In the Eye of the Storm: Firms and Capital Destruction in India*

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Abstract

The number and strength of climate-change-related disasters is increasing, and developing countries are bearing most of the brunt. In this paper we study how firms react to tropical cyclones in India. Using a panel of manufacturing firms between 1995 and 2006 and cyclone data from the National Oceanic and Atmospheric Administration, we find that the average cyclone destroys 2.2% of a firm's fixed assets and decreases its sales by 3.1%. The impacts of the average cyclone are temporary and disappear after one year. Focusing on the heterogeneity of these results by firm and industry quality, we also find that capital and sales reallocate toward better-performing industries. Within industry, firm quality only matters for the response of sales.

Keywords: storms, India, firms, capital
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1 Introduction

Tropical cyclones generate an annual average of US $26 billion of damages worldwide, which are predicted to quadruple to US $100 billion by 2100. According to Mendelsohn et al. (2012), this rise will be caused in equal proportion by increases in the wealth and population located in cyclone-prone areas and by changes in the intensity of cyclones due to climate change (Scott et al., 2004; Webster et al., 2005; Emanuel, 2005, 2011, 2021).[1] In this context, understanding how firms respond to tropical cyclones is important to enhance disaster preparedness and reduce disaster risk.[2] This knowledge is even more relevant for developing countries, which suffer the worse consequences of climate change and have only limited resources available for adaptation and reconstruction (Hallegatte et al., 2018). Yet, there is little evidence so far on how firms in developing countries adjust their inputs and production pattern post-disaster.

In this paper we study the response of firms to storms in India. We first estimate the impacts of cyclones on firms' physical capital and sales. Second, we analyze the dynamics of these impacts and examine how long it takes for firms to rebuild and reboot. We then study the heterogeneity of these impacts by firm and industry quality, effectively looking at adjustments across and within industries. In the analysis we use of a novel and exogenous measure of firm exposure to storms, constructed from variation in wind intensities across postal codes and firms' establishments.

With a coastline of 7,516 kilometers, India is exposed to roughly 10% of the world's cyclones, making it one of the most affected regions in the world. Annually, over 370 million people are affected by cyclones (storms with winds traveling faster than 33 knots) in India alone.[3] The government of India reports that cyclonic winds are typically associated with extensive damages to structures (e.g., residential and private buildings, public infrastructures).[4] The potential for damages on structures is exacerbated by the fact that construction and engineering laws and regulations are not always enforced, professional knowledge is sometimes lacking, and structures often have inadequate foundations and use poor quality materials.[5] While resilience has improved over time,

[1] See also Hallegatte (2007, 2012).

[2] The Sendai Framework for Disaster Risk Reduction lists as Priority IV "enhancing disaster preparedness for effective response and to 'Build Back Better' in recovery, rehabilitation and reconstruction". See https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030.

[3] https://ncrmp.gov.in/cyclones-their-impact-in-india/

[4] Other types of damages include loss of power and communication, injuries and loss of lives, and destruction of crops, vegetation, and livestock. The forces exerted by winds on buildings damage metal sheets as well as wooden structures and expose roofs to lifting forces, potentially causing a failure of the entire roofing system. As this happens, structures' and buildings' interiors are exposed to water damage and exterior walls lose their support and fall down even at relatively low wind intensity. Hence, winds can damage interiors; cause harm to firms' materials, stocks, and machinery; and seriously disrupt firms' operations. See https://rsmcnewdelhi.imd.gov.in/report.php?internal_menu=MjY= for more details on the types of damages caused by cyclones.

[5] Building collapses are a serious issue in India. According to the National Crime Records Bureau, there were 37,514 incidents of structure collapses (bridges, commercial and residential buildings, and dams) over the period 2001–2015, causing the death of 38,363 people.

India is still extremely vulnerable today and considerable efforts are continuously being made to help mitigate the impacts of cyclones.[6]

The literature on the impact of natural disasters often assumes that, through their destruction, disasters foster a more rapid turnover of capital within industries, causing firms to upgrade old capital with newer and more productive vintages (e.g., Hallegatte & Dumas, 2009). Following heterogeneous firms frameworks, it is rather standard to expect differential impacts within industry depending on firm productivity. Resources may also reallocate *across industries*. We expect that reconstruction will be more pronounced in better-performing industries, i.e., industries where the marginal product of capital is relatively high.[7] This may happen because the destruction of capital allows new resources to flow to the best currently available opportunities. Economic conditions change over time, thus decisions that were optimal in the past may no longer be optimal today. Yet, due to the irreversible nature of investments and the industry specificity of capital, firms often stick to their past decisions as long as the revenues generated from their activity cover at least part of the sunk costs incurred. Our conjecture is that, by destroying capital, storms create an opportunity to re-invest, adapt production, and reallocate resources to better-performing industries.[8]

The data we use in our analysis is from Prowess, a panel of firms covering the period 1995–2006 and containing the financial statements of 6,037 manufacturing firms. Every firm is identified by its name and the location of its headquarters. Since production rarely occurs at the headquarters, identifying the location of each of the establishments belonging to a firm is crucial to construct a precise measure of firm exposure to storms. We use the googleplaces algorithm to supplement the Prowess dataset with the coordinates of each of the establishments of a firm. We then construct a yearly firm-specific measure that accounts for the maximum wind exposure at the headquarters and the establishments using storms' best-track data from the National Oceanic and Atmospheric Administration (NOAA).[9]

[6]For instance, the World Bank recently supported the Coastal Disaster Risk Reduction Project, a five-year (2013–2018) project worth US $337.2 million. One of its stated goals was to reduce vulnerability through resilient infrastructure. In the last decade the World Bank supported several disaster recovery projects following major disasters (e.g., Cyclone Phailin, Cyclone Hudhud). The projects focused on a fast, early, and long-term recovery based on building back better.

[7]Heterogeneous cross-industry effects have been observed in other contexts examining the productivity impacts of exogenous shocks. For instance, Topalova & Khandelwal (2011) study the impact of the 1991 trade liberalization in India and find differential effects on firms' productivity across industries. Another example is Albrizio et al. (2017), who show that environmental regulations have heterogeneous impacts on firms' productivity.

[8]A theoretical framework that produces this specific type of adjustment is described in Pelli & Tschopp (2017). The authors analyze exports and not production, yet, inasmuch as exports are just a residual of production, the same framework can be applied directly to production. The framework builds on the implications of Redding (1999), who introduces the notion of endogenous dynamic comparative advantage, and Ishise (2016). Ishise (2016) combines an extended multi-industry putty-clay framework à la Gilchrist & Williams (2005) with a dynamic international trade model in the style of Baxter (1992). Using data aggregated at the country-industry level, Pelli & Tschopp (2017) find that the response of exports to storms (a proxy for physical capital destruction) is monotonically increasing in comparative advantage, which is consistent with the idea that reconstruction occurs in better-performing industries.

[9]A storm's best track reports the position, the wind strength, and the diameter characterizing the eye of a hurricane

We first estimate the impacts of cyclones on firms' physical capital and sales and find that the average cyclone reduces firms sales by 3.1% and destroys 2.2% of firms' fixed assets. This latter effect is consistent across different types of fixed assets, such as land and buildings. A cyclone at the 90th (10th) percentile of the distribution destroys 8.7% (0.3%) of the fixed assets and decreases sales by 7.8% (0.5%). Salaries instead are not affected, suggesting that most of the impact of a storm on a firm works through capital. We then analyze the dynamics of these impacts and find that the impacts of the storms are short lived and indicate a fast recovery, with reconstruction occurring to a larger extent in better-performing industries.

Finally, we study the heterogeneity of these impacts by firm and industry quality. We measure industrial performance using the Balassa index of revealed comparative advantage and firm quality with total factor productivity (TFP). Our findings show that after a storm, capital reallocates toward better-performing industries. This result is mirrored in the pattern of production, with sales shifting toward the top of the comparative advantage distribution. This shift is driven by firms adjusting their production mix within an existing set of industries rather than by firms investing in new industry production lines.

Moreover, in terms of heterogeneity within industry, we find that the shock has differential impacts on sales but not capital. There is no evidence of, within industry, capital flowing toward more productive firms or toward firms characterized by a high marginal revenue product of capital (MRPK). Hence, our estimates indicate that movements of capital are linked to industry quality rather than to firm productivity. However, regarding sales, the results show that within industry, the least productive firms are affected relatively more by storms and experience larger decreases in sales (in percentage).[10] Finally, both across- and within-industry adjustments of sales are equally important and, as expected, depend on the capital intensity of industries. These results hold across a variety of robustness tests.

This paper adds to the growing literature on the impact of storms.[11] Several studies have looked at the impact of natural disasters on economic outcomes, such as fiscal policy, financial aid, investment, consumption growth, exports, or precautionary savings (for a survey of aggregate impacts, see Cavallo & Noy, 2010; Dell et al., 2014). A large body of the literature focuses on economic growth, either using cross-country or within-country data. For instance, Strobl (2011) looks at the economic growth impact of hurricanes across US coastal counties, while Cavallo et al. (2013) examine the average causal impact of natural disasters on economic growth using synthetic controls and counterfactual analysis. Hsiang & Jina (2014) review the hypotheses advanced by the literature concerning the effects of hurricanes on long-run economic growth across countries:

at six-hour intervals.

[10]Since the appearance of a firm in the Prowess database depends on the availability of its financial statements and not on whether the specific firm is active, we cannot study the entry and exit of firms.

[11]For a survey of the literature on tropical cyclones, see Botzen et al. (2019).

creative destruction/build back better (e.g., Skidmore & Toya, 2002; Cuaresma et al., 2008) and recovery to trend/no recovery (e.g., Miguel & Roland, 2011).[12]

More recently, the literature has turned to the adjustment of firms to tropical cyclones. For instance, Elliott et al. (2019) find that cyclones have a considerable negative impact on Chinese firms' performance. Similarly to our findings, this effect is relatively short lived. Seetharam (2018) examines the spatial propagation of job losses occurring within multi-plant firms across undisrupted distant regions in the US. The author finds that within a firm, for every job lost in a county hit by a cyclone, 0.19–0.25 jobs are lost across other regions, suggesting that the network of establishments tend to propagate the effect of a cyclone. Using US administrative data, Basker & Miranda (2018) study firm survival after Hurricane Katrina. They find that smaller and less productive businesses have lower survival rates, while larger and more productive firms hire more. Vu & Noy (2018) look at firms in Vietnam and find that while cyclones have a negative impact on retail sales, they lead to an increase in investments, with large differences between urban and rural areas.

To the best of our knowledge, this paper is the first to unpack the heterogeneity of the effects of storms on firms within and across industries in a major developing country where the dynamics of adjustment may differ from those encountered in a high-income country. Our findings suggest that in the aftermath of storms, in addition to replacing old capital with newer and more productive vintages, firms also tend to re-optimize their production structure by switching to better-performing industries. This additional adjustment mechanism is important because it may help to boost recovery and economic growth. For the design of post-disaster policies, our results indicate that on the firm side, undiscriminating policies, which are easier to implement and potentially less costly than targeted policies, can be successful at helping firms cope with disasters. While undiscriminating

[12] A large share of the existing literature focuses on the impact of storms in developed countries, especially in the US. Deryugina (2017) focuses on the fiscal costs of natural disasters by looking at social safety nets. Observing a substantial increase in non-disaster-related transfers in the decade following the strike, she concludes that the real cost of disasters has probably been underestimated and social safety nets contribute to provide a better insurance from natural disasters to people living in developed countries. In a recent paper, Boustan et al. (2020) look at the US between 1920 and 2010 (the US is affected by over 100 natural disasters every year) and find negative effects on counties' out-migration rates and housing prices. Another large literature focuses on the impact of hurricanes and natural disasters on the labor market, households' finances, and education. Deryugina et al. (2018) find large and persistent effects on peoples' decision regarding where to live but only find small and transitory effects on employment and income following Hurricane Katrina. The impact of Hurricane Katrina on employment has also been analyzed by Groen & Polivka (2008), McIntosh (2008), Belasen & Polachek (2008), and Groen et al. (2020). Gallagher & Hartley (2017) show that Katrina had a positive impact on household finances since insurance money was mainly used to repay loans. Finally, Sacerdote (2012) shows that students who were forced to switch schools after Katrina suffered a sharp decline in test scores, but the hurricane did not have an impact on the decision to attend college.

