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

November 2022

This appendix contains supplementary material not inserted (due to space constraints) in the main text of Pelli, Tschopp, Bezmaternykh and Eklou (2022).

A Alternative Measures of Storm Exposure

This section explores the sensitivity of our main results to other specifications of the storm index as well as alternative wind field models to compute wind speed.

A.1 Alternative Specifications of the Storm Index

Our storm measure 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 US suggest that the energy released by a storm and the force on physical structures may be related in a cubic manner (see the technical HAZUS manual of the Federal Emergency Management Agency (FEMA) of the US Department of Homeland Security and Emanuel, 2005). While this is the case for high-income countries, sub-standard quality of construction materials in India makes buildings and infrastructures vulnerable already at much lower wind intensities. For this reason, while we present results based on alternative specifications of firm exposure to storms in Table A.1, the main analysis sticks to our baseline storm index.

Columns (3) and (4) of Table A.1 follow Emanuel (2011) with a threshold of 50 knots, and the next 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)). In column (7) we replace the storm index by wind speed and evaluate the extent to which a linear damage function allows to capture the effect of storms on capital and production. Column (1) shows results based on our main storm measure.

Starting with Panel I, we find that the estimated destruction of buildings, land and electricity is statistically significant across alternative specifications of the storm index and larger when using a cubic function. However, when looking at fixed assets, the effect of storms becomes imprecisely estimated as we reach a threshold of 50 and use a cubic damage function. This result may be due to the fact that most of India's storms have wind speed intensities below 64 so that as the threshold increases, the share of observations with a positive storm index diminishes drastically, to 3% with a threshold of 50 and to 1% with a threshold of 64. For this reason, while a small number of violent storms might be sufficient to detect an effect on individual measures of firms' physical capital (such as buildings, land and electricity), it might not be enough to obtain a precise estimate on a variable like fixed assets which aggregates several types of physical capital. Most importantly, our findings suggest that, overall, likely due to the widespread poor infrastructures quality in India, even relatively low wind speed intensities can have considerable detrimental effects on capital. Hence, our main measure of firm exposure to storms appears appropriate in the case of India.

Panel II focuses on firm-industry sales. All of our estimates of interest have the expected sign but standard errors increase as we move across specifications. The coefficients on the storm index and the interaction between the storm index and TFP remain statistically significant across the board, at least at the 10% level. For the estimates on the other interaction term, statistical significance is lost when moving to specifications for which only 3% or 1% of the observations have positive measures of storms. Our interpretation is that while there are enough observations with positive storms and while there is enough variation across firms within industry, the samples in columns (3)-(6) lack variation across industries. Finally, the linear damage function also leads to the conclusion that storms have a negative impact on capital and sales, although the effect on one of the interaction terms is imprecisely estimated.

A.2 Alternative Wind Field Models to Compute Wind Speed

As discussed above, we follow the standard practice of parametrically modeling storms as translating ranking vortices and use the formula developped in Deppermann (1947) in our baseline specifications. As an alternative we calculate wind speed using Holland wind field model. We also use the HURRECON model which accounts for the cover type (land or water) and the forward velocity of the hurricane (see Holland, 1980; Boose et al., 2004, for details on each of the wind speed formula).

Similar to Table A.1, for each specification of the storm exposure index, Tables A.2 and A.3 show results based on the Holland and HURRECON models, respectively. Results are similar to the baseline estimates.

Table A.1: Alternative Definitions of the Storm Index (Depperman)

	> 33		> 50		> 64		
	Baseline	Cubic	Quadratic	Cubic	Quadratic	Cubic	Winds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel I: Capital$_{ft}$ (logs)							
Buildings$_{ft}$:							
Storms$_{ft}$	-1.54***	-1.89***	-1.60***	-1.88***	-1.63***	-1.90***	-0.0037***
	(0.48)	(0.44)	(0.45)	(0.37)	(0.42)	(0.31)	(0.0013)
Observations	14,407	14,407	14,407	14,407	14,407	14,407	14,407
Land$_{ft}$:							
Storms$_{ft}$	-1.55***	-1.99***	-1.74***	-2.04***	-1.87***	-2.00***	-0.0035***
	(0.45)	(0.52)	(0.48)	(0.52)	(0.48)	(0.54)	(0.0013)
Observations	13,794	13,794	13,794	13,794	13,794	13,794	13,794
Electricity$_{ft}$							
Storms$_{ft}$	-2.48***	-4.27***	-3.55***	-5.29***	-4.53***	-5.44**	-0.0035*
	(0.86)	(1.27)	(1.04)	(1.80)	(1.41)	(2.43)	(0.0019)
Observations	6,862	6,862	6,862	6,862	6,862	6,862	6,862
Fixed assets$_{ft}$:							
Storms$_{ft}$	-1.42**	-1.46*	-1.37**	-1.16	-1.11	-0.88	-0.0036***
	(0.57)	(0.85)	(0.69)	(0.89)	(0.79)	(0.84)	(0.0012)
Observations	14,936	14,936	14,936	14,936	14,936	14,936	14,936
Panel II: Sales $_{fit}$ (logs)							
Storms$_{ft}$	-5.92***	-8.12***	-6.81***	-8.85**	-7.60**	-9.84*	-0.0058**
	(1.33)	(2.51)	(2.13)	(3.66)	(3.09)	(5.18)	(0.0025)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.92**	1.63*	1.20	2.17	1.68	3.08	0.00015
	(0.39)	(0.94)	(0.74)	(1.74)	(1.46)	(2.50)	(0.00062)
TFP$_{f(t-1)}$ × Storms$_{ft}$	4.24***	5.76**	4.66**	7.02*	5.55*	9.49*	0.0062***
	(1.34)	(2.38)	(1.95)	(3.75)	(3.09)	(5.48)	(0.0021)
Observations	17,952	17,952	17,952	17,952	17,952	17,952	17,952
Share of obs. with pos. storms	10%	10%	3%	3%	1%	1%	10%
Share of firms with pos. storms	28%	28%	8%	8%	4%	4%	28%
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are two-way clustered at the firm and district-year levels in Panel I and three-way clustered at the firm, district-year and industry-year levels in Panel II. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. In Panel I, the dependent variables are, in turn, the log of firms' buidings, land, electricity and fixed assets. In Panel II, the dependent variable is the log of firms' industry sales. Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE and district trends. Additionally, Panel II also includes postal code FE. The set of industry FE corresponds to the ISIC 4-digits classification. In Panel I, the industry FE is associated with the industry in which the firm's sales are the largest. All the specifications exclude always-multi-ISIC firms. The terms "> 33", "> 55" and "> 64" mean that thresholds of 33, 55 and 64 knots are used to compute the measure of storm, respectively. The terms "quadratic" and "cubic" indicate the exponent of the damage function. Finally, in column (7) storm exposure is measured by maximum wind speed.

Table A.2: Alternative Definitions of the Storm Index (Holland)

