on ZIP Code Business Patterns from Census Bureau. The main variables of interest are interactions between insurance policy measures 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, and state-by-year fixed effects. Standard errors are clustered at the ZIP and year level, with t-statistics in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

			Establishments$_{z,t}$					
	Employment$_{z,t}$		All		<20 ppl		$\geq$ 50 ppl	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AfterFirstFlood$_t$ × PolicyCount$_{z,t}$	0.0033***		0.0004***		0.0008**		0.0010	
	(3.415)		(4.787)		(2.527)		(1.352)	
AfterFirstFlood$_t$ × CommPolicyCount$_{z,t}$		0.0706		0.0167**		0.0258**		0.0011
		(1.020)		(3.235)		(2.550)		(0.0373)
Flooded$_i$ × Post$_t$	0.0101	0.0024	-0.0041	-0.0072	-0.0045	-0.0086	0.0376	0.0402
	(0.1687)	(0.0416)	(-1.075)	(-1.648)	(-0.8370)	(-1.501)	(1.152)	(1.213)
Total Disaster Loss$_{i,t}$	-0.0008	-0.0007	-0.0001	-0.0001	0.0006**	0.0006**	-0.0035***	-0.0035***
	(-1.092)	(-0.9895)	(-1.626)	(-1.601)	(2.459)	(2.490)	(-4.074)	(-4.064)
Number of Floodings$_{a,t}$	-0.0330	-0.0321	-0.0049	-0.0046	-0.0041	-0.0036	-0.0242	-0.0245
	(-0.4294)	(-0.4207)	(-1.362)	(-1.229)	(-0.7133)	(-0.6260)	(-0.9383)	(-0.9411)
High Flood Risk Area %$_{z,t}$	0.0045	0.0045	0.0000	0.0000	0.0000	0.0000	0.0052*	0.0052*
	(1.601)	(1.603)	(0.1108)	(0.0623)	(-0.0082)	(-0.0402)	(1.963)	(1.956)
Female Population$_{z,t}$	-0.0026	-0.0026	0.0001	0.0001	0.0000	0.0000	0.0002	0.0002
	(-1.383)	(-1.381)	(0.7160)	(0.7178)	(-0.0875)	(-0.0848)	(0.3715)	(0.3733)
Establishment$_{z,t-1}$	-0.0011	-0.0011	0.0012***	0.0012***	0.0009***	0.0009***	-0.0015	-0.0015
	(-1.148)	(-1.154)	(11.99)	(12.01)	(5.236)	(5.225)	(-1.322)	(-1.324)
Zip, State×Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238,331	238,331	238,331	238,331	238,331	238,331	238,331	238,331
R^2	0.81981	0.81980	0.99587	0.99587	0.99008	0.99008	0.94311	0.94311

Table 14: Firm Insurance Disclosure and Post-Sandy Outcomes

This table presents triple- and quadruple-difference estimates of whether firms' pre–Hurricane Sandy insurance-related disclosures predict stronger post-flood recovery among their establishments, using establishment-level data from 2000-2018. The dependent variables are log employment (columns 1–3) and log sales (columns 4–6). The key variable of interest is PreInsuranceDisclosure, which is the percentage of pre-Sandy calls in which the parent firm discussed insurance coverage, payouts, or related opportunities. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Employment			Sales		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Flooded}_i \times \text{AfterSandy}_t$	-0.0048	-0.0100	-0.0097	-0.0184	-0.0209	-0.0205
	(-0.5808)	(-1.197)	(-1.167)	(-1.348)	(-1.529)	(-1.497)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{PreInsuranceDisclosure}_i$	0.0099**	0.0099**	0.0049*	0.0193***	0.0192***	0.0132***
	(2.497)	(2.513)	(1.939)	(2.783)	(2.805)	(3.031)
$\text{Flood Risk}_{i,t}$	-0.0570***	-0.0570***	-0.0570***	-0.0177	-0.0172	-0.0172
	(-2.609)	(-2.613)	(-2.613)	(-0.5878)	(-0.5723)	(-0.5728)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre}$		0.0972***	0.0925**		0.1339	0.1280
		(2.674)	(2.546)		(1.321)	(1.263)
$\text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre}$		-0.0711**	-0.0706**		-0.0950	-0.0951
		(-2.160)	(-2.144)		(-0.9634)	(-0.9646)
$\text{Flooded}_i \times \text{AfterSandy}_t \times \text{I(FloodPlain)}_{i,pre} \times \text{PreInsuranceDisclosure}_i$			0.0484**			0.0720**
			(2.435)			(2.077)
Establishment, Nbh×Year, Industry×Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,938	101,938	101,938	85,912	85,912	85,912
R^2	0.92515	0.92516	0.92518	0.92240	0.92240	0.92243

Table 15: 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		Fama French 5 Factors	
Event Window	CAAR_t(%)	t-stats	CAAR_t(%)	t-stats	CAAR_t(%)	t-stats
$[-5, -5]$	-0.0056	-2.4481	-0.0035	-1.5366	-0.0056	-2.4183
$[-5, -4]$	-0.0107	-2.3459	-0.0066	-1.4576	-0.0105	-2.2932
$[-5, -3]$	-0.0165	-2.4079	-0.0103	-1.5079	-0.0158	-2.3143
$[-5, -2]$	-0.0229	-2.4936	-0.0145	-1.5901	-0.0218	-2.3786
$[-5, -1]$	-0.0305	-2.6384	-0.0196	-1.7060	-0.0287	-2.4926
$[-5, 0]$	-0.0387	-2.7746	-0.0248	-1.7887	-0.0361	-2.6037
$[-5, 1]$	-0.0465	-2.8490	-0.0297	-1.8294	-0.0432	-2.6553
$[-5, 2]$	-0.0537	-2.8644	-0.0339	-1.8224	-0.0495	-2.6511
$[-5, 3]$	-0.0616	-2.9067	-0.0391	-1.8584	-0.0564	-2.6720
$[-5, 4]$	-0.0694	-2.9331	-0.0441	-1.8741	-0.0632	-2.6795
$[-5, 5]$	-0.0783	-2.9908	-0.0497	-1.9108	-0.0711	-2.7231
$[-5, 6]$	-0.0875	-3.0488	-0.0554	-1.9427	-0.0793	-2.7668
$[-5, 7]$	-0.0967	-3.0903	-0.0611	-1.9634	-0.0877	-2.8043
$[-5, 8]$	-0.1075	-3.1665	-0.0678	-2.0091	-0.0974	-2.8707
$[-5, 9]$	-0.1192	-3.2524	-0.0755	-2.0714	-0.1081	-2.9464
$[-5, 10]$	-0.1307	-3.3173	-0.0833	-2.1243	-0.1185	-3.0007
$[-5, 15]$	-0.1940	-3.6095	-0.1270	-2.3751	-0.1756	-3.2457
$[-5, 20]$	-0.2765	-3.9897	-0.1839	-2.6589	-0.2517	-3.5929

