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 Indian firm sales data and tropical storms as an exogenous shock on firms' capital, we find evidence of creative destruction. Within industry, less productive firms suffer disproportionately more, both along the intensive (firm sales) and extensive (firm exit) margins. The effect found across industries is 33% larger, and indicates that capital destruction leads to a shift in sales towards comparative advantage 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. Our baseline estimates imply that for the top 25% of storms, the median firm's industry sales decrease by at least 2.5%. The exit rate of the median firm increases by at least 2% for the top 25% of storms.

Keywords: Firms, Capital Destruction, Creative Destruction, Hurricanes, India.
JEL Codes: F14, O10, Q54

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1 Introduction

The production pattern of a country is shaped by factors such as technology, institutions or trade policy. Changes in these factors affect the competitivity of firms and industries. In a broad class of models with vintage capital and embodied technological change, capital is malleable and firms can adjust their input mix and production relatively rapidly. In practice, the adaptation of firms' production structures to these changes seems to be a slow process. This sluggish adjustment could be due to the presence of imperfect markets (e.g. frictions on the labor and capital markets), as well as sunk costs related to the putty-clay nature of capital. When capital is putty-clay, investments are irreversible; i.e. capital and labor can be substituted ex-ante but once capital is installed, the production technology becomes Leontief (see Boucekkine et al., 2011, for a review of vintage capital models).[1] Hence, investors' hands are tied to the decisions made in the past and as long as revenues cover at least part of the sunk-cost incurred previously, capital may not be replaced. The putty-clay nature of capital affects industrial dynamics, for instance by slowing down the decay of declining industries and keeping in activity unproductive firms that barely manage to cover their fixed costs. In such an environment a government could boost economic growth by putting in place policies that reduce the adjustment cost of capital (for instance a tax break for new machines). However, the effectiveness of these adjustment policies is difficult to evaluate because of their endogeneity; they often target specific industries and tend to be implemented in times of economic crisis or political changes (e.g. electoral cycle).

In this paper, we use storms as exogenous shocks to study the adjustment of firms to the destruction of part of their capital. This destruction is akin to a reduction in the adjustment costs when capital is putty-clay. The question we are interested in is: if part of a firm's capital is destroyed and investments are made anew, how will the firm's sales and industry production mix change?

Our hypothesis is that capital destruction generates effects akin to Shumpeterian creative destruction, leading unproductive firms to exit the market and surviving firms to build back better. This adjustment process may occur through two channels, within and across industries. First, within industry, we expect the least productive firms to suffer disproportionately more, and, firms which can afford reconstruction to replace destroyed capital with newer and more productive vintages. The second effect takes place across industries. Our conjecture is that reconstruction should be more pronounced in industries with high demand and where the opportunity cost of production is relatively low. In order to rank industries along these

[1] For the seminal model of vintage capital with putty-clay capital, see Johansen (1959), and with putty-putty capital, see Solow (1960).

two dimensions, we use the Balassa Index of revealed comparative advantage, and expect production to shift towards comparative advantage industries. This shift may be accentuated by an effect arising across industries, as firms cease or reduce operations in comparative disadvantage industries to invest in sectors that align more closely with comparative advantage. In this paper we propose an identification strategy to uncover creative destruction and disentangle these two channels. In addition, understanding whether production reallocates towards more productive firms and towards better industries is important as it would inform us on the effectiveness of broad-based adjustment policies.

To capture the exogenous destruction of capital, we construct a measure of firm-affectedness by storms. Storms are exogenous phenomena since it is not possible to predict their occurence nor their 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). A detailed discussion of the exogeneity of storms can be found in Pelli & Tschopp (2017). We focus on India, which, over the period considered (1995-2006), is regularly subject to storms of various intensities. Importantly, we observe a high concentration of firms and economic activity in storm-prone areas (e.g. Gujarat or West Bengal). Moreover, we find strong and statistically significant evidence that storms destroy firm-level capital. With a cost line of 7,516 kilometres India is among the most affected regions in the world (it is exposed to roughly 10% of the world's cyclones). Annually over 370 million people are affected by cyclones (storms with winds travelling faster than 33 knots) in India alone.[2]

We implement our identification strategy using PROWESS, a firm-level database for India covering the period 1990-2014 and containing the financial statements of 27,794 firms.[3] This firm-level panel contains information on product and industrial sales, and capital assets. The database also provides detailed firms' identifiers such as the exact location of the headquarter and the company name, which, as described below, allow us to identify the location of each of the establishments belonging to a firm. Matched with storms' best track data, this location information allows us to construct an index of yearly firm-affectedness by storms which accounts for wind exposure at both the headquarter and each of the establishments. In addition, the richness of the PROWESS dataset allows us to conduct a detailed analysis of the adjustment of both single- and multi-industry firms, along the two margins of adjustment (intensive and extensive).

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

[3]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. The latter ones participate on a voluntary basis.

In order to identify whether production shifts towards comparative advantage industries, we exploit within-space across-industry variation and compare the adjustment of firms with similar storm affectedness and comparable productivity levels, but producing in industries with distinct comparative advantages. Specifically, we assess whether comparative disadvantage industries suffer disproportionately more by regressing the outcome variable at the firm level (e.g. firm-specific industry sales, capital assets or exit) on our storm index of firm-affectedness and the interaction of this storm measure with an industry-specific measure of comparative advantage. We then examine whether this is also the case for unproductive firms. In order to do this, we repeat the previous exercise but interact the storm index with lagged firm-level total factor productivity. The approach of interacting a measure of storm with comparative advantage is similar to that used in Pelli & Tschopp (2017) to explain how the pattern of exports at the industry-country level evolves in the aftermath of storms.[4] However, in this paper we focus on production and carry out the analysis at the firm level, which allows us to propose a refined identification strategy and deepen our understanding of the micro mechanisms underlying the aggregate adjustment found in Pelli & Tschopp (2017).

We find evidence that, for the median firm (in terms of both TFP and comparative advantage), storms can destroy up to 43% of its capital assets. In addition, our estimates indicate that, within a year, capital reallocates towards the top of the comparative advantage distribution. This effect holds for two types of firms, *single-ISIC firms*, to which we refer as firms which produce in a single industry over the period of time we consider, and *multi-ISIC firms*, which sometimes produce in multiple industries. In contrast, this type of adjustment does not seem to take place for firms which are continuously multi-ISIC firms, *always-multi-ISIC firms*. We argue that their resilience to storms is likely explained by the fact these companies have easier access to cutting-edge technologies and more durable capital.

Our baseline estimates imply that for the top 25% of storms, the median firm's industry sales decrease by at least 2.5%. When taking into account the full distribution of comparative advantages, results show that in the aftermath of a storm, firms' industry sales shift towards comparative advantage industries. This finding, along with the results on capital reallocation, is in line with the aggregate shifts in export pattern found in Pelli & Tschopp (2017) and suggests that the build-back better mechanism discussed above is at work. In addition, our results indicate that, within industry, the least productive firms suffer relatively more from storms and experience larger decreases in sales.

The analysis on the extensive margin reveals that storms increase firms' exit rate, with the least productive firms exiting the market at a higher rate. The exit rate of the median

[4] A similar methodology is also used in Rajan & Zingales (1998), Nunn (2007) and Levchenko (2007) to examine the pattern of trade at the industry-country level.

one-establishment firm increases by at least 2% (6%) for the top 25% (10%) of storms. This result is consistent with the idea of creative destruction. There is no evidence, however, of heterogenous effects across industries. Hence, it appears that firms' exit rate depend on productivity rather than the type of industry in which a firm operates.

We then examine the entry and exit of firms' industry lines, and changes in firms' industry mix. We do not find evidence that capital destruction affects the entry rate of industry lines. Conversely, our results suggest that storms do increase the exit rate of firms' industry production lines and that lines characterized by low comparative advantage have a higher exit probability. Unlike for the exit probability of a firm, productivity does not seem to have an heterogeneous impact on the exit of specific firms' industry lines. Finally, we also show that firms adjust their production mix within an existing set of industries, increasing sales in industries that align more closely with the comparative advantage, and abandoning unproductive lines.

This paper also contributes to the ever growing literature on the impact of cyclones and storms; an important literature in a global warming context. Warmer oceans contribute to more powerful storms. According to Munich Re, tropical cyclones have generated over US$ 1.3 trillion of damages since 1980. In 2017 alone Asia suffered damages in excess of US$ 30 billion. The existing literature focuses on a large variety of aspects of the impact of cyclones on economic activity. For instance, Hallegatte et al. (2018) focuses on how to adapt and improve post disaster reconstruction. Hsiang & Jina (2014) examine the impact of cyclones on long-run growth across countries. In a recent paper, Elliott et al. (2019) at Chinese plants' reactions and find a considerable negative impact on firm performance. Similarly to our findings, this effect is relatively short-lived. To the best of our knowledge, we are the first to unbox potential heterogeneous effects of cyclones across industries and firms' productivity levels.

This paper is organized as follows. Section 2 describes firm-level production data, comparative advantage and the construction of the measure of firm-affectedness by storms. In Section 3 we show evidence that storms destroy firm capital. The empirical strategy is described in Section 4. The subsequent section present the baseline results and robustness. We take a closer look at the adjustment of firms in Section 6, examining switches across industries, entry and exit of new industry lines, as well as firm exit. 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 the annual reports and quarterly statements of companies. The data include information on the financial performance of Indian companies since 1990 until 2014. The database 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 the data. In this paper, we focus solely on firms operating in the manufacturing sector (defined by the ISIC Rv.4 2-digit classification of industries) – i.e. 12,636 firms out of 27,794 firms. To our knowledge, PROWESS is the largest dataset on the financial performance of Indian individual firms and the only detailed database on firms' level product mix and sales in India. In addition, this dataset provides information on headquarters' postal codes (pincode) and company names, information which is particularly useful to us in order to construct a measure of firm-affectedness by storms. A caveat of this database is that it is not representative of the Indian economy. Firms contribute on a voluntary basis and, as a consequence, large firms are better represented than smaller firms. The informal sector is not present in this database.

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.[5] 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).[6] Table 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.

[5] 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).

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

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 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: Division 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}.