	>33 Baseline	>33 Cubic	>50 Quadratic	>50 Cubic	>64 Quadratic	>64 Cubic	Winds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<u>Panel I:</u> Capital$_{ft}$ (logs)							
Buildings$_{ft}$:							
Storms$_{ft}$	-1.44***	-1.93***	-1.64***	-2.02***	-1.77***	-2.03***	-0.0032**
	(0.43)	(0.44)	(0.42)	(0.43)	(0.42)	(0.42)	(0.0015)
Observations	14,407	14,407	14,407	14,407	14,407	14,407	14,407
Land$_{ft}$:							
Storms$_{ft}$	-1.39***	-1.96***	-1.66***	-2.12***	-1.94***	-2.12***	-0.0036**
	(0.40)	(0.47)	(0.43)	(0.51)	(0.44)	(0.55)	(0.0016)
Observations	13,794	13,794	13,794	13,794	13,794	13,794	13,794
Electricity$_{ft}$							
Storms$_{ft}$	-1.90**	-3.54***	-2.92***	-4.86***	-3.99***	-5.62**	-0.0026
	(0.80)	(1.19)	(0.98)	(1.62)	(1.32)	(2.35)	(0.0024)
Observations	6,862	6,862	6,862	6,862	6,862	6,862	6,862
Fixed assets$_{ft}$:							
Storms$_{ft}$	-1.36***	-1.65**	-1.52**	-1.50	-1.45*	-1.18	-0.0027*
	(0.47)	(0.77)	(0.60)	(0.95)	(0.80)	(0.96)	(0.0015)
Observations	14,936	14,936	14,936	14,936	14,936	14,936	14,936
<u>Panel II:</u> Sales $_{fit}$ (logs)							
Storms$_{ft}$	-5.35***	-7.83***	-6.58***	-8.94***	-7.58***	-10.4**	-0.0047*
	(1.15)	(2.18)	(1.78)	(3.39)	(2.82)	(4.57)	(0.0025)
Comp. adv.$_{it}$ $\times$ Storms$_{ft}$	0.71***	1.29***	1.03***	1.82**	1.35**	2.92**	0.00041
	(0.25)	(0.48)	(0.37)	(0.81)	(0.61)	(1.40)	(0.00042)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$	4.11***	5.89***	4.66**	7.12*	5.76*	9.66*	0.0063***
	(1.29)	(2.25)	(1.83)	(3.67)	(2.97)	(5.35)	(0.0016)
Observations	17,952	17,952	17,952	17,952	17,952	17,952	17,952
Share of obs. with pos. storms	10%	10%	3%	3%	1%	1%	10%
Share of firms with pos. storms	28%	28%	8%	8%	4%	4%	28%
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are two-way clustered at the firm and district-year levels in Panel I and three-way clustered at the firm, district-year and industry-year levels in Panel II. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j\in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. In Panel I, the dependent variables are, in turn, the log of firms' buidings, land, electricity and fixed assets. In Panel II, the dependent variable is the log of firms' industry sales. Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE and district trends. Additionally, Panel II also includes postal code FE. The set of industry FE corresponds to the ISIC 4-digits classification. In Panel I, the industry FE is associated with the industry in which the firm's sales are the largest. All the specifications exclude always-multi-ISIC firms. The terms ">33", ">55" and ">64" mean that thresholds of 33, 55 and 64 knots are used to compute the measure of storm, respectively. The terms "quadratic" and "cubic" indicate the exponent of the damage function. Finally, in column (7) storm exposure is measured by maximum wind speed.

Table A.3: Alternative Definitions of the Storm Index (HURRECON)

	> 33		> 50		> 64		
	Baseline	Cubic	Quadratic	Cubic	Quadratic	Cubic	Winds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<u>Panel I:</u> Capital$_{ft}$ (logs)							
Buildings$_{ft}$:							
Storms$_{ft}$	-1.69***	-2.15***	-1.93***	-2.12***	-2.07***	-1.97***	-0.0045**
	(0.43)	(0.44)	(0.39)	(0.45)	(0.42)	(0.35)	(0.0020)
Observations	14,407	14,407	14,407	14,407	14,407	14,407	14,407
Land$_{ft}$:							
Storms$_{ft}$	-1.68***	-2.25***	-2.14***	-2.26***	-2.21***	-1.98***	-0.0046**
	(0.43)	(0.54)	(0.48)	(0.62)	(0.62)	(0.56)	(0.0019)
Observations	13,794	13,794	13,794	13,794	13,794	13,794	13,794
Electricity$_{ft}$							
Storms$_{ft}$	-2.45***	-4.30***	-4.00***	-5.32**	-4.97**	-3.94**	-0.0024
	(0.89)	(1.38)	(1.30)	(2.18)	(2.12)	(1.97)	(0.0034)
Observations	6,862	6,862	6,862	6,862	6,862	6,862	6,862
Fixed assets$_{ft}$:							
Storms$_{ft}$	-1.56***	-1.69*	-1.56*	-1.22	-1.08	-0.77	-0.0041**
	(0.56)	(0.94)	(0.85)	(0.99)	(0.93)	(0.80)	(0.0020)
Observations	14,936	14,936	14,936	14,936	14,936	14,936	14,936
<u>Panel II:</u> Sales $_{fit}$ (logs)							
Storms$_{ft}$	-6.43***	-9.03***	-8.14***	-11.1**	-11.7**	-17.5	-0.011***
	(1.47)	(3.01)	(3.00)	(4.67)	(5.24)	(10.7)	(0.0035)
Comp. adv.$_{it}$ × Storms$_{ft}$	0.93***	1.69***	1.48**	3.24**	3.87**	6.64*	0.0010
	(0.30)	(0.63)	(0.59)	(1.42)	(1.74)	(3.87)	(0.00063)
TFP$_{f(t-1)}$ × Storms$_{ft}$	4.71***	6.92**	6.24**	10.3*	11.2*	19.7*	0.011***
	(1.54)	(3.03)	(3.03)	(5.30)	(5.78)	(11.1)	(0.0031)
Observations	17,952	17,952	17,952	17,952	17,952	17,952	17952
Share of obs. with pos. storms	10%	10%	3%	3%	1%	1%	10%
Share of firms with pos. storms	28%	28%	8%	8%	4%	4%	28%
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are two-way clustered at the firm and district-year levels in Panel I and three-way clustered at the firm, district-year and industry-year levels in Panel II. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. In Panel I, the dependent variables are, in turn, the log of firms' buidings, land, electricity and fixed assets. In Panel II, the dependent variable is the log of firms' industry sales. Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE and district trends. Additionally, Panel II also includes postal code FE. The set of industry FE corresponds to the ISIC 4-digits classification. In Panel I, the industry FE is associated with the industry in which the firm's sales are the largest. All the specifications exclude always-multi-ISIC firms. The terms "> 33", "> 55" and "> 64" mean that thresholds of 33, 55 and 64 knots are used to compute the measure of storm, respectively. The terms "quadratic" and "cubic" indicate the exponent of the damage function. Finally, in column (7) storm exposure is measured by maximum wind speed.

B Additional Robustness

In this section, we perform additional robustness checks of our baseline results, focusing on the impact of storms on firm-industry sales.

B.1 No Extremes

First, we evaluate whether our results are driven by the strongest storms and eliminate from the sample values of the storm index associated with winds falling in the top 1% of the wind distribution. Results are shown in column (2) of Table B.1 shows and, as expected, excluding the strongest winds from the sample leads to smaller impacts on sales. However, the estimates of interest have the expected signs and remain statistically significant at least at the 5% level, suggesting that the mechanisms highlighted are at play even when removing the largest shocks from the sample.

B.2 Storm Timing

Second, we examine whether the timing of the storms may cause an attenuation bias. The storm measure includes occurrences spread over the entire year. If a storm hits towards the end of the year, its impact on sales may be felt only in the next fiscal year, therefore creating an attenuation bias.

Table B.2 shows the number of postal codes (for which we have firm-level data) hit by winds over 33 knots by month (panel I), as well as summary statistics of winds (over 33 knots) over six-months periods (panel II). The first panel of the table indicates that out of all the postal codes experiencing wind speeds above 33 knots, about 52% were impacted before the end of June, with the largest frequencies occuring in May and October. The first panel also shows that January to March, and July to September are quiet months. The second panel suggests that the average wind speed is similar between the first and second half of the year.

In column (3) of Table B.1 we propose to explore the timing of our main effect within one year, splitting the storm index into the two storm seasons, before and after June 30. We restrict the sample to firms which are hit either during the first or the second half of a given year but not both. For this reason, our sample shrinks from 17,952 to 11,207 observations. Estimates suggest that storms happening after June 30 have no effects on sales, whereas the estimates corresponding to storms in the first semester of the year are both statistically significant and in line with our baseline estimates (note that a direct comparison of the magnitudes is not possible since we exclude firms which experience storms over both 6-months periods). On the one hand, the lack of statistical significance on $Storm_{ft}^{after}$ suggests that it takes some time for changes in sales to appear in the accounts of a firm. In fact, since storms have, on average, similar magnitudes before and after June 30, there is no reason to expect capital destruction to differ across periods. On the other hand, the estimates based on variables including $Storm_{ft}^{before}$ suggest that reconstruction happens relatively rapidly and is felt and registered already within the first six months following the strike.

B.3 Local Demand Effects and Local Trends

Column (4) of Table B.1 examines whether our baseline effects are driven by local demand effects. By construction, the Balassa index likely correlates with exports, which implies that firms selling mainly to local markets tend to be located at the bottom of the comparative advantage distribution. For this reason, our main findings may mechanically reflect the negative effects of storms on local demand, as a fall in demand would lower the sales of firms selling to the local market while leaving exporters unaffected.

