Disasters, Capital, and Productivity*

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Abstract

The fixed nature of physical capital could delay adjustment to rapidly occurring weather shocks. Prior theoretical work predicts this would amplify economic damages from climate change as global warming intensifies disaster risk. Using rich confidential microdata from the US Census Bureau, I establish novel causal evidence on how manufacturing plants readjust their capital, particularly their machinery, in response to large, federally declared floods. While floods degrade machinery, surviving plants replace capital and see higher productivity because they upgrade technology as they rebuild. I document substantial reallocation of second-hand capital across plants following floods, notably from low-productivity exiters toward well-performing entrants. Ultimately, capital adjusts productively, and is reallocated toward better use following flooding, boosting aggregate productivity. These outcomes stem from the expanded financing access that federal disaster spending facilitates. My findings reveal a new channel through which government disaster spending revives disaster-hit economies and underscore its critical importance in a warming world.

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1 Introduction

A long-standing question in climate economics concerns the effect of climate change on physical capital. According to early models, the fixed nature of physical capital stock—such as machinery and buildings—could delay firms' response to weather hazards, and, in aggregate, distort the allocation of economic resources away from their most efficient use, exacerbating climate damages.[1] If true, these predictions have crucial implications for both academic and policy discussions on climate change, particularly because global warming worsens future disaster risk.[2] In this chapter, I leverage rich confidential microdata from the US Census Bureau to provide novel evidence on manufacturing plants' capital adjustment and the implications for allocative efficiency following large, federally declared floods.

The impact of floods on firm capital and allocative efficiency is far from obvious. Flooding is a negative shock to capital stock and productivity: when a flood happens, manufacturing plants may suffer damage to their machinery due to inundation or power outages, or face other disruptions to their supply chain and/or workforce. 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, this spending could enable capital repair/upgrading and accelerate 'cleansing': 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. In a similar vein, federal spending could facilitate productive capital redistribution after disasters and potentially enable capital repair/upgrading among rebuilding firms. On the other hand, federal spending could contribute to frictions, such as credit market imperfections, that distort post-disaster reallocation and hurt aggregate productivity.[3]

I show that capital does, in fact, adjust productively following flooding: I document substantial capital replacement that boosts plant productivity and across-plant reallocation of used capital, including from low-performing exiters toward high-potential entrants, that

[1] Physical capital, which is normally meant to be durable and converted to income over its long life-time, requires adjustment costs for repurposing or redirection. Early work on climate damages, which characterized climate costs as adjustment costs, predicted that adjustment of sticky, fixed physical capital would be far outpaced by rapid climate shocks, worsening the economic costs of climate change. (See Yohe and Neumann (1997); Quiggin and Horowitz (2003)). Fisher and Hanemann (1993) discuss that climate change can, if not destroy capital stocks, render them prematurely obsolete, highlighting the importance capital adjustment implications of weather shocks.

[2] Global warming drives increased frequency and/or intensity of extreme weather (IPCC, 2021).

[3] 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.

ultimately improves allocative efficiency. A key mechanism is the conducive financing environment unlocked by federal disaster spending, demonstrating a novel channel through which government spending revitalizes disaster recovery.

I focus on large floods that triggered a presidential disaster declaration—a place-based designation that unlocks substantial disaster assistance to affected counties.[4] Federal disaster spending can directly help firms cover under- or uninsured losses as they rebuild from flood damage. It also supplements regional credit supply, which particularly increases access to bank credit for young and small firms after disasters (Erda, 2024).[5] Thus, financing constraints, which may normally weaken post-destruction recovery, are likely loosened in the declared disaster setting.[6] Importantly, the fact that I am looking at the manufacturing sector is an asset for this study because increased local demand from federal disaster spending is unlikely to affect plant outcomes.[7]

To observe plant outcomes, I use 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. Notably, it also provides information on plants' capital retirement (i.e., sale or disposal), which I use as a proxy to infer physical damage from flooding. 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 in flooded counties.

I document three key results that demonstrate how capital adjusts productively following flooding. First, exit rates rise after flooding, primarily among the least productive units. 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 baseline exit rate. Importantly, plants that were already in the pre-disaster period in the bottom quartile of their own industry's productivity distribution, both in terms of pre-

[4] Federal disaster spending funds infrastructure reconstruction, cash grants to households, and low-interest recovery loans to affected firms.

[5] In Erda (2024), I showed that federal disaster spending can *indirectly* offset the restricted access to bank credit that young and small firms may otherwise face after disasters.

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

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

flood total factor productivity ("TFP") and profitability, are least likely to survive flooding. Post-flood plant shutdowns are primarily concentrated among the lowest performing plants, reflecting a weeding out of less efficient forms of production after flood shocks.[8]

Second, I show that surviving incumbents scrap/sell their machinery and invest in replacement capital following flooding, ultimately seeing a boost to their labor productivity. Conditional on not exiting, i.e., surviving for at least 3 more years, plants persistently increase their capital retirement for about 5 years after flooding, consistent with the corrosive effect of water/humidity on metal.[9] Plants also increase their net capital investment, suggesting that rebuilding investments more than compensate for their flood-related capital retirement.[10] This investment is associated with a statistically insignificant increase in labor productivity, as measured by output per hour. Yet, these aggregate outcomes mask meaningful variation, particularly across plants that do/do not retire capital in the same year as a flood.[11] I find that plants which retire capital in a flood year substantially increase their capital investment by about 24% and subsequently exceed their pre-disaster labor productivity baseline by about 4.5%. This suggests that plants adopt technology upgrades as they rebuild: indeed, I find that plants primarily invest in brand new machinery and structures, which are more likely to carry more advanced vintages relative to used capital. In contrast, plants that do not retire capital in the year of a flood invest later and relatively buy more second-hand capital, suggesting capital reallocation. These plants see lower labor productivity, reflecting weaker post-flood recovery. Overall, these results indicate substantial and heterogeneous investment dynamics and disparate productivity recovery patterns among surviving incumbents after flooding.

Third, as low-productivity plants are forced to shut down and (older) survivors replace their capital with new machines, local entrants and young plants increase their purchase of second-hand machinery and build up their capacity.[12] I find no evidence that post-flood machinery reduces the productivity of these new and young plants. In fact, post-flood entrants appear positively selected and pay higher wages, suggesting a reallocation of used capital from less productive exiters to more productive entrants after flood shocks.

[8] Similarly, Foster et al. (2016) find excess exits among low performing units during recessions.

[9] Other explanations include machinery damage due to sudden power outages; and supply chain reorganization, which may require firms to switch to different production technologies.

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

[11] Given the coarse-nature of the county-level flood treatment indicator, I use this market as a proxy to infer flood-related impacts at the plant level.

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

Ultimately, post-disaster capital adjustment and reallocation enhances allocative efficiency. To study allocative efficiency, I focus on the dispersion in marginal revenue product of capital, namely the inter-quartile range of revenue output per capital stock between plants at the 75th and 25th percentiles in similar industries and locations.[13] This is a useful measure because, in a frictionless world, the marginal product of capital should be equal across firms, so deviations–such as higher dispersion–suggest inefficiencies. I find that after flooding, capital productivity dispersion declines within similar industries in the same county. This indicates that physical capital is, on average, reallocated toward plants which can make better use of it. I also find a statistically insignificant rise in county-level labor productivity after floods, which suggests that post-flood reallocation boosts aggregate productivity.