Our final sample covers the period 1995-2006. As we discuss later on, we start in 1995 because our export data are not available earlier on and stop in 2006 as India did not experience winds that qualify as storms between 2006-2011. We use ISIC Rev.4 as our benchmark industry classification and focus on 4-digit industries in the manufacturing sector.[7] Our 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 single 4-digit ISIC industry. For reasons that will become clear later on, our analysis differentiates between firms which produce within a single industry (ISIC code) over the period 1995-2006 (*single-ISIC firms*), those which operate within more than one ISIC code every single year over the entire period of time (*always-multi-ISIC firms*) and

[7] The manufacturing sector corresponds to Section C, Divisions 10-33 of ISIC Rev.4.

those which switch from being a single-ISIC to multi-ISIC firm (and vice versa) over time (*multi-ISIC firms*). Table 2 indicates that 7% of the firms contained in our final sample are always single-ISIC , 45% switch status from single- to multi-ISIC firms (and vice versa) over time, and 48% are always-multi-ISIC firms.

Table 2: Firm type

	Freq.	Percent	Cum
	(1)	(2)	(3)
Single-ISIC	3,461	7.28	7.28
Always-multi-ISIC	22,609	47.54	54.82
Multi-ISIC	21,487	45.18	100.00
Total	47,557	100.00	

Note: The term "single-ISIC" denotes firms which produce one single ISIC industrial good over the period 1995-2005. "Always-multi-ISIC firms" refers to firms which produce more than one single ISIC industrial good every single year from 1995 until 2005. Finally, "multi-ISIC" refers to firms which switch from being single-ISIC to multi-ISIC firm (and vice versa) over time.

2.1.1 Total Factor Productivity estimates

Total factor productivity (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 estimation is that firm-level productivity is unobserved and correlated with firm input choices, therefore, 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).[8] TPF is estimated from the following equation:

$$\mathrm{VA}_{ft} = \alpha_0 + \alpha_1 L_{ft} + \alpha_2 S_{ft} + \boldsymbol{IN\alpha} + \omega_{ft} + \epsilon_{ft}, \tag{1}$$

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. Value added is measured as the sum of

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

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. To compute the stock of capital, we follow the Perpetual Inventory Method (PIM) using firms' gross fixed assets, the book value of the firms' gross fixed asset depreciation and the ASIA KLEMS 2-digit industry level (ISIC Rev.4 2-digits level) of gross output price index.[9] 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.[10]

Finally, Hicks-neutral TFP estimates are obtained from equation (1) by subtracting firm f predicted output from its actual output at time t.

2.1.2 Identifying establishments

In order to evaluate firm-level response to storms, one needs to construct a measure that takes into account the degree of affectedness by winds at each of the establishments belonging to a firm. As a consequence, an important step of this research consists in identifying and geo-referencing all of a firms' establishments.

PROWESS provides the name of the firm and exact location of its headquarter. To obtain the coordinates of each of the establishments of a firm, we turn to Google maps. We use the googleplace algorithm using company names.[11] The algorithm returns Google maps results based on the company name, for a maximum of 20 results. The results are establishments with names and corresponding coordinates. Our sample focuses only on

[9]Specifically, the stock of capital A_{ft} is computed as follows:

$$A_{ft} = (1 - \delta_{ft})A_{f(t-1)} + I_{ft}, \tag{2}$$

where the depreciation rate δ_{ft}, is given by $\delta_{ft} = \frac{DEPR_{ft}}{GFA_{f(t-1)}}$, the first value ($t = 0$, corresponding to a firm's first appearance) of real capital stock is $A_{f,t=0} = \frac{GFA_{f,t=0}}{PI_{f,t=0}}$ and where the real investment I_{ft} is given by $I_{ft} = \frac{GFA_{ft} - GFA_{f(t-1)} + DEPR_{ft}}{PI_{ft}} \times 100$. GFA and $DEPR$ denote firm gross fixed assets and the book value of the firm gross fixed asset depreciation, respectively. Both variables are taken from the PROWESS database. PI_{ft} is the ASIA KLEMS industry-level (ISIC 4 digits) gross output index price, base year 2005. For a firm producing in multiple industries, PI_{ft} corresponds to the industry in which the firm's sales are the largest.

[10]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.

[11]The algorithm we run, uses google places in 2018.

manufacturing firms (and not retailers or services, such as banks, which are likely have far more than 20 subsidiaries), 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 run 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.

A caveat we are all familiar with when using a Google search is that Google tends to report also a variety of results that are not related to the original query. Also in our case, we 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. The Levenshtein distance yields the number of character changes that would be required to switch from one series of characters to another one. 38% 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 9,130 unique manufacturing firms, of which 25% have one single establishment. The median firm is composed by 2 establishments, while the average firm is composed by 2.5 establishments. Figure 1 presents the distribution of firms by number of establishments. Not surprisingly, about 43% of firms have one establishments, 21% of firms have two and only 10% have between 8 and 32 establishments. Finally, the postal codes (pincodes) corresponding to each establishment are retrieved using the coordinates returned by Google places.

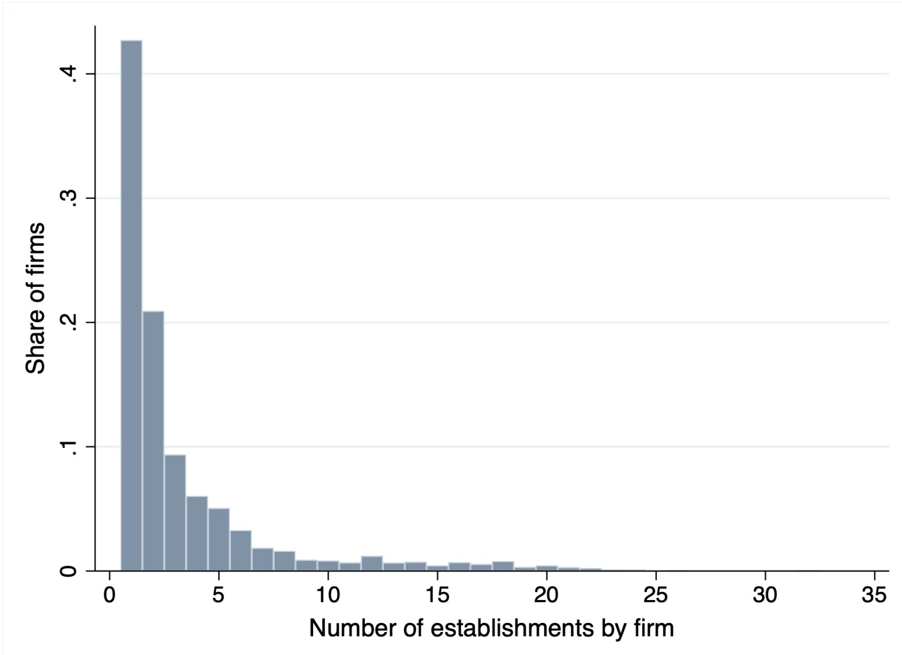
2.2 Storms

In this paper, we construct a tropical storm measure that captures the force exerted by winds on structures.[12]

Index of firms' affectedness by storms To capture the destructive potential of tropical storms on a firm's capital we construct an index that accounts for severe winds to which the establishments of a firm are exposed within a given year. Similar to Yang (2008), our storm

[12]Storms can also destroy capital by causing floodings. However, damages associated with surges are endogenous as they heavily depend on land usage such as excessive deforestation.

Figure 1: Firm distribution by number of establishments



measure is given by:

$$H_{ft} = \sum_{p \in F} \sum_{h \in T} x_{ph}, \tag{3}$$

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.[13]

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

$$x_{ph} = \frac{(w_{ph} - 33)^2}{(w^{max} - 33)^2} \quad \text{if} \quad w_{ph} > 33, \tag{4}$$

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 wind is classified as a tropical storm, the weakest form of storm. 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.[14] By

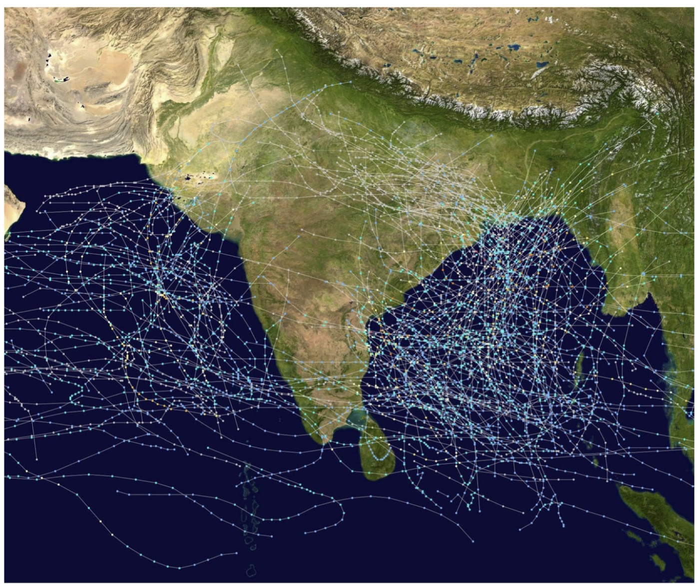
[13] The maximum of storms by pincode-year is two. Only 1% of our sample is hit by two hurricanes within the same year.

[14] Our rationale for a threshold of 33 knots is twofold. First, India is subject to a large number of storms

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's level In what follows we describe the construction of w_{ph}, i.e. the maximum wind speed associated with storm h and to which pincode p is exposed. We construct the variable w_{ph} using storms' best tracks in the North Indian and South Indian basins over the period 1995-2006.[15] Best tracks provide information on a storm's history, including the latitude and longitude, date and wind speed at the storm's eye every six hours. Figure 2 shows India best tracks for all tropical cyclones between 1970-2005.

Figure 2: Best tracks, 1970-2005



Source: National Hurricane Center (NOAA).

We start by linearly interpolating storms' best tracks, obtaining a waypoint k for the

with wind speeds between 33 and 64 knots. Tropical cyclones – tropical storms with windspeeds 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. Nevertheless, although a threshold of 33 knots seems reasonable in a developing country, we propose alternative definitions of the storm index in Appendix 8.1: on the one hand we increase the threshold to 50 and 64 knots to account for the possiblity that 33 knots may be too low for winds to destroy buildings, 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.

