Loss of Schooling from Tropical Cyclones: Evidence from 13 Low- and Middle-income Countries

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Increasing educational attainment is one of the most important and effective tools for health and economic improvements. The extent to which extreme climate events disrupt education, resulting in fewer years of schooling and reduced educational attainment, remains under-studied. Children in low- and middle-income countries may be uniquely vulnerable to loss of schooling after such disasters due to the poor physical condition of schools and the lack of resources to rebuild and mitigate unexpected household shocks. Our analysis assesses this overlooked social cost of tropical cyclones on schooling attainment.

We study the education records of nearly 5.1 million people living in 13 low- and middle-income countries that were exposed to tropical cyclones between 1954-2010. We find that exposure to tropical cyclones during preschool age is associated with a 2.7 percentage point decrease in primary school enrollment on average (14.2% decrease), with larger effects from more intense storms (up to 28% decrease for the most intense storms). These effects are more pronounced among school-age girls compared to boys and are greater in areas less accustomed to experiencing tropical cyclones. We estimate that, across all LMICs, tropical cyclone exposure has resulted in more than 410,000 children not attending primary school in the last 20 years, leading to a reduction of more than 4.1 million total years of schooling. These impacts, identified among some of the world's poorest populations, may grow in importance as exposure to severe tropical cyclones is projected to increase with climate change.

Introduction

Schooling and education are among the most important tools for improving health and reducing poverty in low- and middle-income countries (LMICs) (*1–5*). Children in LMICs typically attend fewer years of school compared to children in wealthier nations, and reducing the gap is considered an important development goal (*6–8*). While substantial progress has been made in recent decades in improving education and schooling in LMICs, natural disasters, such as tropical cyclones, can hinder such progress and compound existing challenges to educational attainment (*9–11*). Tropical cyclones are destructive natural disasters that have substantial economic and health consequences (*12–16*), and their impacts are projected to increase in a warmer climate due to changes in intensity and population growth. (*17–19*) However, the extent to which tropical cyclones pose barriers to educational attainment across LMICs remains under-studied (*20*).

Tropical cyclones can plausibly affect several stages of a child's schooling, including school enrollment and attendance, completion of grade levels, and learning (*20*). The high winds and heavy rainfall that come with tropical cyclones can cause physical destruction and school closures (*21*). At the household level, storms can cause economic shocks that drive families to prioritize school-age children for domestic work over school attendance (*22*, *23*). These impacts could even result in long-term educational consequences, especially in communities with limited resources to mitigate economic shocks and where school attendance rates are lower.

The literature on this topic is commonly localized (*20*). In particular, existing research has typically focused on single countries – often developed countries – and/or examined the impacts of individual severe tropical cyclones (*24–26*). Those papers that do focus on LMICs suggest that large effects. For example, a study in India found that exposure to tropical cyclones during school years was associated with a 2.4-percentage-point increase in educational delays and a 2-percentage-point decline in post-secondary attainment (*27*). Similar impacts were observed in the Philippines, where extreme exposure to tropical cyclones at age 6 led to slower grade progression and lower test performance (*10*). However, the localized nature of existing research means that there is still uncertainty regarding the overall effect of tropical cyclones on education attainment in LIMCs, as well as the specific characteristics of individuals and locations that are particularly vulnerable.

In this study, we contribute to the existing literature by examining the effects of tropical cyclones on schooling outcomes in 13 LMICs that have experienced tropical cyclones, focusing on all tropical cyclone events dating back to the 1950s. To achieve this, we combine child-level schooling attainment data from nationally representative household surveys with gridded tropical cyclone wind exposure data, and estimate the effects using causal inference methods. Our sample covers approximately 73% of the population living in LMICs that were exposed to tropical cyclones (*28*), which span over 5 decades and cover a full range of storm intensity and locations with varying return period. The breadth of this analysis allows for a broad understanding of how tropical cyclones impact human capital development in LMICs, and how this impact varies by child sex, urban/rural, storm intensity, storm return period as a proxy of adaptation, and baseline level of education, which provides new insights into the possible mechanistic pathways linking tropical cyclone exposure and loss of schooling.

Results

Sample characterization

Our data contains the schooling records of 5.1 million individuals obtained from 32 nationally representative household surveys in 13 LMICs, including information on primary school enrollment, primary school completion, secondary school enrollment, and total years of schooling for each household member. The global distribution of tropical cyclone exposure and variation in exposure for each study country are shown in Figure 1a and Figure S1, respectively. Figure 1b shows the spatial distribution of the primary school enrollment rate for each survey location in our sample. Figures 1c and Figure S2 show the average total years of schooling for each survey location and the distribution within each survey country. Figure S3 shows the trends in the primary school enrollment rate among boys and girls obtained from enrollment records between 1954 and 2010. In all study countries, the majority of school-bound children enrolled between the ages of 5 and 7 (Figure S4).

