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

by Martino Pelli, Jeanne Tschopp, Natalia Bezmaternykh, and Kodjovi M. Eklou

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

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Abstract

This paper examines the response of firms to capital destruction, using a new measure of firm exposure to tropical storms as a negative exogenous shock on firms' capital stock. Drawing on a panel of Indian manufacturing firms between 1995 and 2006, we establish that, depending on their strength, storms destroy up to 75.3% of the fixed assets of the median firm (in terms of its productivity and industry performance). We quantify the response of firm sales within and across industries and find effects akin to Schumpeterian creative destruction, where surviving firms build back better. Within an industry, the sales of less productive firms decrease disproportionately more, while across industries capital destruction leads to a shift in sales towards more performing industries. This build-back better effect is driven by firms active in multiple industries and, to a large extent, by shifts in the firm-level production mix within a firm's active set of industries. Finally, while there is no evidence that firms adjust by investing in new industry lines, firms tend to abandon production in industries that exhibit lower comparative advantage.

JEL classification: D22, D24, Q54.

Keywords: firms, capital, creative destruction, storms

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1 Introduction

Over the past four decades, tropical cyclones caused over US$1.3 trillion in damage (Munich Re). In 2017 alone Asia suffered damages in excess of US$30 billion. The Stern Report (2007) estimates that the costs associated to extreme weather events will reach 0.5% to 1% of current world GDP by 2050. Among other impacts, storms destroy tangible assets such as infrastructures, houses, buildings and equipment. Firms, because of the destruction of physical capital, suffer much harm. Understanding how firms and industries recover and adjust to this capital destruction is therefore a first-order concern for economists and policy-makers (e.g. Hallegatte et al., 2018). Without such knowledge, policy-makers are ill-prepared to address the challenges posed by the potential increased occurrence and severity of natural disasters (Emanuel, 2005; Webster et al., 2005; Scott et al., 2004).

Naive observers often believe that storms generate pure losses: machines and buildings are damaged and, if replaced, capital is restored with identical replicas. This paper shows that this naive perspective fails to capture the complex changes that follow a storm's destruction. When capital is destroyed, new resources will flow to the best currently available opportunities, opportunities that may not have existed when factories were initially built. We show that storms generate a reallocation of resources both within and across industries. These reallocations create dynamics akin to Schumpeterian creative destruction and enable storm-ravaged regions and storm-battered industries to offset some of the damage.

The central claim of the paper is that the destruction of firms' capital assets leads surviving firms to build back better. The adjustment process occurs over two margins. First, within industries, the sales of the least productive firms decrease disproportionately more and firms which can afford reconstruction replace destroyed capital with newer and more productive vintages. Second, across industries, our conjecture is that reconstruction will be more pronounced in better performing industries; i.e. industries with high demand and where the opportunity cost of production is relatively low.

It is important to understand which features of the economic environment drive these adjustments. Essentially, our results depend on two crucial attributes, irreversible investments and industry-specific capital, committing investors to prior decisions. If capital could be replaced costlessly and move freely across sectors, old vintages would be replaced, and incumbents would adjust their input mix to shifts in economic conditions and gear production towards currently more performing industry lines. However, when investments are irreversible, as long as revenues cover at least part of the sunk costs incurred, capital may not be replaced, leading firms to leapfrog generations of capital and the adaptation of production. Hence, the irreversibility of capital may keep less performing firms in activity and contribute to a slowdown in the decay of declining industries. If incumbents were given the opportunity to reinvest, the patterns of production would differ from the ones received from the past. A theoretical framework that produces this specific type of adjustment process 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.[1] The authors find that the response of exports to the destruction of part of the capital stock is monotonically increasing in comparative advantage. However, using data aggregated at the country-industry level, they are not able to disentangle the two adjustment margins and gauge their relative importance.

The objective of this paper is to quantify the within- and across-industry responses of Indian firms to an unanticipated reduction in their capital stock, taking advantage of variation across firms, postal codes and industries. The key element of our identification strategy is the use of a novel measure of firm exposure to storms as an exogenous and unanticipated source of negative variation in the capital stock of firms. First, a storm is exogenous to economic activity and unanticipated by firms. It is not possible to predict its occurence, nor its path (Elsner & Bossak, 2001; Pielke et al., 2008). In addition, evidence suggests that investments and location decisions of firms are unaffected by the possibility of a storm's strike (Lindell et al., 2007; Wu & Lindell, 2014; Dessaint & Matray, 2014).[2] Second, with a coastline of 7,516 kilometres India is exposed to roughly 10% of the world's cyclones, which makes it one of the most affected regions in the world. Annually over 370 million people are affected by cyclones (storms with winds travelling faster than 33 knots) in India alone.[3] Over the period considered in this paper, 1995-2006, India has regularly been subjected to storms of various intensities. EM-DAT reports 431 natural disasters (out of which 21% were tropical cyclones) from 1980-2010. Despite the continuous efforts from the National Institute of Disaster Management (NIDM), natural disasters have affected 1.5 billion people and caused approximately $48 billion economic damage over that period. Moreover, we observe

[1] The main elements of the framework in Pelli & Tschopp (2017) are the following. Countries move through different phases of development, each characterized by a different distribution of comparative advantage. The move from one phase to the next happens for exogenous reasons. Investors optimize over the information set at their disposal and, therefore, decisions that were optimal in the past may no longer be optimal today. The irreversible nature of investments implies that firms are stuck with their past decisions and may explain why countries export over the entire spectrum of comparative advantage. In this framework, if investors were offered the opportunity to re-invest, they would not necessarily replicate their production structure. The framework builds on the implications of Redding (1999), which 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).

[2] A detailed discussion of the exogeneity of storms to economic activity can be found in Pelli & Tschopp (2017).

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

a high concentration of firms and economic activity in storm-prone areas (e.g. Gujarat and West Bengal, see Figure 1 of the Online Appendix), which lends additional support to the hypothesis of storms' exogeneity.

Using storms' best track data, provided by the National Oceanic and Atmospheric Administration (NOAA), we construct a yearly firm-specific measure that accounts for the maximum wind exposure at the headquarters and each of the establishments belonging to a firm.[4] We show that our storm index is a good proxy for capital destruction at the firm level. For the median firm (in terms of its productivity and industry performance), we find that storms destroy up to 75.3% of its fixed assets, and, interestingly, that within a year following the shock, capital tends to reallocate towards more performing industries.

In order to study the response of firms across and within industries, we measure the relative performance of industries using the Balassa index of revealed comparative advantage and the productivity of firms using total factor productivity (TFP). We start by exploiting within-space across-industry variation and compare the adjustment of firms with similar storm exposure and comparable productivity, but producing in industries with distinct performance levels. Specifically, we assess whether firms in less performing industries (lower comparative advantage) are affected disproportionately more by regressing their sales on the index of firm exposure to storms and its interaction with the industry-specific measure of comparative advantage.[5] However, in this paper we work at a finer disaggregation level (firm-postal code-industry), which has the advantage of allowing us to appropriately control for confounding factors and rule out alternative stories. We then examine whether this is also the case for unproductive firms, by repeating the previous exercise but interacting the storm index with firm TFP.

We use a panel of Indian firms (Prowess) covering the period 1990-2014 and containing the financial statements of 27,794 firms.[6] This panel contains information on product-level sales

[4]The index focuses on winds speeds over 33 knots (tropical storms) and is computed from a quadratic damage function. In developing countries where construction materials are often of poor and sub-standard quality, a threshold of 33 knots is high enough for winds to impair buildings, materials and infrastructures. This function generates a measure that captures the force exerted by the wind on physical structures. We also propose alternative specifications of the storm index based on higher thresholds and a cubic damage function.

[5]A similar functional form has been used in ealier studies to examine the pattern of trade at the industry-country level. For example, Rajan & Zingales (1998) evaluates 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 leads countries to specialize in goods relying strongly on institutions.

[6]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). The Prowess database is not representative of the Indian economy. It contains all listed firms and a large proportion of unlisted one. More details on the firms contained in the database are provided in Section 2.

and firm-level capital assets. Every firm is identified by its company name and the location of its headquarters. No information on establishments is provided. Since production rarely occurs at the headquarters, identifying the location of each of the establishments belonging to a firm is crucial to construct a suitable measure of firm-exposure to storms. To deal with this issue, we turn to Google Maps and use the googleplaces algorithm. This algorithm allows us to supplement the Prowess data with the coordinates of each of the establishments of a firm. Finally, our sample, focuses on manufacturing firms between 1995 and 2006 and excludes firms that, over the whole period covered, have always been active in at least two different 4-digits ISIC industries. The excluded firms are likely to have sturdier capital and tend to be sheltered from storms. Indeed, this appears to be the case in the data as we find that the capital stock of these firms is unaffected by storms.

Our main results are the following. First, we find that, for the median firm, storms cause a decrease in sales that can reach 99%. Our baseline estimates imply that, for storms in the top quartile of the storm index distribution, the median firm's industry-specific sales decrease by at least 3%. When taking into account the full distribution of comparative advantages, results show that in the aftermath of a storm, a firms' industry sales shift towards comparative advantage industries. This finding, along with the results on capital reallocation, is in line with the aggregate shift in the export pattern found in Pelli & Tschopp (2017) and is suggestive of a build-back better mechanism.

If the mechanism of interest is at play and is generated by capital destruction, results should differ depending on the capital intensity of each industry. Specifically, capital-intensive industries are expected to drive the decrease in sales at the bottom of the comparative advantage distribution. At the higher end of the distribution, reconstruction should occur in both high- and low-capital intensity industries, leading to a near-zero net response of sales in the former industries and a positive effect in the latter ones. Our findings indicate that this is indeed the case. In addition, our results indicate that, within industry, the least productive firms are affected relatively more by storms and experience larger decreases in sales, which is consistent with the notion of Shumpeterian creative destruction. We find the across- and within-industry adjustments to be of similar magnitudes. These results hold across a variety of robustness tests, including alternative explanations. A closer look at the dynamics of the adjustment shows that these effects take place quickly. By the end of the year following the storm the adjustments of fixed assets and sales are complete, which is in line with the findings of Elliott et al. (2019), according to which the effects of hurricanes on the performance of Chinese firms lasts for one year.

Second, we examine the entry and exit of firms' industry lines.[7] We do not find evidence

[7]Since the appearance of a firm in the Prowess database depends on the availability of its financial

that capital destruction affects the entry rate of industry lines. Conversely, our results suggest that storms do increase their exit rate and that low-performance industry lines have a higher exit probability. Productivity does not have an heterogeneous impact on the exit of specific firms' industry lines. We then move to a within-firm analysis and study the changes in a firm's industry mix. We show that firms adjust their production mix within the existing set of industries, increasing sales in better performing industries. Overall, our findings confirm the presence of creative destruction.

This paper adds to the growing literature on the impact of cyclones and storms; an important literature in a global warming context. 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 (see Cavallo & Noy, 2010; Dell et al., 2014, for a survey of aggregate impacts). A large body of the literature focuses on economic growth, either using cross-country or within-country data. For instance, Strobl (2011a), looks at the economic growth impact of hurricanes across US coastal counties, while Cavallo et al. (2013), examine the average casual impact of natural disasters on economic growth using synthetic controls and counterfactual analysis. Hsiang & Jina (2014) reviewed the hypotheses advanced by the literature concerning the effects of hurricanes on long-run economic growth across countries and grouped them into four categories: (i) creative destruction (e.g. Skidmore & Toya, 2002); (ii) build back better (e.g. Cuaresma et al., 2008); (iii) recovery to trend (e.g. Miguel & Roland, 2011); and (iv) no recovery. 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 are affected by over one hundred 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 people's decision regarding where to live, but only 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) and Belasen & Polachek (2008). Gallagher & Hartley (2017) show that Katrina had a positive impact on household finances since insurance money was mainly used to repay loans. Finally,

statements and not on whether the specific firm is active, we are not able to study the entry and exit of firms.

Sacerdote (2012), shows that students who were forced to switch school in the aftermath of Katrina suffered a sharp decline in test scores, but the hurricane did not have an impact on the decision to attend college.

More recently, the literature has turned to the adjustment of firms to hurricanes. For instance, Elliott et al. (2019) find that hurricanes have a considerable negative impact on Chinese firms' performance. Similarly to our findings, this effect is relatively short-lived. Vu & Noy (2018) look at firms in Vietnam and find that while hurricanes have a negative impact on retail sales, they lead to an increase in investments, with large differences between urban an rural areas. While we also look at sales and capital, our paper is among the first to unpack the heterogeneity of the effect of storms within and and across industries. Seetharam (2018), focusing on the U.S., examines the spatial propagation of job losses occurring within multi-plant firms across undisrupted distant regions. The author finds that, within a firm, for every job lost in a county hit by a hurricane, 0.19-0.25 jobs are lost across other regions, suggesting that the network of establishments tend to propagate the effect of a hurricane.

The remainder of the paper is organized as follows. Section 2 describes the firm panel and the construction of the measure of firm exposure to storms. In Section 3 we show evidence that storms destroy the capital of firms. Adjustments within and across industries are discussed in Section 4. Section 5 presents the analysis of entry and exit of firm's industry lines as well as shifts in the industrial mix of firms. In Section 6 we take a closer look at the capital channel. The dynamics of adjustment are shown in Section 7. Finally, the last section concludes.

