Disasters, Capital, and Productivity*

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This version: October 31, 2025

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Abstract

Natural disasters devastate economies, yet regional productivity often improves in their wake. Why? Using administrative plant-level microdata from the US Census Bureau and an event study design, I trace the creative destruction process that follows large, federally declared floods. Exits rise after flooding, primarily among the least productive plants. Their second-hand machines are then reallocated toward more productive survivors and, notably, toward high-productivity entrants. Survivors also upgrade their capital as they rebuild, seeing productivity gains. A key mechanism for these outcomes is that federal disaster spending expands access to finance, particularly for nimble, entrepreneurial young firms, which play an outsized role in reviving regional dynamism and productive churn. My findings reveal a novel, underappreciated channel through which government spending supports disaster-hit economies and underscore its critical role in a warming world.

Data disclaimer: Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2851. (CBDRB-FY24-P2851-R11684, -R11700, -R11775, -R11815; CBDRB-FY25-P2851-R11940, -R11949, -R12521, R-12639, R-12640).

* I am deeply grateful to Sandra Black, Jeffrey Shrader, Suresh Naidu, and Xavier Giroud for their continuous guidance and encouragement. For feedback and helpful discussions, I thank Seula Kim (Discussant), Doug Almond, Liz Ananat, Gadi Barlevy, Joel David, Mark Dean, Ryan Decker, Mike Ewens, Jorge Guzman, Dan Hartley, Bart Hobijn, Michelle Jiang, Hyunseob Kim, Ralf Meisenzahl, Rob Metcalfe, Filippo Mezzanoti, Anushka Mitra, Roman Rivera, Chad Syverson, Eric Verhoogen, Micah Villarreal, Nico Werquin, and seminar participants at the NBER Summer Institute (Macro and Productivity), Columbia, APPAM, the Chicago Fed, and WEFI Fellows group. I am indebted to Shirley Liu and Census Disclosure Avoidance reviewers for help with data access and disclosure. I thank Shahin Davoudpour (Chicago FSRDC), and Shital Sharma and Sari Pekala-Kerr (Boston FSRDC) for hosting me during temporary visits. I thank Thomas Walstrum for help with survey dissemination. I acknowledge generous funding from the Washington Center for Equitable Growth and the Columbia Center for Political Economy. Human subjects research approval was obtained from Columbia IRB (Protocols: AAAU-4263 and AAAV-4701). All errors are mine.

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1 Introduction

Climate change magnifies natural disaster risk, with significant implications for economic reallocation, government spending, and aggregate productivity.[1] Despite their first-order importance to economic science and policy conversations, however, our understanding of these issues remains incomplete. In this paper, I examine post-disaster reallocation and its aggregate implications focusing on firm dynamics—the entry, growth, downsizing, and exit of firms that is the quintessential feature of economic churn and, in healthy economies, a key driver of productivity growth. In particular, I use confidential microdata from the US Census Bureau to examine the behaviors and productivity outcomes of exiters, survivors, and entrants, and allocative efficiency—i.e., the extent to which resources are allocated to the most productive firms—following large, federally declared floods.

The impact of floods on firm dynamics and allocative efficiency is not ex ante obvious. Flooding is a negative shock to firms' capital stock and productivity: when a flood happens, firms face disruptions to their workforce, physical capital, and/or production process, and may have to shut down if they are unable to weather the shock. Yet, large disasters in the US, like the ones I focus on here, are often accompanied by substantial federal recovery spending that expands firms' access to financing. On one hand, since Schumpeter (1939), crises like recessions have been characterized as having a 'cleansing' effect, whereby low productivity units are forced out of market, freeing up resources to be redirected toward more productive uses. Similarly, federal disaster response may similarly facilitate productive economic redistribution and investment after disasters. On the other hand, the rebuilding spending could create or contribute to frictions, such as credit market imperfections, that may misallocate resources and hurt aggregate productivity.[2]

Consistent with the cleansing hypothesis, I find that post-flood reallocation enhances aggregate productivity, particularly due to young firm activity. After flooding, the least productive plants are forced to shut down, while their capital is reallocated toward more productive survivors, including to positively-selected entrants.Young plants also take advantage of the expanded supply of (cheap) second-hand capital following disasters to build up their capacity. A key mechanism for these outcomes is that federal disaster spending crowds in private loans and expands access to financing, thereby democratizing credit access for new

[1] Scientists predict a greater frequency of intense weather extremes (see (Mora et al., 2018; IPCC, 2021)). These weather shocks are expected to be a primary manifestation of global warming, and hurt aggregate growth (Nath et al., 2024; Bilal & Känzig, 2024)

[2] Credit market imperfections, mainly constraints, have been modeled in various ways that partially dampen (Osotimehin & Pappadà, 2017) or even substantially undo (Barlevy, 2003) cleansing from recessions.

and young firms, whose nimbleness fuels aggregate dynamism and regional recovery.

I focus on large floods that triggered a presidential disaster declaration—a place-based designation that unlocks substantial disaster assistance to affected counties. Low-interest recovery loans—which are the only kind of support firms can get—have been shown not only to achieve their intended goal of helping borrower firms cover under- or un-insured damages, but they also to crowd in additional private financing by help borrowers get *additional* loans from private lenders.[3] Thus, financing constraints, which would typically weaken recovery, are less likely to bind in the declared disaster setting.[4] Importantly, my focus on the manufacturing sector is an asset for this study because the potential increase in local demand from federal spending is unlikely to affect plant outcomes.[5]

My main data sources are the confidential plant-level microdata from the Annual Survey of Manufactures ("ASM") and the Longitudinal Business Database ("LBD") from 1977 to 2017. The ASM provides rich information on plant output, productivity, as well as book values of capital stock and investments in building and machinery assets. Since it is impossible to observe quantity-based Total Factor Productivity ("TFP") in these data, I use revenue-based TFP as the primary indicator of productivity. The ASM's intermittent information on plants' capital retirement (i.e., sale and disposal) helps me approximate the post-flood damage and disinvestment, while its breakdown and also breaks down capital investments as new versus used capital enables me to study capital replacement and reallocation. Isolating post-flood entry-exit dynamics from surviving plants' capital readjustment requires comprehensive information on plants' life cycle. To observe this, I use the LBD—the Census Bureau's workhorse economic dataset tracking the birth, death, and year-to-year performance of all businesses in the US. Leveraging plausibly exogenous variation in the timing of flooding, I use an event study design to compare the pre- and post-flood outcomes of plants and industries in flooded counties.

I document three key results. First, exit rates rise after flooding, primarily because the least productive plants shut down. I find that plants' probability of exiting within two years increases by 3.6 percentage points (p.p.) after flooding, representing a substantial—more than 30%—increase compared to the pre-disaster baseline. Importantly, plants that were already in the bottom quartile of TFP distribution in their narrowly-defined industry *before* the disaster are more likely to exit after it relative to their counterparts in the top three

[3] See Collier et al. (2024).

[4] Feigenbaum et al. (2022) show that, after large capital destruction shocks, regions with under-developed credit markets see weaker economic recovery.

[5] Roth Tran and Wilson (2023) show that household consumption increases after declared disasters.

quartiles. This demonstrates that post-flood exits are primarily concentrated among the lowest performing plants, suggesting a weeding out of less efficient forms of production after the negative productivity shock.[6]

Second, I show that surviving plants invest to replace their capital and see productivity gains. Conditional on not exiting, i.e., surviving for at least 3 more years, surviving plants have a substantial and persistent increase their capital retirement, standing at more than 60% higher retirement in the 5 year relative to the pre-flood baseline.[7] Plants also increase their *net* capital investment, suggesting that rebuilding investments more than compensate for the flood-related capital retirement.[8] Overall, surviving plants' productivity increases by more than 11% in the 5 year following the flood, consistent with their positive selection into survival as well as their capital investments in brand new machinery.

Third, as the local supply of second-hand capital increases following disasters, young plants and new entrants acquire that used capital to build up their capacity.[9] While we may worry that used machines—especially in the post-flood context—might be lemons, or that their increased supply and lower prices may attract low quality entrants, I find no evidence of this. In fact, post-flood entrant firms are positively selected, boasting about a 14% higher TFP compared to pre-flood entrants. More broadly, young plants below age 5 also increase their purchase of used capital. This is partly explained by young firms' nimbleness: using data from the Management and Organizational Practices Survey (MOPS), I show that younger firms have better organizational practices in fixing and responding to crises (like machines breaking down) than older ones.[10] As the disaster amplifies the already-intense up-or-out selection that young firms typically face, their superior agility enables them to survive and even capitalize on the disaster 'opportunity' to scale.

Ultimately, post-disaster reallocation enhances allocative efficiency at the aggregate level, particularly due to the role of young firm activity. To study this, I focus on the average and TFP as well as dispersion in revenue TFP using various measures, including the standard deviation as well as the inter-quartile range of TFP between plants at the

[6]Similarly, Foster et al. (2016) show that exits are concentrated among low performers during recessions.

[7]This is consistent with the corrosive effect of water/humidity on metal. Other explanations include machinery damage due to sudden power outages; and supply chain reorganization, which may require firms to switch to different production technologies.

[8]This increased investment reflects disaster-induced capital replacement as incumbents' county-level total investment also rises after flooding.

[9]This is consistent with prior findings that young firms typically purchase used capital from incumbents. See Ma et al. (2022); Eisfeldt and Rampini (2008).

[10]The MOPS is an addendum to the ASM. See Buffington et al. (2017).

75th and 25th percentiles within similar industries and locations.[11] Measures of dispersion are useful here because, in a frictionless world, marginal productivity of inputs should be equal across firms, so deviations–such as higher dispersion–suggest inefficiencies. I find that increased young firm activity is associated with declining productivity dispersion along with an increased average TFP after declared flood. Capital and other inputs are, on average, reallocated toward plants which can make better use of them, primarily in regions with a larger share of young firms, and those where younger and older firms are co-located. This highlights that young firm activity drives post-flood creative destruction.

These outcomes stem from the expanded access to financing that federal disaster spending facilitates. Using the Community Reinvestment Act's data on bank loans to businesses, I find that banks particularly reduce lending in the smallest loan-size category after non-declared floods—i.e., those that only receive local but not federal relief assistance. Following prior seminal work and using loan size as a proxy for firm size and age,[12], this suggests a reallocation of credit supply *away* from smaller, younger firms (≈8% decline) toward more established incumbents. However, after declared floods, business loans in the smallest loan size category *increase* by more than 3%. This offsets the constrained access to credit that young and small firms would have faced in the post-disaster context, sustaining young firm activity. Further, I show that, despite typically being vulnerable to financing constraints, small, young manufacturing firms have greater post-flood investment relative to larger, older, more established firms. This further indicates that federal spending expands access to finance for small, young firms. In contrast, in the absence of federal assistance, plants' capital investment and labor productivity suffer after flooding, which demonstrates the critical role of government spending in smoothing recovery.[13] My findings from a qualitative survey of manufacturers based in the Midwestern U.S. also corroborate these takeaways: if hit by major floods, manufacturers would look to upgrade their capital as they rebuild so long as they had ample access to financing.

This paper contributes to several strands of literature, primarily that on firms' responses to weather shocks and the role of government relief spending. Previous work shows how firms are affected by natural disaster shocks and how they recover (Barrot & Sauvagnat,

[11] This is a common measure used in studies of productivity dispersion and resource (mis)allocation. See (Hsieh & Klenow, 2009; Syverson, 2011).

[12] This follows seminal work on the lifecycle financing patterns of firms (see Berger and Udell (1998)).

[13] I also find suggestive evidence that allocative efficiency following floods that coincided with the 2008 Financial Crisis, which was marked by the crash of credit markets, saw distorted productivity recoveries, particularly in regions where younger and older firms were co-located. This illustrates that the crash of credit markets has the opposite impact of exacerbating misallocation in the wake of disasters

2016; Carvalho et al., 2021; Basker & Miranda, 2018; Gallagher et al., 2023; Collier et al., 2024), with the findings indicating a strong role of local demand in affecting post-disaster firm outcomes. My paper offers novel evidence based on a tradable sector—manufacturing—that is less sensitive to local demand, and characterizes the heterogeneity in plants' behavior and outcomes by firm age and size, thereby expanding our understanding of the nexus of climate change, firm productivity, and disparities in recovery. My study also provides new evidence on the role of managerial quality in post-disaster recovery. Complementing recent insights on firms' disaster management (Norris Keiller & Van Reenen, 2024) and the role of management in economic dynamism (Sadun et al., 2025), my work provides new evidence on how managerial agility enables firms—particularly young ones—to respond to shocks and drive broader business dynamism in post-disaster settings.