A key mechanism for these results is expanded financing access from federal disaster spending. In prior work, I showed that, after disasters, federal recovery spending supplements regional credit supply, with positive spillovers onto small and young firms' bank credit access, ultimately propping up economic dynamism and speeding up wage recovery after disasters (see Erda (2024)). Here, I show that smaller manufacturing firms, which are generally more vulnerable to financing constraints relative to larger ones, have greater post-flood investment—both on the extensive and intensive margins—and see higher productivity gains. This suggests that federal spending relieves firms' financing constraints.[14] My findings from a qualitative survey of manufacturers based in the Mid-Western US 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. Overall, my findings highlight a crucial but underappreciated channel through which federal disaster spending supports post-disaster recovery: by expanding firms' access to financing, it enables productive capital upgrading and reallocation.

This paper contributes to several strands of literature, primarily, that on the impact of climate change on capital, growth, and the spatial (re)allocation of economic activity. Early theoretical work on these areas worried that, due to the fixed nature of physical capital stock, weather shocks would far outpace society's ability to readjust, exacerbating welfare losses (see Quiggin and Horowitz (2003); Yohe and Neumann (1997)). My paper

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

[14]Further, I show suggestive evidence that capital reallocation following floods that coincided with the 2008 Financial Crisis, which was marked by the crash of credit markets, was less productivity-enhancing relative to reallocation after floods that occurred around previous recessions. This is consistent with prior findings that credit market distortions during the 2008 recession drove dampened the intensity of productivity-enhancing job reallocation. See Osotimehin and Pappadà (2017).

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. Caggese et al. (2024) show that firms' slow capital adjustment in response to temperature increase drives productivity losses in Italy. In contrast, my results demonstrate that firms are quite responsive to discrete shocks rather than slow-onset climate phenomena like temperature increase.

A small but growing literature has studied how global warming might affect aggregate growth via its impact on capital, primarily from a theoretical standpoint or from a cross-country and/or global analyses that lack the granular focus (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 greater detail and accuracy.

Additionally, my paper contributes to the literature on firm responses to climate change. While previous work shows how firms are affected by natural disaster shocks and how they recover (Barrot & Sauvagnat, 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 builds on this prior work by providing novel causal evidence based on a tradable sector—manufacturing—that is less sensitive to local demand, thereby expanding our understanding of the nexus of climate change and firm productivity.

This paper also contributes to the macroeconomics literature on capital reallocation across the business cycle, and on the role of government spending. Prior papers primarily focus on more traditional measures like job reallocation or entry and exit around recessions (see Barlevy (2002, 2003); Foster et al. (2016); Osotimehin and Pappadà (2017)), with the latter two suggesting that while recessions are times of accelerated reallocation, the financial collapse of the 2008 Great Recession was associated with less intense cleansing. My paper provides new evidence related to capital reallocation—another vital component of aggregate dynamics—and on how this was dampened for disasters around the Great Recession of 2008 due to financing constraints, deepening our understanding of this major global crisis in recent history. In this respect, my paper 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 potentially financing constraints–that make reallocation costlier during downturns. My paper confirms this mechanism by causally demonstrating that expanded access to financing due to government spending after a negative productivity shock like flooding facilitates greater and more efficient reallocation of capital.[15]

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 capital upgrading by incumbents leads to higher used capital purchase by younger firms.[16]

Section 2 below provides institutional background on federal disaster declarations. Section 3 describes the data and empirical strategy. Sections 4 presents the results and Section 6 offers a discussion. Section 7 concludes.

2 Institutional Background: Disaster Declarations

In accordance with the Robert T. Stafford Disaster Relief and Emergency Assistance Act, 42 U.S.C. §§ 5121-5207 (the Stafford Act), 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

[15]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.

[16]Notably, Ma et al. (2022) use loan filing data to track the age and sales of machines that businesses put up as collateral and show that younger firms are more likely to buy used machinery from incumbents. Yet, there is likely unobserved selection in the kinds of firms which put machines (instead of other types of capital) as collateral, and in the kinds of machines they pick as collateral. Given the representative nature of the ASM survey, my paper offers more generalizable evidence on this phenomenon. Additionally, the results linking the incumbents' machinery turnover with increased purchase of used machinery by young firms in Ma et al. (2022) rely on lagged measures of new machinery purchase by local incumbents. However, such a pattern could arise from reverse causality, for instance: incumbents' forward-looking investment from their anticipation of rising young firm activity in their industry.

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. While FEMA provides assessments and advice,[17] 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 make individual and business grants and loans.[18] 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 (directly) increase business survival and crowd in private credit (see Collier et al. (2024); Gallagher et al. (2023)). Additionally, my prior work shows their positive spillover impact on regional liquidity, particularly expanding young and small firms' access to bank credit (Erda, 2024). Therefore, manufacturers are expected to enjoy broad access to financing following government spending after federally declared disasters.

3 Data and Empirical Strategy

3.1 Data

Flood Declarations: I observe the incidence of floods from the Federal Emergency Management Agency's disaster declaration records.[19] 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.

Data on manufacturing plants come from the following confidential survey and admin-

[17] 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)).

[18] 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).

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

istrative microdata maintained by the US Census Bureau.[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 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 publishable 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. 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 second-hand machinery after disasters.

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

[20]These confidential datasets can be accessed by qualified researchers at Federal Statistical Research Data Centers (FSRDCs).

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 starting in 1977, which is why my sample starts from the year 1977.

3.2 Sample

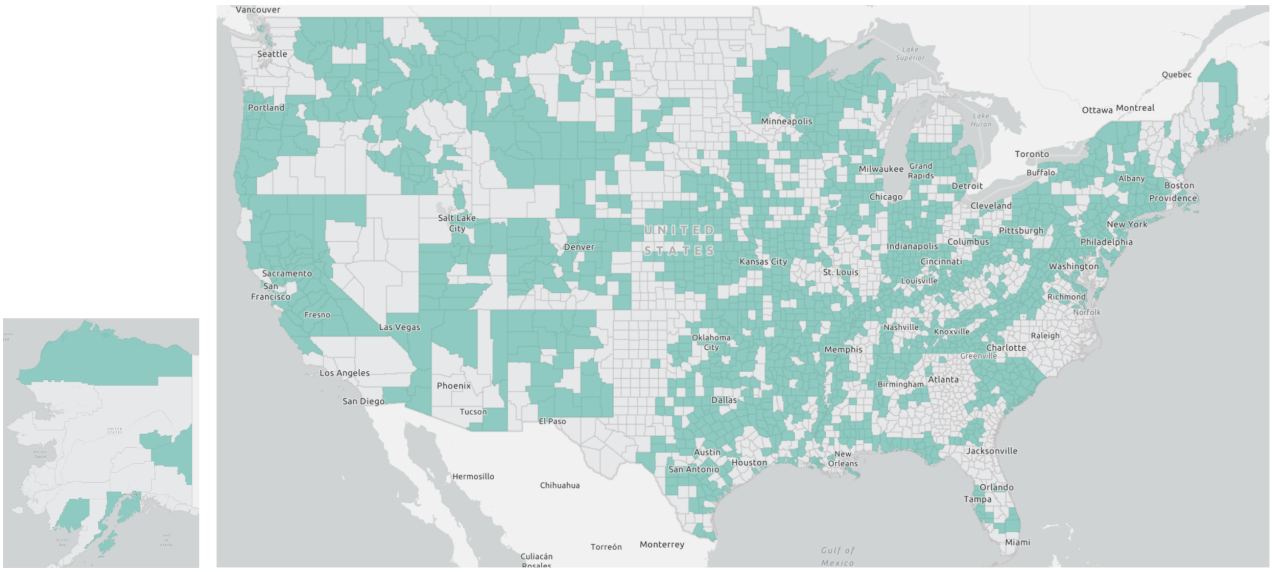
I start out with all ASM plants in the 1977-2017 period whose North American Industry Classification System ("NAICS") industry code falls under the core manufacturing codes between 31-33, then apply some key restrictions to make the estimation sample more relevant for the purpose of my analyses. First, 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.[21]

