Disasters, Capital, and Productivity*

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Abstract

Climate change magnifies natural disaster risk, yet little is known about the implications for physical capital, business dynamism, and productivity. Using confidential US Census microdata and an event study design, I examine how manufacturing plants react to large, exogenous flood shocks that triggered federal disaster declaration and rebuilding assistance. I find a substantial and persistent increase in capital retirement (i.e., scrapping and sales) among flooded plants, reflecting the degradation of their capital from water damage. Flooded plants invest in new capital and ultimately overshoot their pre-disaster labor productivity baseline because they adopt extensive, simultaneous upgrades to their production technology. Beyond inducing capital replacement by survivors, flooding also increases plant exits, particularly among the least productive plants. This expands the local supply of used machinery, which is primarily reallocated toward local entrants and young plants. In aggregate, post-disaster capital reallocation improves county-level productivity, highlighting a crucial channel through which federal disaster spending smooths and revitalizes regional disaster recovery. My findings provide novel causal evidence on climate hazards as drivers of capital depreciation and reallocation, and demonstrate the critical role of technology for firm productivity. More broadly, this paper offers key insights for climate damage assessment and industrial policy in our warming world.

Disclaimer: Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2851. (CBDRB-FY24-P2851-R11684, -R11700; -R11774, -R11775, -R11815).

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1 Introduction

Increasing global temperatures have been linked with growing intensity and frequency of natural disasters since pre-industrial times.[1] Climate-driven disaster risk has significant implications for economic growth and reallocation. Since at least Schumpeter (1942), economists have understood market economies to be driven by a perennial gale of creative destruction whereby new technology, products, and entrepreneurs continually render old ones obsolete. As exogenous gales of destruction, natural disasters are expected to intensify this process of reallocation and affect economies. Yet, the exact nature and mechanisms of their impact, as well as the mediating role of the rebuilding response, are poorly understood. To fill this gap, I examine how manufacturing plants react to large flood shocks that trigger major federal disaster declarations using confidential microdata from the US Census Bureau.

While it is straightforward that flooding damages physical capital, it is ex-ante ambiguous how exactly firms would respond and recover. Aside from completely washing away a factory, flooding is expected to speed up the wear and tear of physical capital, particularly by corroding production machinery.[2] A standard neoclassical model of growth would predict that, conditional on surviving the disaster, flooded plants would invest in replacement capital to return to their steady state path of productivity growth. For instance, studies find that major bombing episodes during wars had a negligible impact on the long run growth of affected cities.[3] However, instead of recovering back to their pre-disaster trend, firms may use post-disaster rebuilding as an opportunity to revitalize their capital stock and build back *better*.[4] Conversely, firms may build back *worse* or have highly delayed recovery due to credit constraints and other factors.[5] The net implications for regional productivity are also not ex-ante obvious. On one hand, capital and other economic resources may be reallocated from less to more productive units, improving aggregate productivity. On the other hand, distortions in the rebuilding process may result in misallocation, hurting aggregate growth.

In this paper, I show that, when replacing their capital after flooding, manufacturing plants adopt substantial technology upgrades that improve their labor productivity. As flooded plants shed their old machines and county-wide plant exits rise due to the disaster shock, I document substantial reallocation of used machinery and building capital, notably

[1] IPCC (2021).

[2] Oxygen and humidity are conducive to rust. Flood waters can also intensify metal corrosion because they carry other chemical contaminants and debris Rubin and Garcia (2020).

[3] See Davis and Weinstein (2002); Miguel and Roland (2011).

[4] See Hornbeck and Keniston (2017).

[5] See Feigenbaum et al. (2022).

toward local entrants and young plants. This reallocation, which is partly enabled by the expanded access to financing from federal disaster spending, ultimately enhances aggregate productivity, highlighting a novel channel through which government spending smooths post-disaster recovery of regional economies.

I focus on large floods that triggered a presidential disaster declaration—a place-based designation that unlocks various forms of relief assistance and recovery loans to households and firms affected by destructive disasters. These floods typically result from adverse weather events, the exact timing of which cannot be anticipated at the yearly level. The exogenous timing of the flood event forms the basis of my event study approach, which compares the post-flood outcomes of plants (or counties) to their own pre-flood baseline. The concurrent federal disaster spending is also relevant here because it can support the survival of plants which face direct physical damage, and also supplement regional credit supply, thereby expanding young and small firms' access to bank credit.[6] Thus, financing constraints, which may otherwise weaken post-destruction recovery,[7] are less likely to bind in the declared disaster setting I study. Note that while federal disaster spending can affect local consumption, the fact that the manufacturing sector is highly tradable also helps to isolate such aggregate demand channels that may affect plant behavior and outcomes.

To observe plants' capital and productivity outcomes, I use plant-level microdata from the Annual Survey of Manufactures ("ASM"). The ASM is a survey that follows about 70,000 manufacturing plants in 5-year cycles, collecting rich information on their output, productivity, as well as capital stock and investments in building and machinery assets. Importantly, it also provides information on plants' capital retirement (i.e., sale or disposal), which I use as a proxy to infer physical damage from flooding.

