

Pelli, Martino; Tschopp, Jeanne

**Working Paper**

## Storms, early education, and human capital

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# **APPENDIX**

## **Storms, Early Education, and Human Capital**

Martino Pelli and Jeanne Tschopp

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## A Storms and Migration

In this section, we use the Pyramids Dx dataset to investigate the possibility that people may migrate out of their district in response to storms. While the Pyramids Dx only introduced migration questions in their survey in 2020, we still have a panel of 367,378 individuals aged 5 to 33, who are interviewed every four months, providing us with six observations over the two years of available data. We run the following specification:

$$M_{it} = \zeta_0 + \zeta_1 x_{d\tau} + \zeta_2 x_{d\tau-1} + \zeta_3 x_{d\tau-2} + \delta_i + \delta_\tau + \delta_{dt} + \varepsilon_i,$$

where  $i$  denotes an individual and  $\tau$  denotes time (a quadrimester-year pair).  $M_{it}$  is a dummy equal to one if the individual migrated out of their district of residence in the last four months, and  $x_{d\tau}$  ( $x_{d\tau-1}$ ) captures district storm exposure over the period  $\tau - 1$  to  $\tau$  ( $\tau - 2$  to  $\tau - 1$ ).  $\delta_i$ ,  $\delta_\tau$  and  $\delta_{dt}$  represent individual, time, and district-year FE, respectively.  $\zeta_1$  captures the percentage points changes in the contemporaneous probability of out-of-district migration. We use weights provided by Pyramids Dx and cluster standard errors at the state level.

Table D.2 displays the results from estimating the above equation. Panel A pertains to individuals aged 5 to 33, while Panel B focuses on children aged 5 to 15, the compulsory schooling age range. Column (1) shows the contemporaneous effect of storm exposure on the probability of migration. In column (2), we add the first lag of storm exposure (4 months prior), and in column (3), we include a second lag (8 months prior).

The estimates obtained are negative and generally precisely estimated, indicating that the occurrence of a storm does not increase the likelihood of moving to another district but, in fact, lowers the probability of migration. We interpret this result as indicating that the period following a strike is typically not an opportune time for individuals to start anew, severing ties with their support networks, family, and friends. As we demonstrate in Section 4.1, storms typically do not entirely destroy people's homes and possessions, but they do cause substantial income losses that diminish individuals' ability to move. Therefore, we do not anticipate post-disaster migration to bias our estimates.

The existing research on the migration impacts of disasters presents mixed evidence (see Berlemann and Steinhardt, 2017, for a review of empirical studies). Our finding aligns with recent studies indicating that disasters and migration have a negative or statistically insignificant relationship (e.g., Shakya et al., 2022; Beine et al., 2021; Gröschl and Steinwachs, 2017; Cattaneo and Peri, 2016). Mueller et al. (2014) and Gray and Mueller (2012) show that persistent and slowly worsening disasters, such as heat,

may result in migration, while floods and storms do not significantly alter individuals' propensity to migrate. This may be because, during times of distress, individuals who are economically disadvantaged are often reluctant to abandon their local adaptation capacity.<sup>1</sup>

## B Computing Wind Speed

### B.1 Baseline Wind Field Model: the Rankine-combined Formula (Deppermann, 1947)

In this appendix, we explain how we calculate  $w_{dh}$ , which represents the maximum wind speed associated with storm  $h$  in district  $d$ . We use data from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center, specifically the best tracks of storms in the North Indian and South Indian basins from 1990 to 2010 (Knapp et al., 2010). The best tracks provide a comprehensive record of each storm, including latitude, longitude, date, and wind speed at 6-hour intervals for the eye of the storm.

We begin by linearly interpolating the best tracks of storms at every kilometre, resulting in a set of landmarks  $k$ , each with a set of coordinates and a corresponding wind speed at the eye of the storm, denoted as  $e_k$ . Next, for each district falling within the vortex associated with a landmark, we use the Rankine-combined formula (Deppermann, 1947) to compute the winds at the district's centroid. This formula describes wind fields as follows:

$$w_{dk} = e_k \cdot \left( \frac{D_{dk}}{26.9978} \right) \text{ if } D_{dk} \leq 26.9978$$

$$w_{dk} = e_k \cdot \left( \frac{26.9978}{D_{dk}} \right)^{0.5} \text{ if } D_{dk} > 26.9978,$$

where  $D_{dk}$  is the distance between the centroid of district  $d$  and landmark  $k$ . The number 26.9978 corresponds to the Simpson and Riehl radius of maximum wind speed in knots, which is the distance between the eye and the point where wind reaches its maximum speed.<sup>2</sup> According to this formula, winds first increase exponentially up to a maximum and then decrease rapidly.

<sup>1</sup>For contrasting findings indicating a positive relationship between disasters and migration in the US, see for instance Sheldon and Zhan (2022) and Parag and Yang (2020).

<sup>2</sup>In reality, the radius of maximum wind speed for each cyclone varies, and is calculated using the difference in barometric pressure between the center and the outskirts of the storm. However, cyclone data are often characterized by a high number of missing data when it comes to barometric pressure. Therefore, we follow the approach of Simpson and Riehl (1981) and Hsu and Zhongde (1998) and apply the average radius of maximum wind speed, 50 km, to all the cyclones considered in this paper.