Reduced school enrollment following tropical cyclones

We find that exposure to tropical cyclones at age 5 or 6 reduced primary school enrollment. On average, exposure to any tropical cyclone at the age of 5 to 6 was followed by a 2.7 percentage point (pp) lower primary school enrollment compared to if they had not been exposed to tropical cyclones (95% CI 1.4-4.0 pp). This reduction in school enrollment was monotonically more pronounced with increased storm intensity: 0.8 pp (95% CI -0.1-1.9 pp), 1.5 pp (0.4-2.7 pp), 3.6 pp (1.4-5.8 pp), 4.9 pp (2.5-7.3 pp) and 5.4 pp (3.5-7.4 pp) for exposure to Tropical Storm, Category 1, Category 2, Category 3, and Category 4 or more intense tropical cyclones, respectively (Figure 2a). Against a baseline rate of school non-enrollment of 19.1% in our sample, this represents enrollment reductions of 4.2% (not significant, $p = 0.08$), 7.9%, 18.9%, 25.7% and 28.3%, respectively.

Heterogeneity in child sex, education priority and adaptation levels

Figures 2b-f demonstrate heterogeneity in school enrollment after exposure to tropical cyclones by child sex (b), urban/rural (c), average recurrence interval between storms (return period) (d), average baseline school enrollment rate (e), and distance from the edge of exposure (f). We observe a more pronounced loss of school enrollment among girls, with an average effect of 3.8 pp (1.9-5.8 pp) compared to 1.3 pp (0.2-2.8 pp) for boys ($p = 0.05$ for the difference between the effect for boys and girls). We found no statistically significant differences in the effects observed in rural areas (2.5 pp, CI: 1.1-4.0 pp) compared to urban areas (1.3 pp, CI: -0.9-3.4 pp). We observe smaller effects in communities with higher baseline enrollment, consistent with the notion that children are more likely to stay out of school after a tropical cyclone in areas where school attendance norms are lower ($p = 0.015$ between the lowest and highest enrollment groups). Finally, we also show that the impacts decrease with distance from the storm, with effects no longer statistically significant among children beyond 150 kilometers from the storm edge.

Tropical cyclones exhibit a periodic nature that may facilitate adaptation to storms from repeated experiences. We use the return period of tropical cyclones (average recurrence interval, see Methods) to examine the extent to which areas experiencing more frequent exposure to tropical cyclones adapt, as observed in changes in school non-enrollment. Our analyses indicate that the loss of school enrollment is meaningfully greater in communities less frequently exposed to tropical cyclones compared to communities frequently exposed (Figure 2d). For example, we estimate that tropical cyclones can reduce primary education by 3.3 pp in regions that are rarely exposed to TC, while such effects are much smaller in regions with more frequent exposure. The differences are statistically significant (p-value <0.001), consistent with the idea that adaptation to tropical cyclones reduces storm impacts for communities living in regions prone to tropical cyclones.

We do not observe trends in effects, but temporal trends in exposure (Figure S1) and patterns in effect size after excluding years (Figure S8) suggest that our effects are not dependent on any specific year during our study period, but that we identify long-term effects given the role of return periods and the low frequency of storm events in some countries.

We perform multiple robustness analyses and demonstrate that our results are consistent with the alternative model specification (Supplementary Figure S5, Figure S6 and Figure S7) and we show that effect sizes are not driven by a single country or a single year (Figure S8). We also examine the effects on school enrollment following exposure at ages older than 6. Given the mechanisms linking tropical cyclones and schooling, we expected to see minimal or no effect at older ages. The results of exposure at ages other than 5-6 are shown in Figure S9.

Longer-term impacts of tropical cyclone exposure at pre-school age can be detected in later school outcomes, including primary school completion (Figure S10), secondary school enrollment (Figure S11), and total years of schooling (Figure S12). As with school enrollment, we observe greater impacts with higher wind speeds, for girls compared to boys, in rural compared to urban areas, and in communities exposed to tropical cyclones less frequently.

Years of education lost due to tropical cyclone exposure

We use our findings to estimate the total number of children who would have enrolled in primary school had there been no tropical cyclones. Our calculations reveal that if the impacts of tropical cyclones on schooling had been fully mitigated, a total of 280,000 children would have received at least some schooling in the 13 study countries between 2000 and 2019 (Figure 3a), averaging 14,000 additional children enrolling in primary school per year. This would have resulted in a total of 2.8 million additional years of schooling, largely driven by primary school enrollment. The top 3 countries in our sample with the most children losing out on enrollment and years of schooling due to tropical cyclones are India, Bangladesh and Madagascar (Figure 3), reflecting their large population and exposure patterns. The estimated loss of enrollment and the loss of total years of schooling in other LMICs, assuming uniform effects, are also shown in the figure. In all countries, more school-age girls are affected than boys by up to 3.0 (0.6-5.4) times.