Given the inherent link between firm life-cycle dynamics and capital (dis)investment, I combine the ASM data with administrative microdata that allow me to account for plants' life history, including entry, exit, and continuing activity. Capital investment is a forward-looking feature of starting out or continuing in business: entrants/young plants have to invest in capital to build up their capacity, while soon-to-exit plants ramp down investments and instead liquidate assets in anticipation of their closure. Isolating these ubiquitous patterns from capital readjustment induced by *physical* flood damage requires focusing only on

[6] Federal disaster spending expands regional liquidity supply, particularly expanding young and small firms' access to bank credit (Erda, 2024). It also supports business survival, primarily for non-manufacturing sector firms that rely on local demand (Collier et al., 2024; Gallagher et al., 2023)

[7] Feigenbaum et al. (2022) show that, after large capital destruction shocks, regions with under-developed credit markets see weaker economic recovery. Thus, such financing constraints are less likely to bind in the federally declared disaster settings I study.

incumbents that are neither too young nor too close to exit. To identify these, I use the Longitudinal Business Database ("LBD")—the Census Bureau's workhorse economic dataset tracking the birth, death, employment and pay of the universe of business establishments in the US.[8] In particular, I restrict my analyses of post-flood rebuilding to incumbents that are at least 5 years old and survive for at least 3 more years.

I start by documenting the destruction from flood shocks and plants' capital adjustment responses. Plants' probability of exiting within two years increases by 3.6 percentage points (p.p.) after flooding. These exits are concentrated among the least productive plants, which is consistent with the cleansing role of macroeconomic crises like recessions (see Foster et al. (2016)). Among surviving plants, I find a large and persistent pattern of capital retirement (≈9.2% on average). This reflects the degradation of firms' capital from water damage. I then use capital retirement in the same year as the flood as a proxy for physical damage and study the outcomes of plants based on whether or not they retired capital in the same year as the flood. I find that plants which retire capital in a flood year subsequently increase their capital investment by about 25%, reflecting their rebuilding expenditures. County-level total investment also increases following flooding, suggesting that the increased investment after flooding is not merely a feature of survivorship but also reflects disaster-induced investments.

After rebuilding, flooded plants overshoot their pre-disaster labor productivity, suggesting that they adopt upgrades to their production technology during their rebuilding process. I find that flooded plants which retire capital in a flood year and subsequently invest in replacement see a 4.5% increase in output per hour. This suggests that there is something fundamentally different about plants' post-flood capital investment, like more advanced technology. Consistent with this, I show that the plants which retire capital in a flood year primarily invest in brand new machines, which likely carry newer technology compared to the pre-flood capital. In comparison, plants in flooded counties which do not replace their capital see a persistent decline in their labor productivity.

As (older) incumbent plants replace their capital with brand new machines and others are forced to exit after flooding, I trace that the resulting excess supply of (cheap) used capital is reallocated toward entrants and young plants. Plants aged 4 or lower have about a 12% higher probability of purchasing used capital in post-flood years relative to the pre-flood baseline for their age group. This is consistent with prior findings that young and small firms typically purchase used capital from incumbents, in part due to financing constraints.[9]

[8] Further, pairing the ASM with the LBD helps identify whether ASM plants that 'disappear' over time represent survey attrition or plant exit, which is itself a relevant post-disaster outcome to examine.

[9] See Ma et al. (2022); Eisfeldt and Rampini (2008).

Further, I study the productivity of plants which buy used capital by focusing on young plants of age between 0 to 4. I find suggestive evidence that, in post-flood settings, investment in used capital is associated with lower productivity and long-run survival for small young firms. Among entrant plants, those which purchase used capital have a statistically insignificant but lower labor productivity relative to the productivity of pre-flood entrants. However, among the broader group of young plants aged 0-4, used capital has a negative relationship with productivity, particularly for small, single-unit firms–these small young firms which purchase used machinery have more than a 10% lower output per hour.[10] Taken together, these results suggest that the increased availability of cheap used capital may enable the 'marginal,' and/or financing-constrained young firms to acquire some capital.[11]

In aggregate, I show that the dispersion in output per capital stock among plants within the same narrowly defined industry in the same county drops, suggesting that post-disaster reallocation is productivity-enhancing. Assuming firms equate marginal product of capital with its rental rate, I examine how the inter-quartile range of the marginal productivity of capital (i.e., difference in productivity between plants at the 75th and 25th percentiles) changes after a flood. I find that this dispersion declines, while average labor productivity increases. These findings suggest that

This paper contributes to several strands of literature, primarily, that on the impact of climate change on physical capital and growth. Prior work shows how firms react to natural disaster shocks (Carvalho et al., 2021; Barrot & Sauvagnat, 2016), or even anticipate them in their location decisions (Castro-Vincenzi, 2024). Yet, the questions of how firms react to capital depreciation shocks from disasters, and how hazard events factor into capital reallocation remain relatively underexplored but for a few papers that have studied theoretical or global versions of the question, with coarse data that mask the rich heterogeneity of the investment and reallocation dynamics (see Nath et al. (2024); Casey et al. (2024); Bilal and Rossi-Hansberg (2023); Bilal and Känzig (2024)). My paper presents novel, direct, and detailed evidence on how disasters affect capital depreciation, as well as how plants adapt to capital depreciation shocks from climate disasters, and how these shocks and the redbuilding responses further shape regional entry-exit dynamics and firm outcomes not only expanding the local supply of used capital, but also potentially *dragging backward* its average technology

[10] Studying single-unit plants is most suitable to examine the relationship between firm age and capital vintage since plants belonging to multi-unit parent firms enjoy relative advantages of experience/knowledge transfers, physical capital access, and intra-firm insurance from their parent firm.

[11] There is likely unobserved selection in when plants choose to enter and invest, and if so, whether in used or new or both types of capital. Thus, it is not clear whether this negative labor productivity associated with used capital is a reflection of the inherent low-productivity 'type' of the young plants themselves, or the fact that old-technology embodied in second-hand machines may become a drag on labor productivity.

vintage and/or quality.

