Childhood Exposure to Storms and Long-Term Educational Attainments in India

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Abstract

This paper examines how exposure to storms over the course of compulsory schooling affects educational attainments and the type of activity performed by individuals in young adulthood. We construct a unique continuous measure of childhood exposure to storms that varies by birth-year cohort and district for young adults in rural and urban India. We find that storms have substantial disruptive impacts on education. In the districts exposed to the most powerful winds, the estimates imply that children are 9% more likely to accumulate an educational delay and 6.5% less likely to obtain higher levels of education (beyond secondary school). In the long run, these delays have an impact on the type of labor market activity that these individuals perform. Using childhood exposure to storms as an instrument, we find that a one-year educational delay leads to a 42.6% drop in the probability of accessing regular salaried jobs. We determine that the impact of storms on education works through a permanent negative income shock.

Keywords: storms, natural disasters, education, labor markets
JEL Codes: I25, Q54.

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1 Introduction

The short- and long-term impacts of natural disasters on economic growth have been studied extensively (e.g. Cavallo & Noy, 2010; Strobl, 2011; Cavallo et al., 2013; Dell et al., 2014). There is a general consensus on the negative contemporaneous consequences of natural disasters, yet recent findings are in disagreement regarding their long-term effects.[1] The majority of studies relates the path of GDP growth to physical capital reconstruction and potential technological upgrading, yet, to the best of our knowledge, causal evidence of the long-run effects of the impact of natural disasters on human capital formation is still lacking.

The literature has long established that education is an important determinant of an individual's earnings and that, in the aggregate, human capital contributes to the economic growth of a nation.[2] As a consequence, if natural disasters hinder academic achievements, we may still expect economic growth to slow down in the long run, even if environmental disruption stimulates innovation and assets are replaced with newer and more productive vintages.

In this paper we focus on tropical cyclones and quantify the long-term effects of childhood exposure to storms on educational attainments in India.[3] Specifically, we consider storms that struck over the course of compulsory schooling and examine their impacts on long-term educational delays within completed levels of schooling, the probability of completing higher education and labor market prospects in young adulthood.

To fulfill this goal, data requirements are high. For each individual we need information on both, current outcomes and exposure to storms during compulsory schooling. We combine data from the 2018 release of the Periodic Labour Force Survey (PLFS) with storms' best tracks data from the National Oceanic and Atmospheric Administration (NOAA) over the period 1990-2010. Our identification strategy relies on the use of a unique measure of childhood exposure to storms constructed from exogenous variations in wind exposure across birth-year cohorts and districts during compulsory schooling.[4,5] We proceed in two steps.

[1] Hsiang & Jina (2014) summarize the literature that describes the long-term evolution of GDP per capita in the aftermath of a natural disaster. The authors put foward four hypotheses: *(i) creative destruction*, *(ii) build back better*, *(iii) recovery to trend* and, *(iv) no recovery*. In the long run, each of these hypotheses predicts a different level of GDP per capita.

[2] See for instance Topel (1999) for a study on the role of human capital in economic growth. See Card (2001) for a survey of papers that attempt to identify the impact of education on labor market earnings using supply-side features of the education system (e.g. compulsory schooling laws or differences in the accessibility of schools) as determinants of schooling outcomes.

[3] Roughly 10% of the world's cyclones hit India, making it one of the most affected regions in the world. Furthermore, every year, over 370 million people are affected by cyclones in India alone. See `https://ncrmp.gov.in/cyclones-their-impact-in-india/`

[4] See Pelli & Tschopp (2017) for a detailed discussion regarding the exogeneity of storms to economic activity, and Pelli et al. (2020) for a discussion centered on India.

[5] We use the district of residence as the inferred place of birth of individuals given the low out-of-district

First, for each year between 1990 and 2010, we build an index of yearly district exposure to storms that accounts for the force exerted by winds on physical structures at the district's geographical centroid. Second, for each district and birth-year cohort aged between 23 and 33 in 2018, we aggregate the index over years of compulsory schooling and obtain a continuous treatment that varies by birth-year cohort and district.

We find that exposure to storms over the course of compulsory schooling impacts long-term educational attainments and the type of activity performed in young adulthood. In the districts exposed to the most powerful winds, the estimates imply an average schooling delay of 8-weeks and suggest that children are 9% more likely to repeat a year or drop out of school. While affected children still complete primary schooling, the delays accumulated over time translate in a lower propensity to complete higher education (i.e. secondary and higher). Estimates suggest that children exposed to storms are 6.5% less likely to obtain higher levels of education. These delays also manifest themselves later on, once affected individuals reach young adulthood. Positive exposure reduces the likelihood of working a formal job or being self-employed, while it increases the probability of being an unpaid family worker. For instance, we find that individuals who were attending school in 1999 when super storm BOB 06 hit Orissa are on average 7.5% less likely to be regular workers, 6% less likely to be self-employed and 5.5% more likely to be an unpaid family worker. Finally, the exogeneity of the exposure measure also allows us to quantify the importance of education on long-term employment opportunities. Using an IV approach we find that a one-year delay in education leads to a 42.6% drop in the probability of accessing regular salaried jobs.

Natural disasters can disrupt education through two channels: the supply or the demand for schooling. The former channel likely operates through the destruction of schools and roads infrastructures, which have been shown to play a key role in promoting education (see for instance Psacharopoulos, 1994; Strauss & Thomas, 1995; Duflo, 2001; Schultz, 2002). The demand channel may be linked to the impact of storms on the psychological health of children (see Kar & Bastia, 2006; Neria et al., 2008) and/or on households' income. To examine the importance of these channels, we perform an analysis by gender and across urban and rural areas. Our results suggest that the demand channel dominates and that, to a great extent, storms work as a permanent negative income shock. If, on the one hand, storms foster innovations and technological advancement, on the other hand, our findings indicate that they have permanent negative effects on households and human capital formation, therefore compromising the recovery of GDP per capita in the long run. Pinning down the channel through which storms operate allows us to formulate policy recommendations specific to urban and rural areas.

migration observed in India (see Topalova, 2010).

Our paper is closely related to Maccini & Yang (2009) who adopt a similar methodology to quantify the impact of early-life (0 to 5 years) rainfall shocks on adult outcomes (health, schooling and wealth) in Indonesia. While our identification strategy is similar in essence, we use a different type of shock, focusing on exposure to storms during years of compulsory schooling. Our paper informs on public policies that respond to extreme events whereas their findings arise from more typical year-to-year variation in rural households' economic conditions (variation in agricultural output) around the time of birth. The authors find evidence that early-life rainfall is an important determinant of adult socioeconomic status.

This paper contributes to the literature on the effect of natural disasters on education, yet the literature has mainly focused on the contemporaneous effects of disasters while our focus resides on their long-term effects. Deuchert & Felfe (2015) look at a super typhoon on Cebu island in the Philippines and show a negative effect on children's education, probably due to a shift in households' spending towards reconstruction. Groppo & Kraehnert (2017) look at the impact of severe winters in Mongolia and find, as we do, that children's education suffers, likely because severe winters act as a negative income shock. Rosales-Rueda (2018) shows lower test score results for children affected by floods while in utero in Ecuador. Spencer et al. (2016) look at the contemporaneous effect of cyclones on educational results in the Caribbeans, which turn out to be negative.[6]

This paper also speaks to the literature on education in developing countries. Evidence suggests that improving school attendance, subsidizing textbooks (Glewwe et al., 2009) or even increasing the number of teachers (Banerjee et al., 2004) does not necessarily ameliorate learning. Therefore, recent findings suggest that improving the quality of teaching is a first-order concern (see for instance Banerjee et al., 2007) and that policies promoting school enrollment should, at the very least, be coupled with interventions improving the pedagogy or curriculum of schooling.[7] While we do not provide direct evidence on the quality of teaching, our results seem to indicate that school attendance remains very important as the delays which appear to result from absenteeism or school removals do have long-term consequences on the probability of completing higher education and on future labor market outcomes.