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

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

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: 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 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 LBD). This map represents 349 unique floods, and 1703 affected counties.

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 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 two main subsamples that will allow me to study post-disaster capital readjustment and young firms' outcomes on the most appropriate group of plants. This is because isolating these ubiquitous patterns from flood-induced capital readjustment and the reallocation of capital from older to younger

firms effectively requires confronting the inherent link between firm life-cycle dynamics and capital (dis)investment: 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 upto 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 the intermittent nature of how certain questions are asked in the ASM surveys 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 aggregate 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 Results

4.1 Documenting the destruction from 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 of age 5 or above, 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 latter two columns of the table examine the

heterogeneity in exit likelihood based on the plant's rank in the productivity distribution of its narrowly defined 6-digit NAICS industry in the year prior to a flood. In particular, I examine the heterogeneity in exit likelihood based on whether a plant falls in the bottom quartile of TFP (total factor productivity) or value added per hour measures in its industry. I find that, while 2-year exit likelihood generally increases after flooding, plants in the lowest 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 those in the top three quartiles. Similarly, plants in the lowest quartile of their industry's value added per hour distribution have an additional 2 p.p. higher likelihood of exit after a disaster relative to those in the top three quartiles.

Table 2: Plants' 2-year exit likelihood increases after flooding, particularly for lowest performing units

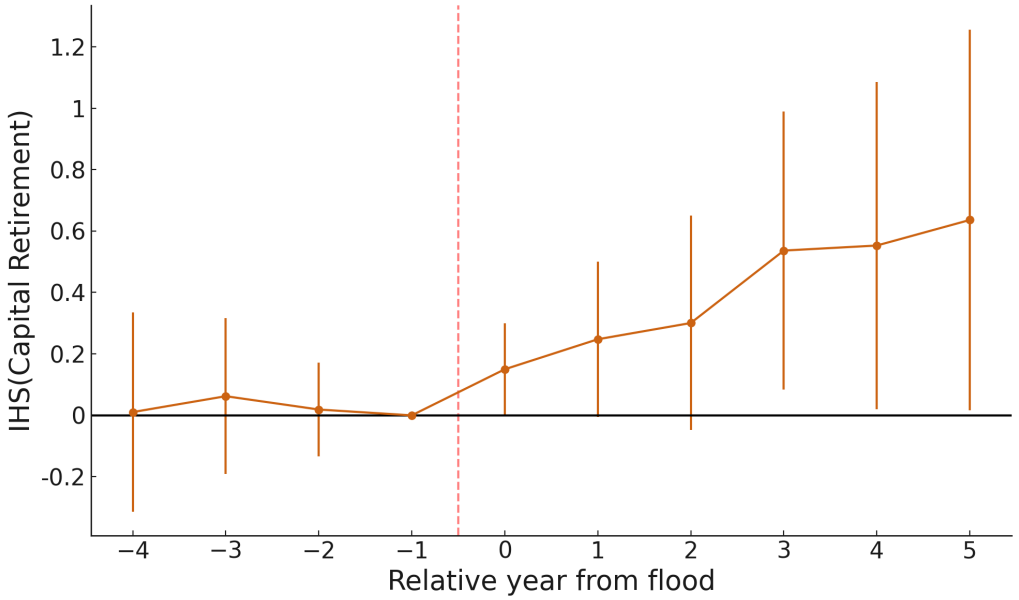
	All plants	**Heterogeneity by pre-flood performance**	
		TFP	Value added/hour
1.Post flood	0.036***	0.049***	0.048***
	(0.005)	(0.006)	(0.006)
1.LowestQuartile		-0.002	-0.007
		(0.007)	(0.009)
1.Post flood#1.LowestQuartile		0.011**	0.02***
		(0.005)	(0.005)
N	422,000	257,000	257,000
Y-mean	0.11	0.10	0.10
Y-sd	0.32	0.29	0.29

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; -R11775)

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 upto 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. It shows that, in addition to capital retirement, plants also see higher likelihood of incurring capital repair costs (2% more) and refuse (water and waste) removal costs after flooding. Overall, these results of persistent capital retirement are consistent with the interpretation that water damage from flooding degrades capital and speeds up machinery corrosion such that plants increase their sale and disposal of machinery assets.

Metal corrosion as a mechanism of flood damage: To shed light on the physical damage to physical capital from flooding, Table 3 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 3 shows some supporting evidence for the hypothesis that water damage from flooding can induce metal rust. 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.

This inventory loss is potentially consequential: the latter two columns of Table 3 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)).

4.2 Investment Response and Productivity Outcomes

Table 4 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%.

Table 3: 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)

Table 4: 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)

Note here 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 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, while that on the and 'Retire in flood year' dummy indicates that relative to periods in which plants are observed to *not* retire capital, they invest more when they do retire capital in the year of a flood. 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 5: Flooded plants invest in rebuilding capital

	IHS(Investment)			Binary		
	Total	Building	Machine	Machine	Log(Capital stock)	Share of investment in new assets
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

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

	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

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 5 examines how much plants invest in brand new building and machinery assets as a share of their total capital expenditures. It shows that, plants which retire capital in the same year as a flood invest 2.8 percentage points more in brand new assets. In contrast, the post-flood period sees the opposite: the share of investment in new assets drops by 2.7 percentage points relative to the pre-flood period. These results generally suggest that while plants which retire capital in the same year the flood replace it with brand new capital, potentially adopting later technology vintages, the post-disaster period is marked by substantial reallocation of second-hand capital.