In this respect, my paper also contributes to the broader literature on recovery after natural disasters and other destructive shocks. Prior studies document how broad-based rebuilding after destructive episodes like wars (Iklé, 1951; Davis & Weinstein, 2002) and disasters (Skidmore & Toya, 2002) may be followed by extensive renewal and growth, but primarily focus on building capital and aggregate cross-country or city-level outcomes whereas my paper shows finer micro-level evidence related to production machinery, a vital physical embodiment of technology. Most relevant to my paper, Hornbeck and Keniston (2017) show that, after the Great Boston Fire of 1872, widespread simultaneous rebuilding introduced upgrades not just to burned buildings but also to nearby un-burned buildings, releasing constraints of simultaneous capital upgrading that had restricted urban growth before the fire. My findings offer complementary insight on the critical contribution of *simultaneous* capital upgrading to growth by showing that when flooded plants go beyond their business-as-usual behavior of incremental machinery replacements and instead use their post-disaster rebuilding process to make extensive, potentially assembly-line-level, upgrades to their machinery capital stock, they see outsized gains in productivity.

This paper also contributes to the literature on the importance of physical capital and technology for entrepreneurial firms. Much prior work has shown the importance of financial capital (Lerner & Nanda, 2020) and human capital (Choi et al., 2021) for the productivity and long-term outcomes of young firms. But relatively little has been said about the role of physical capital. Notably, Ma et al. (2022) use loan filing data to track the age and sales of machines that businesses put up as collateral and show that younger firms are more likely to buy second hand machinery from incumbents. Yet, there is likely unobserved selection in the kinds of firms which put machines (instead of other types of capital) as collateral, and in the exact kinds of machines they pick as collateral. By virtue of the representative nature of the ASM survey, my paper offers more generalizable evidence on younger plants' increased likelihood to purchase used capital. Additionally, the results linking the incumbents' machinery turnover with increased purchase of used machinery by entrants and incumbents in Ma et al. (2022) rely on lagged measures of new machinery purchase by local incumbents, but this could potentially reflect incumbents forward-looking investments due to their anticipation of changing demand for used capital and increased young firm activity in their industry. By leveraging the exogenous timing of flooding, my study offers more reliable causal evidence on how machinery replacement by flooded incumbents leads to more used capital purchase by young firms.

This paper is also the first to document the link between second-hand capital and firm productivity, showing suggestive yet still compelling evidence on the negative association between the two. In this respect, my paper is related to Hornbeck et al. (2024), who show descriptive evidence that, in the early 20th century, entrants which were unincumbered by sunk costs in (older) water power technology were able to adopt the new steam power, and leapfrog incumbents. My paper shows causal evidence of how disaster shocks may give rise to the reverse phenomenon, whereby older incumbents upgrade to more advanced technology and thus leapfrog entrants and young firms which may get locked into old technology embodied in second-hand capital. Overall, my findings highlight the importance of technology and physical capital for young firms.

The paper is organized as follows. Section 2 below describes the data and empirical strategy. Section 3 presents the results and Section 5 discusses the broader implications. Section 6 concludes.

2 Data and Empirical Strategy

2.1 Data

Flood Declarations: I observe the incidence of floods from the Federal Emergency Management Agency's disaster declaration records.[12] Given that they are a federal record, these data provide an exhaustive list of all declared disaster events since the 1950s. Therefore, they are a reliable data source to capture the universe of declared flood events.

Data on manufacturing plants come from the following confidential administrative and survey microdata maintained by the US Census Bureau.[13]

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

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

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

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

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

The Longitudinal Business Database ("LBD"): is the workhorse microdataset among economic data on businesses, providing entry, exit, survival, and employment and payroll records information on 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, survival, and even county location of plants in years in which they are not observed in the ASM. In particular, having the exit year information from the LBD helps identify whether ASM plants that 'go missing' from the ASM sample reflect survey attrition or plant exit, which is itself a relevant post-disaster outcome to examine. I link ASM plant-year data with the LBD using internal plant identifiers. While the LBD is available starting in 1976, information on whether plants are entrants or continuers is only reliably tracked starting in 1977, which is why I start my sample in 1977.