Table 16: Cross-Sectional Regressions: CAR Determinants

This table presents the results of what determinants can explain the cumulative abnormal returns across firms with data from 2000 to 2018. Abnormal returns are calculated using the Fama-French Five Factor Model with an estimation window of $[-275, -20]$. In Panel A), B) and C), I include govPriorDisclosure$_i$, insurancePriorDisclosure$_i$ and FloodRiskDisclosure$_i$ respectively, and they are standardized measure of prior disclosures. For each category (government spending-related opportunity, insurance-related opportunity, and flood risk disclosure in 10-K filings), I compute the cumulative average of the firm's past disclosures (up to the flooding event) that contain at least one disclosure in that category. $I(PreviouslyFlooded)_i$ indicates whether the firm has been flooded before. NumEstbsInFP$_i$ is the log number of establishments in FEMA floodplain.

Panel A:				
	$CAR_{i,j,[-5,T_2]}$			
Model:	(1) [-5,0]	(2) [-5,5]	(3) [-5,10]	(4) [-5,20]
govPriorDisclosure$_i$	0.0303*	0.0611*	0.0905**	0.1585**
	(1.986)	(2.106)	(2.161)	(2.258)
I(PreviouslyFlooded)$_i$	0.0654*	0.1274*	0.2024*	0.3530
	(2.001)	(1.925)	(1.847)	(1.620)
NumEstbsInFP$_i$	0.0118	0.0264	0.0407	0.0652
	(1.429)	(1.676)	(1.626)	(1.384)
FloodDisplacement$_j$	-0.0118***	-0.0214***	-0.0294**	-0.0370**
	(-4.353)	(-3.356)	(-2.817)	(-2.651)
FloodDeath$_j$	-0.0198*	-0.0407	-0.0545	-0.0761
	(-1.782)	(-1.597)	(-1.337)	(-1.098)
Controls, Year, industry FE	Yes	Yes	Yes	Yes
Observations	5,894	5,894	5,894	5,894
R^2	0.02663	0.02664	0.02590	0.02618
Panel B:				
Model:	(1) [-5,0]	(2) [-5,5]	(3) [-5,10]	(4) [-5,20]
insurancePriorDisclosure$_i$	0.0043	0.0149	0.0318	0.0729
	(0.3969)	(0.6949)	(0.9309)	(1.047)
I(PreviouslyFlooded)$_i$	0.0649*	0.1268*	0.2020*	0.3534
	(2.026)	(1.916)	(1.820)	(1.589)
NumEstbsInFP$_i$	0.0122	0.0269*	0.0407*	0.0641
	(1.656)	(1.900)	(1.795)	(1.506)
FloodDisplacement$_j$	-0.0117***	-0.0212***	-0.0291**	-0.0365**
	(-4.331)	(-3.411)	(-2.881)	(-2.729)
FloodDeath$_j$	-0.0197*	-0.0405	-0.0543	-0.0760
	(-1.768)	(-1.591)	(-1.334)	(-1.092)
Controls, Year, industry FE	Yes	Yes	Yes	Yes
Observations	5,894	5,894	5,894	5,894
R^2	0.02309	0.02305	0.02282	0.02361

Table 16: Cross-Sectional Regressions: CAR Determinants (Continued)

Panel C:				
	$CAR_{i,j,[-5,T_2]}$			
Model:	(1) [-5,0]	(2) [-5,5]	(3) [-5,10]	(4) [-5,20]
Flood Risk Disclosure (10K)$_i$	0.0399**	0.0824**	0.1329**	0.2661**
	(2.074)	(2.104)	(2.107)	(2.078)
I(PreviouslyFlooded)$_i$	0.0696*	0.1394*	0.2293*	0.4239*
	(1.706)	(1.739)	(1.841)	(1.841)
FloodDisplacement$_j$	-0.0124**	-0.0211**	-0.0266*	-0.0312
	(-2.464)	(-2.179)	(-1.789)	(-1.140)
FloodDeath$_j$	-0.0226**	-0.0426**	-0.0556*	-0.0774
	(-2.278)	(-2.208)	(-1.858)	(-1.419)
NumEstbsInFP$_i$	0.0115	0.0184	0.0247	0.0411
	(1.540)	(1.280)	(1.098)	(0.9522)
Controls, Year, industry FE	Yes	Yes	Yes	Yes
Observations	7,934	7,934	7,934	7,934
R^2	0.02518	0.02525	0.02562	0.02748

A Appendix

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A.1 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.

Disclosure

For 10-K annual reports, I classify text into physical risk, regulatory risk, and opportunity. Physical risk captures adverse operational effects directly tied to flooding, such as facility damage, temporary shutdowns, or supply-chain disruptions. Regulatory risk captures exposure to rules or standards intended to manage flood hazard, such as elevation requirements, building codes, or zoning constraints. Opportunity captures favorable implications related to flooding, such as strategic positioning, product demand for flood-resistant solutions, or relocation to lower-risk assets and markets. I use these 10-K indicators to characterize firms' baseline risk and opportunity environment; the main analyses rely on the more granular earnings-call measures that distinguish insurance-related opportunities from government-spending-related opportunities. Appendix Tables A3-A4 provide 10-K disclosure and classification examples. For earnings calls, I also record whether the disclosure was firm-initiated in prepared remarks or prompted by analysts during the Q&A segment. This distinction helps separate proactive communication from reactive responses to investor concerns.