Lastly, Table 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 3: Evolution of investment based on capital retirement

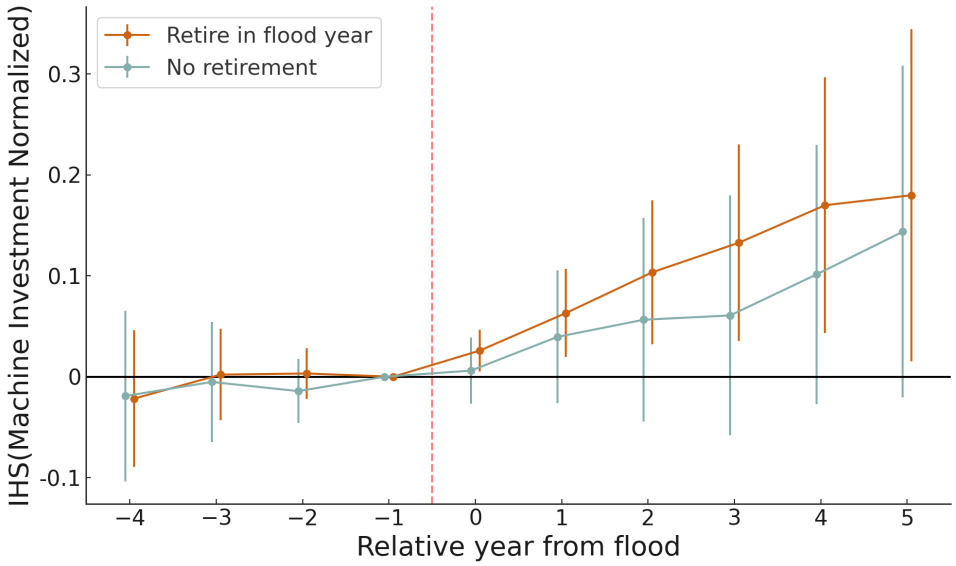


Figure shows the time path of investment (normalized by pre-disaster capital stock), separately for plants that retired capital in the year of the flood (in orange), and those that did not. 95% confidence intervals are computed based on standard errors are clustered at the county level. Estimates in this figure were disclosed under (CBDRB-FY25-P2851-R11940).

Figure 3 shows the dynamics of machinery investments for plants which did and did not retire capital in the same year as a flood, with investment amounts normalized by machinery

capital stock from the year prior to the disaster. The top panel shows that generally both categories of plants increase their investments following flooding, but that the investment of plants which retired capital in the year of the disaster starts rising first and remains higher throughout the post-flood period. These magnitude differences as well as the chronological order of how investment rises in this graph is potentially consistent with a reallocation of capital from the plants which replace their capital (marked by the orange line) to others (marked by the green line): which is also consistent with the previous finding in Table 5 that plants which retire capital in the flood year primarily buy brand new assets while used capital purchase remains high in post-disaster periods.

The next natural step is to study plants' performance, which is presented in Table 7. The first column examines labor productivity, as measured by real output per total plant hours. It shows that plants which retire any capital in the year of a flood see a 4.5% increase in their labor productivity relative to their pre-disaster baseline. This is an economically significant increase, representing about a 5 dollar increase in real output per hour compared to the control mean of $110.10. The second column of this paper then examines the hourly wage outcome of plants which retired capital the same year as the flood and replaced it thereafter. I find that hourly wages rise by 2.7%, representing about a 32 cents increase in hourly wages relative to the mean of $11.9 dollars. These results suggest that only a share of the gains to labor productivity trickle down to workers' wages. The last column in this table shows the IHS-transformed values of value added per hour to gain more understanding of the heterogeneity in hourly profits across plants which did/did not reitre capital after a flood. That result shows that post-flood capital retirers see about a 2.1% increase in value added per hour—an 83-cent increase compared to the control mean of about 40 dollars.

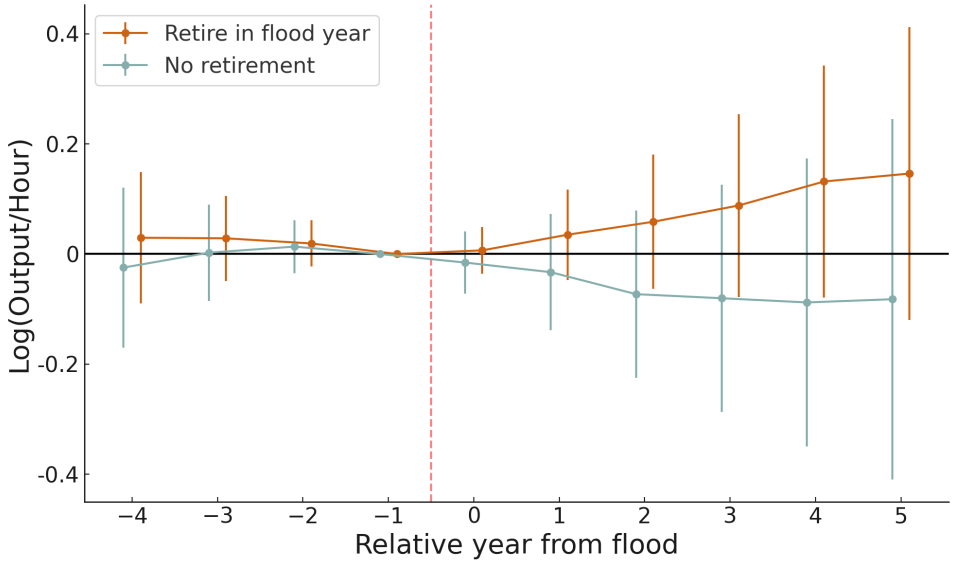
To examine the dynamics of productivity, Figure 4 shows the respective time paths of output per hour for plants which did and did not retire capital in the same year as a flood. It shows that these two groups have highly divergent paths in their labor productivity, with flood-damaged plants seeing higher productivity and non-damaged plants seeing lower productivity compared to their pre-flood baselines. These event study findings further lend support to the aforementioned results that plants which replaced their capital after flooding substantially overperform those which did not in their labor productivity.

Table 7: Flooded plants which replace their capital see higher labor productivity

	Log(Output/hour)	Log(Hourly wage)	IHS(Value added/hour)
Post flood X Retire in flood year	0.045**	0.027*	0.021
	(0.019)	(0.014)	(0.035)
Post flood	-0.022	-0.032*	–
	(0.024)	(0.017)	
Retire in flood year	-0.043	-0.0006	–
	(0.038)	(0.026)	
N	68,000	68,000	68,000
Y-mean	$110.1	$11.9	$39.67
Y-sd	$279.3	$8.61	$91.97

This table shows the relationship between firm performance and disaster experience. The outcomes in Columns 1, 2, and 3 measure the log of output per hour, log of total wages per total hours, and the inverse transformed measure of value added per hour, with value added calculated by deducting costs from revenues. 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 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)

Figure 4: 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).

4.3 Reallocation of Used Capital and Aggregate Implications

An important implication of disaster shocks is that they can increase the local supply of used capital: exiting plants would liquidate their physical capital, i.e., machinery and buildings/structures. Additionally, surviving incumbents that rebuild may sell their pre-existing machinery. 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)). The productivity impacts are ex-ante ambiguous, but crucial to study given that young plants' capital investments in their earliest years can have lasting impacts (see Hornbeck et al. (2024)). On one hand, used machinery may help young plants to build their capacity and grow faster. On the other hand, given that second-hand machinery from incumbents likely carries older (potentially obsolete) technology vintages, acquiring used capital may hurt young plants' productivity in the short term. In the long term, second-hand machinery may have the negative impact of locking in young plants to old technology that increasingly becomes incompatible to integrate with future technological upgrades, thereby putting a premature upperbound on their long-run technology use as well.