2.2 Sample

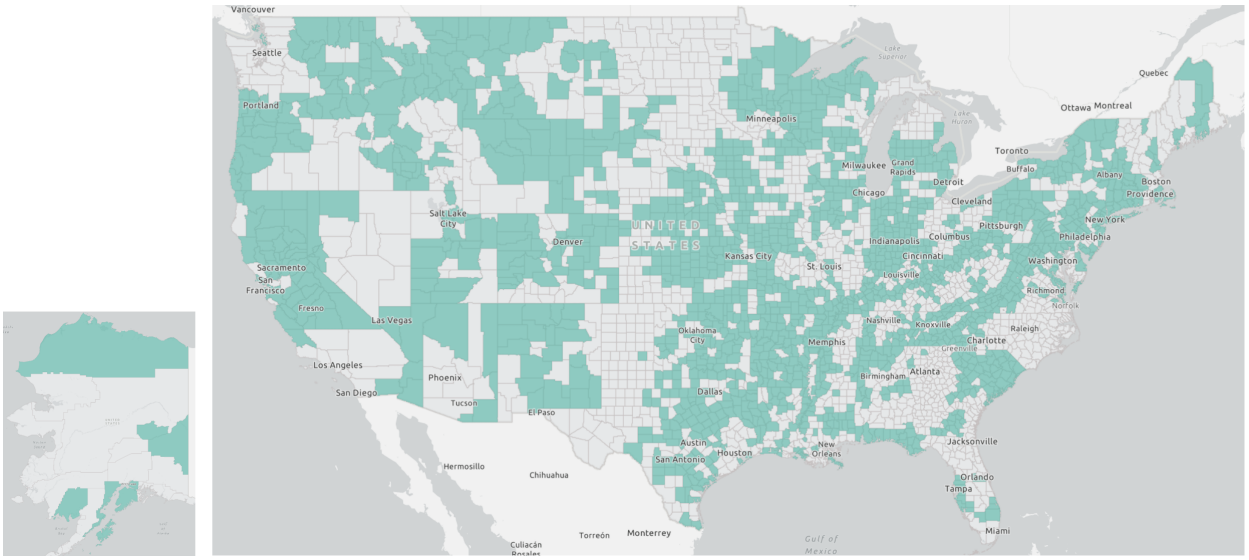
I start out with all ASM plants in the 1977-2017 period whose North American Industry Classification System ("NAICS") industry code falls under the core manufacturing codes between 31-33, then apply some key restrictions to make the estimation sample more relevant for the purpose of my analyses. First, 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. This restriction ensures that my analyses capture employer establishments where production takes place, and not, for example, administrative units of manufacturing firms.[14]

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. Due to US Census Bureau rules for confidentiality, there are limitations 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 sample. As such, Figure 1 gives the underlying *superset* of counties from which my sample of ASM plants is drawn. In particular, it shows counties which had a declared flood in the 1976-2018 period and also had at least one manufacturing establishment reported in the BDS data (a publicly-accessible equivalent of the LBD). The map captures 349 unique declared flood events across 1703 affected counties. These affected regions are spread out throughout the US, and are primarily caused by adverse weather events like severe storms and flash floods.

I then leverage the information about plant age and exits to define two main subsamples that will allow me to study post-disaster capital readjustment and young firms' outcomes

[14] 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 counties which had a declared flood in the 1976-2018 period and also had at least one manufacturing establishment reported in the BDS data (a publicly-accessible equivalent of the LBD). This map represents 349 unique floods, and 1703 affected counties.

on the most appropriate group of plants. This is because isolating these ubiquitous patterns from flood-induced capital readjustment and the reallocation of capital from older to younger firms effectively requires confronting the inherent link between firm life-cycle dynamics and capital (dis)investment: entrants/young plants have to invest in capital to build up their capacity, while soon-to-exit plants would likely ramp down investments and instead liquidate assets in anticipation of their closure. Thus, I define my main sample for studying continuing plants' post-flood capital adjustment by focusing on plants that both: survive for at least 3 more years, and are at least 5 years old. This restriction yields approximately 318,000 plant-year observations.

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

larger, multi-unit firms.

Table 1: Summary statistics for sample of continuers

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

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

Note that the intermittent nature of how certain questions are asked in the ASM surveys gives rise to some notable elements: in particular, 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.

2.3 Empirical Strategy

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

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

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

Identification comes from the assumption that the timing of the flood event is unanticipated by plants, which is trivial given the exogenous timing of weather disasters, and that there are no other events to confound effect of flood 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 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.

3 Results

3.1 Documenting the destruction from disasters

Table 2 provides evidence on how disasters affect plant exits. Flooding is associated with an increase of 3.6% in the probability of plant exit within two years.

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

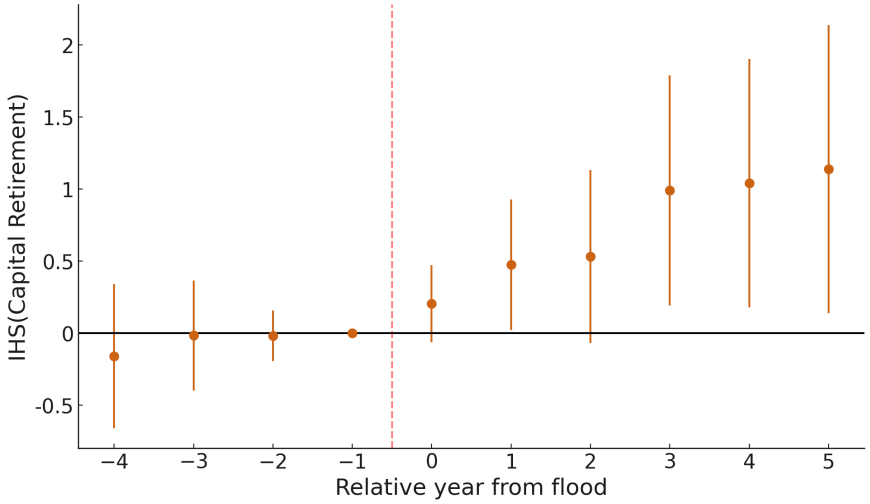
	All plants	**Heterogeneity by pre-flood performance**	
		TFP	Value added/hour
1.Post flood	0.036***	0.049***	0.048***
	(0.005)	(0.006)	(0.006)
1.LowestQuartile		-0.002	-0.007
		(0.007)	(0.009)
1.Post flood#1.LowestQuartile		0.011**	0.02***
		(0.005)	(0.005)
N	422,000	257,000	257,000
Y-mean	0.11	0.10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

Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11684; -R11775)

Focusing on the subset of surviving plants (i.e., that continue in business for at least 3 more years), Figure 2 shows the dynamics of capital retirement among surviving plants, i.e., those that continue in business for at least 3 more years. The figure shows that, while there are no pre-trends in capital retirement before the flood, there is a substantial and persistent

increase in capital disposal following flooding. 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. Table A.3 in the Appendix presents a more general description of the destruction caused by flooding. It shows that, in addition to capital retirement, plants also see higher likelihood of incurring capital repair and refuse (water and waste) removal costs following flooding. Overall, these results suggest that water damage from flooding degrades capital and speeds up machinery corrosion such that plants increase their sale and disposal of machinery assets.