This paper also relates to studies that seek to estimate the causal effects of education on earnings. The main challenge faced by the literature results from both, individuals'

[6] Many papers focus on developed countries. Karbownik & Wray (2019) investigates the impact of exposure to cyclones on fetal and early life in the US and find a negative income effect in adulthood for white males. Billings et al. (2020) show a decrease in enrolment numbers and in graduation rates and, Sacerdote (2012) finds an initial decrease in test scores of students affected by Hurricanes Katrina and Rita but a subsequent increase for students moving out of Louisiana to states with better school systems.

[7] Duflo (2001) and Duflo (2004) estimate the impact of school construction on education and labor market outcomes in Indonesia. For more references, see Glewwe & Kremer (2006).

unobserved abilities and the endogeneity of schooling with respect to employment and wages. Many papers have credibly come up with instruments based on institutional features of the educational system (see Card, 2001, for a survey of this literature). As an alternative to these supply-side features, we use childhood exposure to storms as an exogeneous demand shock to schooling to evaluate the causal impact of educational attainment on future labor market prospects.

Finally, our findings are helpful to infer the potential long-term effects of the COVID-19 pandemic on long-term labor markets perspectives of children attending school during the years 2019-2020. In this sense, we also relate to the vast emerging literature on COVID that looks the impacts of government-mandated school closures, associated Post-Traumatic Stress Disorder (PTSD) in children and drops in parents' income.[8]

2 Data

Our empirical analysis uses two sources of data: *i)* the 2018 release of the PLFS – used to measure educational delay and labor market variables, and *ii)* tropical storms data from the NOAA – used to construct an index of childhood exposure to storms.

2.1 Individual and household data

The PLFS is an individual- and household-level representative survey of the Indian population collected by the National Sample Survey Office (NSSO) of the Ministry of Statistics and Program Implementation. The survey provides a variety of information on individuals' characteristics such as age, gender, educational level and the number of years spent at school. In India, children typically start school at the age of 6. Without delays, compulsory schooling lasts 9 years, i.e. until a child is 15 years old. Table 1 summarizes the schooling system, including the various paths to higher education. Column (1) indicates the number of years needed to complete each individual category of schooling. For graduate and postgraduate levels, the numbers correspond to the modal duration across disciplines. Column (2) shows the total cumulated number of years needed to complete any given level of education. For instance, middle school lasts 3 years. At the end of middle school, a child should have accumulated 8 years of education; 5 years of primary and 3 years of middle school. The PLFS provides information on the highest level of education completed and on whether an individual earned a diploma/certificate. These two pieces of information allow us to infer

[8]See for instance Phelps & Sperry (2020); Yue et al. (2020); Zhou (2020) for papers on PTSD, and Di Pietro et al. (2020) for a study on the heterogeneous employment effects of the pandemic.

the path of individuals who continued into higher education and compute the corresponding theoretical number of years of education (in the absence of an educational delay).

[Table 1 here]

For each individual, we measure educational delay as the difference between the actual number of years in formal education and the number of years needed to achieve the reported level of education. For example, suppose an individual reports seven years of formal schooling but has only completed primary school. This individual has a two-years delay in educational attainment, a delay which may be caused either by repeating grades or by dropping out from a higher educational level (middle school, in this particular example).[9] Thus, our analysis will inform on whether storms increase educational delays but it will not be able to tell us anything about the likelihood of repeating grades versus dropping out of school. As an alternative measure of educational delay we also construct an indicator variable taking the value of 1 for individuals with positive educational delays and 0 otherwise.

The PLFS provides information on the primary activity status of individuals.[10] For instance, we know whether an individual's primary activity takes place in the formal labor market or at home (e.g. performing domestic duties – collecting vegetables, firewood, cattle feed, sewing, etc.). Included among formal labor market activities are regular work (i.e. work associated with a formal job and an employment contract), casual work (i.e. work with a daily or periodic contract only), self-employment, and unpaid family work (e.g. work in the family business/farm without pay). The survey also contains labor market indicators such as hours of work and earnings, yet this information only pertains to individuals who perform paid activities and report being part of the labor force.

Importantly, the PLFS provides information on the district of residence of individuals, which, combined with information on individuals' age, allows us to create a unique measure of childhood exposure to storms that vary by birth-year cohort and district. As we describe below, our measure is a continuous treatment taking into account the intensity of the storms to which children of a given cohort and living in a specific district were exposed over the course of compulsory schooling. Given the very small proportion of individuals migrating outside if their birth's district (see, for instance, Gupta, 1987; Munshi & Rosenzweig, 2009; Edmonds et al., 2010; Topalova, 2010), we assume that individuals completed their compul-

[9]While it would be interesting to distinguish between both types of delays, the PLFS does not provide sufficient information to distinguish between the two cases.

[10]Details and definitions can be found here (p.35): http://mospi.nic.in/sites/default/files/publication$_$reports/Annual$_$Report$_$PLFS$_$2018$_$19$_$HL.pdf

sory schooling in the same district in which they are living in 2018.[11] This assumption is important for the construction of the childhood exposure index.

As benchmark age for young adulthood we choose the age of an individual at the time of completing postgraduate education (master degree). Without delays, obtaining a postgraduate degree takes 17 years. Children usually start school at the age of 6 and, therefore, young adulthood is reached at the age of 23. As a consequence, the youngest cohort considered in the paper was born in 1995 and should have completed compulsory schooling in 2010. The oldest cohort examined is dictated by the quality of satellite coverage. World Meteorological Organization (WMO)-sanctioned cyclone data for the North Indian Ocean only goes back to 1990.[12] As illustrated in Figure 1, this means that the oldest cohort we consider was born in 1985, and is 33 years old in 2018.

[Figure 1 here]

Therefore, our analysis focuses on the 81,542 individuals born between 1985 and 1995 (i.e. the cohorts aged 23-33 in 2018) and storms which took place between 1990 and 2010.

2.2 Childhood exposure to tropical storms

In order to understand how childhood exposure to storms impacts long-term education levels and labor market outcomes, we create an index based on storms' wind speed that varies by birth-year cohort and district . This measure captures storms occurring in the first nine years of compulsory schooling starting at age six and in the pre-school year. This additional year allows us to account for children born early in the year and, therefore, integrating school a year earlier. Childhood exposure to storms is computed as follows:

$$C_{bd} = \sum_{t=b+5}^{t=b+15} x_{dt}, \tag{1}$$

where b denotes a birth-year cohort, d a district, t a year. The variable x_{dt} is an index of yearly district exposure to storms and accounts for the force exerted by winds on physical structures. Details on the construction of x_{dt} are presented in Appendix B. Consider for instance the timeline of the oldest cohort (born in 1985). As illustrated in Figure 1, the index of childhood exposure, C_{bd}, sums districts' exposure from 1990 (the pre-school year)

[11] Migration in India is low and, according to Topalova (2010), only less than 4% (13%) of rural (urban) individuals migrate out of district. The main reason for migration is women's marriage. Men rarely move while women are more likely to move to the place of residence of their spouse.