Finally, we obtain a single wind speed measure per district and storm by selecting the maximum wind speed to which the district was exposed, i.e.:

$$w_{dh} = \max_{k \in H_t} \{w_{dk}\}.$$

## B.2 Alternative Wind Field Model: the HURRECON Model (Boose et al., 1994)

As an alternative wind field model, we use the HURRECON model (see Boose et al., 1994, 2001, 2004). The model uses information on the track, size, intensity, and cover type (land or water) of a hurricane to describe sustained wind velocity at any point within a cyclone's vortex. Specifically, the computation of sustained wind velocity at each district centroid is done using the following equation:<sup>3</sup>

$$w_{dk} = F \left[ V_k - S(1 - \sin T) \frac{V_f}{2} \right] \left[ \left( \frac{R_m}{R} \right)^B e^{1 - \left[ \frac{R_m}{R} \right]^B} \right]^{1/2}$$

where  $F$  is a scaling parameter capturing the effect of friction. Usually this parameter is set to 1 for points over water and to 0.8 for points over land. In our case,  $F = 0.8$ .  $V_k$  captures the wind velocity at the eye at landmark  $k$ , which we linearly interpolate from the best track data.  $S$  is a scaling parameter for the asymmetry due to the forward motion of the storm, set to 1 as in Boose et al. (2001);  $T$  is the clockwise angle between the forward path of the hurricane and a radial line connecting the eye of the hurricane to the centroid of a district;  $V_f$  denotes the forward velocity of the hurricane;  $R_m$  is the radius of maximum winds, set as in the baseline at 26.9978;  $R$  is the Euclidean distance from the center of the hurricane to the centroid of a district. Finally, the parameter  $B$  controls for the shape of the wind profile curve and is set at 1.35. The parameters of this equation are chosen following Boose et al. (2004) who parameterized and validated the model.

## C Robustness

In this Appendix, we show the robustness results for the type of activity performed by individuals once they reach early adulthood.

Table D.6 evaluates the importance of early-life exposure to storm on individuals' type of activity. The measure is constructed as described in Section 3.4 of the paper. Panel A presents the baseline specification, Panel B reports results on the restricted subsample

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<sup>3</sup>Velocity and wind direction are measured relative to the surface of the Earth, and angles are measured in degrees.

of individuals born after 1989. Panel C replaces school-age ( $C_{bd}$ ) with early-life exposure, and Panel D includes both early-life and school-age exposures simultaneously. Notably, compared to the subsample, the inclusion of a measure that accounts for early-life shocks does not affect the estimate on the school-age exposure index, indicating that the period of school years is also highly responsive to shocks.

Table D.8 presents the results of the falsification test and reports the proportion of replications that yield statistically significant estimates at the 1%, 5%, and 10% levels, respectively. Overall, the results suggest that our coefficients do not capture spurious correlations. The numbers in column (1) indicate that statistically significant estimates at the 1% level are produced in only 1.8% (Panel E) to 2.7% (Panel B) of the cases. As expected, the proportion of significant estimates increases when considering higher levels of statistical significance, reaching a maximum of 8.5% (Panel D) at the 5% level and 13.8% (Panel B) at the 10% level.

In Table D.9, we explore the sensitivity of our results to extreme values of exposure. Panel A shows the baseline results, and Panel B excludes individuals residing in Odisha. In Panel C, we recompute the exposure index by removing winds at the top 5% of the wind distribution. The estimates obtained in Panel B and C are consistent with the baseline results in Panel A. Panels D and E of the table control for climate variables, constructed as described in Section 3.4 of the paper. Panel D runs the baseline specification on the subsample for which rainfall and temperature data are available, and Panel E includes the climate controls in the regression. Finally, Panels F and G exclude married females and highly educated workers from the sample, respectively. Incorporating these additional variables does not alter the conclusions we derive from the baseline results.

In Table D.10 we account for individuals' education as described in Section 3.4 of the paper. Panel A of the table shows the baseline results and Panel B includes the predicted probability of completing the reported level of education as a control variable. The inclusion of this variable does not affect the baseline estimates; exposure to storms during compulsory schooling reduces the probability of being employed as a regular worker and increases the likelihood of performing domestic duties in a statistically significant manner. Panel C replicates the baseline regression on the subsample that includes information on parental education. The estimate of the probability of performing regular work is slightly less precise in this subsample. However, including parental education as a control variable (Panel D) produces estimates that are very similar to those obtained in Panel C.

Finally, Table D.11 shows results obtained with using alternative specifications of our measure of school-age exposure to storms. While the magnitudes of the estimates are similar to the baseline, they are generally less precise. Notably, the impact on casual

labor, unpaid family work, and involvement in domestic duties is consistent across all specifications. However, we find that the negative and statistically significant effect on regular work is estimated imprecisely when the definition of storm is altered. In terms of self-employment, we obtain negative and precise estimates with all alternative measures except for the one computed from all winds.

## D Appendix Tables

Table D.1: Schooling System in India

	Duration (1)	Cumulated Years of Education (2)
<b>Lower education:</b>		
Primary	5	5
Middle	3	8
Secondary	2	10
Higher secondary	2	12
<b>Higher education:</b>		
<b>Path 1:</b>		
Diploma/certificate course	1	13
<b>Path 2:</b>		
Graduate	3	15
<b>Path 3:</b>		
Diploma/certificate course	1	13
Graduate	3	16
<b>Path 4:</b>		
Graduate	3	15
Postgraduate and above	2	17
<b>Path 5:</b>		
Diploma/certificate course	1	13
Graduate	3	16
Postgraduate and above	2	18

Notes: Column (1) shows the duration of each category of schooling, which is the standard time required to complete each level of education. For categories such as *Graduate* and *Postgraduate*, the duration corresponds to the mode across disciplines. Column (2) gives the total number of years of education accumulated after completion of each category of schooling (and path in the case of higher education).