In this respect, this study also contributes to the broader literature on the impact of government spending on recovery after negative productivity shocks. With the exception of Gallagher et al. (2023), most other existing studies on post-disaster recovery focus exclusively on large, presidentially-declared storm-related disasters, showing that federal aid helps with household recovery and incumbent firm survival (Roth Tran & Wilson, 2023; Deryugina, 2017). The evidence I provide on non-declared floods helps illustrate the role of federal disaster spending. Consistent with Walsh (2023)'s finding that new firms can act as a significant multiplier of both positive and negative local shocks, this paper demonstrates a novel channel through which government spending supports recovery in disaster-hit regions—a boost to economic dynamism via the firm entry margin.

More broadly, this paper adds to the macroeconomics literature on capital reallocation across the business cycle, and on the role of government spending after negative productivity shocks. My work complements Eisfeldt and Rampini (2006), who show that capital reallocation is (counter-productively) cyclical when its benefits are, in fact, counter-cyclical, inferring the presence of frictions, including financing constraints, that make reallocation costlier during downturns. My paper confirms this mechanism by using the exogenous timing of floods to causally demonstrate that government spending after a negative productivity shock like flooding facilitates greater and more efficient reallocation of capital, particularly by propping up the firm entry margin and young firm activity.[14] This is consistent with (Caballero & Hammour, 1996), who show that frictions may decouple creation and destruction, which would, in an ideal world, simultaneously happen during downturns, but that incentives for

[14]While the previous literature on costly capital reallocation and the role of government spending (see Ramey and Shapiro (1998, 2001)) has primarily focused on demand shocks, my use of exogenous weather shocks reveals cleaner causal evidence on the impact of government spending on capital reallocation.

the creative margin of an economy increase the pace of reallocation and help restore efficiency. (Kerr & Nanda, 2009) illustrate that democratizing access to financing is critical for entrepreneurial experimentation, young firm activity, and ultimately, productivity-enhancing business churn. In line with this, my paper shows that the financing unlocked due to federal disaster spending counteracts the shock's destruction and reinforces the economy's creative margin, improving allocative efficiency during recovery.

This paper also contributes to the literature on the impact of climate change on physical capital depreciation, reallocation, and growth. Early theoretical work on these areas worried that the fixed nature of physical capital stock would drive slow adjustment to rapid weather shocks and thus exacerbate welfare losses from climate change (see Quiggin and Horowitz (2003); Yohe and Neumann (1997); Fisher and Hanemann (1993)). My paper provides a much-needed empirical test, showing that capital appears to be more mobile—i.e., adjustable within plant and redistributable across plants—than previously thought, at least in the short run. Existing work in this area has studied how global warming might affect aggregate growth via its impact on capital, primarily from a theoretical standpoint or from coarse cross-country and/or global analyses (see Nath et al. (2024); Casey et al. (2024); Bilal and Känzig (2024)). Highly relevant to my paper, Bilal and Rossi-Hansberg (2023) use predicted severe storm incidences to simulate a capital depreciation shock and study county-level migration and investment responses, with the latter measured from manufacturing firm investment data at 5-year intervals and imputed in between. My use of rich plant-level annual data (including on capital retirement) and real incidence of major declared floods allows me to capture the dynamics and heterogeneity of post-disaster investment with more granular detail and greater accuracy. Thanks to the richness of the ASM in capturing capital retirement (including scrapping), this paper adds to this literature what is, to my knowledge, the most direct empirical evidence to date on the impact of climate hazards on capital depreciation.

Lastly, this study adds to the literature on entrepreneurship and physical capital. Existing work has shown that young (and small) firms typically buy used capital from incumbents, in part due to financing constraints (Eisfeldt & Rampini, 2008; Ma et al., 2022), primarily using descriptive approaches and/or potentially non-representative samples. By leveraging the representative nature of the ASM data and the exogenous timing of flooding, my study offers novel and generalizable causal evidence on how increased exits and capital upgrading among incumbents lead to higher used capital purchase by new and young firms.[15]

[15] Ma et al. (2022) use loan filing data to show that younger firms are more likely to buy used machinery from incumbents. However, their analysis may be affected by selection—both in which firms use machines as collateral and which machines are chosen. Moreover, their findings linking incumbents' machinery turnover

2 Institutional Background

Large disasters often trigger federal disaster declarations in the US. In accordance with the Robert T. Stafford Disaster Relief and Emergency Assistance Act, 42 U.S.C. §§ 5121-5207 (the Stafford Act), a federal disaster declaration relates to major disaster events and emergencies, and it can only be made by the President of the United States. This process is initiated when a state governor, or as of 2017, a federally-recognized Indian tribal government, provides evidence that their state/locality cannot manage a certain disaster and requests federal assistance on behalf of the disaster-affected county/counties in their jurisdiction. The evidence that will be presented to the president is a Preliminary Damage Assessment (PDA), within 30 days of the event, conducted jointly by the Federal, State/Tribal body that initiated the request and the Federal Emergency Management Agency ("FEMA") Regional Office that handles the request. FEMA provides assessments and advice,[16] yet the declaration is at the discretion of the President.

Once the US president approves the request, federal funds can be used to repair public structures and to provide individual and business grants and loans.[17] FEMA's stated policy goal is to *supplement* disaster-affected communities' recovery efforts. In particular, federal disaster assistance only covers damages that are not already covered by insurance. Disaster assistance is provided under four major programs: public assistance (e.g. debris removal), individual and household assistance (e.g. legal assistance, counseling, and special unemployment payments), hazard mitigation (to reduce long-term exposure to similar risks), and low-interest disaster loans to households and firms under the Small Business Administration. Among these programs, the last one is most relevant for firms. Federal disaster spending, and in particular SBA loans, have been shown to increase business survival and crowd in private credit (see Collier et al. (2024); Gallagher et al. (2023)). Therefore, manufacturers are expected to have broad access to financing following government spending after federally declared disasters.

While the negative impact of disasters on firm survival and new entries is obvious,

to young firms' used capital purchases rely on lagged local investment, which may reflect reverse causality if incumbents invest in anticipation of entrant activity. By leveraging the representative nature of ASM data and the exogeneity of the timing of disasters, this paper provides more generalizable and causal evidence.

[16] There are thresholds of the per-capita property damage that must be reached or surpassed for certain kind of assistance such as broad-based public assistance to be unlocked. These vary across years, but are usually about 3 dollars per county resident (see (FEMA, 2023)).

[17] If the federal aid request is denied, the state/tribal government can appeal the decision within 30 days by providing supporting information about the inadequacy of their resources to respond to the disaster. However, denials are rare (Malewitz & Vock, 2013; CRS, 2017).

the impact of federal disaster spending on business dynamics and productivity is ex-ante ambiguous. On one hand, federal disaster assistance may facilitate reallocation of economic resources from less to more productive plants.[18] Models of firm dynamics conceptualize job creation as an aspect of productive firms that expand in response to positive business conditions; Haltiwanger et al. (2013) also show that new firms play an outsized role in job creation in the U.S. economy. So if the positive role of federal spending wins out, then the firm entry and young firm activity margins—which are marked by the nimble and responsive nature of young firms—would be key channels through which aggregate productivity impacts materialize. On the other hand, however, the expansion of credit access after federal spending may directly or indirectly (e.g., through private lenders) avail cheap capital for lower-productivity survivors and new entrants, potentially crowding out more productive uses of the public funds.[19] As such, increased access to financing in the wake of major disasters may hurt aggregate productivity growth.

3 Data and Empirical Strategy

3.1 Data

Data on firms:[20]

- *The Annual Survey of Manufactures ("ASM")*: The primary data source I use in the ASM survey, which follows about 50-70,000 establishments for 5 years at a time, selecting a new sample in years ending with 4 and 9. The ASM is a smaller, annual complement to the Census of Manufactures ("CMF"), the full census of all ≈200,000 manufacturing establishments that the Census Bureau conducts in years ending with 2 and 7. ASM sampling is based on plant size, with plants that have more than 500 workers surveyed annually. I use the version of the ASM data which include TFP information and the capital stock of manufacturing plants in each period, all

[18] For example, exogenous crisis events, such as the Great Boston Fire of 1872 (Hornbeck & Keniston, 2017) or the Mississippi River flooding of 1927 (Hornbeck & Naidu, 2014) have been followed by efficiency-improving reallocation as rebuilding/recovery efforts introduced updated technology and materials.

[19] For example, Chava et al. (2023) find that lower entry costs are associated with higher rates of lower quality entrepreneurs who default on loans years after entry, particularly in states enacting business-friendly subsidies and taxes.

[20] These data are restricted-access datasets from the US Census Bureau and can be accessed by qualified researchers at Federal Statistical Research Data Centers (FSRDCs).

of which were calculated as part of the Collaborative Microproductivity Project (see Cunningham et al. (2023)).

The ASM data have several features that make them suitable for my analyses. First, response is required by law, which implies that attrition or non-response related to disasters should not systematically affect my results. Second, misreporting is punishable by law, making the data reliable. Any imputations, i.e., data that are edited and entered by Census staff, are known. And third, the sample weight for each plant is provided, which allows me to account for sampling design in my analyses and work to obtain representative estimates.

Importantly for my study, the ASM offers information plants' capital investment behavior separately for two categories of capital, machinery/equipment, and building/structures capital (see Figure A.1). Machinery and equipment capital encompass: all production machinery and transportation equipment (automobiles, trucks, etc.), motors, lathes, punch presses, office equipment and machines; computers; furniture and fixtures for offices, cafeterias, dressing rooms; and warehouse equipment. Buildings and structures capital exclude the value of land itself, but encompass elevators, cranes, blast furnaces, brick kilns, fractionating towers, shipways and similar structures, as well as the usual factory office and warehouse type of buildings. While capital investment data are available for every year, the ASM provides an even more granular breakdown between used and new capital, within each machinery and building capital type category, up to 1996. The latter is what allows me to study the reallocation of used machines after disasters.

Another useful feature of the ASM data is that they have additional data on Management and Organizational Practices in years 2010 and 2015, which helps me study plant-level managerial responses to problems (in my case, flooding). See Figure A.2 for the specific question.

- *The Longitudinal Business Database ("LBD")*: is the Census Bureau's main economic microdataset, providing detailed information on their entry, exit, survival, and employment and payroll records information on the universe of business establishments in the US. The LBD is the longitudinal version of the broader Business Register dataset, which the Census Bureau maintains based on the tax records of businesses from the Internal Revenue Service ("IRS"). See Chow et al. (2021) for more details.

  The annual nature of LBD makes a useful complement for the ASM data: first, given

that the ASM is an unbalanced panel that generally only follows most plants for five years at a time, it is useful to observe the entry, exit, and survival of manufacturing plants in years in which they are not observed in the ASM. In particular, having the exit year information from the LBD helps identify whether ASM plants that 'go missing' from the ASM sample reflect survey attrition or plant exit, which is itself a relevant post-disaster outcome to examine. I link ASM plant-year data with the LBD using internal plant identifiers. While the LBD is available starting in 1976, information on whether plants are entrants or continuers is only reliably tracked from 1977 onward, which is why my sample starts from the year 1977.

Data on flooding

- *FEMA Disaster Declaration Summaries*: I observe the incidence of floods from the Federal Emergency Management Agency's disaster declaration records.[21] Given that they are a federal record, these data provide an exhaustive list of all declared disaster events since the 1950s. Therefore, they are a reliable data source to capture the universe of declared flood events.

- *Spatial Hazard Events and Losses Database for the US ("SHELDUS")*: For mechanisms analyses, in which I examine non-declared floods, I use data from SHELDUS provides annualized information on various hazard events and perils starting from 1960 along with the damage associated with those incidents, including the human and financial losses associated with those events and the duration of the incidents in days. I use the Version 20.0 SHELDUS database to identify flood hazards that were *not* associated with a presidential disaster declaration.

Data on financing

- *Community Reinvestment Act (CRA) bank loan data*: I use data on small business loans availed by the Federal Financial Institutions Examination Council (FFIEC) under the Community Reinvestment Act (CRA), which was enacted to encourage banks to meet the credit needs of the communities in which they operate. These data cover both secured and unsecured small business loans and provide, for each county, the numbers and dollar amounts of small business that banks originated by loan size—below 100k USD, 100k-250k USD and 250k-1 million USD—from 1996 onward. I

[21] FEMA's disaster declaration records can be accessed here.

follow seminal work around the size and credit seeking behavior of young firms (see Berger and Udell (1998)) and use the smallest loan size category as a proxy for the smallest and/or youngest firms, which are widely understood to be more sensitive to access to financing—and vulnerable to financial constraints.