2 Data

2.1 Firm-level production data

Firm-level data are taken from Prowess, a large panel database created by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE). These data are constructed from annual and quarterly statements of companies. The database includes information on the financial performance of Indian companies from 1990 until 2014 and is continuously updated. The version of the data we use contains 27,794 unique firms registered in 35 states. On average a firm is observed for 15.5 years. In this paper, we focus solely on firms operating in the manufacturing sector (defined by the ISIC Rev. 4 2-digit classification of industries, Section C, Divisions 10-33) – i.e. 9,130 out of 27,794 firms.[8] To our knowledge, Prowess is the

[8]Our estimation sample contains 6,037 out of the 9,130 manufacturing firms. This change in the number of firms is due to two reasons: *i)* missing values; *ii)* firm-industry-year triplets are kept only if observed for at least two consecutive years.

largest dataset on the financial performance of Indian firms and the only detailed database on firm-level product mix and sales in India.[9] In addition, this dataset provides information on headquarters' postal codes (which in India are called *pincodes*) and company names – information which is particularly useful to us in order to construct a measure of firm exposure to storms.

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".[10] Following this criterion, 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, large firms are better represented than smaller firms and the informal sector is not present in this database.

Even though the data cover the period 1990-2014, we restrict attention to 1995-2006 for two reasons. First, we require export data to construct the Balassa index of revealed comparative advantage and these data are only available from 1995. Second, India did not experience any storm-level winds between 2007 and 2014. We use ISIC Rev.4 as our benchmark industry classification and focus on 4-digit industries in the manufacturing sector.[11]

The sample contains two types of firms: single-ISIC firms which produce manufacturing goods in a single 4-digit ISIC industry, and multi-ISIC firms which produce manufacturing goods in more than one 4-digit ISIC industry. We differentiate between firms which produce within a single industry (ISIC code) over the period 1995-2006 (*single-ISIC firms*), those which operate in more than one ISIC industry every year over the entire period of time (*always-multi-ISIC firms*) and those which switch from being a single-ISIC to a multi-ISIC firm (and vice versa) over time (*multi-ISIC firms*). Table 1 indicates that 15% of the firms contained in our final sample are always single-ISIC, 52% switch status from single- to multi-ISIC firms (and vice versa), and 33% are always-multi-ISIC firms.

[Table 1 here]

Summary statistics for the main variables are shown in Table 2. Annual real sales for the average firm in our sample are 40.1 crores Rs (equivalent to roughly 5.7 million USD).[12]

[9] Prowess does not provide plant-level sales.

[10] 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; *iii)* availability of quarterly financial statements.

[11] CMIE uses its own product codes. Appendix A.1 provides more detail on how we matched their product codes to international product classifications, in this specific case ISIC Rev. 4 4-digit.

[12] We use an exchange rate of 70 Rs for 1 USD.

The maximum value reported is roughly 5.9 billion USD in sales. When focusing on the sample excluding always-multi-ISIC firms, these values become significantly smaller, with an average value of roughly 2.7 million USD and a maximum values of 808 million USD.

[Table 2 here]

2.2 Ranking of firms and industries

In order to disentangle the two mechanisms of interest, the adjustment across industries and the adjustment within industries (across firms), we need to rank firms and industries. First, we characterize industries according to their performance, which we measure using the Balassa Index of revealed comparative advantage. This index tells us whether, in terms of exports, a given industry is performing better or worse in India relative to the world average. Second, we rank firms according to their TFP, computed using the methodology proposed by Levinsohn & Petrin (2003).

Comparative Advantage We follow Pelli & Tschopp (2017), and are agnostic about the source of comparative advantage. Accordingly, we use the traditional Balassa index of revealed comparative advantage. The index 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. More details about the construction of this index are provided in Appendix A. Since we focus on a single country, our measure of comparative advantage is industry-time-specific. Moreover, since our analysis uses within country (across firms, pincodes, industry and time) 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. Table 2 shows that the distribution of comparative advantage is relatively similar between the whole sample and the sample excluding always-multi-ISIC firms.

Total Factor Productivity estimates TFP estimates are typically obtained from the estimation of production functions; more specifically they 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 estimations 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 which essentially consists in using input demand functions to proxy for unobserved TFP (see for instance Ackerberg et al., 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996). We follow Topalova & Khandelwal (2011) and Goldberg et al. (2010) and estimate TFP using the methodology developed in Levinsohn & Petrin (2003).[13] More details on the construction of TFP can be found in Appendix A. Table 2 reports summary statistics for TFP.

Always-multi-ISIC firms Throughout the paper we exclude always-multi-ISIC firms. In Figure 1 we show that always-multi-ISIC firms differ from single- and multi-ISIC firms. On average, always-multi-ISIC firms have higher sales at the industry level and produce in industries with higher comparative advantage.[14] 4-digit ISIC industries are large industrial definitions covering many products and, therefore, we assume that firms active every year in two or more of these industrial classifications are large. These firms tend to have cutting-edge technologies, a closer alignment to comparative advantage and better, sturdier and more durable capital. In Section 3 we establish that these firms are indeed more resilient to storms, which corroborates our choice to exclude them from the analysis.

[Figure 1 here]

2.3 Storms

While storms inflict damages through three different channels (wind, flood, and surges), we only focus on wind. This choice is dictated by the fact that only wind can be considered completely exogenous; flood depend on land management, while surges only affect coastal areas. For a more extensive discussion of the exogeneity of storms, we refer to Pelli & Tschopp (2017).

In order to evaluate the firm-level response to storms, we need to construct a firm-level measure that takes into account the degree of exposure to winds at each of the establishments belonging to a firm. We construct the index of firm exposure to storms in two steps. The first step of this research design consists in identifying and geo-referencing all of a firm's establishments since Prowess only provides the address of a firm's headquarters. Second, once all the establishments are identified, we proceed to compute the maximum windspeed that hit each of them during each storm. For each firm, we then sum windspeed across establishments in order to obtain a measure of firm-level exposure to storms.

[13] We achieve this using the stata routine developed in Rovigatti & Mollisi (2016), which implements the estimation algorithm described in Levinsohn & Petrin (2003).

[14] Figures D.1 and D.2 in Appendix D show the same picture using regression coefficients.

2.3.1 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 googleplace algorithm returns a maximum of 20 Google Maps results.[15] 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 are likely have far more than 20 establishments), for this reason we argue that this limit is reasonable and does not put too much 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, but some differ. Eventually, only 1% of the firms in our final sample has more than 17 establishments, and only 1 firm has the maximum number of establishments observed, 32.

In the analysis we distinguish between single- and multi-establishment firms. We propose two definitions for single-establishment firms. In the first one, a firm owns a single establishment if the firm appears in the Prowess database but not in Google Places (probably because the firm merged or went bankrupt between 2013 and 2018) or if it appears in Google Places as a single-establishment firm. In the second definition, we drop firms that do not appear in Google Places and define as a single-establishment firm, a firm which has a unique establishment in Google Places. Hence, under the second definition, our sample of single-establishment firms is smaller. The first definition is our benchmark.

A caveat of a Google search is that it usually reports a few results that are unrelated to the original query. In our case, we also observe a tendency to over-report establishments. We deal with this issue – eliminating irrelevant results – 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.[16] The Levenshtein distance yields the number of character changes that are required to switch from one series of characters to another. 38% of the establishments reported by Google Places had a distance of zero. We checked the remaining 62% of establishments by hand. While 66% of the query results were correctly reported, we identified and dropped all the irrelevant results, 34% of the total. Our final sample contains 10,969 unique manufacturing firms. The median firm

[15] 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.

[16] Before calculating the Levenshtein distance, we perform a series of text manipulations in order to ensure comparability between the company names from Prowess and those found by Google. For instance we change all the mentions of *Company* to *Co*, or all the mentions of *Incorporated* to *Inc*.

is composed by 1 establishment, while the average firm is composed by 2.3 establishments. Figure 2 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 (pincodes) corresponding to each establishment are retrieved using the coordinates returned by Google Places.

[Figure 2 here]

Figure 2 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. While 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 in order to be able to measure correctly the capital destruction inflicted by storms.

2.3.2 Storms

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

Index of firm exposure to storms To capture the destructive potential of tropical storms on a firm's 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. Similar to Yang (2008), this index is given by:

$$H_{ft} = \sum_{p \in F} \sum_{h \in T} x_{ph}, \tag{1}$$

where f, p, h and t are firm, pincode, storm and year subscripts, respectively. F denotes the set of pincodes corresponding to the establishments of firm f, and T is the set of storms within year t.[17]

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

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

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

where w_{ph} is the maximum wind speed associated with storm h and to which pincode 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 more rare. 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.[18] 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 that the wind speed in that area was too low to even reach the tropical storm threshold. A value of 1 would be obtained in pincodes experiencing the strongest winds.

Measuring wind speed at the establishment level In what follows we describe the construction of w_{ph}, i.e. the maximum wind speed associated with storm h at pincode p. We construct the variable w_{ph} using storms' best tracks in the North Indian and South Indian basins over the period 1995-2006.[19] 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 hours intervals. Figure 1 of the Online Appendix shows India's best tracks for all tropical cyclones between 1970-2005.

We start by linearly interpolating storms' best tracks, obtaining a waypoint k for the eye of the storm at every kilometre. Each waypoint is associated to a set of coordinates and the windspeed 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 pincode containing an establishment or the headquarters of a firm within the storm maximum radius. This formula describes wind fields by considering that first, winds increase exponentially up to a maximum and then, decrease

[18] Although a threshold of 33 knots seems reasonable in a developing country, we propose alternative definitions of the storm index in Appendix B: on the one hand we increase the threshold to 50 and 64 knots to account for the possibility that 33 knots may be too low for winds to affect installations, and, on the other hand, we allow for the energy released by a storm and the force on physical structures to be related in a cubic manner.

[19] Raw data are taken from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center.

rapidly:

$$
\begin{aligned}
w_{pk} &= e_k \cdot \left(\frac{D_{pk}}{26.9978}\right) \text{ if } D_{pk} \leq 26.9978 \\
w_{pk} &= e_k \cdot \left(\frac{26.9978}{D_{pk}}\right)^{0.5} \text{ if } D_{pk} > 26.9978,
\end{aligned} \tag{3}
$$

where D_{pk} is the distance between pincode 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. Finally, for each storm, we retain the maximum windspeed to which a pincode was exposed:

$$
w_{ph} = \max_{k \in H}\{w_{pk}\},
$$

and, therefore, obtain a measure of wind speed for each affected pincode and storm.

The boxplots in Figure 3 describe winds (w_{ph}, left panel) and the index of firms' affectedness (H_{ft}, right panel) for each state for the period 1995-2006. Only states with $w_{ph} > 0$ and $H_{ft} > 0$ are represented. The figure shows that the median windspeed lies between 30 and 40 knots and that, by construction, $H_{ft} \in (0, 1)$. Both boxplots exhibit substantial variation within and across states. Table 2 shows descriptive statistics of the storm index for all observations and only for those hit by a storm. Focusing on the latter measure, in Panel B, we can observe the average value of the index is 0.027 with a maximum value of 0.525.

[Figure 3 here]

Figure 3 of the Online Appendix provides an example of the importance of the location of a company's establishments. The left panel shows the location of the establishments of the company "Steel Authority of India". The yellow dot pinpoints the location of the headquarters and the red dots the location of each of the establishments. The green areas represent pincodes affected by windspeeds (w_{ph}) of various intensities in 1998. The figure shows that while the headquarters is located in the North of the country in an area that appears protected from storms, several of the company's establishments are located in areas which, in 1998, experienced severe winds. This figure highlights the importance of accounting for establishments when computing H_{ft}. In fact, ignoring establishments would lead to conclude that "Steel Authority of India" was unaffected ($H_{ft} = 0$) and likely to underestimate the effect that storms might have had on that firm.

The right panel of Figure 3 of the Online Appendix illustrates how the index of firm exposure to storms, H_{fh}, is distributed across pincodes in 1998. Green areas represent pincodes affected by windspeed of various intensities, with darker colors indicating higher windspeeds. The figure shows that the South-Eastern and North-Western coasts of India were more affected in 1998. This picture only presents the headquarters location for each firm. The circles represent clusters of firms. The diameter of the circles is proportional to the number of firms in a pincode. Our database contains 677 active firms in 1998, located in 436 pincodes. The map shows how firms are distributed across India and most importantly that an important fraction of firms are located in storm-prone areas. Red (blue) circles indicate positive (zero) values of firms' exposure to storms. There were 315 firms (205 pincodes) with positive values of H_{fh} in 1998. $H_{fh} > 0$ occurs if at least one of the establishments of firm f is affected by windspeeds above 33 knots. For this reason, a firm operating in a sheltered place may still be indirectly affected by a storm, and the map suggests that this is the case for many firms in the center and north of the country.

2.4 Other controls

Local GDP Growth We use the growth of district night lights to proxy for local GDP growth. 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 twenty years (1993 to 2013) and 600 000 villages.[20] 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 4 of the Online Appendix shows boxplot summary statistics of the mean yearly night-lights growth rate at the state level for the period 1995-2006 (left panel) and yearly growth rate of night lights by district, averaged over the same period (right panel).

3 Stylized facts

In this section we quantify the destruction that storms inflict on firm-level capital. We first look at various components of the capital stock individually, i.e. buildings, land, and electric equipments and, eventually focus on an indicator that summarizes all these measures: fixed assets.[21]

In order to analyze the impact of storms on capital, we run the following specification:

$$y_{ft} = \alpha_0 + \alpha_1 H_{ft} + \boldsymbol{V}\boldsymbol{\eta} + \varepsilon_{ft}, \tag{4}$$

[20] More details on the data used are provided in Appendix A.4.