A.2 Flood Events 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.

$$Y_{i,t} = \sum_{\tau=-4,\tau\neq-1}^{10} \beta_\tau Flood_{i,\tau} + X_{i,t} + FloodRisk_{i,t} + \alpha_{s,t} + \alpha_{ind,t} + \alpha_i + \epsilon_{i,t} \tag{6}$$

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 Appendix Figure A1. There are significant patterns in the left-hand-side plot where the employee numbers significantly increased in the long term. In terms of sales revenue, the estimates are noisier but the results are consistent and we could observe significant recovery since year 2. The estimation results are in Appendix Table A11. 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.

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 dynamics 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 A6 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.

A.3 Insurance Channel: Intensive Margin

Although establishments on both sides of the threshold can purchase flood insurance, the cap induces a discrete change in potential indemnity depth at $500,000: properties just below the cap can be fully indemnified by NFIP for structural losses, while those just above face partial coverage unless they layer on private insurance.

As a robustness check to the panel triple difference and quadruple-difference estimates in Section 4.3, I implement a boundary-localized difference-in-differences design (RD–DiD) that measures whether, after Hurricane Sandy, outcomes exhibit a new discontinuity at the NFIP insurance building coverage cap for flooded establishments located within FEMA SFHAs. This design complements the baseline results by providing a local, design-based estimate that relies on weaker functional-form assumptions.

I estimate the following specification:

$$\begin{aligned} y_{i,t} =& \beta D_i \times Flooded_i \times Post_t + \gamma_- Post_t x_i 1\{x \leq 0\} + \gamma_+ Post_t x_i 1\{x \geq 0\} \\ &+ \sigma_- Post_t \times Flooded_i x_i 1\{x \leq 0\} + \sigma_+ Post_t \times Flooded_i x_i 1\{x \geq 0\} \\ &+ \alpha_i + \alpha_{industry,t} + \alpha_{nbh,t} + \epsilon_{i,t} \end{aligned}$$

where the outcome variables are log employment and log sales, the running variable x_i is $V_i - 500,000$ where V_i is pre-Sandy building value, the threshold indicator $D_i = 1\{x_i \leq 0\}$ (at or below the \$ 500k cap). β is the the RD–DiD effect—the extra post-Sandy jump at the \$500k cap for flooded establishments. A positive β means that flooded establishments' building values are just below the cap recovered more than those just above (partially covered). γ_- and γ_+ allow the post-Sandy trend in outcomes to vary smoothly with the running variable on the left and right of the cutoff. σ_- and σ_+ are same as γ, but permitting flooded establishments to have different post-Sandy slopes on each side of the cutoff.

Table A14 reports the RD-DiD estimates for log employment and log sales. Across kernels (triangular, uniform), bandwidth choices (MSE-optimal and fixed), and polynomial orders (local linear baseline; quadratic robustness), the coefficient on $D_i \times Post_t \times Flooded_i$. is positive and statistically significant across specifications. Point estimates are stable across columns and economically meaningful, indicating that, conditional on being flooded within SFHA, establishments just below the $500k cap recover more strongly than those just above. Visual evidence in Figure A5 mirrors the estimates: (i) no pre-Sandy discontinuity in residualized levels at the cutoff; (ii) a clear downward jump in recovery (post – pre) just above the cap, consistent with lower indemnity depth.

A.4 Establishment-level Chronic Risk

Insurance and government can only help recover but they cannot eliminate long-run vulnerability. 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.

$$Y_{i,t} = \beta_1 FloodRisk_{i,t} + \beta_2 Flood_{i,t} + X_{i,t} + \alpha_{s,t} + \alpha_i + \epsilon_{i,t} \tag{7}$$

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 A17. 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 A18 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.

A.4.1 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:

$$Y_{a,t} = \beta_1 FloodRisk_{a,t} + X_{i,t} + \alpha_{s,t} + \alpha_a + \epsilon_{a,t} \tag{8}$$

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 A19 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. (2025a), 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.

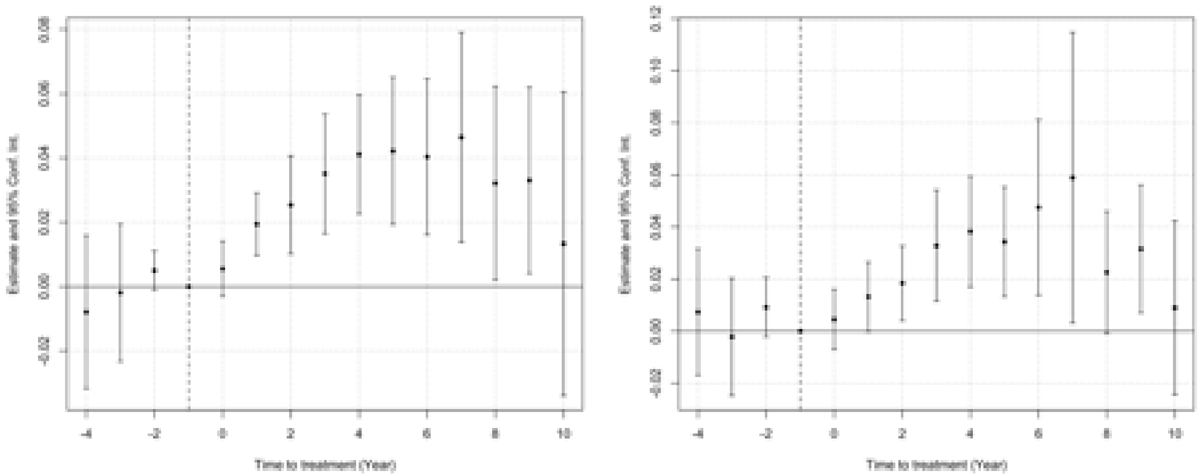
To assess the role of insurance cost, I include the NFIP commercial insurance premium costs and also interact them with local flood risk measure. Including the interaction term allows me to test whether the economic impact of insurance costs depends on the degree of flood exposure in a given area. Conceptually, 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 A19 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 A20 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.