3.2 Sample

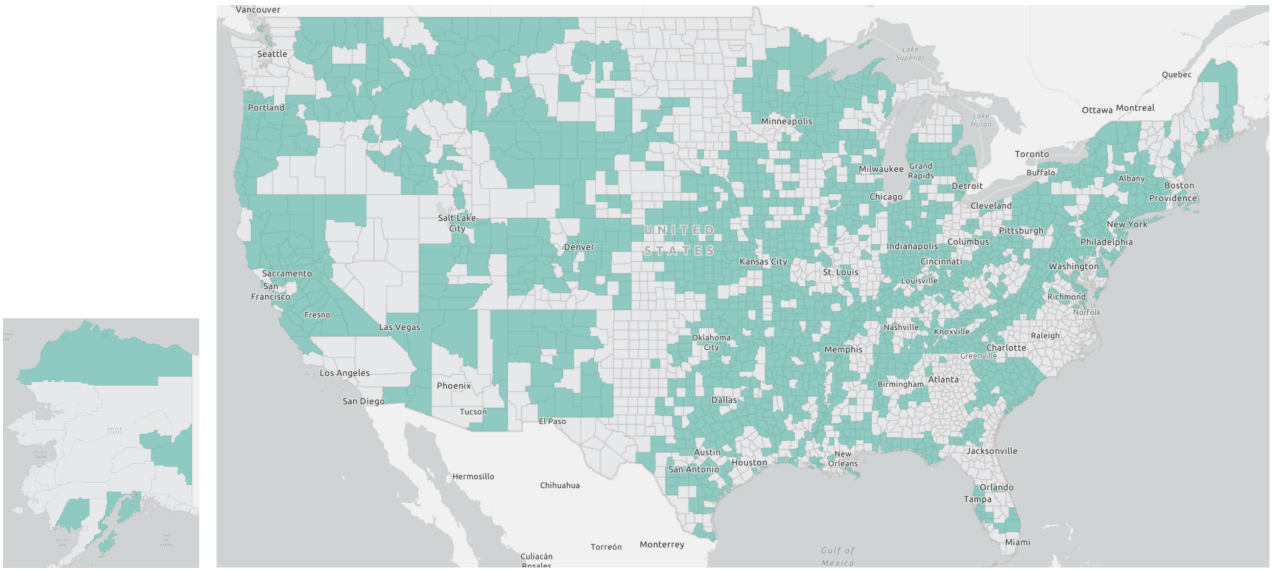
I start out with all ASM plants in the 1977-2017 period whose North American Industry Classification System ("NAICS") industry code falls under the core manufacturing codes between 31-33, then apply some key restrictions to make the estimation sample more relevant for the purpose of my analyses. First, I apply basic restrictions to ensure that each plant-year observation has a TFP estimate, which helps to ensure that this important productivity outcome, but also serves as a certification for data quality since the TFP-enhanced ASM data have undergone careful cleaning by Census researchers and have full data on plants' capital stock calculated via the perpetual inventory method (see Cunningham et al. (2023)). Second, I keep only ASM plants which have a matching record in the LBD, and are marked as employer plants and in-scope for the publicly-accessible version of the LBD, the Business Dynamics Statistics ("BDS"). This restriction ensures that my analyses capture employer establishments where production takes place, rather than, for instance, administrative units of manufacturing firms.[22]

Third, given the cyclical nature of disasters like floods, which often occur due to weather events, it is useful to isolate individual flood events as much as possible and avoid too much repetition. As such, I restrict my sample to plants located in counties which received at most 1 flood in any consecutive six years. Additionally, I keep only plants located in counties that received at least 1 federally-declared flood and at most 3 declared floods in the overall 1976-2018 period. Lastly, since my event window covers the four years before flooding and the five years after it, I only keep these relevant years around the year of flood treatment. With these restrictions, I ultimately end up with 422,000 plant-year observations associated with about 58,500 unique firms.

Figure 1 gives the underlying *superset* of counties from which my sample of ASM plants is drawn. Due to US Census Bureau rules for confidentiality, there can be disclosure concerns around how much detail can be revealed about exactly which federally declared flood events and which affected counties had ASM surveyed plants were included in my broad sample. As

[22] See discussion on *bds_tab* variable in (Chow et al., 2021).

Figure 1: Counties with federally declared floods in the 1976-2018 period



Note: This map shows the underlying *superset* of counties from which my sample of all ASM plants (including exiters) is drawn. In particular, it shows, in teal, the counties which had 1-3 declared floods in the 1976-2018 period and also had at least one manufacturing establishment reported in the BDS data—the publicly-accessible equivalent of the restricted-access LBD. This map represents 349 unique floods, and 1703 unique counties that were affected.

a workaround, this figure shows the superset by showing counties which had at least 1 and at most 3 declared flood in the 1976-2018 period and also had at least one manufacturing establishment reported in the BDS data in the 1977-2017 window. The figure represents 349 unique declared flood events across 1703 affected counties. These affected regions are spread out throughout the US, and are primarily caused by adverse weather events like severe storms and flash floods.

I then leverage the information about plant age and exits to define subsamples that will allow me to study post-disaster responses and productivity outcomes among suriving plants and brand new entrants. This is because isolating these business-as-usual patterns of capital (dis)investment from flood-induced capital readjustment and reallocation across plants of various ages effectively requires confronting the inherent link between firm life-cycle dynamics and capital adjustment: entrants/young plants have to invest in capital to build up their capacity, while soon-to-exit plants would likely ramp down investments and instead liquidate assets in anticipation of their closure. Thus, I define my main sample for studying continuing plants' post-flood capital adjustment by focusing on plants that both: survive for at least 3 more years, and are at least 5 years old. This restriction yields approximately 318,000 plant-year observations corresponding to about 42,500 unique firms.

Table 1 presents summary statistics for my main sample of continuing plants. More than two-thirds of these plants belong to multi-unit firms, with revenues of more than 60 million dollars on average with the standard deviation being about 5 times larger, suggesting substantial dispersion. Similarly, these plants have more than 16 million dollars of machinery capital stock, with a standard deviation of about 78 million. The plants have an average of about 239 employees, the majority of which are production workers actually engaged in manufacturing work. Formally, this refers to factory workers up to the line-supervisor level. Overall, my sample is primarily composed of fairly large plants that themselves belong to larger, multi-unit firms.

Table 1: Summary statistics for sample of continuers

	Mean	SD
Multi-unit firms	0.68	0.47
Production workers	169.1	382.1
Total employees	238.9	609.1
Total value of shipments (in 1000s)	61,780	296,000
Total machinery capital stock (in 1000s)	16,450	78,950
N	318,000	

Statistics in this table were disclosed under (CBDRB-FY24-P2851-R11684)

Note that certain ASM questions are asked intermittently, which gives rise to some notable elements, such as the fact that questions about capital retirement are only asked in Economic Census years (years ending in 2 and 7) starting in 1987. Additionally, the ASM discontinued questions about the breakdown of plants' capital investments in new versus used capital in 1996.

3.3 Empirical Strategy

I estimate the following main specification at the plant-year level:

$$Y_{p,t} = \sum_{j=-4, j\neq -1}^{5} \gamma_j Flood_{p(c),t+j} + \alpha_p + \tau_{i,t} + \theta_{s,t} + \varepsilon_{p,t}$$

where $Y_{p,t}$ represents various outcomes of plant p, located in county c in year t, such as capital retirement. The main explanatory variable of interest is $Flood_{p(c),t+j}$, a binary dummy indicating whether the county c in which the plant is located received a declared flood j years ago. α_p denotes plant fixed effects–it helps account for plant-specific characteristics that do

not change across time. $\theta_{i,t}$ denotes 4-digit NAICS industry code interacted with year: it helps to absorb potential trends faced by plants in related industries. Lastly, $\theta_{s,t}$ represents state-by-year fixed effects, which help to absorb geographic factors that may be experienced by plants located in the same state. $\varepsilon_{p,t}$ is the error term, which I cluster at the county level.

Identification comes from the assumption that the timing of the flood event is unanticipated, which is generally plausible given the exogenous timing of weather disasters, and that there are no other events to confound effect of flooding in the event window. The latter assumption also passes given the narrow event window, and also the fact that other potential confounders related to business cycles, industry dynamics, or regulation would be orthogonal to the timing of an exogenous flood. Under these identifying assumptions, we can attribute changes in plant outcomes in the post-flood period to the impact of the disaster shock.

Note that, following prior literature, all regressions based on ASM data are weighted by ASM sample weights (see Ponticelli et al. (2023); Giroud (2013); Greenstone et al. (2012)). By design, the ASM sample selection process generally prioritizes larger plants, assigning a lower probability of selection to smaller plants. Weighting regressions thus helps account for such unequal sample selection probabilities and generate estimates that are more representative of the full population.

4 Main Results

4.1 Exits following disasters

Table 2 provides evidence on how disasters affect plant exits and the productivity attributes of exiters. The first column shows that, among all plants, the probability of exiting within two years increases by 3.6 percentage points (p.p.) in the 5 years following a flood compared to the 4 years before it. The second columns of the table examines the heterogeneity in exit likelihood based on whether or not the plant ranked in the bottom 25% of the TFP distribution of its narrowly defined 6-digit NAICS industry in the year prior to a flood (-1 relative period). I find that, while 2-year exit likelihood generally increases after flooding, plants in the bottom quartile of the pre-flood year's TFP distribution in their industry have an additional 1.1 p.p. higher likelihood of exit after a disaster relative to their counterparts in the top three quartiles. This suggests that it is the factories that were already marginal or low-performing during the pre-disaster period that are most likely to shutdown after it.

This phenomenon of excess exists among the lowest performing units appears remark-

ably consistent when looking at other indicators of firm productivity, including labor productivity (output per hour), value added per hour, and even firm-level revenue labor productivity (using LBD data), suggesting that the negative productivity shock from disasters particularly distresses and eventually winnows out the least performing firms. Importantly, these findings are consistent with prior evidence that exits are most concentrated among the lowest performing units during recessions, which also represent a negative productivity shock for firms (Foster et al., 2016).

Table 2: Plants' 2-year exit likelihood increases after flooding, particularly among the least productive plants

	Likelihood to exit within 2 years	
	All plants	Heterogeneity
1.Post flood	0.036***	0.049***
	(0.005)	(0.006)
1.LowestQuartile of TFP		-0.002
		(0.007)
1.Post flood#1.LowestQuartile of TFP		0.011**
		(0.005)
N	422,000	257,000
Y-mean	0.11	0.10
Y-sd	0.32	0.29

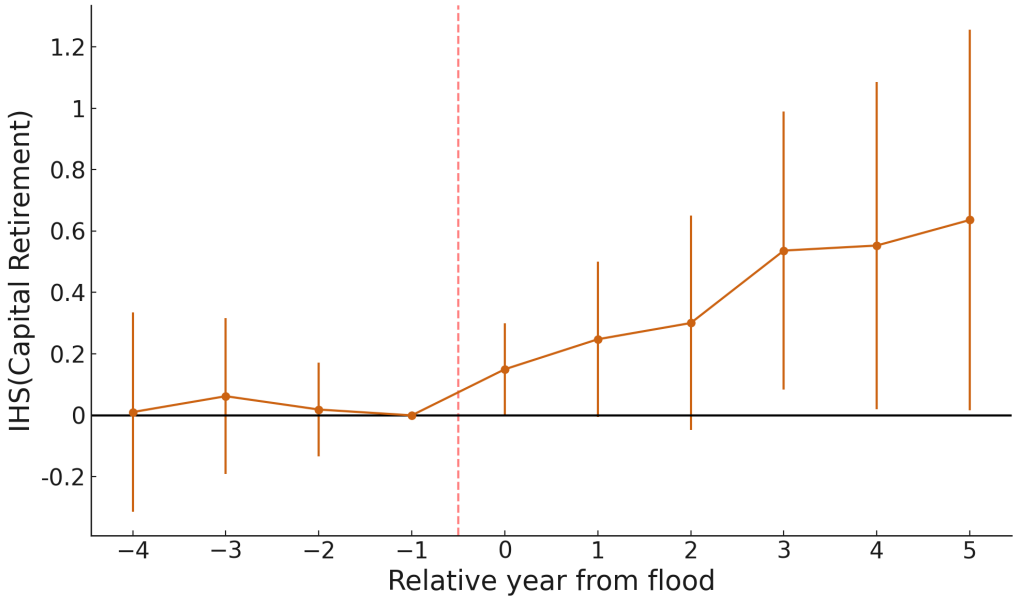
This table shows plants' likelihood to shut down within 2 years and how flooding affects it. The first column shows the event study coefficient for all plants in my overall sample, while the second column shows the heterogeneity in exit likelihoods based on whether the plant was in the lowest quartile of TFP distribution in its 6-digit NAICS industry in the year right before the flood. Thus, the sample for column 2 is the subset of plants which were observed in the ASM in the -1 relative period. Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11684)

In terms of heterogeneity by plant characteristics, Appendix Table A.3 shows how this two-year exit likelihood might vary across plants that were, in the year right before the flood, young (age 4 or below) and/or part of to a single-unit parent firm. I find that flooding, as before, raises exit risk, especially for young plants, but that single-unit status attenuates the increase. This suggests that the plants that are most likely to shut down after flooding are younger plants that belong to multi-unit parent firms, while small, young firms (i.e., single-unit young plants) relatively show more resilience.

