Disasters, Capital, and Productivity*

Tarikua Erda†

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Abstract

Large disasters devastate economies, yet regional productivity and household income often improve in their wake. Why? Using administrative plant-level microdata from the US Census Bureau and an event study design, I trace the creative destruction process that follows large, federally declared floods. Exits rise after flooding, primarily among the least productive plants. Their second-hand machines are then reallocated toward more productive survivors and, notably, toward high-productivity entrants. Survivors also upgrade their machinery as they rebuild and see productivity gains. A key mechanism is that federal disaster spending expands access to financing, particularly for nimble, well-managed new and young firms that disproportionately drive job creation and productive churn. In the absence of federal aid, however, financing constraints dampen this creative destruction, misallocating resources and lowering residents' income. My findings reveal a novel, underappreciated channel through which government spending supports disaster-hit economies and underscore its critical role in a warming world.

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†Erda: New York University, tarikua.erda@nyu.edu.

1 Introduction

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

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

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

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

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

firms, which fuel dynamism and job creation during recovery. Federal disaster spending also boosts incomes—which, in its absence, would have declined—ultimately paying back for itself via tax revenues.

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

My main data sources are the confidential plant-level microdata from the Annual Survey of Manufactures ("ASM") and the Longitudinal Business Database ("LBD") from 1977 to 2017. The ASM provides rich information on plant output, productivity, as well as book values of capital stock and investments in building and machinery assets. I use revenue-based TFP as the primary indicator of productivity. The ASM's intermittent information on plants' capital retirement (i.e., sale and disposal) helps me approximate post-flood disinvestment, while its breakdown of capital expenditures as new versus used capital enables me to study capital replacement and reallocation. Isolating post-flood entry-exit dynamics from surviving plants' capital readjustment requires comprehensive information on plants' life cycle. Thus, I use the LBD—the Census Bureau's workhorse economic dataset tracking the birth, death, and year-to-year performance of all businesses in the US. Leveraging plausibly exogenous variation in the timing of flooding, I use an event study design to compare the pre- and post-flood outcomes of plants and industries in flooded counties. I restrict my sample to counties which experienced 1-3 declared floods over the 1976–2018 period, with at least 6 years between any two events. This ensures cleaner identification by focusing on rare, unanticipated disasters and isolating the impact of a single event. As a complement to my empirical analyses, I also conducted my own qualitative survey on manufacturers located in the Midwestern US.

I document three key results. First, exit rates rise after flooding, primarily among

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

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

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

the least productive plants. Plants' probability of exiting within two years increases by 3.6 percentage points (p.p.) after flooding, representing a substantial—more than 30%—increase compared to the pre-disaster baseline. However, plants that were already in the bottom quartile of TFP distribution in their narrowly-defined industry *before* the disaster are far more likely to exit after it relative to their higher-productivity counterparts. This reflects a weeding out of less efficient forms of production after the negative productivity shock.[6]

Second, surviving plants invest to replace their capital and see productivity gains. Conditional on not exiting, i.e., surviving for at least 3 more years, surviving plants have a substantial and persistent increase in machinery sales/scrapping, standing at more than 60% higher retirement in the 5th year relative to the pre-flood baseline.[7] Plants also increase their *net* capital investment, often in brand new machinery, suggesting that rebuilding investments more than compensate for the flood-related capital retirement.[8] Consistent with this, my qualitative survey finds that manufacturers see flooding as an "opportunity to modernize," and that "... when replacing by necessity, [they would] stay current." Ultimately, survivors' productivity increases by more than 11% in the 5th year following the flood, reflecting their positive selection into survival as well as their increased capital investments.

Third, as the local supply of second-hand capital increases following disasters, young plants and new entrants acquire that used capital to build up their capacity.[9] While we may worry that used machines—especially in the post-flood context—might be lemons, or that their increased supply and lower prices may attract entrants with low productivity, I find no evidence of such phenomena. In fact, post-flood entrants are positively selected, boasting about a 14% higher TFP compared to pre-flood entrants. One explanation for this is young firms' nimbleness and managerial quality: using measures from the Management and Organizational Practices Survey (MOPS), I show that younger firms follow better, more structured organizational practices in fixing and responding to crises—like flooding that disrupts their production process—relative to older firms.[10] As the disaster amplifies the already-intense up-or-out selection that young firms typically face, their superior agility enables them to survive and even capitalize on the disaster opportunity to scale.

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

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

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

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

[10] The MOPS is an addendum to the ASM's 2010 and 2015 waves. See Buffington et al. (2017).

Even outside of the tradable sector that anchors my productivity analyses, the firm entry margin and entrepreneurial activity drive the substantial churn that disaster-hit regions experience. The retail, construction, and food/accommodation sectors experience sharp post-disaster churn—establishment exits rise (3.5%), but entries rise even more (4.5%)—and employment growth, thanks to new establishments and firms that absorb increased local demand and disproportionately drive job creation relative to continuers.

At the aggregate level, post-disaster reallocation enhances allocative efficiency and also boosts income per capita. To study this, I focus on the average TFP, the dispersion in revenue TFP mainly using inter-quartile range of TFP, as well as the interquartile range of marginal revenue product of capital (MRPK) between plants operating within similar industries and locations.[11] Measures of dispersion are useful here because, in a frictionless world, marginal productivity of inputs should be equal across firms, so deviations–such as higher dispersion–suggest inefficiencies. I find that the interquartile range of output per capital declines by 0.011 log points, implying a compression in the 75th-to-25th percentile gap in MRPK by roughly 1.1% in each post-flood year. In other words, capital inputs are, on average, reallocated toward plants which can make better use of them after flooding. I also show suggestive evidence that average productivity rises while TFP dispersion declines. These results are consistent with post-flood creative destruction improving allocative efficiency. Income per capita also rises by 0.6% annually relative to the preflood baseline, further reflecting that post-disaster churn strengthens local economies.

These outcomes stem from the expanded access to financing that federal spending facilitates. Based on a counterfactual set of severe but non-declared floods—where disaster-hit counties only had access to local/state level assistance but not to federal funds—I show that per capita incomes decline by 0.4% after flooding, while TFP declines by 0.72%. Relative to the aforementioned 0.6% annual income *gain* after declared disasters, this implies an annualized 1 percentage point *net* increase ($p < 0.001$) in per capita incomes from the pre-disaster baseline, demonstrating the causal effect of federal relief spending on recovery. Additionally, despite typically being vulnerable to financing constraints, small, young manufacturing firms have greater post-flood investment relative to larger, older firms.[12] These results demonstrate the critical role of government spending in smoothing recovery and facilitating productive churn, in large part by expanding the financing access of young and small firms.

[11] These are common measures used in studies of productivity dispersion and resource (mis)allocation. See (Hsieh & Klenow, 2009; Syverson, 2011).

[12] The insights from my qualitative survey also corroborate these takeaways: if hit by major floods, small manufacturers would upgrade their capital as they rebuild so long as they had ample access to financing.

Turning to the fiscal implications, federal disaster spending pays for itself through increased tax revenues. The productivity gains, entrepreneurial activity, and job creation facilitated by disaster relief raise incomes in flooded areas, which in turn boost tax collections. Under conservative assumptions, the coefficients calculated in my income regressions imply that each dollar of FEMA and SBA spending between 1993-2017 generated approximately $11 in benefits for recipients while also yielding positive net revenue for the government, implying an infinite Marginal Value of Public Funds (MVPF). Thus, federal disaster spending is a remarkably high bang-for-buck policy that supports recovery and fuels creative destruction in disaster-hit regions.[13]

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

In this respect, this study also contributes to the broader literature on the impact of government spending on recovery after negative productivity shocks. With the exception of Gallagher et al. (2023), most other existing studies on post-disaster recovery focus exclusively on large, presidentially-declared storm-related disasters, showing that federal aid helps with household recovery and incumbent firm survival (Roth Tran & Wilson, 2023; Deryugina, 2017). The evidence I provide on non-declared floods helps illustrate the role of federal disaster spending. Consistent with Walsh (2023)'s finding that new firms can act as a

[13]These MVPF calculations apply to regions like those in my sample, which excludes counties with frequent or repeated flooding to ensure clean identification—specifically, to satisfy the no-anticipation assumption and isolate the impact of a single disaster. Moral hazard concerns around rebuilding may be more relevant in coastal areas facing repeated events. Nevertheless, since climate change is expected to increase flood risk even in inland regions, my findings are important and policy-relevant.

significant multiplier of both positive and negative local shocks, this paper demonstrates a novel channel through which government spending supports recovery in disaster-hit regions—a boost to economic dynamism via the firm entry margin.