A.5 Figures

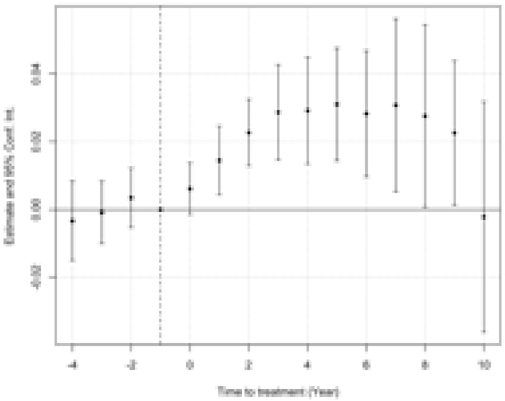
Figure A1: Event Study: The Impact of Flooding on Establishment



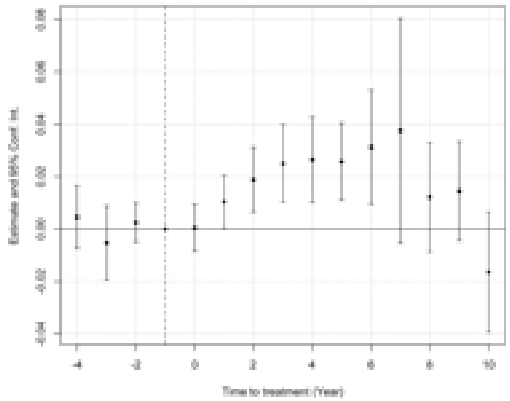
(A) Employment **(B)** Sales

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.

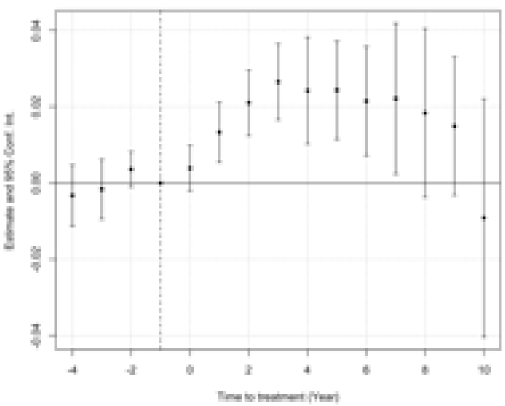
Figure A2: Event Study: The Impact of Flooding on Establishment with Spatial Buffers



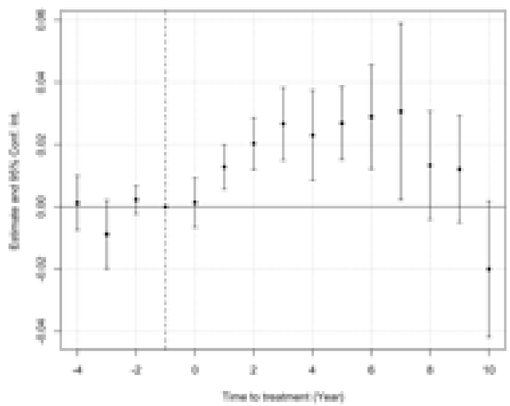
(A) Employment: 250-meter Buffer



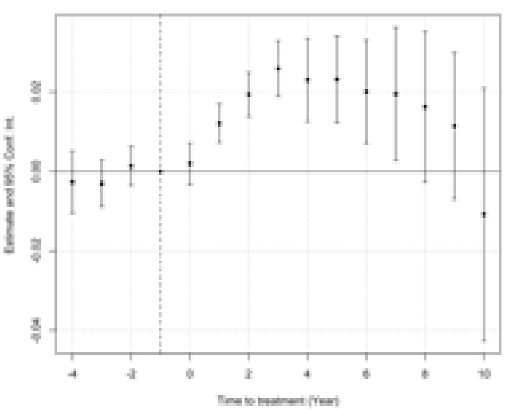
(B) Sales: 250-meter Buffer



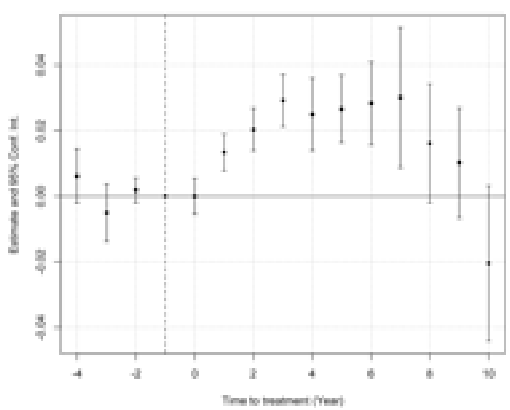
(C) Employment: 500-meter Buffer



(D) Sales: 500-meter Buffer



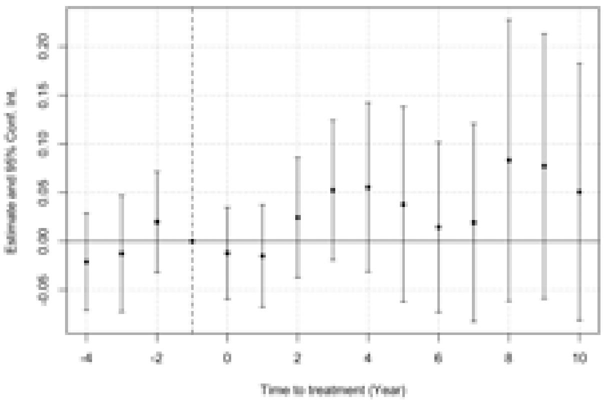
(E) Employment: 1km-meter Buffer



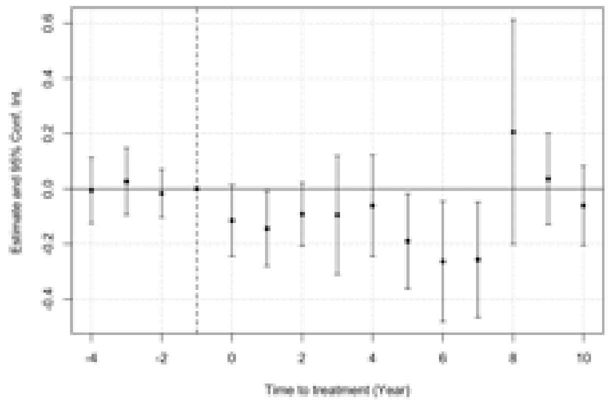
(F) Sales: 1km-meter Buffer

Notes: Figures present the event study regression plots

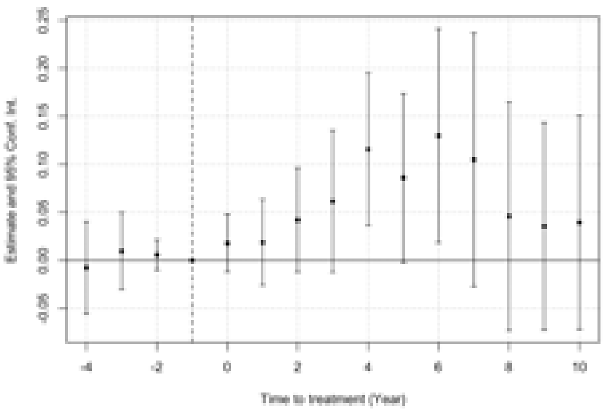
Figure A3: The Effects of Floods on Establishment Employment