[21] The variable land includes for instance depreciation due to landslides or other damages that could be inflicted to the land by a storm.

where y_{ft} denotes one of the measures of capital for firm f in year t. For each firm, we have information regarding the industry(ies) in which it operates and the pincode (and thus, district) in which it is located. 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 a pincode and d a district. $\boldsymbol{V}$ is a vector of controls containing firm-specific TFP, the district-level yearly growth of night-light intensity (a proxy for local GDP growth), the number of establishments, firm-type fixed effects (single-ISIC, always-multi-ISIC and multi-ISIC firms), 4-digits ISIC industry-year fixed effects (FE) and district-specific time trends.[22] The set of industry-year FE controls for the capital intensity of the main industry of the firm, as well as for major aggregate industry-specific technological shocks. ε is the error term, which is two-way clustered at the firm and district-year level. We expect α_1 to be negative if our measure of firm exposure is a good proxy of capital destruction.

Through the destruction of capital, storms may mechanically alter our measure of TFP. As discussed in Section 2.2, TFP estimates are typically obtained from the estimation of production functions; specifically, they are the residuals of a regression of firm-level output on inputs. Hence, holding other inputs constant (i.e. if firms do not adjust their input mix), 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 for instance Elliott et al., 2015; Bertinelli & Strobl, 2013; Strobl, 2011b; Hsiang, 2010). Thus, in order to avoid a bad-control issue, we use the lag of TFP and the lag of growth in night-light intensity.[23]

Table 3 presents the results from the estimation of equation (4). The impact of a storm on all these measures of capital is negative and statistically significant at least at the 5% level. Column (1) through (3) present results for buildings, land, and electric equipment, respectively; while column (4) shows the results for fixed assets. With the exception of the coefficient on electric equipment, the others are relatively similar in magnitude. For this reason, we focus the interpretation on the coefficient on fixed assets, -1.42. This coefficient implies that the strongest storm observed in our sample (0.53) would reduce the fixed assets of the median firm (in terms of its productivity and industry performance) by 75.3%, or that storms at the 90^{th} percentile of the distribution would lead to a minimum reduction of 11.4% in fixed assets.[24] Column (5) presents the results for fixed assets for a sample that only includes always-multi-ISIC firms. As expected, since these firms are likely to have access to sturdier capital, the estimate of the impact of storms is statistically insignificant. This

[22] For multi-ISIC firms, the industry FE captures the effect associated with the industry in which the firm's sales are the largest.

[23] In using the lag of TFP and growth of night-light intensity we assume that shocks are not persistent.

[24] The 90^{th} percentile of the storm distribution is 0.08, which we multiply by the destruction of 142% observed in response to a storm of value 1.

result supports our choice of excluding these firms from the rest of the analysis. In column (6), we also show results of a regression on real salaries. The estimate on the storm measure is statistically insignificant and suggests that the effect of storms on firms works through capital and not labor inputs.

[Table 3 here]

Another interesting question is whether a storm's destruction occurs contemporaneously or is protracted over several years. In order to answer this question we include in equation (4) up to 3 lags of storm exposure.

Table 4 shows the results for these specifications. The results obtained are similar to the ones observed in Table 3, and confirm our priors: the destruction of the capital stock inflicted by a storm happens contemporaneously and it is not protracted over the following periods. This pattern is clear for buildings, land and fixed assets. The variable electrical equipment shows a different pattern, yet two things should be noted. First, electrical equipment are more easily broken and fixed than buildings or land, and second, with data for half of the sample it is expected to loose some precision.[25]

[Table 4 here]

4 Adjustments across and within industries

In this section we evaluate the importance of the across- and within-industry channels highlighted earlier. First, we examine whether, in the aftermath of a storm, firms tend to reconstruct in industries which exhibit a higher comparative advantage:

$$s_{fit} = \delta_0 + \delta_1 TFP_{f(t-1)} + \delta_2 H_{ft} + \delta_3 \left(CA_{it} \cdot H_{ft}\right) + \boldsymbol{Z\delta} + \upsilon^{CA}_{fit}, \tag{5}$$

where s_{fit} are log revenues generated from sales by firm f in industry i at time t, $TFP_{f(t-1)}$ controls for firm productivity, and CA_{it} is the Balassa index of revealed comparative advantage.[26] The vector of controls $\boldsymbol{Z}$ includes the yearly growth of district night lights, the number of establishments per firm, as well as a set of firm-type FE, pincode FE, district trends and 4-digits ISIC industry-year FE. υ^{CA}_{fit} is the error term. As discussed in Section 3,

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

[26] 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 a pincode and d denotes a district.

TFP and the growth of night lights are lagged by one period in order to avoid a bad control issue.[27]

The inclusion of both the growth of district night lights and district trends allows us to control for district-level economic changes. The number of establishments per firm controls for the fact that firms with multiple establishments may cope better with storms as they can reallocate production or inputs across establishments, 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 with one establishment only. Firm-type FE control for the fact that, as discussed in Figure 1, multi-ISIC firms tend to have higher sales per industry. Pincode FE capture fixed local characteristics that may affect firm-industry sales. For instance, a firm located in an urban area likely benefits from a better market access, e.g. through proximity to other firms or access to high-quality road infrastructures, and may react differently to a storm than a firm located in a rural or more remote region. Finally, industry-year FE control for industrial shocks such as technological changes, but also for the capital intensity of an industry which may affect the way production in an industry is affected by storms.[28]

We expect more productive firms to have higher sales than less productive firms irrespective of the industry in which they operate ($\delta_1 > 0$). Since storms destroy capital, we expect production to be impaired or at least slowed down and thus, the coefficient on storms to be negative ($\delta_2 < 0$). The coefficient on the interaction term, δ_3, captures the differential impact of storms on sales across industries with different levels of comparative advantage. We are interested in both δ_2 and δ_3, as they jointly determine the way a storm strike reshapes the pattern of industrial production. If industries with a relatively low comparative advantage suffer disproportionately more, one would expect the marginal effect of storms on industry-firm sales to be monotonically increasing in comparative advantage; i.e. $\delta_3 > 0$ and $\delta_2 < 0$.[29]

Second, we move to the within-industry effect and ask whether the least productive firms of each industry are affected disproportionately more by storms:

$$s_{fit} = \gamma_0 + \gamma_1 TFP_{f(t-1)} + \gamma_2 H_{ft} + \gamma_3 \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \boldsymbol{Z}\boldsymbol{\gamma} + \upsilon_{fit}^{TFP}, \tag{6}$$

where υ_{fit}^{TFP} is the error term. As for the previous regression, we expect more productive firms to have higher sales ($\gamma_1 > 0$) and storms to have a negative effect on sales ($\gamma_2 < 0$). The coefficient on the interaction term captures the differential impact of storms on sales

[27] CA_{it}, the measure of comparative advantage, is absorbed by the set of industry-year fixed effects included in $\boldsymbol{Z}$ and, therefore, does not appear on its own in equation (5).

[28] Section 6 provides more details on the importance of capital intensity.

[29] The marginal effect of storms on sales for each level of comparative advantage is given by $\delta_2 + \delta_3 \cdot CA_{it}$.

across firms with varying levels of productivity. If $\gamma_2 < 0$, a positive estimate of γ_3 would suggest that the least productive firms suffer more than firms at the top of the productivity distribution. Note that the inclusion of industry-year FE allows us to interpret the marginal effect of storms on sales for each level of TFP as a within-industry across-firm effect that does not reflect differential impacts across industries.

Finally, to disentangle the two mechanisms and to examine their relative importance, we combine equations (5) and (6), and estimate the following equation:

$$s_{fit} = \phi_0 + \phi_1 TFP_{f(t-1)} + \phi_2 H_{ft} + \phi_3 \left(CA_{it} \cdot H_{ft}\right) + \phi_4 \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \boldsymbol{Z\phi} + \upsilon_{fit}, \quad (7)$$

where υ_{fit} is the error term. We expect the sign of ϕ_1 to ϕ_4 to be similar to those obtained from the estimation of equations (5) and (6). The standardized estimates of ϕ_3 and ϕ_4 will inform us on the relative importance of the across- and within-industry effects.

4.1 Results

The results presented in table 5 are based on a sample that includes only positive values of sales and, therefore, reflect adjustments at the intensive margin. The extensive margin (in terms of entry and exit of 4-digit ISIC industry lines) is treated in Section 5. Errors are three-way clustered at the firm, district-year and industry-year levels in the specifications that include both interaction terms. In the specifications which exclude the interaction between the storm measure and the index of comparative advantage, standard errors are two-way clustered at the firm and district-year levels.[30]

[Table 5 here]

We start by estimating equation (5) over the entire sample, including always-multi-ISIC firms. The estimates of interest have the expected sign and are both statistically significant. Hence, it appears that the negative impact of storms on firms' sales is disproportionately larger for firms producing in industries characterized by a relatively lower comparative advantage. This result is in line with Pelli & Tschopp (2017) and indicates the presence of a build-back better mechanism: firms replace destroyed capital with newer more productive

[30] Note that the number of observations changes between Table 3 and Table 5 because in the former the unit of observation is the firm, while in the latter the cross-sectional unit is formed by an industry-firm pair. Finally, also note that we lose 219 and 281 singleton observations in the specifications that include all firms and those that exclude always-multi-ISIC firms, respectively. Hence, the number of observations in Table 5 differs from that presented in Table 2.

vintages and they do so by putting more weight on reconstruction in more performing industries. As this happens, patterns of production shift towards the top of the distribution of comparative advantages.

Column (2) shows that excluding always-multi-ISIC firms from the sample nearly doubles the estimate of δ_3 from roughly 0.5 to 1, which suggests that the build-back better mechanism found in column (1) is, to a large extent, driven by single-ISIC and multi-ISIC firms. As shown previously, these types of firms tend to produce in industries with substantially lower comparative advantages and, therefore, are more likely to exploit the capital destruction to adapt their production.

Columns (3) and (4) report results for the estimation of equation (6). The estimates have the expected sign and are statistically significant. Whether always-multi-ISIC firms are included or not in the sample, estimates of γ_2 and γ_3 do not statistically differ from each other, which is expected as average TFP is similar for single-ISIC, multi-ISIC and always-multi-ISIC firms, as shown in Figure 4. Taken together, both estimates imply that, within industry, the response of sales to storms is monotonically increasing in productivity, with sales shrinking for firms with relatively low TFP and growing at the top of the productivity distribution.

[Figure 4 here]

Columns (5) and (6) disentangle the two effects – within and across industries. As before, the estimate on the interaction term between comparative advantage and storm doubles when excluding always-multi-ISIC firms (column 6). In column (7), we compute standardized coefficients to compare the magnitude of the estimates obtained on each of the interaction terms. Results suggest that the adjustments across and within industries are similar.

The estimates of column (6) imply that for the median firm (in terms of both TFP and comparative advantage), a storm of maximum strength (i.e. $H_{ft} = 1$) would lead to a 190% decrease in a firm's industry sales.[31] It is important to note that this number is not excessively large as the median of the storm index is 0.0006.[32] For a storm at the 75th (90th) percentile of the distribution, these estimates imply a 3% (15%) decrease in firms' industry sales.[33] In Figure D.3 of the Appendix we use the estimates obtained in column (6) 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 log sales resulting from a storm of

[31] This result is obtained as follows, $[-5.92 + (0.750 * 0.92) + (0.785 * 4.24)] * 100$, using median comparative advantage (0.750) and median TFP (0.785).

[32] The median is computed conditional on positive values of the storm index.

[33] $-190 * 0.0156$ for a storm at the 75th, and $-190 * 0.0794$ for a storm at the 90th percentile of the distribution.

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.[34]

4.2 Robustness

In this section, we perform several robustness checks of our baseline results. First, to evaluate whether our results are driven by the strongest storms, we eliminate from the sample values of the storm index associated with winds falling in the top 1% of the wind distribution. Second, we examine the extent to which reconstruction may span over a few months. We decompose the storm index in two components; one which captures storms that occurred before June 30 and another one including storms hitting afterwards. Third, we examine whether our findings capture an alternative mechanism working through local demand effects. Finally, we run a series of placebo regressions in which we randomize the occurrence of storms. Results are shown in Tables 6 and 8.

Column (2) of Table 6 shows results obtained for the first robustness test. In the top panel of the table the dependent variable is fixed assets while in the bottom panel it is sales.[35] As expected, excluding the strongest winds from the sample leads to smaller estimates on capital destruction and smaller effects on sales. However, the estimates of interest have the expected signs and remain statistically significant at least at the 5% level, suggesting that the mechanisms highlighted are at play even when removing the largest shocks from the sample.

[Table 6 here]

The storm measure includes occurrences spread over the entire year. Table 7 shows the number of pincodes (for which we have firm-level data) hit by winds over 33 knots by month (panel I), as well as summary statistics of winds (over 33 knots) over six-months periods (panel II). The first panel of the table indicates that out of all the pincodes experiencing wind speeds above 33 knots, about 52% were impacted before the end of June, with the

[34] In Section B of the Appendix we discuss results based on alternative definitions of the storm index. First, we use a cubic relationship between the energy released by a storm and the force exerted on physical structures and, second, we move the windspeed threshold up to 50 and 64 knots.

[35] Estimates of storms on buildings, land and electrical equipment for the corresponding specifications can be found in Table C.2 of the Appendix. Results are qualitatively similar.

largest frequencies occuring in May and October. The first panel also shows that January to March, and July to September are quiet months. The second panel suggests that the average wind speed is similar between the first and second half of the year.