Extending to all LMICs exposed to tropical cyclones (including countries for which we did not have outcome data), we estimate that 410,000 students did not enroll in primary school as a result of tropical cyclones, with the most notable losses observed in regions with less frequent exposure to tropical cyclones. Consequently, the overall loss of schooling in LMICs attributable to tropical cyclones has exceeded 4.1 million years in the past 20 years.

Discussion and Conclusion

Using more than 50 years of school attendance records collected from nationally representative surveys in 13 LMICs, we provide evidence to suggest that exposure to tropical cyclones is robustly related to losses of schooling. Our primary estimates of a 7.9% reduction in school enrollment following exposure to Category 1 storms and up to a 28.3% reduction following Category 4+ storms are meaningful obstacles to educational goals (*6*). In our primary analyses, the largest reductions in school enrollment are among groups that typically face higher susceptibility to schooling loss. These include girls, children in rural areas, and children living in places with initially low baseline schooling rates. Consistent with the mechanisms of schooling loss relative to the severity of storm's physical destruction and economic shocks, we find larger impacts when storms are closer, wind speeds are higher, and efforts to mitigate storm impacts are less common. We also observe lasting effects of tropical cyclone exposure as reductions in primary school completion, secondary school enrollment, and years of schooling among exposed children.

We find that countries with more frequent exposure to tropical cyclones suffer smaller effects, possibly driven by adaptation measures. Adaptation to frequent tropical cyclones, such as increased population preparedness and construction resistant to storm winds and surges, would be consistent with this pattern, as would lack of adaptation in regions with infrequent exposure, where storm-resistant construction can be viewed as a lesser priority (*29*, *30*). We find more pronounced effects in communities that are less frequently exposed to tropical cyclones, and this pattern is sustained for primary school completion, secondary school enrollment, and total years of schooling.

Our study suggests several mechanisms that may be at play in schooling disruptions following exposure to tropical cyclones. Physical damage to schools or school access (e.g. roads) is a plausible consequence of severe storms, and, in the absence of adequate recovery, could lead to reduced enrollment in the 1-2 years following exposure, as we observe. Physical damage to the child's household that results in an increased need for children to participate in household labor is also consistent with our findings, including the finding of greater schooling losses among girls.(*31*, *32*) This mechanism also aligns with our findings that schooling losses are more pronounced in communities where keeping children out of school can be more common. Beyond physical damages, short-term displacements after disasters could also lead to non-enrollment. Furthermore, loss of education may result from the long-term economic impacts of tropical cyclones, although this is beyond the scope of this study (*13*).

Our findings highlight an important feature about schooling in LMICs: shocks (tropical cyclones in this study) that disrupt school enrollment reduce schooling attainment through secondary school. We estimate downstream reductions in primary school completion, secondary school enrollment, and total years of schooling, all of which can be linked to disruptions in primary school enrollment. The lingering effects also indicate that the exposed group of students does not catch up even with successful enrollment. Catching up that could result from improved school retention or completion (for example, by long-term economic growth following the exposure (*13*)) is not apparent in the data. These findings suggest a path to respond to tropical cyclones and mitigate their effects on schooling: support families and boost school enrollment, especially among the most vulnerable children - girls, those living in rural areas, and those exposed to intense storms.

The limitations of the study warrant special consideration. An important limitation is the measurement error in identifying the child's place of residence during his or her school years. The location of the household members at the time of the interview may be different from their location during their school-age years. Some children we identify as exposed may have lived away from the exposed area at the time of the storm, while others we identify as unexposed may have been exposed while they were 5-6 years old if they moved out of the exposed area after disaster. This could introduce bias into our estimates, especially if displacement into or away from exposed areas was induced by storms. In the DHS household survey, the migration history of household members is not available, making it challenging to thoroughly examine possible biases related to displacement. However, previous studies have indicated that, unlike slow-onset climate change, which often results in permanent and widespread displacement, disasters often trigger large but short-term displacement, typically to nearby regions, followed by relatively rapid return (*33–35*). The small-scale of permanent displacements from affected areas following sudden-onset disasters, such as tropical cyclones in our case, should make this bias small.

Second, while we use the best available wind data, the wind fields are modeled and hence there is measurement error in our treatment assignment. As shown in the Supplementary Methods and Figure S13, insufficient storm size information for severe storms can lead to underestimated wind speeds in their outer regions, potentially causing misidentification of affected areas as unaffected. We interpret this uncertainty from two perspectives. First, we show that large uncertainties are present only in storms with atypical structures (Figure S13). For most storms, the uncertainty is minimal. Second, even if exposed areas are mislabeled as unexposed due to measurement errors in the wind modeling approach, correcting this could exacerbate the observed effects, particularly given that educational outcomes tend to be worse in affected areas, as indicated in our primary analysis.