To separately identify local demand and build-back-better effects, we test whether exporters respond differently to storms than firms selling exclusively on the domestic market. We create an indicator variable equal to one if a firm is an exporter over the period 1995-2006, and zero otherwise. We then include in the baseline specification this exporter indicator as well as interaction terms between *i)* the exporter indicator and the storm index, and *ii)* the latter interaction term and the measure of comparative advantage. The coefficients on these extra interaction terms are statistically insignificant and, most importantly, our estimates of interest are unaltered, which suggests that our main findings do not capture the effects of storm-induced shifts in local demand.

We then explore the distinction between build-back-better effects and recovery to local trends, since storms may exacerbate pre-existing trends. In column (5) of Table B.1 we replace district trends by as set of district FE and postal code trends. The estimates obtained from this exercise are not statistically different from the baseline results, suggesting that the issue of capturing recovery to trend is not a significant concern.

B.4 Firm Fixed Effects

If wind speeds are as-good-as-randomly assigned, our baseline results should hold without controlling for lagged TFP and night-lights growth, conditional on firm FE, year FE and district trends. In column (6) of Table B.1 we show that the coefficients of interest remain similar even when using this stricter specification. The inclusion of firm FE implies that the identification of ϕ_2 in equation (2) of the manuscript is achieved using within-firm variation, specifically, comparing industrial sales of multi-ISIC firms (within and across years) and, for single-ISIC firms, switches in industry lines over time.

Importantly, adding firm FE allows us to rule out other mechanisms that may generate the pattern observed in the data. For instance, suppose that unobserved firm (fixed) characteristics (other than firm productivity) are determinants of success and that better firms self-select into comparative advantage industries. In that case, our results would also capture the fact that these unobserved components determine the speed with which (or the probability that) a firm gets back on its feet.

Alternatively, our findings might be driven by the presence of financial constraints. For instance, Basker & Miranda (2018) use US administrative data to study business survival in the aftermath of Hurricane Katrina. They find low survival rates for smaller and less productive firms and, among surviving firms, more hiring among larger and more productive firms. Importantly, they find evidence that these differential effects are tied to the presence of firms' financial constraints. Our results could also reflect the presence of frictions in the capital market, especially in a case where credit access determines a firm's capacity to rebuild and comparative advantage correlates with access to external finance.[1] Although industry FE in the baseline already control for the degree of financial dependence of an industry, adding firm FE allows us to purge the effects of firm financial constraints from our estimates. The coefficients obtained in column (6) are smaller in magnitude but, crucially, remain qualitatively similar and statistically significant at the 5% level.

[1]The question of reliance on external credit is even more relevant in the context of a developing country like India where only a small fraction of individuals can afford insurance against natural calamities. 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.

B.5 All Firms

Our baseline results exclude *always multi-ISIC firms* which produce in multiple industries over the entire sample period. *Multi-ISIC firms* which expand operations from a single industry to multiple ones (and vice versa) are always part of the baseline sample. As discussed in the manuscript, except for their average TFP, *always multi-ISIC firms* are very different from the rest of the firms. In addition, the event study shows that these firms exhibit pre-trends and that neither fixed assets nor sales are particularly affected by storms (see Figure F.1). For these reasons our baseline results focus on the reallocative channels for *single-* and *multi-ISIC firms*. Nevertheless, for completeness column (7) of Table B.1 the results obtained on the full sample of firms. As one can see, including *always-multi-ISIC firms* does not alter our conclusions qualitatively.

The estimate of ϕ_2 in equation (2) in the manuscript nearly halves, which suggests that our baseline estimates are, to a large extent, driven by *single-* and *multi-ISIC firms*. As discussed above, these types of firms tend to produce in industries with substantially lower comparative advantages and, therefore, are more likely to exploit capital destruction to adapt their production. Whether *always-multi-ISIC firms* are included or not in the sample, estimates of ϕ_3 do not statistically differ from each other, which is expected as average TFP is similar for all types of firms.

B.6 Placebo

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

Focusing on column (1), results suggest that in only 2.7% of the cases, the randomization produces estimates on the storm index which are statistically significant at the 1%. This share amounts to 2.1% for the estimates on $CA_{it} \times H_{ft}$ and 4.7% for the estimates on $TFP_{f(t-1)} \times H_{ft}$. Instead, in 100% of the cases the estimate on $TFP_{f(t-1)}$ stays statistically significant, and this at each level of statistical significance. Therefore, we conclude that our main results do not capture spurious correlations.[2]

B.7 Non Linearities

Finally, we explore potential non-linear effects and extend the baseline specification to a polynomial of order 3 in the storm index. We add the square and cube of the index, while maintaining the baseline interaction terms with TFP and comparative advantage. We report the result of this exercise graphically in Figure B.1 where we plot, for the median firm (median TFP and median comparative advantage), the marginal response of sales at varying values of storm exposure.

The figure shows that the marginal effects are negative across the distribution of exposure values. As expected, we do not find statistically significant impacts at the bottom of the distribution where winds may be too low to impair capital. The effect only kicks in with higher exposures, intensifies as we move to larger storm intensities and becomes diluted once we reach levels that are rarely observed.

In Figure B.2 we present marginal effects for firms with different values of TFP and comparative advantage. In panels A and C we fix comparative advantage at the median and TFP at the 25th (panel A) and 75th (panel C) percentiles of the distribution. In the right panels we use median TFP and fix comparative advantage at the 25th (panel B) and 75th (panel D) percentiles. Consistent with our previous baseline findings, the figure highlights that impacts are more pronounced for firms that have relatively lower TFP and comparative advantage and that for these firms, the effects are precisely estimated over a wider range of storm intensities.

[2]We also tried four alternative randomizations – within firms, industries, districts and years – and draw similar conclusions. Results are available upon request. While we prefer reporting results from 1000 randomizations, another placebo exercise consists in considering whether leads of the storm index are statistically significant. This type of exercise produces statistically insignificant estimates on the first, second and third leads of the storm measure, supporting the argument that baseline results do not reflect spurious correlations.

Table B.1: Robustness

Sales $_{fit}$ (logs)	Baseline	No extremes	Storm timing	Local demand effects	Recovery to trend	Firm FE	All firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Storms$_{ft}$	-5.92***	-2.81***		-5.98***	-5.93***	-0.91**	-5.91***
	(1.33)	(0.57)		(1.31)	(1.33)	(0.40)	(1.41)
Comp. adv.$_{it}$ $\times$ Storms$_{ft}$	0.92**	0.39**		1.05***	0.92**	0.33**	0.50**
	(0.39)	(0.16)		(0.37)	(0.39)	(0.14)	(0.24)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$	4.24***	1.91***		4.48***	4.24***		5.01***
	(1.34)	(0.61)		(1.09)	(1.34)		(1.87)
Storms$_{ft}^{before}$			-3.33***				
			(0.89)				
Comp. adv.$_{it}$ $\times$ Storms$_{ft}^{before}$			0.33*				
			(0.20)				
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}^{before}$			2.52**				
			(0.99)				
Storms$_{ft}^{after}$			14.9				
			(25.0)				
Comp. adv.$_{it}$ $\times$ Storms$_{ft}^{after}$			-2.88				
			(2.62)				
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}^{after}$			-1.82				
			(24.6)				
Exporter$_{ft}$				0.94***			
				(0.096)			
Storms$_{ft}$ $\times$ Exporter$_{ft}$				2.61			
				(2.58)			
Exporter$_{ft}$ $\times$ Comp. adv.$_{it}$				-0.0094			
				(0.029)			
Exporter$_{ft}$ $\times$ Comp. adv.$_{it}$ $\times$ Storms$_{ft}$				-2.68			
				(2.33)			
TFP$_{f(t-1)}$	Yes	Yes	Yes	Yes	Yes	No	Yes
Night-lights growth$_{d(t-1)}$	Yes	Yes	Yes	Yes	Yes	No	Yes
Comp. adv.$_{it}$	No	No	No	No	No	Yes	No
# of establishments$_{ft}$	Yes	Yes	Yes	Yes	Yes	No	Yes
Firm-type FE	Yes	Yes	Yes	Yes	Yes	No	Yes
Postal code FE	Yes	Yes	Yes	Yes	No	No	Yes
District trends	Yes	Yes	Yes	Yes	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No
Year FE	No	No	No	No	No	Yes	No
Industry-year FE	Yes	Yes	Yes	Yes	Yes	No	Yes
District FE	No	No	No	No	Yes	No	No
Postal code trends	No	No	No	No	Yes	No	No
Observations	17,952	17,952	11,207	17,952	17,952	17,641	34,886

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. The dependent variable is the log of firms' industry sales. The set of industry FE corresponds to the ISIC 4-digits classification. In columns (6) and (7) the number of observations differ from that of column (1) because of singleton observations. Each specification excludes always-multi-ISIC firms.