Source: Authors' estimates.



Table D.2: Probability of migration

	Probability of migration		
	(1)	(2)	(3)
<b>Panel A: 5 to 33 years old</b>			
Storm exposure	-0.020*** (0.0062)	-0.012*** (0.0022)	-0.014 (0.0083)
L.Storm exposure		-0.0087** (0.0037)	-0.012*** (0.0023)
L2.Storm exposure			-0.0095*** (0.00076)
Controls	Yes	Yes	Yes
Observations	1,490,058	1,189,250	908,242
<b>Panel B: 5 to 15 years old</b>			
Storm exposure	-0.011*** (0.0038)	-0.017*** (0.0022)	-0.011*** (0.0038)
L.Storm exposure		-0.010* (0.0052)	-0.020*** (0.0037)
L2.Storm exposure			-0.018*** (0.0012)
Controls	Yes	Yes	Yes
Observations	479,970	375,652	280,078

Notes: The table estimates the effect of storm exposure on the probability of an individual migrating. The dependent variable is a binary variable that takes the value of one if the individual migrated and zero otherwise. The data come from the Consumer Pyramids DX, in which each individual is surveyed every four months. The first lag, *L.Storm exposure*, corresponds to a four-month lag, and the second lag, *L2.Storm exposure*, corresponds to an eight-month lag. Controls include time FE, district-year FE, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. Time FE represent a FE for each four-month-year cell. In each regression, the weights provided by the Consumer Pyramids DX dataset are used. Standard errors are clustered at the state level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Source: Authors' estimates.

Table D.3: Summary Statistics

	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	N (5)
<i>A. School-age exposure to storm</i>					
$C_{bd}$	0.029	0.095	0	1.003	70,003
$C_{bd} > 0$	0.098	0.154	1.23e-08	1.003	20,750
<i>B. Educational delay</i>					
Educational delay (# of years)	0.52	0.89	0	6	70,003
Educational delay (yes=1, no=0)	0.331	0.471	0	1	70,003
<i>C. Educational attainment (yes=1, no=0)</i>					
Below primary	0.027	0.161	0	1	70,003
Primary	0.098	0.297	0	1	70,003
Middle	0.239	0.427	0	1	70,003
Secondary	0.365	0.481	0	1	70,003
Above secondary	0.272	0.445	0	1	70,003
<i>D. Primary activity status (yes=1, no=0)</i>					
Regular work	0.196	0.397	0	1	70,003
Casual labor	0.093	0.29	0	1	70,003
Self-employment	0.132	0.338	0	1	70,003
Unpaid family work	0.079	0.269	0	1	70,003
Domestic duties	0.329	0.47	0	1	70,003
<i>E. Wages and hours worked</i>					
(Real) log hourly wage	3.713	0.654	-1.142	7.796	29,399
Weekly hours worked	53.603	13.148	2	105	29,399
<i>F. Controls (yes=1, no=0)</i>					
Female	0.472	0.499	0	1	70,003
First born	0.308	0.462	0	1	70,003
Hindu	0.740	0.439	0	1	70,003

Note: The category *below primary* refers to individuals who received some education but did not complete primary school. This category excludes illiterate individuals and those without any formal education. Wages are reported in rupees.

Source: Authors' estimates.

Table D.4: Alternative Clustering (Education)

	Baseline	District	District-cohort
	(1)	(2)	(3)
<b>Panel A:</b>			
<b>Educ. delay: # of years</b>			
School-age exposure	0.43*** (0.14)	0.43** (0.17)	0.43** (0.17)
<b>Panel B:</b>			
<b>Educ. delay: yes=1, no=0</b>			
School-age exposure	0.24*** (0.080)	0.24*** (0.072)	0.24*** (0.079)
<b>Panel C:</b>			
<b>Educ. attainment</b>			
School-age exposure	-1.18*** (0.31)	-1.18*** (0.35)	-1.18*** (0.31)
Controls	Yes	Yes	Yes
Observations	70,003	70,003	70,003
Panel A: Mean dep. var.	0.52		
Panel B: Mean dep. var.	0.33		

Notes: The table presents results on educational delay and attainment, with alternative clustering methods. In Panel A, educational delay is measured as the difference between reported years of schooling and the minimum number of years needed in the schooling system to achieve the reported educational attainment. In Panel B, educational delay is measured with a dummy variable taking the value of one in the case of an educational delay of at least one year. In Panel C, educational attainment is a categorical variable indicating the reported educational attainment (0=no formal schooling, 1=primary school, 2=middle school, 3=secondary education, 4=above-secondary education), where category 0 includes individuals who received some education but did not complete primary school. Column (1) shows the baseline estimates with state clustering, column (2) uses district clustering, and in column (3) standard errors are clustered at the district-cohort level. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Source: Authors' estimates.