Third, some LMICs affected by tropical cyclones, such as Cuba and Vietnam, do not have Demographic and Health Surveys (DHS). However, the 13 countries included in our analysis cover 73% of all population exposure in LMICs, including countries from three continents - Asia, South America, and Africa, making our sample representative of the globally affected population in LMICs. Lastly, when estimating the total number of children affected by tropical cyclones worldwide, we assume that the average effects observed in our sample apply to all LMICs. However, it is important to acknowledge that tropical cyclones can have different effects in exposed countries for which we do not have data. Furthermore, we only provide the number of affected students for the period from 2000 to 2019 due to the absence of age-gender population data before 2000.

In this study, we investigate the impacts of tropical cyclones on education in 13 LMICs with education records of more than 5.1 million people obtained from survey data. Our analysis spans a broad range of geographical locations and storm events with a wide variety of intensities, enabling a comprehensive understanding of the heterogeneity of the effects and the generalization of the effects across LMICs. We find that exposure to tropical cyclones during preschool years is associated with decreased primary enrollment, primary completion, and secondary enrollment. The effects are particularly more pronounced in vulnerable communities, such as school-aged girls and people less frequently exposed to strong storms. Our analysis sheds light on a plausible pathway through which climate extremes impact human capital development, an area that has received less attention in previous studies.

Figures

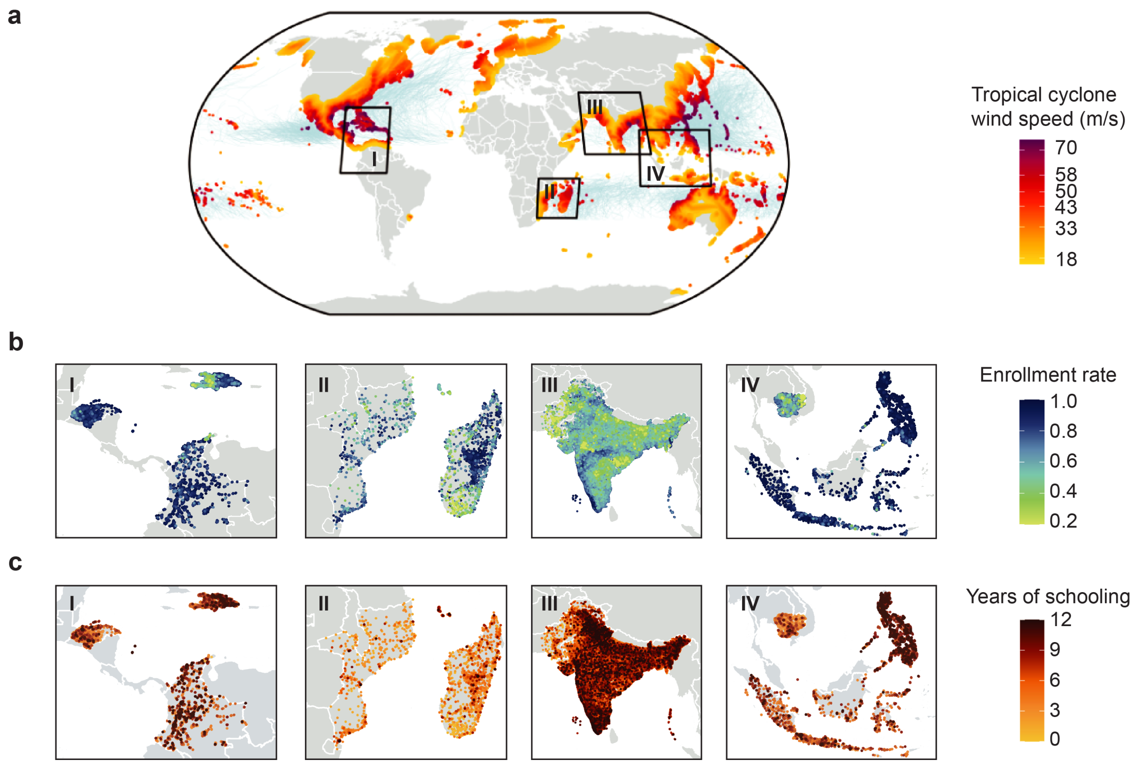

Figure 1: **Description of data.** Subplot (a) shows global distribution of maximum wind speeds (in unit of m/s) of tropical cyclones in 2000- 2019. Storm tracks are shown in light blue curves. Four subregions that include 13 LMICs in our sample are enlarged: (I) Madagascar, Mozambique and Comoros (II) India, Pakistan and Bangladesh (III) Philippines, Indonesia and Cambodia (IV) Dominican Republic, Honduras, Haiti and Colombia. Subplot (b) shows the average primary school enrollment rate, and subplot (c) shows the average total years of schooling for each DHS cluster. The country outlines were obtained from Global Administrative Areas, version 4.1. (*36*)