4.2 Survivors' Investment Response and Productivity Outcomes

Focusing on the subset of surviving plants—i.e., that continue in business for at least 3 more years—I then study their dynamics of capital retirement, which is shown in Figure 2. In particular, Figure 2 shows the total dollar value of machinery and building capital that is retired (i.e., scrapped, or sold). There are no pre-trends in capital retirement before the flood, which is consistent with our key identifying assumption about the exogenous timing of the shock. After the disaster, however, there is a substantial and persistent increase in capital disposal. The Census survey can technically include all capital sales, disposal, scrapping, as well as capital retirement from depreciation schedules under the broad 'capital retirement' term. Yet, given that exogenous flood shocks are entirely independent of the depreciation schedule of the assets of a plant, such a persistent increase in capital retirement after flooding must be a reflection of increased disposal and sales of capital. Moreover, this broader pattern holds even when further restricting the sample to plants which survive for much longer (e.g., 6 years), suggesting that this capital retirement is indeed a reflection of flood-related damage rather than exits.

Figure 2: Persistent increase in capital retirement among surviving plants



This figure shows event study coefficients for capital retirement from 4 periods before flooding up to 5 periods treatment, based on plants that continue in business for at least 3 more years. 95% confidence intervals are computed based on standard errors are clustered at the county level. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R11940)

In addition, Table A.1 in the Appendix presents broader evidence of the damaging

impacts of flooding on physical capital. It shows that, in addition to capital retirement, plants also see higher likelihood of incurring capital repair costs (2% more) as well as refuse (water and waste) removal costs after flooding. These results demonstrate the physical damage and disruption from flooding that requires plants to repair/replace their capital.

Table 3 summarizes the investment and productivity outcomes of plants following disasters. The first two columns show how net investment evolves–in raw and inverse-hyperbolic sine transformed terms. Those columns show that manufacturing plants invest more, including net of their capital retirement in post-flood years. These findings demonstrate that plants in flooded regions not only retire capital but also invest in capital, more than offsetting their retirements. As the last column in this table shows, these investments are associated with a positive but very small, and statistically insignificant increase in labor productivity of 0.05%. However, as discussed at more length in Section A.3 in the Appendix, this average effect masks substantial heterogeneity, primarily on the basis of whether or not plants retired capital in the same year as the flood, which can serve as a potential proxy for whether the plants faced disaster-related negative impacts to their physical capital. In a nutshell, plants which retire capital in the same year as the flood subsequently invest earlier, more, and in newer capital relative to those that did not, and see 4.5% higher labor productivity gains, suggesting that survivors upgrade capital as they rebuild.

Table 3: Investment and Productivity Outcomes

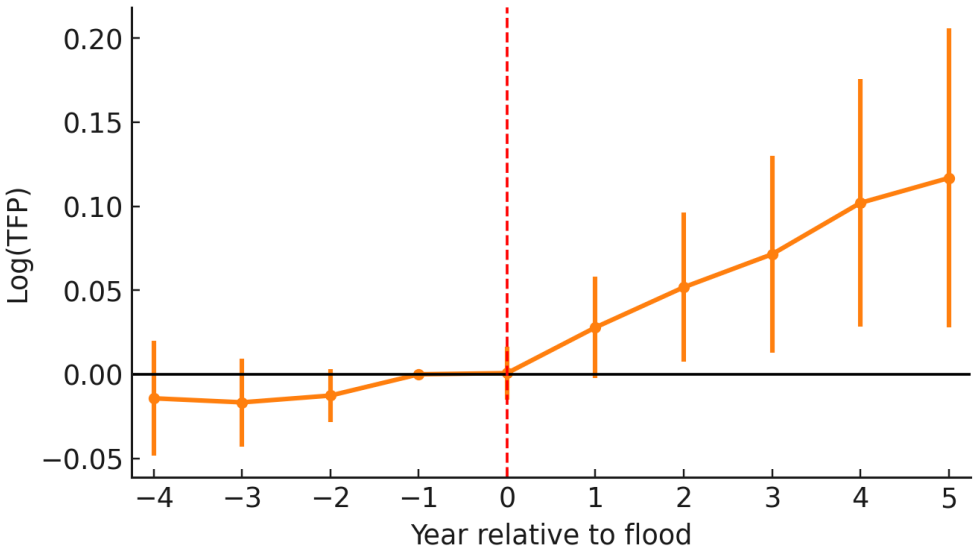
	Normalized Net Investment	IHS(Net Investment Normalized)	Log(Output/Hour)
Post flood	0.019*	0.015**	0.0005
	(0.0101)	(0.007)	(0.017)
N	66,000	66,000	66,000

This table shows plant investment and productivity as a function of disaster experience. In the first two dependent variables, normalized net investment is calculated as total capital investment minus total capital retirement, divided by pre-flood year capital stock. The last column examines labor productivity as measured by real revenue output over total hours. Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this table were disclosed under (CBDRB-FY25-P2851-R11949)

To illustrate the dynamics of total factor productivity, Figure 3 shows the time path of total factor productivity for surviving manufacturing plants, i.e., those which continue to operate for at least three years after being observed in the ASM data. The figure shows a persistent rise in TFP among these plants that, by the 5th year after the flood, reflects over a 10% increase over the pre-flood baseline TFP. The aforementioned findings about the

weeding of the least productive plants as well as the investment in replacement capital could be contributing to this productivity increase, suggesting a role of both selection and capital upgrading in post-disaster productivity gains among survivors.

Figure 3: Post-flood TFP increase among surviving manufacturing plants



Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12639)

Table 4: Crisis management and productivity outcomes of young firms

	(1) Problem Fix	(2) Log(TFP)
Post flood	+	−
Young firm	−	+
Post flood X Young firm	0.097**	0.089
	(0.044)	(0.105)
N	8300	8300

This table shows event study coefficients for the monotonized score of plants for managing—and fixing—problems from the MOPS data (column 1), and Log of TFP (column 2). Standard errors are reported in parentheses and are clustered at the county level. The numerical coefficients for the (non-interacted) post-flood and young firm dummies are only shown with sign and significance to reduce disclosure risks and implicit sample concerns. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12639).

Part of the success of young survivors over older ones is that they are more nimble in responding to problems. Table 4 uses data from MOPS to compare the monotonic scores of

young (age 4 and below) versus older firms and how this is associated with their productivity. In particular, Column 1 in that table shows that younger firms have better strategies for responding to problems and setting up systems for the future compared to older ones: they have about a 10 percentage point lead over the older firms, which corresponds to a (suggestive) TFP gain. These findings are consistent with the widely documented phenomenon around how younger firms have to stay nimble and responsive to their environment, including by swiftly and conclusively responding to crisis shocks like flooding, to survive the pronounced selection pressure that they face relative to older, more established firms.

4.3 New Entrants

An important implication of the aforementioned results is that they can increase the local supply of used capital as exiting plants liquidate their physical capital, i.e., machinery and buildings/structures, and survivors also sell their pre-existing machinery as their replace their capital. Both of these factors would contribute to a higher supply of second-hand capital, reducing its equilibrium price. A lower price of capital is likely going to be attractive for younger plants, which have been shown to buy used capital from incumbents in previous research, in part due to financing constraints that may make it much unattainable to buy brand new capital (see Ma et al. (2022)).

Table 5: Post-disaster entrants purchase used machinery, and are positively selected

	(1) Share of New Machine Investment	(2) Log(TFP)
Post flood	-0.019*	0.139**
	(0.011)	(0.058)
N	1200	1500

This table shows event study coefficients for investment in brand new machines as a share of all machinery investment (column 1), and Log of TFP (column 2). Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12639).

Table 5 shows the investment behavior and productivity of single-unit entrant firms post-flood entrants in comparison to pre-flood entrants. The first column examines machinery investment dollars going toward brand new machinery as a share of all machinery investment as a function of flooding, while the second column shows the TFP of entrants.

On average, the share of machinery going toward brand new machinery among post-flood entrants declines by 1.9 percentage points after flooding relative to pre-flood entrants. This suggests that, indeed, post-flood entrants do acquire the second-hand capital of older incumbents after flooding. Their productivity is also about 13.9% higher than pre-flood entrants, suggesting strong positive selection on the firm entry margin in the post-flood setting. Together, these findings illustrate that the post-flood setting sees a redistribution of capital from less to more productive firms.

4.4 Aggregate Implications

Table 6: Central tendency and dispersion of TFP [Quantitative results for this table are pending disclosure]

	Central measures of TFP		**Measures of TFP Dispersion**		
	Log(Mean TFP)	Median Log(TFP)	IDR	IQR	SD
Post flood	+	−	+	−	+
IQR Firm age	−*	−*	−	+	−
Post flood × IQR Firm age	+**	+**	+	−	+
N	177,000	177,000	177,000	177,000	177,000

This table shows how aggregate examines of productivity evolve after flooding, and the heterogeneity by pre-flood mix of young and old firms (as representated by the interquartile range of firm age) within a narrowly-defined, 4-digit code NAICS industries in the same county. Regressions is at the county-four digit NAICS code level-year level, and regressions include county-industry fixed effects as well as state by year and 3 digit industry by year fixed effects. Columns group central tendency and dispersion outcomes. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12640).

Table 6 shows how the level and dispersion of productivity change in narrowly defined industries in the same county after flooding, and the heterogeneity by the extent of age dispersion among firms in the pre-flood period (as measured by the interquartile range of firm age), which can be a helpful proxy for the colocation of younger and older firms. I find mixed results in how average and median TFP, as well as the various measures of TFP dispersion evolve after flooding in general. But when considering age-dispersion, markets with greater pre-flood firm-age heterogeneity exhibit slightly lower central TFP and a wider middle but thinner tails (IQR +; IDR/SD –), suggesting variation clustered around the center rather than extremes. The interaction between Post flood × IQR of firm age is positively associated with the mean and median, and statistically significantly so. This suggests that average and median productivity rise in the aftermath of flooding in counties where there is greater age heterogeneity among firms in the same industry. However, this interaction term is negative for IQR, and positive for IDR/SD: while these results are imprecise (statistically

insignificant), their signs suggest that floods in age-heterogeneous markets stretch the tails, intensifying winner–loser dynamics. This pattern fits the cleansing results presented above: weaker producers shut down while adaptable firms—particularly young firms and positively selected new entrants—reoptimize and pull ahead. Overall, floods appear to trigger efficient reallocation on average but greater dispersion in outcomes, a mix that may call for policies that preserve productivity gains while cushioning the most vulnerable cohorts.

4.5 Evidence on the Role of Financing Access

4.5.1 Bank Lending

Using the CRA data and using loan size as a proxy for firm size and age, I show that small sized bank loans increase after flooding. If federal disaster spending expands access to financing for especially the smaller and younger plants, then we ought to see an increase in loans in the smallest loan size categories. This is exactly what my analysis finds.

Table 7 shows business loan dynamics following federally declared floods, focusing both on the total number and dollar amount of loans originalted (first two columns), as well as the average loan size, and the breakdown of sub-100,000$ versus over 100,000$ loan sizes (latter four columns). The findings indicate that the number of loans originated by banks to small businesses increases after federally declared floods by about 3.1%, but with a statistically insigifnicant increase of about 2% in the total loan dollars originated (column 2). This increase in lending is almost entirely driven by the smallest loan size category—the sub-100,000 USD loan size group—which also sees an increase of more than 3.5% in both dollar amounts of loans and the number of loans originated. Lastly, the share of loans in this category increases relative to larger loan sizes as well by about .3 percentage points, which is a 0.32% increase over the pre-flood baseline of 93.5 percent of loans in this small loan size category. Overall, these results suggest that bank loan supply increases after major, federally declared floods, and that this is particularly most pronounced in the smallest loan size categories, suggesting disproportionate benefits to young and small firms.