A smaller but growing literature focuses on the impact of tropical cyclones on household welfare and inequalities in developing countries. Sedova et al. (2020) shows that cyclones increase inequalities among rural households in India by reducing consumption for poor households, especially for households involved in farming (for other studies on the impact of cyclones on inequalities in developing countries see also Bui et al., 2014; Keerthiratne & Tol, 2018; Warr & Aung, 2019). Another strand of the literature focuses on the response of households in terms of expenditures and labor market outcomes (see, e.g., Arouri et al., 2015; Karim, 2018).

policies might work at the firm level, some firms and industries are still going to be more affected than others, and therefore it is crucial that the government assists workers who must switch to a different firm and/or industry.

2 Setting and Data

2.1 Firm Data

Our firm data come from Prowess, a large panel database constructed by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE) from the annual and quarterly statements of companies.[13] To our knowledge, Prowess is the largest dataset on the financial performance of Indian firms and is the only detailed database on firm-level product mix and sales in India. The data contain information on headquarters' postal codes and company names, which is essential to construct a measure of firm exposure to storms.[14] For each firm, Prowess also contains information on salaries and on various types of fixed capital, including total fixed assets. We aggregate firm product sales at the firm-industry level using the International Standard Industrial Classification (ISIC) Rev. 4 four-digit industrial classification and keep a firm-industry pair if observed for at least two consecutive years.[15] We focus on the 6,037 firms operating in the manufacturing sector (Section C, Divisions 10–33) between 1995 and 2006.

To capture the heterogeneity of the adjustments by firm and industry quality, we rank firms and industries. We measure firm quality using TFP and classify industries according to the Balassa index of revealed comparative advantage. We also use the MRPK as an alternative way to rank firms. Details about the construction of the Balassa index, TFP, and the MRPK are provided in Appendices A.2, A.3, and A.4, respectively.

Table 1 shows summary statistics for the main variables. Annual real sales for the average firm in our sample are Rs 40.1 crores (equivalent to roughly US $5.7 million).[16] The maximum value

[13]Prowess has been used widely in the literature to study multi-product firms; see, e.g., Goldberg et al. (2010) and De Loecker et al. (2016). A caveat of this database is that it is not representative of the Indian economy. The main criterion for inclusion in the Prowess database is "unencumbered availability of information." Companies are included if they meet any of these criteria: *i)* availability of annual audited profit and loss statement and balance sheet, *ii)* availability of share prices either from the National Stock Exchange or the Bombay Stock Exchange, and *iii)* availability of quarterly financial statements. After they have met these criteria, all listed companies and their subsidiaries are included in Prowess. A certain number of unlisted companies is also included, especially public and private limited companies. However, not all unlisted companies are included since information is not easily available. As a consequence, the panel of firms is unbalanced, large firms are better represented than smaller firms, and the informal sector is not present in this database.

[14]In India, postal codes are composed of six digits and are called *pincodes*. There are roughly 20,000 pincodes in India.

[15]CMIE uses its own product classifications. Appendix A.1 provides details on how we match their product codes to the ISIC Rev. 4 four-digit level.

[16]Throughout the paper, we use an exchange rate of Rs 70 for US $1.

reported is roughly US $5.9 billion in sales. The fixed assets of the average firm in the sample are valued at Rs 23.6 crores (US $3.4 million), with a maximum of US $1.6 billion.

[Table 1 here]

2.2 Storms

2.2.1 Exogeneity of Storms

The central identifying assumption of this paper is that storms are exogenous to economic activity. In this section we first discuss storms' exogeneity in general and then look at storms' exogeneity with respect to the firms considered in our sample.

Tropical storms are unpredictable, and the frequency of their occurrence is stationary; i.e., the past does not provide any information on the exact timing and location of future occurrences (see, e.g., Elsner & Bossak, 2001; Lindell et al., 2007; Pielke et al., 2008). They are more likely to happen in coastal areas yet are perceived as extremely unlikely even in these areas.[17] Moreover, firms' and people's investment and location decisions do not seem to be affected by the possibility of being on the path of a tropical storm. In an experimental setting, Wu & Lindell (2014) show that decision makers tend to wait too long to evacuate areas at risk. Dessaint & Matray (2017) find that, in the US, managers tend to react to hurricanes in their vicinity by increasing cash holdings but only for a short period. Anecdotal evidence indicates that storm-prone areas are not abandoned or less developed but instead are characterized by a lot of economic activity. For instance, Pelli & Tschopp (2017) show a high concentration of firms in storm-prone areas in India and in the Philippines.

While storms inflict damages through three different channels (winds, floods, and surges), we only focus on winds. This choice is dictated by the fact that winds can be considered exogenous, whereas the impact of flood and surges may depend on land management and may be taken into account by people settling decisions (see, e.g., Petkov, 2018). In Table 2 we perform a series of balance tests to ensure that storms can be considered exogenous in our sample. These tests compare the average of industry-firm sales, TFP, the Balassa index, and fixed assets between firms that are about to get hit by a storm and firms that are not. For instance, consider the year 1996. We divide the sample into two sets: the first one includes all the firms that are hit for the first time in 1997, and the second includes all the firms that are not hit up to 1997. We then test whether the difference in the average of each variable up to 1996 across the two sets is statistically different from zero.

[17]Tropical storms form above the sea if a set of particular conditions is met, one of which is that the ocean must reach at least 79.7°F (26.5°C) to a depth of 50 meters for a tropical storm to arise.

[Table 2 here]

We cannot test the difference of means for all the years. This is true especially for later years, as it becomes more difficult to find a set of firms that has not been affected by a storm in any of the previous years. Because the Balassa index is not a firm-specific variable but is instead industry specific, in Panel D we focus on single-ISIC firms.[18] Most of these differences are statistically not significant except for three differences in means, of which two go in the opposite direction of what would be expected if one believed that firms anticipated tropical storms.

2.2.2 Firm Exposure to Storms

To evaluate the response of firms, we construct a firm-level measure that takes into account establishments' exposure to winds. To build this measure, denoted by H_{ft} (where f is the firm subscript and t denotes time), we first identify and geo-reference all of a firm's establishments, as described in Appendix A.5. We then compute the maximum wind speed (hereafter "wind speed") that hit each establishment during each storm and sum wind speed across the establishments of a firm. To calculate wind speed, we follow the standard practice in the climate literature and parametrically model storms as translating ranking vortices. We use the formula developed in Deppermann (1947) in our baseline estimations and show in Section A of the Online Appendix that our results are similar when using both the Holland (Holland, 1980) and HURRECON (Boose et al., 2004) wind field models.

Wind speed is also used as a measure of incidence in other studies (see, e.g., Hsiang, 2010; Hsiang & Narita, 2012; Anttila-Hughes & Hsiang, 2013; Hsiang & Jina, 2014). As argued by Hsiang & Jina (2014), it is the relevant dimension to capture capital degradation as the materials used to build durable capital only tend to break at a critical level of pressure. However, instead of using wind speed directly, we construct an index of firm exposure that accounts for the fact that the relationship between winds and the force exerted on physical structures is often non-linear (see the technical HAZUS manual of the Federal Emergency Management Agency). As detailed in Appendix A.6, our index is computed from a quadratic damage function that captures the force exerted by winds on physical structures. Furthermore, the index focuses on tropical storms, i.e., storms defined by winds speeds over 33 knots. In developing countries, construction materials are often of poor and sub-standard quality, and therefore a threshold of 33 knots is high enough for winds to impair buildings, materials, and infrastructure.[19]

[18] Single-ISIC denotes firms that are active in a single 4-digit ISIC industry over the entire period.

[19] Our baseline index uses a quadratic function to be directly comparable to Pelli & Tschopp (2017). In Section A of the Online Appendix we propose alternative specifications of the storm index based on higher thresholds and a cubic damage function. We also show results where we replace the storm index by wind speed.

The boxplots in Figure 1 describe winds (w_{ph}, where p denotes a postal code and h a hurricane, left panel) and the index of firm exposure (H_{ft}, right panel) for each state over the period 1995–2006. Only states with $w_{ph} > 0$ and $H_{ft} > 0$ are represented. The figure shows that the median wind speed lies between 30 and 40 knots. Both boxplots exhibit substantial variation within and across states. Table 1 shows descriptive statistics of the storm index for all observations and only for those hit by a storm. The average value of the index is 0.02 with a maximum value of 0.525.

[Figure 1 here]

As an example of the importance of accounting for establishments when computing H_{ft}, the left panel of Figure 2 shows the location of the establishments of the company Steel Authority of India. The yellow dot pinpoints the location of the headquarters, the red dots pinpoints each establishment's location, and the green areas represent postal codes affected by wind speeds (w_{ph}) of various intensities in 1998. The figure shows that while the headquarters are located in the north of the country in an area that appears to be sheltered from storms, several of the establishments are in areas that, in 1998, experienced severe winds. Ignoring establishments would lead to conclude that Steel Authority of India was unaffected ($H_{ft} = 0$) and would likely produce an attenuation bias.

[Figure 2 here]

The right panel illustrates how the index of firm exposure to storms, H_{fh}, is distributed across postal codes in 1998. Red (blue) circles indicate positive (zero) values of firm exposure to storms. Importantly, the map shows that a firm may be affected by a storm even though its headquarters is located in an area sheltered from tropical storms.

3 How Much Damage Do Storms Do?

In this section we quantify the destruction that storms inflict on firm capital, salaries, and sales. We first look at various components of the capital stock individually (buildings, land, and electrical equipment) and then focus on fixed assets.

We run the following specification:

$$y_{ft} = \alpha_0 + \alpha_1 H_{ft} + \boldsymbol{V}\boldsymbol{\eta} + \varepsilon_{ft}, \tag{1}$$

where y_{ft} denotes the logarithm of either one of the measures of capital for firm f in year t, salaries, or firm-industry sales. While we drop the location and industry subscripts where possible, it is understood that $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes postal codes, and d denotes districts. H_{ft} is the index of firm exposure to storms, and $\boldsymbol{V}$ is a vector of controls containing firm-specific TFP, the yearly growth of district night-light intensity (a proxy for local GDP growth; see Appendix A.7 for details), the number of establishments per firm, four-digit ISIC industry-year fixed effects (FE), district trends, and firm-type FE. Firm-type FE indicate whether a firm is active in a single-ISIC industry or whether it operates in multiple ISIC industries.[20] In the sales regressions $\boldsymbol{V}$ also contains postal code FE. ε_{ft} is the error term.