[Table 7 here]

Based on Table 7 we propose to explore the timing of our main effect within one year, splitting the storm index into events before and after June 30. In order to disentangle the effects of first- versus second-semester storms on yearly sales, we restrict the sample to firms which are hit either during the first or the second half of a given year but not both. For this reason, our sample shrinks from 17,952 (14,936) to 11,207 (9,524) observations in the sales' (capital's) regressions. Results are shown in column (3) of Table 6. The first panel indicates that the estimated effect of storms on capital in the baseline specification is driven by storms occurring in the first half of the year; both coefficients are negative but only the estimate associated with storms in the first half of the year is statistically significant. Since storms have, on average, similar magnitudes before and after June 30, there is no reason to expect capital destruction to differ across periods. Hence, we interpret the absence of statistical significance for storms occurring in the second half of the year as an accounting effect indicating that it takes some time for capital destruction to show in the books. Panel II suggests that storms happening after June 30 have no effects on sales, whereas the estimates corresponding to storms in the first semester of the year are both statistically significant and in line with our baseline estimates (note that a direct comparison of the magnitudes is not possible since we exclude firms which experience storms over both 6-months periods). On the one hand, the lack of statistical significance on $Storm_{ft}^{after}$ is in line with panel I and is suggestive that, as for capital, it takes some time for changes in sales to appear in the accounts of a firm. On the other hand, the estimates based on variables including $Storm_{ft}^{before}$ suggest that reconstruction happens relatively rapidly and is felt and registered already within the first six months following the strike.

Column (4) of Table 6 examines whether our baseline effect captures local demand effects. By construction, the Balassa index likely correlates with exports, which implies that firms selling mainly to the local market tend to be located at the bottom of the comparative advantage distribution. For this reason, our main findings may mechanically 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. To separately identify local demand and build-back-better effects, we test whether exporters respond differently to storms than firms serving exclusively the domestic market. We create an indicator variable equal to one if a firm is an exporter over the period 1995-2006, and zero otherwise. We then include in the baseline specification this exporter indicator as well as interaction terms between (i) the exporter indicator and the storm index, and (ii) the latter interaction term and the measure of comparative advantage. Results are presented in Panel II of column (4). The coefficients on these extra interaction terms are statistically insignificant and, most importantly, our estimates of interest are unaltered, which suggests that our main findings do not capture the effects of storm-induced shifts in local demand.

Finally, we verify that the relationships obtained are not spurious. We replace the storm index in the baseline regression by a random measure obtained by reshuffling the occurrence of storms over the entire sample. We repeat the exercise 1000 times and report in columns (1), (2) and (3) of Table 8 the share of replications that produce statistically significant estimates at the 1%, 5% and 10% levels, respectively. We expect this exercise to produce mostly insignificant estimates on storms and their interactions, while leaving the significance of the estimates on other variables largely unchanged.

[Table 8 here]

Focusing on column (1), results suggest that in only 2.7% of the cases, the randomization produces estimates on the storm index which are statistically significant at the 1%. This share amounts to 2.1% for the estimates on $Comp.\ adv._{it} \times Storm_{ft}$ and 4.7% for the estimates on $TFP_{f(t-1)} \times Storm_{ft}$. Instead, in 100% of the cases the estimate on $TFP_{f(t-1)}$ stays statistically significant, and this at each level of statistical significance. Therefore, we conclude that our main results do not capture spurious correlations. In Table C.4 of the Appendix we propose four alternative randomizations – within firms, industries, districts and years – and draw similar conclusions.

5 A closer look at multi-ISIC firms

In this section, we look at the extensive margin and examine whether storms increase the probability of entry and exit of firm-industry production lines. In our sample, only 2 out of 1,625 single-ISIC firms switch industries from one year to the next. For this reason, we argue that our baseline result is not driven by industry switches of single-ISIC firms and focus on multi-ISIC firms. We conclude the section by looking at how multi-ISIC firms adjust their current industry mix in the aftermath of storms.

5.1 Entry and exit of firm-industry production lines

In Table 9, we concentrate on the entry of new industry lines. We run a linear probability model where the dependent variable takes the value 1 if, conditional on producing in the previous year, a firm adds a 4-digit ISIC industry to its portfolio of industries and 0 otherwise. At each step of the analysis, we distinguish firms with one establishment from those with more than one. We do not expect to observe an effect when including multi-establishment firms. These firms are better sheltered from shocks as production may be reorganized and relocated from affected towards unaffected establishments. Hence, owning multiple establishments can be seen as an insurance against the risk of storms. We present results according to both definitions of one-establishment firms presented in Section 2.3.1. Overall, we find no evidence that firms adjust to capital destruction by investing in new industry lines.

[Table 9 here]

Next, we investigate whether storms increase the exit rate of firm-industry production lines. We run a linear probability model where the dependent variable takes the value 1 if, from one year to the next, a firm stops the production of an industry line and 0 otherwise, conditional on the firm surviving in the next period. Results are shown in Table 10. Focusing on the most complete specification (column 7), we find that storms have heterogenous effects across industries. However, there is no evidence that the effect varies depending on productivity. Combined with a positive (albeit statistically insignificant) estimate on the storm index, the coefficient on the interaction term (Comp. adv.$_{it}$ $\times$ Storms$_{ft}$) implies that industry lines characterized by low comparative advantage have a higher exit probability. However, given the imprecisely estimated coefficient on the storm index, this heterogenous effect will be statistically significant only for certain values of comparative advantage. Nevertheless, the result is consistent with the idea that when the 'opportunity' arises, most likely because of massive capital destruction, firms abandon lines of production with low comparative advantage to switch to higher segments of the comparative advantage distribution. However, this effect disappears once we switch to one-establishment firms.

[Table 10 here]

While storms destroy the capital stock, they do not destroy firms' know-how, marketing, customers and the network of intermediaries, or intangible assets. Hence, it is expected that most of the storms' effects would occur through the intensive margin and that adjustments would be negligible (if not inexistant) along the extensive margin.

5.2 Shifts in firm industry mix

The absence of entry along with a mild effect on exit of industry lines suggests that the across-industry baseline effect, presented in Table 5, is driven to a large extent by shifts in the existing firm-level production mix. To study this possibility we regress a measure of firm industrial mix at a given time on firm exposure to storms and a set of controls including, lagged TFP, lagged district night-light growth, and a set of firm FE, year FE and district trends. Note that, by including firm FE, we look at adjustments within firms. We also control for 2-digits ISIC industry trends to account for the fact that the set of industries where a firm is active depends on the main industry in which a firm operates (e.g. through the value chain or input-output linkages).

The measure capturing firms' industry mix is constructed using the following firm industrial composition index:

$$IM_{ft} = \sum_{j \in J} \eta_{jft} CA_{j(t-1)}, \tag{8}$$

where $\eta_{jft} = \frac{s_{fjt}}{\sum_{j \in J} s_{fit}}$ is the share of industry j in the total sales of firm f at time t. An increase in IM_{ft} indicates that the pattern of production of the firm has shifted towards comparative advantage industries. Such a shift may happen either because the firm has shifted production away from low comparative advantage industries or, holding production shares across industries constant, because the Balassa index of some industries has increased. Since the comparative advantage of a country changes slowly over time, most of the variation in IM_{ft} comes from shifts in the pattern of production of firms.

Results from this exercise are presented in Table 11. We identify an effect for firms which own one establishment only. For the latter firms the estimate on the storm index is positive and statistically significant, indicating a positive effect on firms' industrial composition index. Therefore, it appears that firms adjust to storms by shifting their production towards the industries which align better to the comparative advantage of India, which is a strong indication of a process of creative destruction where surviving firms build back better.

[Table 11 here]

6 Capital Channel

6.1 Capital reconstruction

We have shown that storms have a direct impact on firms' physical capital and lead firms to reorganize production. In this section we examine whether more reconstruction occurs in industries that perform better (i.e. industries with a high comparative advantage). Evidence of this heterogeneity in reconstruction would strengthen our claim that, in a world characterized by irreversible investements and industry-specific capital, a decrease in adjustment costs allows firms to re-optimize production.

In order to test for this heterogeneity, we run the following specification:

$$y_{ft} = \lambda_0 + \lambda_1 H_{ft} + \lambda_2 \left(CA_{it} \cdot H_{ft}\right) + \lambda_3 \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \boldsymbol{V\zeta} + u_{ft}^{REC}, \tag{9}$$

where u^{REC} is the error term, which is three-way clustered at the firm, district-year and industry-year level.[36]

Columns (1) to (3) of Table 12 report results. In columns (1) and (2) we add the two interactions terms one after the other, while in column (3) both are introduced. In column (1), the coefficient on storm is negative and statistically significant at the 1% level, suggesting that storms destroy firms' assets. The estimate on the interaction term is positive and statistically significant at the 1% level, indicating that reconstruction is taking place, and is concentrated in high performance industries.

[Table 12 here]

In column (2), the coefficient on the interaction is not statistically significant. The lack of an effect indicates that different TFP levels are not systematically linked to more or less durable capital varieties. These results hold in column (3) and confirm our story; more capital reconstruction is observed in industries that perform better, yet TFP does not play a role in how capital is affected by a storm.

Expanding on these results, we investigate the dynamics of the mechanism. To examine whether reconstruction takes longer than a year, we use the following specification:

$$y_{ft} = \chi + \sum_{j=0}^{k} \chi_j H_{ft-j} + \sum_{j=0}^{k} \psi_j \left(CA_{it-j} \cdot H_{ft-j}\right) + \theta \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \boldsymbol{V\eta} + u_{ft}^{LAG} \tag{10}$$

[36] Specifications that include only the storm measure are two-way clustered at the firm and district-year level.

where $k \in (0, 2)$, meaning that we include up to two lags of the storm measure and comparative advantage. We limit ourselves to a maximum of two lags because, as shown in Table 12, the results become statistically insignificant already after the first lag. We do not include lags of TFP since, as seen in columns (2) and (3), TFP does not have an impact on capital reconstruction.

Columns (4) and (5) of Table 12 report results for equation (10). First, we include one lag of the storm measure and of its interaction with comparative advantage and, then, two lags. Column (4) shows that the reconstruction in high comparative advantage industries takes place within the year of the storm and the following year. In column (5) we see that the reconstruction is over by the end of the year following the strike. The coefficients on the second lag are not statistically significant. This result is consistent with Elliott et al. (2019) which find that the negative effects of hurricanes on Chinese firms' performance are relatively short-lived; up to one year after the shock.

6.2 Capital intensity

If the effects of storms on sales work through capital destruction, we would expect capital-intensive industries to be hit harder and go through a more important reorganization of their production structure. In addition, as reconstruction should take place at the top of the comparative advantage distribution (irrespective of the capital intensity of the industry), we would expect sales to increase in low-capital-intensity industries. In what follows we investigate whether this is the case. The first step in this direction is to compute an industry-level measure of capital intensity for India. We compute such a measure in the following way:

$$y_{ft} = \varphi_0 + \varphi_1 TFP_{f(t-1)} + d_i + d_t + u_{ft}^{CAP} \tag{11}$$

where y is the logarithm of a firm's fixed assets and d_i represents 4-digit ISIC industry FE. d_t denotes year FE and controls for effects such as technological innovation, and TFP captures firm-specific effects. We then retrieve the coefficients on the industry FE and use them as measures of industry-level capital intensity, which we denote κ_i.

Using this new measure we augment the baseline specification with a triple-interaction term that interacts the storm index with comparative advantage and the measure of industry-specific capital intensity. Specifically, we run the following specification:

$$\begin{aligned} s_{fit} &= \mu_0 + \mu_1 TFP_{f(t-1)} + \mu_2 H_{ft} + \mu_3 \left(TPF_{f(t-1)} \cdot H_{ft}\right) \\ &+ \mu_4 \left(H_{ft} \cdot \kappa_i\right) + \mu_5 \left(CA_{it} \cdot H_{ft}\right) + \mu_6 \left(CA_{it} \cdot H_{ft} \cdot \kappa_i\right) + \boldsymbol{Z\phi} + u_{fit}^{INT}, \end{aligned} \tag{12}$$

where u_{fit}^{INT} is the error term. To simplify the reader's job, we present the marginal effects of this regression graphically. We fix κ_i and $TFP_{f(t-1)}$ at high and low values and plot the marginal effect of a storm across the comparative advantage distribution. We identify high (low) capital intensity industries by using the 75^{th} (25^{th}) percentile of the distribution of κ_i. Similarly, we use three different levels of TFP: the 25^{th}, the 50^{th}, and the 75^{th} percentiles of its distribution.

Figures 5, 6, and 7 show the marginal effect for the 25^{th}, the 50^{th}, and the 75^{th} percentile of the TFP distribution, respectively. In each of the figures the maroon line represents the marginal effect for high capital intensity industries, while the blue one is for low capital intensity industries, with their respective 95% confidence bands represented by the dashed lines. The shaded areas represent areas where the marginal effect is statistically significant at the 95% level, and maroon (blue) shading indicates statistical significance for the industry with high (low) capital intensity.

[Figures 5, 6, and 7 here]

As expected, the figures show that industries with a high capital intensity are affected disproportionately more from storms, the maroon marginal response is always below the blue one, indicating that sales in high capital intensity industries decrease more than sales in low capital intensity industries. At the bottom of the comparative advantage distribution, industries that rely heavily on physical capital show a statistically significant drop in sales across all except the highest levels of TFP, while marginal effects are statistically insignificant for industries with low values of physical capital. As for the baseline estimates, the marginal effects are monotonically increasing in comparative advantage irrespective of the industry's capital intensity or the firm's TFP. As one moves towards higher levels of comparative advantage, the marginal effect become statistically insignificant for capital-intensive industries. Instead, for low physical capital intensity industries, at high levels of comparative advantage, effects are positive and statistically significant. This suggests that these industries, which are initially sheltered from storms thanks to their low capital intensity, subsequently benefit from a reconstruction effect in which firms in comparative disadvantage industries reinvest in industries with a higher comparative advantage.