[15]Raw data are taken from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center. We start in 1995 because our measure of comparative advantage is not available earlier on. We do not consider the period after 2006 as there were too few storms in India between 2007 and 2011.

storm's eye at every kilometre. Each waypoint is associated to a set of coordinates and the eye's windspeed, 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 the storm. Using this formula we compute the wind speed hitting each pincode containing an establishment or a firm within the storm maximum radius. This formula describes wind fields by taking into account the fact that winds first exponentially increase to a maximum and then rapidly decrease:

$$\begin{aligned} w_{pk} &= e_k \cdot \left(\frac{D_{pk}}{26.9978}\right) \text{ if } D_{pk} \leq 26.9978 \\ w_{pk} &= e_k \cdot \left(\frac{26.9978}{D_{pk}}\right)^{0.5} \text{ if } D_{pk} > 26.9978, \end{aligned} \tag{5}$$

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, the radius where the wind reaches its maximum speed. Finally, for each storm, we retain the maximum windspeed to which a pincode was exposed:

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

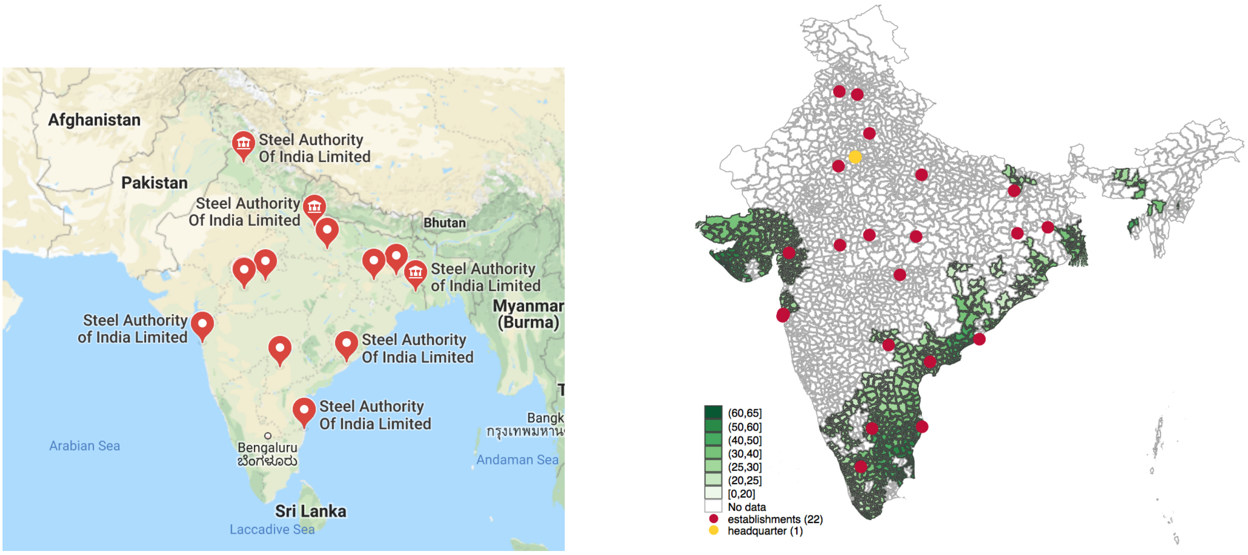
and, therefore, obtain a measure of wind speed for each affected pincode and storm.

Figure 3 provides an example of the establishments' location of the company "Steel Authority of India". The left panel is a screenshot from google map. The right panel shows the establishments' location returned by google places in the Summer of 2018. The yellow dot pinpoints the location of the headquarter and the red dots the location of each of the establishments. The green areas represent pincodes affected by windspeed (w_{ph}) of various intensities in 1998. The figure shows that while the headquarter 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. Therefore, this figure highlights the importance of accounting for establishments' affectedness by storms when computing H_{ft}. In fact, ignoring establishments' affectedness 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 boxplots in Figure 4 describe winds (w_{ph}, left panel) and the index of firms' affectedness by storms (H_{ft}, right panel) by 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.

Figure 5 illustrates how the index of firms' affectedness by storms, H_{fh}, is distributed

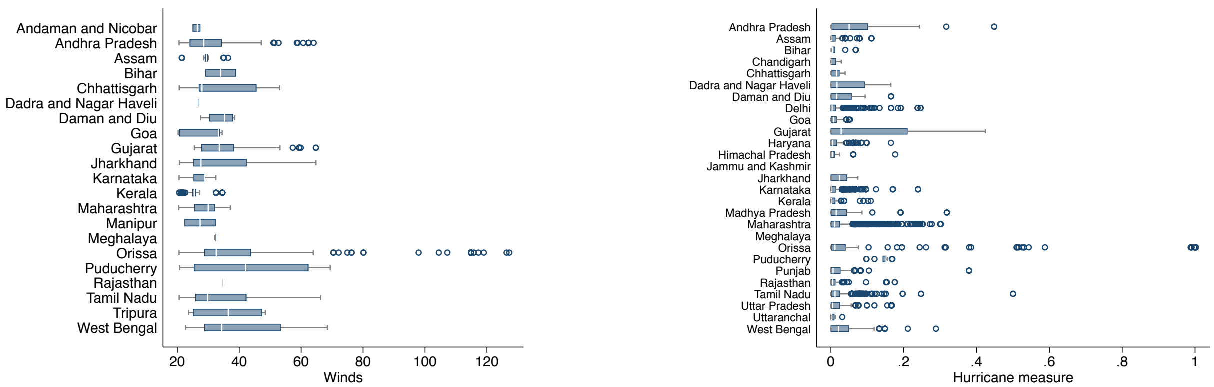
Figure 3: Example: establishments' location of the company "Steel Authority of India"



Notes: The figure shows where the establishments of the company "Steel Authority of India" are located. The left panel is a screenshot from google map. The right panel shows the establishments' location returned by google places in Summer 2018. The yellow dot denotes the headquarter and the red dots are the establishments. The green areas represent pincodes affected by windspeed (w_{ph}) of various intensities in 1998.

across pincodes of India 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 Central west coasts of India are most affected by storms. 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. The set of pincodes in which these firms are located is composed by 436 distinct 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' affectedness by 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, simply because one or many of its establishments are located in storm-prone areas. The map suggests that this is the case for many firms in the center and north of the country.

Figure 4: Winds (w_{ph}, left panel) and Index of firms' affectedness by storms (H_{fh}, right panel), 1995-2006



Notes: 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.

2.3 Comparative Advantage

We follow Pelli & Tschopp (2017), and choose to be agnostic about the source of comparative advantage. Accordingly, we also use the traditional Balassa index as our measure of comparative advantage. The index is given by the share of industry i in India's total exports, relative to the share of that industry in the world's aggregate exports. Specifically, the index is constructed as follows:

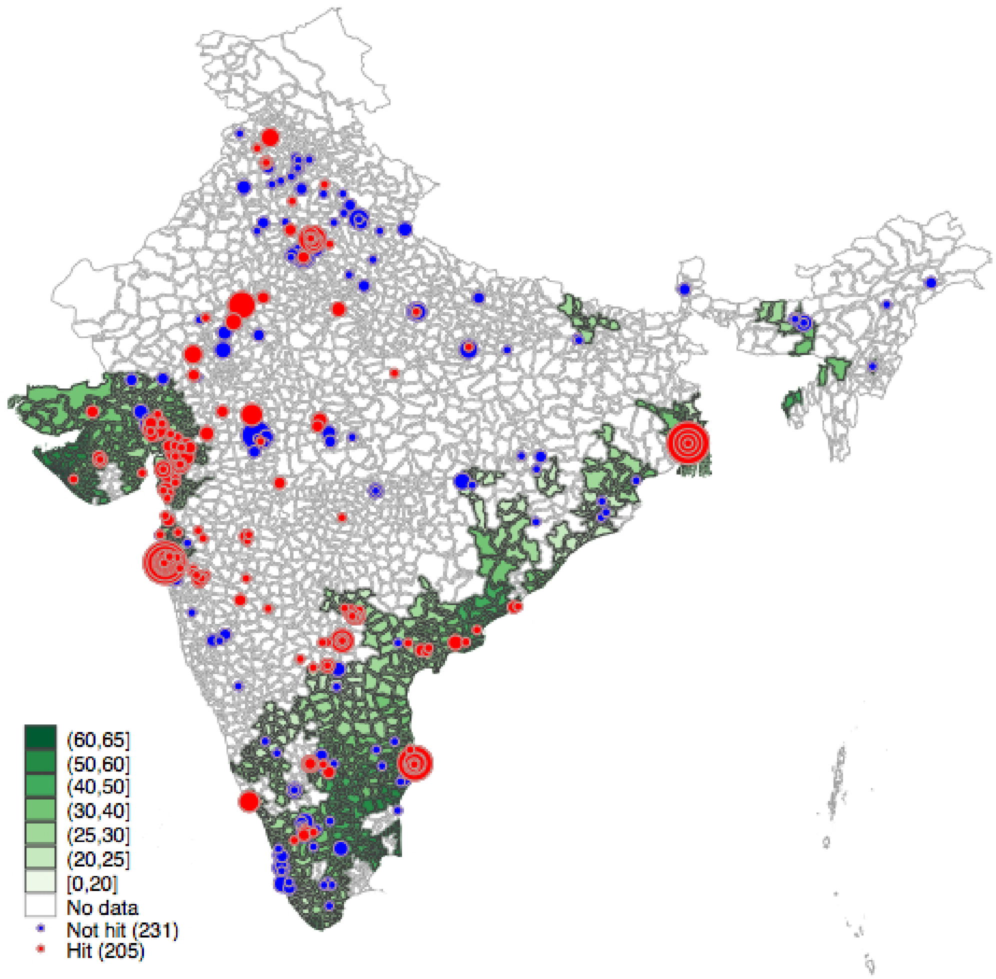
$$CA_{it} = \left(\frac{X_{it}^{India}}{\sum_i X_{it}^{India}} \Big/ \frac{X_{it}}{\sum_i X_{it}} \right),$$

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.

Since we focus on a single country, India, our measure of comparative advantage is industry-time-specific. Moreover, since our analysis uses within country (across firms, pin-codes, industry and time) data variation, the Balassa index will be less prone to the usual criticisms, according to which the index may reflect country-specific confounding factors distorting trade rather than an underlying comparative advantage.

We construct the index using Indian exports taken from the BACI International Trade Database. BACI provides bilateral trade flows disaggregated at the HS 6-digit level since

Figure 5: Winds and firms, 1998



Notes: The figure shows the location of each of the firms included in PROWESS in 1998 and highlights the areas and firms affected by storms. The green areas represent pincodes affected by windspeed of various intensities. The circles represent clusters of headquarters. The diameter of the circles is proportional to the number of headquarters in a pincode. A red (blue) circle indicates that the measure of firms' affectedness by storms, H_{fh}, is positive (zero), which occurs if at least one (none) of the establishments of the firm is affected by windspeeds above 33 knots. PROWESS contains 677 active firms in 1998. The set of pincodes in which these firms are located contains 436 distinct pincodes. 315 firms (205 pincodes) were affected by storms (i.e. $H_{fh} > 0$).