More broadly, this paper adds to the macroeconomics literature on capital reallocation across the business cycle, and on the role of government spending after negative productivity shocks. My work complements Eisfeldt and Rampini (2006), who show that capital reallocation is (counter-productively) cyclical when its benefits are, in fact, counter-cyclical, inferring the presence of frictions, including financing constraints, that make reallocation costlier during downturns. My paper confirms this mechanism by using the exogenous timing of floods to causally demonstrate that government spending after a negative productivity shock like flooding facilitates greater and more efficient reallocation of capital, particularly by propping up the firm entry margin and young firm activity.[14] This is consistent with Caballero and Hammour (1996), who show that frictions may decouple creation and destruction, which would, in an ideal world, simultaneously happen during downturns, but that incentives for the creative margin of an economy increase the pace of reallocation and help restore efficiency. Kerr and Nanda (2009) illustrate that democratizing access to financing is critical for entrepreneurial experimentation, young firm activity, and ultimately, productivity-enhancing business churn. In line with this, my paper shows that the financing unlocked due to federal disaster spending counteracts the shock's destruction and reinforces the economy's creative margin, improving allocative efficiency during recovery.

This paper also contributes to the literature on the impact of climate change on physical capital depreciation, reallocation, and growth. Early theoretical work on these areas worried that the fixed nature of physical capital stock would drive slow adjustment to rapid weather shocks and thus exacerbate welfare losses from climate change (see Quiggin and Horowitz (2003); Yohe and Neumann (1997); Fisher and Hanemann (1993)). My paper provides a much-needed empirical test, showing that capital appears to be more mobile—i.e., adjustable within plant and redistributable across plants—than previously thought, at least in the short run. Existing work in this area has studied how global warming might affect aggregate growth via its impact on capital, primarily from a theoretical standpoint or from coarse cross-country and/or global analyses (see Nath et al. (2024); Casey et al. (2024); Bilal and Känzig (2024)). Highly relevant to my paper, Bilal and Rossi-Hansberg (2023) use predicted severe storm incidences to simulate a capital depreciation shock and study county-level migration

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

and investment responses, with the latter measured from manufacturing firm investment data at 5-year intervals and imputed in between. My use of rich plant-level annual data (including on capital retirement) and real incidence of major declared floods allows me to capture the dynamics and heterogeneity of post-disaster investment with more granular detail and greater accuracy. Thanks to the richness of the ASM in capturing capital retirement (including scrapping), this paper adds to this literature what is, to my knowledge, the most direct empirical evidence to date on the impact of climate hazards on capital depreciation.

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

2 Institutional Background

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

[15] Ma et al. (2022) use loan filing data to show that younger firms are more likely to buy used machinery from incumbents. However, their analysis may be affected by selection—both in which firms use machines as collateral and which machines are chosen. Moreover, their findings linking incumbents' machinery turnover to young firms' used capital purchases rely on lagged local investment, which may reflect reverse causality if incumbents invest in anticipation of entrant activity. By leveraging the representative nature of ASM data and the exogeneity of the timing of disasters, this paper provides more generalizable and causal evidence.

[16] There are thresholds of the per-capita property damage that must be reached or surpassed for certain kind of assistance such as broad-based public assistance to be unlocked. These vary across years, but are

declaration is at the discretion of the President.

Once the US president approves the request, federal funds can be used to repair public structures and to provide individual and business grants and loans.[17] FEMA's stated policy goal is to *supplement* disaster-affected communities' recovery efforts. In particular, federal disaster assistance only covers damages that are not already covered by insurance. Disaster assistance is provided under four major programs: public assistance (e.g. debris removal, infrastructure reconstruction), 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 regarding loans is most relevant for firms as it is the only *direct* government recovery assistance they can receive. SBA disaster loans to businesses have been shown to increase survival and crowd in private credit for SBA borrower firms (see Collier et al. (2024); Gallagher et al. (2023)). Therefore, manufacturers are expected to have broad access to financing after federally declared disasters.[18]

While the (negative) impact of disasters on plant survival, productivity, and new entries may be more straightforward, the impact of federal disaster spending on business dynamics and productivity is ex-ante ambiguous. On one hand, federal disaster assistance may facilitate reallocation of economic resources from less to more productive plants.[19] So if the positive role of federal spending wins out, then the firm entry and young firm activity margins—which are marked by the nimble and responsive nature of young firms—would be key channels through which aggregate productivity impacts materialize. On the other hand, however, the expansion of credit access after federal spending may avail cheap capital that ultimately sustains for lower-productivity units, or potentially crowds out more efficient private market lending, contributing to misallocative frictions.[20] As such, increased access

usually about 3 dollars per county resident (see (FEMA, 2023)).

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

[18] It is also plausible that the other federal programs could also indirectly support firm recovery by repairing the infrastructure that's integral to manufacturers' activity, and/or enabling their employees to weather the storm of disasters.

[19] For example, exogenous crisis events, such as the Great Boston Fire of 1872 (Hornbeck & Keniston, 2017) or the Mississippi River flooding of 1927 (Hornbeck & Naidu, 2014) have been followed by efficiency-improving reallocation as rebuilding/recovery efforts introduced updated technology and materials. Models of firm dynamics conceptualize job creation and reallocation a key aspect of productive firms that expand in response to positive business conditions, with new entrants and young firms playing an outsized role (see Haltiwanger et al. (2013)

[20] For example, Chava et al. (2023) find that lower entry costs are associated with higher rates of lower

to financing in the wake of major disasters may hurt aggregate productivity growth. These starkly different potential outcomes inherently call for an empirical analysis, whose data and methodology I discuss below.

3 Data and Empirical Strategy

3.1 Data

Data on firms:[21]

- *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 punishable by law, making the data reliable. Any imputations, i.e., data that are edited and entered by Census staff, are known. And third, the sample weight for each plant is provided, which allows me to account for sampling design in my analyses and work to obtain representative estimates.

  Importantly for my study, the ASM offers information plants' capital investment behavior separately for two categories of capital, machinery/equipment, and building/structures capital (see Figure A.1). Machinery and equipment capital encompass: all production machinery and transportation equipment (automobiles, trucks, etc.),

quality entrepreneurs who default on loans years after entry, particularly in states enacting business-friendly subsidies and taxes.

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

motors, lathes, punch presses, office equipment and machines; computers; furniture and fixtures for offices, cafeterias, dressing rooms; and warehouse equipment. Buildings and structures capital exclude the value of land itself, but encompass elevators, cranes, blast furnaces, brick kilns, fractionating towers, shipways and similar structures, as well as the usual factory office and warehouse type of buildings. While capital investment data are available for every year, the ASM provides an even more granular breakdown between used and new capital, within each machinery and building capital type category, up to 1996. The latter is what allows me to study the reallocation of used machines after disasters.

Another useful feature of the ASM data is that they have additional data on Management and Organizational Practices in years 2010 and 2015, which I use to study the nature and quality of plants' managerial responses to problems that arise in the production process (in my case, flooding). See Figure A.2 for the relevant question.