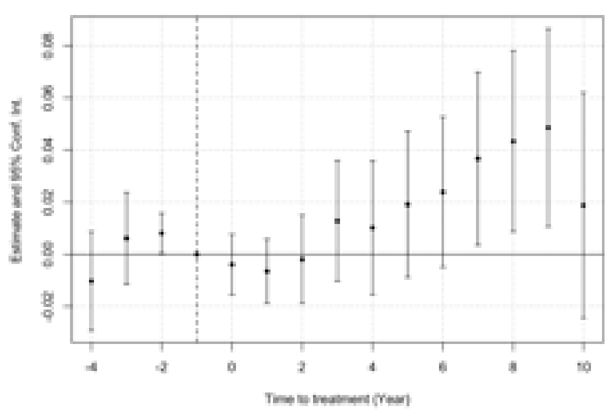
(A) Manufacturing



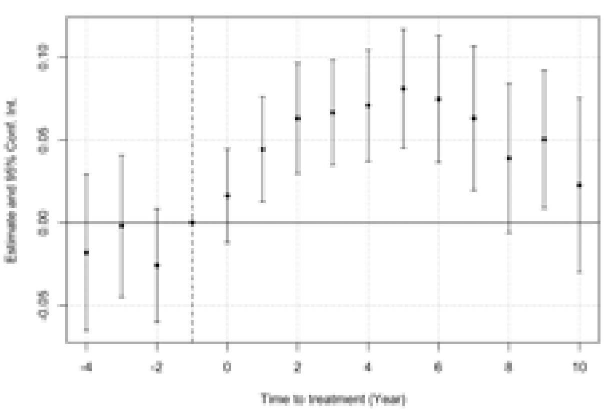
(B) Utilities



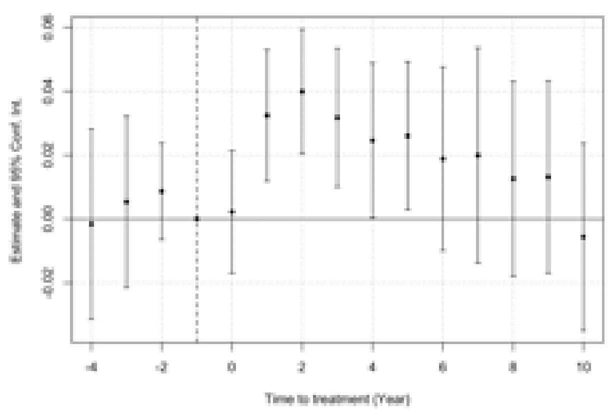
(C) Wholesale Trade



(D) Retail Trade



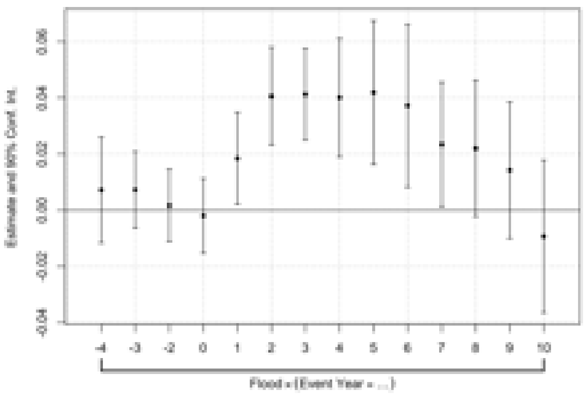
(E) Real Estate



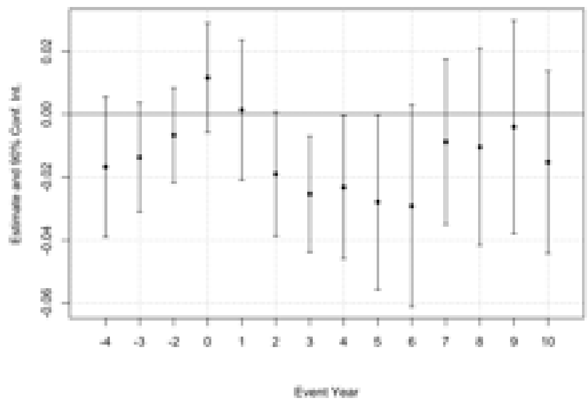
(F) Accommodation and Food Services

Notes: Figures present the event study regression plots

Figure A4: Event Study: Insurance - National

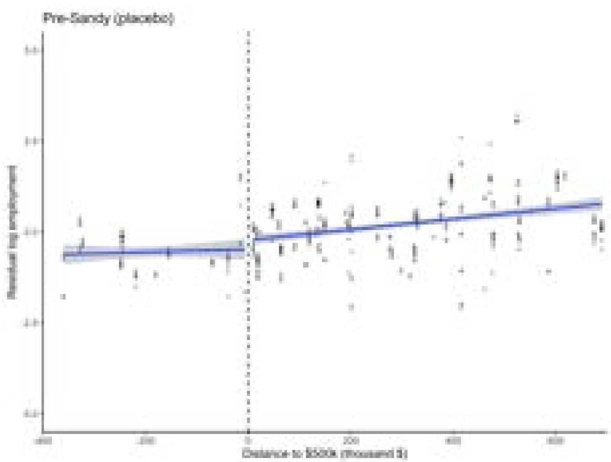


(A) Flooding

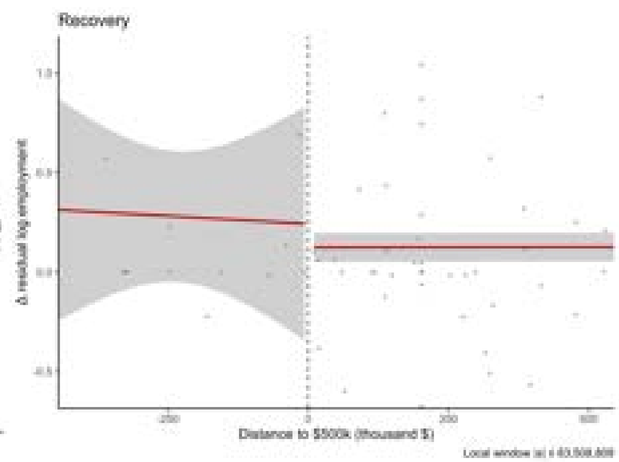


(B) Interaction: I(Outside Floodplain)