1995. First, we aggregate Indian bilateral exports at the 4-digits ISIC Rev.4 level.[16] We then create the Balassa index and retain measures of 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

[16] 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.

2.4 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 indicator of the economic growth of a region. Night light output data come from the India light project and cover twenty years (1993 to 2013) and 600 000 villages.[17] 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 6 shows boxplot summary statistics of the mean yearly nightlight 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).
Summary statistics for the main variables used in the paper are shown in Table 3.

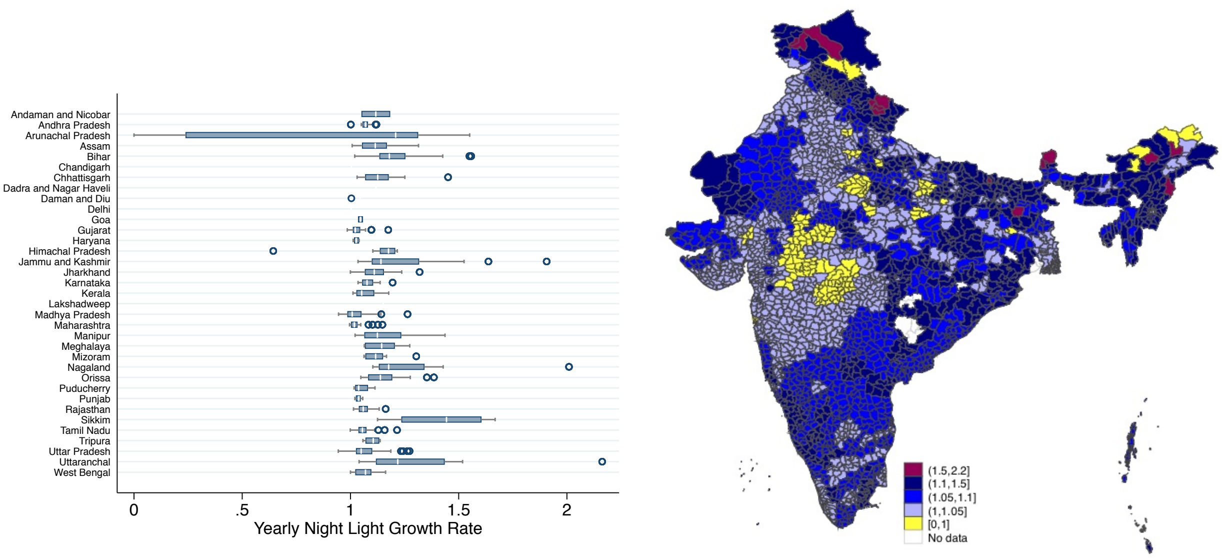
Table 3: Summary statistics of main variables

Variable	Mean	Std. Dev.	Min.	Max.	N
All firms:					
Firm sales at the ISIC level	29.594	424.125	0.002	37505.676	47557
Firm total factor productivity	0.812	0.492	0	19.075	47557
Yearly district night light growth	1.021	0.172	0.363	2.677	47557
Comparative advantage	1.58	2.192	0	24.346	47557
Firm affectedness by storms	0.002	0.018	0	0.998	47557
Firm affectedness by storms if $H_{ft} > 0$	0.018	0.050	9.94e-09	0.998	5487
Excluding always-multi-ISIC firms:					
Firm sales at the ISIC level	15.196	76.878	0.002	6349.292	24948
Firm total factor productivity	0.819	0.446	0	11.215	24948
Yearly district night light growth	1.023	0.176	0.363	2.677	24948
Comparative advantage	1.632	2.261	0	24.346	24948
Firm affectedness by storms	0.003	0.021	0	0.998	24948
Firm affectedness by storms if $H_{ft} > 0$	0.025	0.061	9.94e-09	0.998	2617

Note: Sales are expressed in rupees. Total factor productivity is computed using LP approach. Number of establishments per firm obtained using headquarters' names along with a google algorithm. Top firms refer to firms which produce more than one single ISIC industrial good every year over the period 1995-2006. Comparative advantage refers to Balassa index of revealed comparative advantage.

[17]The database is the result of a joint effort between the University of Michigan and the World Bank. The original data were generated by the Defense and Meteorological Satellite Program (DMSP) which took pictures of the Earth every night for twenty years. The nightlight 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.

Figure 6: Yearly nightlight growth rates, 1995-2006



Notes: The left panel shows boxplots of yearly nightlight growth rates by state for the period 1995-2006. 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. The right panel provide a visual illustration of the yearly nightlight growth rates by district, averaged over the period 1995-2006.

3 Do Storms Destroy Firms' Capital?

Two important premises to the hypothesis formulated in the introduction are that, first, storms destroy firms' capital, and second, when capital is destroyed, firms invest in industries that align better with comparative advantage. To investigate whether this is the case, we exploit the richness of the PROWESS dataset and run the following specification:

$$K_{ft} = \beta_0 + \beta_1 H_{ft} + \beta_2 \left(CA_{it} \times H_{ft} \right) + \boldsymbol{V}\boldsymbol{\beta} + \varepsilon_{ft} \tag{6}$$

where K_{ft} denotes the log of total assets of 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 the Balassa index of comparative advantage, firm-specific TFP, the district-level yearly growth in night lights intensity and a set of firm, 4-digits ISIC industry, year and 2-digits ISIC industry-year fixed effects (FE).[18] ε is the error term, which is two-way clustered at the firm and industry-year level given that our variables of interest vary at the firm and industry-year level. We expect $\beta_1 < 0$ if the first premise is verified and $\beta_2 > 0$ if the second one holds.

By destroying capital, storms may mechanically alter our measure of TFP. As discussed in Section 2.1.1, TFP estimates are typically obtained from the estimation of production functions; specifically, they are given by 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, 2011; Hsiang, 2010). Thus, in order to avoid a bad control issue, we use the lag of TFP and the lag of growth in night lights intensity.[19] The sets of industry FE and 2-digits industry-year FE control for the capital intensity of the main industry of the firm, as well as for major aggregate industry-specific technological shocks. Finally, the introduction of firm FE allows to purge physical capital from any local fixed characteristics that may affect firms' input choices beyond local economic growth. Importantly, firm FE imply that the effect of storms is identified using variation within firm across years, and although this type of specification is particularly demanding, it is what is needed to identify the adjustment of firms. Results are presented in Table 4.

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

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

Table 4: Do storms destroy firms' capital?

Capital$_{ft}$	All firms		Excl. always-multi-ISIC firms		
	(1)	(2)	(3)	(4)	(5)
Storms$_{ft}$	-0.30**	-0.39*	-0.36**	-0.55***	-0.59***
	(0.15)	(0.20)	(0.14)	(0.19)	(0.20)
Comp. adv.$_{it}$ × Storms$_{ft}$		0.075		0.16**	0.17**
		(0.070)		(0.070)	(0.071)
Storms$_{f(t-1)}$					-0.24
					(0.18)
Comp. adv.$_{i(t-1)}$ × Storms$_{f(t-1)}$					0.075
					(0.047)
Comp. adv.$_{it}$	No	Yes	No	Yes	Yes
Comp. adv.$_{i(t-1)}$	No	No	No	No	Yes
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes
Nightlights growth$_{d(t-1)}$	Yes	Yes	yes	yes	yes
Firm FE	Yes	Yes	Yes	Yes	yes
Industry FE	Yes	Yes	Yes	Yes	yes
Year FE	Yes	Yes	Yes	Yes	yes
2 digits industry-year FE	Yes	Yes	Yes	Yes	yes
Observations	22858	22858	15136	15136	15136
R^2	0.97	0.97	0.96	0.96	0.96

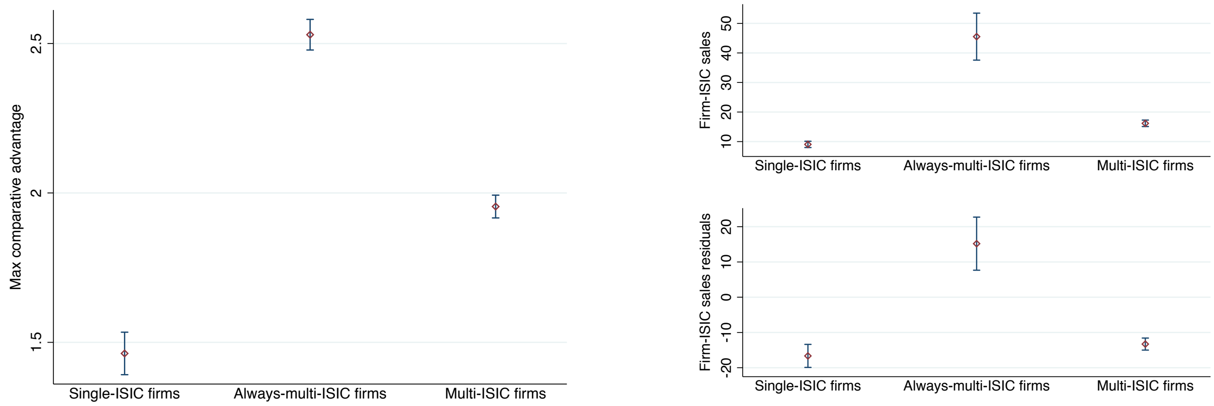
Note: Standard errors are clustered at the firm level in columns (1) and (3) and two-way clustered at the firm and industry-year level in columns (2), (4) and (5). *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j\in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a pincode and d a district. The dependent variable is the log of a firm's total assets. The set of industry FE corresponds to the ISIC 4-digits classification. For multi-ISIC firms, the industry FE is associated with the industry in which the firm's sales are the largest. "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.

In column (1), we estimate the effect of storms on firms' capital only, excluding comparative advantage (CA_{it}) and its interaction with the storm measure ($CA_{it} \times H_{ft}$) from specification (6).[20] The estimate of interest is negative and statistically significant at the 5% level, suggesting that storms do indeed destroy firms' capital. The full specification is presented in the next column. While both β_1 and β_2 have the expected sign, they are imprecisely estimated. In particular, the estimate on the interaction term is not statistically significant at the conventional levels.

This result could be driven by the presence of large and productive firms (e.g. multinationals), which tend to have cutting-edge technologies, a closer alignment to comparative advantage and better, sturdier and more durable capital. These firms are likely to be relatively more resilient to storms and, given the tighter match of their industrial production to comparative advantage, one would expect that excluding these firms from the sample would

[20]Specifications that only include the storm measure are clustered at the firm level.