These figures suggest that the drop in sales observed in the baseline specification is driven by comparative disadvantage industries with high physical capital intensity. The figures also indicate that comparative advantage industries with low physical capital intensity drive the positive shifts in sales observed at the top of the distribution of comparative advantage. Hence, by decreasing adjustment costs, storms provide an opportunity for firms to reorganize their production structure.

7 Dynamics

We have shown that the impact of a storm on capital reconstruction lasts for one year after the strike. In this section we study the dynamics of the response of sales by adding to equation (7) one lag of the storm measure and its interaction with comparative advantage.

Results are shown in column (2) of table 13. The contemporaneous coefficients are similar between the two specifications, with a negative effect of the storm on impact, attenuated for high comparative advantage industries and for highly productive firms. As expected, the impact of a storm on sales is mainly contemporaneous: the coefficient on the lag of the storm measure is still negative, albeit smaller in magnitude and imprecisely estimated. Instead, we still observe an adjustment across industries in the first year following the strike. The coefficient is smaller in size, roughly a half of the contemporaneous one, but still positive and statistically significant at the 5% level. This result shows that firms, especially those hit towards the end of the year, may take up to one year after the storm in order to completely reorganize their production structure.

[Table 13 here]

8 Conclusions

This paper examines the response of manufacturing firms to the capital destruction triggered by tropical storms that affected India between 1995 and 2006. Specifically, we investigate whether capital destruction creates an opportunity for firms to adapt to changes in the economic environment, leading some to exit and others to build back better. In the absence of capital destruction, firms' adjustment may be slow because of the irreversibility of investments. Our objective is to unravel some of the adjustment mechanisms, within and across industries, specific to manufacturing firms.

The analysis is run using the Prowess firm-level panel matched with data on storms and cyclones from NOAA. Using Google Places 2018, we locate all the establishments of each of the firms in the dataset. This additional information allows us to obtain a more precise measure of the wind strength that affects each firm. Using this measure, we establish a relationship between storms and firm-level capital destruction in India. We then analyze the reaction of sales and find evidence of the two channels of adjustment, within and across industries, consistent with a build-back better mechanism. Across industries, we show that sales shift towards more performing industries, confirming the results of Pelli & Tschopp (2017). The effects across and within industry are similar in size, and show evidence of an evolution towards new and more productive vintages of capital, and of an adjustment of the production mix towards more performing industries. Moreover, there is no evidence that firms adjust to capital destruction by investing in new industry lines. This result seems to be driven to a large extent by shifts in the firm-level production mix within an existing set of industries. Finally, the adjustment process is complete by the end of the first year following the storm.

On a final note, we should remember that the results presented in this paper are based only on a fraction of the firms composing the Indian economy. The Prowess dataset includes all listed companies and their subsidiaries plus a certain number of unlisted companies (inclusion depends on the availability of quarterly and yearly statements), meaning that only the biggest and more established firms are found in it. For instance, small family-run firms and the informal sector are not captured. Our results indicate that for smaller and more vulnerable firms the adjustment in the aftermath of a hurricane is more important. When we include always-multi-ISIC firms in the baseline estimation the coefficient on the adjustment across industries is halved. In light of this evidence, the results obtained could represent a lower bound of the total effect.

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Tables

Table 1: Firm type

	Freq.	Percent	Cum
	(1)	(2)	(3)
Single-ISIC	890	14.74	14.74
Always-multi-ISIC	1,979	32.78	47.52
Multi-ISIC	3,168	52.48	100.00
Total	6,037	100.00	

Note: The term "single-ISIC" denotes firms which produce in a single 4-digit ISIC industry over the period 1995-2005. "Always-multi-ISIC firms" refers to firms which produce in more than a single 4-digit ISIC industry every year from 1995 until 2005. Finally, "multi-ISIC" refers to firms that switch from being single-ISIC to multi-ISIC firms (and vice versa) over time.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: All firms					
Firm sales at the ISIC level (real)	40.151	591.806	0.002	41518.016	35105
Firm total factor productivity	0.801	0.474	0	19.075	35105
Yearly district night-lights growth	1.015	0.183	0.363	2.677	35105
Comparative advantage	1.575	2.162	0	24.346	35105
Firm exposure to storms	0.002	0.017	0	0.525	35105
Firm exposure to storms if $H_{ft} > 0$	0.02	0.054	0	0.525	3288
Panel B: Excluding always-multi-ISIC firms					
Firm sales at the ISIC level (real)	18.637	89.241	0.002	5661.934	18233
Firm total factor productivity	0.812	0.43	0	11.215	18233
Yearly district night-lights growth	1.017	0.188	0.363	2.677	18233
Comparative advantage	1.627	2.226	0	24.346	18233
Firm exposure to storms	0.002	0.021	0	0.525	18233
Firm exposure to storms if $H_{ft} > 0$	0.027	0.066	0	0.525	1593

Note: Sales are expressed in crores (10 millions) of Indian Rupees and are deflated using the industry-level price gross output, base year 2005. Total factor productivity is computed using the approach developed by Levinsohn & Petrin (2003). "Always-multi-ISIC firms" refer to firms which produce in more than a single 4-digit ISIC industry every year over the period 1995-2006. "Comparative advantage" refers to Balassa index of revealed comparative advantage.

Table 3: Stylized Facts

Dependent variable	Buildings$_{ft}$ (logs)	Land$_{ft}$ (logs)	Electricity$_{ft}$ (logs)	Fixed assets$_{ft}$ (logs) Excl. always-multi-ISIC	Fixed assets$_{ft}$ (logs) Only always-multi-ISIC	Salaries$_{ft}$ (logs)
	(1)	(2)	(3)	(4)	(5)	(6)
Storms$_{ft}$	-1.54***	-1.55***	-2.48***	-1.42**	1.598	-0.312
	(0.48)	(0.45)	(0.86)	(0.57)	(1.864)	(0.198)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{dt}$	Yes	Yes	Yes	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14407	13794	6862	14936	7618	14489

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 pincode and d a district. In column (1), the dependent variable is the log of firm net buildings. In column (2), "land" refers to the log of firm net land. The term "electricity" in column (3) refers to the log of firm net electrical installations and fittings. In columns (4) and (5), the term "fixed assets" refers to the log of firm net fixed assets. In the last column, the term "real salaries" refers to the log of firm real salaries. The set of industry FE corresponds to the ISIC 4-digits classification. All the specifications exclude always-multi-ISIC firms from the sample.

Table 4: Stylized facts – long-term

Dependent variable	Buildings$_{ft}$ (logs)				Land$_{ft}$ (logs)			
	(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)	(0.45)	(0.47)	(0.57)	(0.69)
Storms$_{f(t-1)}$		-0.69	0.015	0.26		-0.24	-0.44	-0.070
		(0.57)	(0.68)	(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)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{dt}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14407	14407	11665	9736	13794	13794	11203	9363

Dependent variable	Electricity$_{ft}$ (logs)				Fixed assets$_{ft}$ (logs)			
	(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)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{dt}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6862	6862	5460	4492	14936	14936	12040	9996

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 pincode and d a district. In columns (1)-(4), the dependent variable is the log of firm net buildings. In column (5)-(8), "land" refers to the log of firm net land. The term "electricity" in column (9)-(12) refers to the log of firm net electrical installations and fittings. In column (13)-(16), the term "fixed assets" refers to the log of firm net fixed assets. The set of industry FE corresponds to the ISIC 4-digits classification. All the specifications exclude always-multi-ISIC firms from the sample.

Table 5: Baseline – across and within industry effects

Sales_{fit} (logs)	All firms	Excl. always-multi-ISIC firms	All firms	Excl. always-multi-ISIC firms	All firms	Excl. always-multi-ISIC firms: Non-stand.	Excl. always-multi-ISIC firms: Stand.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{TFP}_{f(t-1)}$	0.23***	0.66***	0.23***	0.65***	0.23***	0.65***	0.126***
	(0.070)	(0.079)	(0.062)	(0.079)	(0.069)	(0.079)	
Storms_{ft}	-2.17***	-2.82***	-5.32***	-4.96***	-5.91***	-5.92***	-0.009***
	(0.82)	(0.86)	(1.40)	(1.38)	(1.41)	(1.33)	
Comp. $\text{adv.}_{it} \times \text{Storms}_{ft}$	0.51**	0.98***			0.50**	0.92**	0.019**
	(0.24)	(0.35)			(0.24)	(0.39)	
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$			5.03***	4.41***	5.01***	4.24***	0.017***
			(1.63)	(1.48)	(1.87)	(1.34)	
Night-lights growth_{dt}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34886	17952	34886	17952	34886	17952	17952

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels in columns (1), (2) and (5)-(7), and two-way clustered at the firm and district-year level in columns (3) and (4). *** 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 pincode and d a district. The dependent variable is the log of firm sales in industry i at time t. The set of industry FE corresponds to the ISIC 4-digits classification. "All firms" indicates that the specification includes all firms and "Excl. always-multi-ISIC firms" means that always-multi-ISIC firms are excluded from the sample. Columns (1)-(5) show non-standardized estimates. In the last two columns, "Non-stand." stands for non-standardized estimates and "Stand." for standardized results.

Table 6: Robustness

	Baseline	No extremes	Before/After June 30	Local demand effects
	(1)	(2)	(3)	(4)
Panel I: Fixed assets$_{ft}$ (logs)				
Storms$_{ft}$	-1.42**	-0.67***		-1.42**
	(0.57)	(0.26)		(0.57)
Storms$_{ft}^{before}$			-0.96***	
			(0.26)	
Storms$_{ft}^{after}$			-4.81	
			(3.48)	
Observations	14936	14936	9524	14936
Panel II: Sales $_{fit}$ (logs)				
Storms$_{ft}$	-5.92***	-2.81***		-5.98***
	(1.33)	(0.57)		(1.31)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.92**	0.39**		1.05***
	(0.39)	(0.16)		(0.37)
TFP$_{f(t-1)}$ × Storms$_{ft}$	4.24***	1.91***		4.48***
	(1.34)	(0.61)		(1.09)
Storms$_{ft}^{before}$			-3.33***	
			(0.89)	
Comp. adv.$_{it}$ × Storms$_{ft}^{before}$			0.33*	
			(0.20)	
TFP$_{f(t-1)}$ × Storms$_{ft}^{before}$			2.52**	
			(0.99)	
Storms$_{ft}^{after}$			14.9	
			(25.0)	
Comp. adv.$_{it}$ × Storms$_{ft}^{after}$			-2.88	
			(2.62)	
TFP$_{f(t-1)}$ × Storms$_{ft}^{after}$			-1.82	
			(24.6)	
Exporter$_{ft}$				0.94***
				(0.096)
Storms$_{ft}$ × Exporter$_{ft}$				2.61
				(2.58)
Exporter$_{ft}$ × Comp. adv.$_{it}$				-0.0094
				(0.029)
Exporter$_{ft}$ × Comp. adv.$_{it}$ × Storms$_{ft}$				-2.68
				(2.33)
Observations	17952	17952	11207	17952
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes	Yes
# of establishments$_{ft}$	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes

Note: In Panel I, standard errors are two-way clustered at the firm and district-year levels. In Panel II, standard errors are three-way clustered at the firm, district-year and industry-year levels. *** 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 pincode and d a district. In the first panel, the dependent variable is the log of firms' fixed assets. In the second panel, the dependent variable is the log of firms' industry sales. The set of industry FE corresponds to the ISIC 4-digits classification. In panel I, the industry FE is associated with the industry in which the firm's sales are the largest. In addition to the listed set of controls, panel II also includes pincode FE. Each specification excludes always-multi-ISIC firms.

Table 7: Wind speeds at the pincode level, by month, 1995-2006

I. Number of pincodes hit each month (wind > 33 knots)

	Freq.	Percent	Cum
	(1)	(2)	(3)
Month:			
April	2	0.04	0.04
May	1,980	35.93	35.97
June	904	16.41	52.38
October	1,454	26.39	78.77
November	958	17.39	96.15
December	212	3.85	100.00

II. Winds

	Mean	Std. Dev.	Min.	Max.	N
	(1)	(2)	(3)	(4)	(5)
Time period:					
January-June	51.563	17.552	33.009	102.772	2886
July-December	47.879	16.799	33.005	139.99	2624

Note: The table shows winds only for pincodes for which firm-level data is available. Wind speeds are expressed in knots.

Table 8: Placebo

Sales$_{fit}$ (logs)	Share with statistical significance at: 1% (1)	5% (2)	10% (3)
TFP$_{f(t-1)}$	1	1	1
Storms$_{ft}$	0.027	0.096	0.154
Comp. adv.$_{it}$ × Storms$_{ft}$	0.021	0.081	0.143
TFP$_{f(t-1)}$ × Storms$_{ft}$	0.047	0.117	0.181
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes
# of establishments$_{ft}$	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes

Note: Results show the share of statistically significant results over 1000 randomizations, where the storm measure is randomized over the entire sample. Statistical significance corresponds to three-way clustered standard errors at the firm, district-year and industry-year levels. 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 pincode and d a district. The dependent variable is the log of firm sales in industry i at time t. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification excludes always-multi-ISIC firms.