Figure A5: Spatial Regression Discontinuity: Insurance - Below Vs Above Cap



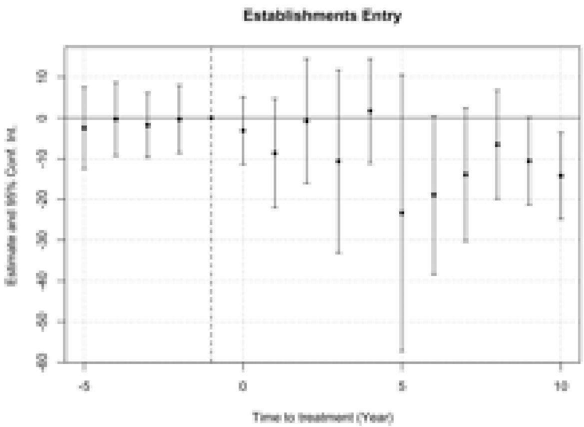
(A) Pre-Sandy: 2000-2011



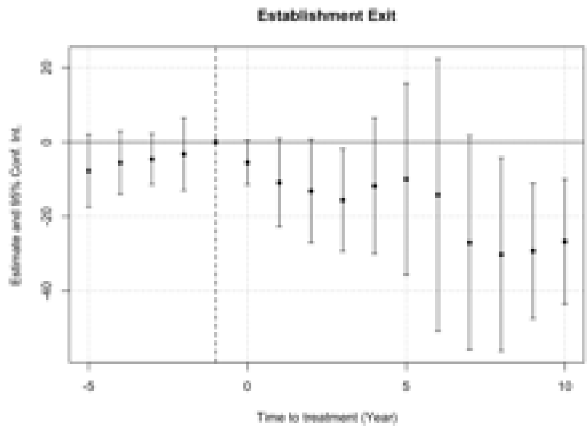
(B) Post-Sandy: 2012-2018

Notes: Figures present spatial regression discontinuity plots with a local linear fit on either side of the flood zone boundary. Distance to cap is measured in thousand dollars, using market values. Plotted points are binned averages of observations. Estimates are residualized of neighborhood, industry, and year fixed effects.

Figure A6: County-level Survivor Bias: Flood effects

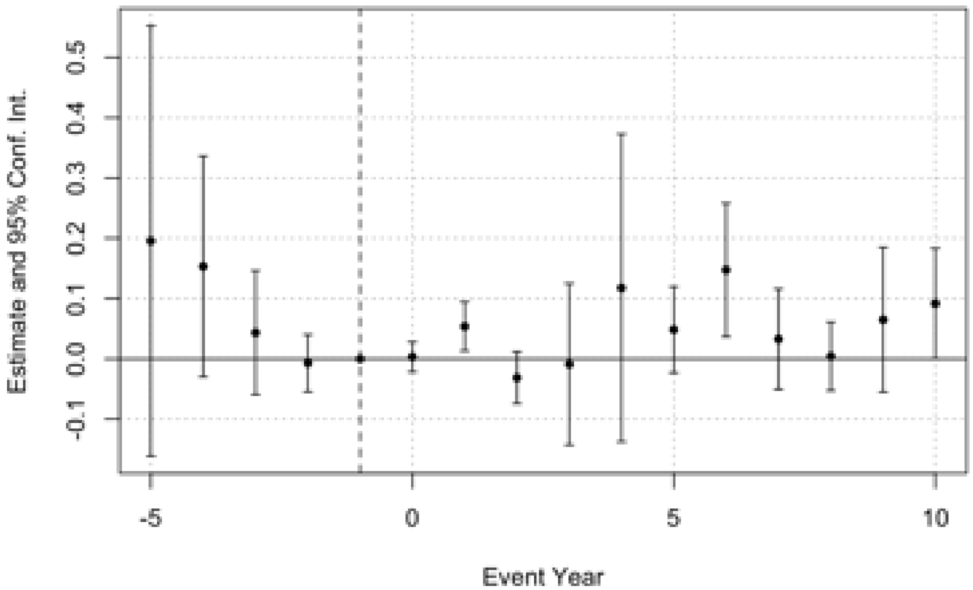


(A) Establishments Entry

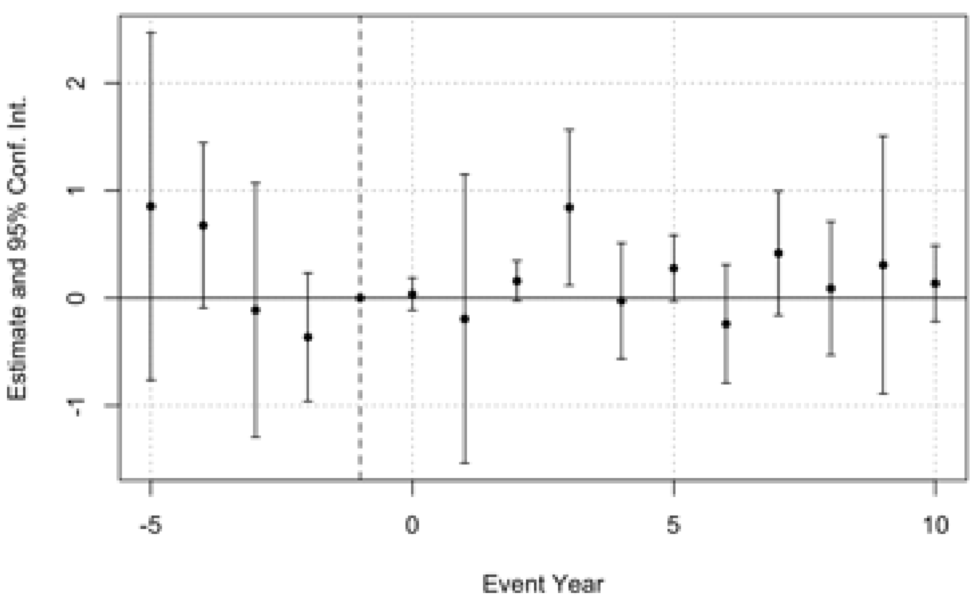


(B) Establishment Exit

Figure A7: Extended Diff-in-Diff: Small Business Administration (SBA) Total Disaster Loans