Table D.5: Alternative Clustering (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
<b>Panel B:</b>					
<b>District</b>					
School-age exposure	-0.16** (0.079)	-0.0093 (0.064)	-0.046 (0.058)	0.016 (0.052)	0.16*** (0.054)
<b>Panel C:</b>					
<b>District-cohort</b>					
School-age exposure	-0.16** (0.066)	-0.0093 (0.060)	-0.046 (0.054)	0.016 (0.044)	0.16*** (0.054)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	70,003	70,003	70,003	70,003	70,003

Notes: The table presents results on the employment status of young adults, with alternative clustering methods. The dependent variable is a dummy variable that takes the value of 1 if the individual's main activity is regular work (column 1), casual labor (column 2), self-employment (column 3), unpaid family work (column 4), or domestic duties (column 5). In Panel A, baseline estimates are shown with state clustering. Panel B uses district clustering, and in Panel C, standard errors are clustered at the district-cohort level. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Source: Authors' estimates.

Table D.6: Controlling for Early-life Exposure (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
Observations	70,003	70,003	70,003	70,003	70,003
<b>Panel B:</b>					
<b>Sub-sample</b>					
School-age exposure	0.000098 (0.032)	-0.10 (0.11)	-0.11*** (0.029)	-0.020 (0.045)	0.18** (0.069)
Observations	41,892	41,892	41,892	41,892	41,892
<b>Panel C:</b>					
<b>Early life</b>					
Early-life exposure	-0.024 (0.067)	-0.051 (0.040)	0.068 (0.054)	-0.058* (0.030)	-0.21*** (0.070)
Observations	41,892	41,892	41,892	41,892	41,892
<b>Panel D:</b>					
<b>School &amp; early life</b>					
School-age exposure	0.00028 (0.032)	-0.100 (0.11)	-0.11*** (0.029)	-0.020 (0.046)	0.19*** (0.067)
Early-life exposure	-0.024 (0.067)	-0.051 (0.039)	0.069 (0.055)	-0.058* (0.031)	-0.21*** (0.071)
Observations	41,892	41,892	41,892	41,892	41,892
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The table presents results on the employment status of young adults, controlling for early-life exposure to storms. The dependent variable is a binary variable taking the value of 1 if the main activity of the individual is to perform regular work (column 1), casual labor (column 2), self-employment (column 3), unpaid family work (column 4) or domestic duties (column 5). Panel A presents the baseline estimates, while Panel B reports the results for the sub-sample of individuals born after 1989. In Panels C and D, the analysis focuses on the same sub-sample. Panel C replaces the school-age exposure measure with the early-life exposure index, and Panel D includes both measures simultaneously. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.

Table D.7: Controlling for After-school Exposure (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
<b>Panel B:</b>					
<b>School &amp; after-school</b>					
School-age exposure	-0.16** (0.076)	-0.010 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
After-school exposure	0.64*** (0.19)	-0.50*** (0.15)	0.072 (0.11)	0.22* (0.12)	-0.44*** (0.13)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	70,003	70,003	70,003	70,003	70003

Notes: The table presents results on the employment status of young adults, controlling for after-school exposure to storms. The dependent variable is a dummy variable that takes the value of 1 if the individual's main activity is regular work (column 1), casual labor (column 2), self-employment (column 3), unpaid family work (column 4), or domestic duties (column 5). Panel A shows the baseline estimates, while Panel B includes a control for after-school storm exposure, computed by summing yearly exposures over the after-school period up to 2018. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.

Table D.8: Falsification Test (Type of Activities)

	<b>Placebo</b>		
	Share of estimations with statistical significance at:		
	1%	5%	10 %
	(1)	(2)	(3)
<b>Panel A:</b>			
<b>Regular work</b>			
School-age exposure	0.023	0.066	0.119
<b>Panel B:</b>			
<b>Casual work</b>			
School-age exposure	0.027	0.077	0.138
<b>Panel C:</b>			
<b>Self-employed</b>			
School-age exposure	0.022	0.06	0.127
<b>Panel D:</b>			
<b>Unpaid family work</b>			
School-age exposure	0.022	0.085	0.133
<b>Panel E:</b>			
<b>Domestic duties</b>			
School-age exposure	0.018	0.076	0.125
Controls	Yes	Yes	Yes
Observations	70,003	70,003	70,003

Notes: The table reports the results of falsification tests for the regression on the employment status of young adults. In Panels A-E, the dependent variable is a binary variable taking the value of one if an individual's primary activity is regular work, casual work, self-employment, unpaid family work, or domestic duties, respectively. Columns (1)-(3) show the share of statistically significant results over 1000 randomizations, where the school-age exposure measure is randomized over the entire sample. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.