Including both the growth of district night-light intensity and district trends allows us to control for district-level economic changes as well as pre-existing regional trends. The number of establishments per firm controls for the fact that multi-plant firms may cope better with storms as they can reallocate production or inputs across their production network, at least temporarily. In addition, since our storm measure is the sum of winds across establishments, the same storm is likely to be more severe for a firm composed of a single establishment. Firm-type FE control for the fact that multi-ISIC firms tend to have higher sales per industry. Industry-year FE control for industrial shocks such as technological changes and for the capital intensity of an industry that may affect the way production in that industry is affected by storms. Postal code FE capture fixed local characteristics that may affect firm-industry sales. For instance, a firm located in an urban area likely benefits from better market access, e.g., through proximity to other firms or access to high-quality road infrastructure, and may react differently to a storm than a firm in a rural or more remote region.

As discussed in Appendix Section A.3, TFP estimates are typically obtained from estimating production functions; specifically, they are the residuals of a regression of firm-level output on inputs. Hence, holding other inputs constant, TFP may be altered by construction if storms destroy capital. There is also evidence that, by disrupting production, storms can impact local economic growth (see, e.g., Hsiang, 2010; Strobl, 2011; Bertinelli & Strobl, 2013; Elliott et al., 2015; Naguib et al., 2022). Thus, to avoid a bad control issue, we use the lag of TFP and the lag of night-light intensity growth.

Panel A of Table 3 presents the results from estimating equation (1).[21] The impact of a storm on all the measures of capital and on sales is negative and statistically significant, while it is statis-

[20] We divide firms into three categories: *i)* firms that produce within a single industry over the entire period (single-ISIC firms), *ii)* firms that operate in more than one ISIC industry every year over the entire period (always-multi-ISIC firms), and *iii)* firms that switch from being a single- to a multi-ISIC firm (and vice versa) over time (multi-ISIC firms). Fifteen percent of the firms contained in our sample are always single-ISIC, 52% switch status from single- to multi-ISIC firms (and vice versa), and 33% are always-multi-ISIC firms. For multi-ISIC firms, the industry FE capture the effect associated with the industry in which the firm's sales are the largest.

[21] Note that the number of observations changes between columns because in the first fifth columns the unit of observation is the firm, while in the last one the cross-sectional unit is formed by an industry-firm pair. Finally, also note that we lose singleton observations, and hence the number of observations in Table 3 differs from that presented in Table 1.

tically insignificant on salaries, suggesting that the effect of storms on firms works through capital and not labor inputs. Columns (1)–(3) present the results for buildings, land, and electrical equipment, respectively, and column (4) shows the results for fixed assets. Focusing on fixed assets, the estimate implies that the strongest firm exposure observed in our sample (0.53) reduces a firm's fixed assets by 57.8% or that storms at the 90th percentile of the distribution lead to a reduction of 5.5% in fixed assets.[22] For the average exposure, fixed assets drop by 2.2% (for the average firm, this corresponds to a reduction of roughly US $74,000). Column (6) shows the impact of a storm on sales. The average storm reduces sales by 3.1% (i.e., a reduction of roughly US $178,000 for the average firm), while storms in the top decile of the distribution decrease sales by at least 7.8% (roughly US $447,000 for the average firm).

[Table 3 here]

We expect the largest firms in the sample to have access to better and more durable capital and therefore be less affected by storms. Table 4 shows that always-multi-ISIC firms differ from the rest of the sample and have, on average, more fixed assets and higher sales at the industry level. For always-multi-ISIC firms, fixed assets and sales have average values of roughly US $6.5 million and US $9 million, respectively. In the sample excluding always-multi-ISIC firms, the corresponding average values are US $1.8 million and US $2.7 million.[23] Four-digit ISIC industries are large industrial definitions covering many products, and therefore it is reasonable to expect always-multi-ISIC firms to have better access to innovative technologies and sturdier and more durable capital.

[Table 4 here]

Panel B of Table 3 focuses on fixed assets, salaries, and sales and examines whether always-multi-ISIC firms respond differently from the rest of the sample. The estimates obtained on the sample of always-multi-ISIC firms (columns (7), (9), and (11)) are all statistically insignificant, which suggests that these firms are indeed more resilient. Instead, once we exclude them, the coefficients on fixed assets and sales not only maintain their statistical significance but also increase in magnitude. The estimates imply that the average storm (storm index of 0.027) destroys roughly 3.8% of firm capital (roughly corresponding to US $68,000) and decreases firm sales by 4.5%, which corresponds to a decrease of roughly Rs 8.4 million (or roughly US $120,000) for the average firm. Overall, Panel B indicates that always-multi-ISIC firms are not impacted by storms and hence the rest of our analysis focuses on the adjustments of all the other firms.

[22] The 90th percentile of the storm distribution is 0.05, which we multiply by the destruction of 109% observed in response to a storm index of value 1.

[23] Additional summary statistics by firm type are shown in Table E.1 of Section E of the Online Appendix.

4 How Long Does It Take for Firms to Rebuild and Reboot?

We next examine if a storm's destruction is only contemporaneous or if it is protracted over several years as well as how long it takes for firms to recover. We first include in equation (1) up to three lags of storm exposure and then perform an event study. Table 5 shows the results for the specifications adding three lags. The estimates suggest that the destruction of the capital stock happens contemporaneously and is not protracted over the following periods. For electrical equipment, however, the estimates are statistically insignificant, likely because electrical equipment are more easily broken and fixed than buildings or land. Moreover, we might lose some precision as data for this variable are only available for half of the sample.[24] Sales also seem to be affected only in the year during which the storm occurs.[25]

The lack of protracted effects aligns with previous evidence, such as Raddatz (2007), Noy (2009), Hsiang (2010), Bertinelli & Strobl (2013), Cavallo et al. (2013), Elliott et al. (2019), and Naguib et al. (2022), and could depend on several factors. The firms observed in the sample are those that necessarily survived and recovered at least partly. In addition, our sample consists of relatively large firms that are more likely to recover quickly. Eventually, our results could also hide some heterogeneity, which we thoroughly investigate in Section 5.

[Table 5 here]

We then examine the effects of storms using an event study approach with firm FE.[26] Besides offering a visual representation of the effects, an event study conveniently allows us to check for pre-trends. However, unlike policies that are implemented at a given point in time and are not revoked thereafter, it is not clear whether storms (and more generally natural disasters), which are just passing events, should be treated as binary or staggered and how one would treat units exposed to multiple treatments over time. For these reasons, we restrict the sample to firms that experienced storms only once over the entire period and treat exposure as a binary treatment. The left panel of Figure 3 presents the average effects on firm fixed assets, where $t = -1$ is the year before the event. The pre-trends p-value is for the null hypothesis of no pre-trends, and the leveling-off p-value is for the null hypothesis that the dynamics have leveled off by the end of the window period. Confidence intervals represent 95% bounds.

[Figure 3 here]

[24] All the estimates for a specification on salaries that includes three lags are statistically insignificant.

[25] Table E.2 of Section E of the Online Appendix shows results for the sample that includes all firms.

[26] Similar to Table 3, we control for (the lag of) local GDP growth and include district trends as well as industry-year FE. Firm-type FE and the number of establishments are dropped due to the inclusion of firm FE. Also note that we exclude TFP as it moves slowly over time and cannot be identified separately from firm FE.

The left panel suggests that treated firms do not exhibit differential trends before the event. After the storm, firm fixed assets drop, and, consistent with our previous results, the effects level off quickly, disappearing within one year after the shock. The right panel presents the average effects on firm sales, obtained using the same event study methodology and set of controls as the left panel. The p-value at the bottom of the figure indicates the absence of pre-trends. In addition, the figure shows that immediately after the storm, firm sales mirror fixed assets, yet sales recover more slowly, with the negative effects lasting for two more periods.[27]

5 Heterogeneous Impacts by Firm and Industry Quality

In this section we examine whether storms have heterogeneous impacts by firm and industry quality. We measure firm quality using TFP and proxy industry quality with the Balassa index of revealed comparative advantage, and we use the MRPK as an alternative measure of firm quality.

5.1 Heterogeneous Effects on Impact

We evaluate whether storms have heterogeneous effects within and across industries using the following specification:

$$y_{ft} = \phi_0 + \phi_1 H_{ft} + \phi_2 \left(CA_{it} \times H_{ft}\right) + \phi_3 \left(TFP_{f(t-1)} \times H_{ft}\right) + \boldsymbol{V}\boldsymbol{\zeta} + u_{ft}, \qquad (2)$$

where f denotes a firm, i an industry, and t a year.[28] y_{ft} is the outcome of interest, consisting of the logarithms of either firm fixed assets or firm-industry sales. H_{ft} is the index of firm exposure to storms, CA_{it} is the Balassa index of revealed comparative advantage, and $TFP_{f(t-1)}$ captures firm productivity. The vector of controls $\boldsymbol{V}$ includes firm-specific TFP, the yearly growth of district night-lights, the number of establishments per firm, a set of firm-type FE, district trends, and four-digit ISIC industry-year FE. In the sales regressions $\boldsymbol{V}$ also contains postal code FE. u_{ft} is the error term. As discussed in Section 3, TFP and the growth of night-lights are lagged by one period to avoid a bad control issue.[29]

Given the results of Section 3, we expect the coefficient on firm exposure to storms to be negative ($\phi_1 < 0$). The coefficient on the interaction term, ϕ_2, captures the differential impact of

[27]In Figure F.1 of Section F of the Online Appendix, we present event study plots obtained when restricting the sample to always-multi-ISIC firms. Two things are worth pointing out. First, the pre-trend p-values are zero, indicating the presence of pre-trends. Second, the plots suggest that neither fixed assets nor sales are impacted by the event. Hence, the event study produces results in line with the findings in Table 3 and the notion that always-multi-ISIC firms differ from the rest of the sample.

[28]Recall that, as defined earlier on, $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p is the postal code, and d denotes the district of the headquarters.

[29]CA_{it} is absorbed by the set of industry-year FE included in $\boldsymbol{V}$.

storms on firms by industry quality. ϕ_1 and ϕ_2 jointly determine the way in which a storm affects the allocation of capital across industries and reshapes the pattern of industrial production.[30] In particular, if industries with a relatively low comparative advantage are affected disproportionately more, one would expect the marginal effect of storms on firm capital and sales to be monotonically increasing in comparative advantage; i.e., $\phi_1 < 0$ and $\phi_2 > 0$. The coefficient ϕ_3 captures the differential impact of storms by firm quality. If $\phi_1 < 0$, a positive estimate of ϕ_3 would suggest that the least productive firms are impacted relatively more than firms at the top of the productivity distribution.[31]

We first introduce each interaction term in separate regressions. In the specifications that include the interaction between comparative advantage and the storm index, errors are three-way clustered at the firm, district-year, and industry-year levels. The firm dimension accounts for the fact that the treatment varies at the firm level and allows for the errors to be correlated within firm over time and, for multi-ISIC firms, across industry production lines. Clustering at the district-year level accounts for the spatial nature of storms, and clustering at the industry-year level accounts for the fact that comparative advantage is an industry-specific measure. When the term $CA_{it} \times H_{ft}$ is excluded, standard errors are two-way clustered at the firm and district-year levels.[32]

Results on firm capital The results on firm fixed assets are shown in Table 6, columns (1)–(5). In column (1), we focus on the coefficient on the interaction term between the storm index and comparative advantage, thereby restricting our attention to the heterogeneity of the effect by industry quality. The estimate on the interaction term is positive and statistically significant at the 1% level, which implies that the decrease in capital is disproportionately larger in low comparative advantage industries. These findings could be explained by the fact that reconstruction tends to occur in better-performing industries, which are also industries that have, on average, a higher MRPK.[33] In column (2) we estimate the impact of storms on capital by firm quality. Interestingly, the estimate on the interaction term is not statistically significant and shows that the shock has no differential impacts within industries.

[30] The marginal effect of storms on capital and sales for each level of comparative advantage is given by $\phi_1 + \phi_2 \times CA_{it}$.