[12] See https://climatedataguide.ucar.edu/climate-data/ibtracs-tropical-cyclone-best-track-data.

up to 2000 (the end of the nine years of compulsory schooling); i.e. $C_{1985,d} = \sum_{t=1990}^{t=2000} x_{dt}$. Within birth-year cohort across district variation in the index results from the fact that at a given point in time, the exact same storm exerts different windspeed intensities at various locations, while some areas are simply sheltered. Accounting for wind speed lends us with a continuous treatment that varies across space. Within district across birth-year cohorts variation results from the fact that different cohorts may be subject to different storms over the course of compulsory schooling.

The left panel of Figure 2 presents the measure of childhood exposure to storms at the state level.[13] In our sample, children living in 28 out of the 35 Indian states experienced tropical storms between the ages of 5 and 15. Importantly, the boxplots show substantial variation in childhood exposure to storms within and across states, with Andhra Pradesh, Gujarat, Maharashtra, Orissa and Telangana displaying the largest median exposures. The right panel of Figure 2 provides a visual of the distribution of C_{bd} across districts for the cohort born in 1987, with darker reds indicating higher exposure. The darkest shade indicates districts for which the index of childhood exposure falls above the 90th percentile in the distribution of C_{bd} in 1987. Each shade contains 15% of the districts with a positive childhood exposure. The landlocked part of India in the North exhibits nearly zero exposure, which is consistent with storms' best tracks data which typically indicate a high concentration of storms along coastal areas. The map reveals that the cohort of 1987 living in the remainder of India experienced positive exposure to storms, with districts around the South-Eastern coast being the most affected.

[Figure 2 here]

In Table 2 we provide summary statistics for the main variables used in the paper. Panel A shows figures for the measure of childhood exposure to storms. 52,059 out of the 81,542 individuals included in the sample – close to 64% – were exposed to storms over the course of compulsory schooling. Columns (1) and (2) of Panel B show the mean and standard deviation of dummy variables for the highest category of schooling completed by individuals. About 11% of our sample falls in the category *below primary*, 76% of these individuals did not attend (formal) school at all, while the remaining 24% are primary school dropouts. 9% completed primary school only, 23% middle school and 32 % secondary school. Finally, 25% of the sample obtained a diploma (completed a certificate course) or obtained a post-/graduate degree. Columns (3) and (4) of Panel B show means of the variables with zero and positive exposure, respectively. The last column displays the difference between the

[13] Only states with positive exposures are included.

latter two means and tests its statistical significance. Means do not statistically differ from each other for individuals falling in the categories *below primary* and *primary*. However, they differ in a statistically significant manner for individuals who completed higher levels of education. In particular, the share of individuals in higher categories is relatively larger for people with zero exposure. Similarly, among individuals with positive exposure, the proportion of individuals in the lowest category of schooling is larger, suggesting that shocks during compulsory schooling tend to hinder progression into higher education.

Looking at Panel B, prima facie evidence suggests that, on average, the educational delay is greater for individuals with positive exposure. Individuals with zero exposure experience an average delay of 0.38 years, which amounts to about 16 weeks.[14] The delay is on average two weeks longer for individuals with positive exposure (0.42 years, i.e. about 18 weeks). We check whether the same difference exists within educational categories, distinguishing between individuals who have completed at most primary, middle, secondary or higher secondary school. The difference in educational delays between the zero and positive exposure groups is particularly marked for individuals who did not go past secondary schooling, with childhood shocks being particularly harmful for the lowest educational group. For higher secondary and categories of schooling that fall into *higher education*, there is no statistically significant difference in educational delays between the zero and positive exposure groups. With compulsory schooling lasting roughly until completion of secondary schooling, results in Panel B suggest that delays associated with storms tend to occur quite immediately, rather than appearing gradually over the years. Combining the results from Panel B and C, it appears that while the delays accumulated over the period of compulsory schooling do not prevent its completion, they have long-term impacts by reducing the likelihood of going past *higher secondary* education levels.

Regarding labor market indicators, the statistics suggest that for the subsample of individuals who have positive salaries and report belonging to the labor force, positive exposure is associated with lower earnings and shorter workweeks. Finally, the bottom of Panel C presents binary variables for the primary activity status of individuals. Among these individuals, the largest share, 41%, carries out domestic duties while only 22% has a formal job with a regular employment contract and salary. Columns (3) and (4) suggest that the probability of performing unpaid family work or being self-employed is similar among the two exposure groups. However, it appears that positive exposure is associated with a higher share of individuals performing casual labor and a relatively lower proportion of people involved in regular and domestic work.

[14]The school year lasts 42 weeks.

[Table 2 here]

Table 3 shows descriptive statistics for the control variables. The table indicates that the average individual in our sample is 27 years old and lives with 4 other persons. Each gender is represented equally in the sample. 29% of the individuals are first born, 54% live in rural areas, 74% are Hindus and 67% are married. 16% of individuals in our sample are heads of household.

[Table 3 here]

3 Baseline Results

3.1 Educational delay

Specification

We evaluate the impact of early childhood exposure to storms on individuals' educational delay with the following specification:

$$Y_i = \alpha_0 + \alpha_1 C_{bd} + \mathbf{X_i'}\boldsymbol{\beta} + \mathbf{W_h'}\boldsymbol{\gamma} + \delta_d + \delta_{eb} + \epsilon_i, \tag{2}$$

where i is an individual's subscript and Y_i captures an individual's educational delay. $\mathbf{X_i'}$ is a vector of individual characteristics including gender, marital status, a dummy indicating if the individual is first born and another dummy indicating if the individual is the household head. While we drop subscripts where possible it is understood that $i = (h, b, d)$, where h denotes the household, b the birth-year cohort and d the district. $\mathbf{W_h'}$ is a vector of household controls including household size, a dummy for hinduism, and an indicator variable taking the value of one if the household is located in a rural area. $\mathbf{W_h'}$ also includes gender and education fixed effects (FE) for the household head. The household head level of education serves as a proxy for parental education, which has been shown to be an important predictor of children educational achievements (Guryan et al., 2008; Björklund & Salvanes, 2011; Kim et al., 2021).

δ_d is a set of district FE to control for fixed district characteristics that may affect the education level of individuals or their employment outcomes. δ_{eb} is a set of education-birth-year cohort FE.[15] The inclusion of both district and education-birth-year cohort FE

[15]Educational categories to which δ_{eb} refers correspond to the categories in Table 1.

implies that identification is achieved using two sources of data variation, i.e. by comparing the educational delays of first, cohorts with different levels of exposure within districts, and second, the same education-birth-year cohort across districts that exhibit differential exposures. We also experiment with a different set of FE (birth-year and education-district FE) to explore different sources of variation for identification. Finally, ϵ_i is the error term.

It is important to note that the estimate of α_1 captures educational delays conditional on school attendance. The most vulnerable children (e.g. those belonging to schedule castes) would likely be most affected by storms, yet, often these children are not enrolled in the schooling system. Therefore, we do not observe their educational delay, which may generate a downward selection bias. Nevertheless, we find no evidence that early life exposure to storms (0-5 years) affects the probability of primary school enrolment, suggesting that the selection bias may be small.