Figure 2: Persistent increase in capital retirement among surviving plants



Note: This figure is based on plants that continue in business for at least 3 more years. The broader result 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. Results disclosed under (CBDRB-FY24-P2851-R11775)

3.2 Investment Response

Table 3 subsequently 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 non-interacted dummies 'Post flood' and 'Retire in flood year' indicate that the post-disaster period is associated with lower average plant investment but that capital retirement and investment are positively correlated.

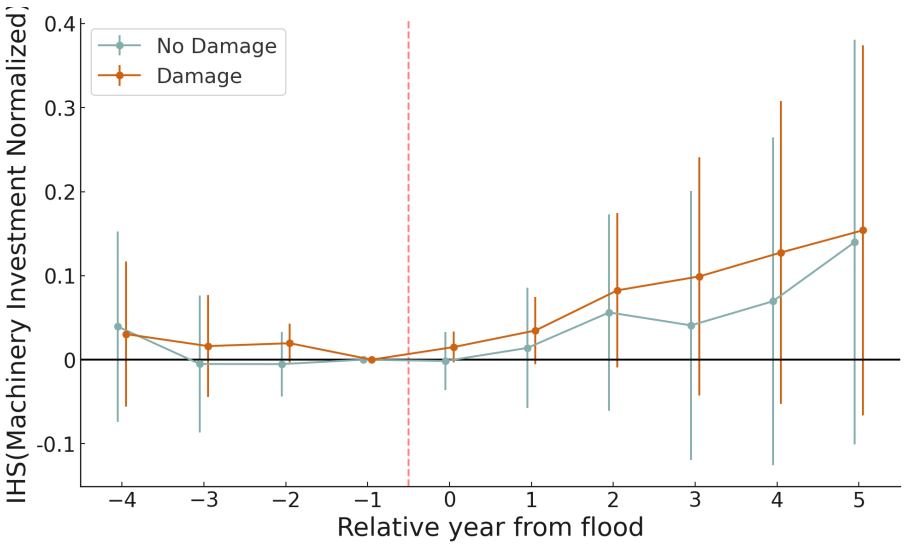
In the post-flood period, however, the correlation between 'bundled' disinvestment and investment episodes is even more pronounced: the interaction term of the two dummies shows that conditional on retiring any capital in the same year as a flood, plants' probability of investing in machinery increases 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.

Table 3: Flooded plants invest in rebuilding capital

	IHS(Investment)			
	Total	Building	Machine	Any machine invest?
Post flood	-0.212**	-0.207**	-0.168*	-0.026
	(0.098)	(0.097)	(0.099)	(0.021)
Retire in flood year	0.236*	0.193	0.193	0.0143
	(0.131)	(0.152)	(0.132)	(0.021)
Post flood X Retire in flood year	0.257***	0.281***	0.237***	0.037**
	(0.077)	(0.073)	(0.0773)	(0.018)
N	68,000	68,000	68,000	68,000
Y-mean	1,995K	418.3K	1,577K	0.84
Y-sd	12,870K	5,490K	9,310K	0.36

Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11775)

Figure 3: Time path of productivity based on capital retirement



The physical damage line in orange is inferred based on whether a plant retired capital in the same year as a flood (in relative year 0). These results were disclosed under (CBDRB-FY24-P2851-R11775).

3.3 Productivity Outcomes

Table 4 presents event study results on how the productivity of flooded plants evolves. In particular, it shows the results of a triple interaction between binary indicators for the post-flood period, capital retirement, and capital investment on labor productivity indicators (real output per worker, and output per plant hour), as well as total factor productivity. The triple interaction helps to isolate the kind of capital readjustment plants engage in after facing flood damage from the business-as-usual capital readjustment they 'voluntarily' engage in. In particular, the triple interaction shows that flooded plants' capital readjustment during their post-disaster rebuilding is associated with a 6.9% increase in output per worker and a 6.3% increase in output per plant hour relative to the productivity associated with capital readjustment in the pre-disaster baseline.

Table 4: After rebuilding, flooded plants see higher labor productivity

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

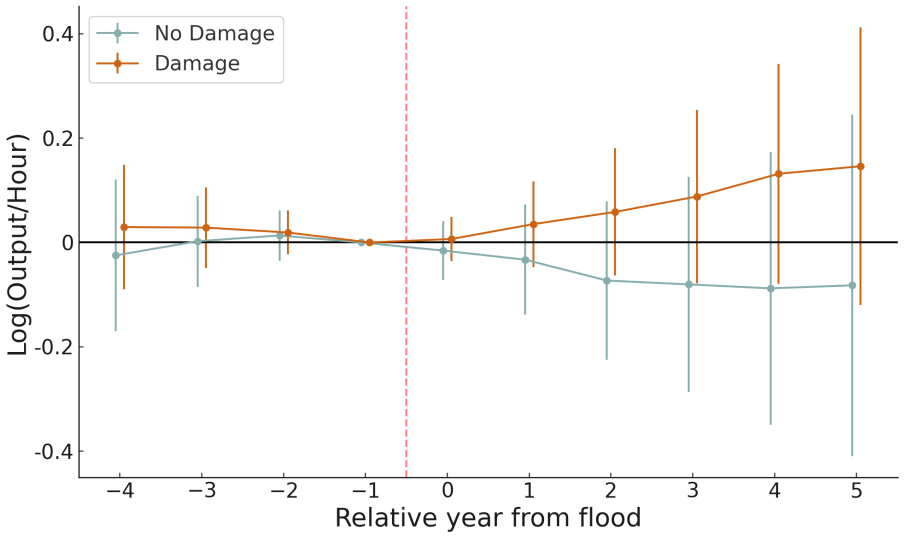
Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11775)