Table B.2: Wind Speeds at the Postal Code Level, by Month, 1995-2006

	I. Number of postal codes hit each month (wind > 33 knots)				
	Freq.	Percent	Cum		
	(1)	(2)	(3)		
Month:					
April	2	0.04	0.04		
May	1,980	35.93	35.97		
June	904	16.41	52.38		
October	1,454	26.39	78.77		
November	958	17.39	96.15		
December	212	3.85	100.00		
	II. Winds				
	Mean	Std. Dev.	Min.	Max.	N
	(1)	(2)	(3)	(4)	(5)
Time period:					
January-June	51.563	17.552	33.009	102.772	2,886
July-December	47.879	16.799	33.005	139.99	2,624

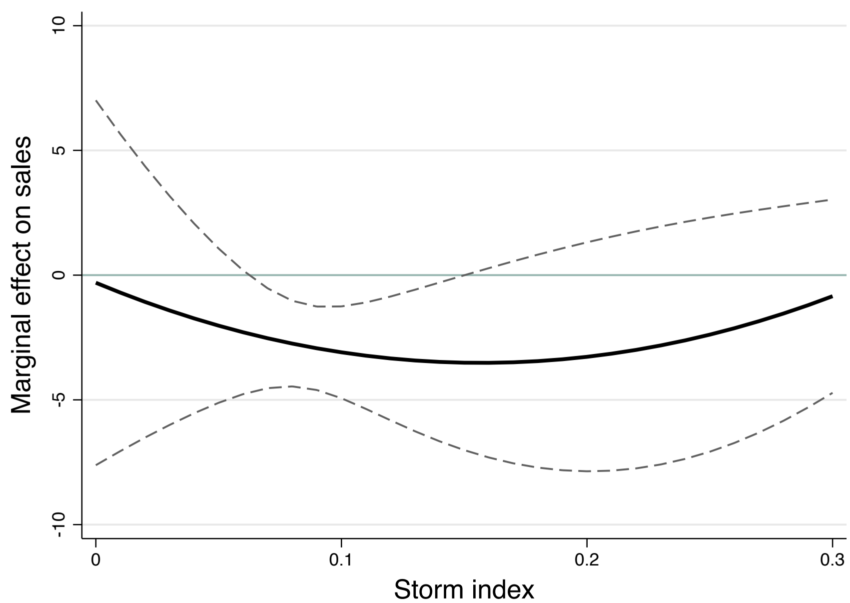
Note: The table shows winds only for postal codes for which firm-level data is available. Wind speeds are expressed in knots.

Table B.3: Placebo

Sales_{fit} (logs)	Share with statistical significance at: 1%	5%	10%
	(1)	(2)	(3)
$\text{TFP}_{f(t-1)}$	1	1	1
Storms_{ft}	0.027	0.096	0.154
Comp. $\text{adv.}_{it} \times \text{Storms}_{ft}$	0.021	0.081	0.143
$\text{TFP}_{f(t-1)} \times \text{Storms}_{ft}$	0.047	0.117	0.181
Controls, FE and trends	Yes	Yes	Yes

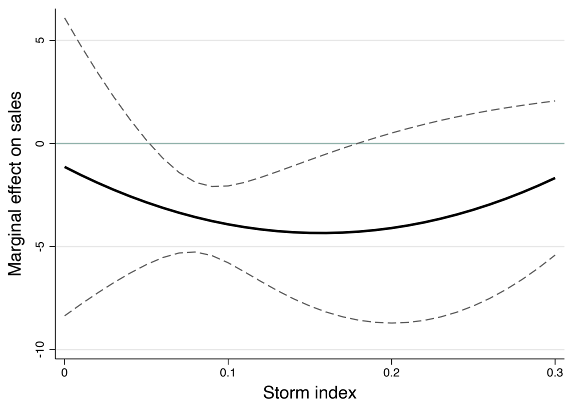
Note: Results show the share of statistically significant results over 1000 randomizations, where the storm measure is randomized over the entire sample. Statistical significance corresponds to three-way clustered standard errors at the firm, district-year and industry-year levels. The firm subscript $f = (\{j\}_{j\in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. The dependent variable is the log of firm sales in industry i at time t. Controls, FE and trends include the following: night-lights $\text{growth}_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, postal code FE and district trends. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification excludes always-multi-ISIC firms.

Figure B.1: Marginal Response of Sales to a Storm

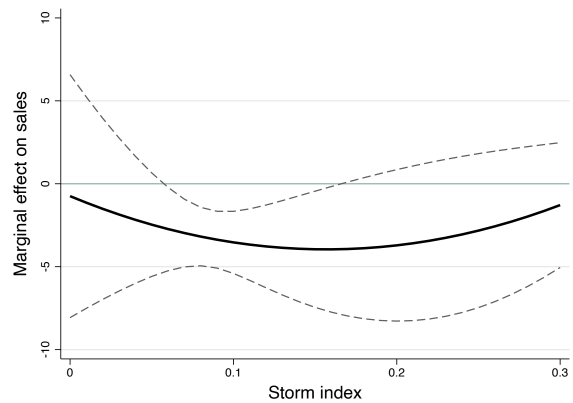


Notes: The specification used to produce the marginal response includes a polynomial of order 3 in the storm index. The black line shows the response for the median firm (median TFP and median comparative advantage) and the dashed lines are the 95% confidence intervals. The scale on the x-axis corresponds to values taken by the storm index.

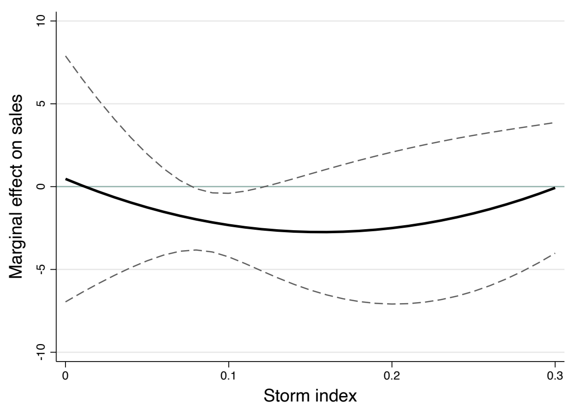
Figure B.2: Marginal Response of Sales to a Storm



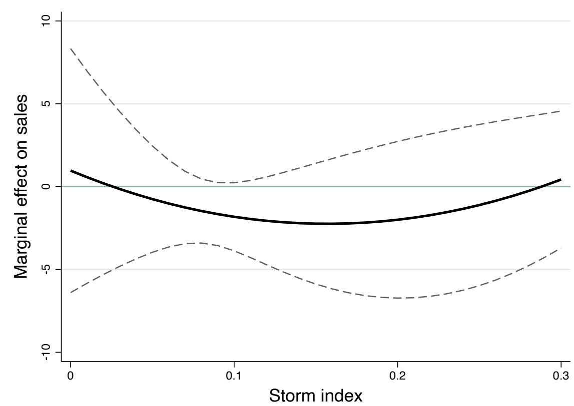
(a) 25^{th} percentile of TFP, median comp. adv.



(b) Median TFP, 25^{th} percentile of comp. adv.



(c) 75^{th} percentile of TFP, median comp. adv.



(d) Median TFP, 75^{th} percentile of comp. adv.

Notes: The specification used to produce the marginal responses includes a polynomial of order 3 in the storm index. In each panel, the black line shows the response for different values of TFP and comparative advantage, and the dashed lines are the 95% confidence intervals. The scale on the x-axis corresponds to values taken by the storm index.

C A Closer Look at Multi-ISIC Firms

In this section, we look at the extensive margin and examine whether storms increase the probability of entry and exit of firm-industry production lines. In our sample, only 2 out of 890 *single-ISIC firms* switch industries from one year to the next. For this reason, we argue that our baseline result is not driven by industry switches of *single-ISIC firms* and focus on *multi-ISIC firms*. We conclude the section by looking at how *multi-ISIC firms* adjust their current industry mix in the aftermath of storms.