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

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

Data on flooding

- *FEMA Disaster Declaration Summaries*: I observe the incidence of floods from the Federal Emergency Management Agency's disaster declaration records.[22] Given that

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

they are a federal record, these data provide an exhaustive list of all declared disaster events since the 1950s. Therefore, they are a reliable data source to capture the universe of declared flood events.

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

Other data

- *Business Dynamics Statistics (BDS)*: To complement the productivity analyses based on the tradable manufacturing sector, I draw on the BDS—the Census Bureau's publicly available version of the LBD—to study business churn and employment dynamics in the non-tradable sectors driven by local consumption. The BDS provides annual measures of establishment and firm entries and exits as well as job creation and destruction by industry, location (including county), and firm and establishment size and age.

- *Bureau of Economic Analyses (BEA) income data*: I use county-level personal income data from the BEA's Regional Economic Accounts, specifically the CAINC1 table, which provides annual personal income and population estimates at the county level from 1969 onward. These data enable me to calculate per capita income for treated counties and track income recovery. The BEA constructs personal income from tax records and surveys, offering comprehensive coverage of all US counties and consistent measurement over time, making it well-suited for studying aggregate income effects of disaster shocks.

- *Community Reinvestment Act (CRA) bank loan data*: I use data on small business loans availed by the Federal Financial Institutions Examination Council (FFIEC) under the Community Reinvestment Act (CRA), which was enacted to encourage banks to meet the credit needs of the communities in which they operate. These data cover both secured and unsecured small business loans and provide, for each county, the

numbers and dollar amounts of small business that banks originated by loan size—below 100k USD, 100k-250k USD and 250k-1 million USD—from 1996 onward. I follow seminal work around the size and credit seeking behavior of young firms (see Berger and Udell (1998)) and use the smallest loan size category as a proxy for the smallest and/or youngest firms, which are widely understood to be more sensitive to access to financing—and vulnerable to financial constraints.

3.2 Sample

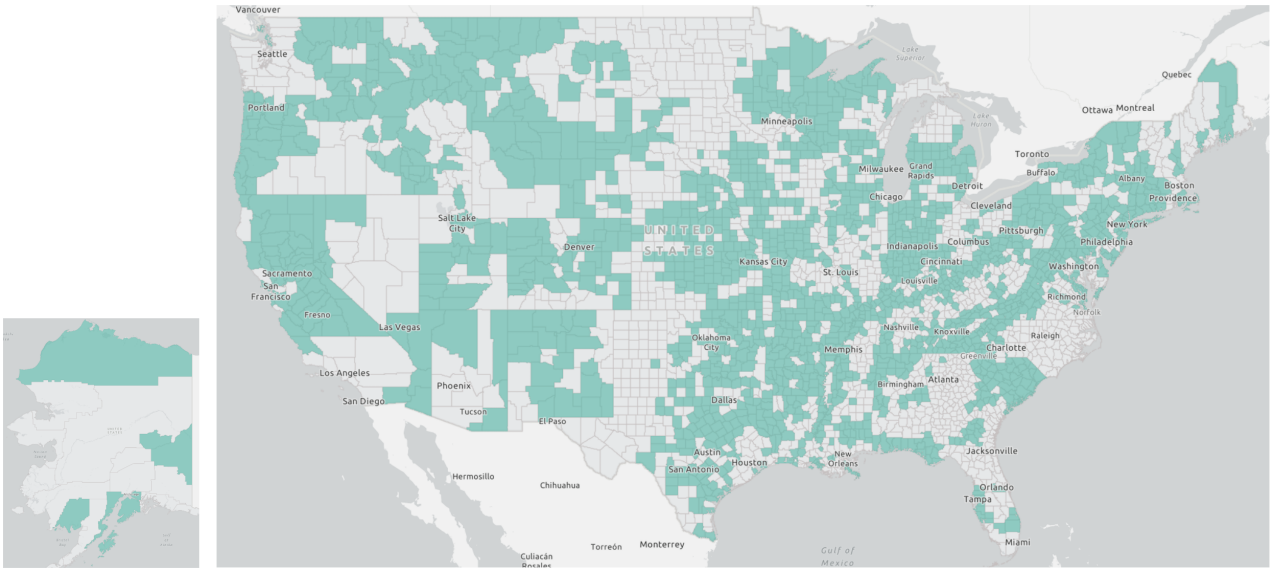
I start out with all ASM plants in the 1977-2017 period whose North American Industry Classification System ("NAICS") industry code falls under the core manufacturing codes between 31-33, then apply some key restrictions to make the estimation sample more relevant for the purpose of my analyses. First, I apply basic restrictions to ensure that each plant-year observation has a TFP estimate, which helps to ensure that this important productivity outcome, but also serves as a certification for data quality since the TFP-enhanced ASM data have undergone careful cleaning by Census researchers and have full data on plants' capital stock calculated via the perpetual inventory method (see Cunningham et al. (2023)). Second, I keep only ASM plants which have a matching record in the LBD, and are marked as employer plants and in-scope for the publicly-accessible version of the LBD, the Business Dynamics Statistics ("BDS"). This restriction ensures that my analyses capture employer establishments where production takes place, rather than, for instance, administrative units of manufacturing firms.[23]

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

Figure 1 gives the underlying *superset* of counties from which my sample of ASM plants is drawn. Due to US Census Bureau rules for confidentiality, there can be disclosure concerns

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

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



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

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.

My main sample contains approximately 422,000 plant-year observations corresponding to about 58,500 unique firms. From this sample, I leverage the information about plant age and exits to define subsamples that will allow me to study post-disaster responses and productivity outcomes among surviving plants and brand new entrants. This is because isolating these business-as-usual patterns of capital (dis)investment from flood-induced capital readjustment and reallocation across plants of various ages effectively requires confronting the inherent link between firm life-cycle dynamics and capital adjustment: entrants/young plants have to invest in capital to build up their capacity, while soon-to-exit plants would likely ramp down investments and instead liquidate assets in anticipation of their closure.

Thus, the subsample I use to study continuing plants' post-flood capital adjustment by focuses on plants that both: survive for at least 3 more years, and are at least 5 years old.

Table 1: Summary statistics for overall sample

Variable	**Mean**	**SD**
Total value of shipments (in $1000)	51,770	262,500
Multi-unit firm	0.6732	0.469
Production workers	146.8	350.4
All employees	207.3	559.1
Machinery capital stock (in $1000s)	13,900	71,070
Total capital stock	23,230	108,300
N	422,000	
Unique firms	58,500	

Statistics in this table were disclosed under (CBDRB-FY26-P2851-R12896).

Table 1 presents summary statistics for my full sample of manufacturing plants. More than two-thirds of these plants belong to multi-unit firms, with revenues averaging approximately 52 thousand dollars and output (q) averaging 55 thousand dollars—though standard deviations roughly five times larger suggest substantial dispersion. These plants hold about 14 thousand dollars in machinery capital stock and 23 thousand in total capital stock, again with considerable heterogeneity. The plants employ an average of about 207 employees, the majority of which are production workers directly engaged in manufacturing. Overall, my sample captures a broad cross-section of manufacturing establishments with substantial variation in size and capital intensity.

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

3.3 Empirical Strategy

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

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

where $Y_{p,t}$ represents various outcomes of plant p, located in county c in year t, such as capital retirement. The main explanatory variable of interest is $Flood_{p(c),t+j}$, a binary dummy indicating whether the county c in which the plant is located received a declared flood j years ago. α_p denotes plant fixed effects–it helps account for plant-specific characteristics that do not change across time. $\theta_{i,t}$ denotes 4-digit NAICS industry code interacted with year: it helps to absorb potential trends faced by plants in related industries. Lastly, $\theta_{s,t}$ represents state-by-year fixed effects, which help to absorb geographic factors that may be experienced by plants located in the same state. $\varepsilon_{p,t}$ is the error term, which I cluster at the county level.