Results

Table 4 shows results for equation (2). Standard errors are two-way clustered at the state and district-birth year level. Clustering at the state level accounts for the fact that the largest part of funding for education and the coordination of education programs are administered at the state level.[16] We also cluster at the district-birth year level because children of a given cohort and district share the same exposure index.[17]

In the first three columns we use the measure of delays computed as the difference between reported years of schooling and the number of years corresponding to the reported educational attainment. The estimate of interest suggests that, conditional on educational categories, exposure to storms leads to a statistically significant delay in completing a given level of education. The estimate indicates that a child with unit exposure will be delayed by 0.18 years on average, which amounts to a delay of approximately 7.5 weeks (unit values are observed for instance in the state of Orissa). For the average storm exposure in our sample, this corresponds to roughly three and a half school days.[18] Results are quantitatively similar if we condition on education-birth year FE. Even when adding district-education FE to the baseline specification, the estimate in column (3) remains statistically significant at the 10% level and positive, albeit it drops by about 60%. We attribute the difference in the precision and magnitude of this last estimate to the fact that the small number of birth-year cohorts within district-education cells does not offer sufficient variation for identification. Nevertheless, it is interesting to note that even in the most demanding specification, we

[16] http://countrystudies.us/india/37.htm

[17] Clustering at the district-birth year level yields similar results.

[18] Given an average storm exposure of 0.09, this number is computed as $0.18 \cdot 0.09 \cdot 42 \cdot 5$.

observe detrimental consequences on education.

In the last three columns we run a linear probability model to explore the effect of childhood exposure to storms on the probability of having an educational delay of at least one year. The estimates obtained suggest that this probability increases with the occurence of storms during the years of compulsory schooling. Focusing on column (4), the estimate implies that children with unit exposure to storms are close to 9% more likely to repeat a year or dropping out.

[Table 4 here]

3.2 Educational attainment

In Table 5 we examine whether, in addition to creating delays within each category of schooling, storms also impact the probability of completing a given level of education. Accordingly, we run equation (2) replacing education-birth year FE by cohort-birth year FE. Estimates are statistically insignificant for primary school. Yet, positive exposure tends to reduce the probability of successfully completing higher levels of education, with values reaching 10% for secondary school and close to 6.6% for above-secondary categories of schooling in the case of unit exposure to storms.

[Table 5 here]

Hence, it appears that affected children still complete primary school but take longer to do so. This might have harmful consequences on future employment prospects, especially if these effects also correlate with drops in literacy and numeracy rates. In the long run, they are less likely to obtain higher levels of education, possibly because they do not enroll or because they simply drop out. If they do complete higher education levels, results suggest that individuals that were exposed to natural disasters as children might take longer to graduate.

3.3 Type of activity

We expect this educational disruption to be reflected in the type of labor market activity performed in young adulthood, as certain categories of jobs require higher levels of education or at the very least adequate reading, writing and computing skills. We investigate this issue by estimating a reduced-form specification of childhood exposure to storms on an indicator variable for each activity. For instance, in column (1) the dependent variable is a dummy variable equal to 1 if the main activity of individual i is to perform regular work. Estimates in Panel A suggest that within categories of education, individuals that were exposed to storms during years of compulsory schooling are less likely to work as regular labor, to be self-employed and more likely to work as family workers. However, we find no statistically significant effect on the likelihood to be a casual worker or to perform domestic duties as primary activity. To give a sense of the magnitudes, a unit childhood exposure like the one experienced in Orissa makes individuals 7.5% less likely to be regular workers, 6.1% less likely to be self-employed and 5.4% more likely to work as unpaid family workers.

We then move to an IV approach where we instrument educational delay with childhood exposure. This allows us to examine how educational delays caused by positive exposure affect the probability of performing regular work versus unpaid labor market activities. Estimates from this exercise are shown in Panels B and C, where we use the measure of educational delay and the dummy of educational delay, respectively. Estimates in Panel B (C) are in line with the reduced-form results and point towards substantial effects of educational delays on labor market outcomes. Specifically, the estimates indicate that a delay of at least one year leads to a 42.6% (84%) fall in the probability of working as regular labor, a 34.6% (68.2%) fall in the probability of being self-employed and a 30.7% (60.4%) increase in the probability of performing unpaid family work. For completeness, both panels also show OLS results which display a substantial endogeneity bias, highlighting the importance of instrumenting the education variable. Therefore, the exogenous nature of childhood exposure to storms also allows us to identify and quantify the importance of education on long-term labor market prospects.

[Table 6 here]

Finally, Table 7 examines whether positive exposure is associated with lower wages and longer hours of employment within categories of education, as suggested in the summary statistics earlier on. In column (1) the sample is restricted to workers who receive a salary. In the second column the sample contains all the individuals who report positive hours of work, including people performing unpaid tasks. We find no evidence that, conditional on education and being employed as regular labor, childhood exposure to storms has permanent effects on wages. Hence, by disrupting the education of children, storms are likely to exacerbate income and social inequalities across districts and cohorts in the long run. This occurs not so much by reducing wages but by restricing access to good (regular) jobs while inducing relatively more unpaid work which does not provide the social security that formal jobs can supply. Disparities along the income distribution will also widen as individuals with the largest delays tend to belong to particulary vulnerable social groups.

[Table 7 here]

4 Robustness

Falsification tests

In this section, we propose two falsification tests. We start with a placebo exercise in which we replace the index of childhood exposure to storms in equation (2) with a random measure obtained by reshuffling C_{bd} over the entire sample. We perform this operation 1000 times and report in Panel A of Table 8 the share of replications that produce statistically significant estimates at the 1%, 5% and 10% levels. Results suggest that our coefficients do not capture spurious correlations. The number in column (1) indicates that in only 2.2% of the cases, the randomization produces estimates which are statistically significant at the 1% level. Not surprisingly, this share increases when considering higher levels of statistical significance, reaching 6.5% at the 5% level and 10.7% at the 10% level. We obtain similar conclusions if we use the alternative dummy measure of educational delay, as shown in columns (4)-(6).

In Panel B of Table 8 we implement a second falsification exercise. We assign a positive value of exposure to older cohorts which were not included in our sample initially. One would expect educational attainments of older cohorts to be unaffected by the occurence of future storms. Specifically, for each birth-year cohort and district, we assign the value of C_{bd} to the cohort born 10 years earlier. We then examine the effect of this artificial exposure measure on the educational delay of the cohorts born between 1975 and 1985. We also perform this exercise using the cohorts born 15 years earlier, between 1970-1980. Regardless of the sample and measure of educational delay used, the estimates obtained (columns 7-10) are highly statistically insignificant, suggesting once again that the baseline estimates do not capture spurious correlations.

[Table 8 here]

Alternative measures of childhood exposure to storms

Table 9 experiments with alternative specifications of C_{bd} by altering the threshold and the functional form between district exposure to storms and winds (see equation 3 of Appendix B). In India, lower quality construction materials and techniques may cause physical structures to be vulnerable already at relatively low wind intensities. However, in high-income countries, a threshold of 33 knots is generally too low for winds to damage materials. For example, Emanuel (2011) uses a threshold of 50 knots in a study of U.S. hurricane damage. Moreover, a few studies in the U.S. claim that the energy released by a storm and the force exerted by winds on physical structures are related in a cubic and not a quadratic manner (see the technical HAZUS manual of the Federal Emergency Management Agency – FEMA – of the U.S. Department of Homeland Security and Emanuel, 2005). We account for this fact in column (1) where we adapt the baseline measure to a cubic specification. In the subsequent columns we move up the threshold, first, consistent with Emanuel (2011), to 50 knots (columns 2 and 3), and then, to include tropical cyclones only, to 64 knots (columns 4 and 5). Results based on a cubic damage function are also shown for each threshold (columns 3 and 5).