[31] A similar functional form has been used in earlier studies to examine the pattern of trade at the industry-country level. For example, Rajan & Zingales (1998) evaluate whether industries that heavily depend on external financing expand faster in countries with better financial markets. Nunn (2007) examines whether contract-intensive industries tend to be more widespread in countries with better contract enforcement. Levchenko (2007) tests if better institutions lead countries to specialize in goods relying strongly on institutions.

[32] Table E.3 of Section E of the Online Appendix shows results based on three alternative ways of clustering the standard errors: *i)* one-way clustered at the district level, *ii)* two-way clustered at the district and industry levels, and *iii)* two-way clustered at the district-year and industry-year levels. In all cases, the estimates remain statistically significant at least at the 5% level.

[33] Note that the Balassa index of comparative advantage is a strong predictor of firm MRPK, even after controlling for a variety of FE (industry, year, postal code FE, and district trends). These results are available upon request.

Column (3) estimates equation (2) and depicts a similar picture. Hence, it appears that the reallocation of capital is linked to industry quality rather than to firm productivity. In columns (4) and (5) we examine whether using the MRPK as an alternative measure of firm quality would lead to a different conclusion. Specifically, we replace the interaction $TFP_{f(t-1)} \times H_{ft}$ with $MRPK_{f(t-1)} \times H_{ft}$ in equation (2). Now, the coefficient ϕ_3 measures the extent to which, within industries, capital flows toward firms characterized by a high marginal productivity of capital. The estimates are qualitatively similar to the baseline results, confirming that storms have differential impacts on fixed assets across industries but not between firms within industries.

[Table 6 here]

Results on firm sales The remainder of Table 6 analyzes firm-industry sales. Column (6) examines whether the reallocation of capital toward comparative advantage industries is reflected in the pattern of production. The estimate on the storm index and the interaction term are both precisely estimated. Taken together, these estimates indicate that the negative impact of storms on sales is disproportionately larger for firms producing in industries characterized by a relatively lower comparative advantage, which is consistent with our results on capital. This result is also in line with Pelli & Tschopp (2017) and indicates that firms replace destroyed capital by putting more weight on reconstruction in better-performing industries, shifting production toward the top of the distribution of comparative advantages.

Next, we study the heterogeneity of the effect within industry, including only the interaction term between TFP and firm exposure to storms. Both estimates are statistically significant and imply that, within industry, the response of sales to storms is monotonically increasing in productivity, with sales shrinking relatively less or even growing at the top of the productivity distribution. This result is in line with heterogeneous firms frameworks where continuing firms respond differentially to an industry-wide shock. Movements within industries may also be compounded by the exit of the least productive firms; however, our data do not allow us to examine this margin of adjustment.

Finally, column (8) estimates equation (2) and confirms that patterns of production shifts toward comparative advantage industries and, within industries, toward more productive firms. Standardized coefficients suggest that both adjustment margins are similar.[34] The estimates of column (8) imply that for the median firm (in terms of both TFP and comparative advantage), an average

[34] Standardized results are available upon request. Also note that the results stay the same if we exclude firms that are never affected by tropical storms.

storm exposure (0.027) causes a 5% drop in sales.[35] For a storm at the 75th (90th) percentile of the distribution, these estimates imply a 3% (15%) decrease in firms' industry sales.[36] In the last two columns we use our alternative measure of firm quality and obtain results qualitatively similar to our baseline estimates.

In Figure F.2 of Section F of the Online Appendix we use the estimates obtained in column (8) to illustrate the marginal effects of a storm by comparative advantage and TFP level. The figure shows that the change in a firm's industry sales resulting from a storm of mean intensity varies between –15% and 17%, depending on a firm's TFP level and the industry in which it operates. The figure also suggests that producing in an industry with high comparative advantage can more than compensate for the negative effect associated with a low productivity and even lead to a positive marginal effect. Similarly, it appears that a high productivity level can shelter a firm from the negative effects of operating in an industry with a relatively low Balassa index of revealed comparative advantage.

Robustness For brevity, we present details of all our robustness tests in the Online Appendix. In Section A of the Online Appendix we explore the sensitivity of our main results to other specifications of the storm index. We first use a cubic relationship between the energy released by a storm and the force exerted on physical structures. We then move the wind speed threshold up to 50 and 64 knots and replace the storm index by wind speed. We also present estimates obtained when wind speed is computed using different wind field models. These alternative measures of storm exposure yield similar results.

In Section B of the Online Appendix we perform another set of robustness checks. We first evaluate whether our results are driven by the strongest storms and then examine the eventuality of an attenuation bias resulting from the storms' timing. We next examine whether our results are driven by local demand effects. Since non-exporters tend to operate in industries that have relatively lower comparative advantage, our baseline estimate of ϕ_2 may reflect the negative effects of storms on local demand, as a fall in demand would lower the sales of firms selling to the local market while leaving exporters unaffected. We also explore whether our effects capture pre-existing local trends that may be exacerbated by storms and implement a stricter specification using firm FE. If wind speeds are as good as randomly assigned, our baseline results should hold without controlling for lagged TFP and night-light growth, conditional on firm FE, year FE, and district trends. Including firm FE also allows us to rule out other mechanisms related to unobserved firm

[35] This result is obtained as follows: $[-5.92 + (0.750 * 0.92) + (0.785 * 4.24)] * 0.027 * 100$, using median comparative advantage (0.750) and median TFP (0.785). The average of storm exposure is computed conditional on positive values.

[36] $-190 * 0.0156$ for a storm at the 75th percentile and $-190 * 0.0794$ for a storm at the 90th percentile of the distribution.

characteristics. For instance, if credit access determines a firm's capacity to rebuild and comparative advantage correlates with access to external finance, then our results may be driven by firms' financial constraints. Finally, we also show results based on the full sample of firms, run a series of placebo regressions, and consider possible non-linearities.

The sample we use for the heterogeneity analysis includes only positive values of sales and therefore reflects adjustments at the intensive margin. In Section C of the Online Appendix we study the extensive margin in terms of entry and exit of four-digit ISIC industry lines (our data do not allow us to investigate firm entry and exit) and find no effects of storms on entry and exit. Instead, our findings suggest that firms adjust by reallocating production among existing industry lines, toward products that align better with comparative advantage.

In Section D of the Online Appendix we examine the role of capital intensity. In fact, capital-intensive industries should be hit harder and are likely to go through greater reorganizations of their production structure. As expected, our results indicate that low comparative advantage industries with high capital intensity experience the largest drops in production, while high comparative advantage industries with low capital intensities exhibit positive sales growth.

5.2 Dynamics Effects by Industry Quality

Results on firm capital We have shown that storms have heterogeneous effects on firms' capital by industry quality. In this section we focus on the dynamics of these effects by running the following specification:

$$y_{ft} = \chi + \sum_{j=0}^{k} \chi_j H_{ft-j} + \sum_{j=0}^{k} \psi_j \left(CA_{it-j} \times H_{ft-j}\right) + \theta \left(TFP_{f(t-1)} \times H_{ft}\right) + \boldsymbol{V\eta} + u_{ft}^{LAG}, \quad (3)$$

where $k \in (0, 2)$, meaning that we include up to two lags of the storm measure and their interaction with comparative advantage. The results are reported in columns (2) and (3) of Table 7, where we introduce lags gradually. Two findings stand out: the estimate of the coefficient on the first lag of $CA_{it} \times H_{ft}$ is positive and precisely estimated, and there is no effect on the second lag. Hence, capital reconstruction is relatively larger in comparative advantage industries, and it occurs fast, within the year of the storm and in the following year.[37] In the last two columns we replace the measure of firm quality by the firm MRPK and obtain qualitatively similar results.

[Table 7 here]

[37]Note that the coefficients become imprecisely estimated if we include always-multi-ISIC firms in the sample, which is in line with the idea that these firms have more durable capital. The results are available upon request.

Results on firm sales In Table 8 we add to equation (2) one lag of the storm measure and its interaction with comparative advantage. The contemporaneous coefficients are similar to the baseline estimates. As expected, the impact of a storm on sales occurs mainly on impact: the coefficient on the lag of the storm measure is still negative, albeit smaller in magnitude and imprecisely estimated. By contrast, we still observe an adjustment across industries in the first year following the strike. The coefficient on the lagged interaction term is smaller in size, roughly a half of the contemporaneous one, but is still positive and statistically significant at the 5% level. This result shows that firms, especially those hit toward the end of the year, may take up to one year after the storm to completely reorganize their production structure.[38] The last two columns show a similar picture using the firm MRPK as an alternative to TFP.

[Table 8 here]

6 Concluding Remarks

This paper examines the response of manufacturing firms to tropical cyclones in India. We investigate the impact of cyclones on firms' fixed assets and sales, study how long it takes for firms to rebuild and reboot, examine whether capital destruction causes firms to adapt to changes in the economic environment, and unravel some of the adjustment mechanisms, within and across industries.

We use firm-level panel data between 1995 and 2006 from Prowess and match it with data on tropical storms and cyclones from NOAA. Using the googleplaces algorithm, we locate the establishments of each of the firms in the dataset and construct a precise measure of firm exposure to storms. We then quantify the reaction of fixed assets and sales and find that the effect of storms is short-lived. We also find evidence of adjustment channels consistent with a build back better mechanism. Across industry, we find that sales shift toward higher quality industries, confirming the results of Pelli & Tschopp (2017). Within industry, we find that the sales of less productive firms are affected relatively more. These two effects are similar in size. Moreover, there is no evidence that firms adjust to capital destruction by investing in new industry lines. Our results are driven to a large extent by shifts in the firm-level production mix within an existing set of industries.

Our estimates are lower bounds on reallocation since, by the very nature of the firms in our sample, even the low-performing firms are relatively efficient. Since the Prowess dataset includes

[38]Including all firms in the sample in column (4) leads to a similar conclusion. The results are available upon request.

all listed companies and their subsidiaries plus a certain number of unlisted companies (inclusion depends on the availability of quarterly and yearly statements), less established firms, small businesses, and the informal sector are not captured. The results indicate that for smaller and more vulnerable firms, the adjustment after a hurricane is more important.[39] Moreover, including always-multi-ISIC firms in the baseline estimation reduces the coefficient on the adjustment across industries by half. Hence, we expect that expanding the Prowess sample to include smaller businesses would lead to larger reallocation effects.

[39]Note that it is unlikely that the results are impacted by differential firm entry and exit for the following reasons. First, we do not expect the typical firm in our sample to be completely wiped out after a storm since the Prowess dataset is selected toward the largest, most productive firms, and even the low-performing firms are relatively efficient. In line with this idea, baseline estimates indicate that firm fixed assets drop by 4% and sales by about 5% following the average storm, suggesting that, on average, firms do not disappear after a storm. Second, the results suggest that the adjustments occur essentially at the intensive margin. Hence, if a firm's set of industry lines is not impacted, it is unlikely that storms would have an effect on that firm's exit rate.

References

Ackerberg, D., Caves, K., & Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, 83, 2411–2451.

Albrizio, S., Kozluk, T., & Zipperer, V. (2017). Environmental Policies and Productivity Growth: Evidence across Industries and Firms. *Journal of Environmental Economics and Management*, 81, 209–226.

Anttila-Hughes, J. K. & Hsiang, S. M. (2013). *Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster*. Working paper.

Arouri, M., Nguyen, C., & Youssef, A. (2015). Natural DIsasters, Household Welfare, and Resilience: Evidence from Rural Vietnam. *World Development*, 70, 59–77.