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

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

4 Main Results

4.1 Exits following disasters

Table 2 provides evidence on how disasters affect plant exits and the productivity attributes of exiters. The first column shows that, among all plants, the probability of exiting within two years increases by 3.6 percentage points (p.p.) in the 5 years following a flood compared to the 4 years before it. The second columns of the table examines the heterogeneity in exit likelihood based on whether or not the plant ranked in the bottom 25% of the TFP distribution of its narrowly defined 6-digit NAICS industry in the year prior to a flood (-1 relative period). I find that, while 2-year exit likelihood generally increases after flooding, plants in the bottom quartile of the pre-flood year's TFP distribution in their industry have

an additional 1.1 p.p. higher likelihood of exit after a disaster relative to their counterparts in the top three quartiles. This suggests that it is the factories that were already marginal or low-performing during the pre-disaster period that are most likely to shutdown after it.

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

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

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

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

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

are younger plants that belong to multi-unit parent firms, while small, young firms (i.e., single-unit young plants) relatively show more resilience.

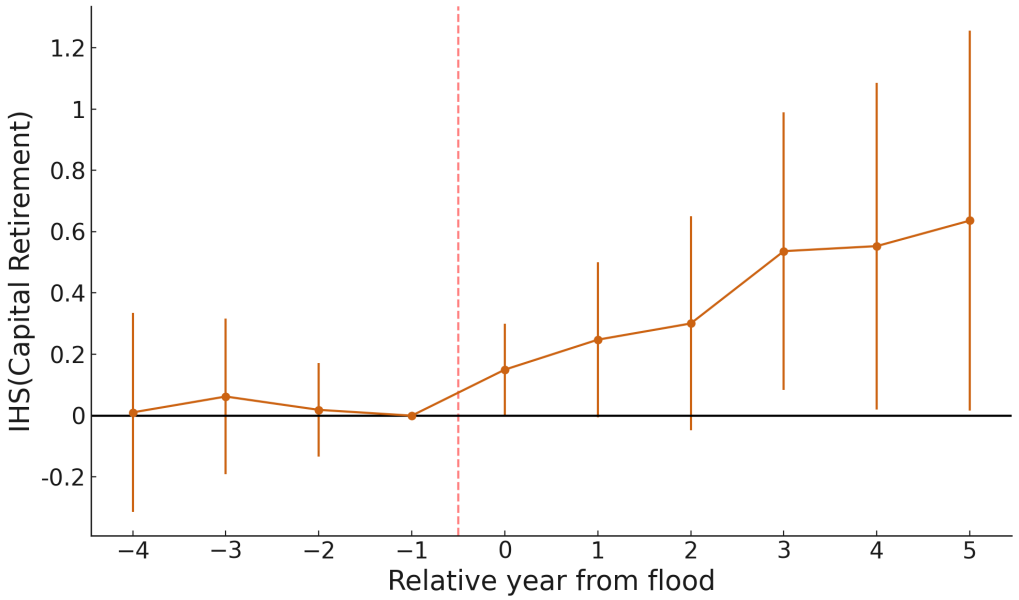
4.2 Survivors' Investment Response and Productivity Outcomes

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

In addition, Table A.1 in the Appendix presents broader evidence of the damaging impacts of flooding on physical capital. It shows that, in addition to capital retirement, plants also see higher likelihood of incurring capital repair costs (2% more) as well as refuse (water and waste) removal costs after flooding. These results demonstrate the physical damage and disruption from flooding that requires plants to repair/replace their capital.

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

Figure 2: Persistent increase in capital retirement among surviving plants



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

plants faced disaster-related negative impacts to their physical capital. In a nutshell, plants which retire capital in the same year as the flood subsequently invest earlier, more, and in newer capital relative to those that did not, and see 4.5% higher labor productivity gains, suggesting that survivors upgrade capital as they rebuild.

Table 3: Investment and Productivity Outcomes

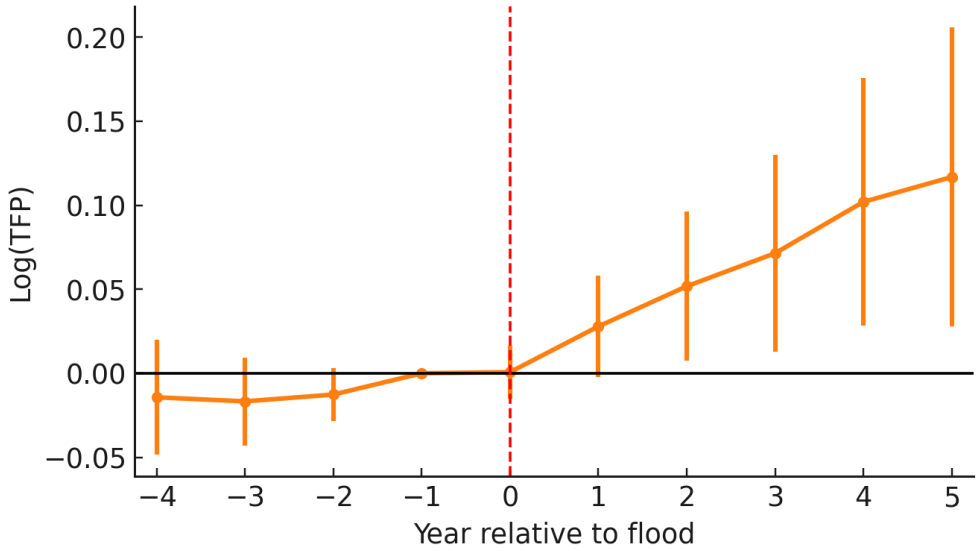
	Normalized Net Investment	IHS(Net Investment Normalized)	Log(Output/Hour)
Post flood	0.019*	0.015**	0.0005
	(0.0101)	(0.007)	(0.017)
N	66,000	66,000	66,000

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

To illustrate the dynamics of total factor productivity, Figure 3 shows the time path

of total factor productivity for surviving manufacturing plants, i.e., those which continue to operate for at least three years after being observed in the ASM data. The figure shows a persistent rise in TFP among these plants that, by the 5th year after the flood, reflects over a 10% increase over the pre-flood baseline TFP. The aforementioned findings about the weeding of the least productive plants as well as the investment in replacement capital could be contributing to this productivity increase, suggesting a role of both selection and capital upgrading in post-disaster productivity gains among survivors.

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



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

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

Table 4: Crisis management and productivity outcomes of young firms

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

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

4.3 New Entrants

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

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

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

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

Table 5 shows the investment behavior and productivity of single-unit entrant firms post-flood entrants in comparison to pre-flood entrants. The first column examines machinery investment dollars going toward brand new machinery as a share of all machinery investment as a function of flooding, while the second column shows the TFP of entrants. On average, the share of machinery going toward brand new machinery among post-flood entrants declines by 1.9 percentage points after flooding relative to pre-flood entrants. This suggests that, indeed, post-flood entrants do acquire the second-hand capital of older incumbents after flooding. Their productivity is also about 14% higher than pre-flood entrants, suggesting strong positive selection on the firm entry margin in the post-flood setting. Together, these findings illustrate that the post-flood setting sees a redistribution of capital from less to more productive firms.