Table D.9: Additional Robustness (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
Observations	70,003	70,003	70,003	70,003	70,003
<b>Panel B:</b>					
<b>Excl. Orissa</b>					
School-age exposure	-0.26*** (0.083)	-0.069 (0.11)	0.026 (0.051)	0.066 (0.12)	0.19** (0.088)
Observations	67,770	67,770	67,770	67,770	67,770
<b>Panel C:</b>					
<b>Excl. extremes</b>					
School-age exposure	-0.15*** (0.051)	-0.022 (0.065)	-0.0056 (0.052)	0.026 (0.058)	0.089* (0.046)
Observations	70,003	70,003	70,003	70,003	70,003
<b>Panel D:</b>					
<b>Sub-sample (climate)</b>					
School-age exposure	-0.15* (0.076)	-0.011 (0.079)	-0.066 (0.048)	0.031 (0.072)	0.16** (0.060)
Observations	66,702	66,702	66,702	66,702	66,702
<b>Panel E:</b>					
<b>Climate controls</b>					
School-age exposure	-0.13* (0.074)	-0.053 (0.085)	-0.070 (0.048)	0.026 (0.072)	0.17** (0.064)
Observations	66,702	66,702	66,702	66,702	66,702
<b>Panel F:</b>					
<b>Excl. females</b>					
School-age exposure	-0.25** (0.11)	0.00027 (0.076)	-0.024 (0.10)	0.030 (0.092)	0.18*** (0.035)
Observations	43,989	43,989	43,989	43,989	43,989
<b>Panel G:</b>					
<b>Excl. high educ.</b>					
School-age exposure	-0.082** (0.039)	-0.064 (0.10)	-0.022 (0.034)	0.024 (0.093)	0.17 (0.12)
Observations	50,981	50,981	50,981	50,981	50,981
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The table reports results on the employment status of young adults, after removing extreme exposures or controlling for climate variables. The dependent variable is a dummy equal to 1 if the main activity of the individual is to perform regular work (column 1), casual labor (column 2), be self-employed (column 3), work as an unpaid family worker (column 4), and perform domestic duties (column 5). Panel A presents baseline estimates, while Panel B presents results for the baseline specification estimated on a subsample that excludes individuals located in Orissa. In Panel C, we recompute the exposure index by removing all the winds with values falling above the 95th percentile of the wind distribution. Panel D replicates the baseline specification on the subsample for which climate variables are available. In Panel E, we include climate controls, such as a district-specific measure capturing the average yearly precipitation (in millimeters) between ages 5-15. We also include the average temperature (in °C) and the number of exposure days within temperature bins (0-10, 10-20, 20-30, and above 30°C) to which children of a given district were exposed during school age. Panel F excludes married females and Panel G removes individuals with above-secondary education from the sample. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.



Table D.10: Controlling for Parental Education (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
Observations	70,003	70,003	70,003	70,003	70,003
<b>Panel B:</b>					
<b>Predicted educ. attainment</b>					
School-age exposure	-0.16** (0.075)	-0.0087 (0.075)	-0.047 (0.059)	0.015 (0.067)	0.16*** (0.056)
Predicted educ. attainment	Yes	Yes	Yes	Yes	Yes
Observations	70003	70003	70003	70003	70003
<b>Panel B:</b>					
<b>Sub-sample</b>					
School-age exposure	-0.18* (0.10)	0.0019 (0.060)	-0.11 (0.11)	0.036 (0.090)	0.15*** (0.050)
Observations	31,243	31,243	31,243	31,243	31,243
<b>Panel C:</b>					
<b>Parental education</b>					
School-age exposure	-0.18 (0.11)	0.00050 (0.059)	-0.11 (0.11)	0.036 (0.090)	0.15*** (0.050)
Observations	31,243	31,243	31,243	31,243	31,243
Controls	Yes	Yes	Yes	Yes	Yes
Parental education	Yes	Yes	Yes	Yes	Yes

Notes: The table presents results on the employment status of young adults, controlling for education. The dependent variable is a dummy equal to 1 if the main activity of the individual is to perform regular work (column 1), casual labor (column 2), be self-employed (column 3), work as an unpaid family worker (column 4), or perform domestic duties (column 5). Panel A shows baseline estimates. Panel B replicates the baseline specification on a subsample for which parental education is available. In Panel C, we use the same subsample as in Panel C and additionally control for parental education. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.

Table D.11: Alternative Measures of Storm Exposure (Type of Activities)

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
<b>Panel A:</b>					
<b>Baseline</b>					
School-age exposure	-0.16** (0.076)	-0.0093 (0.075)	-0.046 (0.059)	0.016 (0.067)	0.16*** (0.056)
<b>Panel B:</b>					
<b>Sum of squares</b>					
School-age exposure	-0.072 (0.065)	0.029 (0.037)	-0.14*** (0.020)	-0.012 (0.032)	0.19** (0.087)
<b>Panel C:</b>					
<b>50, cubic</b>					
School-age exposure	-0.12 (0.096)	0.016 (0.060)	-0.11** (0.046)	-0.0032 (0.052)	0.21** (0.096)
<b>Panel D:</b>					
<b>64, quadratic</b>					
School-age exposure	-0.12 (0.086)	0.012 (0.062)	-0.093* (0.051)	-0.0025 (0.055)	0.21** (0.088)
<b>Panel E:</b>					
<b>64, cubic</b>					
School-age exposure	-0.069 (0.063)	0.034 (0.032)	-0.14*** (0.019)	-0.016 (0.028)	0.20* (0.100)
<b>Panel F:</b>					
<b>All winds</b>					
School-age exposure	-0.011 (0.011)	0.00010 (0.015)	-0.022 (0.019)	0.00032 (0.0091)	0.013 (0.012)
<b>Panel G:</b>					
<b>HURRECON</b>					
School-age exposure	-0.13 (0.083)	0.016 (0.073)	-0.087* (0.051)	0.0044 (0.060)	0.17** (0.065)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	70,003	70,003	70,003	70,003	70,003

Notes: The table presents results on the employment status of young adults, using alternative specifications of school-age exposure to storms. The dependent variable is a dummy equal to 1 if the main activity of the individual is to perform regular work (column 1), casual labor (column 2), be self-employed (column 3), work as an unpaid family worker (column 4) and perform domestic duties (column 5). Panel A shows baseline estimates, and Panel B to Panel G shows results using different specifications of the storm exposure measure. In Panel B, storm exposure is computed using the sum of the squares of yearly exposures. In Panel C, storm exposure is computed using a threshold of 50 knots and a cube function. In Panel D, exposure is computed using a threshold of 64 knots and a square function. In Panel E, exposure is computed using a threshold of 64 knots and a cube function. In Panel F, exposure is computed using all winds. Finally, in Panel G, exposure is computed using the HURRECON model, a threshold of 50 knots, and a square function. Controls include district FE, cohort FE, district trends, and individual controls, including dummy variables indicating if the individual is female, first-born, and Hindu. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Standard errors are clustered at the state level.