Table 7: Bank business loans following declared floods

	(1) IHS(Total lending)	(2) IHS(Total Loans #)	(3) IHS(Avg loan amount)	(4) IHS(# of sub100k loans)	(5) IHS(Total sub100k lending)	(6) Share of sub100k loan dollars	(7) Share of sub100k loan #
Post flood	0.019	0.031***	-0.013	0.035***	0.039**	0.006	0.003**
	(0.020)	(0.012)	(0.013)	(0.012)	(0.016)	(0.005)	(0.001)
Observations	10272	10272	10270	10272	10272	10270	10270

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Bank business loans following non-declared floods

	(1) IHS(Total lending)	(2) IHS(Total Loans #)	(3) IHS(Avg loan amount)	(4) IHS(# of sub100k loans)	(5) IHS(Total sub100k lending)	(6) Share of sub100k loan dollars	(7) Share of sub100k loan #
Post flood	-0.034	-0.079***	0.044**	-0.085***	-0.055**	-0.009	-0.006***
	(0.029)	(0.021)	(0.018)	(0.021)	(0.026)	(0.007)	(0.002)
Observations	4994	4994	4994	4994	4994	4994	4994

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5.2 Recovery After Non-Declared Floods

One straightforward way to isolate the role of financing in post-disaster recovery is to examine contexts where disaster-affected regions did not receive large federal assistance after flooding—a scenario for which non-declared disasters can serve as a proxy. I study this by using SHELDUS data to identify non-declared floods. In particular, I focus on disasters which, in the SHELDUS data, were recorded to last for 3 or more days—the median duration of declared floods. This sample restriction serves two purposes: first, it helps ensure comparably of severity of disasters in recognition of the fact that non-declared disasters are often less severe than declared ones. Second, this restriction also helps ensure a large enough sample to enable the disclosure of results from the Census Bureau.

Table 9: Plant investment and labor productivity decline following non-declared floods [Quantitative results for this table are pending disclosure]

	(1) IHS(Retirement)	(2) IHS(Investment norm.)	(3) Log(Output/Hour)	(4) IHS(Net inv.)	(5) IHS(Net inv. norm.)	(6) Log(Output/Hour)
Post flood	+**	+***	–**	–**	–	–
N	44,000	59,000	59,000	44,000	20,000	20,000

This table shows the relationship between non-declared floods and plant-level measures of investment and productivity. The dependent variable in Column 1 is capital retirement, that in Column 2 is total investment normalized by pre-flood capital stock, and in Column 3 the outcome is output per hour for the sample referenced in Column 2. The outcome variable in Column 4 is the net investment of plants (investment minus retirements), while that in the Column 5 is this net investment measure normalized by the pre-flood year total capital stock. The outcome in Column 6 is output per hour for the sample referenced in the second column. The investment and retirement amounts are presented in their invest hyperbolic sine transformed versions (Cols 1, 2, 4 & 5), while output per hour is log transformed (Cols 3 & 6). The explanatory variable indicates the 0-5 year window following a non-declared flood. Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this table were disclosed under (CBDRB-FY25-P2851-R12521).

As shown in Table 9, capital retirement rises while investment and labor productivity suffer following non-declared floods. Capital retirement increases following non-declared floods (Column 1). While plants do invest in recovery (Column 2), net investment in fact declines after non-declared floods, suggesting that their investment response is weak. This pattern is in sharp contrast to the *increase* of 1.5 percent in normalized net investment following declared floods. The decline investment following non-declared floods is associated with a reduction in plants' output per hour, as shown in Columns 3 and 6 of Table 9. Overall, these findings of weak investment and productivity recovery after non-declared floods suggest that the documented boost to investment and productivity recovery following declared floods

may, at least in part, be explained by the role of federal disaster spending.

In line with this, Table 8 shows business loan dynamics following substantial but non-declared floods. It shows that bank lending in fact weakens following these non-declared floods, with a particular shrinkage in the number and amount of loans in the smallest loan-size category (sub 100,000 USD category). The overall number of originated loans decreases by about 8%, which mirrors the decline in the number and dollar amount of loans in the smallest loan size category here as well. Consistent with this, the share of sub-$100k loans among all loans drops by 0.6 percentage points—a 6.5% drop relative to the pre-flood baseline. The average loan amount also increases by 1.4% , suggesting that bank loan supply is primarily going toward larger loan size groups, which may proxy for more established firms. However, per the plant outcome results shown above, such bank lending behavior and the way in which private credit markets act when left to their own devices may be consequential in the real economy—it weakens survivors' investment and labor productivity recovery.

4.5.3 Relationship between firm size, plant age, and investment

Another indicator of the expansion of access to financing in the wake of large disasters is the relationship between firm size, plant age, and investment. Table 10 examines how plant-level investment and total factor productivity evolve following flooding, and how responses vary by pre-flood characteristics of plant age (with age 4 or below being young) and firm size (single vs multi unit parent firm). The baseline (omitted) group is older (age 5 or above) plants that also belong to multi-unit parent firms. The first column shows that on average, total investment sees a small, statistically insignificant decline after flooding in this baseline group. Young plants (age 0–4 in the pre-flood year) and small (single-unit) plants invest less than older and multi-unit firms do. Crucially, the triple interaction (Post × Young × Single-unit) is positive and statistically significant, indicating that young, small (single-unit) firms invest the most following floods. The second column shows investment in brand new (as opposed to used) capital as an outcome: young small firms are most likely to invest in used capital, while young plants belonging to older firms are more likely to buy new capital. The fact that small, young firms—which typically face harsher financing constraints—are investing more here suggests that financing constraints are loosened in the post-disaster setting. Interpreted together, the interaction terms show heterogeneous rebuilding consistent with credit expansion enabling economic revival that is driven by younger plants. By defining size and age in the year before treatment, these categories are time-invariant and not themselves affected by the flood, strengthening the heterogeneity interpretation. These results

also point to expanded financing access as a key mechanism behind the surge in post-flood investment and economic dynamism.

Table 10: Investment, Investment Composition, and Productivity

	(1) **IHS(Investment)**	(2) **Share of *New* Capital Investment**	(3) **Log(TFP)**
Post flood	-0.029	0.003	0.003
	(0.041)	(0.006)	(0.007)
Young plant	0.006	-0.031**	-0.014
	(0.101)	(0.013)	(0.028)
Post flood X Young plant	-0.215***	0.022***	0.028**
	(0.046)	(0.007)	(0.011)
Single-unit firm	0.025	0.03	-0.033
	(0.121)	(0.021)	(0.023)
Post flood X Single-unit firm	-0.123***	-0.012	0.009
	(0.042)	(0.007)	(0.006)
Young plant X Single-unit firm	-0.23	-0.011	0.065
	(0.349)	(0.041)	(0.104)
Post flood X Young plant X Single-unit firm	0.206**	-0.041**	0.027
	(0.095)	(0.021)	(0.026)
N	234,000	129,000	234,000

This table shows how plant-level investment and productivity evolve after flooding, with a focus on the heterogeneity by whether the plant was young (age 4 or below) or a single-unit firm in the year before the flood. Column 1 captures the inverse hyperbolic sine transformed version of total capital investment, Column 2 captures the share of dollars invested toward brand new capital (instead of used capital) as a share of total investment, and Column 3 captures the log of TFP. Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12639)

4.5.4 Credit Markets

As a final piece of evidence, I study how aggregate productivity recovered following floods that coincided with the height of the 2008 Financial Crisis, i.e., floods that occurred in 2008, 2009, and 2010, relative to other floods. I test the hypothesis that tightened credit during that Financial Crisis was associated with distorted productivity outcomes. Particularly given the evidence presented above about how banks tend to reduce smaller sized loans in non-declared flood settings—which I interpret as a reallocation of loan supply away from small and young firms—then this test is particularly helpful to understand how flooded regions with higher versus lower firm age heterogeneity fared around the Crisis.

Table 11 texts this hypothesis and finds it to hold. Building on the results and model presented in Table 6, this table examines how floods shift both the level and the dispersion of TFP within narrowly defined industries within the same county, and further unpacks the

heterogeneity by pre-flood firm age dispersion and by whether or not the flood occurred in 2008, 2009, or 2010 as a proxy for tightened financing constraints. Central tendency (log mean and median TFP) barely moves with the age-dispersion interaction terms—coefficients are small and not significant—so the is in productivity dispersion. Where the IQR of firm age is larger (i.e., markets with more age heterogeneity), floods compress the TFP distribution at the center: Post flood × IQR Firm age is negative and significant for the TFP IQR (-0.011**, s.e. 0.004), with no clear effect on SD or IDR. In contrast, during the 2008 crisis, places with greater age dispersion tended to have narrower TFP tails even absent floods (2008 Crisis × IQR Firm age: IDR -0.017*, SD -0.012**). But when floods hit during the crisis, dispersion widens in age-heterogeneous places: the triple interaction Post flood × 2008 Crisis × IQR Firm age is positive and highly significant for the IQR (+0.013***) and SD (+0.012***). Taken together, floods in normal times compress the middle of the TFP distribution where firm-age heterogeneity is high, whereas floods in crisis times amplify performance dispersion.

Table 11: Aggregate implications of post-flood recovery

	Central measures of TFP		**Measures of TFP Dispersion**		
	Log(Mean TFP)	Median Log(TFP)	IDR	IQR	SD
Post flood	+	-	+	-	+
IQR Firm age	-	-	-	+	-
Post fld × IQR Firm age	0.007	0.010	0.001	-0.011**	-0.004
	(0.008)	(0.008)	(0.011)	(0.004)	(0.004)
2008 Crisis	-	+	-	-	-
Post flood × 2008 Crisis	+	-	+	+	+
2008 Crisis × IQR Firm age	-0.003	0.001	-0.017*	-0.013	-0.012**
	(0.013)	(0.012)	(0.010)	(0.008)	(0.006)
Post flood × 2008 Crisis × IQR Firm age	0.004	0.001	0.016	0.013***	0.012***
	(0.008)	(0.009)	(0.011)	(0.005)	(0.004)
N	177,000	177,000	177,000	177,000	177,000

This table shows event study coefficients for measures of centrality and dispersion of TFP. Standard errors are reported in parentheses and are clustered at the county level. Regressions is at the county-four digit NAICS code level-year level, and regressions include county-industry fixed effects as well as state by year and 3 digit industry by year fixed effects. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R12639).

4.6 Robustness Checks

Survivor Bias: Given that plant response to disasters is endogenous, a key potential confounder for how to interpret continuing plants' post-disaster productivity improvements is survivorship bias: if the post-disaster period is marked by cleansing such that post-disaster

exits are concentrated among the lowest productivity plants, then this naturally implies that survivors have, on average, higher productivity and, by virtue of staying in business, higher higher investment. Even with fairly localized physical damage, large disasters can cause various (negative) productivity shocks to non-flooded plants in broader regions, including supply chain disruptions and worker absences.[23] Regardless of whether they are themselves physically flooded or not, we expect lower productivity plants to have lower capacity to weather disaster-related negative shocks and thus, to be more likely to exit. Indeed, Table 2 shows that exits are concentrated among the least productive units.

This consideration is particularly relevant for my study because the flood declaration treatment is defined at a coarse, county-level geography and I do not directly observe plants which are physically struck by the disasters. It is possible that the county-level geographic focus is too coarse to pick up actual physical damage suffered by plants. Businesses regularly experience idiosyncratic productivity shocks – both positive and negative – throughout their lifetime, and unsurprisingly, positive productivity shocks are associated with higher capital investment. Even more, plants with higher productivity are more likely to have a preference for investing in machines with advanced technology as well. Thus, given that post-flood exits are concentrated among lower productivity plants, and if my analyses based on a county-level flood treatment only pick up only the machinery investments of surviving plants that happen to face positive productivity shocks independent of the disaster, then this could mean that I may misattribute productivity increases that reflect cleansing to induced capital readjustment.

However, as Table A.4 shows, my robustness checks confirm that the productivity increase I document for plants' post-disaster investments is strongly consistent with flooded plants' readjustment of their capital stock rather than a mere feature of the cleansing effect of disasters. In particular, I re-estimate my analysis of plant-level capital investment at the county level to examine how aggregate investment in machinery evolves following disaster shocks: if aggregate county-level machinery investment increases after disasters, this would support the forced capital readjustment channel of my study, but otherwise, no statistically significant change in aggregate investment would suggest that the machinery investment and higher productivity I document for continuing plants is only derived from the outcomes of plants which make machinery investments after facing positive idiosyncratic shocks, whose distribution should not be affected by a disaster. I find that flooding is associated with a statistically significant increase in county-level machinery and total capital investment,

[23] See Barrot and Sauvagnat (2016); Carvalho et al. (2021).

including when these outcomes are normalized by the pre-flood year's aggregate capital stock in the county (see Table A.4). This suggests that, the county-level flood treatment is still meaningful to approximate plant-level disaster damage, and while survivorship plays some role in explaining the post-disaster capital investiment dynamics documented in this paper, it is unlikely to be the *only* driver of the results.

Serial Auto-correlation: Given the forward looking nature of investment, another consideration when studying post-disaster investments is that those plants which retire and replace capital after a disaster are simply continuing a pre-disaster investment pattern. However, accounting for such serial autocorrelation in investment by controlling for cubic polynomials for pre-flood investment (in the style of Olley and Pakes (1996) production function estimation) does not substantially change the results. This means that it is unlikely to be the only explanation for the post-flood investment documented in this paper.