Basker, E. & Miranda, J. (2018). Taken by Storm: Business Financing and Survival in the Aftermath of Hurricane Katrina. *Journal of Economic Geography*, 18(6), 1285–1313.

Bau, N. & Matray, A. (2020). *Misallocation and Capital Market Integration: Evidence from India*. Working Paper 2, NBER.

Baxter, M. (1992). Fiscal Policy, Specialization, and Trade in the Two-Sector Model: the Return of Ricardo? *Journal of Political Economy*, 100, 713–744.

Belasen, A. & Polachek, S. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *American Economic Review*, 98(2), 49–53.

Bertinelli, L. & Strobl, E. (2013). Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean. *Journal of Applied Meteorology and Climatology*, 52(8), 1688–1697.

Boose, E. R., Serrano, M., & Foster, D. R. (2004). Landscape and Regional Impacts of Hurricanes in Puerto Rico. *Ecological Monographs*, 74(2), 335–352.

Botzen, W., Deschene, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, 13(2), 167–188.

Boustan, L., Kahn, M., Rhode, P., & Yanguas, M. (2020). The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data. *Journal of Urban Economics*, 118, 103257.

Bui, A., Dungeu, M., Nguyen, C., & Pham, T. (2014). The Impact of Natural Disasters on Household Income, Expenditure, Poverty and Inequality: Evidence from Vietnam. *Applied Economics*, 46(15), 1751–1766.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic Natural Disasters and Economic Growth. *The Review of Economics and Statistics*, 95(5), 1549–1561.

Cavallo, E. A. & Noy, I. (2010). *The Economics of Natural Disasters: A Survey*. Technical report, IDB.

Cuaresma, J., Hlouskova, J., & Obersteiner, M. (2008). Natural Disasters As Creative Destruction? Evidence From Developing Countries. *Economic Inquiry*, 46(2), 214–226.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, Markups, and Trade Reform. *Econometrica*, 84(2), 445–510.

Dell, M., Jones, B., & Olken, B. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature*, 52(3), 740–98.

Deppermann, C. (1947). Notes on the Origin and Structure of Philippine Typhoons. *Bulletin of the American Meteorological Society*, 28(9), 399–404.

Deryugina, T. (2017). The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy*, 9(3), 168–198.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns. *American Economic Journal: Applied Economics*, 10(2), 202–233.

Dessaint, O. & Matray, A. (2017). Do Managers overreact to Salient Risks? Evidence from Hurricane Strikes. *Journal of Financial Economics*, 126(1), 97–121.

Elliott, E., Strobl, E., & Sun, P. (2015). The Local Impact of Typhoons on Economic Activity in China: A View from Outer Space. *Journal of Urban Economics*, 88, 50–66.

Elliott, R., Liu, Y., Strobl, E., & Tong, M. (2019). Estimating the Direct and Indirect Impact of Typhoons on Plant Performance: Evidence from Chinese Manufacturers. *Journal of Environmental Economics and Management*, 98, 102252.

Elsner, J. & Bossak, B. (2001). Bayesian Analysis of U.S. Hurricane Climate. *Journal of Climate*, 14, 4341–4350.

Emanuel, K. (2005). Increasing Destructiveness of Tropical Cyclones over the Past 30 Years. *Nature*, 436(7051), 686–688.

Emanuel, K. (2011). Global Warming Effects on U.S. Hurricane Damage. *Weather, Climate, and Society*, 3(4), 261–268.

Emanuel, K. (2021). Response of Global Tropical Cyclone Activity to Increasing CO2: Results from Downscaling CMIP6 Models. *Journal of Climate*, 34, 57–70.

Gallagher, J. & Hartley, D. (2017). Household Finance after a Natural Disaster: The Case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9(3), 199–228.

Gilchrist, S. & Williams, J. (2005). Investment, Capacity, and Uncertainty: a Putty-Clay Approach. *Review of Economic Dynamics*, 8, 1–27.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., & Topalova, P. (2010). Multiproduct Firms and Product Turnover in the Developing World: Evidence from India. *Review of Economics and Statistics*, 92(4), 1042–1049.

Groen, J., Kutzbach, M., & Polivka, A. (2020). Storms and Jobs: The Effect of Hurricanes on Individuals' Employment and Earnings over the Long Term. *Journal of Labor Economics*, 38(3).

Groen, J. & Polivka, A. (2008). The Effect of Hurricane Katrina on the Labor Market Outcomes of Evacuees. *American Economic Review Papers and Proceedings*, 98(2), 43–48.

Hallegatte, S. (2007). The Use of Synthetic Hurricane Tracks in Risk Analysis and Climate Change Damage Assessment. *Journal of Apllied Meteorology and Climatology*, 46, 1956–1966.

Hallegatte, S. (2012). The Rising Costs of Hurricanes. *Natural Climate Change*, 2, 148–149.

Hallegatte, S. & Dumas, P. (2009). Can Natural Disasters Have Positive Consequences? Investigating the Role of Embodied Technical Change. *Ecological Economics*, 68, 777–786.

Hallegatte, S., Rentschler, J., & Walsh, B. (2018). *Building Back Better: Achieving resilience through stronger, faster, and more inclusive post-disaster reconstruction*. Technical report, IBRD, The World Bank.

Henderson, J., Storeygard, A., & Weil, D. (2012). Measuring Economic Growth from Outer Space. *American Economic Review*, 102(2), 994–1028.

Holland, G. J. (1980). An Analytical Model of the Wind and Pressure Profiles in Hurricanes. *Monthly Weather Review*, 108, 1212–1218.

Hsiang, S. & Jina, A. (2014). *The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones*. NBER Working Papers 20352, National Bureau of Economic Research, Inc.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of Sciences*, 107(35), 15367–15372.

Hsiang, S. M. & Narita, D. (2012). Adaptation to Cyclone Risk: Evidence from the Global Cross-Section. *Climate Change Economics*, 3(2), 1–28.

Hsu, S. & Zhongde, Y. (1998). A Note on the Radius of Maximum Wind for Hurricanes. *Journal of Coastal Research*, 14(2), 667–668.

Ishise, H. (2016). Capital Heterogeneity as a Source of Comparative Advantage: Putty-Clay Technology in a Ricardian Model. *Journal of International Economics*, 99, 223–236.

Karim, A. (2018). The Household Response to Persistent Natural Disasters: Evidence from Bangladesh. *World Development*, 103, 40–59.

Keerthiratne, S. & Tol, R. (2018). Impact of Natural Disasters on Income Inequality in Sri Lanka. *World Development*, 105, 217–230.

Levchenko, A. (2007). Institutional Quality and International Trade. *Review of Economic Studies*, 74(3), 791–819.

Levinsohn, J. & Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, 70(2), 317–341.

Lindell, M., Prater, C., & Perry, R. (2007). *Introduction to Emergency Management*. Wiley.

McIntosh, M. (2008). Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas. *American Economic Review*, 98(2), 54–57.

Mendelsohn, R., Emanuel, K., Chonabayashi, S., & Bakkensen, L. (2012). The Impact of Climate Change on Global Tropical Cyclone Damage. *Nature Climate Change*, 2, 205–209.

Miguel, E. & Roland, G. (2011). The Long-Run Impact of Bombing Vietnam. *Journal of Development Economics*, 96(1), 1–15.

Naguib, C., Poirier, D., Pelli, M., & Tschopp, J. (2022). The Impact of Cyclones on Local Economic Growth: Evidence from Local Projections. *Economic Letters*, 220, 110871.

Noy, I. (2009). The Macroeconomic Consequences of Disasters. *Journal of Development Economics*, 88, 221–231.

Nunn, N. (2007). Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade. *The Quarterly Journal of Economics*, 122(2), 569–600.

Olley, G. & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6), 1263–1297.

Pelli, M. & Tschopp, J. (2017). Comparative Advantage, Capital Destruction, and Hurricanes. *Journal of International Economics*, 108, 315–337.

Petkov, I. (2018). *Weather Shocks, Housing Prices, and Population: the Role of Expectation Revisions*. mimeo.

Pielke, R., Landsea, C., Mayfield, M., Laver, J., & Pasch, R. (2008). Hurricanes and Global Warming. *American Meteorological Society*, (pp. 1571–1575).

Raddatz, C. (2007). Are External Shocks Responsible for the Instability of Output in Low-Income Countries? *Journal of Development Economics*, 84(1), 155–187.

Rajan, R. & Zingales, L. (1998). Financial Dependence and Growth. *American Economic Review*, 88(3), 559–86.

Redding, S. (1999). Dynamic Comparative Advantage and the Welfare Effects of Trade. *Oxford Economic Papers*, 51, 15–39.

Rovigatti, G. & Mollisi, V. (2016). PRODEST: Stata module for production function estimation based on the control function approach. Statistical Software Components, Boston College Department of Economics.

Sacerdote, B. (2012). When the Saints Go Marching Out: Long-Term Outcomes for Student Evacuees from Hurricanes Katrina and Rita. *American Economic Journal: Applied Economics*, 4(1), 109–35.

Scott, P., Stone, D., & Allen, M. (2004). Human Contribution to the European Heatwave of 2003. *Nature*, 432, 610–614.

Sedova, B., Kalkuhl, M., & Mendelsohn, R. (2020). Distributional Impacts of Weather and Climate in Rural India. *Economics of Disasters and Climate Change*, 4, 5–44.

Seetharam, I. (2018). *The Indirect Effects of Hurricanes: Evidence from Firm Internal Networks*. mimeo.

Simpson, R. & Riehl, H. (1981). *The Hurricane and Its Impact*. Louisiana State University Press.

Skidmore, M. & Toya, H. (2002). Do Natural Disasters Promote Long-Run Growth? *Economic Inquiry*, 40(4), 664–687.

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *The Review of Economics and Statistics*, 93(2), 575–589.

Topalova, P. & Khandelwal, A. (2011). Trade Liberalization and Firm Productivity: The Case of India. *The Review of Economics and Statistics*, 93(3), 995–1009.

Vu, T. B. & Noy, I. (2018). Natural Disasters and Firms in Vietnam. *Pacific Economic Review*, 23(3), 426–452.

Warr, P. & Aung, L. (2019). Poverty and Inequality impact of a Natural Disaster: Myanmar's 2008 Cyclone Nargis. *World Development*, 122, 446–461.

Webster, P., Holland, G., Curry, J., & Chang, H.-R. (2005). Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment. *Science*, 309(5742), 1844–1846.

Wu, H. & Lindell, M. (2014). *Perceptions on Hurricane Information and Protective Action Decisions*. Technical report, XVIII ISA World Congress of Sociology.

Tables

Table 1: Summary Statistics (All Firms)

Variable	Mean	Std. dev.	Min.	Max.	N
Firm buildings (real)	3.352	22.138	0.001	879.599	22,192
Firm land (real)	1.174	8.573	0.001	588.682	21,331
Firm electrical equipment (real)	0.456	4.445	0.001	270.979	10,243
Firm fixed assets (real)	23.628	202.998	0.002	11169.715	22,924
Firm salaries (real)	2.644	18.411	0	1101.175	22,322
Firm sales at the ISIC level (real)	40.151	591.806	0.002	41518.016	35,105
Firm TFP	0.801	0.474	0	19.075	35,105
Industry-year comparative advantage	1.575	2.162	0	24.346	35,105
District-year night-light growth	1.015	0.183	0.363	2.677	35,105
Firm exposure to storms	0.002	0.017	0	0.525	35,105
Firm exposure to storms if $H_{ft} > 0$	0.02	0.054	0	0.525	3,288

Note: Buildings, land, electrical equipment, fixed assets, salaries, and sales are expressed in crores (10 million) of Rs and are deflated using the industry-level price gross output, base year 2005.