The aforementioned results take capital retirement in any of the post flood years as indicative of exposure to physical flood damage. However, using a more immediate measure for post-flood capital retirement would help to more precisely identify the instantaneous nature of flood damage. Given that the capital retirement question is only asked sporadically in the Census' ASM survey, I thus focus on the subset of my sample which was observed to receive a flood in years in which the Census asked manufacturers about capital retirement, and use any non-zero capital retirement in the same year as a flood as a proxy for physical damage.

Figure 4 shows the respective time paths for plants which did and did not retire capital in the same year as a flood. The top panel shows that generally both (likely) flooded and not-flooded plants increase their investments following flooding, but that the investment of plants physically damaged by flooding start rising first (right in the same year as the

flood). The bottom panel shows that these two groups have highly divergent paths in their labor productivity, with flood-damaged plants seeing higher productivity and non-damaged plants seeing lower productivity compared to their pre-flood baselines. These event study findings further lend support to the aforementioned results that investment and productivity improvement after flooding is primarily driven by plants which faced physical damage.

Figure 4: Time path of productivity based on capital retirement



The physical damage line in orange is inferred based on whether a plant retired capital in the same year as a flood (in relative year 0). These results were disclosed under (CBDRB-FY24-P2851-R11775).

3.4 Reallocation of used machinery and productivity implications

An important implication of disaster shocks is that they can increase the local supply of used capital: exiting plants would liquidate their physical capital, i.e., machinery and buildings/structures. Additionally, incumbent plants that face physical damage and carry out extensive capital readjustment may remove old (even non-damaged) machinery and put those up for sale. Both of these factors would contribute to a higher supply of second-hand capital, reducing its equilibrium price.

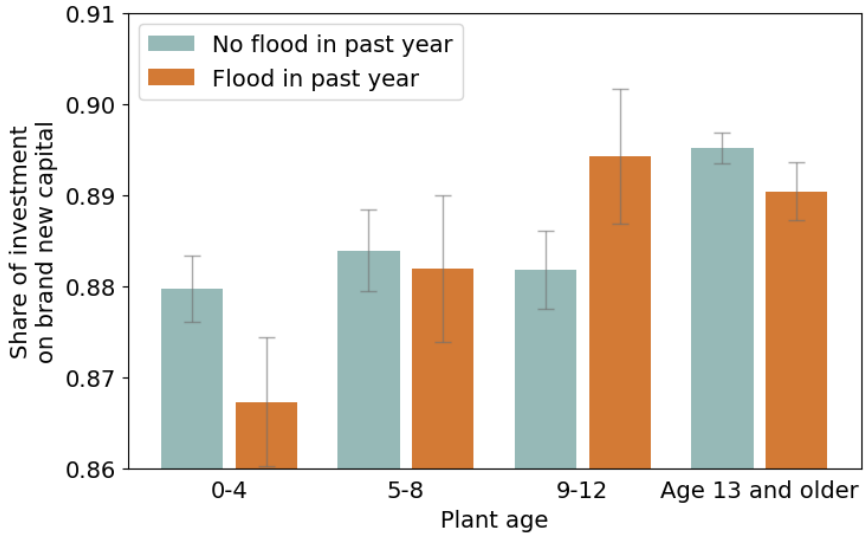
A lower price of capital is likely going to be attractive for younger plants, which have been shown to buy used capital from incumbents in previous research, in part due to financing constraints that may make it much unattainable to buy brand new capital (see Ma et al. (2022)). The productivity impacts are ex-ante ambiguous, but crucial to study given that young plants' capital investments in their earliest years can have lasting impacts (see

Hornbeck et al. (2024)). On one hand, used machinery may help young plants to build their capacity and grow faster. On the other hand, given that second-hand machinery from incumbents likely carries older (potentially obsolete) technology vintages, acquiring used capital may hurt young plants' productivity in the short term. In the long term, second-hand machinery may have the negative impact of locking in young plants to old technology that increasingly becomes incompatible to integrate with future technological upgrades, thereby prematurely bounding the young plants' long-run technology use as well.

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

Tables 6 and 7 investigate the productivity implications of young plants' used capital purchase following disasters. Table 5 used cross-sectional regressions and shows that among entrant plants, investment in used machinery following flooding is associated with higher productivity, potentially suggesting that they are able to build their capacity quicker than their peers which buy more expensive newer capital. However, it also appears to drive lower long-term survival. The purchase of used buildings and machinery is ultimately associated with about a year and a half shorter stay in the market. One potential explanation to the reconcile these seemingly disparate results is accounting for those entrants decision-making process: Eisfeldt and Rampini (2008) characterize used capital as cheap upfront, but generally more expensive in terms of long-term maintenance, and show that financially constrained agents start smaller firms and remain small. Similarly, here, it could be possible that entrants which primarily rely on used capital to build up their early production capacity already do not plan to stay very long in the market.