5 Non-tradable Sector

Disasters and the household assistance that follows presidential disaster declarations are shocks to local demand—disasters are likely to reduce household consumption, while federal assistance likely offsets or may even increase it. This means that non-tradable sectors that are sensitive to local demand will be affected after disasters. While my previous analyses have focused on the tradable manufacturing sector to isolate impacts on plant fundamentals, in this section, I use the publicly available BDS (Business Dynamics Statistics) data to provide additional results on how firm dynamics evolve in non-tradable sectors relying on local demand, namely: "Accommodation and Food Services" (NAICS 72), "Retail Trade" (NAICS 44–45), and "Construction" (NAICS 23).[24]

Table 6 presents the results of this analysis, showing considerable churn after disasters. Post-flood counties experience measurable growth in locally demand-driven sectors, with firm counts rising by 1.1% and employment by 1.5%, indicating an aggregate expansion of non-tradable activity. Establishment churn intensifies: exits increase by 2.3%, but entries rise even more—by 3.5%—yielding a positive net-entry effect of 5.4% consistent with rapid replacement and rebuilding of local service capacity. Job creation by new establishments jumps by 4.4%, whereas job creation by incumbents remains essentially flat, reinforcing that the entry margin and young-firm activity plays a large role in post-disaster economic adjustment. Entrants' contribution to total job creation also increases: the share of all

[24]This is consistent with prior work examining job creation activity in response to demand shocks (see Adelino et al. (2017)).

new jobs created by entrants rises by 0.5 percentage points, a 1.6% increase relative to the baseline mean of about 31%. These results underscore that, during the post-disaster recovery period, entrepreneurial activity disproportionately drives economic churn and job creation in non-tradable sectors tied to local demand.

Table 6: Post-flood effects on firm and job dynamics

	Aggregate totals		Establishment entry and exit dynamics			Job creation		
	(1) IHS(Firms)	(2) IHS(Employment)	(3) IHS(Exits)	(4) IHS(Entries)	(5) IHS(Net entries)	(6) IHS(Job creation by births)	(7) IHS(Job creation by continuers)	(8) Share of all new jobs created by entrant establishments
Post flood	0.011***	0.015**	0.023***	0.035***	0.054**	0.044***	0.010	0.005**
	(0.004)	(0.006)	(0.007)	(0.007)	(0.022)	(0.011)	(0.007)	(0.002)
Constant	4.813***	6.998***	2.509***	2.535***	0.207***	3.782***	4.742***	0.318***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.014)	(0.007)	(0.004)	(0.001)
Observations	74,859	74,859	74,859	74,859	74,859	74,859	74,859	73,461
Y-mean	174.200	2,546.172	22.615	23.348	0.733	175.888	259.957	0.309
Y-SD	409.508	7,004.140	61.636	62.184	17.416	549.746	706.725	0.238
R^2	0.978	0.968	0.854	0.862	0.191	0.807	0.906	0.213

Notes: Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01; **p < 0.05; *p < 0.1.

5.1 Aggregate Implications

Table 7 examines aggregate productivity dynamics and income recovery following federally declared floods. The results suggest that disaster declarations facilitate productive reallocation of resources within affected regions. While mean TFP shows a positive but imprecise increase (column 1), the dispersion of output per capital stock (MRPK) declines significantly following declared disasters (column 3), indicating that capital is being reallocated away from low-productivity uses toward higher-productivity ones—a hallmark of efficient "cleansing" dynamics. In a frictionless economy, MRPK would be equalized across firms; the observed compression of the MRPK distribution thus implies that disaster-induced reallocation moves the economy closer to this efficient benchmark. The statistically significant increase in income per capita (column 4) cements the broader economic benefits of federal disaster assistance: not only does federal spending facilitate productivity-enhancing reallocation at the firm level, but these gains translate into meaningful income growth for affected communities. Together, these findings suggest that federal disaster declarations support regional economic recovery by enabling resources to flow toward their most productive uses.

Table 7: Aggregate productivity and income recovery following declared disasters

	(1) Log(TFP)	(2) IQR(Log(TFP)	(3) IQR(Log(Q/Capital stock))	(4) IHS(Income per capita)
Post flood	0.003212	−0.000627	−0.01141*	0.0057***
	(0.00434)	(0.003248)	(0.006701)	(0.0019)
N	210,000	210,000	210,000	25,476

This table examines aggregate productivity and allocative efficiency indicators following declared disasters. The outcome in the first column is the log of mean TFP among plants in the same 4-digit industry within the same county; while columns 2 and 3 measure the interquartile range of TFP and of output per capital stock (MRPK) among those plants. The outcome in the fourth column shows average income per capital in the county (as obtained from the BEA). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates in the first three columns were disclosed under (CBDRB-FY26-P2851-R12806).

5.2 Evidence on the Role of Financing Access

5.2.1 Recovery After Non-Declared Floods as a Counterfactual

The most straightforward way to isolate the role of financing in post-disaster recovery is to examine contexts where disaster-affected regions did not receive large federal assistance after flooding—a scenario for which non-declared disasters can serve as a proxy. I study this

by using SHELDUS data to identify non-declared floods. In particular, I focus on disasters which, in the SHELDUS data, were recorded to last for 4 or more days, i.e., just above the median duration of declared floods of 3 days. This sample restriction serves two purposes: first, it helps ensure comparably of severity of disasters in recognition of the fact that non-declared disasters are often less severe than declared ones. Second, this restriction also helps ensure a large enough sample to enable the disclosure of results from the Census Bureau.

Table 8: Aggregate productivity and income recovery following non-declared floods

	(1) Log(TFP)	(2) IQR(Log(TFP))	(3) IQR(Log(Q/Capital stock))	(4) IHS(Income per capita)
Post flood	−0.007298*	−0.00594**	–	−0.0043**
	(0.004064)	(0.002831)		(0.0018)
N	142,000	142,000	142,000	20,855

This table examines aggregate productivity and allocative efficiency indicators following non-declared floods. The outcome in the first column is the log of mean TFP among plants in the same 4-digit industry within the same county; while columns 2 and 3 measure the interquartile range of TFP and of output per capital stock (MRPK) respectively among those plants. The outcome in the fourth column shows average income per capita in the county (as obtained from the BEA). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates in the first three columns were disclosed under (CBDRB-FY26-P2851-R12835).

Table 8 examines aggregate productivity dynamics and income recovery following floods that did not receive federal disaster declarations. In contrast to declared floods, non-declared ones show no evidence of productivity-enhancing reallocation. I find that mean TFP declines by approximately 0.73% and that the dispersion of TFP and output per capital stock (MRPK) declines—a set of results that, taken together, suggests that declining churn and experimentation that may stagnate aggregate productivity. Most strikingly, income per capita declines in the years following non-declared floods (column 4), falling, on average, by approximately 0.43%. These results highlight the crucial role of federal disaster assistance in facilitating economic recovery: absent the expanded credit access and direct aid that accompany disaster declarations, affected regions experience persistent income losses without the offsetting productivity gains from efficient reallocation. The contrast between declared and non-declared floods provides compelling evidence that federal disaster spending is not merely transfers to affected communities, but rather enables the productive restructuring that transforms disaster-induced destruction into an opportunity for economic renewal.

5.2.2 Crowding in of bank loans

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

Table 9 shows business loan dynamics following federally declared floods, focusing both on the total number and dollar amount of loans originated (first two columns), as well as the average loan size, and the breakdown of sub-100,000$ versus over 100,000$ loan sizes (latter four columns). The findings indicate that the number of loans originated by banks to small businesses increases after federally declared floods by about 3.1%, but with a statistically insigifnicant increase of about 2% in the total loan dollars originated (column 2). This increase in lending is almost entirely driven by the smallest loan size category—the sub-100,000 USD loan size group—which also sees an increase of more than 3.5% in both dollar amounts of loans and the number of loans originated. Lastly, the share of loans in this category increases relative to larger loan sizes as well by about .3 percentage points, which is a 0.32% increase over the pre-flood baseline of 93.5 percent of loans in this small loan size category. Overall, these results suggest that bank loan supply increases after major, federally declared floods, and that this is particularly most pronounced in the smallest loan size categories, suggesting disproportionate benefits to young and small firms.