Heterogeneity in treatment effects: In a setting with variation in the timing of the flood treatment across regions, potential heterogeneity in treatment effects across time can spuriously give rise to apparent pre-trends in standard two-way fixed effects event study designs. To account for this, I conduct robustness checks using Sun and Abraham (2021) event study approach, which interacts relative period indicators with cohort indicators, by using the last-treated as a control. In particular, the last-treated comparison cohort refers to units treated in year 2018, or 2017 for cases where the capital retirement variable (which is primarily only available in years ending with 2 and 7) is a key input into regressions. With the use of this estimator, always-treated units – i.e., those treated in 1977 or earlier – are dropped so that effectively all treated units are compared against the last-treated cohort. My results are generally robust to the use of this alternative method. See for example Appendix Figure A.6, which replicates the main results from the survivors' outcomes using the this approach.

5 Evidence from Qualitative Survey on Firms

To complement the aforementioned quantitative results based on administrative data, I conduct a qualitative survey on manufacturing firms in the US. While the data-driven analyses illustrate key insights into how firms respond to and recover from disasters, there is still much we do not know about firms' incentives and barriers around capital investment, as well as about the translation between book value of capital assets—which is what the Census data contain—and the market value—which are better suited to understand disaster impacts.

Thus, the qualitative survey is useful to gain a fuller understanding of such important issues.

The survey was designed and disseminated in collaboration with various governmental and non-governmental organizations, including the Federal Reserve Bank of Chicago, the Wisconsin Center for Manufacturing and Productivity, the Manufacturing Extension Partnership centers of the National Institute of Standards and Technology (NIST), and the Center for Industrial Research and Service (CIRAS) at Iowa State University.[24] To incentivize participation in the survey, I offered the incentive that a randomly-chosen respondent would get to donate $1000 a non-profit organization of their choice (among a pre-selected list of 50 organizations located in the Midwestern US), anonymously if preferred.[25] This is because the majority of contacts that received the direct survey invitation via the aforementioned partners were likely time-constrained (and high-earning) CEOs, owners, or other high-level executives for whom philanthropic incentives might be more appealing than traditional survey incentives like direct monetary rewards.

The survey starts out with questions about firm characteristics, such as industry, employment size, and assets, before delving deeper into more granular questions around capital investment and natural disasters. Another key component of this survey was a hypothetical exercise asking respondents to imagine a flood event that causes a range of different levels of loss—5%, 25%, and 65%—to the fair market value of their machinery, and asking them how they would react, namely: whether they would shut down, relocate, repair/restore their damaged machines, or entirely replace the damaged machines with technology of a higher, lower, or same grade as what they had before. These three hypothetical loss events were presented in random order to each respondent in order to avoid any potential impact of the chronological sequence of these loss scenarios on the answers. Next, came questions around respondents' views on climate change and the risks it poses to their operations, including via weather-related natural disasters. Lastly, the survey contained an optional set of questions on firms' machinery maintenance protocols, climate views, and related policy preferences.

Twenty-one respondents completed the survey in full. The majority of participants are CEOs, owners, or other high-level executives at small and mid-size manufacturing firms located in the Midwest. Most respondents were part of small, single-unit manufacturing firms with fewer than 100 employees and an average age of more than 50 years since founding.

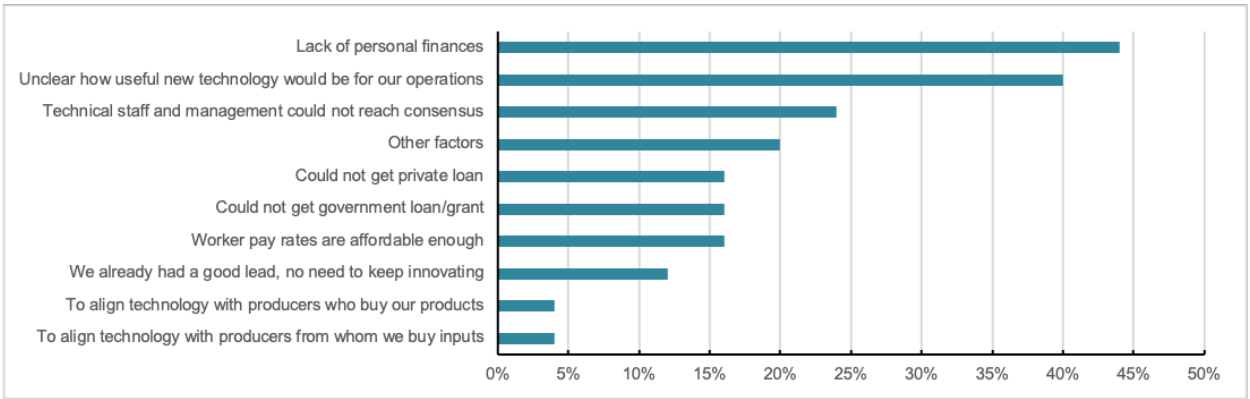
[24] See Figure A.3 for a template of the survey invitation message.

[25] The funds for the donation were secured via a grant from the Columbia Center for Political Economy. The list of 50 potential organizations among which the lottery winner could pick one donation recipient was prepared and IRB approved before the survey dissemination, with priority for themes like early childhood development, poverty alleviation, and environment & sustainability.

Slightly more than half (52%) of all respondents are engaged in export trade. The average survey duration was about 40 minutes.

Though relatively small in number, the responses received lend two key qualitative insights that corroborate the quantitative findings of discussed above. First, the top-most barrier for investment that firms cite is financing constraints, followed by uncertainty around how useful new technology would be for their operations. Given that financing is a necessary condition for investment, it makes sense that a lack of it was the predominant constraint that the majority of firms pointed to across categories like lack of personal finances and inability to secure private and/or government loans. The second most important barrier that firms pointed to concerns uncertainty about the return on new technology investments: this involves considerations around whether new equipment would integrate seamlessly with the existing machines and assembly lines, and would be worth the associated fixed costs of machinery installment such as having to tear down/reconfigure building structures and retrain workers, all the while pausing revenue-generating production.

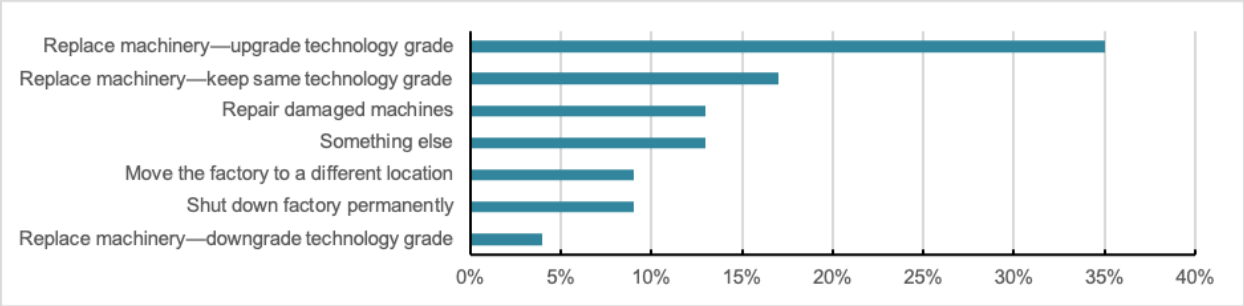
Figure 4: Barriers for investing in new equipment and technology



Second, in a hypothetical flood scenario, firms' tendency to report that they would upgrade their machinery following a destructive damage increases substantially with the severity of the disaster. In particular, in scenarios with minimal damage (5% loss), the overwhelming majority of respondents—about 70% to be precise—indicated an intention to pursue basic repairs, while the rest (22%) reported that they would upgrade the damaged machines. Under the 25% loss scenario, the response pattern showed substantially more variation. In particular, 39% of respondents favored repairs, while 30% indicated a preference for machinery replacements that involve technology upgrades and 17% for replacements of the same technology grade (see Figure A.4). However, in scenarios involving substantial damage (65% loss), responses were even more varied, but the predominant response among

firms was toward modernization, with 35% of respondents expressing intent to upgrade their equipment rather than merely repair existing infrastructure. A smaller share of respondents reported that they would replace machinery with technology of the same grade (17%) or repair damages (13%). Others indicated that they would entirely shut down or relocate (9% each). In this 65% loss scenario, the least commonly chosen response was that firms would purchase machinery that involved technology downgrades (4%). Overall, these patterns in the responses show that as the hypothetical damage increases from 5% to 65%, it is no longer obvious that firms would simply repair damages, but their courses of action also generally show more heterogeneity. More importantly, the fact that rebuilding with upgrades emerges as the predominant post-disaster response in the most severe (65%) flood loss scenario suggests that firms would look to undertake major.

Figure 5: If they faced a major flood that destroyed 65% of the market value of their machinery, firms would primarily look to upgrade machinery as they rebuild



When asked why they would upgrade when rebuilding after a hypothetical disaster but not in their current reality (in the absence of a disaster), firms' responses highlight the unique ways in which the post-disaster environment may allow them broader room to reoptimize their production technology and even alleviate common barriers to investment. Respondents report that insurance proceeds and government loans/assistance that would be availed after a (hypothetical) disaster would be a key mechanism through which they would pay for technological upgrades as they rebuild, but that they typically have to operate under more limited resources in the (non-disaster) status quo. The fixed costs of capital investment also matter: some respondents who indicated they would upgrade if their factory faced a major disaster stated that they would not want to shut down production (in the absence of a disaster). Another respondent explained that normally, "I would not have time to investigate new technology," highlighting the time-intensive nature of studying technologies to resolve uncertainties around whether and to what extent a new technology may be useful for a firm's operations. These factors are closely related to the second most important barrier

firms raised for capital investment (uncertainties around the usefulness of new technology).

Taken together, these insights from the qualitative survey complement the quantitative findings in this paper. The qualitative findings broadly demonstrate that a disaster-induced disruption implies lower opportunity costs to allocating their resources toward researching new technology and rebuilding and away from revenue-generating production, while the concurrent federal disaster spending and insurance after flooding also give firms expanded access to financing that can allow them to pay for the rebuilding.

6 Conclusion and Discussion

In this paper, I study how manufacturing plants respond to natural disasters and the implications for aggregate productivity. I show that low-TFP plants are disproportionately forced to exit, while resources flow to more productive survivors and positively selected entrants, raising average productivity and improving allocative efficiency. Young and new firms play an outsized role in this process, scaling up in the post-flood environment and—where their activity is greater—coinciding with lower TFP dispersion and higher average productivity within narrowly defined markets. These outcomes stem from the expanded financing access that government relief spending unlocks. In particular, federal disaster spending loosens financing constraints, and young, small firms with nimble management convert that credit into rapid retooling and expansion, while survivors upgrade capital as they rebuild. In settings without federal assistance, investment and productivity falter, underscoring the credit channel behind recovery. During credit crunches (e.g., 2008 Financial Crisis), reallocation is less productivity-enhancing, highlighting the importance of maintaining access to finance for constrained cohorts.

While the entry and exit-related results are easier to measure and identify, the intensive-margin issues around survivors warrant closer consideration. For instance, one key consideration is related to measurement. Capital retirement is a potentially imperfect measure of disaster-related physical damage because it does not distinguish between sales, scrapping, disposal, or general retirement (including from depreciation schedule). The ideal way to measure physical damage would be to, following the guidelines of the IRS for disaster-related tax write-offs, study the loss of fair market value (FMV) resulting from the disaster. In contrast, the reported amounts for capital retirement are based on book values from the seller's accounting records, which suggests that those figures reflect the willingness to pay of buyers of that capital and not necessarily direct loss to the value of the machine. Thus, the capital

retirement measures reported in this paper cannot directly reflect the loss of fair market value of assets, but can be interpreted to reflect the general degradation and displacement of capital following disaster shocks.

Beyond underscoring the critical role of government recovery spending for regional recovery and economic revival, my findings call attention to the need to understand the state of (mis)allocation in the US economy. Disaster shocks combined with federal spending provide a useful, albeit tragic, context from which this study identifies the presence of wedges inhibiting productive reallocation in the US, which has generally been understood as a low misallocation context relative to other countries (see Hsieh and Klenow (2009)). Yet, since we cannot observe federal disaster aid in the absence of a disaster shock, we cannot distinguish whether access to financing, which my results establish as a *necessary* condition for allocative efficiency gains, is also a *sufficient* one. A curious question remains: would a cash influx to (new) firms similarly boost allocative efficiency? It is potentially unlikely, given that current work has already documented concurrent trends of declining responsiveness of firms to shocks, increasing market concentration, and declining firm entries (Decker et al., 2020; Akcigit & Ates, 2021). Within the post-disaster context, however, this paper demonstrates that well-funded and functioning disaster management policies are important in a warming world.