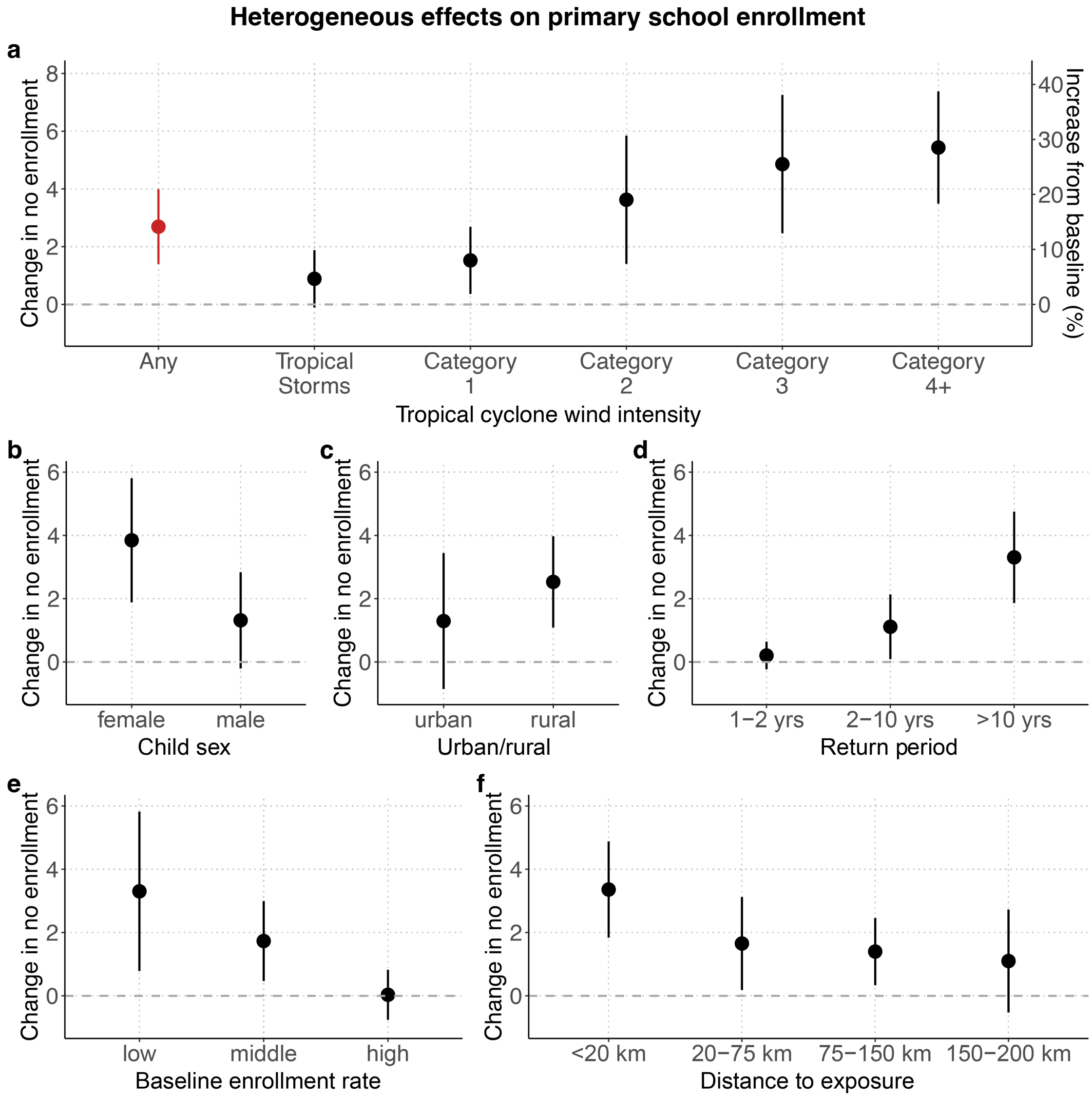

Figure 2: **Heterogeneous effects of tropical cyclone exposure on primary school enrollment by wind intensity, gender, urban/rural, return period, baseline enrollment rate, and distance to exposure.** (a) The impacts of tropical cyclone exposure on primary school enrollment increase monotonically with intensity. The main y-axis shows effects in percentage points, and the secondary y-axis represents the relative increase from baseline non-enrollment rate. The intensities of tropical cyclones are classified into Tropical Storms (<33 m/s), Category 1 (33-43 m/s), Category 2 (43-50 m/s), Category 3 (50-58 m/s) and Category 4+ (>58 m/s), based on the Saffir-Simpson Hurricane Wind Scale. (b) Effects on enrollment by child sex. More pronounced effects are observed among school-age girls. (c) Effects on enrollment by urban/rural. (d) Effects on enrollment in regions with frequent exposure versus those with infrequent exposure, measured by the average return period of tropical cyclones at the Category 1 wind level. More pronounced effects are observed in regions that are less frequently exposed to tropical cyclones. (e) Effects on enrollment by average enrollment rate. More pronounced effects are observed in communities with lower baseline enrollment rate. (f) Effects on enrollment gradually decrease with increasing distance from tropical cyclone exposure.