Table 9: Bank business loans following declared floods

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

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Relationship between firm size, plant age, and investment

Table 10: Investment, Investment Composition, and Productivity

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

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

Another indicator of the expansion of access to financing in the wake of large disasters is the relationship between firm size, plant age, and investment. Table 10 examines how plant-level investment and total factor productivity evolve following flooding, and how responses vary by pre-flood characteristics of plant age (with age 4 or below being young) and firm size (single vs multi unit parent firm). The baseline (omitted) group is older (age 5 or above) plants that also belong to multi-unit parent firms. The first column shows that on average, total investment sees a small, statistically insignificant decline after flooding in this baseline group. Young plants (age 0–4 in the pre-flood year) and small (single-unit) plants invest less than older and multi-unit firms do. Crucially, the triple interaction (Post $\times$ Young $\times$ Single-unit) is positive and statistically significant, indicating that young, small (single-unit) firms invest the most following floods. The second column shows capital expenditures in brand new (as opposed to used) capital as an outcome: young small firms are most likely to invest in used capital, while young plants belonging to older firms are more likely to buy new capital. The fact that small, young firms—which typically face

harsher financing constraints—are investing more here suggests that financing constraints are loosened in the post-disaster setting. Interpreted together, the interaction terms show heterogeneous rebuilding consistent with credit expansion enabling economic revival that is driven by younger plants. By defining size and age in the year before treatment, these categories are time-invariant and not themselves affected by the flood, strengthening the heterogeneity interpretation. These results also point to expanded financing access as a key mechanism behind the surge in post-flood investment and economic dynamism.

5.2.4 Evidence from Qualitative Survey on Firms

To complement the administrative data analyses, I conducted a qualitative survey of manufacturing firms in the Midwest, in collaboration with the Federal Reserve Bank of Chicago and other organizations. The survey collected 21 complete responses from CEOs or other high-level executives of manufacturing firms. The findings corroborate insights from the quantitative analysis for two main reasons. First, financing constraints and uncertainty about technology returns are the primary barriers to capital investment under normal conditions. Second, in hypothetical flood scenarios, firms' propensity to upgrade machinery during rebuilding increases sharply with damage severity—while 70% would simply repair under minimal (5%) damage, 35% would upgrade under severe (65%) damage. Respondents explain that disaster-induced production shutdowns reduce the opportunity cost of researching and implementing new technology while post-disaster insurance proceeds and government assistance would provide financing typically unavailable in normal times. These insights demonstrate how disasters create conditions that simultaneously lower investment barriers and expand access to capital, enabling productivity-enhancing reallocation. See Appendix Section B.

6 Marginal Value of Public Funds

I calculate the marginal value of public funds (MVPF) of federal disaster spending by comparing beneficiaries' willingness to pay (WTP) for a policy to its net cost to the government as shown in Equation 2. I focus on a subsample covering the years 1993-2017, which is when data on federal disaster spending outlays are most reliably and readily available. Overall, I find that federal disaster spending has an infinite MVPF, i.e., pays back for itself via tax revenues. See Table B.7 for detailed calculations.

$$\text{MVPF} = \frac{\text{Willingness to Pay (WTP) of beneficiaries}}{\text{Total upfront cost} - \text{Tax revenues}} \tag{2}$$

On the cost side, the primary upfront expenditure is federal outlays for flood-related disaster declarations, totaling roughly $35.0 billion (in 2022 US dollars). I additionally account for the budgetary cost of the SBA disaster lending. Specifically, I assume $25.0 billion in SBA disaster loans are disbursed to affected businesses; applying a 14% credit-subsidy rate and allocating 25% of that subsidy to the first six years implies an additional $0.88 billion in federal cost. Total gross fiscal cost is therefore $35.88 billion.

On the revenue side, I translate the estimated income gains in disaster-declared counties into incremental federal receipts. The disparate, opposite-signed, coefficients estimated on how personal income per capita recovers following floods that did (Table 7) versus did not (Table 8) receive federal disaster assistance suggests that there may be incremental tax revenues to offset federal disaster spending. In the subsample data window between 1993-2017 also indicates a relative per capital income increase of .96% after flooding (p¡0.05). This implies an estimated annual income gain of $87.15 billion, sustained for six years, implying cumulative incremental income of $522.88 billion by the 5th year from the flood. Assuming an effective tax rate of 15%, this means an incremental tax revenue of $78.43 billion. The difference between the gross upfront cost minus these incremental revenues simplies a fiscal surplus of $42.56 billion (i.e., net cost = −$42.56 B).

Beneficiaries' WTP is the sum of (i) the post-tax portion of the incremental income per capita of $444.45 billion and (ii) the direct transfers through SBA lending of $25 billion, totaling $469.45 billion. Because net fiscal cost is negative, the MVPF is effectively infinite: the policy pays for itself in budgetary terms, so any positive WTP implies an MVPF exceeding any finite bound.

The resulting infinite MVPF indicates that federal disaster assistance pays for itself while generating nearly $11 in beneficiary value for every dollar of government savings. This places disaster assistance among the most cost-effective government programs documented in the MVPF literature. This underscores the broader policy relevance of my results: federal disaster spending facilitates productivity-enhancing reallocation—including by supporting entrepreneurial activity that creates jobs—ultimately generating large fiscal returns that outweigh upfront government costs.

Note that these MVPF calculations only apply to regions like those in my sample, which excludes counties with frequent or repeated flooding to ensure clean identification.

Moral hazard concerns around rebuilding are, understandably, more salient in coastal areas facing repeated events. My MVPF estimates do not speak to those settings, but rather, they do apply to and lend key policy insights relevant to the broader majority of regions where climate change is expected to increase flood risk—and with it, policy debates the fiscal implications of rebuilding.

7 Conclusion and Discussion

In this paper, I study how manufacturing plants respond to natural disasters and the implications for aggregate productivity. I show that low-TFP plants are disproportionately forced to exit, while resources flow to more productive survivors and positively selected entrants, raising average productivity and improving allocative efficiency. Young and new firms play an outsized role in this process, scaling up in the post-flood environment and—where their activity is greater—coinciding with lower TFP dispersion and higher average productivity within narrowly defined markets. These outcomes stem from the expanded financing access that government relief spending unlocks. In particular, federal disaster spending loosens financing constraints, and young, small firms with nimble management convert that credit into rapid retooling and expansion, while survivors upgrade capital as they rebuild. In settings without federal assistance, allocative efficiency and productivity falters while per capita incomes fall, underscoring a financing channel behind recovery and indicating a key role of federal disaster spending in strengthening recovery.

My findings are robust to a range of potential alternative explanations for the observed results. For instance, 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. Additionally, given the 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. My results are generally robust to the use of this alternative method.