Figure 7: Comparative advantage and firm-industry sales by firm type



Notes: 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 one single ISIC industrial good over the period 1995-2005. "Always-multi-ISIC firms" refers to firms which produce more than one single ISIC industrial good every single year from 1995 until 2005. "Multi-ISIC" refers to firms which switch from being single-ISIC to multi-ISIC firm (and vice versa) over time. The figure shows 95% confidence intervals.

turn both β_1 and β_2 into statistically significant estimates.

How can we identify these firms in order to take them out of the sample? We propose to define these firms as being the firms which never operate in less than two different industries and, as per Section 2, refer to them as always-multi-ISIC firms. Figure 7 shows that always-multi-ISIC firms actually differ from single- or multi-ISIC firms (defined as per Section 2); on average, these firms have higher sales at the industry level and, most importantly, produce in industries with higher comparative advantage.[21]

Columns (3)-(5) of Table 4 show results based on a sample that excludes always-multi-ISIC firms. In column (3) the estimate obtained on the storm index is negative and statistically significant, and similar to what was obtained on the full sample.[22] More importantly, excluding always-multi-ISIC firms renders the estimates of column (4) larger in magnitude and statistically significant at the 5% level. Hence, our findings support both premises: on the one hand they indicate that (apart from the resilient top companies) firms lose part of their capital in the strike of a storm, and on the other hand, the positive estimate on the interaction term implies a marginal effect consistent with a build-back better mechanism. To give an order of magnitude, the estimates in column (4) indicate that, for the median firm (in terms of both TFP and comparative advantage), a storm of maximum firm-affectedness

[21] Figures 11 and 10 of the Appendix show the same story using regression coefficients.

[22] Appendix 8.1 discusses and presents results based on alternative definitions of the storm index.

would result in a 43% decrease in firms' total assets.[23] For a storm at the 90th (95th) percentile of the distribution, these estimates imply a 3% (7.5%) decrease in firms' capital.[24]

To examine whether reconstruction takes longer than a year, we add, in column (5), the lag of both the storm measure and the interaction term ($CA_{it} \times H_{ft}$) to the baseline specification. The estimates on the storm index are negative, but only precisely estimated in the current period, indicating that storms destroy capital on impact. Both coefficients on the interaction terms are positive, yet the estimate on the interaction term is about half smaller in the following period and imprecisely estimated, suggesting that firms tend to reconstruct rapidly. This result is consistent with Elliott et al. (2019) which find that the negative effects of hurricanes on Chinese firms' performance is relatively short-lived; up to one year after the shock. For this reason, what follows focuses on short-term adjustments.

4 Empirical Strategy

Our primary goal is to evaluate the relative importance of the two channels of creative destruction highlighted earlier – within and across industries.

We start by examining whether storms lead to a process of natural selection in which the least productive industries of the economy are weeded out. In order to do so, we run the following regression:

$$s_{fit} = \gamma_0 + \gamma_1 TFP_{f(t-1)} + \gamma_2 H_{ft} + \gamma_3 \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \boldsymbol{Z\gamma} + \upsilon_{fit}^{TFP}, \tag{7}$$

where s_{fit} are log revenues generated from sales by firm f in industry i at time t and $\boldsymbol{Z}$ is a vector of controls including the yearly growth of district nightlights (to proxy for the level of economic activity at the district level), the number of establishments per firm, as well as a set of firm-type FE (single-ISIC, always-multi-ISIC and multi-ISIC firms), pincode FE, 4-digits ISIC industry-year FE and district trends. The number of establishments 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, by construction, 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.[25] υ_{fit}^{TFP} is the error term. As discussed in Section 3, TFP and the growth of night lights are lagged by one period

[23] The result is obtained as follows, $(-0.55 + (0.16 * 0.737)) * 100$, using median comparative advantage (0.737) of the sample that excludes always-multi-ISIC firms.

[24] $-43*0.0624$ for a storm at the 90th, and $-43*0.1639$ for a storm at the 95th percentile of the distribution.

[25] 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.

in order to avoid a bad control issue.

We expect more productive firms to have higher sales than less productive firms irrespective of the industry in which they operate ($\gamma_1 > 0$). Since storms destroy the capital of firms, we also expect production to be impaired or at least slowed down and thus, the coefficient on firm-affectedness by storms to be negative ($\gamma_2 < 0$). The coefficient γ_3 indicates whether storms have a differential impact on firms with varying levels of productivity. We are interested in both γ_2 and γ_3, as they jointly determine the way a storm strike shapes the pattern of production across firms. If storms hurt the least productive firms disproportionately more, one would expect the marginal effect of storms on industry-firm sales to be monotonically increasing in firm productivity.[26] If $\gamma_2 < 0$, this monotonic increase can only occur if $\gamma_3 > 0$. Importantly, the inclusion of industry-year FE allows us to interpret this marginal effect as a within-industry across-firm effect that does not reflect differential impacts across industries.

We then move on to the second mechanism under study and ask whether, in the aftermath of a storm, firms tend to reconstruct in industries which exhibit a higher comparative advantage. We answer this question using the following specification:

$$s_{fit} = \delta_0 + \delta_1 TFP_{f(t-1)} + \delta_2 H_{ft} + \delta_3 \left(CA_{it} \cdot H_{ft}\right) + \boldsymbol{Z\delta} + \upsilon^{CA}_{fit}, \tag{8}$$

where υ^{CA}_{fit} is the error term and $TFP_{f(t-1)}$ controls for firm productivity. The Balassa index of revealed comparative advantage CA_{it} is absorbed by the set of industry-year fixed effects included in $\boldsymbol{Z}$ and, therefore, does not appear in equation (8).

In this case, we also expect storms to have a negative effect on sales, i.e. $\delta_2 < 0$. The coefficient on the interaction term captures the differential impact of storms on sales across industries with different levels of comparative advantage. If $\delta_2 < 0$, a positive estimate of δ_3 would be suggestive of a build-back better mechanism and specifically show that the production of firms in comparative disadvantage industries suffers more than production at the top of the distribution of comparative advantages.

Finally, to disentangle the two mechanisms and to examine their relative importance, we combine equations (7) and (8) and estimate the following equation:

$$s_{fit} = \phi_0 + \phi_1 TFP_{f(t-1)} + \phi_2 H_{ft} + \phi_3 \left(TPF_{f(t-1)} \cdot H_{ft}\right) + \phi_4 \left(CA_{it} \cdot H_{ft}\right) + \boldsymbol{Z\phi} + \upsilon_{fit}, \tag{9}$$

where υ_{fit} is the error term and the ϕs are the coefficients of interest. We expect the signs of each of these coefficients to be similar to those obtained from the estimation of equation (7) and (8). The standardized estimates of ϕ_3 and ϕ_4 will inform us on the relative importance of the two mechanisms of interest.

[26] The marginal effect of storms on sales for each level of TPF is given by $\gamma_2 + \gamma_3 \cdot TFP_{ft}$.

5 Results

5.1 Baseline Results

Table 5 presents baseline results.[27] In all the specifications including only the interaction between the storm measure and TFP, errors are clustered at the firm level, while in the specifications including the interaction with comparative advantage, errors are two-way clustered at the firm and industry-year levels.[28]

Table 5: Shifting pattern of production

Sales_{fit}	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***	0.65***	0.24***	0.66***	0.23***	0.65***	0.126***
	(0.058)	(0.073)	(0.067)	(0.074)	(0.067)	(0.074)	
Storms_{ft}	-4.23***	-3.95***	-1.46*	-2.10**	-4.58***	-4.98***	-0.003***
	(1.59)	(1.42)	(0.79)	(0.94)	(1.70)	(1.43)	
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	4.15**	3.85**			4.13**	3.82***	0.015***
	(1.84)	(1.52)			(1.89)	(1.29)	
$\text{Comp. adv.}_{it} \times \text{Storms}_{ft}$			0.33	0.96**	0.31	0.95**	0.020**
			(0.28)	(0.44)	(0.30)	(0.46)	
Nightlights growth	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	37475	19063	37475	19063	37475	19063	19063
R^2	0.31	0.39	0.31	0.39	0.31	0.39	0.39

Note: Standard errors are clustered at the firm level in columns (1) and (2), and two-way clustered at the firm and industry-year level in columns (3)-(7). *** 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. "Non-stand." stands for non-standardized estimates and "Stand." for standardized results.

We start by estimating equation (7) over the entire sample, including single-ISIC, multi-ISIC and always-multi-ISIC firms. The estimates of interest have the expected sign and are both statistically significant. Column (2) shows that excluding always-multi-ISIC firms from the sample does not significantly alter the estimates of γ_2 and γ_3. Our findings indicate that storms reduce firms' sales and have an heterogenous effect across firms depending on

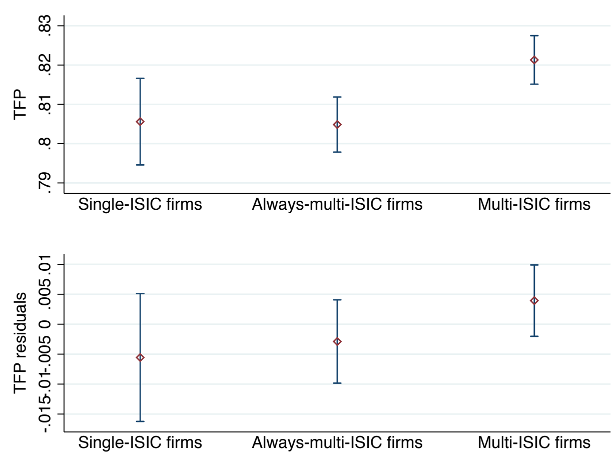
[27] Industry production lines appear in the database only when they have positive values of sales. For this reason, baseline results focus on the intensive margin. The extensive margin is treated in Section 6.

[28] Note that the number of observations changes between Table 4 and Table 5 because in the former the unit of observation is the firm, while in the latter the unit of observation is the couple industry-firm.

their idiosyncratic productivities. Both estimates imply that the response of firms' sales to storms is monotonically increasing in firms' productivity. Since we include industry-year FE, our results are to be interpreted as within-industry effects implying some level of creative destruction: within an industry, firms with relatively low TFP levels experience decreases in sales while firms at the top of the productivity distribution increase their sales.

In the previous section we have shown that multi-ISIC, single-ISIC and always-multi-ISIC firms differ in a statistically significant way in terms of average sales and comparative advantage. Instead, these three typologies of firms do not differ in terms of average TFP, as it is shown in Figure 8. The similarity in average TFP across the three groups is likely a consequence of putty-clay capital, which implies that an industry line will not be closed down if its fixed costs are covered. Consequently, by construction, the average TFP of always-multi-ISIC firms also captures productivity in the least productive industry lines. For this reason, it is not surprising that the coefficients in columns (1) and (2) do not differ in a significant way.