C.1 Entry and Exit of Firm-Industry Production Lines

In Table C.1, we concentrate on the entry of new industry lines. We run a linear probability model where the dependent variable takes the value 1 if, conditional on producing in the previous year, a firm adds a 4-digit ISIC industry to its portfolio of industries and 0 otherwise.

At each step of the analysis, we distinguish firms with one establishment from those with more than one. Moreover, we present results according to two definitions of one-establishment firms. In the first one (definition I), a firm owns a single establishment if the firm appears in the Prowess database but not in Google Places (probably because the firm merged or went bankrupt between 2013 and 2018) or if it appears in Google Places as a single-establishment firm. In the second definition (definition II), we drop firms that do not appear in Google Places and define as a single-establishment firm, a firm which has a unique establishment in Google Places. Hence, under the second definition, our sample of single-establishment firms is smaller.

We do not expect to observe an effect when including multi-establishment firms. These firms are better sheltered from shocks as production may be reorganized and relocated from affected towards unaffected establishments. Hence, owning multiple establishments can be seen as an insurance against the risk of storms. Overall, 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 firm-industry production lines. We run a linear probability model where the dependent variable takes the value 1 if, from one year to the next, a firm stops the production of an industry line and 0 otherwise, conditional on the firm surviving in the next period. Results are shown in Table C.2. Focusing on the most complete specification (column (7)), we find that storms have heterogenous effects across industries. However, there is no evidence that the effect varies depending on productivity. Combined with a positive (albeit statistically insignificant) estimate on the storm index, the coefficient on the interaction term $(CA_{it} \times H_{ft})$ implies that industry lines characterized by low comparative advantage have a higher exit probability. However, given the imprecisely estimated coefficient on the storm index, this heterogenous effect will be statistically significant only for certain values of comparative advantage. Nevertheless, the result is consistent with the idea that, following massive capital destruction, firms abandon lines of production with low comparative advantage to switch to higher segments of the comparative advantage distribution. This effect disappears for one-establishment firms.

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

C.2 Shifts in Firm Industrial Mix

The absence of entry and a mild effect on exit of industry lines suggests that the across-industry effect is driven to a large extent by shifts in the existing firm-level production mix. To study this possibility we regress a measure of firm industrial mix on the index of storm exposure and a set of controls including firm FE, year FE, 2-digits ISIC industry trends and district trends. Industry trends account for the fact that the set of industries where a firm is active depends on the main industry in which a firm operates (e.g. through the value chain or input-output linkages). We also include TFP and district night-light growth, as in the baseline specification.

The measure capturing firms' industrial mix is constructed as follows:

$$IM_{ft} = \sum_{j \in J} \eta_{jft} CA_{j(t-1)}, \tag{C.2.1}$$

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. An increase in IM_{ft} indicates that the pattern of production of the firm has shifted towards comparative advantage industries. Such a shift may happen either because the firm has shifted production away from low comparative advantage industries or, holding production shares across industries constant, because the Balassa index of some industries has increased. Since the comparative advantage of a country changes slowly over time, most of the variation in IM_{ft} comes from shifts in the pattern of production of firms.

Results are presented in Table C.3. We identify an effect for single-establishment firms. For these firms, we obtain a positive coefficient on exposure to storms, indicating that they seem to adjust by shifting their production towards industries which align better to comparative advantage.

Table C.1: Entry of Industry Lines

		One estab.			One estab.			One estab.	
Entry of industry line$_{ft}$	All	I	II	All	I	II	All	I	II
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Storms$_{ft}$	0.15*	0.25	-0.18	0.23	0.53	-0.26	0.29	0.63	-0.21
	(0.089)	(0.16)	(0.13)	(0.21)	(0.61)	(0.25)	(0.19)	(0.45)	(0.17)
Comp. adv.$_{it}$ × Storms$_{ft}$	-0.053	-0.078	0.0070				-0.053	-0.076	0.0083
	(0.068)	(0.11)	(0.029)				(0.069)	(0.11)	(0.030)
TFP$_{f(t-1)}$ × Storms$_{ft}$				-0.19	-0.52	0.10	-0.19	-0.54	0.039
				(0.28)	(0.81)	(0.20)	(0.30)	(0.76)	(0.21)
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,760	6,499	2,501	15,760	6,499	2,501	15,760	6,499	2,501

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels in columns (1)-(3) and (7)-(9), and two-way clustered at the firm and district-year level in columns (4)-(6). *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j\in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code 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). Controls, FE and trends include the following: TFP$_{f(t-1)}$, CA$_{it}$, night-lights growth$_{d(t-1)}$, industry FE, year FE, postal code FE and district trends. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification focuses on multi-ISIC firms. The term *All* indicates all firms except always-multi-ISIC firms are included in the sample. The terms *One estab. I* and *One estab. II* indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

Table C.2: Exit of Industry Lines

Exit of industry line$_{ft}$	All	One estab. I	One estab. II	All	One estab. I	One estab. II	All	One estab. I	One estab. II
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Storms$_{ft}$	0.49*	0.78*	-0.45	-0.059	-0.064	1.13	0.069	0.16	0.97
	(0.25)	(0.42)	(0.51)	(0.52)	(0.96)	(1.20)	(0.52)	(0.92)	(1.34)
Comp. adv.$_{\cdot it}$ × Storms$_{ft}$	-0.10**	-0.12*	0.17				-0.10**	-0.12	0.10
	(0.048)	(0.069)	(0.16)				(0.050)	(0.074)	(0.15)
TFP$_{f(t-1)}$ × Storms$_{ft}$				0.59	0.89	-2.04	0.56	0.81	-1.93
				(0.55)	(1.19)	(1.79)	(0.46)	(1.19)	(1.85)
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,258	4,962	1,955	12,258	4,962	1,955	12,258	4,962	1,955

Note: Standard errors are three-way clustered at the firm, district-year and industry-year levels in columns (1)-(3) and (7)-(9), and two-way clustered at the firm and district-year level in columns (4)-(6). *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code 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. Controls, FE and trends include the following: TFP$_{f(t-1)}$, CA$_{it}$, night-lights growth$_{d(t-1)}$, industry FE, year FE, postal code FE and district trends. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification focuses on multi-ISIC firms. The term *All* indicates all firms except always-multi-ISIC firms are included in the sample. The terms *One estab. I* and *One estab. II* indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

Table C.3: Shifts in the Industry Mix of Firms

Industrial mix$_{ft}$	All	One estab. I	One estab. II
	(1)	(2)	(3)
Storms$_{ft}$	0.18	1.85**	2.54***
	(0.56)	(0.81)	(0.88)
Controls, FE and trends	Yes	Yes	Yes
Observations	12,109	5,047	2,043

Note: Standard errors are two-way clustered at the firm and district-year level. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, firm FE, year FE, 2-digits industry trends and district trends. The set of industry trends corresponds to the ISIC 2-digits classification. The industry we use for the trend is associated with the industry in which the firm's sales are the largest. Each specification focuses on multi-ISIC firms. The term *All* indicates all firms except always-multi-ISIC firms are included in the sample. The terms *One estab. I* and *One estab. II* indicate that firms with more than one establishment (according to definition I or II) and always-multi-ISIC firms are excluded from the sample.

D Capital Intensity

We expect capital-intensive industries to be hit harder and go through a more important reorganization of their production structure. In addition, as reconstruction should take place at the top of the comparative advantage distribution (irrespective of the capital intensity of the industry), we expect sales to increase in low-capital-intensity industries. In what follows we investigate whether this is the case.

To do so, we first estimate the following regression:

$$K_{ft} = \varphi_0 + \varphi_1 TFP_{f(t-1)} + d_i + d_t + \epsilon_{ft} \tag{D.1}$$

where K_{ft} denotes firm fixed assets, d_i represents 4-digit ISIC industry FE and d_t year FE. We retrieve the coefficients on the industry FE and use them as a measure of capital intensity, which we denote κ_i.

We then augment the baseline specification with a triple-interaction term that interacts exposure to storms (H_{ft}), comparative advantage (CA_{it}) and capital intensity (κ_i):

$$\begin{aligned} s_{fit} &= \mu_0 + \mu_1 TFP_{f(t-1)} + \mu_2 H_{ft} + \mu_3 \left(TFP_{f(t-1)} \cdot H_{ft}\right) \\ &+ \mu_4 \left(H_{ft} \cdot \kappa_i\right) + \mu_5 \left(CA_{it} \cdot H_{ft}\right) + \mu_6 \left(CA_{it} \cdot H_{ft} \cdot \kappa_i\right) + \boldsymbol{Z\phi} + \epsilon_{fit}^{INT}, \end{aligned} \tag{D.2}$$

where ϵ_{fit}^{INT} is the error term.