Source: Authors' estimates.

Table D.12: Summary Statistics: Consumer Pyramid DX and DISE

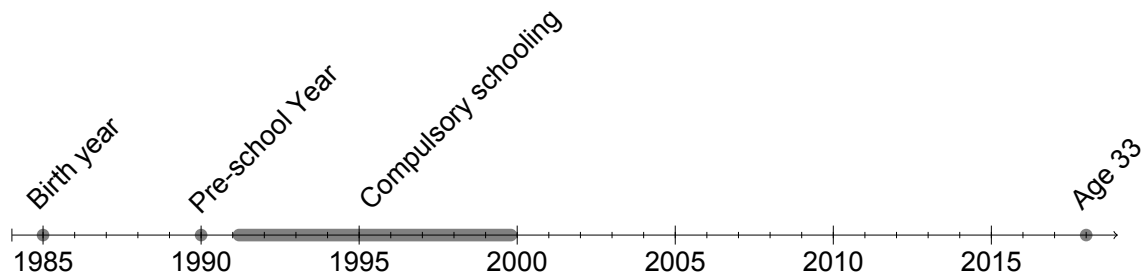
Variable	Mean	Std. Dev.	Min.	Max.	N
<b>I. Consumer Pyramid DX:</b>					
<b>Household income:</b>					
Overall	12,299	13,111	0	2,722,678	9,932,098
From wages	8,745	9,690	0	1,413,483	9,932,098
From business profits	2,328	9,634	0	2,719,837	9,932,098
<b>II. DISE:</b>					
<b>Avg. # of classrooms:</b>					
In good conditions	4.36	2.795	0	94.5	153,789
<b>Share of schools:</b>					
With electricity	0.688	0.334	0	1	153,789
Without electricity	0.285	0.325	0	1	153,789
With unreliable electricity	0.026	0.055	0	1	153,789
Exiting	0.026	0.09	0	1	110,099
Under construction	0.008	0.032	0	1	110,099
<b>Avg. # of kids:</b>					
In primary school:					
C1	20.102	14.415	0	616.5	143,853
C2	19.588	14.097	0	426	143,853
C3	19.524	14.205	0	421	143,853
C4	19.264	14.047	0	438.5	143,853
C5	19.11	14.502	0	489	143,853
In Middle school:					
C6	17.917	14.766	0	519.5	143,853
C7	17.603	14.833	0	527.5	143,853
C8	16.388	15.634	0	677.333	143,853
Appearing at the exam:					
C5	8.140	13.006	0	923	126,981
C7	0.976	4.839	0	280	65,386
Passing the exam:					
C5	8.048	12.882	0	923	126,981
C7	0.912	4.492	0	257	65,386
Scoring above 60% at the exam:					
C5	5.665	9.867	0	827	126,981
C7	0.473	2.714	0	205	65,386

Notes: Income, wages, and business profits are obtained from the Consumer Pyramid DX dataset and are expressed in lakhs of rupees in real terms using the CPI with a base year of 2010. The remaining variables in the table present summary statistics constructed from the DISE data. Averages and shares are computed at the postal code-year level. School ratios are expressed relative to the number of schools in 2010 for a given postal code-year, thus having a potential maximum value over 1. The maximum average number of kids appearing at/passing the exam at C5 (C7) may exceed the maximum average number of kids at C5 (C7) since not all schools offer exams, which means that some students may have to take their exams in other schools.

Source: Authors' estimates.