Figure 8: Average TFP by firm type



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

The next two columns, (3) and (4), estimate equation (8). While δ_2 is statistically significant all along, the exclusion of always-multi-ISIC firms (column 4) turns δ_3 into a precisely estimated coefficient. This result is consistent with a better alignment of always-multi-ISIC firms to India's comparative advantage. As in the previous specifications, storms have a negative impact on firms' sales. The estimate on the interaction term is positive and statistically significant at the 5% level, and implies that firms producing in comparative disadvantage industries are affected disproportionately more. This result is in line with Pelli & Tschopp (2017) and suggests that, in the aftermath of storms, firms build-back better and move up the ladder of comparative advantage.

Columns (5) and (6) propose to disentangle the two effects – within and across industries. As before, when using the entire sample (column 5), the estimation of equation (9) returns statistically insignificant estimates for the coefficient on the interaction with the comparative advantage measure. While when we exclude always-multi-ISIC firms (column 6), it appears that both mechanisms are at work. In order to compare the magnitude of the estimates obtained on each of the interaction terms, we compute standardized coefficients, in column (7). Results suggest that the adjustment across industries dominates and is about 33% larger than the effect that occurs within industries. Yet, both mechanisms are at play in a statistically significant way in the aftermath of a storm.[29]

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 127% decrease in firms' industry sales.[30] It is important to note that this number is not excessively large as the median of the measure of firm-affectedness by storms is 0.0008 (for positive values of storms). For a storm at the 75th (90th) percentile of the distribution, these estimates imply a 2.5% (8%) decrease in firms' industry sales.[31]

In Figure 9 we use the estimates obtained in column (6) to illustrate the marginal effects of storms by comparative advantage and productivity level. In order to give a proper representation of reality we leave out extreme values, i.e. we drop the top 5% of the distribution of TFP and of the Balassa Index. Specifically, for each level of $TFP_{ft} \in (0, 1.5)$ and $CA_{it} \in (0, 7)$, the marginal effect is computed as:

$$\widehat{\phi_2} + \widehat{\phi_3} TFP_{ft} + \widehat{\phi_3} CA_{it},$$

where the $\widehat{\phi}$s are the estimates obtained in column (6). The marginal effect captures the change in firms' industry log sales in the aftermath of a storm of maximum firm-affectedness

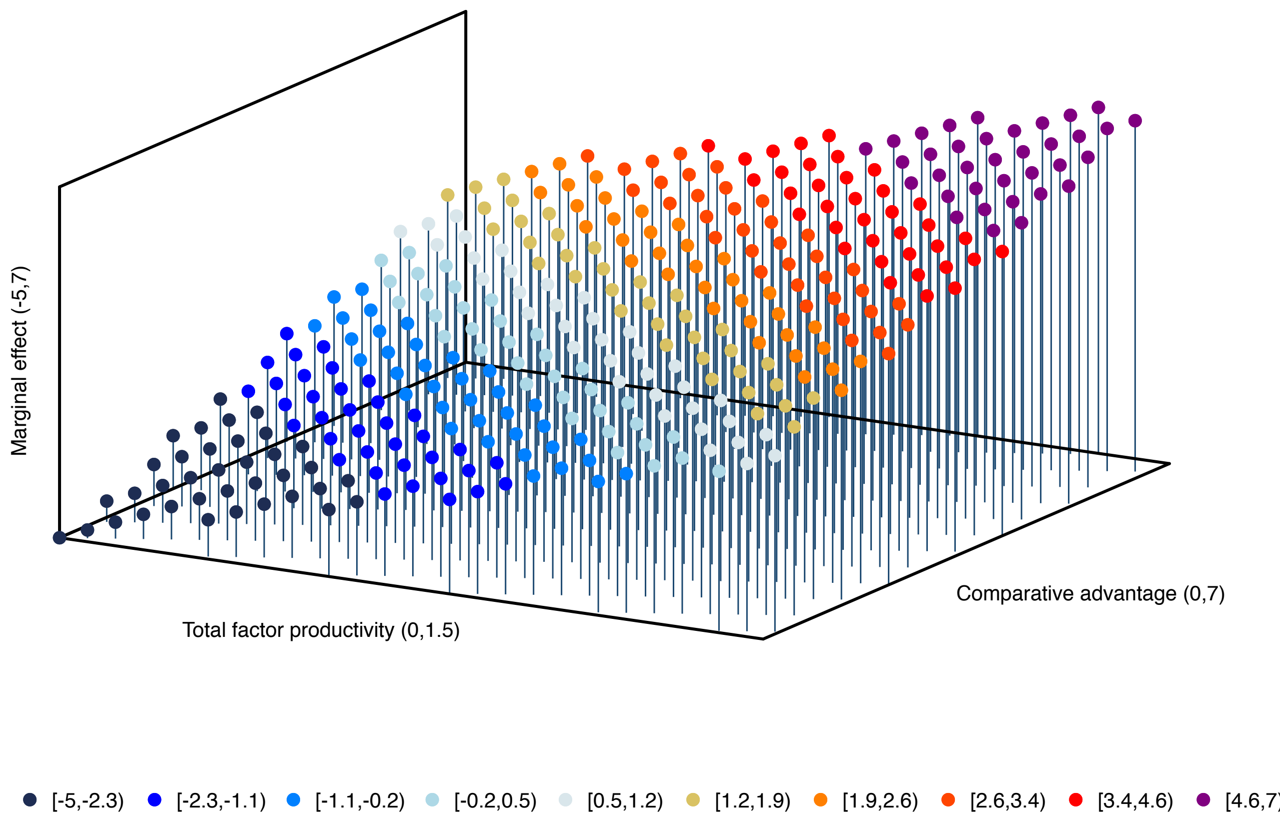
[29] In Table 14 of the Appendix we also present the baseline estimates using alternative measures of the storm index. First, we use a cubic relationship between the energy released by a storm and the force exerted on physical structures and, second, by moving the windspeed threshold up to 50 knots.

[30] This result is obtained as follows, $(-4.98 + (3.82 * 0.788) + (0.95 * 0.737)) * 100$, using the median TFP (0.788) and median comparative advantage (0.737) of the sample that excludes always-multi-ISIC firms.

[31] $-127 * 0.0196$ for a storm at the 75th, and $-127 * 0.0624$ for a storm at the 90th percentile of the distribution.

($H_{ft} = 1$).

Figure 9: Marginal effects of storms on firms' production



Notes: The marginal effect is computed as $\widehat{\phi_2} + \widehat{\phi_3} TFP_{ft} + \widehat{\phi_4} CA_{it}$, 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 firms' industry log sales in the aftermath of a storm of maximum firm-affectedness ($H_{ft} = 1$).

The figure shows that the change in firms' industry log sales resulting from storms can vary greatly, between -500% and +700%, depending on a firm's TFP level and the industry in which it operates. While these numbers imply important percentage changes in sales, it is important to keep in mind that they reflect the effect of a unit change in the storm index, or in other words, the effect of a storm of maximum firm-affectedness. More importantly, the figure suggests that the firms which suffer the most from storms have low productivities and operate in comparative disadvantage industries. On the other hand, highly productive firms, which produce in industries that exhibit high comparative advantage, experience an increase in sales. 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 (firm) productivity and even lead to a positive marginal effect. Similarly, it appears that a high (firm) 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.

5.2 Robustness

In this section, we undertake several robustness checks of our results. First, we focus on the fact that, as mentioned above, some storms may hit towards the end of the year. As a consequence we could either not be capturing the ensuing reconstruction, or depending on how firms' handle their distribution chain, by looking at sales we may not be able to capture the impact of the storm. Second, we eliminate from the sample extremes values in the storm distribution, in order to make sure that our results are not driven by it. Finally, we run a series of placebo regressions in which we randomize firm affectedness within the whole sample, firms, industry, district and year.

Our storm measure includes storms occurring over the entire year. Table 6 shows the frequency with which firms are hit by storms for each month of the year (panel I) as well as summary statistics of firm-affectedness by storms over a six-months period (panel II). The first panel of the table indicates that out of all the firms experiencing wind speeds above 33 knots, about 43% are affected in May, and 56% of them are impacted before the end of June. The first panel also shows that January to March, and July to September are quiet months. The second panel suggests that the average firm-affectedness by winds is similar between the first and second half of the year.

Including storms happening towards the end of the year in our storm measure could bias our results in two different ways. First, a contemporaneous specification could pick up some of their destruction but none of the following reconstruction. In order to observe the effect of interest, firms need time to reconstruct at least part of the destroyed capital. It is possible that including storms striking towards the end of the year does not allow enough time for firms to adjust. As a result, one would expect the baseline estimate on the storm index to be larger in magnitude and the estimate on the interaction term to be smaller, generating a bias towards zero in the marginal effect. Second, depending on how firms' handle their distribution chain, since our variable of interest are sales, we may not be able to capture the impact of the storm, which could take a few months before showing up in a firm's accounts. In this case the coefficient on the impact of the storm may be downward biased in absolute value in our baseline specification. We investigate this possibility in columns (3) and (5) of

Table 6: Wind speed at the establishment level, by month

I. # of firms hit each month (wind > 33 knots)

	Freq.	Percent	Cum
	(1)	(2)	(3)
Month:			
April	495	4.66	4.66
May	4,606	43.35	48.00
June	935	8.80	56.80
October	1,456	13.70	70.51
November	1,610	15.15	85.66
December	1,524	14.34	100.00

II. Firm-affectedness by winds

	Mean	Std. Dev.	Min.	Max.	N
	(1)	(2)	(3)	(4)	(5)
Time period:					
January-June	49.552	17.172	33.002	104.72	6036
July-December	48.718	16.434	33.005	139.99	4590

Table 7. First, we adjust the measure H_{ft} to exclude storms occurring in the second half of the year – column (3) – and, second, we adjust it to include only storms occurring in the second half of the year – column (5).

The results suggest that including in our storm measure the latest storms of the year leads to a smaller standardized coefficient on ϕ_2; i.e. since our baseline measure also includes storms happening in November and December, the estimates in Table 5 tend to capture a smaller decrease in sales because the destruction caused in these later months does not show up in the firms' accounts yet. Once the measure H_{ft} is adjusted to the first 6 months of the year, the estimate of ϕ_2 becomes larger, while the coefficient on the interaction ϕ_4 stays roughly constant. In column (5) all the coefficients are statistically insignificant, which is consistent with the fact that the damages will be felt by the firms only later on.