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A Appendix

A.1 Tables and Figures

Table A.1: Plants retire capital; incur capital repair and refuse removal costs due to flooding

	Capital Retirement		Operating costs	
	Any retire?	IHS(Retired capital $)	Any capital repair?	Any refuse removal?
Post flood	0.013	0.092**	0.018**	0.029**
	(0.013)	(0.046)	(0.009)	(0.014)
N	116,000	116,000	107,000	88,500
Y-mean	0.65	619.3K	0.86	
Y-sd	0.48	12,540K	0.35	

Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11700; CBDRB-FY25-P2851-R11949)

Metal corrosion as a mechanism of flood damage:

To shed light on the physical damage to physical capital from flooding, Table A.2 shows the heterogeneity in outcomes of manufacturing plants belonging to industries that process more versus less corrosion-prone metals. This is because humidity accelerates chemical processes that accelerate metal corrosion, particularly for ferrous metals like iron, and its alloys. In contrast, 'non-ferrous' metals like aluminum, copper, and silver are more resistant to corrosion because they form protective layers. Under this framework, looking at how work-in-process inventory changes within plant across ferrous and non-ferrous metal processing industries in the year of a flood would be a direct and meaningful way to test whether flood waters intensify metal corrosion, and what the downstream impacts may be.

Table A.2 shows some supporting evidence for the hypothesis that water damage from flooding can accelerate metal corrosion. According to the first three columns of the table, plants which process ferrous metals end up with a lower work-in-process inventory of iron at the end of the year compared to the work-in-process inventory they started out with at the beginning of the year relative to plants which process non-ferrous metals. They are 6 percentage points more likely to end post-flood years with lower inventory than they started out with at the beginning, and on the intensive margin, this corresponds to 66% lower work-in-process inventory at the end of the year on average relative to the beginning of year inventory. This becomes a 10% drop once inventory change is normalized by pre-flood total work-in-process inventory size, still a significant indication that ferrous metal producers face inventory losses related to flood waters. This is consistent with how, particularly in its

unfinished, processing stage, iron is even more sensitive to humidity and thus, more prone to rust and waste away.

Table A.2: Due to the effect of moisture on metal corrosion, manufacturing plants in industries that process ferrous metals experience rust-related inventory loss and subsequently downsize

	Dependent variable: Inventory change			**Employment and payroll**	
	Any loss?	IHS(Invent. change)	IHS(Normalized invent. change)	Log(Employment)	Log(Payroll)
	(1)	(2)	(3)	(4)	(5)
Post flood X Ferrous	0.06	-0.667*	-0.104**	-0.049**	-0.048**
	(0.042)	(0.372)	(0.048)	(0.020)	(0.022)
N	9,000	9,000	7,700	28,500	28,500
Y-mean	0.384	127.4	-0.242	146.2	5,520
Y-sd	0.486	8,404	10.74	463.7	21,800

This table shows how plant inventory, employment, and payroll evolve after flooding, with a particular focus on the heterogeneity across plants which process metals that are more prone to rust (ferrous metals) relative to less rust-prone metals. All results are based on the specific samples of metal processors in the ASM data (Columns 1-3), and LBD data (Columns 4-5). The dependent variable in column 1 is a binary indicator for whether end of year work-in-process inventory is lower than the beginning of year amount, while columns 2 and 3 are continuous measures of the difference between the end of year and beginning of year amounts, with column 3 further being normalized by the pre-flood year's beginning of year inventory to account for size. The dependent variables in columns 4 and 5 represent plant employment and total annual payroll. Standard errors are reported in parentheses and are clustered at the county level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1. Results in this table were disclosed under (CBDRB-FY25-P2851-R11949)

This inventory loss is potentially consequential: the latter two columns of Table A.2 show that in the 5 years following a flood, plants which process ferrous metals have about 5% lower employment and payroll relative to non-ferrous metal producers. Taken together, these results are consistent with the interpretation that inventory-loss induced by flooding causes plants to downsize. Importantly, iron and steel production is itself a critical industry that provides raw materials for construction and other *durable* goods production. Thus, these inventory losses themselves are likely to have large implications in downstream *capital (durable) goods* production, and add more insight to the small but growing literature demonstrating on the impact of climate change on investment goods (see Casey et al. (2024)).

Table A.3: Heterogeneity in likelihood to exit within 2 years by pre-flood plant age and parent firm size

	Exit within 2 years
Post flood	0.053***
	(0.006)
Young plant	-0.048***
	(0.016)
Post flood X Young plant	0.059***
	(0.009)
Single-unit firm	0.007
	(0.014)
Post flood X Single-unit firm	-0.017***
	(0.005)
Young plant X Single-unit firm	-0.113*
	(0.062)
Post flood X Young plant X Single-unit firm	-0.011
	(0.016)
N	257,000

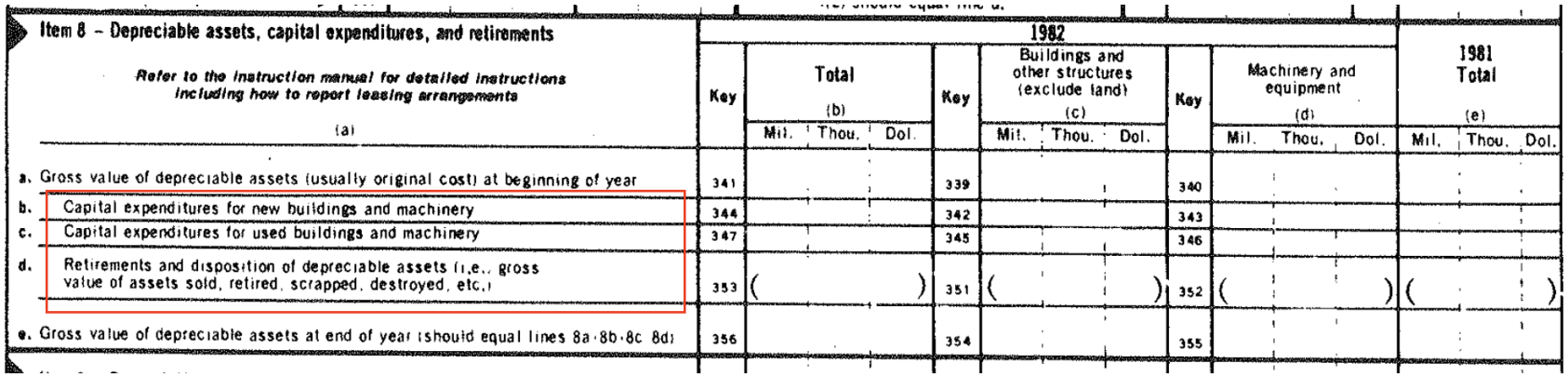
This table shows event study results on how plants' 2-year exit likelihood is affected after flooding and the heterogneity by plant age (age 0-4 being young) and firm size (single vs multi-unit parent firm). Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this table were disclosed under (CBDRB-FY25-P2851-R12639)

Table A.4: County-level total investment increases following flooding

	(1) IHS(Capital Investment)	(2) IHS(Normalized Investment)	(3) IHS(Normalized Net Investment)
Post Flood	0.073*	0.0312***	0.019**
	(0.044)	(0.008)	(0.009)
N	21,500	17,500	5,700

This table shows how county-level investment changes after flooding. Column 1 focuses on total capital investment, column 2 captures investment normalized by pre-flood year capital stock, and column 3 shows net investment (investment-retirement) normalized by pre-flood capital stock in the county. All outcome variables are shown in their inverse hyperbolic sine transformed formats. Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this table were disclosed under (CBDRB-FY25-P2851-R11949)

Figure A.1: ASM survey questionnaire form from 1982: section on capital expenditures for building, and machinery assets as well as capital .pngs

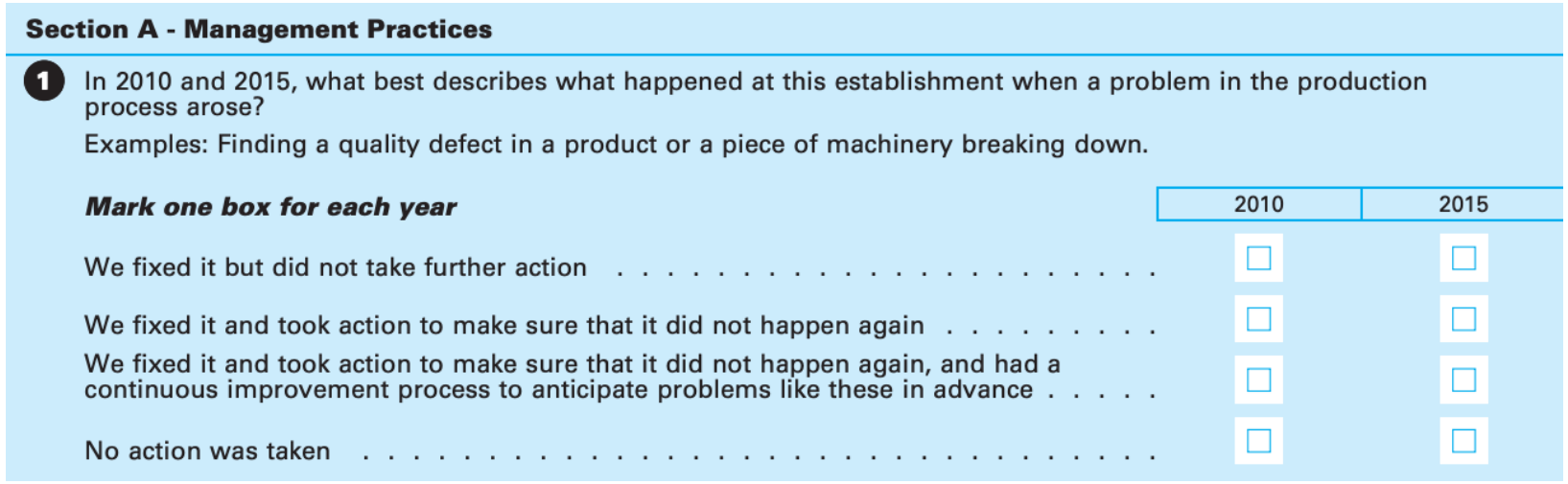


Item 8 – Depreciable assets, capital expenditures, and retirements

Refer to the instruction manual for detailed instructions including how to report leasing arrangements

(a)	Key	1982 Total (b) Mil. Thou. Dol.	Key	1982 Buildings and other structures (exclude land) (c) Mil. Thou. Dol.	Key	1982 Machinery and equipment (d) Mil. Thou. Dol.	1981 Total (e) Mil. Thou. Dol.
a. Gross value of depreciable assets (usually original cost) at beginning of year	341		339		340		
b. Capital expenditures for new buildings and machinery	344		342		343		
c. Capital expenditures for used buildings and machinery	347		345		346		
d. Retirements and disposition of depreciable assets (i.e., gross value of assets sold, retired, scrapped, destroyed, etc.)	353	( )	351	( )	352	( )	( )
e. Gross value of depreciable assets at end of year (should equal lines 8a-8b-8c-8d)	356		354		355		

Figure A.2: MOPS survey questionnaire from 2015 asking about how the establishment responded to a problem



Section A - Management Practices

1 In 2010 and 2015, what best describes what happened at this establishment when a problem in the production process arose?

Examples: Finding a quality defect in a product or a piece of machinery breaking down.

Mark one box for each year	2010	2015
We fixed it but did not take further action	☐	☐
We fixed it and took action to make sure that it did not happen again	☐	☐
We fixed it and took action to make sure that it did not happen again, and had a continuous improvement process to anticipate problems like these in advance	☐	☐
No action was taken	☐	☐

Figure A.3: Survey invitation email sent to manufacturing firms by the Federal Reserve Bank of Chicago

Opportunity to share information about investment decisions at manufacturing plants

Walstrum, Thomas <thomas.walstrum@chi.frb.org> Tue, Oct 22, 2024 at 12:08 PM
Cc: Tarikua Erda <te2289@columbia.edu>

Dear CFSEC respondent,

I'm writing to invite you to take part in a short survey (unaffiliated with the CFSEC) about organizational practices around capital investment and technology adoption at manufacturing plants.

This survey is being conducted by Tarikua Erda, a doctoral student at Columbia University as part of her dissertation research, which studies manufacturing plants' capital investment behavior. The survey should take 10–15 minutes, and your participation is entirely voluntary.

If you complete the survey, you will be entered into a raffle to win the opportunity to choose a non-profit/charity to which Tarikua will donate $1,000 on your behalf (anonymously if needed).

To participate, please click this link: [redacted]

Please feel free to share this email and survey link to anyone else at your organization who may have relevant information to share about the questions.

I've copied Tarikua on this email in case you have any questions for her (tarikua.erda@columbia.edu).

Thanks, as always, for sharing your knowledge to help us gain a better understanding of the economy.