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

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

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A Appendix

A.1 Tables and Figures

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

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

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

Metal corrosion as a mechanism of flood damage:

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

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

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

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

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

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

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

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

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

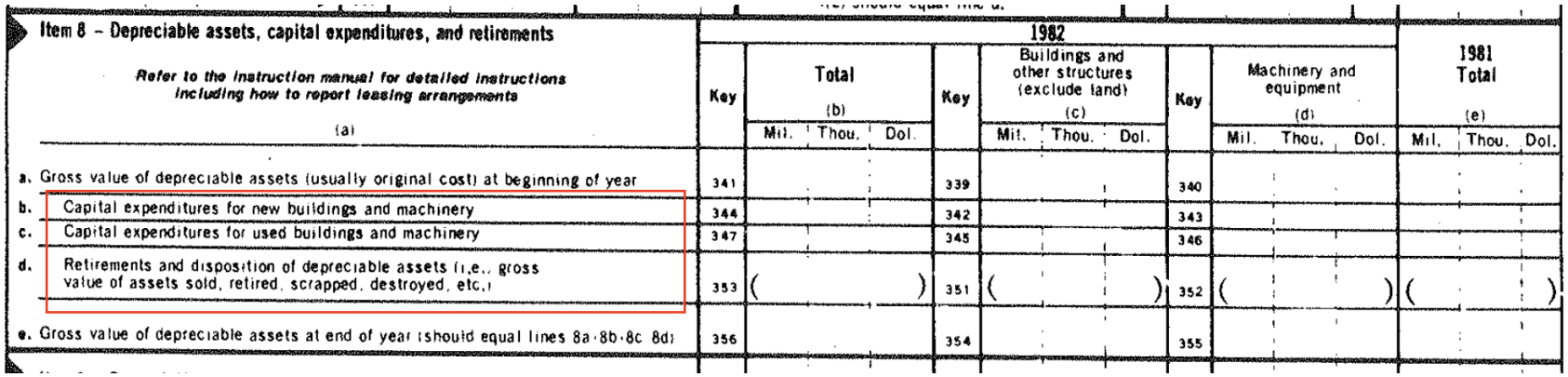
This table shows event study results on how plants' 2-year exit likelihood is affected after flooding and the heterogneity by plant age (age 0-4 being young) and firm size (single vs multi-unit parent firm). Standard errors are reported in parentheses and are clustered at the county level. ***p < 0.01;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

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

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

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

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

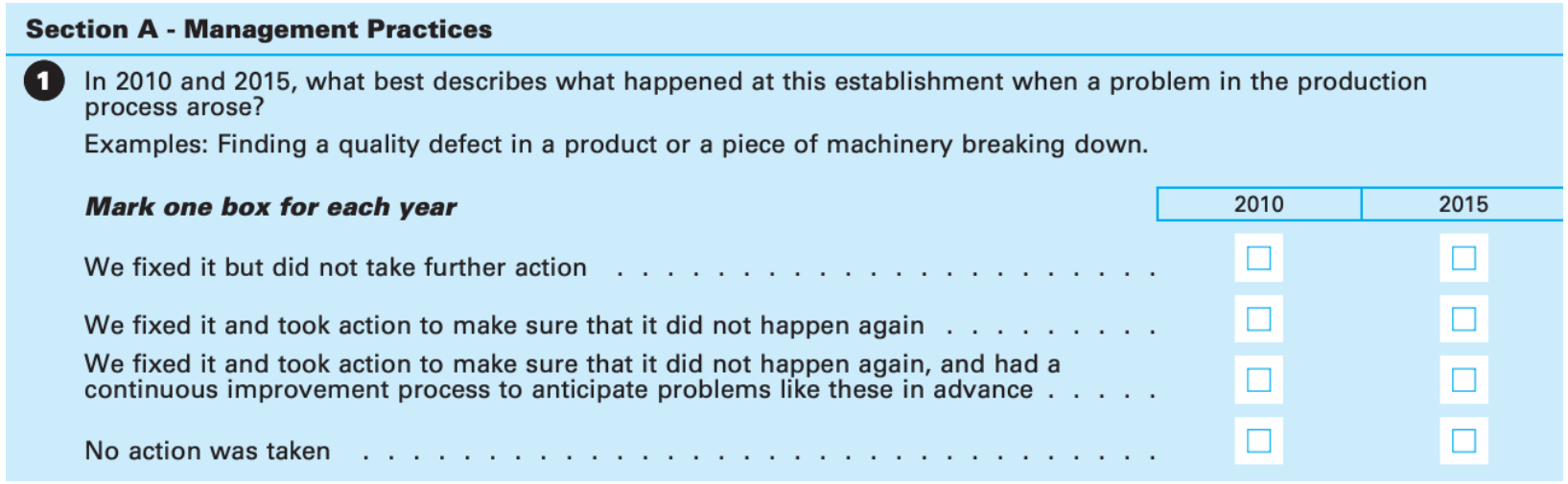


Item 8 – Depreciable assets, capital expenditures, and retirements

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

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

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



Section A - Management Practices

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

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

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

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

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

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

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

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

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

Table A.5: Flooded plants invest in rebuilding capital

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

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

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

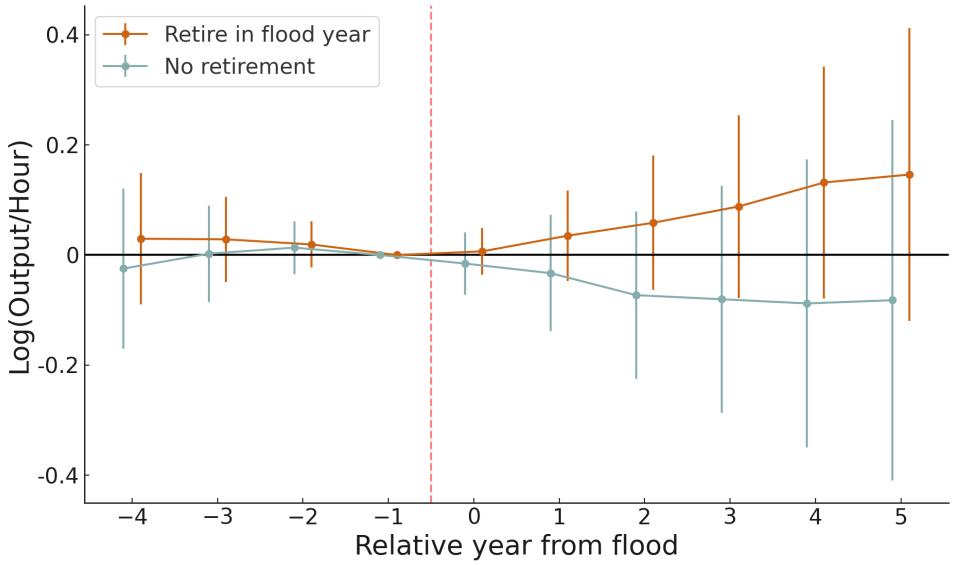
	(1)	(2)	(3)
	IHS(Total Investment)	IHS(Machine Investment)	IHS(Normalized mach. investment)
Post flood X IHS(Retirement)	0.03***	0.026**	0.003*
	(0.010)	(0.010)	(0.002)
Post flood	-0.119	-0.076	0.020*
	(0.088)	(0.089)	(0.012)
IHS(Retirement)	0.062***	0.057***	-0.0004
	(0.018)	(0.020)	(0.003)
N	68,000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

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

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

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

Figure A.3: Time path of productivity based on capital retirement



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

To illustrate the dynamics of labor productivity, Figure A.3 shows the respective time paths of output per hour for plants which did and did not retire capital in the same year as a flood. It shows that these two groups have highly divergent paths in their labor productivity,

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

B Evidence from Qualitative Survey on Firms

To complement my analyses 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.[25] 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.[26] 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

[25] See Figure B.7 for a template of the survey invitation message.

[26] 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.