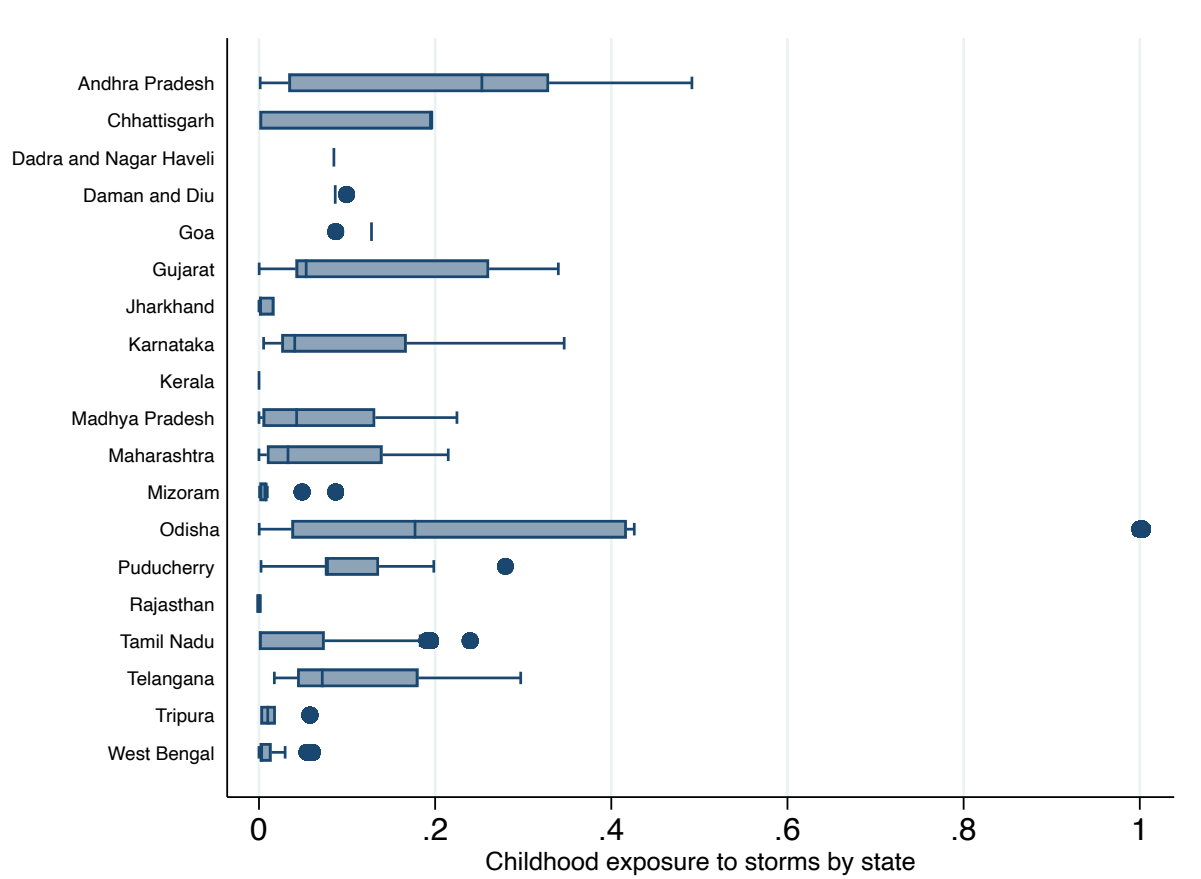
## E Appendix Figures

Figure E.1: Oldest Cohort



Source: Authors' estimates.

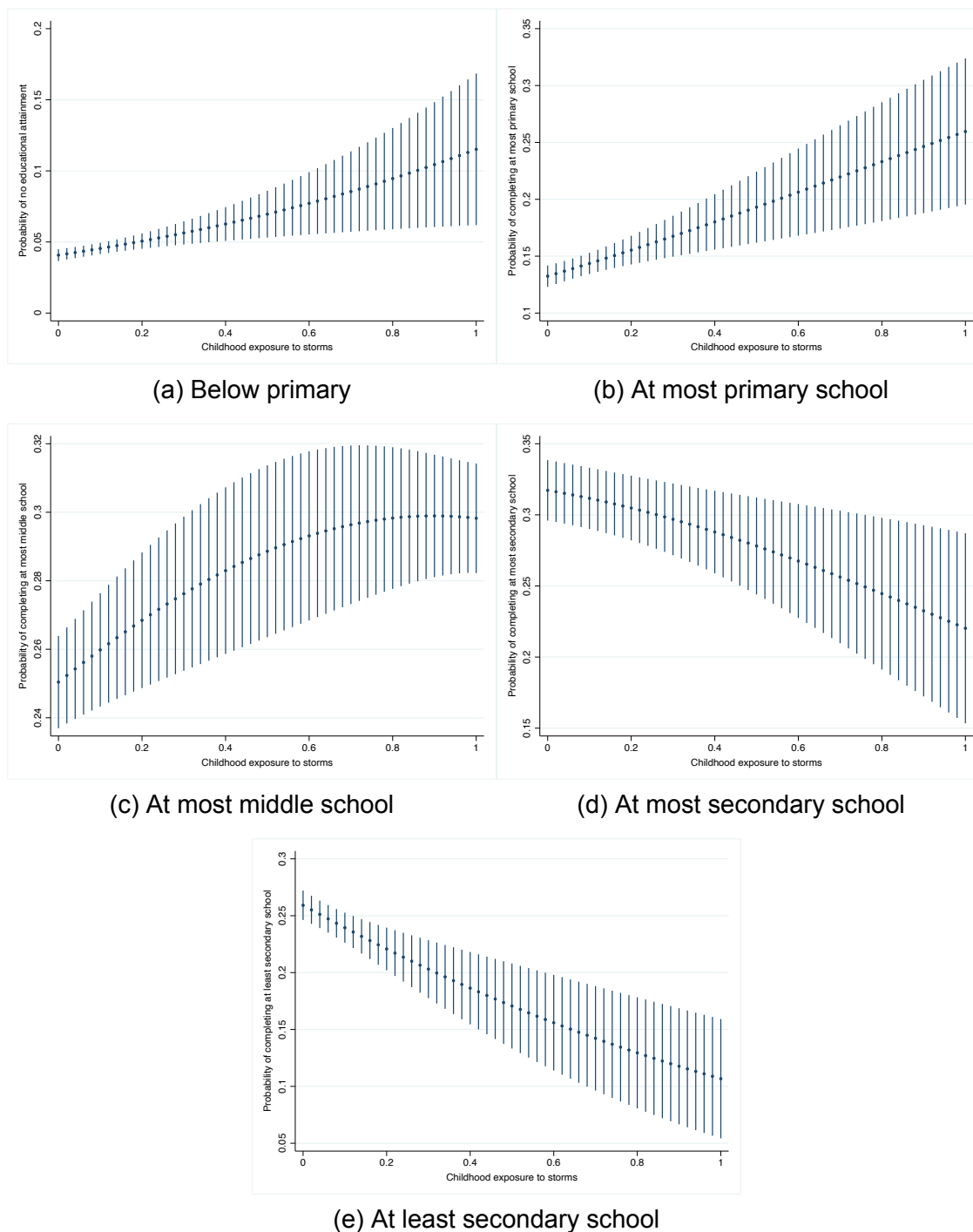
Figure E.2: School-age Exposure to Storms



Notes: The figure displays boxplots that describe the measure of school-age exposure to storms for individuals born between 1985 and 1995, with positive exposure ( $C_{bd} > 0$ ), by state in alphabetical order. The figure only includes states with positive exposure. The blue line in each box represents the median, and the lower and upper bounds of the box are the first and third quartiles, respectively. The end of the left (right) whisker represents the 1st percentile (99th percentile). Circles without a box indicate that all observations are clustered around the median, and circles outside of the box represent outliers.