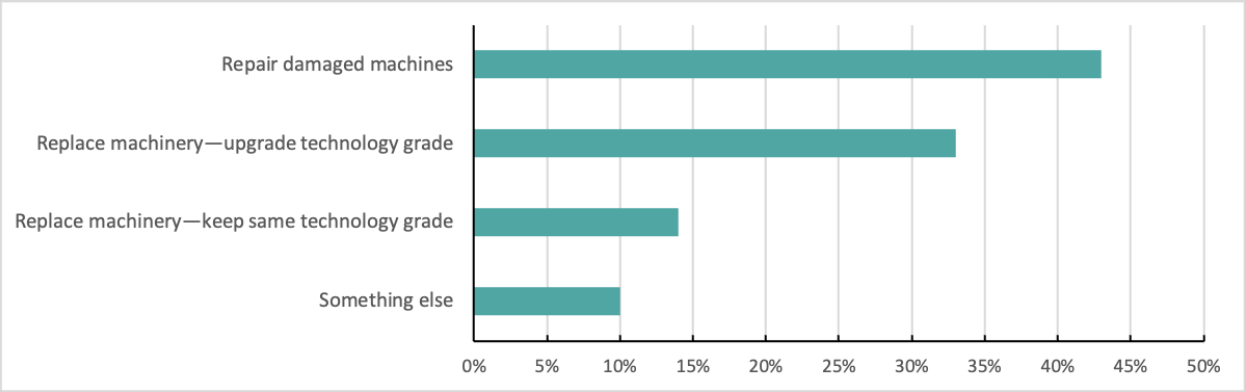
Regards,

Thomas Walstrum

Principal Business Economist

Federal Reserve Bank of Chicago

Figure A.4: If they faced a flood that destroyed 25% of the market value of their machinery, firms would primarily look to repair the damage, with a second course of action being upgrading technology as they rebuild



A.2 Calculation of plant age across the ASM and LBD

By combining information from the ASM and LBD, I calculate plant age in a similar manner as previous studies (see Haltiwanger et al. (2013)) by marking the first year of observation as the year of entry and letting the plant age naturally by 1 year in each following year after that. The only difference in my setting is that since I have ASM data from 1972, with full information on whether plants are age 0-4 or age 5 and above, in addition to the LBD data (which only start in 1976), I can cross reference the two datasets to construct a more accurate age for each manufacturing establishment. I proceed in the following two steps.

1. First, identify year of entry across ASM and LBD
    - Start with year first observed (as an employer business) in the LBD
    - If the year that the plant is observed in the ASM is earlier, I update the entry year to the year of first observation in the ASM data (if that year's value is flagged as young), and if it's not, to the ASM first year minus 5 years.
2. Then to identify age, deduct the year of entry from the 'current' year for any ASM plant year observation

A.3 Heterogeneity in Plant Investment and Labor Productivity Recovery by Flood-year Capital Retirement

Note that the coarse county-level definition of the flood treatment does not permit a detailed differentiation among plants which were/were not physically damaged/inundated, especially since granular damage maps for flood inundation are not widely available before the early 2000s. As a workaround, I use capital retirement in the same year as a flood to capture the reaction of plants to potential physical damage or direct and immediate (even if not physical) flood-related impacts. I then examine the heterogeneity in investment response and productivity outcomes across plants which did and did not retire capital in the same year as a flood. Given that the capital retirement question is only asked sporadically in the Census' ASM survey, this also means that I focus on the subset of cohorts whose flood year coincides with years in which the Census asked manufacturers about capital retirement.

Table A.5 studies the post-flood rebuilding process among surviving plants by examining the capital investment behavior of plants which suffer physical damage from flood shocks, as inferred from capital retirement. The coefficient on non-interacted dummy for 'Post flood' indicates that the post-disaster period is associated with lower average plant investment. The coefficient on the non-interacted dummy 'Retire in flood year' indicates that relative to periods in which plants are observed to *not* retire capital, they invest more when they do retire capital. This is consistent with the expectation that capital retirement and investment are generally positively correlated as it may be cost effective for plants to carry out capital disinvestment and investment episodes together. In the post-flood period, however, the correlation between capital retirement and investment is even more pronounced: the interaction term of the two dummies shows that, conditional on retiring any capital in the same year as a flood, plants' probability of investing in machinery increases by 3.7 percentage points, and their average investment in machinery capital increases by 23.7%. This represents a substantial increase in machinery investment alongside retirement, relative to the baseline association between capital disinvestment and investment the per-flood baseline. In line with these findings of increased investment, the fifth column of the table shows that total capital stock among plants which retire capital in the flood year increases by about 2.7%.

Table A.5: Flooded plants invest in rebuilding capital

	IHS(Investment)			Binary		
	Total	Building	Machine	Machine	Log(Capital stock)	Share of investment in new assets
	(1)	(2)	(3)	(4)	(5)	(6)
Post flood X Retire in flood year	0.257***	0.281***	0.237***	0.037**	0.027**	0.028**
	(0.077)	(0.073)	(0.0773)	(0.018)	(0.011)	(0.012)
Post flood	-0.212**	-0.207**	-0.168*	-0.026	-0.0311*	-0.039***
	(0.098)	(0.097)	(0.099)	(0.021)	(0.017)	(0.013)
Retire in flood year	0.236*	0.193	0.193	0.0143	-0.043	-0.027**
	(0.131)	(0.152)	(0.132)	(0.021)	(0.043)	(0.012)
N	68,000	68,000	68,000	68,000	68,000	54,000
Y-mean	1,995K	418.3K	1,577K	0.84	29,880	0.90
Y-sd	12,870K	5,490K	9,310K	0.36	123,900	0.23

This table shows the relationship between investment and flooding. The outcomes in the first three columns measure the inverse hyperbolic sine transformed measures of total capital expenditures (1), building expenditures (2), and machinery expenditures (3). The outcome variable in Column 4 is a binary dummy indicating whether the plant invested any non-zero amount in machinery or not. Columns 5 and 6 study the log-transformed version of total capital stock, and the share of capital expenditures going toward new assets (as opposed to used ones), respectively, as outcomes. The explanatory variables are interactions of the post-flood period and an indicator for whether the plant retired any capital in the same year as a flood. The base for comparison is the baseline (non-flood-year) outcome of plants that retire capital in the same year of a flood in the pre-flood years. Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11775)

Table A.6: Plant investment per each additional percent of flood-year capital retirement

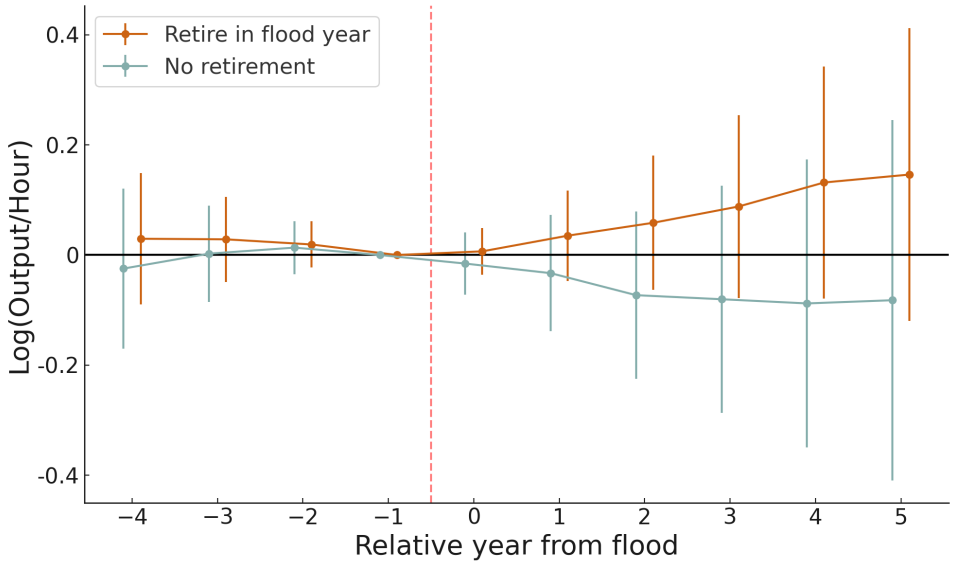
	(1)	(2)	(3)
	IHS(Total Investment)	IHS(Machine Investment)	IHS(Normalized mach. investment)
Post flood X IHS(Retirement)	0.03***	0.026**	0.003*
	(0.010)	(0.010)	(0.002)
Post flood	-0.119	-0.076	0.020*
	(0.088)	(0.089)	(0.012)
IHS(Retirement)	0.062***	0.057***	-0.0004
	(0.018)	(0.020)	(0.003)
N	68,000	68,000	56,000

This table shows the relationship between investment and flooding. The outcomes represent the inverse hyperbolic sine transformed versions of total capital investment (column 1), machinery investment (column 2), and machinery investment normalized by the pre-flood year machinery capital stock (column 3). Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01; **p < 0.05; *p < 0.1. Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11775)

The last column of Table A.5 examines how much plants invest in brand new building and machinery assets as a share of their total capital expenditures. It shows that, relative to pre-flood baselines, plants which retire capital in the same year as a flood invest 2.8 percentage points more in brand new assets compared to their counterparts which do not retire capital in the flood year. These results suggest that while plants which retire capital in the same year the flood replace it with brand new capital, potentially adopting newer technology vintages.

Lastly, Table A.6 shows that the relationship between capital retirement and investment is also monotonically positive on the intensive margin. In particular, a 1% increase in the amount of capital retirement in the same year as a flood is associated with higher total investment (by 3%), machinery investment (by 2.6%), as well as machinery investment normalized by pre-disaster machinery capital stock (0.3% higher). These results illustrate that plants which retire capital in a flood year carry out extensive capital replacement investments in the following years.

Figure A.5: Time path of productivity based on capital retirement



This figure shows the time path of labor productivity as measured by real output per total plant hours (in logs), separately for plants that retired capital in the year of the flood (in orange), and those that did not. 95% confidence intervals are computed based on standard errors which are clustered at the county level. Estimates in this figure were disclosed under (CBDRB-FY24-P2851-R11775).

To illustrate the dynamics of labor productivity, Figure A.5 shows the respective time paths of output per hour for plants which did and did not retire capital in the same year as a flood. It shows that these two groups have highly divergent paths in their labor productivity,

with flood-damaged plants seeing higher productivity and non-damaged plants seeing lower productivity compared to their pre-flood baselines. These event study findings further lend credence to the finding that plants which replaced their capital after flooding substantially overperform those which did not in their labor productivity.

A.4 Robustness Checks

Figure A.6: Increase in capital retirement among surviving plants, as estimated by Sun and Abraham (2021) approach

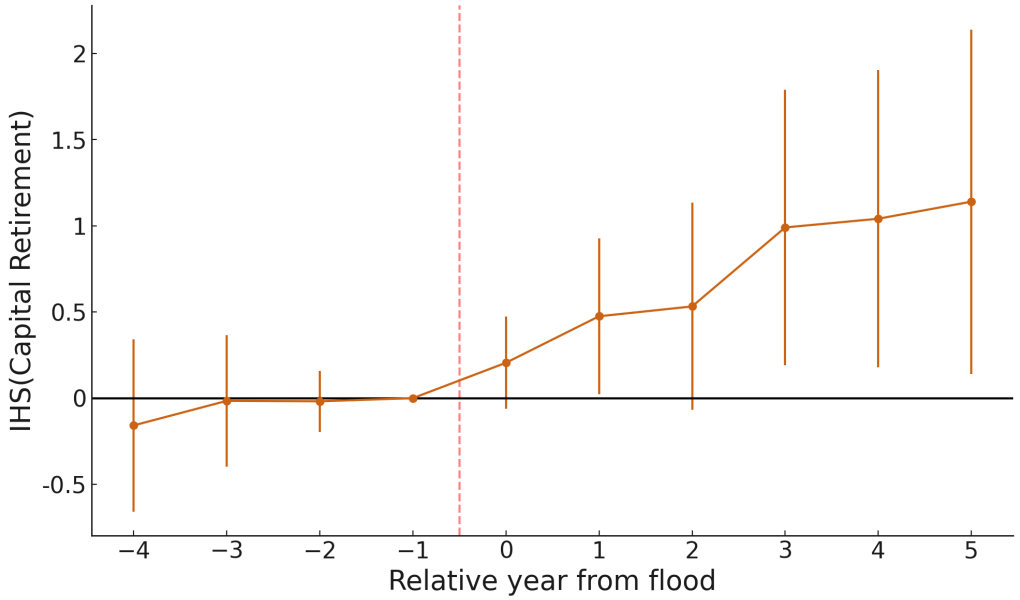


Figure shows event study coefficients for capital retirement from 4 periods before flooding up to 5 periods treatment, based on plants that continue in business for at least 3 more years. 95% confidence intervals are computed based on standard errors are clustered at the county level. Estimation follows the Sun and Abraham (2021) approach. Estimates in this figure were disclosed under (CBDRB-FY24-P2851-R11775)