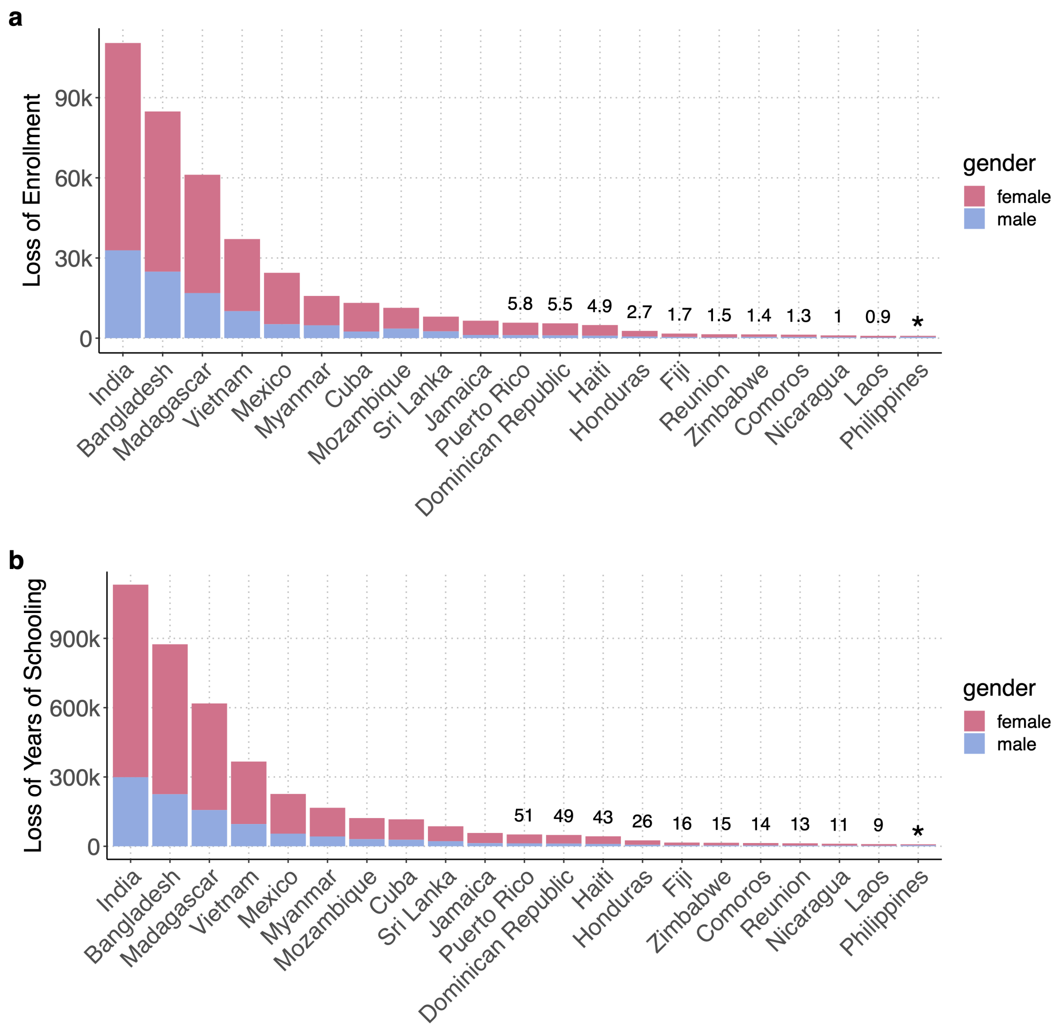

Figure 3: **Estimated losses of enrollment and losses of years of schooling attributable to tropical cyclone exposure.** (a) Estimated number of individuals in LMICs that would have enrolled in primary school had they not been affected by tropical cyclones between 2000-2019, broken down by child sex. This estimate takes into account the heterogeneous effects caused by variations in sex and adaptation levels. The top 20 countries with the most children affected are shown, and the top three countries affected are India (110k), Bangladesh (85k), and Madagascar (61k). (b) Estimated losses in years of schooling associated with tropical cyclone exposure between 2000-2019, broken down by child sex. Similarly, the 20 countries with the most children affected are shown, and the top three countries affected are India (1.1 mi), Bangladesh (0.8 mi), and Madagascar (0.6 mi). On a special note, we denote the Philippines with an asterisk '*' in both panels. Despite its large population and the high probability of exposure, the Philippines experiences a relatively small number of children not enrolled in primary school due to tropical cyclones, as its baseline enrollment rate has been consistently high over the years.