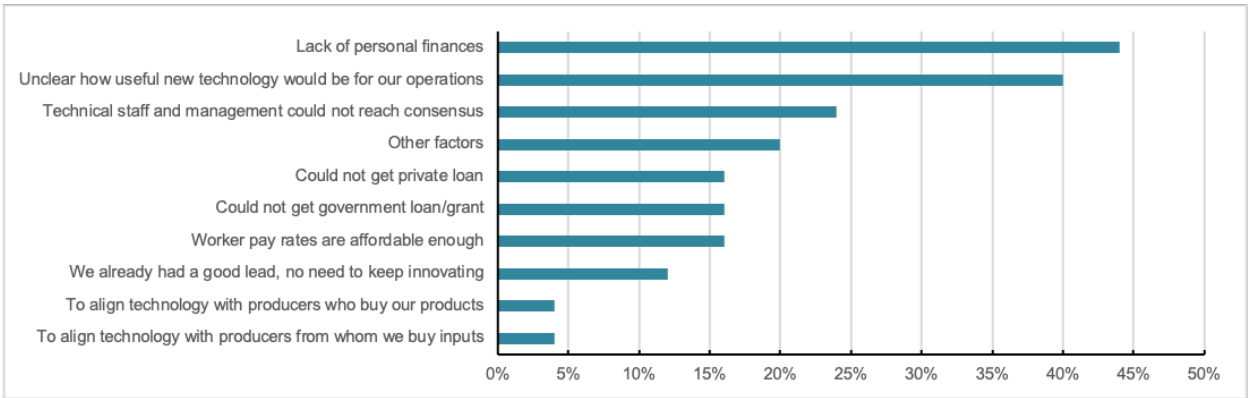
of loss—5%, 25%, and 65%—to the fair market value of their machinery, and asking them how they would react, namely: whether they would shut down, relocate, repair/restore their damaged machines, or entirely replace the damaged machines with technology of a higher, lower, or same grade as what they had before. These three hypothetical loss events were presented in random order to each respondent in order to avoid any potential impact of the chronological sequence of these loss scenarios on the answers. Next, came questions around respondents' views on climate change and the risks it poses to their operations, including via weather-related natural disasters. Lastly, the survey contained an optional set of questions on firms' machinery maintenance protocols, climate views, and related policy preferences.

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

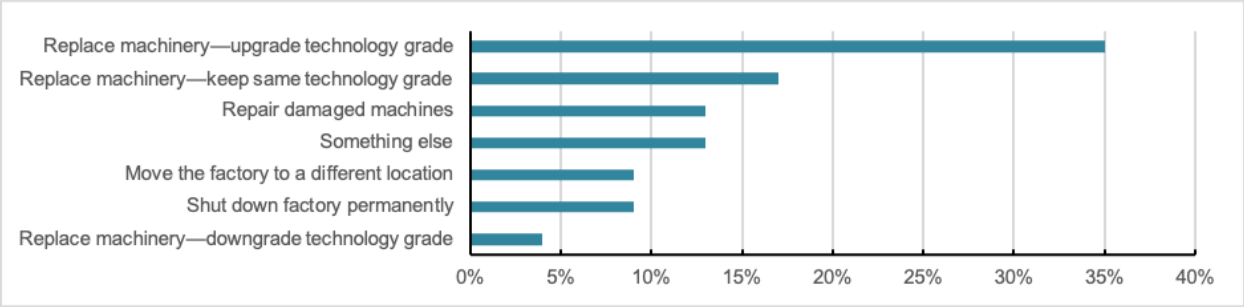
Second, in a hypothetical flood scenario, firms' tendency to report that they would upgrade their machinery following a destructive damage increases substantially with the severity of the disaster. In particular, in scenarios with minimal damage (5% loss), the overwhelming majority of respondents—about 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 prefer-

Figure B.4: Barriers for investing in new equipment and technology



ence for machinery replacements that involve technology upgrades and 17% for replacements of the same technology grade (see Figure B.6). 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 B.5: If they faced a major flood that destroyed 65% of the market value of their machinery, firms would primarily look to upgrade machinery as they rebuild



When asked why they would upgrade when rebuilding after a hypothetical disaster

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

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

Figure B.6: 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

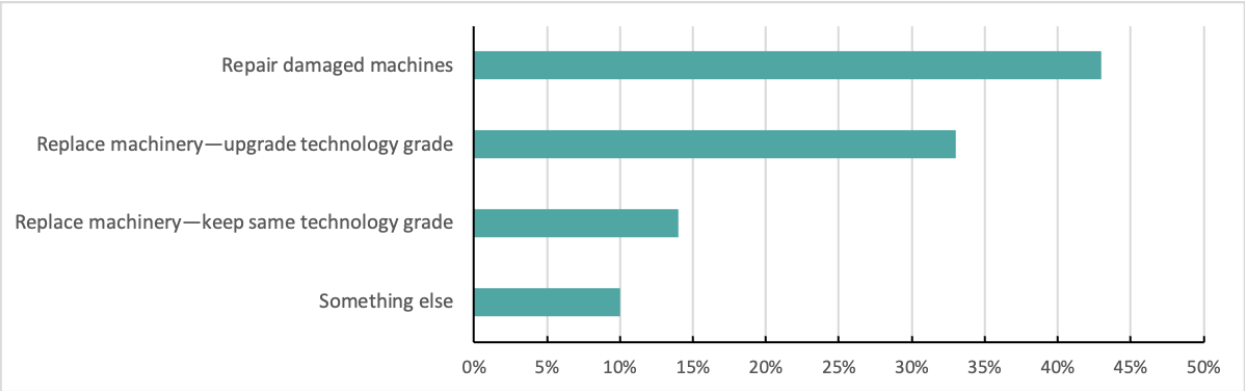


Figure B.7: Survey invitation email sent to manufacturing firms by the Federal Reserve Bank of Chicago

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

B.1 MVPF Calculation and Detailed Notes

Table B.7: MVPF calculation details for federal spending on declared floods (1993–2017)

Row	Component	Value	Source / Calculation
I. Estimated income effects (inputs)			
(A)	Federal aid effect on per capita income	0.0096**	Declared vs. non-declared flood coefficients
(B)	Pre-disaster per-capita income ($)	44,000	BEA (CAINC1) county income data
(C)	Average county population	136,000	BEA county population (for CAINC1)
(D)	Number of treated counties	1,517	In-sample counties in BEA income regression
(E)	Years of effect	6	Event-study window (relative years 0–5)
II. Incremental income			
(F)	Annual incremental income ($B)	87.15	(A)×(B)×(C)×(D)
(G)	Total incremental income ($B)	522.88	(F)×(E)
III. Government costs and fiscal externality			
(H)	FEMA flood spending ($B)	35.00	CBO DRF outlays × flood-share allocation
(I)	SBA disaster loans disbursed ($B)	25.00	Program totals from SBA/CRS reporting
(J)	SBA credit-subsidy rate	0.14	CRS-based input
(K)	Six-year share of subsidy realized	0.25	Assumption
(L)	SBA six-year budget cost ($B)	0.88	(I)×(J)×(K)
(M)	Gross cost ($B)	35.88	(H)+(L)
(N)	Effective tax rate	0.15	Implied from IRS/BEA mapping
(O)	Incremental tax revenue ($B)	78.43	(G)×(N)
(P)	Net cost ($B)	-42.56	(M)-(O)
IV. Willingness to pay (WTP) and MVPF			
(Q)	SBA loans received ($B)	25.00	(I)
(R)	Post-tax income gain ($B)	444.45	(G)×(1−(N))
(S)	Total WTP ($B)	469.45	(Q)+(R)
(T)	MVPF	∞	Infinite if (P)< 0

Notes. All dollar amounts are in $2022 and reported in billions; rows may not sum due to rounding. Annual incremental income in (F) is computed as the estimated percent effect on per-capita income (A) multiplied by baseline per-capita income (B), average county population (C), and the number of treated counties (D). Total incremental income (G) cumulates (F) over the six-year event-study window (E). FEMA flood spending (H) is constructed by combining CBO Disaster Relief Fund (DRF) *outlays* with an incident-type allocation based on publicly available FEMA disaster declaration and published-spending information; I use a conservative flood share when mapping total DRF outlays into flood-category spending. SBA budget costs (L) are proxied by applying a credit-subsidy rate (J) to disaster loan disbursements (I) and allocating a fraction (K) of the subsidy to the six-year horizon. Incremental tax revenue (O) is computed as an effective tax rate (N) times total incremental income (G). Post-tax income gains (R) net out federal taxes using (1–N). Because net fiscal cost (P) is negative, the MVPF (T) is effectively infinite: the policy pays for itself in budgetary terms, so any positive WTP implies an MVPF exceeding any finite bound.