Figure 5 describes the relationship between plant age and the purchase of new and used (second-hand) capital using ASM data from 1985-1996, with a particular focus on the heterogeneity in this relationship in the immediate aftermath of a flood (i.e., when there is a flood in the same year or prior year). The y-axis shows the average share of investment toward brand new versus used capital (across both building and machinery asset categories) by plant age category. In contexts without a recent flood, plant age and investment generally do not appear to be statistically significantly different at least among plants aged 12 and below. Plants aged 13 and above have higher share of their investments going to new capital. However, in the immediate aftermath of flooding, these patterns become even more stark: older plants in the 9-12 age group increase their relative investments in new capital (potentially reflective of replacement assets they purchase as they rebuild), while the youngest plants (aged 4 or younger) appear to disproportionately invest in more used capital, giving rise to about a 3% *net* difference in the share of new capital investment across these two groups. Overall, I find strong evidence that second hand machinery is reallocated from older plants (including exiters) to younger ones following disasters.

Figure 5: In the immediate aftermath of disasters, (older) flooded plants increasingly buy brand new replacement machinery, while younger plants acquire the used capital

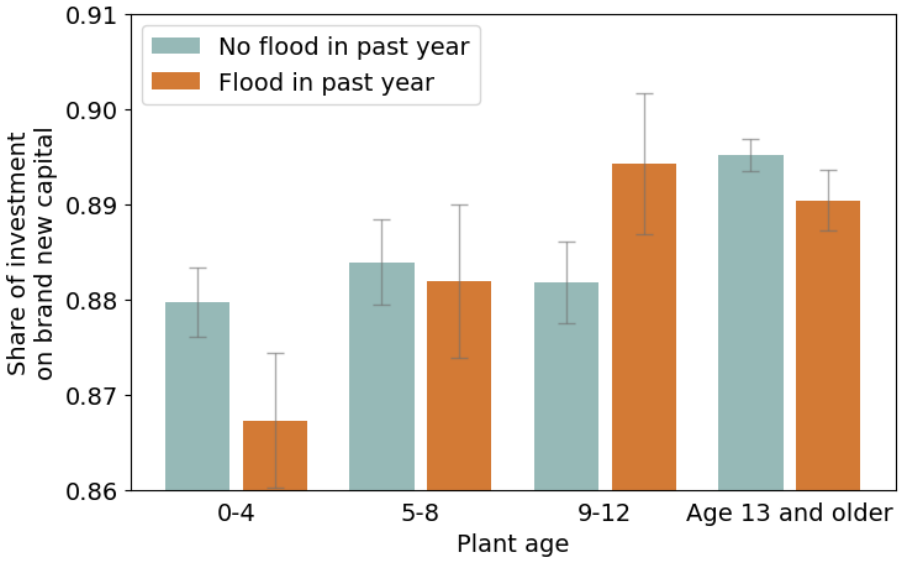


Figure shows the relationship between plant age and the investment in brand new assets (across machinery and building capital categories), and how this relationship may change in the immediate aftermath of a disaster. The orange shaded bars indicate counties in which there was a recent flood (in the same year or year prior), while the green shaded bars show years with no flooding in current or prior year. Underlying ASM data cover the years 1985-1996, which is the maximum data window for which capital investment questions are broken down by new and used, and relatively older plants of upto age 13 and above can be observed. The approach to calculate plant age is described in Appendix Section A.2. Estimates in this figure were disclosed under (CBDRB-FY24-P2851-R11684)

Table 8: Post-flood entrants pay higher average wages compared to pre-flood entrants

	Log(Payroll)	Log(Employment)	Log(Payroll per employee)
Post flood	0.045**	0.007	0.038***
	(0.022)	(0.013)	(0.014)
N	193,000	193,000	193,000

This table shows the relationship between flooding and entrant plants' outcomes. The outcome variables are the log-transformed measures of total annual payroll, employee count, and payroll-per-employee (i.e., total annual payroll divided by number of employees). 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).

Importantly, Table 8 shows that entrants are positively selected. Using LBD data on a broad sample of entrants, I show that payroll and payroll per employee (average wage) are both higher among post-flood entrants compared to pre-flood entrants. This result also holds when restricting the sample to only single-unit firms (and excluding new plants that pre-existing parent firms may open). These findings demonstrate that post-flood entrants are high-performing not, for example, low-quality plants which only entered because of conducive financing conditions or expanded availability of (cheap) used capital in the federally-declared flood environment.

Table 9 shows regression results on the association between used capital purchase and young plant productivity/survival. In particular, the first three columns show cross-sectional regressions on the labor productivity and survival of entrant plants (across both single and multi-unit firms). The first two columns show that purchase of used machinery in particular is statistically insignificantly associated with about 7 percent higher labor productivity, and lower survival (by about 8 months). The third column shows that, still among entrant plants, the purchase of used capital (across both machinery and structures asset types) is associated with a statistically significant decrease in long-term survival by about 1.45 years (i.e., 18 months). Finally, the last column examines productivity among small young firms, i.e., those which belong to a single-unit parent firm. It shows that, for single-plant firms aged 0-4, investment in used machinery after disasters is associated with about a 10% lower output per hour. Controlling for the productivity of young plants in the pre-flood years does not substantially change this result, suggesting that lower productivity of a plant may itself drive self-selection into purchase of used capital after flooding, it does not entirely explain

the negative associated observed here between used capital purchase and productivity. In other words, some role of the quality and old vintage of used capital in restricting labor productivity. Overall, while these results cannot be interpreted causally, they are consistent with a negative association between used capital purchase and plant productivity for the smallest young firms that are most sensitive to financing.

Table 9: Purchase of used capital and young plants' performance

	Entrant Plants (all single & multi-unit firms)			**Small Young Firms**
	Log(Output/hour)	Survival (Max age observed)		Log(Output/hour)
	(1)	(2)	(3)	(4)
Post flood	0.026	0.462	0.883	0.122**
	(0.0534)	(1.036)	(1.037)	(0.051)
Used machine	-0.026	-0.799		0.076
	(0.043)	(0.618)		(0.048)
Post flood X Used machine	0.0689	-0.769		-0.101*
	(0.051)	(0.799)		(0.06)
Used capital			-0.462*	
			(0.608)	
Post flood X Used capital			-1.455*	
			(0.819)	
N	5,300	5,300	5,400	7,800
Y-mean	7.685	16.94		52.09
Y-SD	5.694	10.92		73.49

This table shows the relationship between flooding and young plant performance and survival. The dependent variables in columns 1 and 4 is labor productivity (as measured by output per hour), while in columns 2 and 3, it is the maximum age that the plant is observed to attain in the LBD data (and equals age at exit, for plants which are observed to shut down). 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-R11700)

Table 10 shows regression results to make sense of the aggregate implications of the within-plant capital replacement and across-plant reallocation that has been captured by the results presented thus far. In particular, this table shows the outcomes of county-industry level dispersion of the marginal product of plant capital, and average labor productivity. The first column, in particular, shows the interquartile range–i.e., the difference in productivity between plants at the 75th and the 25th percentile of the productivity distribution in the narrowly defined 3-digit NAICS code within the same county. I find a negative and statistically significant change in the dispersion of productivity, suggests that capital is, on average, being reallocated and put toward better use after disasters. The second column shows that

county-level output-per-hour also rises by a statistically insignificant 1.1% after flooding, suggesting a boost to aggregate productivity associated with flooding. Overall, these results indicate that the reallocation that follows after federally-declared floods enhances allocative efficiency at the aggregate level.