In each panel, the estimated coefficients on these alternative measures remain positive and precisely estimated, and, as expected, the magnitudes of the estimates become larger as the threshold used to compute district exposure increases to capture less frequent but more powerful winds. Using cubic specifications also tend to inflate the estimates. For instance, in column (4) of Panel A, where district exposure is computed using a threshold of 64 and a quadratic function, the estimates grows to 0.408 against 0.176 in the baseline (column 2 of Table 4). This number corresponds to 8.5 school days for the corresponding average exposure index and 17 weeks in districts with the highest exposure.[19] The corresponding estimate in Panel B implies that in these districts, individuals are 25% more likely to have an educational delay of one year or more, in comparison to storm-sheltered places.

[Table 9 here]

5 Channels

In order to formulate precise policy advice on how to deal with the negative consequences of a storm on education, we need to understand the channels through which storms disrupt education. In theory, natural disasters can affect supply and demand for schooling. On the supply side, disasters may destroy public infrastructure, like roads and schools, creating punctual delays in schooling due to the impossibility to attend classes (see for instance Psacharopoulos, 1994; Strauss & Thomas, 1995; Duflo, 2001; Schultz, 2002). On the demand side two things may happen. First, a disaster could generate PTSD in children, a condition that has been shown to hinder their scholastic and labor market performance (e.g. Cutter

[19] Summary statistics for each alternative measure are shown in Table C.1 of the Appendix.

et al., 2003; Kar & Bastia, 2006; Neria et al., 2008; Blaikie et al., 2014). Second, a disaster may result in a negative income shock, e.g. by destroying crops and farms in rural areas or part of production facilities in both, rural and urban areas (see for instance Pelli et al., 2020). Negative income shocks can be temporary, and last until physical assets are rebuilt, or permanent. For instance, losing one season's crop can put a farming household in debt and cripple it financially for years to come.

In this section we show that the negative effects of storms on education derive to a large extent from permanent negative income shocks. We reach this conclusion by examining men and women separately, as well as rural and urban areas. If storms were operating through the schooling supply or PTSD channels, one would expect similar effects across genders and between regions. Instead, we observe sharp differences across groups, which suggest that storms operate through an income channel.

We start by looking at the impact on education across the four groups (men and women, rural and urban). Columns (1) and (2) of Table 10 show results for educational delay, while columns (3) to (6) present results for educational attainment. The four subsamples have roughly the same size. Results for men (in Panel A) contrast sharply from those for women (in Panel B); while storms create an educational delay for men, women are not affected. Looking at Fiji, Takasaki (2017) finds similar results for boys and girls' school enrollment in the aftermath of a cyclone. We attribute our results to the different speed of physical development between genders. Often, boys 10 years and older are already physically capable to help their parents in reconstruction activities. If storms were to damage the family farm or fields, a household may decide to keep boys home to help and send girls to school, causing boys to accumulate a delay but not girls. Columns (3) to (6) tell us that the income shock is not temporary, but has long term consequences and tends to decrease the probability of completing non-compulsory education across the board. To sum up, boys seem to accumulate a delay and, due to the smaller income available going forward, girls drop out of school earlier while boys have a smaller probability to go on to higher education.

Panel C and D show results for rural and urban areas, respectively. In this case as well, results are consistent with a permanent income shock. In rural areas, the majority of households are involved in farming. These households are likely to take their children out of school in the aftermath of a storm to perform reconstruction and fields activities, generating an educational delay, as found in columns (1) and (2) of Table 10. In addition, we find that the probability of completing higher education decreases, which suggests that the loss of revenue is permanent. In urban areas, the story seems to be different. We find no statistically significant impact on educational delay, but a lower probability of attaining every educational level, starting with primary school. Perhaps because owning a farm is unlikely in urban areas, parents do not need to substitute schooling for field or reconstruction work but find themselves unable to support children financially, causing them to drop out of school sooner.

[Table 10 here]

In Table 11, we look at what happens to the type of activity undertaken in young adulthood for each of the four subsamples. First, the probability of being involved in regular work (i.e. high quality salaried jobs) and to be self-employed decreases across the four subgroups, while the probability of performing casual labor increases for everyone except urban people, probably because casual labor is mostly linked with farming. Second, individuals in rural areas appear to increasingly work as unpaid family workers, e.g. as laborers on the family farm. This result is not found for urban individuals, for whom we observe an increase in the probability of being involved primarily in domestic duties.

[Table 11 here]

Discussion

Our findings seem to reflect the impact of permanent negative income shocks rather than the effects of schooling supply shocks or PTSD. This important distinction allows us to offer possible policy recommendations which could limit educational delays and drop outs. Furthermore, according to our results, policy should differ between rural and urban areas.

Results indicate that rural areas go through a temporary income shock that becomes permanent because of the inability of rural households to cope with it. The government could implement an emergency system of Conditional Cash Transfers (CCT). The cash transfer should cover reconstruction and the loss of income (e.g. the value of the crops lost) and be conditional on regular and uninterrupted school attendance. Such a policy should eliminate the delays we observe for boys and allow both, boys and girls, to follow their natural educational path instead of dropping out earlier.

In urban areas the problem seems different and CCTs may not be the best policy. Urban individuals are more likely to lose their job after a storm, because of its impact on firms. An efficient way to deal with job losses would be to strengthen social safety nets like unemployment insurance and social assistance. In the absence of these programs (or if they do not work properly) the loss of a job, even if temporary, may drag a family down a spiral of poverty. As a consequence, children may be taken out of school earlier, jeopardizing their future employment prospects. A possible way to help people in urban areas is to subsidize firms in order for them to keep paying their employees during the reconstruction of their physical infrastructure. These subsidies could be modelled on the policies that have been implemented by many countries during the COVID-19 pandemic. This help should be complemented with tsocial assistance programs targeted at individuals who are not regular salaried workers.

6 Conclusion

In this paper we look at how exposure to storms during compulsory-schooling years affects long-term educational attainments and the type of activity performed in early adulthood. Using storm data from NOAA, we construct a measure of exposure to storms over the course of compulsory schooling for all the individuals aged 23 to 33 in the PLFS. Individuals hit by a storm during these important years tend to accumulate an educational delay and are less likely to complete higher education. Using storm exposure as an instrument for education, we find that educational delays reduce the probability of obtaining a regular salaried job and increase the probability of being involved in unpaid family work and domestic duties in young adulthood. Duflo (2001) finds that economic returns to education range from 6.8 to 10.6 percent in Indonesia. Applying these numbers to India, our estimates of educational delay imply that a unit exposure to storms during the years of compulsory schooling could cause a lifelong 1.3% to 2% fall in returns on average.[20] This is an important number considering that storms typically last less than a week.

Focusing on the heterogeneous effects found across genders and between rural and urban areas, we conclude that the negative impact of storms on children's education is the result of a negative income shock on households, and not of a schooling supply shock or PTSD. Pinning down the channel through which storms affect education allows us to offer policy recommendations, separately for rural and urban areas.

The results obtained in this paper help us predict part of the long-term impacts of the COVID-19 pandemic that started towards the end of 2019. Differently from storms, the literature suggests that the pandemic affects education through each of the three channels mentioned above. Government-mandated school closures led to a reduction in the schooling supply, at least temporarily. On the demand side, the literature documents that the pandemic gave rise to PTSD (see for instance Phelps & Sperry, 2020; Yue et al., 2020; Zhou, 2020) and, by causing heterogeneous losses of employment, heterogeneous negative income shocks (see Di Pietro et al., 2020).