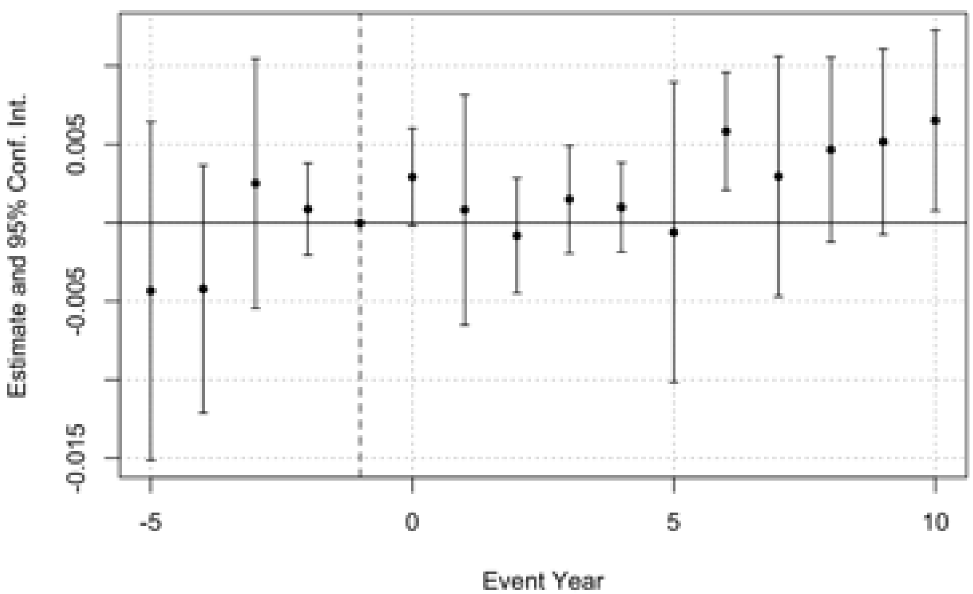


(A) Local Establishments

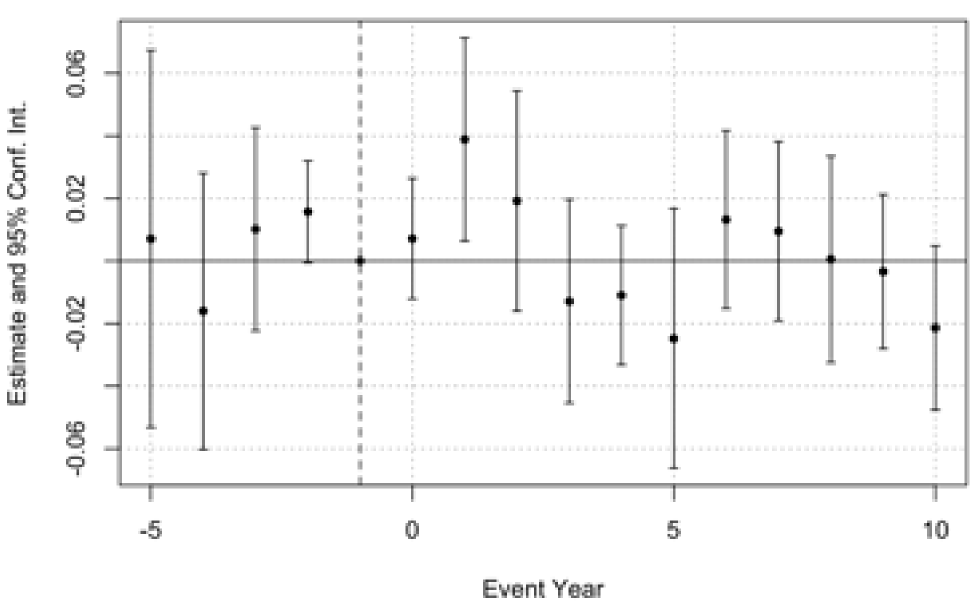


(B) Local Employment

Figure A8: Extended Diff-in-Diff: FEMA Public Assistance Funded Projects



(A) Local Establishments



(B) Local Job Creation

A.6 Tables

Table A1: 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 A2: 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 A3: 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 A4: 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 A5: 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.**

Table A6: 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 $\text{Risk}_{i,t}$ is a dummy variable that equals one if a firm has at least five establishments located in a FEMA-designated floodplain. Cumulative $\text{Floods}_{i,t}$ 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					
	$\text{Disclose}_{i,t}$	$\text{Risk}_{i,t}$	Firm $\text{Initiated}_{i,t}$	$\text{Disclose}_{i,t}$	$\text{Risk}_{i,t}$	Physical $\text{Risk}_{i,t}$	Regulatory $\text{Risk}_{i,t}$	Intangible $\text{Assets}_{i,t}$	$\text{PP\&E}_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Flood $\text{Risk}_{i,t}$	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)
$\text{Asset}_{i,t-1}$	-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)
$\text{Size}_{i,t-1}$	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)
$\text{Revenue}_{i,t-1}$	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)
$\text{PP\&E}_{i,t-1}$	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)
$\text{Capex}_{i,t-1}$	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)
$\text{R\&D}_{i,t-1}$	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					
	$\text{Disclose}_{i,t}$	$\text{Risk}_{i,t}$	Firm $\text{Initiated}_{i,t}$	$\text{Disclose}_{i,t}$	$\text{Risk}_{i,t}$	Physical $\text{Risk}_{i,t}$	Regulatory $\text{Risk}_{i,t}$	Intangible $\text{Assets}_{i,t}$	$\text{PP\&E}_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative $\text{Floods}_{i,t}$	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)
$\text{Asset}_{i,t-1}$	-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)
$\text{Size}_{i,t-1}$	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)
$\text{Revenue}_{i,t-1}$	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)
$\text{PP\&E}_{i,t-1}$	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)
$\text{Capex}_{i,t-1}$	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)
$\text{R\&D}_{i,t-1}$	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 A7: 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 A8: 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 A9: 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 6 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 $\text{risk}_{i,t}$ is a dummy variable indicating whether an establishment is located in the high-risk flood zone by FEMA. $\text{Flood}_{i,t}$ 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.