We present the marginal effects of this regression graphically, fixing κ_i and $TFP_{f(t-1)}$ at high and low values and plotting the marginal effect of a storm across the comparative advantage distribution. High (low) capital intensity is defined by the 75^{th} (25^{th}) percentile of the distribution of κ_i. Similarly, we use three different levels of TFP: the 25^{th}, the 50^{th}, and the 75^{th} percentiles of its distribution.

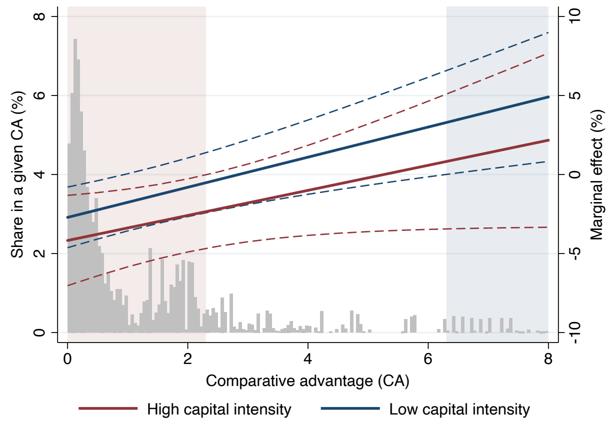
Figure D.1 shows the marginal effect evaluated at the 25^{th} (Panel A), 50^{th} (Panel B), and 75^{th} (Panel C) percentile of the TFP distribution, respectively. In each of the figures the maroon line represents the marginal effect for high capital intensity industries, while the blue one is for low capital intensity industries, with their respective 95% confidence bands represented by the dashed lines. The shaded areas represent areas where the marginal effect is statistically significant at the

95% level, and maroon (blue) shading indicates statistical significance for the industry with high (low) capital intensity.

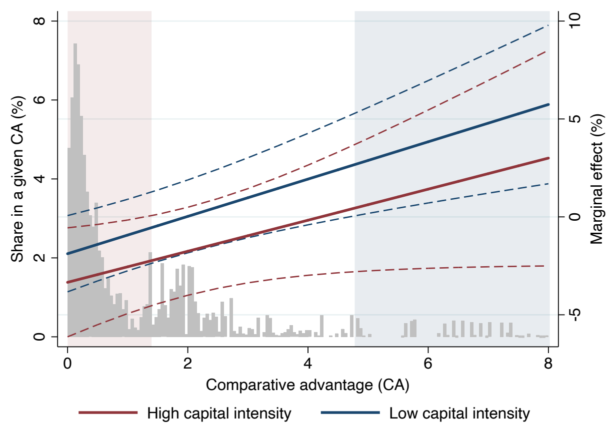
As expected, the figures show that industries with a high capital intensity are affected disproportionately more by storms. The maroon marginal response is always below the blue one, indicating that sales in high capital intensity industries decrease more than sales in low capital intensity industries.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

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

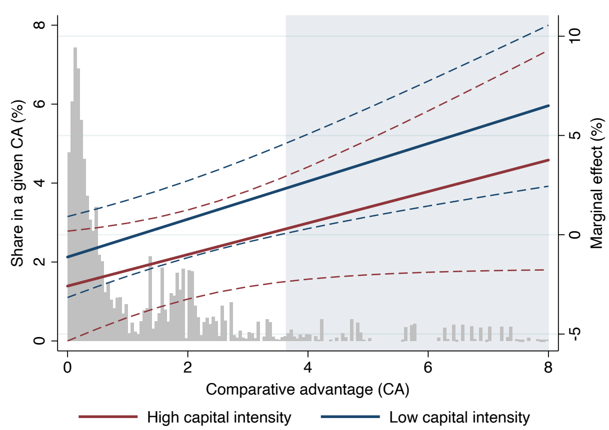
Figure D.1: Capital Intensity



(a) TFP at the 25th percentile



(b) TFP at the median



(c) TFP at the 75th percentile

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

E Other Tables

Table E.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Single ISIC firms:					
Firm buildings (real)	0.906	2.552	0.002	42.893	2,282
Firm land (real)	0.454	2.856	0.002	47.152	2,172
Firm electrical equipments (real)	0.146	0.458	0.002	5.921	1,254
Firm fixed assets (real)	4.202	12.606	0.002	195.218	2,430
Firm salaries (real)	0.6	1.824	0.002	26.678	2,363
Firm sales at the ISIC level (real)	10.372	34.793	0.002	708.202	2,394
Firm TFP	0.803	0.313	0.005	4.201	2,394
Industry-year comparative advantage	1.461	2.084	0	13.678	2,394
Industry-year comparative advantage (ref.)	1.461	2.084	0	13.678	2,394
Always-multi-ISIC firms:					
Firm buildings (real)	6.225	36.012	0.002	879.599	7,608
Firm land (real)	2.073	11.798	0.002	280.551	7,355
Firm electrical equipments (real)	0.897	7.81	0.002	270.979	3,180
Firm fixed assets (real)	45.202	331.431	0.003	11169.715	7,817
Firm salaries (real)	5.484	30.782	0.002	1101.175	7,655
Firm sales at the ISIC level (real)	63.4	847.995	0.002	41,518.016	16,872
Firm TFP	0.79	0.518	0	19.075	16,872
Industry-year comparative advantage	1.519	2.09	0	24.346	16,872
Industry-year comparative advantage (ref)	2.498	2.602	0	24.346	7,757
Multi-ISIC firms:					
Firm buildings (real)	2.029	8.539	0.001	268.644	12,302
Firm land (real)	0.747	6.619	0.001	588.682	11,804
Firm electrical equipments (real)	0.281	1.118	0.001	20.41	5,809
Firm fixed assets (real)	14.048	79.415	0.002	1,908.504	12,677
Firm salaries (real)	1.271	4.139	0	132.891	12,304
Firm sales at the ISIC level (real)	19.887	94.726	0.002	5,661.934	15,839
Firm TFP	0.813	0.445	0	11.215	15,839
Industry-year comparative advantage	1.652	2.245	0	24.346	15,839
Industry-year comparative advantage (ref.)	1.9	2.421	0	24.346	12,499

Note: Buildings, land, electrical equipments, fixed assets, salaries and sales are expressed in crores (10 millions) of Indian Rupees and are deflated using the industry-level price gross output, base year 2005. *Comparative advantage* refers to Balassa index of revealed comparative advantage. *Comparative advantage (ref.)* is the reference comparative advantage in a year. For firms active in multiple industries, we choose as reference the highest comparative advantage in a year.

Table E.2: How Long Does it Take for Firms to Rebuild and Reboot (All Firms)?

	Buildings				Land			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storms$_{ft}$	-1.19**	-1.20**	-1.32***	-1.80***	-0.76*	-0.77*	-1.03*	-1.61**
	(0.49)	(0.49)	(0.44)	(0.42)	(0.44)	(0.45)	(0.55)	(0.65)
Storms$_{f(t-1)}$		-0.46	0.14	0.11		-0.14	0.077	-0.11
		(0.51)	(0.65)	(0.59)		(0.50)	(0.63)	(0.77)
Storms$_{f(t-2)}$			0.11	0.15			-0.010	-0.31
			(0.18)	(0.25)			(0.25)	(0.34)
Storms$_{f(t-3)}$				-0.17				-0.28
				(0.24)				(0.24)
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,047	22,047	17,942	15,100	21,183	21,183	17,288	14,576

Dependent variable	Electricity$_{ft}$ (logs)				Fixed assets$_{ft}$ (logs)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Storms$_{ft}$	-2.99***	-3.02***	-1.43	-1.63	-1.09**	-1.12**	-1.02**	-1.52***
	(0.86)	(0.87)	(1.07)	(1.13)	(0.50)	(0.50)	(0.45)	(0.54)
Storms$_{f(t-1)}$		-0.34	-2.47**	-1.37		-0.73	-0.43	-0.46
		(0.83)	(1.18)	(1.58)		(0.70)	(0.90)	(0.84)
Storms$_{f(t-2)}$			-0.29*	-0.51			0.075	0.16
			(0.16)	(0.34)			(0.27)	(0.32)
Storms$_{f(t-3)}$				-0.044				-0.14
				(0.37)				(0.25)
Controls, FE and trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,052	10,052	7,982	6,591	22,781	22,781	18,449	15,459

Note: Standard errors are two-way clustered at the firm and district-year level. *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j \in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. In columns (1)-(4), the dependent variable is the log of firm net buildings. In column (5)-(8), *land* refers to the log of firm net land. The term *electricity* in column (9)-(12) refers to the log of firm net electrical installations and fittings. In column (13)-(16), the term *fixed assets* refers to the log of firm net fixed assets. Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE and district trends. The set of industry FE corresponds to the ISIC 4-digits classification. All the specifications include all firms.