The second robustness test ensures that our findings are not solely generated by the strongest storms in the sample. For this reason, the storm measure used in column (6) excludes the top 5% of the storm distribution. As shown in the table, our results are robust to this change, the mechanism that we highlight seems to be at play even when the largest shocks are removed from the sample.

Finally, in Table 8 we run a series of placebo tests. We want to make sure that the relationships captured in our baseline specification are not spurious. In order to do this, we randomize the occurrence of storms over the sample. This should render the results on storms statistically insignificant, but not affect the other coefficients in the regressions, such

Table 7: Robustness

Sales_{fit}	Baseline Non-stand.	Baseline Stand.	Before June 30 Non-stand.	Before June 30 Stand.	After June 30 Non-stand.	No extremes Non-stand.	No extremes Stand.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{TFP}_{f(t-1)}$	0.65***	0.126***	0.65***	0.126***	0.66***	0.65***	0.126***
	(0.074)		(0.074)		(0.074)	(0.074)	
Storms_{ft}	-4.98***	-0.003***	-2.47***	-0.009***	-4.80	-2.32***	-0.006***
	(1.43)		(0.76)		(3.80)	(0.63)	
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	3.82***	0.015***	1.62***	0.013***	7.69	1.71***	0.016***
	(1.29)		(0.62)		(4.70)	(0.55)	
$\text{Comp. adv.}_{it} \times \text{Storms}_{ft}$	0.95**	0.020**	0.40*	0.016*	1.22	0.39**	0.018**
	(0.46)		(0.23)		(0.94)	(0.19)	
$\text{Nightlights growth}_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of $\text{establishments}_{ft}$	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	19063	19063	19063	19063	19063	19063	19063
R^2	0.39	0.39	0.39	0.39	0.39	0.39	0.39

Note: Standard errors are two-way clustered at the firm and industry-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 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. "Non-stand." stands for non-standardized estimates and "Stand." for standardized results.

as the impact of TFP. We randomize the occurrence of storms in five different ways. First, over the whole sample, then within firms, within industries, within districts and within years. Table 8 shows the results for these specifications. As expected, the coefficient on TFP is extremely robust across the five specifications, while the coefficients on storm and on the interactions including storm become strongly statistically non insignificant. This table seems to confirm that our baseline findings are not the result of spurious correlations.

6 A Closer Look at the Adjustment of Firms

In this section, we look at the extensive margin and examine whether storms increase the probability of firms' exit.[32] We then look at the entry and exit of firm industry production lines.[33] In our sample, only 2 out of 1,625 single-ISIC firms switch industries from one year

[32] We focus only on firms' exit because the way in which the database is constructed does not allow us to observe entry for single-ISIC firms. Participation in the database is voluntary, therefore, the appearance of a firm in the database does not mean that the firm did not exist the previous year.

[33] In the case of multi-ISIC firms, since we do not focus on entry and exit of the firm, but on the industry line within the firm, we are also able to look at entry.

Table 8: Placebo test

	All	Firm	ISIC	District	Year
Sales_{fit}	(1)	(2)	(3)	(4)	(5)
$\text{TFP}_{f(t-1)}$	0.65***	0.66***	0.66***	0.65***	0.66***
	(0.074)	(0.074)	(0.073)	(0.075)	(0.074)
Storms_{ft}	-0.23	-0.52	0.020	-1.45	0.14
	(1.23)	(1.22)	(1.17)	(1.86)	(2.48)
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	0.70	0.38	-0.81	2.07	0.16
	(0.86)	(1.24)	(1.67)	(1.96)	(2.26)
$\text{Comparative advantage}_{it} \times \text{Storms}_{ft}$	0.016	0.051	0.29	-0.13	-0.56
	(0.35)	(0.28)	(0.22)	(0.22)	(0.68)
$\text{Nightlights growth}_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes
$\text{\# of establishments}_{ft}$	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes
Observations	19063	19063	19063	19063	19063
R^2	0.39	0.39	0.39	0.39	0.39

Note: Standard errors are two-way clustered at the firm and industry-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 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. In column 1, we randomize the storm measure over the entire sample and in columns (2)-(5), the measure is randomized within firm, ISIC, district and year, respectively.

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 by looking at how multi-ISIC firms adjust their current industry mix in the aftermath of storms.

6.1 Firm exit

We study firm exit with a linear probability model in which the dependent variable takes the value of 1 if the firm exits in the next period, and 0 if the firm keeps producing. As for the intensive margin, we begin by investigating whether the exit probability differs across firms with different productivity levels and then look at potential heterogenous effects across industries. In each of the specifications, we control for district-level nightlights' growth, a set of firm FE, 4-digits ISIC industry FE, year FE and district trends. At each step of the analysis, we distinguish firms with one establishment from those with many (excluding always-multi-ISIC all along) and do not expect much action when including multi-establishments firms. Our rationale is that the latter firms may not be wiped out completely if one single establishment is hit by a storm, even in the event of extreme capital destruction, as production may be reorganized and relocated towards other establishments. In that sense, owning multiple establishments can be seen as an insurance against storms' risk. Results are presented in Table 9.

Table 9: Firms' exit

Exit_{ft}	All (1)	One estab. (2)	All (3)	One estab. (4)	All (5)	One estab. (6)
Storms_{ft}	1.02**	1.70***	0.71**	0.97**	1.05**	1.72***
	(0.44)	(0.53)	(0.29)	(0.39)	(0.42)	(0.56)
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	-0.45	-0.97**			-0.46	-0.97**
	(0.38)	(0.38)			(0.34)	(0.40)
$\text{Comp. adv.}_{it} \times \text{Storms}_{ft}$			-0.020	-0.029	-0.021	-0.020
			(0.10)	(0.12)	(0.10)	(0.12)
$\text{TFP}_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Comp. adv._{it}	Yes	Yes	Yes	Yes	Yes	Yes
$\text{Nightlight growth}_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12220	5259	12220	5259	12220	5259
R^2	0.38	0.42	0.38	0.42	0.38	0.42

Note: Standard errors are clustered at the firm level in columns (1) and (2), and two-way clustered at the firm and industry-year level in columns (3)-(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 the firm exits in the next period, and 0 if the firm keeps producing. The set of industry FE corresponds to the ISIC 4-digits classification. For multi-ISIC firms, the industry FE is associated with the industry in which the firm's sales are the largest. Each specification excludes always-multi-ISIC firms. The term "All" indicate all firms except always-multi-ISIC firms are included in the sample. The term "One estab." indicates that firms with more than one establishment and always-multi-ISIC firms are excluded from the sample.

Each specification indicates that storms have a statistically significant positive effect on firms' exit probability, suggesting that some firms cease operations completely in the aftermath of a storm. As expected, this effect expands when excluding firms that own several establishments. The coefficient on the interaction term $\left(\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}\right)$ is negative. It becomes precisely estimated when focusing on single-establishment firms only, implying that, within an industry, the exit probability is more pronounced for unproductive firms. This result is very much in line with the idea of creative destruction and predictions of trade models with heterogenous firms (see for instance Melitz, 2003). As for the estimate on $(\text{Comp. adv.}_{it} \times \text{Storms}_{ft})$, it is statistically insignificant. Hence, firms' exit rate appears to depend on productivity rather than the type of industry in which a firm operates.[34]

[34] The estimates of the most complete specification in column (6) imply that for the median firm (in terms of both TFP and comparative advantage), a storm of maximum firm-affectedness (i.e. $H_{ft} = 1$) would lead to a 95% increase $((1.72 - (0.97 * 0.788)) * 100)$ in firm exit rate. This number seems large, however one should note that the median of the measure of firm-affectedness by storms is close to zero. For a storm at

Arguably, these findings are driven by the exit of unproductive firms which cannot afford to reconstruct in the event of massive capital destruction. In a developing country like India, only a small fraction of individuals can afford insurance against natural calamities. In fact, the managing director and CEO of Bajaj Allianz General Insurance Company reports that less than 1% of individuals in India buy coverage against natural catastrophes. Swiss Re reports that in 2014, only 10% of the losses (amounting to $52 bio) caused by calamities were insured.

6.2 Entry and exit of firm industry lines, and shifts in firm industrial mix

We now turn to multi-ISIC firms and examine how industry lines are impacted. In Table 10, we concentrate on the entry of new industry lines. To do so, we run a linear probability model with the dependent variable taking the value of 1 if, conditional on producing in the previous year, a firm adds an industry to its set of industries (and 0 if no industry is added). The structure of the table and the explanatory variables included in each specification are identical to those of Table 9. We find no evidence that firms adjust to capital destruction by investing in new industry lines.

Next, we investigate whether storms increase the exit rate of a firm's industry line of production. We run a linear probability model where 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 the firm surviving in the next period. Results are shown in Table 11, the structure of which is identical to the previous two tables.

Focusing on the most complete specification in column (6), we find that storms have heterogenous effects across industries. There is no evidence however 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.$_{\cdot it}$ $\times$ Storms$_{ft}$) implies that industry lines characterized by low comparative advantage have a higher exit probability. However, given the highly imprecisely estimated coefficient on the storm index, this heterogenous effect will be statistically significant for certain values of comparative advantage only. 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

the 75th percentile of the distribution, these estimates would imply a 2% increase ($95 * 0.0196$) in firm exit rate, while the rise in exit probability would triple ($95 * 0.0624$) at the 90th percentile.

Table 10: Entry of industry lines

Entry of industry line$_{ft}$	All (1)	One estab. (2)	All (3)	One estab. (4)	All (5)	One estab. (6)
Storms$_{ft}$	0.20	0.32	0.15*	0.20	0.27	0.43
	(0.19)	(0.41)	(0.090)	(0.14)	(0.19)	(0.40)
TFP$_{f(t-1)}$ × Storms$_{ft}$	-0.15	-0.28			-0.16	-0.31
	(0.20)	(0.46)			(0.20)	(0.46)
Comp. adv.$_{it}$ × Storms$_{ft}$			-0.059	-0.069	-0.060	-0.071
			(0.056)	(0.086)	(0.056)	(0.087)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Comp. adv.$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Nightlight growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16779	6971	16779	6971	16779	6971
R^2	0.10	0.16	0.10	0.17	0.10	0.17

Note: Standard errors are clustered at the firm level in columns (1)-(2) and two-way clustered at the firm and industry-year level in columns (3)-(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 term "One estab." indicates that firms with more than one establishment and always-multi-ISIC firms are excluded from the sample.

distribution.