Table 2: Balance Tests

Year	Mean cyclone	Mean no cyclone	Difference
Panel A: Fixed assets			
1999	10.696	9.942	-0.754
2001	11.789	10.36	-1.429
2002	8.227	8.879	0.651
Panel B: Sales			
1996	16.211	11.013	-5.197
1997	11.024	12.677	1.652
1998	8.695	15.56	6.865
1999	26.833	14.989	-11.844*
2000	11.35	10.777	-0.573
Panel C: TFP			
1996	0.805	0.921	0.116*
1997	0.906	0.902	-0.003
1998	0.872	0.896	0.024
1999	0.833	0.857	0.024
2000	0.957	0.831	-0.126***
Panel D: Balassa index			
1996	11.233	1.303	-9.93
1997	0.301	1.709	1.408
1998	1.379	1.783	0.404
1999	0.158	1.795	1.637
2000	0.72	1.836	1.115

Note: We report averages for firms hit by cyclones and firms not hit. For instance, row 1996 compares data up to 1996 for all the firms hit in 1997 (but not before) to data for firms that have not been hit up to 1997. Since the Balassa index is not a firm-specific variable but instead industry specific, in Panel D we perform the same comparison but only include single-ISIC firms.

Table 3: How Much Damage Do Storms Do?

	Buildings_{ft}	Land_{ft}	Electricity_{ft}	Fixed assets_{ft}	Salaries_{ft}	Sales_{fit}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Storms_{ft}	-1.19**	-0.76*	-2.99***	-1.09**	-0.26	-1.56**
	(0.49)	(0.44)	(0.86)	(0.50)	(0.22)	(0.66)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,047	21,183	10,052	22,781	22,166	34,886

	Fixed assets_{ft}		Salaries_{ft}		Sales_{fit}	
	Only always multi-ISIC	Excl. always-multi-ISIC	Only always multi-ISIC	Excl. always-multi-ISIC	Only always multi-ISIC	Excl. always-multi-ISIC
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B:						
Storms_{ft}	1.60	-1.42**	0.077	-0.31	-1.04	-1.67**
	(1.86)	(0.57)	(0.82)	(0.20)	(1.98)	(0.81)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,618	14,936	7,460	14,489	16,703	17,952

Note: Standard errors are two-way clustered at the firm and district-year level. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes a postal code, and d a district. In column (1), the dependent variable is the log of firm net buildings. $\textit{Land}_{ft}$ refers to the log of firm net land, $\textit{Electricity}_{ft}$ to the log of firm net electrical installations and fittings, $\textit{Fixed assets}_{ft}$ to the log of firm net fixed assets, and $\textit{Salaries}_{ft}$ to the log of firm real salaries. $\textit{Sales}_{fit}$ is the log of firm sales in industry i at time t. In Panel A, the sample includes all firms. In columns (7), (9), and (11) of Panel B, the sample consists of always-multi-ISIC firms, and in columns (8), (10), and (12) always-multi-ISIC firms are excluded from the sample. Controls, FE, and trends include the following: $\text{TFP}_{f(t-1)}$, night-light $\text{growth}_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, and district trends. The sales regressions also include postal code FE.

Table 4: Summary Statistics by Firm Type

Variable	Mean	Std. dev.	Min.	Max.	N
Always-multi-ISIC firms:					
Firm buildings (real)	6.225	36.012	0.002	879.599	7,608
Firm land (real)	2.073	11.798	0.002	280.551	7,355
Firm electrical equipment (real)	0.897	7.81	0.002	270.979	3,180
Firm fixed assets (real)	45.202	331.431	0.003	11169.715	7,817
Firm salaries (real)	5.484	30.782	0.002	1101.175	7,655
Firm sales at the ISIC level (real)	63.4	847.995	0.002	41518.016	16,872
Firm TFP	0.79	0.518	0	19.075	16,872
Industry-year comparative advantage	1.519	2.09	0	24.346	16,872
Excluding always-multi-ISIC firms:					
Firm buildings (real)	1.854	7.917	0.001	268.644	14,584
Firm land (real)	0.701	6.187	0.001	588.682	13,976
Firm electrical equipment (real)	0.257	1.034	0.001	20.41	7,063
Firm fixed assets (real)	12.464	73.013	0.002	1908.504	15,107
Firm salaries (real)	1.163	3.869	0	132.891	14,667
Firm sales at the ISIC level (real)	18.637	89.241	0.002	5661.934	18,233
Firm TFP	0.812	0.43	0	11.215	18,233
Industry-year comparative advantage	1.627	2.226	0	24.346	18,233
District-year night-light growth	1.017	0.188	0.363	2.677	18,233
Firm exposure to storms	0.002	0.021	0	0.525	18,233
Firm exposure to storms if $H_{ft} > 0$	0.027	0.066	0	0.525	1,593

Note: Buildings, land, electrical equipment, fixed assets, salaries, and sales are expressed in crores (10 million) of Rs and are deflated using the industry-level price gross output, base year 2005.

Table 5: How Long Does it Take for Firms to Rebuild and Reboot?

	Buildings$_{ft}$				Land$_{ft}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storms$_{ft}$	-1.54***	-1.57***	-1.76***	-1.82***	-1.55***	-1.56***	-1.71***	-1.83***
	(0.48)	(0.49)	(0.42)	(0.44)	(0.46)	(0.47)	(0.57)	(0.69)
Storms$_{f(t-1)}$		-0.69	0.015	0.26		-0.24	-0.44	-0.070
		(0.57)	(0.69)	(0.70)		(0.48)	(0.67)	(0.87)
Storms$_{f(t-2)}$			-0.094	-0.094			0.026	-0.44
			(0.20)	(0.32)			(0.28)	(0.42)
Storms$_{f(t-3)}$				-0.22				0.038
				(0.30)				(0.32)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,407	14,407	11,665	9,736	13,794	13,794	11,203	9,363

	Electricity$_{ft}$				Fixed assets$_{ft}$			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Storms$_{ft}$	-2.48***	-2.51***	-1.93*	-1.88	-1.42**	-1.46**	-1.32**	-1.41**
	(0.86)	(0.88)	(1.01)	(1.33)	(0.57)	(0.58)	(0.52)	(0.62)
Storms$_{f(t-1)}$		-0.32	-1.48	-0.51		-0.81	-0.30	-0.077
		(0.86)	(1.21)	(1.58)		(0.71)	(0.89)	(0.95)
Storms$_{f(t-2)}$			-0.39*	-0.66*			0.063	0.14
			(0.22)	(0.39)			(0.26)	(0.39)
Storms$_{f(t-3)}$				-0.28				-0.099
				(0.36)				(0.29)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,862	6,862	5,460	4,492	14,936	14,936	12,040	9,996

	Sales			
	(17)	(18)	(19)	(20)
Storms$_{ft}$	-1.67**	-1.64*	-0.83	-2.32*
	(0.81)	(0.85)	(1.02)	(1.21)
Storms$_{f(t-1)}$		0.14	0.49	1.27
		(0.59)	(0.91)	(1.11)
Storms$_{f(t-2)}$			-0.90*	-0.49
			(0.52)	(0.68)
Storms$_{f(t-3)}$				-0.77
				(0.50)
Controls, FE, and trends	Yes	Yes	Yes	Yes
Observations	17,952	17,952	14,324	11,805

Note: Standard errors are two-way clustered at the firm and district-year level. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes a postal code, and d a district. In columns (1)–(4), the dependent variable is the log of firm net buildings. *Land*$_{ft}$ refers to the log of firm net land, *Electricity*$_{ft}$ to the log of firm net electrical installations and fittings, *Fixed assets*$_{ft}$ to the log of firm net fixed assets, and *Salaries*$_{ft}$ to the log of firm real salaries. *Sales*$_{fit}$ is the log of firm sales in industry i at time t. All the specifications exclude always-multi-ISIC firms from the sample. Controls, FE, and trends include the following: TFP$_{f(t-1)}$, night-light growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, and district trends. The sales regressions also include postal code FE.

Table 6: Heterogeneous Impacts by Firm and Industry Quality

	Fixed assets$_{ft}$					Sales$_{fit}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Storms$_{ft}$	-2.63***	-0.21	-1.48	-1.02**	-2.22**	-2.82***	-4.96***	-5.92***	-2.33***	-3.37***
	(0.95)	(1.32)	(1.47)	(0.49)	(0.89)	(0.86)	(1.38)	(1.33)	(0.82)	(0.86)
Comp. adv.$_{it}$ $\times$ Storms$_{ft}$	0.85***		0.84***		0.85***	0.98***		0.92**		0.90**
	(0.32)		(0.32)		(0.29)	(0.36)		(0.39)		(0.39)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$		-1.74	-1.64				4.41***	4.24***		
		(1.69)	(1.73)				(1.48)	(1.34)		
MRPK$_{f(t-1)}$ $\times$ Storms$_{ft}$				-0.098	-0.099*				0.13***	0.13***
				(0.063)	(0.053)				(0.025)	(0.036)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,936	14,936	14,936	14,909	14,909	17,952	17,952	17,952	17,946	17,946

Note: Standard errors are three-way clustered at the firm, district-year, and industry-year levels in columns (1), (3), (5), (6), (8), and (10) and are two-way clustered at the firm and district-year level in columns (2), (4), (7), and (9). *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes a postal code, and d a district. *Fixed assets*$_{ft}$ refers to the log of firm net fixed assets, and *Sales*$_{fit}$ is the log of firm sales in industry i at time t. All the specifications exclude always-multi-ISIC firms from the sample. Controls, FE, and trends include the following: TFP$_{f(t-1)}$, night-light growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, and district trends. In columns (4), (5), (9), and (10) MRPK$_{f(t-1)}$ also belongs to the set of controls. Additionally, the sales regressions control for postal code FE.

Table 7: Heterogeneous Impacts of Reconstruction on Fixed Assets

	Fixed assets$_{ft}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Storms$_{ft}$	-1.48	-1.60	-2.10	-2.22**	-2.28**	-2.27**
	(1.47)	(1.49)	(1.83)	(0.89)	(0.91)	(0.97)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.84***	0.87***	0.67	0.85***	0.87***	0.68*
	(0.32)	(0.32)	(0.43)	(0.29)	(0.29)	(0.40)
TFP$_{f(t-1)}$ × Storms$_{ft}$	-1.64	-1.55	-0.34			
	(1.73)	(1.75)	(2.25)			
MRPK$_{f(t-1)}$ × Storms$_{ft}$				-0.099*	-0.098*	-0.012
				(0.053)	(0.052)	(0.023)
Storms$_{f(t-1)}$		-1.44*	-1.34		-1.41*	-1.22
		(0.79)	(1.05)		(0.77)	(1.00)
Comp. adv.$_{i(t-1)}$ × Storms$_{f(t-1)}$		0.33*	0.74**		0.33*	0.66**
		(0.18)	(0.30)		(0.17)	(0.30)
Storms$_{f(t-2)}$			0.098			0.18
			(0.46)			(0.48)
Comp. adv.$_{i(t-2)}$ × Storms$_{f(t-2)}$			-0.016			-0.027
			(0.14)			(0.13)
Controls, FE, and trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,936	14,936	12,040	14,909	14,909	12,017

Note: Standard errors are three-way clustered at the firm, district-year, and industry-year levels in columns. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes a postal code, and d a district. The dependent variable is the log of firm net fixed assets. All the specifications exclude always-multi-ISIC firms from the sample. Controls, FE, and trends include the following: TFP$_{f(t-1)}$, night-light growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, and district trends. In columns (4)–(6) MRPK$_{f(t-1)}$ also belongs to the set of controls.