Table E.3: Alternative Ways of Clustering the Standard Errors

Sales $_{fit}$ (logs)	Baseline	District	District and industry	District-year and industry-year
	(1)	(2)	(3)	(4)
Storms$_{ft}$	-5.92***	-5.92***	-5.92***	-5.92***
	(1.33)	(1.50)	(1.71)	(1.34)
Comp. adv.$_{it}$ $\times$ Storms$_{ft}$	0.92**	0.92***	0.92**	0.92**
	(0.39)	(0.29)	(0.39)	(0.41)
TFP$_{f(t-1)}$ $\times$ Storms$_{ft}$	4.24***	4.24***	4.24***	4.24***
	(1.34)	(1.55)	(1.53)	(1.31)
Controls, FE and trends	Yes	Yes	Yes	Yes
Observations	17,952	17,952	17,952	17,952

Note: *** p<0.01, ** p<0.05, * p<0.1. The firm subscript $f = (\{j\}_{j\in J}, p, d)$ where J is the set of industries in which firm f operates, p denotes a postal code and d a district. The dependent variable is the log of firms' industry sales. Column (1) corresponds to the baseline specification where standard errors are three-way clustered at the firm, district-year and industry-year levels. The other columns show results based on alternative ways of clustering standard errors; one-way clustered at the district level (column 2), two-way clustered at the district and industry levels (column 3) and two-way clustered at the district-year and industry-year levels (column 4). Controls, FE and trends include the following: TFP$_{f(t-1)}$, night-lights growth$_{d(t-1)}$, # of establishments, firm-type FE, industry-year FE, postal code FE and district trends. The set of industry FE corresponds to the ISIC 4-digits classification. Each specification excludes always-multi-ISIC firms.

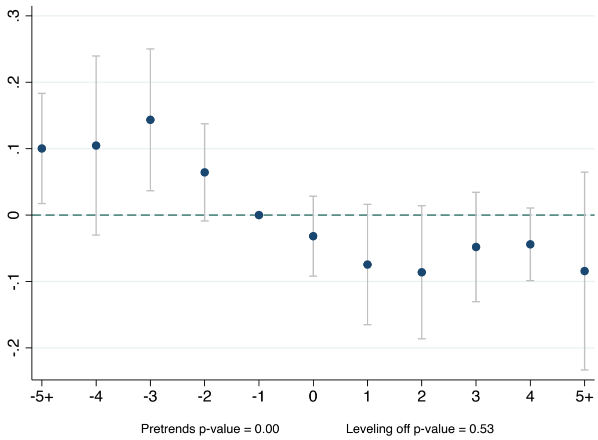
Table E.4: Example of CMIE Product Code Assignment to NIC Division 13 *"Manufacture of Textiles"*

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

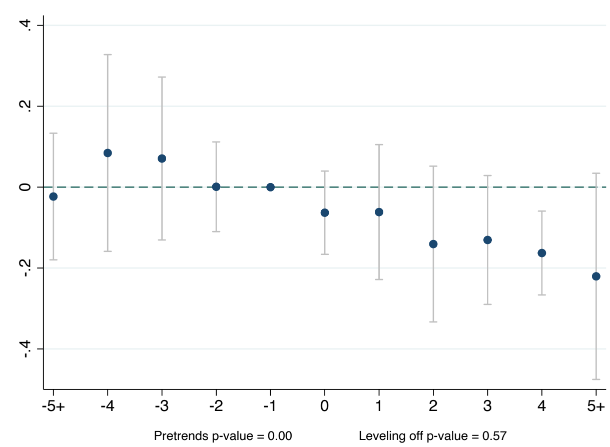
Note: Devision 13 (NIC-2008) has a total of 8 4-digit classes and 50 5-digit product codes. Only a small subset of these products is presented in the table. Source: Prowess database and authors' matching of agency's product codes to NIC-2008 5-digit product codes. ^{p} denotes the product codes which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

F Other Figures

Figure F.1: Event Study (Always-Multi-ISIC Firms)



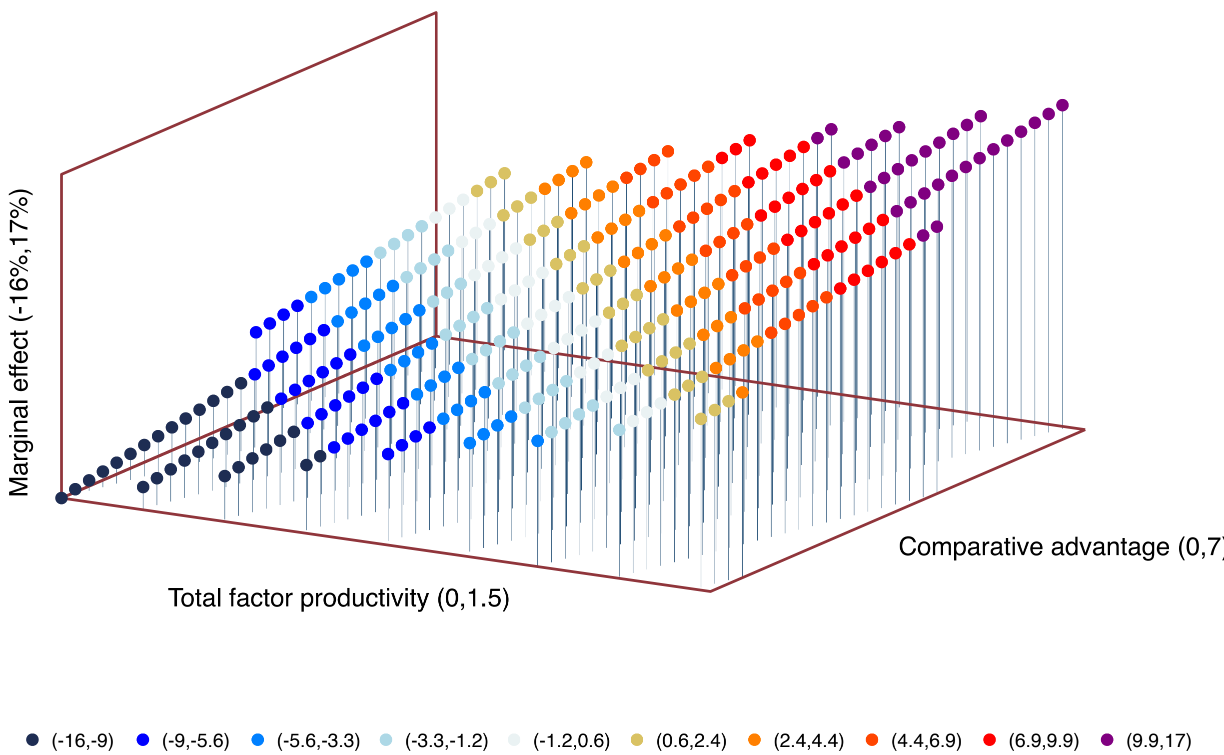
(a) Fixed assets (logs)



(b) Sales (logs)