Table 10: On average, post-flood reallocation enhances productivity

	IQR of Log(Output/Capital stock)	Log(Output/Hour)
Post flood	-0.014*	0.011
	(0.009)	(.016)
N	131,000	21,500

This table shows the relationship between disasters and measures of productivity and allocative efficiency at aggregate levels. The dependent variable in the first column is the interquartile range of output per capital stock as a proxy for marginal revenue product of capital (measured within narrowly-defined 3-digit NAICS county-industry levels). The dependent variable in the second column is output per hour (at the county-level). All outcomes are measured from ASM data. The explanatory variable indicates the 0-5 year window following a 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-R11949).

4.4 Evidence on the Role of Financing Access

Relationship between firm size and investment

Table 11 shows regression results on the relationship between post-flood investments and firm size, as measured by total employment at the main firm in the year prior to a flood. Given that firm size typically has an increasing relationship with access to credit and ability to raise financial capital, this analysis is a useful test to see whether this general relationship holds after flooding, or if investment appears to be primarily driven by smaller firms, which would suggest a relaxation of financing constraints for smaller firms that are typically more likely to face barriers to credit access relative to larger ones. I find evidence in support of the latter hypothesis: smaller firms engage in more capital investment after flooding, and this is true both on the extensive margin (column 1), and the intensive margin (columns 2-4). These results are consistent with prior evidence that federal disaster spending expands regional (bank) credit supply to smaller and younger firms (Erda, 2024), in this case allowing smoother capital reallocation and aggregate recovery.

A similar analysis focusing on the discrete classification across single and multi-unit firms further confirms these results:[22] I find that single-unit plants, which typically enjoy lower access to financing relative to plants which belong to larger, multi-unit firms, invest more in the post-flood period.

Table 11: Financing channel: Firm size is negatively associated with post-flood investment, consistent with an expansion of financing access

	Dependent variable: Machinery investments			
	Extensive	**Intensive Margin** (Total and normalized investment)		
	Any invest?	IHS(Investment)	Norm. Investment	IHS(Norm. Investment)
	(1)	(2)	(3)	(4)
Post flood X Retire X Firm size	-0.02***	-0.081***	-0.36*	-0.007*
	(0.005)	(0.02)	(0.204)	(0.004)
N	56,000	56,000	56,000	56,000

This table shows the relationship between firm size and post-disaster investments. All dependent variables concern machinery investments, with the first column focusing on the extensive margin–i.e., a binary measure of any positive investment in machinery–and the latter columns capturing intensive margin outcomes like the inverse hyperbolic sine transformed measure of dollars invested in machinery (column 2), the investment amount normalized by the pre-flood machinery capital stock in raw dollar terms (column 3), and the inverse hyperbolic sine transformation of the normalized investment (column 4). *Firm size* indicates the log transformed count of total employment at the firm in the year prior to the disaster. Results in this table were disclosed under (CBDRB-FY25-P2851-R11940)

Credit markets

Beyond the above evidence on investment patterns across the firm size spectrum, another approach that can help unpack the role of financing is to closely study post-flood recovery in settings where credit markets are especially weakened. The 2008 Great Recession, which saw a pronounced collapse of financial markets, provides a good setting for such a test. This is an especially salient setting because prior work shows that while the pace of job reallocation and creative destruction is accelerated during recessions, the 2008 recession saw a dampened intensity of cleansing and job reallocation (Foster et al., 2016), which (Osotimehin & Pappadà, 2017) show can be attributed to credit market imperfections. If a similar finding of weaker quality of capital reallocation following floods that coincided with the 2008 Great Financial Recession, then it lends further credence to the financing channel highlighted in this paper. To test this hypothesis, I compare how the marginal revenue product of capital and labor productivity recovered following floods that occurred in the 2008-2010 window

[22]The numerical results for this analysis have not been disclosed from the Census Bureau to reduce volume of output in disclosure requests.

(i.e., coinciding with the start of 2008 Great Financial Recession) relative to prior recessions in my sample period, namely the recessions from 1980, 1981-1982, 1990-1991, and 2001.

The results of this analysis are shown in Table 12, and generally suggest that floods which coincided with the 2008 Great Recession had dampened cleansing relative to floods that coincided with other recessions. Relative to floods that coincided with the Great Recession, dispersion in the county-industry level marginal revenue product of capital was narrowed by a further (statistically insignificant) 1.8 percentage points, while average productivity of labor at the county level was about 7.8% higher following floods that coincided with prior recessions. This evidence complements prior findings that credit market imperfections restricted productivity-enhancing job reallocation during the Great Recession (Osotimehin & Pappadà, 2017) by shedding more light on capital reallocation. Further, my findings highlights the vital role of well-functioning credit markets in facilitating productivity-enhancing economic churn following crises. Together with the evidence in (Erda, 2024) that federal disaster spending props up regional credit markets, these findings highlight that federal relief spending is a key enabler of the productivity-enhancing capital reallocation observed following major disasters.

Table 12: Suggestive: floods that coincided with the 2008 Great Recession were associated with less productivity-enhancing capital reallocation

	IQR of Log(Output/Capital Stock)	Log(Output per hour)
Post flood X Great Recession	0.018	-0.078*
	(0.031)	(0.040)
N	26,500	4,300

This table examines aggregate recovery following floods that coincided with recessions, with a particular focus on the heterogeneity across floods that did and did not coincide with the 2008 Great Recession. The explanatory variables are the interquartile range of marginal revenue product of capital (measured at the county-industry level) and output per hour (at the county level). The regression sample is limited to floods that offurred in the years 1980, 1981-1982, 1990-1991, 2001, 2008, 2009, 2010, coinciding with notable recessions that occurred in the 1977-2017 window. The explanatory variable interacts the post flood period with *Great Recession*—a dummy indicating whether the flood cohort year was between 2008-2010. The excluded (base) category is the average post-flood outcome for disasters that coincided with pre-2008 recessions. Results in this table were disclosed under (CBDRB-FY25-P2851-R11949)

4.5 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.2 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

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

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, including when these outcomes are normalized by the pre-flood year's aggregate capital stock in the county (see Table A.2). 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, as demonstrated by Appendix Figures A.4 and A.5, which replicate the main results from this study 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

[24] See Figure A.2 for a template of the survey invitation message.