The absence of entry-level effects along with mild exit-level adjustments of industry lines suggest that our across-industry baseline effects in Table 5 must be driven to a large extent by shifts in firm-level production mix, within the existing set of industries in which a firm is already active. We study this possibility in Table 12, where we regress a measure of firm industrial mix at a given time on firm-affectedness by storms and a set of controls including the usual lagged firm TFP, lagged district nightlight growth measure, and a set of firm FE, year FE and district trends. The measure capturing firms' industrial mix is constructed using the following firm industrial composition index:

$$IM_{ft} = \sum_{j\in J} \eta_{jft} CA_{j(t-1)}, \tag{10}$$

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} would indicate that the pattern of production of the firm has shifted towards comparative advantage industries, either because the firm has shifted production away from

Table 11: Exit of industry lines

Exit of industry line$_{ft}$	All (1)	One estab. (2)	All (3)	One estab. (4)	All (5)	One estab. (6)
Storms$_{ft}$	0.12	0.33	0.46**	0.74**	0.21	0.51
	(0.44)	(0.62)	(0.23)	(0.35)	(0.43)	(0.68)
TFP$_{f(t-1)}$ × Storms$_{ft}$	0.34	0.32			0.32	0.29
	(0.46)	(0.76)			(0.45)	(0.81)
Comp. adv.$_{it}$ × Storms$_{ft}$			-0.081	-0.14**	-0.078	-0.14**
			(0.068)	(0.070)	(0.067)	(0.069)
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Comp. adv.$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Nightlight growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13216	5403	13216	5403	13216	5403
R^2	0.16	0.26	0.16	0.26	0.16	0.26

Note: Standard errors are clustered at the firm level in columns (1)-(4) and two-way clustered at the firm and industry-year level in columns (5)-(8). *** 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 term "One estab." indicates that firms with more than one establishment and always-multi-ISIC firms are excluded from the sample.

low towards high comparative advantage industries, or holding production shares across industries constant, because of an increase in the Balassa index of some industries. 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 12.

As for Tables 9-11, we distinguish between one- and multi-establishments firms. In the last two columns we include a set of 4-digits ISIC industry FE and 2-digits ISIC industry trends to account for the fact that the set of industries where a firm is active depend on the main industry in which a firm operates (e.g. through the value chain or input-output linkages). In our preferred specification (column 4), 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.

In sum, this section highlights that the within-industry effect occurs at the extensive margin and is driven by the exit of the least productive firms, and this, whether they are

Table 12: Shifts in firms' industrial mix

IM_{ft}	All (1)	One estab. (2)	All (3)	One estab. (4)
Storms_{ft}	0.46	1.41**	0.28	1.18**
	(0.47)	(0.67)	(0.35)	(0.56)
$\text{TFP}_{f(t-1)}$	Yes	Yes	Yes	Yes
Nightlight $\text{growth}_{d(t-1)}$	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
2 digits industry trends	No	No	Yes	Yes
Observations	13015	5517	13012	5513
R^2	0.89	0.89	0.93	0.93

Note: Standard errors are clustered at the firm 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 each colum, the dependent variable is an index of firm industrial composition defined as $IM_{ft} = \sum_{j \in J} \eta_{jft} CA_{j(t-1)}$, 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. 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 term "One estab." indicates that firms with more than one establishment and always-multi-ISIC firms are excluded from the sample.

single- or multi-ISIC firms. We find no evidence that this effect differs across industries. Instead, the across-industry mechanism appears to be driven by multi-ISIC firms and occurs, to a large extent, at the intensive margin by shifting firm production towards the industry lines that exhibit higher comparative advantage.

7 Conclusions

This paper investigates 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 putty-clay nature of capital. 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 dataset matched with hurricanes' data from NOAA. Using google places 2018, we locate all the establishments of each of the firms in the dataset, allowing us to obtain a more precise estimate of the wind strength that affects each firm. First, we establish a relationship between hurricanes and firm level capital destruction in India. As expected, we find this relationship to be stronger for smaller firms, which cannot afford more durable capital. We then analyze firms' reaction. We find evidence of two channels of adjustment, within and across industries. Across industries, we find that sales shift towards comparative advantage industries. We find no evidence that firms adjust to capital destruction by investing in new industry lines. However, it appears that this result is driven to a large extent by shifts in the firm-level production mix within an existing set of industries. Finally, we find that the effect across industry is roughly 33% larger than the within-industry effect. These two channels show evidence of an evolution towards new and more productive vintages of capital, but also of an adjustment of the production mix towards higher comparative advantage industries.

Note that participation to the PROWESS dataset is voluntary on the firm side. As a result, only bigger and more established firms participate to it. For instance, the informal sector is not captured at all. Our results indicate that for smaller and more vulnerable firms the adjustment in the aftermath of a hurricane is more important. Therefore, the results obtained could be interpreted as a lower bound of the total effect.

Overall, our results provide supportive evidence of creative destruction. While we do not provide a formal test of putty-clay models, our findings also seem to be consistent with the presence of putty-clay capital.

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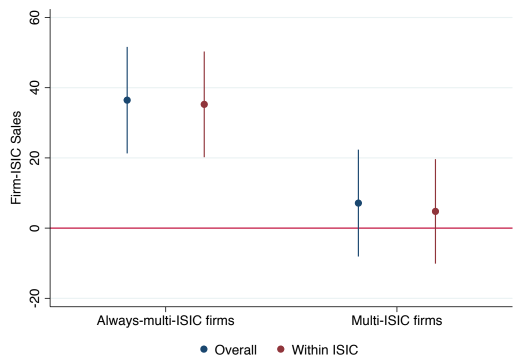
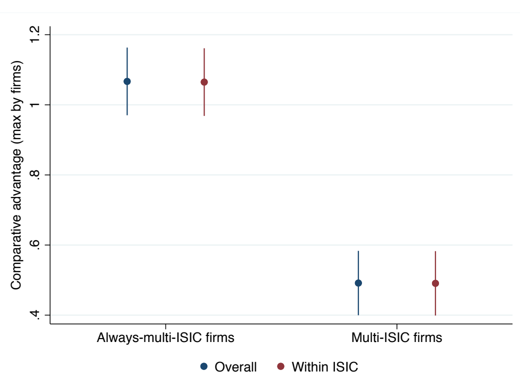
8 Appendix

Figure 10: 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" refers to firms which produce more than one single ISIC industrial good every single year from 1995 until 2005. "multi-ISIC" refers to firms which switch from being single-ISIC to multi-ISIC firm (and vice versa) over time. The figure shows 95% confidence intervals.

Figure 11: 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" refers to firms which produce more than one single ISIC industrial good every single year from 1995 until 2005. "multi-ISIC" refers to firms which switch from being single-ISIC to multi-ISIC firm (and vice versa) over time. The figure shows 95% confidence intervals.

8.1 Alternative definitions of firm affectedness by storms

This Section explores how alternative specifications of the storm index correlate with capital destruction. Our storm index, 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 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 alternative specifications of firm affectedness by storms in Table 13, the main analysis sticks to our baseline storm index.

In Table 13 we propose several modifications of the storm index. First, we move up the threshold: columns (3) and (4) 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 the baseline results. When examining the estimates obtained with alternative definitions of firm affectedness by storms, it is important to note 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. This explains why, although the magnitude of the estimates remains remarkably stable, the effect of storms becomes imprecisely estimated as we move across specifications. Overall, our findings suggest that, likely due to the widespread poor infrastructures quality in India, even relatively low windspeed intensities can have considerable detrimental effects on capital.

Table 14 presents the main results of the paper using alternative definitions of the storm index. We present the results only for the storm definitions that do affect firms' physical capital. As just discussed, when the variation in the storm index becomes too small, we lose precision in our estimates. Estimations using two alternative storm measures – the one with a cubic relationship and the one with a higher windspeed threshold – give coefficients similar to the ones obtained with the baseline measure. While signs are the same, the alternative measures produce slightly larger coefficients. Statistical significance is maintained for the coefficients on storm, TFP and their interaction. Instead the coefficient on the interaction between comparative advantage and storm is estimated less precisely in columns (2) and (3).

Table 13: Capital destruction & alternative definitions of firm affectedness by storms

Capital_{ft}	> 33 Baseline	> 33 Cubic	> 50 Quadratic	> 50 Cubic	> 64 Quadratic	> 64 Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Storms_{ft}	-0.36**	-0.40**	-0.36**	-0.34	-0.31	-0.29
	(0.14)	(0.20)	(0.18)	(0.21)	(0.20)	(0.21)
	[0.014]	[0.047]	[0.045]	[0.106]	[0.110]	[0.156]
$\text{TFP}_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	Yes
Nightlight growth_{dt}	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
2 digits industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Share of observations with positive storms	10	10	3	3	1	1
Observations	15136	15136	15136	15136	15136	15136
R^2	0.96	0.96	0.96	0.96	0.96	0.96

Note: Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. p-values in square brackets. 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 a firm's total assets. The set of industry FE corresponds to the ISIC 4-digits classification. For multi-ISIC firms, 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 14: Robustness – storm definition.

	Baseline	> 33 Cubic	> 50 Quadratic
	(1)	(2)	(3)
$\text{TFP}_{f(t-1)}$	0.65***	0.65***	0.66***
	(0.074)	(0.074)	(0.074)
Storms_{ft}	-4.98***	-7.66***	-6.34***
	(1.43)	(2.46)	(2.13)
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	3.82***	5.84***	4.63***
	(1.29)	(2.02)	(1.70)
Comparative $\text{advantage}_{it} \times \text{Storms}_{ft}$	0.95**	1.83*	1.39
	(0.46)	(1.08)	(0.86)
	[0.041]	[0.091]	[0.108]
Nightlight growth_{dt}	Yes	Yes	Yes
# of establishments	Yes	Yes	Yes
Firm type FE	Yes	Yes	Yes
Pincode FE	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
Share of observations with positive storms	11	11	3
Observations	19063	19063	19063
R^2	0.39	0.39	0.39

Note: Standard errors are clustered at the firm level in columns (1) and (2), and two-way clustered at the firm and industry-year level in columns (3)-(7). *** p<0.01, ** p<0.05, * p<0.1. p-values in square brackets. The firm subscript $f = (\{j\}_{j \in J}, p, d, s)$ where J is the set of industries in which firm f operates, p denotes a pincode, d a district and s a state. The dependent variable is the log of firm sales in industry i at time t. Each specification excludes always-multi-ISIC firms.