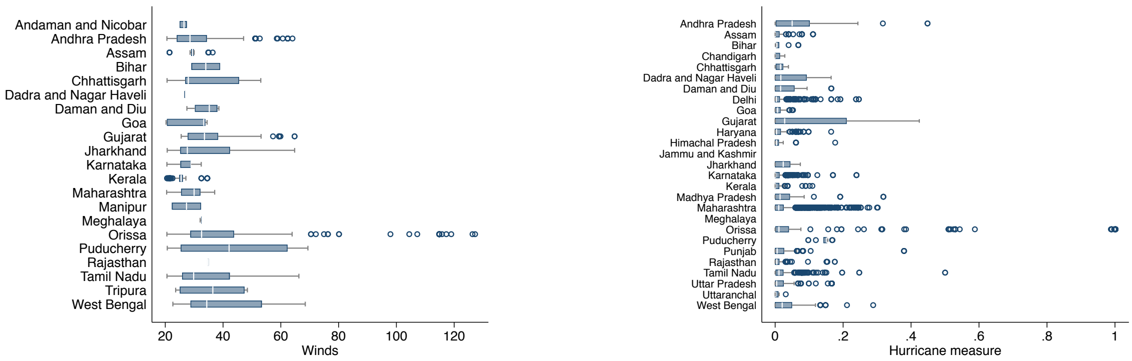
Table 8: Heterogeneous Impacts of Reconstruction on Sales

	Sales$_{fit}$			
	(1)	(2)	(3)	(4)
Storms$_{ft}$	-5.92***	-6.13***	-3.37***	-3.54***
	(1.33)	(1.39)	(0.86)	(0.92)
Comp. adv.$_{\cdot it}$ $\times$ Storms$_{ft}$	0.92**	1.07**	0.90**	1.05**
	(0.39)	(0.42)	(0.39)	(0.42)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$	4.24***	4.30***		
	(1.34)	(1.36)		
MRPK$_{f(t-1)}$ $\times$ Storms$_{ft}$			0.13***	0.13***
			(0.036)	(0.036)
Storms$_{f(t-1)}$		-1.02		-1.08
		(0.75)		(0.74)
Comp. adv.$_{\cdot i(t-1)}$ $\times$ Storms$_{f(t-1)}$		0.57**		0.57**
		(0.24)		(0.23)
Controls, FE, and trends	Yes	Yes	Yes	Yes
Observations	17,952	17,952	17,946	17,946

Note: Standard errors are three-way clustered at the firm, district-year, and industry-year levels in columns. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j\in J}, p, d)$, where J is the set of industries in which firm f operates, p denotes a postal code, and d a district. The dependent variables is the log of firm sales in industry i at time t. All the specifications exclude always-multi-ISIC firms from the sample. Controls, FE, and trends include the following: TFP$_{f(t-1)}$, night-light growth$_{d(t-1)}$, # of establishments, firm-type FE, postal code FE, industry-year FE, and district trends. In columns (3) and (4) MRPK$_{f(t-1)}$ also belongs to the set of controls.

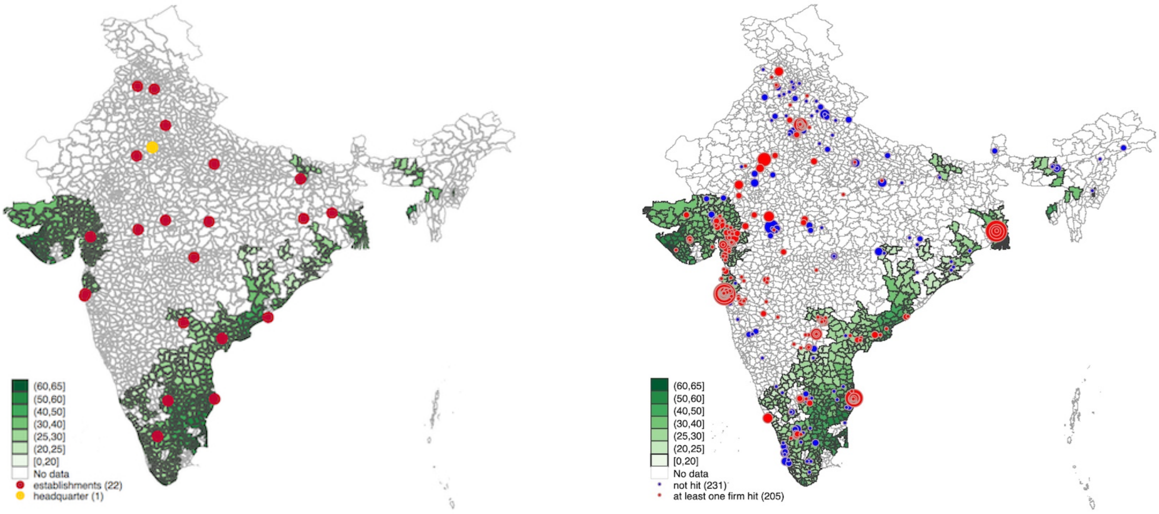
Figures

Figure 1: Winds and Firm Exposure to Storms, 1995–2006



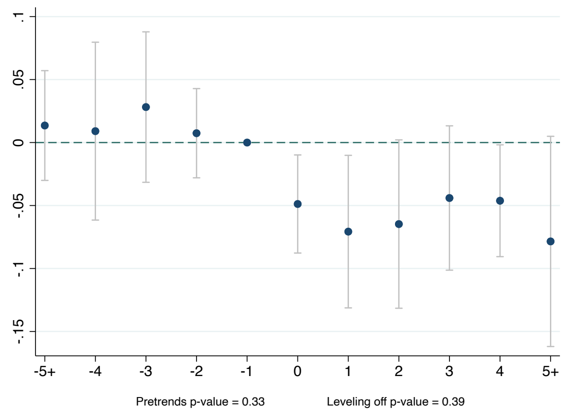
Note: The left (right) boxplot describes w_{ph} (H_{ft}) by state for the period 1995–2006. States with $w_{ph} > 0$ and $H_{ft} > 0$ between 1995 and 2006 are listed in ascending alphabetical order. The white line is the median. The left side of the box is the first quartile ($Q1$ or 25th percentile) and the right the third quartile ($Q3$ or 75th percentile). The end of the left (right) whisker is the 1st percentile (99th percentile). Circles without a box mean that all observations are clustered around the median. The circles outside of the box capture outliers.

Figure 2: Winds and Firms, 1998

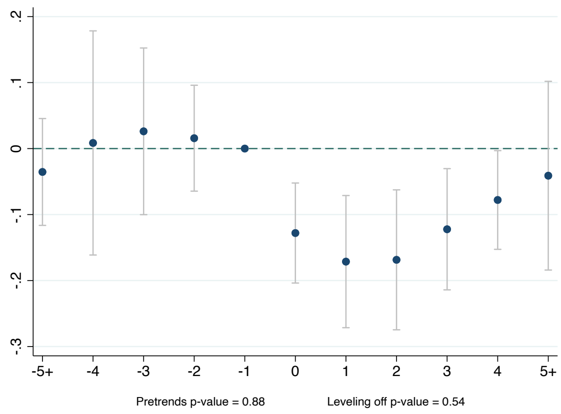


Note: The left panel shows the establishments' location of the company Steel Authority of India. The yellow dot denotes the headquarters, and the red dots denote the establishments. The green areas represent postal codes affected by wind speed (w_{ph}) of various intensities in 1998. The right panel shows the location of each of the firms included in Prowess in 1998 and highlights the areas and firms affected by storms. The green areas represent postal codes affected by wind speeds of various intensities, and circles represent clusters of headquarters. The diameter of the circles is proportional to the number of headquarters in a postal code. A red (blue) circle indicates that the measure of firms' exposure to storms, H_{ft}, is positive (zero), which occurs if at least one (none) of the establishments of the firm is affected by wind speeds above 33 knots. Prowess contains 677 active firms in 1998. The set of postal codes in which these firms are located contains 436 distinct postal codes; 315 firms (205 postal codes) were affected by storms (i.e., $H_{ft} > 0$).

Figure 3: Event Study



(a) Fixed assets (logs)



(b) Sales (logs)

Notes: The figure shows the event study graph for the average effects of storms on firms' fixed assets (left panel) and sales (right panel). The normalization takes place at $t = -1$, the year before the event. The pre-trends p-value is for the null hypothesis of no pre-trends, and the leveling-off p-value is for the null hypothesis that the dynamics have leveled off by the end of the window period. The confidence interval is at the 95% level.

A Appendix: Data

A.1 Product Classification

Prowess reports sales at both the product and firm level. Sales at the product level are reported using the CMIE product codes. In addition, the database reports the National Industrial Classification (NIC) 2008 product codes for the main product (largest sales in value) reported last by the firm. NIC codes coincide with the ISIC Rev. 4 up to the four-digit level.[40] To assign NIC codes to the rest of the products produced, we use the crosswalk between the CMIE product code of the main product last reported and the NIC industry code provided by CMIE. This approach allows us to match about 50% (2,091 codes out of 4,037) of the CMIE product codes to NIC industry codes. We then assign the remainder of the product codes by hand (1,946 out of 4,037 product codes).[41]

Table E.4 of Section E of the Online Appendix provides an illustration of how we assign CMIE products to NIC codes for division 13 "Manufacture of textiles." The first and second columns give NIC industry and CMIE product codes, respectively. The last column provides a description of the product identified by each of the codes. The superscript p denotes product codes that were assigned by the CMIE crosswalk, and a denotes codes that were assigned by hand. Consider, for instance, the bottom panel of the table. Product code 603070615000 "Sarees" was assigned by the CMIE crosswalk as corresponding to NIC 13919 "Manufacture of other knitted and crocheted fabrics." However, the CMIE crosswalk did not assign any NIC to product 603070605000 "Dhoties." Since "Dhoties" are male versions of "Sarees," we assign code 603070605000 to NIC 13919 as well.

A.2 Balassa Computation

The Balassa index of revealed comparative advantage is computed as the share of an industry in India's total exports, relative to the share of that industry in the world's aggregate exports. Since we focus on a single country, our measure of comparative advantage is industry-time specific. Moreover, since our analysis uses within-country data variation, the Balassa index is less prone to the usual criticism according to which the index may reflect country-specific confounding factors distorting trade rather than an underlying comparative advantage.

We construct the Balassa index using Indian exports taken from the BACI International Trade Database. BACI provides bilateral trade flows disaggregated at the Harmonized System (HS) six-digit level since 1995. We first aggregate Indian bilateral exports at the four-digit ISIC Rev. 4

[40] NIC has 21 sections, 88 divisions (two-digit numeric code), 238 groups (three-digit numeric code), 403 classes (four-digit numeric code), and 1,304 sub-classes (five-digit numeric code).

[41] This practice is not new; Goldberg et al. (2010), who uses a slightly different version of Prowess, assigns product codes manually.

level and then create the Balassa index.[42] Note that multi-ISIC firms have a Balassa index for each industry in which they operate, while single-ISIC firms only have one measure of comparative advantage.

The index is constructed as follows:

$$CA_{it} = \left(\frac{X_{it}^{India}}{\sum_i X_{it}^{India}} \Big/ \frac{X_{it}}{\sum_i X_{it}} \right),$$

where X_{it}^{India} denotes industry i's Indian exports toward the world at time t and X_{it} is aggregate exports of industry i at time t. $CA_{it} > 1$ suggests that India has a comparative advantage in industry i, while values between 0 and 1 indicate a comparative disadvantage.