[20] A unit exposure to storms causes an average delay of 8 weeks out of the 42 weeks of a school year, which amounts to 20% of the year. Multiplying this number by Duflo (2001)'s estimates we obtain a reduction of 1.3 to 2% in returns.

In light of our findings, we can infer that the mix of school closures, negative income shocks, and PTSD are likely to generate an educational delay for many students and to increase the drop-out rate. Consistent with this argument, Kuhfeld et al. (2020) predict that returning students will have only approximately 63-68% of the reading capacity and 37-50% of the mathematical knowledge with respect to a usual school year. Interpreting these delays through the lens of our IV results, we expect a change in the activity that current students will engage in during early adulthood. This change will likely be reflected in the share of individuals with regular salaried work and also in the type of occupations or tasks individuals will perform. Furthermore, we expect the ensuing fall (increase) in the supply of high-skill (low-skill) workers for the cohorts attending school during 2020-2021 to contribute to increased wage inequality. In light of this evidence, it should be paramount for policymakers to find a way to allow these students to make up for the delay accumulated. In the absence of such an effort, economic inequalities are meant to increase for individuals who were in school during COVID-19 pandemic.

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Tables

Table 1: Schooling System in India

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

Notes: Column (1) shows the duration of each category of schooling. For *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).

Table 2: Summary Statistics

	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	N (5)
Panel A: Exposure to storms					
C_{bd}	0.06	0.13	0	1.05	81,542
$C_{bd} > 0$	0.09	0.15	8.06e-09	1.05	52,059

	All		Zero exp.	Pos. exp.	Diff.	Diff.
	Mean	Std. Dev.	Mean	Mean	c3-c4	in weeks
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B:						
Highest category of schooling completed (yes=1, no=0)						
Below primary♠	0.11	0.31	0.11	0.11	-0.0009	
Primary	0.09	0.29	0.09	0.09	-0.001	
Middle	0.23	0.42	0.21	0.23	-0.02***	
Secondary	0.17	0.37	0.15	0.17	-0.02***	
Higher secondary	0.15	0.36	0.17	0.15	0.02***	
Higher education♣	0.25	0.43	0.25	0.24	0.01***	
Observations	81,542		29,483	52,059		
Panel C: Main variables						
Educational delay	0.4	0.94	0.38	0.42	-0.05***	2.10***
Primary	0.65	1.002	0.61	0.67	-0.06**	2.52**
Middle	0.43	0.83	0.40	0.43	-0.03***	1.26***
Secondary	0.22	0.66	0.20	0.23	-0.03***	1.26***
Higher secondary	0.3	0.82	0.31	0.29	0.02	0.84
Higher education	0.3	0.83	0.29	0.30	-0.02*	0.84*
Observations	81,542		29,483	52,059		
Labor market						
Log hourly wage	3.69	0.64	3.73	3.67	0.06***	
Weekly hours worked	53.59	13.1	54.29	53.24	1.05***	
Observations	33,156		11,109	22,047		
Primary activity status						
Regular work	0.22	0.41	0.22	0.21	0.009**	
Casual labor	0.12	0.33	0.1	0.13	-0.03***	
Self-employment	0.15	0.36	0.15	0.15	0.0001	
Unpaid family work	0.09	0.29	0.09	0.09	-0.002	
Domestic duties	0.41	0.49	0.43	0.41	0.02***	
Observations	68,507		23,601	44,906		

Notes: The following categories *not literate*, *literate without formal schooling* and *literate below primary* are grouped into the category *lower than primary.*♠ Among those individuals who did not complete primary schooling, approximately 76% did not attend school at all and 24% are primary school dropouts.♣ This category includes all the categories that fall into higher education: *diploma/certificate course*, *graduate*, *postgraduate and above*. Columns (1) and (2) show the mean and standard deviation of the main variables for the entire sample. Columns (3)-(5) distinguish between individuals with zero childhood exposure to storms from those with positive exposure. Column (5) tests whether means statistically differ from each other across these two groups of individuals. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Characteristics of Individuals

	Mean (1)	Std. Dev. (2)	Min. (3)	Max. (4)
Age	27.26	3.15	22	33
Household size	5.14	2.37	1	34
Gender*	0.49	0.50	0	1
First born*	0.29	0.45	0	1
Rural*	0.54	0.50	0	1
Hinduism*	0.74	0.44	0	1
Married*	0.67	0.47	0	1
Household head*	0.16	0.36	0	1
Observations	81,542			

Notes: * indicate dummy variables. The variable *gender* is equal to one for female individuals. *First born*= 1 for first born individuals. *Household head*= 1 if the individual is the head of the household. *Rural*= 1 for individuals living in rural areas. *Hinduism*= 1 for Hindus. Finally, *Married*= 1 if the individual is married.

Table 4: Educational delay

	Educational delay			Educational delay (yes=1, no=0)		
	(1)	(2)	(3)	(4)	(5)	(6)
Childhood exposure: C_{bd}	0.182**	0.176***	0.078*	0.090**	0.089**	0.048*
	(0.071)	(0.062)	(0.042)	(0.040)	(0.037)	(0.027)
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	No	Yes	Yes	No
Educ. FE	Yes	No	No	Yes	No	No
Birth year FE	Yes	No	Yes	Yes	No	Yes
Educ.-Birth year FE	No	Yes	No	No	Yes	No
Educ.-District FE	No	No	Yes	No	No	Yes
Observations	81,542	81,542	81,230	81,542	81,542	81,230

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head. The number of observations differ across specifications due to singleton observations which are dropped in columns (3) and (6).

Table 5: Educational Levels

	Category of schooling completed: yes=1, no=0			
	Primary (1)	Middle (2)	Secondary and higher secondary (3)	Above (4)
Childhood exposure: C_{bd}	-0.036	-0.085*	-0.098**	-0.066**
	(0.048)	(0.049)	(0.037)	(0.032)
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes
Observations	81,542	81,542	81,542	81,542

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Table 6: Type of activity

	Categorical dependent variables: yes=1, no=0				
	Regular work (1)	Casual labor (2)	Self-employed (3)	Unpaid family work (4)	Domestic duties (5)
Panel A: Reduced form					
Childhood exposure: C_{bd}	-0.075***	0.034	-0.061***	0.054***	0.001
	(0.018)	(0.029)	(0.021)	(0.020)	(0.032)
Panel B:					
OLS					
Educational delay	0.001	-0.004	-0.003	-0.002	-0.005
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
IV: Second stage					
Educational delay	-0.426**	0.193	-0.346**	0.307*	0.008
	(0.178)	(0.197)	(0.168)	(0.163)	(0.184)
F-statistics	11.02	11.02	11.02	11.02	11.02
Panel C:					
OLS					
Educational delay (yes=1, no=0)	0.005	-0.014**	-0.014***	-0.003	-0.011
	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)
IV: Second stage					
Educational delay (yes=1, no=0)	-0.840**	0.381	-0.682**	0.604*	0.016
	(0.401)	(0.428)	(0.331)	(0.345)	(0.363)
F-statistics	13.80	13.80	13.80	13.80	13.80
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	Yes	Yes	Yes
Observations	81,542	81,542	81,542	81,542	81,542

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Table 7: Wages and hours of work

	Log hourly wages ($w > 0$) (1)	Hours of work (2)
Childhood exposure: C_{bd}	0.002	2.040
	(0.058)	(2.021)
Controls (indiv. and hh.)	Yes	Yes
District FE	Yes	Yes
Educ.-Birth year FE	Yes	Yes
Observations	33,154	33,154

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Table 8: Falsification Tests