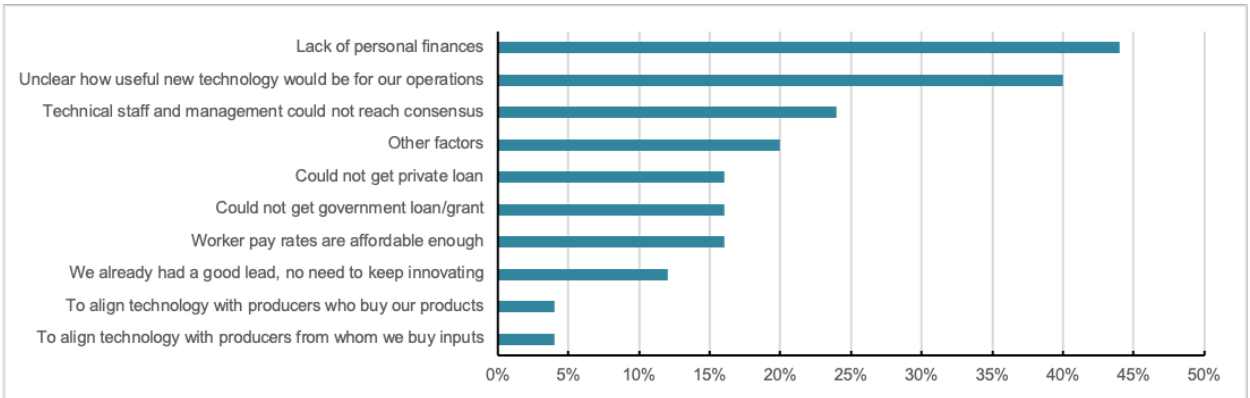
[25] The funds for the donation were secured via a grant from the Columbia Center for Political Economy. The list of 50 potential organizations among which the lottery winner could pick one donation recipient was prepared and IRB approved before the survey dissemination, with priority for themes like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

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.

As of March 2025, about 43 respondents started the survey while 21 completed it 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. 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.

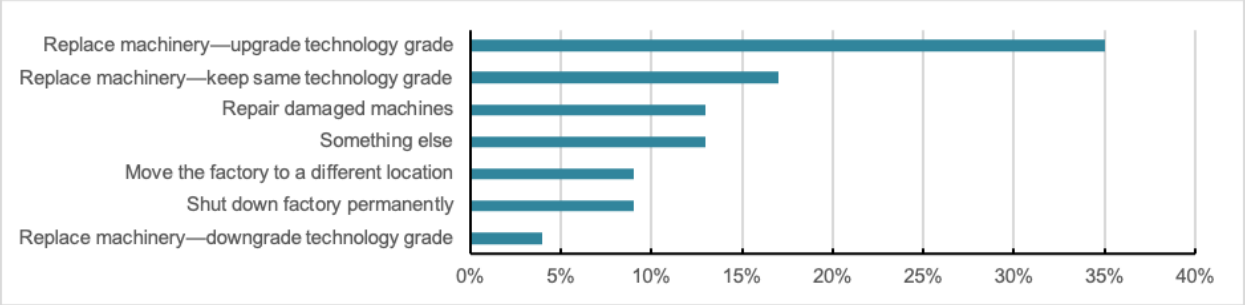
Figure 6: Barriers for investing in new equipment and technology



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.3). 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 7: 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 Discussion

This paper documents substantial capital replacement and reallocation of physical capital, particularly production machinery, in the manufacturing sector following large, federally-declared floods. On aggregate, this reallocation is productivity-enhancing, which suggests a novel channel through which federal disaster spending enables post-disaster recovery– propping up productivity-enhancing creative destruction.

A key consideration in the interpretation of these results is the use of capital retirement information in the ASM as a proxy for physical damage from flooding, particularly in the same year as the flood. There are two relevant considerations here related to potential endogeneity and measurement issues. First, capital retirement is a decision taken by the firm itself, which could be a function of the inherent productivity (e.g., nimble and high-quality management) of the plant itself. Additionally, the severity of the disaster itself could play a role in the capital retirement decision, with the most intensely affected plants expected to react most swiftly by discarding capital right in the same year as a disaster. These factors suggest that the magnitudes of the investment response and productivity gains should be interpreted as upperbounds.

A second consideration is related to measurement. Capital retirement is a poten-

tially 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 asset value, but can be interpreted to reflect the degradation to capital from flood waters. To shed light on these matters, I have a survey underway, examining capital loss events among manufacturing plants and their reactions.

Lastly, this paper motivates further research on the frictions to the extensive and/or simultaneous adoption of complementary technologies by firms. Of course, the findings of this paper do not imply that plants should switch to the newest vintage every single year. But, a potentially meaningful intervention for future work to explore could be the effectiveness of policies like incentives for simultaneous (systemic) capital upgrading in the manufacturing sector. As one step toward this goal, I am currently conducting an original survey on manufacturing firms in the Mid-Western US to complement these insights with qualitative evidence on firms' incentives and barriers for investment and experiences with natural disasters.

7 Conclusion

In this paper, I study how manufacturing plants adjust their capital following large, exogenous floods as well as the implications for their productivity and allocative efficiency. I first show that flooding is followed by large and persistent increases in capital retirement (i.e., disposal or sales). Plants which retire capital subsequently increase replacement investments and ultimately overshoot their pre-flood labor productivity baseline by about 4.5%, suggesting that they adopt upgrades to their machinery during their rebuilding process. Moreover, as flooded incumbents replace their capital and plants forced to exit due to the disaster sell off their assets, I show local entrants and young plants increase their investment in second-hand capital, taking advantage of the opportunity. While one may worry that expanded access to financing and/or cheap used capital in post-disaster contexts may drag down the average quality of entrants, I find no such evidence and in fact find that post-flood entrants

pay higher wages compared to pre-flood entrants. Ultimately, post-flood capital reallocation improves allocative efficiency. These benefits are a feature of federal disaster spending, which props up regional credit markets and, as I previously showed in (Erda, 2024), expands access to financing, particularly for young and small firms.

Beyond underscoring the critical role of disaster recovery spending for capital adjustment, my findings also shed new light on 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 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	

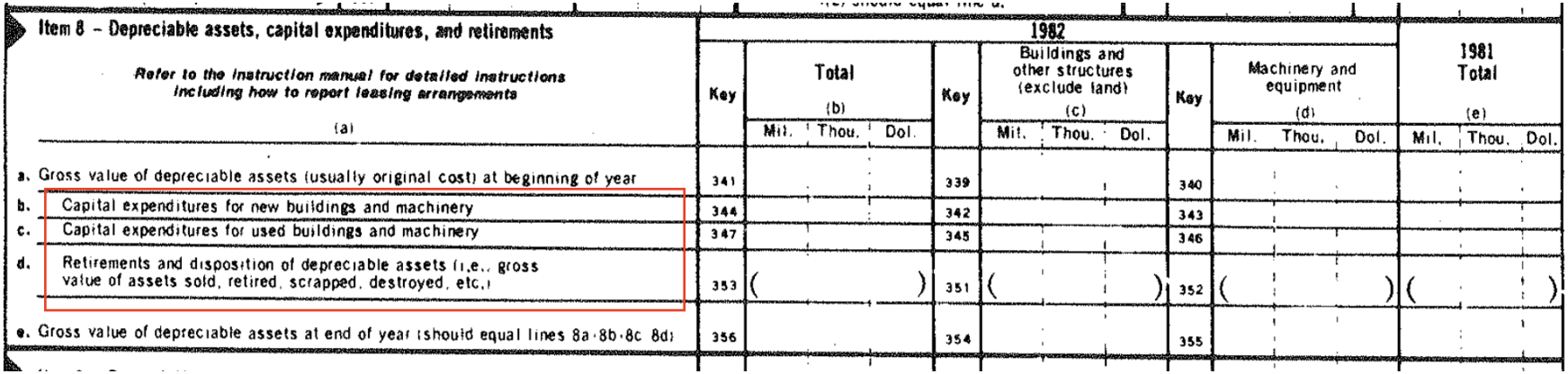
Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11700; CBDRB-FY25-P2851-R11949)

Table A.2: County-level total investment increases following flooding

	IHS(Capital Investment)	IHS(Normalized Investment)	IHS(Normalized Net Investment)
Post Flood	0.073*	0.0312***	0.019**
	(0.044)	(0.008)	(0.009)
N	21500	17500	5700

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 retirements



Item 8 – Depreciable assets, capital expenditures, and retirements

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

(a)	1982 Key	1982 Total (b) Mil. Thou. Dol.	1982 Key	1982 Buildings and other structures (exclude land) (c) Mil. Thou. Dol.	1982 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: 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.