Table 9: Entry of industry lines

Entry of industry line$_{ft}$	All	One estab. I	One estab. II	All	One estab. I	One estab. II	All	One estab. I	One estab. II
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Storms$_{ft}$	0.15*	0.25	-0.18	0.23	0.53	-0.26	0.29	0.63	-0.21
	(0.089)	(0.16)	(0.13)	(0.21)	(0.61)	(0.25)	(0.19)	(0.45)	(0.17)
Comp. adv.$_{it}$ $\times$ Storms$_{ft}$	-0.053	-0.078	0.0070				-0.053	-0.076	0.0083
	(0.068)	(0.11)	(0.029)				(0.069)	(0.11)	(0.030)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$				-0.19	-0.52	0.10	-0.19	-0.54	0.039
				(0.28)	(0.81)	(0.20)	(0.30)	(0.76)	(0.21)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Comp. adv.$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15760	6499	2501	15760	6499	2501	15760	6499	2501

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels in columns (1)-(3) and (7)-(9), and two-way clustered at the firm and district-year level in columns (4)-(6). *** 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 pincode and d a district. The dependent variable takes the value of 1 if, conditional on producing at all in the previous year, a firm adds an industry to its set of industries (and 0 if no industry is added). The set of industry FE corresponds to the ISIC 4-digits classification. The industry FE is associated with the industry in which the firm's sales are the largest. Each specification focuses on multi-ISIC firms. The term "All" indicate all firms except always-multi-ISIC firms are included in the sample. The terms "One estab. I" and "One estab. II" indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

Table 10: Exit of industry lines

Exit of industry line$_{ft}$	All	One estab. I	One estab. II	All	One estab. I	One estab. II	All	One estab. I	One estab. II
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Storms$_{ft}$	0.49*	0.78*	-0.45	-0.059	-0.064	1.13	0.069	0.16	0.97
	(0.25)	(0.42)	(0.51)	(0.52)	(0.96)	(1.20)	(0.52)	(0.92)	(1.34)
Comp. adv.$_{it}$ × Storms$_{ft}$	-0.10**	-0.12*	0.17				-0.10**	-0.12	0.10
	(0.048)	(0.069)	(0.16)				(0.050)	(0.074)	(0.15)
TFP$_{f(t-1)}$ × Storms$_{ft}$				0.59	0.89	-2.04	0.56	0.81	-1.93
				(0.55)	(1.19)	(1.79)	(0.46)	(1.19)	(1.85)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Comp. adv.$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12258	4962	1955	12258	4962	1955	12258	4962	1955

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels in columns (1)-(3) and (7)-(9), and two-way clustered at the firm and district-year level in columns (4)-(6). *** 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 pincode and d a district. The dependent variable takes the value of 1 if, from one year to the next, a firm stops the production of an industry line (and 0 if the firm keeps producing in that specific industry), conditional on remaining active. The set of industry FE corresponds to the ISIC 4-digits classification. The industry FE is associated with the industry in which the firm's sales are the largest. Each specification focuses on multi-ISIC firms. The term "All" indicate all firms except always-multi-ISIC firms are included in the sample. The terms "One estab. I" and "One estab. II" indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

Table 11: Shifts in the industry mix of firms

Industrial mix$_{ft}$	All	One estab. I	One estab. II
	(1)	(2)	(3)
Storms$_{ft}$	0.18	1.85**	2.54***
	(0.56)	(0.81)	(0.88)
TFP$_{f(t-1)}$	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
2-digits industry trends	Yes	Yes	Yes
Observations	12109	5047	2043

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 pincode and d a district. The set of industry trends corresponds to the ISIC 2-digits classification. The industry we use for the trend is associated with the industry in which the firm's sales are the largest. Each specification focuses on multi-ISIC firms. The term "All" indicate all firms except always-multi-ISIC firms are included in the sample. The terms "One estab. I" and "One estab. II" indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

Table 12: Capital Channel

Fixed assets$_{ft}$ (logs)	(1)	(2)	(3)	(4)	(5)
Storms$_{ft}$	-2.63***	-0.21	-1.48	-1.60	-2.10
	(0.95)	(1.32)	(1.47)	(1.49)	(1.83)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.85***		0.84***	0.87***	0.67
	(0.32)		(0.31)	(0.32)	(0.43)
TFP$_{f(t-1)}$ × Storms$_{ft}$		-1.74	-1.64	-1.55	-0.34
		(1.69)	(1.73)	(1.75)	(2.25)
Storms$_{f(t-1)}$				-1.44*	-1.34
				(0.79)	(1.03)
Comp. adv.$_{i(t-1)}$ × Storms$_{f(t-1)}$				0.33*	0.74**
				(0.18)	(0.30)
Storms$_{f(t-2)}$					0.098
					(0.44)
Comp. adv.$_{i(t-2)}$ × Storms$_{f(t-2)}$					-0.016
					(0.15)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{dt}$	Yes	Yes	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes
Observations	14936	14936	14936	14936	12040

Note: Standard errors are two-way clustered at the firm and district-year level in column 2 and three-way clustered at the firm, district-year and industry-year level in the remaining 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 pincode and d a district. In columns (1)-(2), the dependent variable is the log of firm net buildings. In columns (3)-(4), "land" refers to the log of firm net land. The term "electricity" in columns (5)-(6) refers to the log of firm net electrical installations and fittings. In columns (7)-(8), the term "fixed assets" refers to the log of firm net fixed assets. The set of industry FE corresponds to the ISIC 4-digits classification. All the specifications exclude always-multi-ISIC firms from the sample.

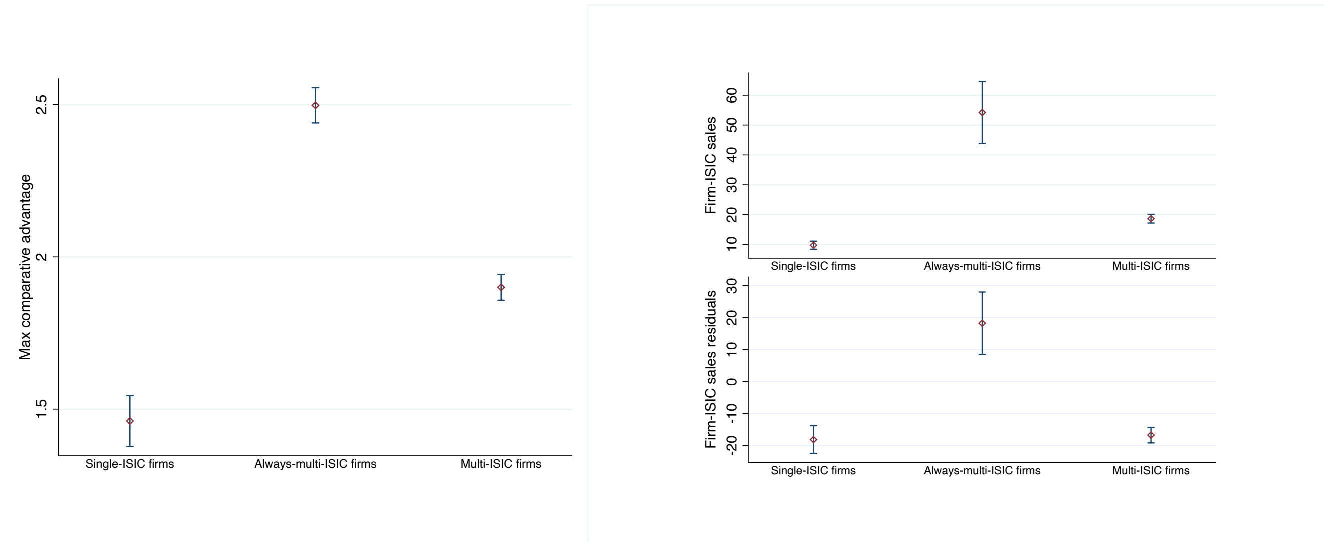
Table 13: Long-term effect

Sales_{fit} (logs)	Baseline	Long-term
	(1)	(2)
Storms_{ft}	-5.91***	-6.13***
	(1.33)	(1.39)
Comp. $\text{adv.}_{it} \times \text{Storms}_{ft}$	0.92**	1.07***
	(0.39)	(0.41)
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	4.24***	4.30***
	(1.34)	(1.36)
$\text{Storms}_{f(t-1)}$		-1.02
		(0.75)
Comp. $\text{adv.}_{i(t-1)} \times \text{Storms}_{f(t-1)}$		0.57**
		(0.24)
$\text{TFP}_{f(t-1)}$	Yes	Yes
Night-lights growth_{dt}	Yes	Yes
# of establishments	Yes	Yes
Firm-type FE	Yes	Yes
Pincode FE	Yes	Yes
Industry-year FE	Yes	Yes
District trends	Yes	Yes
Observations	17952	17952

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels. *** 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 pincode and d a district. The dependent variable is the log of firm sales in industry i at time t. The set of industry FE corresponds to the ISIC 4-digits classification.

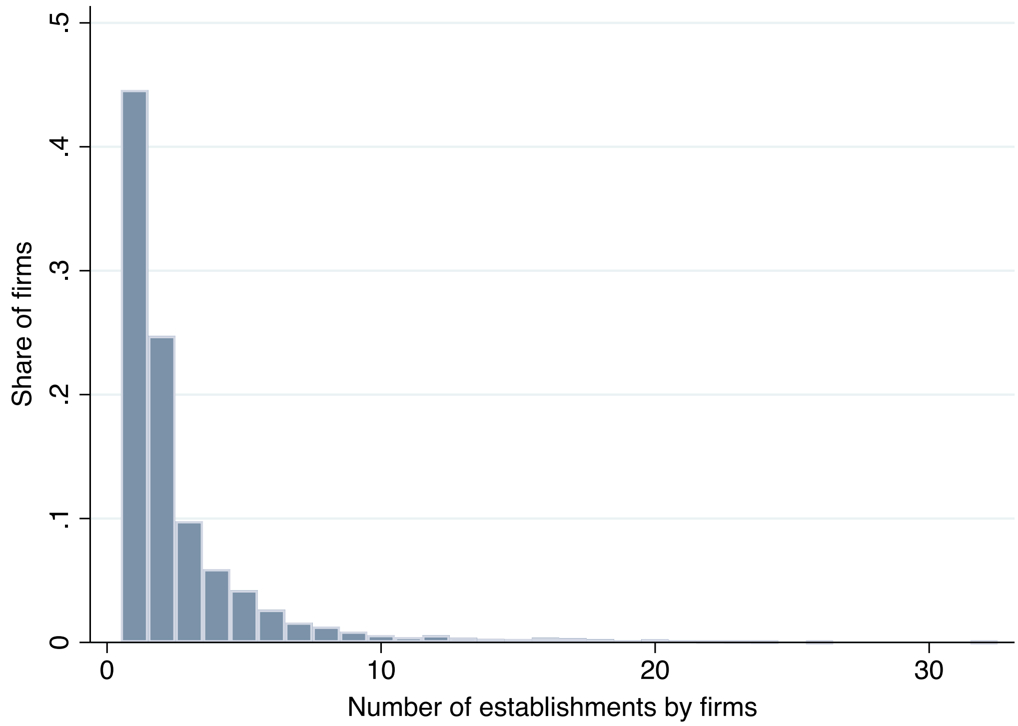
Figures

Figure 1: Comparative advantage and firm-industry sales by firm type



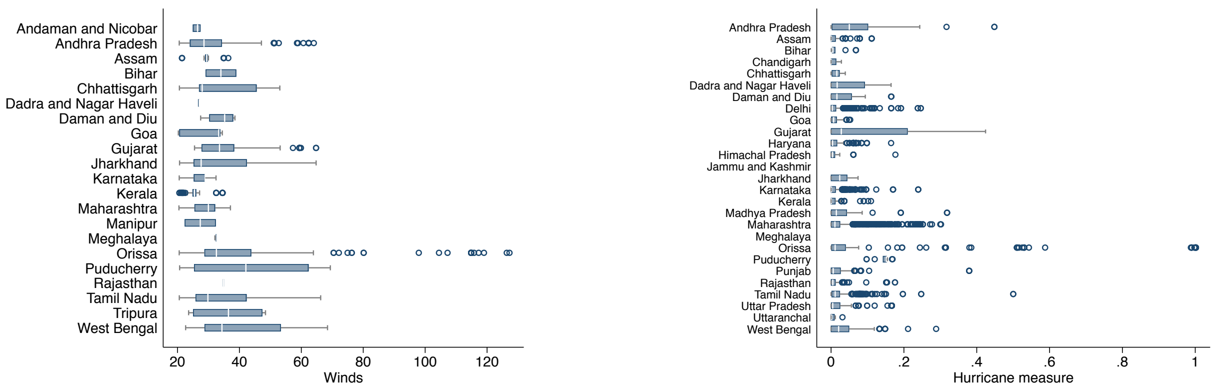
Note: The left panel shows average maximum comparative advantage by firm type. For multi-ISIC firms, we choose as reference the highest comparative advantage in a year. The right panel shows the average firm-industry sales by firm type, overall and within industry. Residuals refer to the residuals of a regression of firm-ISIC sales on industry FE. Thus, the bottom panel of the right figure shows firm-industry sales across firm types within industry. The term “single-ISIC” denotes firms which produce in a single 4-digit ISIC industry over the period 1995-2005. “Always-multi-ISIC firms” refers to firms which produce in more than a single 4-digit ISIC industry every year from 1995 until 2005. Finally, “multi-ISIC” refers to firms that switch from being single-ISIC to multi-ISIC firms (and vice versa) over time. The figure shows 95% confidence intervals.