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Author contributions

R.J. and E.B. conceived the idea. R.J. generated tropical cyclone wind data and processed education data. R.J. led the study design with inputs from all authors. R.J., E.B., S.H.-N, Z. Wang, Z. Wagner, M.Q., I.O. led the causal analysis. R.J. and J.C. led the measurement error analysis. R.J., E.B., Z. Wagner, S.H.-N led the writing of the manuscript. All authors contributed to the interpretation of the results and the revision of the manuscript.

Competing interests

The authors declare no competing interests.

Data and materials availability

Data and code to replicate all results in the main text and supplementary materials will be made available in a public repository.

Materials and Methods

Children schooling records

We obtain data on children's schooling attainment and grade completion records from the Demographic and Health Surveys (DHS), a series of nationally representative household surveys conducted in LMICs (*1*). The DHS follows a two-stage design, where clusters (approximately villages or neighborhoods) are first selected from a list of enumeration areas created in a recent population census, and then households are randomly chosen from each of the DHS clusters. A household census that includes information on schooling history is conducted for all household members in every selected household. Schooling information includes current year schooling status (still in school or not), schooling attainment, and total years of schooling completed. School attainment is incomplete primary education, complete primary education, incomplete secondary education, and complete secondary education (Table S1). Household characteristics such as urban/rural are also documented. Since the late 1990s, DHS surveys have been georeferenced, where longitude and latitude are provided for each cluster's centroid.

We use data from 32 georeferenced surveys carried out between 1997 and 2022 from 13 LMICs that were exposed to tropical cyclones. We restrict our sample to participants over 10 years old at the time of the survey to exclude children that may still enroll in school (and we vary this assumption below). Our sample includes 82,233 DHS clusters with more than 5.1 million individuals born between 1954 and 2010. For each individual, we create a binary indicator to reflect their primary school enrollment based on the person's educational attainment. The baseline enrollment rates for each calendar year are shown over time for both boys and girls, separately for each country, in Figure S3.

In addition to primary school enrollment, we also examine three secondary outcomes. We define primary education completion as a binary variable marked as true if an individual's schooling attainment is not classified as either 'no education' or 'incomplete primary education'. Similarly, we define secondary school enrollment as true if an individual is classified as either 'secondary education' or 'higher education'. Furthermore, the survey data directly provide the total years of schooling completed for each individual at the time of the survey, which we use as a continuous outcome. We limit our samples to individuals aged 22 and above for the secondary outcomes analyses to allow respondents to complete school. We choose thresholds to balance the size and generalizability of our sample with the plausibility of inclusion criteria.

Tropical cyclone affected areas

We use tropical cyclone tracks sourced from the International Best Track Archive for Climate Stewardship (IBTrACS, version v04r00) (*2*, *3*), which provides 6-hourly latitude and longitude of tropical cyclone positions and the maximum sustained wind speed at 10-m height above level ground. To construct the affected area associated with each storm, we use parametric wind models to estimate the complete wind field of each storm. The family of parametric wind models is capable of generating complete wind speed profiles with few inputs, which is particularly suitable for global studies like ours. We opt for the model introduced by Chavas et al. (*4*), which mathematically merges an inner-wind model (*5*) and an outer-wind field model (*6*) to produce the complete azimuthal wind associated with a storm. Although the original wind model was developed based on the structure of mature storms over the ocean, recent studies have also demonstrated its effectiveness over land (*7*). The parametric wind model has proven to be successful in studies examining tropical cyclone population exposure (*8*), tropical cyclone induced flood risks (*9*) and power damage (*10*).

The tropical cyclone parametric model requires the following storm parameters as input: maximum wind speed of the storm V_m, radius of maximum wind speed R_{max} for the inner region or radius of a specific intensity R_{fit} (e.g., R_{34}, which represents the distance from the center of the storm where the wind speed decreases to 34 knots).

In IBTrACS, R_{34} has been available since 2002 and R_{max} has been available throughout the study period, while R_{max} has greater uncertainties compared to R_{34} (*11*). Based on this data availability, we adopt two different approaches to account for wind asymmetries over land. For storms where the outer radius R_{34} is available, we explicitly consider the asymmetry by simulating wind fields in each earth-relative quadrant, using quadrant-specific storm and surface parameters as model inputs. In cases where the outer radius R_{34} is not available, we use R_{max} as model input to compute the axis-symmetric component of the storm's wind field. Additionally, we incorporate an asymmetric component to account for the asymmetry induced by the combined effects of storm movement and ambient wind shear (*12*). We simulate the full wind profile of tropical cyclones for each storm and then integrate the wind fields of all historical storms spanning from 1950 to 2020. We then calculate the annual maximum wind speed for each location and generate a tropical cyclone grid wind data set with a resolution of approximately 10 km.