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



The orange shaded bars indicate counties in which there was a recent flood (in the same year or year prior), while the green shaded bars show years with no flooding in current or year prior. Underlying data cover the years 1985-1996 in the ASM data: 1985 is the first year in which I can identify age 13+ plants with decent certainty, and the ASM discontinued questions about the breakdown of plants' capital investments in new versus used capital in 1996. The approach to calculate plant age is described in Appendix Section A.2. Estimates in these figures were disclosed under (CBDRB-FY24-P2851-R11684)

Table 5: Entrant plant outcomes

	PRODUCTIVITY OUTCOMES			SURVIVAL	
	Log(TFP)	Log(Output/hr)	Log(Revenue/Payroll)	Max age observed	
1.Post flood	-0.094**	0.026	0.110***	0.462	0.883
	(0.038)	(0.053)	(0.039)	(1.036)	(1.037)
1.Used machine	-0.054**	-0.026	0.021	-0.799	
	(0.026)	(0.043)	(0.036)	(0.618)	
1.Post flood#1.Used machine	0.094***	0.069	0.003	-0.769	
	(0.035)	(0.051)	(0.040)	(0.799)	
1.Used capital					-0.462
					(0.608)
1.Post flood#1.Used capital					-1.455*
					(0.819)
N	5,300	5,300	5,300	5,300	5,400
Y-mean	7.69	72.16	6.04	16.94	
Y-sd	5.69	109.4	7.56	10.92	

Sample includes plants that are marked as 'entrants' in the LBD (i.e., those which were observed with positive employment in the current year but no employment in the previous year). Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11700)

Table 6 shows that, for single-plant firms aged 0-4, investment in used machinery after disasters is associated with about a 10% lower labor productivity such as output per hour. This finding is consistent with the interpretation that the quality and old vintage of used capital in post-disaster settings can drive lower productivity, though a lower productivity of the young plants may itself predict self-selection into purchase of used capital,

Table 6: Outcomes of young, small firms

	Log(TFP)	Log(Output/hour)
1.Post flood	0.108	0.122**
	(0.076)	(0.051)
1.Used machine	-0.022	0.076
	(0.034)	(0.048)
1.Post flood#1.Used machine	-0.01	-0.101*
	(0.039)	(0.060)
N	7,800	7,800
Y-mean	8.18	52.09
Y-sd	5.94	73.49

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

3.5 Aggregate Implications

The results above suggest substantial reallocation after floods: the least productive units exit and flood=damaged stayers replace their capital and adopt new technology while younger plants and non-damaged plants buy their used capital.

To investigate aggregate implications of this reallocation, Table 7 shows the outcomes of county-industry level dispersion of the marginal product of plant capital, and average labor productivity. The first column, in particular, shows the interquartile range–i.e., the difference in productivity between plants at the 75th and the 25th percentile of the productivity distribution in the narrowly defined 3-digit NAICS code within the same county. I find a negative and statistically significant change in the dispersion of productivity, suggests that capital is being reallocated and put toward better use after disasters. The second column shows that average labor productivity, measured as output per hour, rises at the county-industry level as well. Overall, these results indicate that the reallocation that follows after federally-declared floods is productivity-enhancing.

Table 7: On net, post-flood reallocation enhances productivity

	IQR(Output/Capital stock)	Log(Output/Hour)
Post flood	–**	+
N	131,000	131,000

Results in this table were disclosed under (CBDRB-FY24-P2851-R11815)

4 Robustness

4.1 Survivor Bias

A key potential confounder for how to interpret continuing plants' post-disaster productivity improvements is survivorship bias: if floods have a 'cleansing' effect whereby post-disaster exits are concentrated among the lowest productivity plants, then this naturally implies an increase in the average productivity that would be estimated for the remaining survivors. Even with fairly localized physical damage, large disasters can cause various (negative) productivity shocks to non-flooded plants in broader regions, including supply chain disruptions and worker absences.[15] Regardless of whether they are themselves physically flooded or not, we expect lower productivity plants to have lower capacity to weather disaster-related negative shocks and thus, to be more likely to exit. Indeed, Table **??** below shows that plants in the lowest quartile of the pre-flood year's TFP distribution in their industry have a/an xyz% higher likelihood of exit after a disaster relative to higher productivity plants. This analysis was done based on the distribution of TFP within each 6-digit NAICS industry code–the finest level possible–and offers compelling evidence on the cleansing role of disasters.

This consideration is particularly relevant for my study because the flood declaration treatment is defined at a coarse, county-level geography and I do not directly observe plants which are physically struck by the disasters. While this county-level flood treatment definition is suitable to get adequate sample sizes that will fulfill the Census Bureau's criteria for disclosure, it is possible that the county-level geographic focus is too coarse to pick up actual physical damage suffered by plants. Businesses regularly experience idiosyncratic productivity shocks – both positive and negative – throughout their lifetime, and unsurprisingly, positive productivity shocks are associated with higher capital investment. Even more, plants with higher productivity are more likely to have a preference for investing in machines with advanced technology as well. Thus, given that post-flood exits are concentrated among

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

lower productivity plants, and if my analyses based on a county-level flood treatment only pick up only the machinery investments of surviving plants that happen to face positive productivity shocks independent of the disaster, then this could mean that I may misattribute productivity increases that reflect cleansing to induced capital readjustment.