	Educational delay			Educational delay (yes=1, no=0)		
Panel A: **Placebo**	Share of estimations with statistical significance at:			Share of estimations with statistical significance at:		
	1%	5%	10 %	1%	5%	10 %
	(1)	(2)	(3)	(4)	(5)	(6)
Childhood exposure: C_{bd}	0.022	0.065	0.107	0.023	0.074	0.12
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,542	81,542	81,542	81,542	81,542	81,542

Panel B: **Older cohort assignment**	+ 10 years	+ 15 years		+ 10 years	+ 15 years	
	(7)	(8)		(9)	(10)	
Childhood exposure: C_{bd}	0.054	-0.058		0.010	0.012	
	(0.088)	(0.066)		(0.036)	(0.028)	
Controls (indiv. and hh.)	Yes	Yes		Yes	Yes	
District FE	Yes	Yes		Yes	Yes	
Educ.-Birth year FE	Yes	Yes		Yes	Yes	
Observations	71,189	68,001		71,189	68,001	

Notes: Panel A of the table shows the share of statistically significant results over 1000 randomizations, where the childhood exposure measure is randomized over the entire sample. Panel B of the table shows the estimates obtained using the synthetic index of childhood exposure over the sample consisting of cohorts born between 1975 and 1985 (columns 7 and 9), as well as cohorts born between 1970 and 1980 (columns 8 and 10). In each column, statistical significance corresponds to two-way clustered standard errors at the state and district-birth year levels. In columns (1)-(3) and (7)-(8), the dependent variable is educational delay and in the remaining columns the dependent variable is a dummy variable that take the value of one if an individual has an educational delay of at least one year. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Table 9: Alternative Measures of Childhood Exposure to Storms

	> 33 Cubic (1)	> 50 Quadratic (2)	> 50 Cubic (3)	> 64 Quadratic (4)	> 64 Cubic (5)
Panel A: Educational delay					
Childhood exposure: C_{bd}	0.337***	0.290***	0.448***	0.408***	0.475**
	(0.083)	(0.073)	(0.122)	(0.093)	(0.180)
Panel B: Educational delay (yes=1, no=0)					
Childhood exposure: C_{bd}	0.177***	0.152***	0.237***	0.211***	0.257***
	(0.047)	(0.045)	(0.047)	(0.041)	(0.065)
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	Yes	Yes	Yes
Observations	81,542	81,542	81,542	81,542	81,542

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head. In Panel A, the dependent variable is educational delay and in Panel B we use the dummy variable for educational delay of at least one year. In columns (1), (3) and (5) childhood exposure to storm is constructed using a cubic function for windspeed exposure. The other columns use a quadratic function. The thresholds used to compute the index of exposure is 33 knots in column (1), 50 knots in columns (2) and (3) and 64 knots in the last two columns.

Table 10: Education: Gender, Rural and Urban Subsamples

	Educational delay		Category of schooling completed: yes=1, no=0			
	# of years	yes=1, no=0	Primary	Middle	Secondary and higher secondary	Above
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Male						
Childhood exposure: C_{bd}	0.288***	0.113***	-0.034	-0.030	-0.100**	-0.109***
	(0.070)	(0.033)	(0.045)	(0.051)	(0.044)	(0.038)
Observations	41,194	41,194	41,194	41,194	41,194	41,194
Panel B: Female						
Childhood exposure: C_{bd}	0.082	0.063	-0.054	-0.122*	-0.119**	-0.059
	(0.094)	(0.046)	(0.078)	(0.066)	(0.046)	(0.042)
Observations	40,348	40,348	40,348	40,348	40,348	40,348
Panel C: Rural						
Childhood exposure: C_{bd}	0.167**	0.095**	-0.000	-0.046	-0.079**	-0.061*
	(0.065)	(0.041)	(0.046)	(0.046)	(0.038)	(0.034)
Observations	44,301	44,301	44,306	44,306	44,306	44,306
Panel D: Urban						
Childhood exposure: C_{bd}	0.110	0.040	-0.153*	-0.195**	-0.130*	-0.055
	(0.112)	(0.050)	(0.078)	(0.095)	(0.066)	(0.067)
Observations	37,234	37,234	37,234	37,234	37,234	37,234
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	No	No	No	No
Birth year FE	No	No	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Table 11: Type of Activity: Gender, Rural and Urban Subsamples

	Categorical dependent variables: yes=1, no=0				
	Regular work (1)	Casual labor (2)	Self-employed (3)	Unpaid family work (4)	Domestic duties (5)
Reduced form:					
Panel A: Male					
Childhood exposure: C_{bd}	-0.129***	0.015	-0.062	0.091***	0.021***
	(0.036)	(0.062)	(0.039)	(0.033)	(0.005)
Observations	41,194	41,194	41,194	41,194	41,194
Panel B: Female					
Childhood exposure: C_{bd}	-0.053**	0.090**	-0.037	0.018	-0.021
	(0.022)	(0.039)	(0.024)	(0.017)	(0.065)
Observations	40,348	40,348	40,348	40,348	40,348
Panel C: Rural					
Childhood exposure: C_{bd}	-0.063***	0.094*	-0.078**	0.081***	-0.069*
	(0.019)	(0.048)	(0.033)	(0.029)	(0.040)
Observations	44,301	44,301	44,301	44,301	44,301
Panel D: Urban					
Childhood exposure: C_{bd}	-0.145***	-0.053***	-0.005	0.008	0.128***
	(0.046)	(0.018)	(0.028)	(0.007)	(0.042)
Observations	37,234	37,234	37,234	37,234	37,234
Controls (indiv. and hh.)	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors presented in parenthesis and clustered at the state and district-birth year level. Individual controls include gender, marital status, a dummy variable indicating if the individual is first born and another dummy indicating if the individual is the household head. Household controls include household size, religion, a dummy variable taking the value of one if the household is located in a rural area, as well as gender and education FE for the household head.

Figures

Figure 1: Oldest Cohort

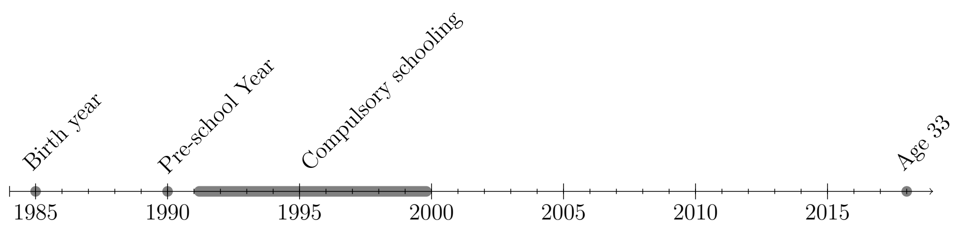
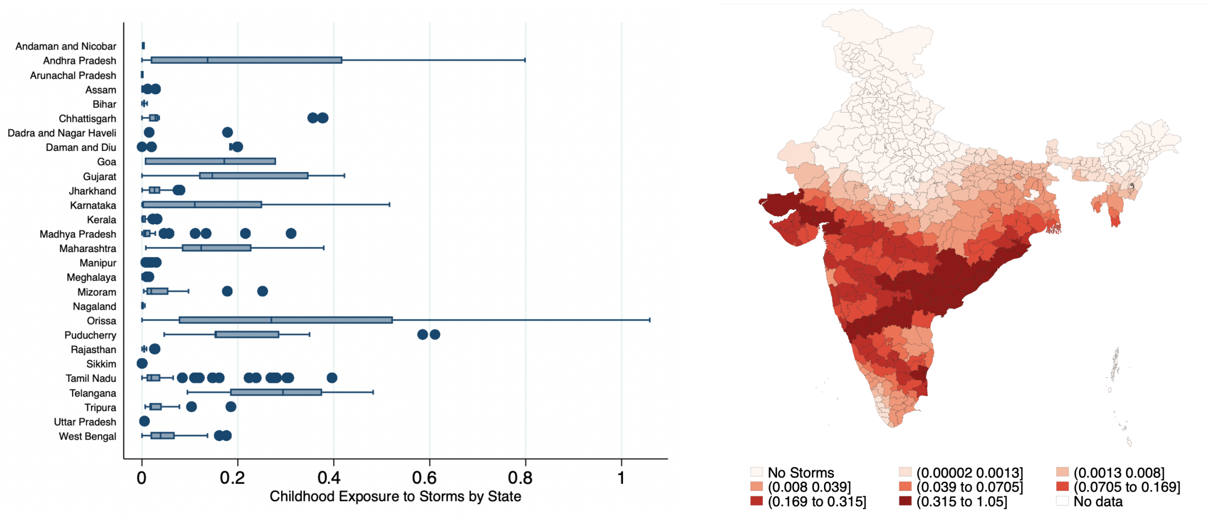