	$\text{Employment}_{i,t}$		$\text{Sales}_{i,t}$	
Model:	(1)	(2)	(3)	(4)
Post × Flood	0.0268***	0.0259***	0.0202*	0.0232**
	(2.899)	(3.009)	(1.654)	(2.061)
Flood $\text{Risk}_{i,t}$	-0.0100***	-0.0099***	-0.0274***	-0.0264***
	(-3.096)	(-3.033)	(-5.179)	(-5.380)
Community $\text{Infrastructure}_{c,t}$		-0.0001		-0.0019***
		(-0.3838)		(-6.725)
Flood $\text{Duration}_{i,t}$		-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 A10: 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 A11: Impact of Flooding On US Establishments: Event Study

This table presents the regression results on the impact of flooding on establishment outcomes in Equation 6 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 A12: 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 A13: Difference in Difference within FEMA Floodplains: Post-Sandy Outcomes

This table presents the estimates of difference in difference specification with establishment-level data from 2000 to 2018 with the subsample of establishments in FEMA floodplains. The outcome variables are log employment and log sales. All specifications include establishment fixed effects, neighborhood-by-year fixed effects, and industry-by-year fixed effects. The standard errors are two-way clustered by establishment and year, and t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Model:	Employment (1)	Sales (2)
$\text{AfterSandy}_t \times \text{Flooded}_i$	0.0757**	0.1711**
	(2.543)	(2.114)
Establishment, Nbh×Year, Industry×Year	Yes	Yes
Observations	11,550	9,497
R^2	0.94093	0.93022

Table A14: RD DiD: NFIP Intensive Margin at $500k cap within SFHA in NYC

This table reports difference-in-discontinuities estimates of the intensive-margin insurance effect at the $500k building-coverage cap. The running variable is the pre-Sandy building value V_i centered at the cap $x_i = V_i - 500,000$. D_i is $1\{x_i \leq 0\}$ and the key coefficient of $D_i \times Post_t \times Flood_i$ measures the additional post-Sandy jump at the cap for flooded establishments, relative to non-flooded, within FEMA SFHAs. Columns (1)–(2) use a triangular kernel and MSE-optimal bandwidth proposed by Calonico et al. (2014). Columns (3)–(4) use a uniform/rectangular kernel with a common fixed bandwidth of 450,000. Columns (5)–(6) use a uniform/rectangular kernel with MSE-optimal bandwidth; Columns (7)–(8) use a triangular kernel with a local quadratic (2nd-order) polynomial. Outcomes are log employment and log sales. All specifications include establishment fixed effects, neighborhood-by-year (NTA×year) and industry-by-year (NAICS2×year) fixed effects. Standard errors are two-way clustered by establishment and year; t-statistics are reported in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

	Triangular kernel, optimal bandwidth, Local linear		Rectangular kernel, constant bandwidth, Local linear		Rectangular kernel, optimal bandwidth, Local linear		Triangular kernel, optimal bandwidth, 2nd-order polynomial	
	Emp	Sales	Emp	Sales	Emp	Sales	Emp	Sales
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D_i \times Post_t \times Flood_i$	0.2606*	0.3654	0.3390*	0.7783**	0.2733*	0.3917*	0.3147*	0.5570**
	(1.858)	(1.704)	(1.879)	(2.157)	(1.964)	(1.809)	(1.943)	(2.512)
Estb, Nbh×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,471	3,899	752	652	4,137	3,621	4,471	3,899
R^2	0.95491	0.95115	0.97671	0.97542	0.95339	0.95086	0.95500	0.95157

Table A15: 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

	Employment$_{z,t}$		Establishments$_{z,t}$					
			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

	Emp$_{a,t}$	Job Creation$_{a,t}$	Estb$_{a,t}$	Estab Entry$_{a,t}$	Estab Exit$_{a,t}$
Model:	(1)	(2)	(3)	(4)	(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 A16: 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.

	$\text{Emp}_{i,t}$	$\text{Sales}_{i,t}$	$\text{Emp}_{i,t}$	$\text{Sales}_{i,t}$	$\text{Emp}_{i,t}$	$\text{Sales}_{i,t}$	$\text{Emp}_{i,t}$	$\text{Sales}_{i,t}$	$\text{Emp}_{i,t}$	$\text{Sales}_{i,t}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(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 A17: 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 7 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 A18: 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 7 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 $\text{risk}_{i,t}$, a dummy indicating whether establishment i is located in a FEMA-designated high-risk flood zone; and $\text{Flood}_{i,t}$ 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						
	$\text{Employment}_{i,t}$			$\text{Sales}_{i,t}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Flood $\text{Risk}_{i,t}$	-0.0101***	-0.0103***		-0.0237***	-0.0268***	
	(-3.101)	(-3.136)		(-4.520)	(-5.504)	
$\text{Flood}_{i,t}$	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 $\text{Infrastructure}_{c,t}$	-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 $\text{Flood}_{i,t}$		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 A18: 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 A19: 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$_{a,t-1}$	$2.08 \times 10^{-5*}$	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 A20: 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

Model:	Employment$_{a,t}$ (1)	Job Creation$_{a,t}$ (2)	Job Destruction$_{a,t}$ (3)	Establishments$_{a,t}$ (4)	Estab Entry$_{a,t}$ (5)	Estab Exit$_{a,t}$ (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

Model:	Employment$_{a,t}$ (1)	Job Creation$_{a,t}$ (2)	Job Destruction$_{a,t}$ (3)	Establishments$_{a,t}$ (4)	Estab Entry$_{a,t}$ (5)	Estab Exit$_{a,t}$ (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