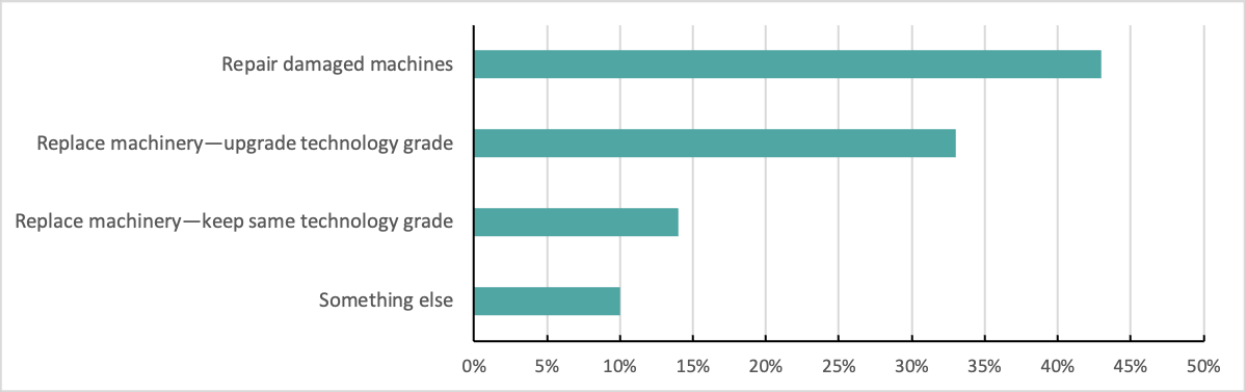
Regards,

Thomas Walstrum

Principal Business Economist

Federal Reserve Bank of Chicago

Figure A.3: 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 Robustness Checks

Figure A.4: Increase in capital retirement among surviving plants, as estimated by Sun and Abraham (2021) approach

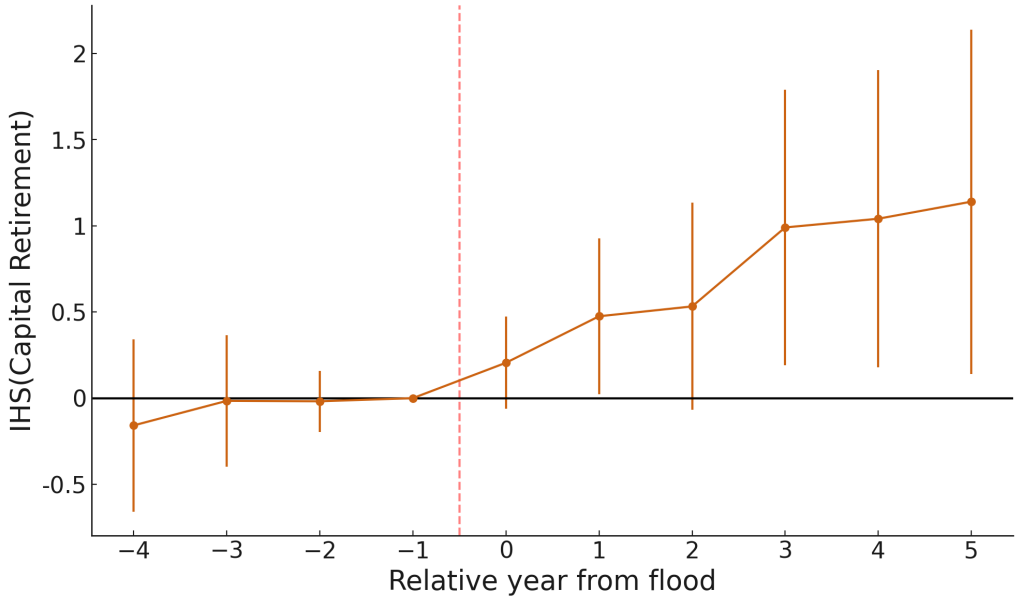


Figure shows event study coefficients for capital retirement from 4 periods before flooding upto 5 periods treatment, based on plants that continue in business for at least 3 more years. 95% confidence intervals are computed based on standard errors are clustered at the county level. Estimation follows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

Figure A.5: Evolution of investment based on capital retirement, as estimated by Sun and Abraham (2021) approach

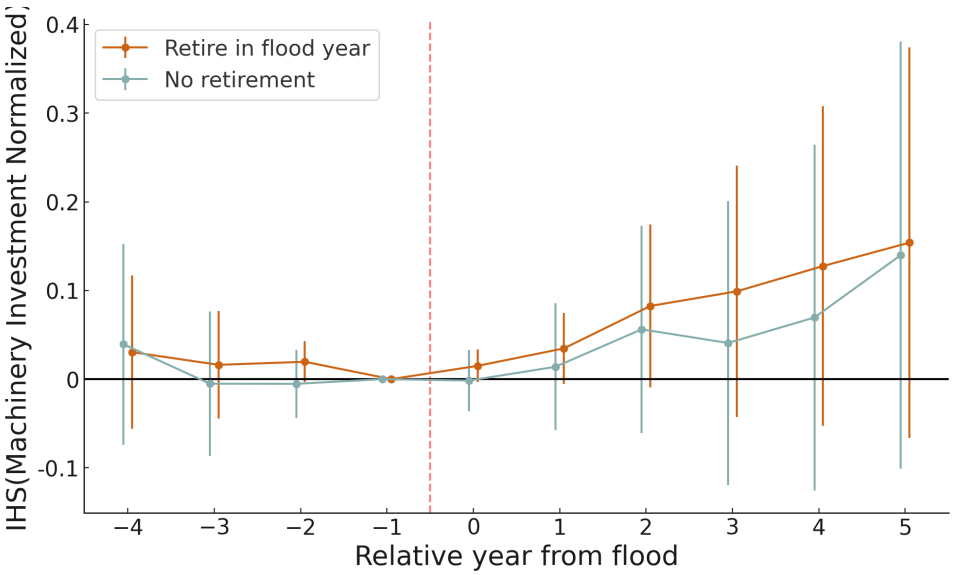


Figure shows the time path of investment (normalized by pre-disaster capital stock), separately for plants that retired capital in the year of the flood (in orange), and those that did not. 95% confidence intervals are computed based on standard errors are clustered at the county level. Estimation follows the Sun and Abraham (2021) approach. Estimates in this figure were disclosed under (CBDRB-FY24-P2851-R11775).