Figure 2: Firm distribution by number of establishments



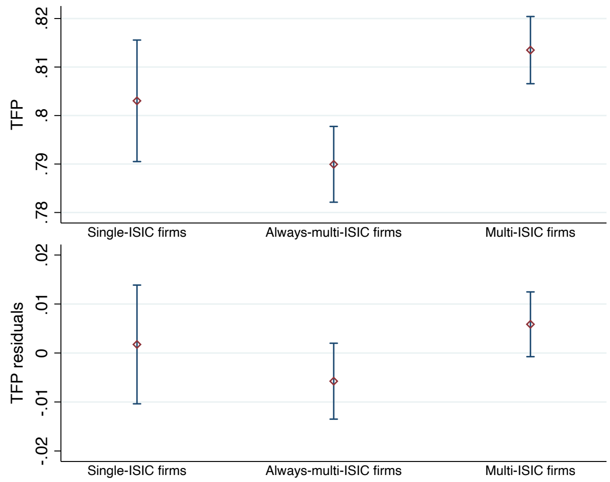
Note: The histogram shows the distribution of firms according to the number of establishments they posses (single establishment firms are defined according to the first definition used in the paper: a firm owns a single establishment if the firm appears in the Prowess database but not in Google places (probably because the firm merged or went bankrupt between 2013 and 2018) or if it appears in Google places as a single-establishment firm). The establishments belonging to each firm have been found using Google Maps.

Figure 3: Winds (w_{ph}, left panel) and Index of firms' exposure to storms (H_{fh}, right panel), 1995-2006



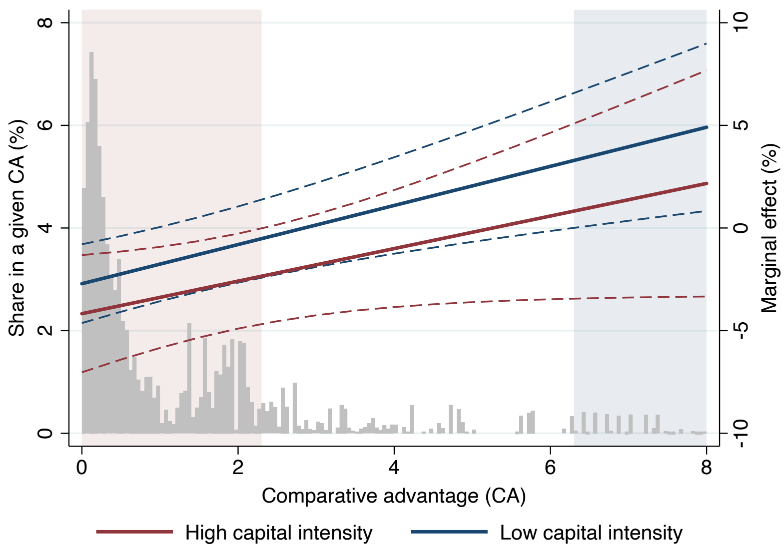
Note: The left (right) boxplot describes w_{ph} (H_{fh}) by state for the period 1995-2006. States with $w_{ph} > 0$ and $H_{fh} > 0$ between 1995 and 2006 are listed in the ascending alphabetical order. The white line is the median. The bottom of the box is the first quartile ($Q1$ or 25th percentile)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

Figure 4: Average TFP by firm type



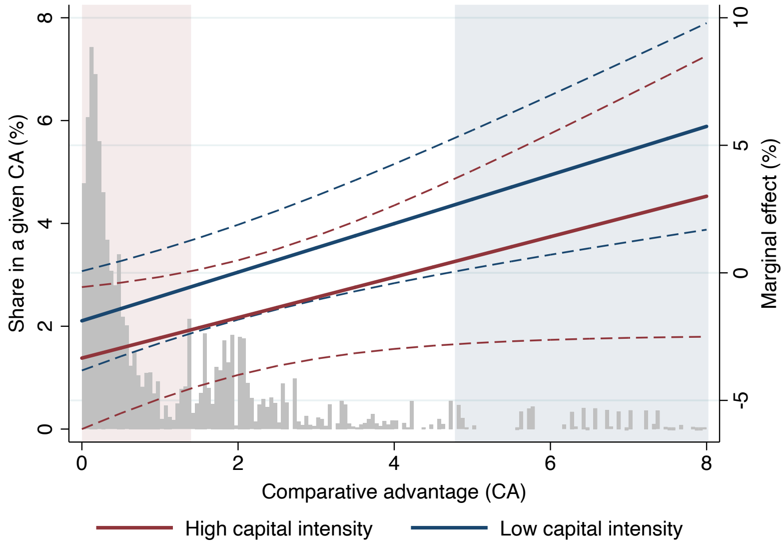
Notes: The term "single-ISIC" denotes firms which produce in a single 4-digit ISIC industry over the period 1995-2005. "Always-multi-ISIC firms" refers to firms which produce in more than a single 4-digit ISIC industry every year from 1995 until 2005. Finally, "multi-ISIC" refers to firms that switch from being single-ISIC to multi-ISIC firms (and vice versa) over time. The figure shows 95% confidence intervals.

Figure 5: Capital intensity - TFP at the 25th percentile



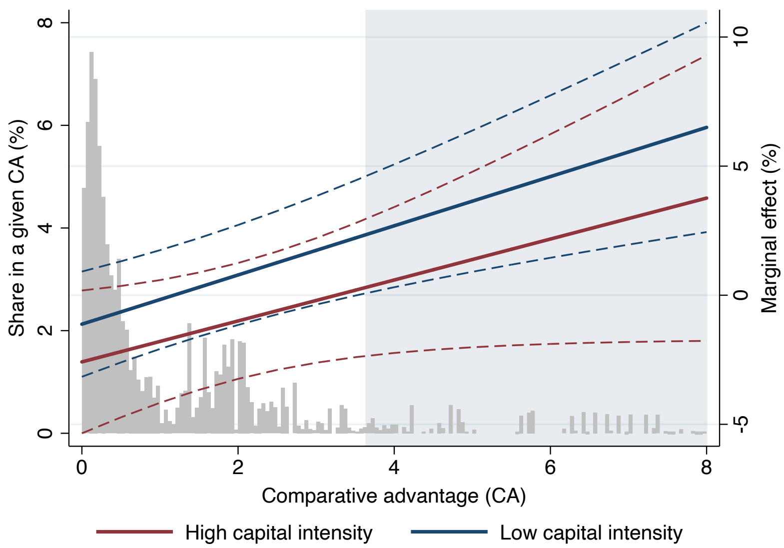
Notes: This graph reports the marginal effect of a storm on sales at the firm-industry level. The marron line reports the marginal effect for a firm in a high capital intensity industry (at the 75^{th} percentile of the capital intensity distribution), while the blue line reports the marginal effect for a firm in a low capital intensity industry (at the 25^{th} percentile of the capital intensity distribution). The shaded areas correspond to areas where the marginal effect is statistically significant at the 95% level, the maroon (blue) area correspond to the high (low) capital intensity industry.

Figure 6: Capital intensity - TFP at the median



Notes: This graph reports the marginal effect of a storm on sales at the firm-industry level. The marron line reports the marginal effect for a firm in a high capital intensity industry (at the 75^{th} percentile of the capital intensity distribution), while the blue line reports the marginal effect for a firm in a low capital intensity industry (at the 25^{th} percentile of the capital intensity distribution). The shaded areas correspond to areas where the marginal effect is statistically significant at the 95% level, the maroon (blue) area correspond to the high (low) capital intensity industry.

Figure 7: Capital intensity - TFP at the 75th percentile



Notes: This graph reports the marginal effect of a storm on sales at the firm-industry level. The marron line reports the marginal effect for a firm in a high capital intensity industry (at the 75^{th} percentile of the capital intensity distribution), while the blue line reports the marginal effect for a firm in a low capital intensity industry (at the 25^{th} percentile of the capital intensity distribution). The shaded areas correspond to areas where the marginal effect is statistically significant at the 95% level, the maroon (blue) area correspond to the high (low) capital intensity industry.

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 own product codes. In addition, the database reports the National Industrial Classification 2008 (NIC) product codes for the last main product (largest sales in value) reported by the firm. NIC codes coincide with the International Standard Industrial Classification (ISIC) Rev. 4 up to the 4-digit level.[37] In order 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% (2091 codes out of 4037) of the CMIE product codes to NIC industry codes. We then assign the remainder of the product codes by hand (1946 out of 4037 product codes).[38] Table C.1 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 choose to assign code 603070605000 to NIC 13919 as well.

[Table C.1 here]

A.2 Balassa computation

We construct the Balassa index of revealed comparative advantage using Indian exports taken from the BACI International Trade Database. BACI provides bilateral trade flows disaggregated at the HS 6-digit level since 1995. First, we aggregate Indian bilateral exports at the 4-digits ISIC Rev. 4 level.[39] We then create the Balassa index and retain measures of

[37] NIC has 21 sections, 88 divisions (2-digit numeric code), 238 groups (3-digit numeric code), 403 classes (4-digit numeric code), and 1304 sub-classes (5-digit numeric code).

[38] This practice is not new, also Goldberg et al. (2010), which uses a slightly different version of Prowess, assigned product codes manually.

[39] We first merge HS92 to ISIC Rev. 3 4-digits using a crosswalk provided by the World Integrated Trade Solution. We then merged ISIC Rev. 3 4-digits to ISIC Rev. 4 4-digits using a correspondance from the United Nations Statistics Division.

comparative advantage for the manufacturing sector. Note that a multi-ISIC firm will have a Balassa index for each industry in which it operates within a given year, while single-ISIC firms will 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 towards 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 computation

TFP is estimated from the following equation:

$$\text{VA}_{ft} = \alpha_0 + \alpha_1 L_{ft} + \alpha_2 S_{ft} + \boldsymbol{IN\alpha} + \omega_{ft} + \epsilon_{ft}, \tag{13}$$

where VA_{ft} is the log of real value added of firm f at time t. L_{ft} denotes the log of labor cost and S_{ft} is the log of the real capital stock. Hicks-neutral TFP estimates are obtained from equation (13) by subtracting firm f predicted output from its actual output at time t.

Value added is measured as the sum of the firm labor cost and its profit before interest, tax and depreciation, and deflated using the ASIA KLEMS 2-digit industry level (ISIC Rev. 4 2-digits 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 stock of capital is proxied by a firm's gross fixed assets. The vector of intermediary inputs $\boldsymbol{IN}$ includes firm-specific real power and fuel expenditures as well as real raw material expenses. Each of these inputs is taken from the Prowess database, expressed in natural logarithms and deflated using the ASIA KLEMS 2-digit industry level (ISIC Rev. 4 2-digits level) series of intermediary input price index. ω_{ft} is the firm-specific time-varying unobserved productivity term (TFP) which we seek to estimate and which 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 Night-lights data

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 (DMSP) which took pictures of the Earth every night for twenty years. The night-lights output measures are derived from the raster image for each date for the pixels that correspond to each village's geographical coordinates (latitude and longitudes). These data are processed following the recommendation of the National Oceanic and Atmospheric Administration (NOAA) and over 4 billion data points are used in the aggregation process. Details and access to the data can be found at `http://api.nightlights.io`.

B Appendix. Alternative Definitions of Storms

This section explores the sensitivity of our main results to alternative specifications of the storm index. Our storm measure, constructed following Yang (2008) and Pelli & Tschopp (2017), focuses on tropical storms and tropical cyclones (i.e. any storm with wind speed over 33 knots) and uses a quadratic damage function. In the United States, a threshold of 33 knots tends to be too low for winds to impair materials and structures (for instance Emanuel, 2011 uses a threshold of 50 knots). In addition, storm models in the U.S. suggest that the energy released by a storm and the force on physical structures may be related in a cubic manner (see the technical HAZUS manual of the Federal Emergency Management Agency (FEMA) of the U.S. Department of Homeland Security and Emanuel, 2005). While this is the case for high-income countries, sub-standard quality of construction materials in India makes buildings and infrastructures vulnerable already at much lower wind intensities. For this reason, while we present results based on alternative specifications of firm exposure to storms in Table C.3, the main analysis sticks to our baseline storm index.

[Table C.3 here]

Columns (3) and (4) of Table C.3 follow Emanuel (2011) with a threshold of 50 knots, and the last two columns are based on a threshold of 64 knots to incorporate tropical cyclones only. For each threshold, we also propose to compute the storm measure using a cubic damage function (columns 2, 4 and 6). Column (1) shows results based on our main storm measure. Starting with Panel I, we find that the estimated destruction of buildings, land and electricity is statistically significant across alternative specifications of the storm index and larger when using a cubic function. However, when looking at fixed assets, the effect of storms becomes imprecisely estimated as we reach a threshold of 50 along with a cubic damage function.

This result may be due to the fact that most of India's storms have windspeed intensities below 64 so that as the threshold increases, the share of observations with a positive storm index diminishes drastically, to 3% with a threshold of 50 and to 1% with a threshold of 64. For this reason, while a small number of violent storms might be sufficient to detect an effect on individual measures of firms' physical capital (such as buildings, land and electricity), it might not be enough to obtain a precise estimate on a variable like fixed assets which aggregates several types of physical capital. Most importantly, our findings suggest that, overall, likely due to the widespread poor infrastructures quality in India, even relatively low windspeed intensities can have considerable detrimental effects on capital. Hence, our main measure of firm exposure to storms appears appropriate in the case of India. Panel II focuses on firm industrial sales. All of our estimates of interest have the expected sign but standard errors increase as we move across specifications. The coefficients on the storm index and the interaction between the storm index and TFP remain statistically significant, at least at the 10% level, throughout. For the estimates on the other interaction term, statistical significance is lost when moving to specifications for which only 3% or 1% of the observations have positive measures of storms. Our interpretation is that while there are enough observations with positive storms and while there is enough variation across firms within industry, the samples in columns (3)-(6) lack variation across industries.