Source: Authors' estimates.

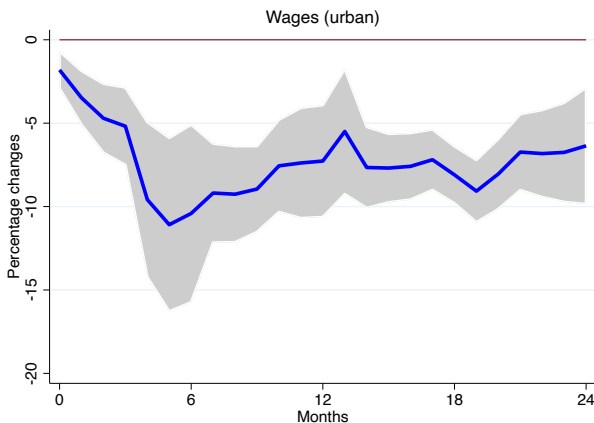
Figure E.3: Effect of School-age Exposure on the Probability of a Given Educational Attainment



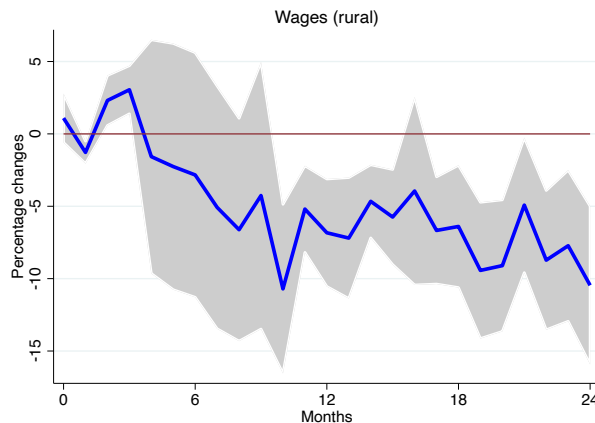
Notes: The figure displays the predicted probabilities (and their corresponding 95% confidence intervals) of not completing primary school (Panel a), completing at most primary school (Panel b), completing at most middle school (Panel c), completing at most secondary school (Panel d), and completing at least secondary school (Panel e), across the range of storm exposures. The estimates are obtained from Panel C in Table 1, which presents an ordered logit regression of educational attainment. The range of exposures is [0,1].

Source: Authors' estimates.

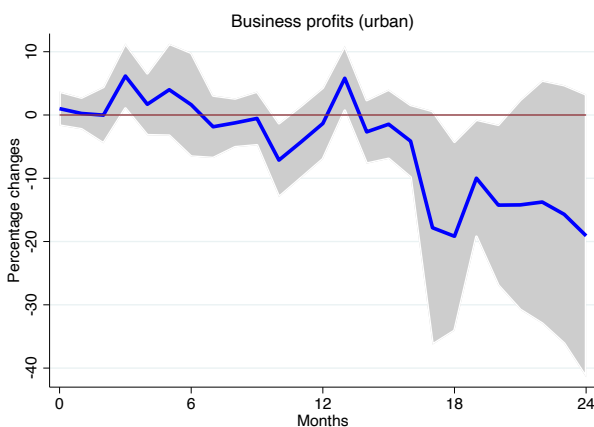
Figure E.4: Local Projections on Household Income, by Source



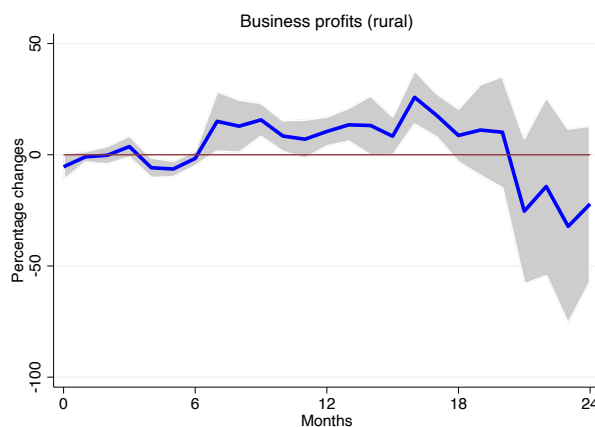
(a) Household wage, urban areas



(b) Household wage, rural areas



(c) Household business profits, urban areas



(d) Household business profits, rural areas

Note: The figure shows the results of local projections (direct effect) on household income by source (wage and business profits) and area (urban and rural), on a 24-month time horizon for the average cyclone exposure. The analysis includes district-year FE, time FE, and household FE. Storm exposure is computed from wind exposures at the district-month level using a quadratic damage function and a 50 knots threshold. The figure presents 95% confidence intervals.

Source: Authors' estimates.