Figure 2: Childhood Exposure to Storms



Notes: The boxplot (left panel) describes the measure of childhood exposure to storms for positive values of exposure ($C_{bd} > 0$) and individuals born between 1985 and 1995 by state, listed in alphabetical order. The figure only shows states with positive exposure. The blue line in a box is the median. The lower bound of a box is the first quartile and the higher bound is the third quartile. The end of the left (right) whisker is the 1st percentile (99th percentile). Circles without a box mean that all observations are clustered around the median. The circles outside of the box represents outliers. The figure (right panel) provides a visual illustration of childhood exposure to storms across districts for the cohort born in 1987. The darkest colored bin contains the districts for which the index of childhood exposure falls above the 90th percentile in the distribution of C_{bd} in 1987. The other bins with positive exposure each contain 15% of the districts.

A Appendix. Indian schooling system

Lower education comprises primary, middle, secondary and higher secondary school. Primary school lasts 5 years, middle school 3 years and the other two categories take 2 years each. Higher education includes the diploma/certificate course, the graduate (bachelor level) and post-graduate (master) levels.[21] It takes 1 year to obtain a diploma, while completing a bachelor and a master degree generally take 3 and 2 years, respectively. As is standard internationally, one needs to graduate first to move to the postgraduate level. However, one can go straight to the diploma/certificate course or bachelor stream after higher secondary school.[22]

[21] The proportion of individuals with a PhD degree is negligible, hence we omit this category.

[22] More details on the educational system of India and how it compares to other systems can be found here: https://wenr.wes.org/2018/09/education-in-india

B Appendix. District exposure and wind speed

B.1 District exposure to tropical storms

In what follows we describe how we construct x_{dt}, the index of exposure to storms of district d in year t. The index accounts for the force exerted by winds on physical structures through the square values (following Yang, 2008; Pelli & Tschopp, 2017) and is given by:

$$x_{dt} = \sum_{h \in H_t} \frac{(w_{dh} - 33)^2}{(w^{max} - 33)^2} \quad \text{if} \quad w_{dh} > 33, \tag{3}$$

where H_t is the set of storms in year t and w_{dh} is the maximum wind speed associated with storm h and to which district d was exposed. We describe the construction of w_{dh} below. The term w^{max} denotes the maximum wind speed observed over the entire sample. In order to capture the force exerted by winds on structures, we assume a quadratic functional form between district exposure to storms and winds.[23] Given the poor quality of construction materials, infrastructures and buildings in India are vulnerable at low wind intensities. For these reasons, we focus on a threshold of 33 knots – defing a tropical storm – as opposed to 64 knots – the threshold for a category 1 tropical cyclone according to the Simpson and Riehl scale. By definition, $x_{dt} \in (0, \mid H_t \mid)$, with a value of 0 indicating zero district exposure to storms (i.e. winds in district d are below the threshold limit) and with $\mid H_t \mid$ indicating the number of elements (storms) in set H_t.

B.2 Wind speed at the district level

We now turn to the construction of w_{dh}, i.e. the maximum wind speed associated with storm h in district d. The variable is constructed using data from the National Oceanic and Atmospheric Administration (NOAA) Tropical Prediction Center and specifically using storms' best tracks in the North Indian and South Indian basins over the period 1990-2010. Best tracks contains the full history of each storm, with information at 6-hours intervals on the latitude, longitude, date and wind speed at the eye of each storm.

We first linearly interpolate storms' best tracks at every kilometre and obtain, for each interpolated kilometre, a landmark k with a set of coordinates and e_k, the windspeed at the eye of the storm. For each district that falls in the vortex associated with a landmark we use the Rankine-combined formula (Deppermann, 1947) and compute winds at the district's

[23] In Section 4 we experiment with a variety of alternative specifications of district exposure to storms.

centroid. The formula describes wind fields in the following way:

$$
\begin{aligned}
w_{dk} &= e_k \cdot \left(\frac{D_{dk}}{26.9978}\right) \text{ if } D_{dk} \leq 26.9978 \\
w_{dk} &= e_k \cdot \left(\frac{26.9978}{D_{dk}}\right)^{0.5} \text{ if } D_{dk} > 26.9978,
\end{aligned} \tag{4}
$$

where D_{dk} is the distance between the centroid of district d and landmark k. The number 26.9978 corresponds to Simpson and Riehl radius of maximum wind speed in knots, i.e. the distance between the eye and the point where wind reaches its maximum speed.[24] Hence, according to this formula, winds first increase exponentially up to a maximum and then, decrease rapidly. Finally, we obtain one measure of windspeed per district and storm by retaining the maximum windspeed to which a district was exposed:

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

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

C Appendix. Tables

Table C.1: Alternative Measures of Childhood Exposure to Storms

	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)	N (5)
Panel A: 33 knots					
Cubic form:					
C_{bd}	0.03	009	0	1.01	81,542
$C_{bd} > 0$	0.04	0.1	7.24e-13	1.01	52,059
% of N with $C_{bd} > 0$: 64%					
Panel B: 50 knots					
Quadratic form:					
C_{bd}	0.03	0.1	0	1.003	81,542
$C_{bd} > 0$	0.1	0.15	1.23e-08	1.003	25,239
Cubic form:					
C_{bd}	0.002	0.08	0	1.0002	81,542
$C_{bd} > 0$	0.05	0.13	1.36e-12	1.05	25,239
% of N with $C_{bd} > 0$: 31%					
Panel B: 64 knots					
Quadratic form:					
C_{bd}	0.02	0.08	0	1	81,542
$C_{bd} > 0$	0.1	0.17	3.35e-08	1	14,501
Cubic form:					
C_{bd}	0.01	0.07	0	1	81,542
$C_{bd} > 0$	0.05	0.16	6.12e-12	1	14,501
% of N with $C_{bd} > 0$: 18%					

Notes: The table shows summary statistics for the alternative measures of childhood exposure to storms. In Panel A, we use a threshold of 33 knots and a cubic functional form to compute district exposure to storms. The threshold used is in Panels B and C are 50 and 64 knots, respectively. Both panels show statistics from a quadratic and a cubic functional form. The share of observations with positive exposure decreases as one increases the threshold, from 64% with 33 knots, to 31% with 50 knots and 18% when using 64 knots.