Table 8: County-level investment

	IHS($ Total Investment)			IHS(Investment normalized by pre-flood stock)	
	Machinery	Buildings	All capital	Machinery	All capital
Post flood	+***	+***	+**	+***	+***
N	20,500	20,500	20,500	16,500	16,500

This table was disclosed under (CBDRB-FY24-P2851-R11700)

However, as Table 8 shows, my robustness checks confirm that the productivity increase I document for plants' post-disaster investments is strongly consistent with flooded plants' readjustment of their capital stock rather than a mere feature of the cleansing effect of disasters. In particular, I re-estimate my analysis of plant-level capital investment at the county level to examine how aggregate investment in machinery evolves following disaster shocks: if aggregate county-level machinery investment increases after disasters, this would support the forced capital readjustment channel of my study, but otherwise, no statistically significant change in aggregate investment would suggest that the machinery investment and higher productivity I document for continuing plants is only derived from the outcomes of plants which make machinery investments after facing positive idiosyncratic shocks, whose distribution should not be affected by a disaster. I find that flooding is associated with a statistically significant increase in county-level machinery and total capital investment, including when these outcomes are normalized by the pre-flood year's aggregate capital stock in the county (see Table 8). This suggests that, the county-level flood treatment is still meaningful to approximate plant-level disaster damage, and while it is likely impossible to entirely rule out the role of survivors' higher average productivity, it is unlikely to be the *only* driver of my findings.

5 Discussion

A key aspect of this paper is the use of capital retirement information in the ASM as an indicator for physical damage from flooding. Yet, capital retirement is a potentially imperfect measure of disaster-related physical damage because it does not distinguish between sales and scrapping, and it is generally based on book values from the seller's data. I find additional

evidence that plants' average likelihood of spending on capital repairs increases by about 2% after flooding, which further lends support to the fact that flooding degrades capital. Since these capital repairs are an operating cost and not a major capital (dis)investment episode, they are not to be treated as a major asset change, but still lend further support to the interpretation that, though coarse, the degradation of physical capital due to flooding is being picked up by the county-level indicator that I use.

Importantly, this paper motivates further research on the frictions to the extensive and/or simultaneous adoption of complementary technologies by firms. Of course, the take-away from my results is not that they should switch to the newest vintage every single year. But, a potentially meaningful intervention for future work to explore could be the effectiveness of policies like subsidies for simultaneous (systemic) capital upgrading in the manufacturing sector.

6 Conclusion

I examine how manufacturing plants' productivity recovers after they rebuild from large, exogenous floods that destroy their capital. Flooded plants overshoot their pre-flood labor productivity baseline by about 4.5% because they make extensive, simultaneous upgrades to their machinery during their rebuilding process that they may not otherwise have made in their business-as-usual investment episodes. Moreover, as flooded incumbents replace their capital and plants forced to exit due to the disaster sell off their assets, I trace that the resulting excess supply of second-hand machinery is acquired by local young plants. However, this used capital potentially locks young firms into old technology, restricting their productivity and long-term survival. These findings highlight the critical role of technology for young firms. This paper also sheds new light on climate hazards as a powerful yet overlooked driver of capital depreciation and reallocation in our warming world.

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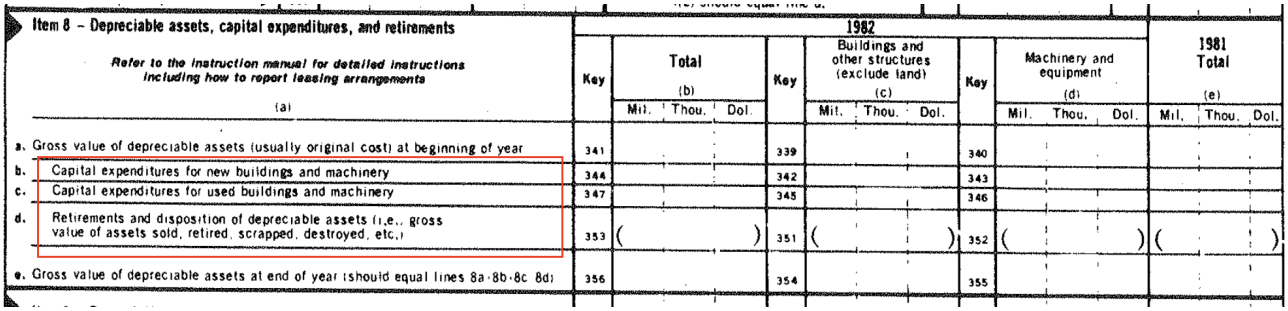
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A Appendix

A.1 Tables and Figures

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



Item 8 – Depreciable assets, capital expenditures, and retirements

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

(a)	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		

Table A.1: Soon-to-exit plants retire/liquidate capital, and cut down on investments

	IHS(Retirement)	Any retire	IHS($ Machines)	IHS($ Bldg)	IHS($ All capital)	Any machine	Any bldg	Any capital
Exit within 2 years	+*	+**	−***	−***	−***	−***	−***	−***
N	45,500	45,500	150,000	150,000	150,000	150,000	150,000	150,000

Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11711)

Table A.2: Entrants invest in capital to build up capacity, they are less likey to retire capital

	IHS(Retirement)	Any retire	IHS($ Machines)	IHS($ Bldg)	IHS($ All capital)
Entrant plant	−***	−**	+***	+***	+***
N	45,500	45,500	150,000	150,000	150,000

Estimates in this table were disclosed under (CBDRB-FY24-P2851-R11711)

Table A.3: 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**	+**
	(0.013)	(0.046)	(0.009)	
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	

This table was disclosed under (CBDRB-FY24-P2851-R11700; -R11815)

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 flag-young==1), 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