A.3 TFP Estimation

TFP estimates are typically obtained from estimating production functions and are given by the residuals of a regression of firm-level output on inputs, e.g., labor, capital, and materials. A major issue of this type of estimation is that firm-level productivity is unobserved and correlated with firm input choices, leading to biased estimates and, consequently, biased residuals when estimated with ordinary least squares. To deal with this issue, the literature has turned to a semi-parametric control function approach that essentially consists of using input demand functions to proxy for unobserved TFP (see, e.g., Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Ackerberg et al., 2015). We follow Goldberg et al. (2010) and Topalova & Khandelwal (2011) and estimate TFP using the methodology developed in Levinsohn & Petrin (2003).[43]

Specifically, TFP is estimated from the following equation:

$$\text{VA}_{ft} = \gamma_0 + \gamma_1 \log L_{ft} + \gamma_2 \log K_{ft} + \boldsymbol{IN\gamma} + \omega_{ft} + \epsilon_{ft}, \tag{4}$$

where VA_{ft} is the log of real value added of firm f at time t. L_{ft} denotes the salaries and K_{ft} fixed assets. Hicks-neutral TFP estimates are obtained from equation (4) by subtracting firm-predicted output from its actual output.

Value added is measured as the sum of the firm labor cost and its profit before interest, tax, and depreciation and is deflated using the ASIA KLEMS two-digit industry-level (ISIC Rev. 4 two-digit level) series of value added prices, using 2005 as a base year. Firm labor cost and profits are both taken from the Prowess database. The vector of intermediary inputs $\boldsymbol{IN}$ includes firm

[42] We first merge HS92 to the ISIC Rev. 3 four-digit level using a crosswalk provided by the World Integrated Trade Solution. We then merge the ISIC Rev. 3 four-digit level to the ISIC Rev. 4 four-digit level using a correspondence from the United Nations Statistics Division.

[43] We obtain TFP estimates by running the stata routine developed in Rovigatti & Mollisi (2016), who implement the estimation algorithm described in Levinsohn & Petrin (2003).

real power and fuel expenditures as well as raw material expenses. Each of these inputs is taken from Prowess, expressed in natural logarithms and deflated using the ASIA KLEMS two-digit industry-level (ISIC Rev. 4 two-digit level) series of the intermediary input price index. ω_{ft} is the firm-specific time-varying unobserved productivity term (TFP) that we seek to estimate and potentially correlates with the firm's input choices. ϵ_{ft} is the error term. As is standard in the literature on the estimation of TFP, we use the elements of the vector $\boldsymbol{IN}$ as proxies for ω_{ft}. In the estimation procedure, we exclude industries with less than 30 firms.

A.4 MRPK Estimation

The MRPK is computed following Bau & Matray (2020). For each industry, the authors assume a Cobb-Douglas revenue production function of the type:

$$R_{ft} = TFPR_{ft} K_{ft}^{\alpha^k} L_{ft}^{\alpha^l} M_{ft}^{\alpha^m}, \tag{5}$$

where f and t denote a firm and a year, respectively. R, K, L, and M represent the value of sales, fixed assets, salaries, and materials, while $TFPR$ is revenue TFP. Therefore, the marginal revenue productivity of capital is computed as:

$$MRPK_{ft} = \frac{\partial R_{ft}}{\partial K_{ft}} = \alpha^k \frac{R_{ft}}{K_{ft}}. \tag{6}$$

We construct this measure using the Prowess database, taking the ratio between the value of sales and the value of fixed assets. Assuming that the share of capital in production is constant within industry, α^k will be captured by industry-year FE in the estimations.

A.5 Identifying Establishments

Prowess provides the name of the firm and the exact location of its headquarters. To obtain the coordinates of each of the establishments of a firm, we turn to Google Places. Plugging company names in the Google Places algorithm returns a maximum of 20 Google Maps results.[44] The results are establishments with names and corresponding coordinates. Our sample focuses only on manufacturing firms (and not retailers or services, such as banks, which likely have far more than 20 establishments); for this reason, we argue that this limit is reasonable and does not put too much

[44] Given that we do not have access to Google Places' archives, the algorithm we run uses Google Places in 2018. For this reason, the number of establishments we report corresponds to the number of establishments of a firm in 2018. Importantly, we do not drop firms that are not found in Google Places in 2018. These firms are still included in the analysis, yet, for each year between 1995–2006, the storm index only captures wind speeds at each firm's headquarters. This means that if a firm is wiped out by a storm in, say, in 2000 (and hence not observed in Google Places in 2018), it will still be included in the analysis for the period 1995–2000.

of a constraint on the establishments' search. Nevertheless, for each company name, we run the algorithm in three different locations and combine the results in one single database. The majority of the results obtained in the three separate runs are exactly the same. Eventually, only 1% of the firms in our final sample has more than 17 establishments, and only one firm has 32 establishments (the maximum number of establishments observed in our sample).

A caveat of a Google search is that it usually reports a few irrelevant results that are unrelated to the original query. We deal with this issue in the following way. First, for each establishment reported by Google Places, we create the Levenshtein distance between the reported name and the corresponding Prowess company name. The Levenshtein distance yields the number of character changes that are required to switch from one series of characters to another. Thirty-eight percent of the establishments reported by Google Places have a distance of zero. We check the remaining 62% of establishments by hand. While 66% of the query results are correctly reported, we identify and drop all the irrelevant results, 34% of the total. The median firm is composed of 1 establishment, while the average firm is composed of 2.3 establishments. Figure F.3 of Section F of the Online Appendix presents the distribution of firms by number of establishments. About 58% of firms have one establishment, 19% have two, and 23% have between 3 and 32 establishments. Finally, the postal codes corresponding to each establishment are retrieved using the coordinates returned by Google Places.

Figure F.4 of Section F of the Online Appendix provides an example of the establishments' location of the company Steel Authority of India. The left panel is a screenshot of the results from one Google Maps search, and the right panel shows the establishments' location returned after executing three Google Maps searches in three different locations and cleaning the results as described above. The yellow dot pinpoints the location of the headquarters and the red dots the location of each of the establishments. This figure shows the importance of locating a firm's establishments so that we can correctly measure the capital destruction inflicted by storms.

A.6 Storms

In what follows we describe how we construct the index of firm exposure to storms that captures the force exerted by winds on structures.

Index of firm exposure to storms To capture the destructive potential of tropical storms on firm capital, we construct an index that accounts for the strength of winds to which each of the establishments of a firm is exposed within a year. This index is given by

$$H_{ft} = \sum_{p \in F} \sum_{h \in T} x_{ph}, \tag{7}$$

where f, p, h, and t are firm, postal code, storm, and year subscripts, respectively. F denotes the set of postal codes corresponding to the establishments of firm f, and T is the set of storms within year t.[45]

The variable x_{ph} captures postal code p exposure to storm h and is computed as follows:

$$x_{ph} = \frac{(w_{ph} - 33)^2}{(w^{max} - 33)^2} \quad \text{if} \quad w_{ph} > 33, \tag{8}$$

where w_{ph} is the maximum wind speed (hereafter “wind speed") associated with storm h and to which postal code p was exposed. The construction of w_{ph} is described below. The term w^{max} denotes the maximum wind speed observed over the entire sample. The number 33 is the threshold (in knots) above which, according to the Saffir-Simpson scale, a storm is classified as a tropical storm, the weakest form taken by a cyclone. Taking the square of wind speeds above 33 knots allows us to obtain a measure that reflects the force exerted by the wind on physical structures. Our rationale for a threshold of 33 knots is twofold. First, India is subject to a large number of storms with wind speeds between 33 and 64 knots. Tropical cyclones – tropical storms with wind speeds above 64 knots – are rarer. Second, relative to high-income countries, construction materials are of poorer and sub-standard quality, making buildings and infrastructures in India vulnerable at much lower wind intensities. By definition, $x_{ph} \in (0, 1)$. A value of 0 indicates that either an area was not affected at all by storm h or the wind speed in that area was too low to even reach the tropical storm threshold. A value of 1 would be obtained in postal codes experiencing the strongest winds.

Measuring wind speed at the establishment level We construct the variable w_{ph} using storms' best tracks in the North Indian and South Indian basins over the period 1995–2006.[46] Best tracks provide information on the history of a storm, including the latitude, longitude, date, and wind speed at the eye of a storm at six-hour intervals. We start by linearly interpolating storms' best tracks, obtaining a waypoint k for the eye of the storm at every kilometer.[47] Each waypoint is associated with a set of coordinates and the wind speed at the eye, e_k. For each waypoint along the storm path, we use the so-called Rankine-combined formula for vortices (Deppermann, 1947), which allows us to compute the wind speed at any point within the vortex created around the eye of a storm.

Using this formula, we compute the wind speed hitting each postal code containing an estab-

[45]The maximum of storms by postal code-year is two. Only 1% of our sample is hit by two hurricanes within the same year.

[46]Raw data are taken from NOAA's Tropical Prediction Center.

[47]A waypoint is defined as an intermediate reference point in physical space on a line of travel (e.g., navigation) and is most often associated with longitudinal and latitudinal coordinates. It is also referred to as a landmark if it corresponds to an element of physical geography.

lishment or the headquarters of a firm within the storm maximum radius. This formula describes wind fields by considering that winds first increase exponentially up to a maximum and then decrease rapidly:

$$\begin{aligned} w_{pk} &= e_k \cdot \left(\frac{D_{pk}}{26.9978}\right) \text{ if } D_{pk} \leq 26.9978 \\ w_{pk} &= e_k \cdot \left(\frac{26.9978}{D_{pk}}\right)^{0.5} \text{ if } D_{pk} > 26.9978, \end{aligned} \tag{9}$$

where D_{pk} is the distance between the centroid of postal code p and waypoint k. The number 26.9978 corresponds to Simpson and Riehl radius of maximum wind speed, i.e., the distance between the eye and the point where wind reaches its maximum speed.[48] Finally, for each storm, we retain the maximum wind speed to which a postal code was exposed:

$$w_{ph} = \max_k \{w_{pk}\},$$

and therefore obtain a measure of wind speed for each affected postal code and storm.

Section A of the Online Appendix explores alternative wind field models and specifications of the storm index.

A.7 Night-Light Data

As discussed in Henderson et al. (2012), the growth of night-light intensity is a good proxy for economic growth. Night-light output data come from the India Light Project and cover 20 years (1993 to 2013) and 600,000 villages. Each pixel is assigned a value between 0 and 63, where 0 indicates no light output and 63 is the highest level of light output. The pixel values are then aggregated at the district level. Figure F.5 of Section F of the Online Appendix shows boxplot summary statistics of the mean yearly night-light growth rate at the state level for the period 1995–2006 (left panel) and the yearly growth rate of night-lights by district, averaged over the same period (right panel).

The database used is the result of a joint effort between the University of Michigan and the World Bank. The original data were generated by the Defence and Meteorological Satellite Program, which took pictures of the earth every night for 20 years. The night-light output measures are derived from the raster image for each date for the pixels that correspond to each village's

[48] In reality, each cyclone has a different radius of maximum wind speed, which is calculated using the difference in barometric pressure between the center and the outskirts of the storm. Unfortunately, cyclone data are characterized by a high number of missing data when it comes to barometric pressure. For this reason, we decided to follow Simpson & Riehl (1981) and Hsu & Zhongde (1998) and apply the average radius of maximum wind speed, 50 km, to all the cyclones considered in this paper.

geographical coordinates (latitude and longitudes). These data are processed following the recommendation of NOAA, and over four billion data points are used in the aggregation process. Details and access to the data can be found at http://api.nightlights.io.