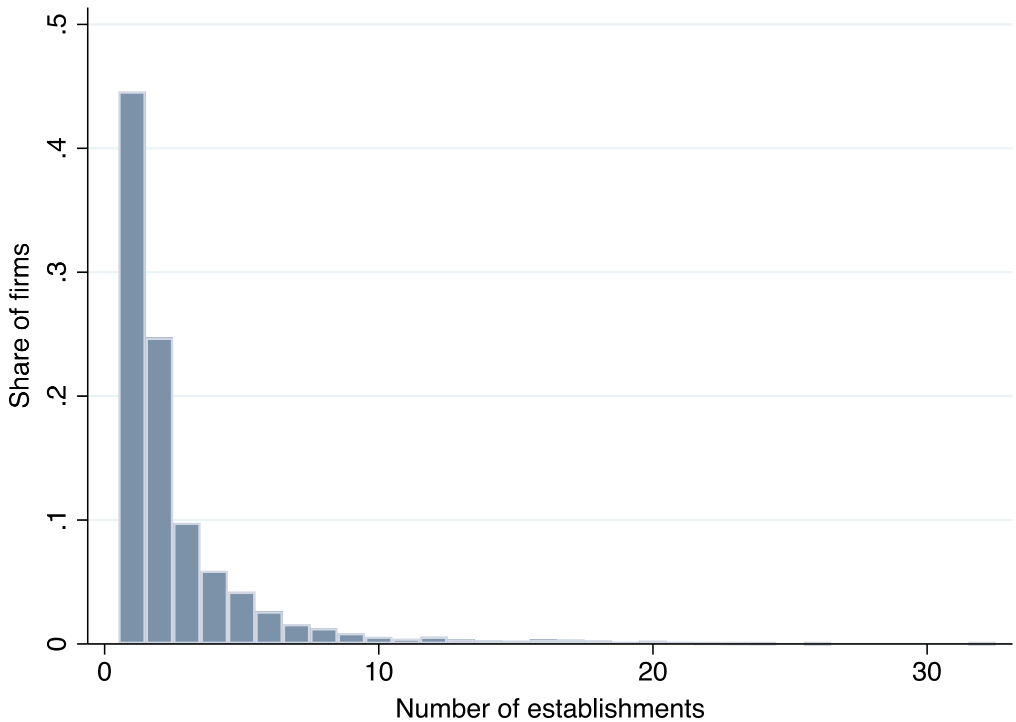
Notes: The figure shows the event study graph for the average effects of storms on always-multi-ISIC firms' fixed assets (left panel) and sales (right panel). The normalization takes place at $t = -1$, the year before the event. The pre-trends p-value is for the null hypothesis of no pre-trends, and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

Figure F.2: Marginal Effect of a Storm on Sales



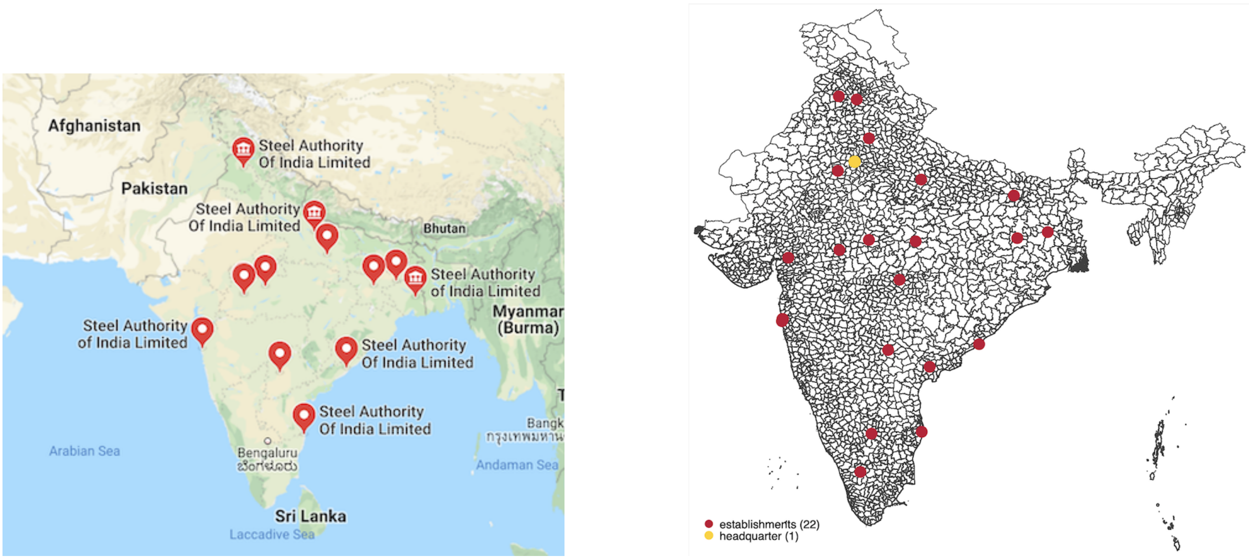
Notes: Extreme values of TFP and comparative advantage (values above the 95th percentile) are left out in the computation of the marginal effect. For each level of $TFP_{ft} \in (0, 1.5)$ and $CA_{it} \in (0, 7)$, the marginal effect is computed as $\widehat{\phi_2} + \widehat{\phi_3}CA_{it} + \widehat{\phi_4}TFP_{ft}$, where $\widehat{\phi_2}$, $\widehat{\phi_3}$, and $\widehat{\phi_4}$ are taken from column (8) in Table 6. The marginal effect captures the change in a firm's industry log sales in the aftermath of a storm of mean intensity ($H_{ft} = 0.027$).

Figure F.3: Distribution of the Number of Establishments Across Firms



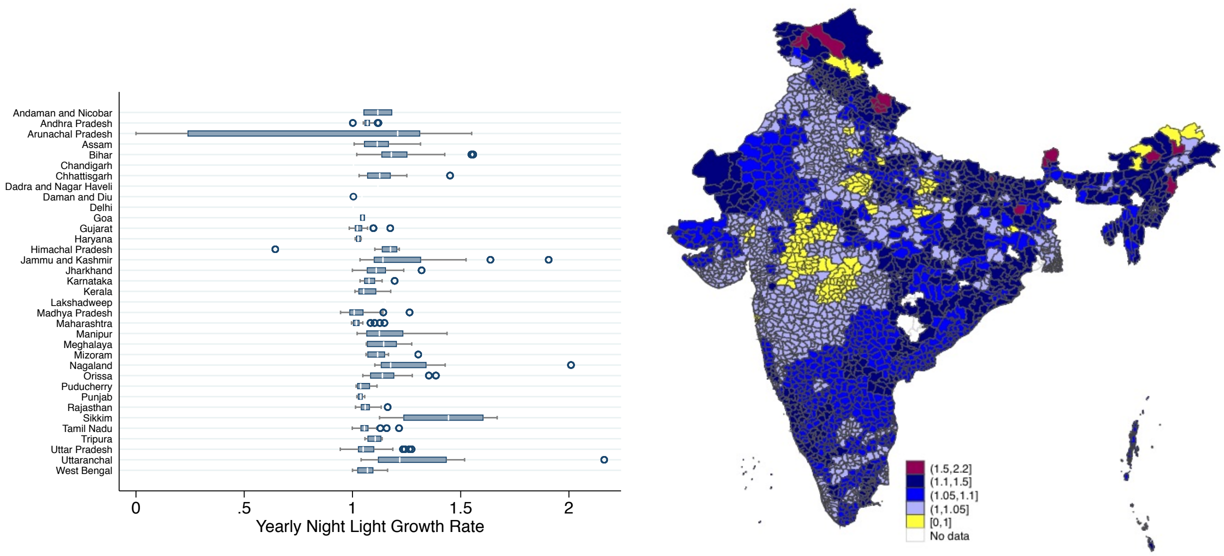
Note: The histogram shows the distribution of firms according to the number of establishments they posses (single establishment firms are defined according to the first definition used in the Online Appendix: a firm owns a single establishment if the firm appears in the Prowess database but not in Google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

Figure F.4: Example – Establishments' Location of the Company Steel Authority of India



Note: The figure shows where the establishments of the company "Steel Authority of India" are located. The left panel is a screenshot from one search on Google Maps before the text analysis that allows us to distinguish between a firm's establishments and random Google Maps results. The right panel shows the establishments' location returned by 3 separate google places in Summer 2018, after the text analysis allowing us to identify the actual establishments of a firm (note that the two maps do not show the same establishments, underlining the importance of repeating the search and cleaning the results). The yellow dot denotes the headquarters and the red dots are the establishments.

Figure F.5: Yearly Night-Light Growth Rates, 1995-2006



Notes: The left panel shows boxplots of yearly night-lights growth rates by state for the period 1995-2006. The white line is the median. The left of the box is the first quartile ($Q1$ or 25th percentile) and the right the third quartile ($Q3$ or 75th percentile). The end of the left (right) whisker is the 1st percentile (99th percentile). Circles without 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 night-lights growth rates by district, averaged over the period 1995-2006.

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