C Appendix. Tables

Table C.1: Example of CMIE product code assignment to NIC Division 13 *"Manufacture of textiles"*

NIC Code	CMIE Product Code	Description
1311		Preparation and spinning of textile fibres
13111		Preparation and spinning of cotton fiber including blended cotton
	603030100000	Cotton yarn[p]
	603030103000	Cotton yarn 24's count[a]
13113		Preparation and spinning of wool, including other animal hair
	602060000000	Woollen yarn[p]
	602050000000	Angora wool/scoured wool/kashmira wool[a]
1312		Weaving of textiles
13123		Weaving, manufacture of wool and wool mixture fabrics
	602090100000	Woollen fabrics[p]
	602090200000	Woollen worsted yarn[a]
13129		Weaving of jute, mesta and other natural fibers including blended natural fibers n.e.c.
	604010000000	Jute goods[p]
	604010500000	Jute carpet[a]
1313		Finishing of textiles
13131		Finishing of cotton and blended cotton textiles
	603080000000	Printed cloth[p]
	603070101030	Printed fabrics[a]
1391		Manufacture of knitted and crocheted fabrics
13919		Manufacture of other knitted and crocheted fabrics
	603070615000	Sarees[p]
	603070605000	Dhoties[a]

Note: Devision 13 (NIC-2008) has a total of 8 4-digit classes and 50 5-digit product codes. Only a small subset of these products is presented in the table. Source: Prowess database and authors' matching of agency's product codes to NIC-2008 5-digit product codes. [p] denotes the product codes which are matched by the agency, and the product codes matched by the authors are identified with [a].

Table C.2: Capital destruction – robustness

	Baseline	No extremes	Before/After June 30
	(1)	(2)	(3)
Buildings$_{ft}$ (logs):			
Storms$_{ft}$	-1.54***	-0.52*	
	(0.48)	(0.27)	
Storms$_{ft,before}$			-0.72***
			(0.26)
Storms$_{ft,after}$			-4.06
			(4.47)
Observations	14407	14407	9139
Land$_{ft}$ (logs):			
Storms$_{ft}$	-1.55***	-0.52**	
	(0.45)	(0.23)	
Storms$_{ft,before}$			-0.65**
			(0.30)
Storms$_{ft,after}$			-1.95
			(2.21)
Observations	13794	13794	8767
Electricity$_{ft}$ (logs):			
Storms$_{ft}$	-2.48***	-0.92**	
	(0.86)	(0.41)	
Storms$_{ft,before}$			-1.62***
			(0.52)
Storms$_{ft,after}$			7.40
			(12.3)
Observations	6862	6862	4366
Fixed assets$_{ft}$ (logs):			
Storms$_{ft}$	-1.42**	-0.67***	
	(0.57)	(0.26)	
Storms$_{ft,before}$			-0.96***
			(0.26)
Storms$_{ft,after}$			-4.81
			(3.48)
Observations	14936	14936	9524
TFP$_{f(t-1)}$	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	
# of establishments$_{ft}$	Yes	Yes	
Firm-type FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes

Note: Standard errors are two-way clustered at the firm and district-year levels. *** 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 pincode and d a district. The dependent variables are, in turn, the log of firms' buidings, land, electricity and fixed assets. The set of industry FE corresponds to the ISIC 4-digits classification. The industry FE is associated with the industry in which the firm's sales are the largest. Each specification excludes always-multi-ISIC firms.

Table C.3: Alternative definitions of the storm index

	> 33		> 50		> 64	
	Baseline	Cubic	Quadratic	Cubic	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Panel I: Capital$_{ft}$ (logs)						
Buildings$_{ft}$:						
Storms$_{ft}$	-1.54***	-1.89***	-1.60***	-1.88***	-1.63***	-1.90***
	(0.48)	(0.44)	(0.45)	(0.37)	(0.42)	(0.31)
Observations	14407	14407	14407	14407	14407	14407
Land$_{ft}$:						
Storms$_{ft}$	-1.55***	-1.99***	-1.74***	-2.04***	-1.87***	-2.00***
	(0.45)	(0.52)	(0.48)	(0.52)	(0.48)	(0.54)
Observations	13794	13794	13794	13794	13794	13794
Electricity$_{ft}$						
Storms$_{ft}$	-2.48***	-4.27***	-3.55***	-5.29***	-4.53***	-5.44**
	(0.86)	(1.27)	(1.04)	(1.80)	(1.41)	(2.43)
Observations	6862	6862	6862	6862	6862	6862
Fixed assets$_{ft}$:						
Storms$_{ft}$	-1.42**	-1.46*	-1.37**	-1.16	-1.11	-0.88
	(0.57)	(0.85)	(0.69)	(0.89)	(0.79)	(0.84)
Observations	14936	14936	14936	14936	14936	14936
Panel II: Sales $_{fit}$ (logs)						
Storms$_{ft}$	-5.92***	-8.12***	-6.81***	-8.85**	-7.60**	-9.84*
	(1.33)	(2.51)	(2.13)	(3.66)	(3.09)	(5.18)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.92**	1.63*	1.20	2.17	1.68	3.08
	(0.39)	(0.94)	(0.74)	(1.74)	(1.46)	(2.50)
	[0.017]	[0.085]	[0.104]	[0.214]	[0.250]	[0.218]
TFP$_{f(t-1)}$ × Storms$_{ft}$	4.24***	5.76**	4.66**	7.02*	5.55*	9.49*
	(1.34)	(2.38)	(1.95)	(3.75)	(3.09)	(5.48)
Observations	17952	17952	17952	17952	17952	17952
Share of observations with positive storms	10	10	3	3	1	1
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
# of establishments$_{ft}$	Yes	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are two-way clustered at the firm and district-year levels. *** 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 pincode and d a district. In the first panel, the dependent variables are, in turn, the log of firms' buidings, land, electricity and fixed assets. In the second panel, the dependent variable is the log of firms' industry sales. The set of industry FE corresponds to the ISIC 4-digits classification. In panel I, the industry FE is associated with the industry in which the firm's sales are the largest. In addition to the listed set of controls, panel II also includes pincode FE. Each specification excludes always-multi-ISIC firms. The terms "> 33", "> 55" and "> 64" mean that thresholds of 33, 55 and 64 knots are used to compute the measure of storm, respectively. Finally, the terms "quadratic" and "cubic" indicate the exponent of the damage function.

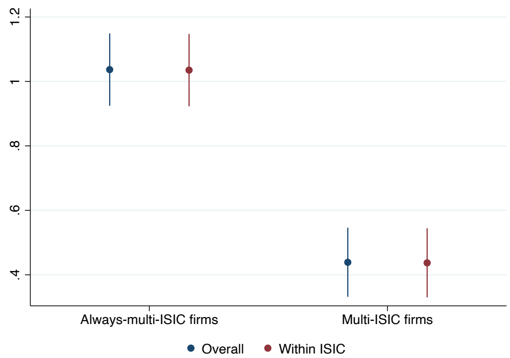
Table C.4: Placebo test, alternative randomization

	Share with statistical significance at:											
	Firm			Industry			District			Year		
Sales_{fit} (logs)	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\text{TFP}_{f(t-1)}$	1	1	1	1	1	1	1	1	1	1	1	1
Storms_{ft}	0.015	0.058	0.114	0.024	0.082	0.149	0.015	0.073	0.127	0.069	0.172	0.258
Comp. $\text{adv.}_{it} \times \text{Storms}_{ft}$	0.007	0.033	0.071	0.025	0.085	0.149	0.015	0.059	0.106	0.044	0.115	0.177
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	0.017	0.063	0.12	0.042	0.093	0.159	0.021	0.076	0.142	0.115	0.257	0.385
Night-lights $\text{growth}_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of $\text{establishments}_{ft}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Results show the share of statistically significant results over 1000 randomizations. In columns (1)-(4), the storm measure is randomized within firms, 4-digit ISIC industries, districts and years, respectively. Statistical significance corresponds to three-way clustered standard errors at the firm, district-year and industry-year levels. 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 pincode and d a district. The dependent variable is the log of firm sales in industry i at time t. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification excludes always-multi-ISIC firms.

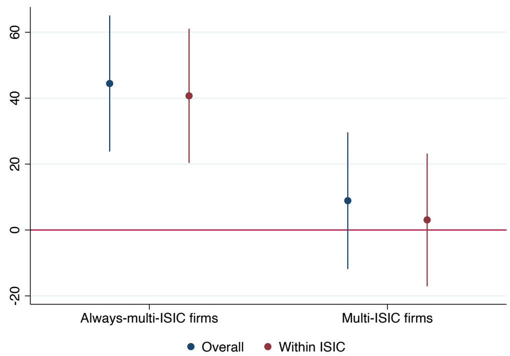
D Appendix: Figures

Figure D.1: Regression of the maximum Balassa by firm-year on firm-type fixed effects, pooled and within ISIC



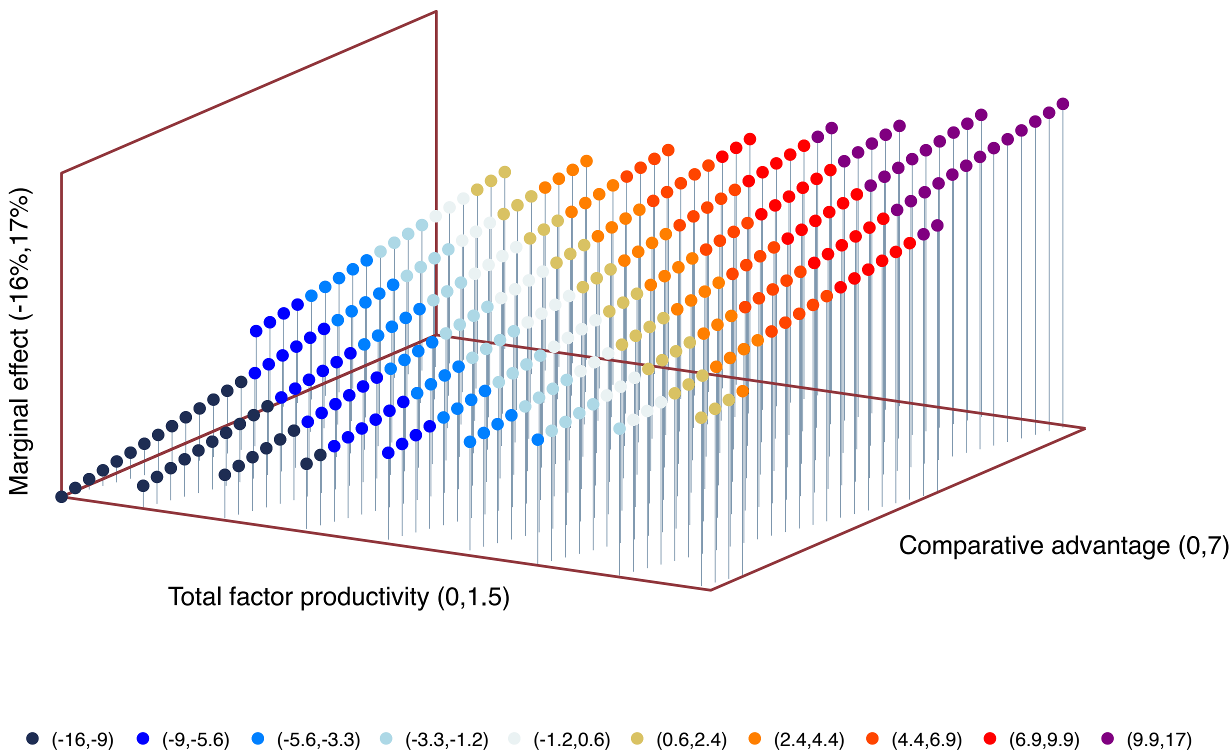
Notes: “Overall” refers to the pooled regression coefficients and “Within ISIC” to regressions which include a full set of ISIC FE. “Always-multi-ISIC firms” refers to firms which produce in more than a single 4-digit ISIC industry every year from 1995 until 2005. “Multi-ISIC” refers to firms that switch from being single-ISIC to multi-ISIC firms (and vice versa) over time.. The figure shows 95% confidence intervals.

Figure D.2: Regression of firm-ISIC sales on firm-type fixed effects, pooled and within ISIC



Notes: "Overall" refers to the pooled regression coefficients and "Within ISIC" to regressions which include a full set of ISIC FE. "Always-multi-ISIC firms" refers to firms which produce in more than a single 4-digit ISIC industry every year from 1995 until 2005. "Multi-ISIC" refers to firms that switch from being single-ISIC to multi-ISIC firms (and vice versa) over time. The figure shows 95% confidence intervals.

Figure D.3: Marginal effect of a storm on sales



Notes: Extreme values of TFP and comparative advantage (values above the 95th percentile) are left out in the computation of the marginal effect. For each level of $TFP_{ft} \in (0, 1.5)$ and $CA_{it} \in (0, 7)$, the marginal effect is computed as $\widehat{\phi_2} + \widehat{\phi_3} CA_{it} + \widehat{\phi_4} TFP_{ft}$, where $\widehat{\phi_2}$, $\widehat{\phi_3}$, and $\widehat{\phi_4}$ are taken from column (6) in Table 5. The marginal effect captures the change in a firm's industry log sales in the aftermath of a storm of mean intensity ($H_{ft} = 0.027$).