Tropical cyclone exposure

We assess tropical cyclone exposure by spatially merging the location of each DHS cluster with the maximum nearby tropical cyclone wind speed in each year from 1950 to 2020. We assign the maximum wind speed within a 20 km buffer zone, which reflects both uncertainty in the exact location of the DHS clusters and the spatial extent of tropical cyclones. We thus obtain an annual panel of maximum wind speeds from tropical cyclones for each cluster. Using these data, we then calculate the maximum wind speed for each year from birth until the age of 14 for each individual in the survey, covering a span of 15 years.

For assessing schooling outcomes, we consider children exposed to a tropical cyclone if their cluster of residence was in the wind field of a tropical cyclone with a maximum wind speed equal to or greater than 33 m/s (Category 1 or higher) when they were 5 or 6 years old. We chose this age of exposure to correspond to the age of enrollment among the children in our sample (Figure S4) and the mechanisms that link tropical cyclones and loss of schooling: physical destruction and household financial shocks. We also generate a categorical variable to denote the intensity of maximum tropical cyclone winds encountered during preschool age, with the following wind thresholds: no exposure (maximum wind speed less than 25 m/s), Tropical Storm (greater than or equal to 25 and less than 33 m/s), Category 1 (greater than or equal to 33 and less than 43 m/s), Category 2 (greater than or equal to 43 and less than 50 m/s), Category 3 (greater than or equal to 50 and less than 58 m/s), and Category 4 and above (greater than or equal to 58 m/s). Following Emanuel and Rotunno (*13*), we set the no-exposure wind cut-off at 25 m/s, assuming that exposure to wind speeds below this threshold is considered to pose no damage.

Finally, we create variables that capture exposures at greater distances from the cluster, 75, 150 and 200 km away. We identify exposure within each region (<20 km, 20-75 km, 75-150 km, 150-200 km) analogously to the primary analyses. We limit the largest radius to 200 km, since this is the typical size of the major circulation of a tropical cyclone over the ocean. Tropical cyclone exposure is classified into these four regions according to their distance from the center of the storm. If the exposure occurs in multiple regions, it is classified according to the closest distance to the storm center. For example, if for a cluster the maximum tropical cyclone wind exceeds 33 m/s in both 20-75 km and 75-150 km regions, and without exposure in other distances, then the exposure is classified as occurring at a distance of 20-75 km.

Empirical approach

For our main schooling outcome, we model the relationship between the probability of enrollment in primary school and tropical cyclone exposure using the following fixed-effects model with a linear link function.

$$Y_{ict} = \alpha + \beta D_i + \lambda \boldsymbol{X}_{ct} + \delta_c + \gamma_{co,t} + \epsilon_{ict}$$

where Y_{ict} is an indicator of whether child i in the DHS cluster c enrolled in primary school, where t indexes the year of age 6. D_i is a binary variable equal to 1 if the child i was exposed to tropical cyclones at the age of 5 or 6, and equal to 0 if not; $\boldsymbol{X}_{ct}$ is a vector of additional controls potentially correlated with both tropical cyclone exposures and school enrollments, including household and individual characteristics, such as child sex, urban/rural and wealth quantile, and climate variables that vary over time, such as local temperature at 2 meters (*14*). δ_c and $\gamma_{co,y}$ are DHS cluster and country-year effects, respectively. ϵ_{ict} denotes the error terms. The cluster effects control for time-invariant cross-village differences (for example, higher or lower average school enrollment rates) and country-year effects control for trends or abrupt shocks common to all locations (for example, macroeconomic shocks or increases in enrollment over time). To ensure that our estimates can reflect the entire 13-country sample, we adjust observations using combined values of country-specific household survey weights (provided by DHS) and the weights of the country's population, following the previous study (*15*). We clustered standard errors at the DHS cluster level as this is the level at which TC exposure varies in our data (*16*).

Heterogeneity analyses

We assess heterogeneity across a variety of child and household characteristics, including urban/rural, child sex, baseline enrollment rate, and distance to exposure. Additionally, we introduce the return period of TCs for each cluster to assess whether areas that are exposed more frequently, and thus might have taken more adaptive measures, experience smaller education consequences compared to areas exposed less often.

The return period of a cluster refers to the average time interval between the occurrences of a tropical cyclone at a specific wind level. We calculate the return period of each cluster using 70 years of data (from 1950 to 2019) to estimate the average time interval in years that each cluster is exposed to tropical cyclone winds of a certain intensity. For example, if a cluster was exposed to Category 1 or more intense storms 7 times during the 70-year period 1950 - 2019, then the annual exceedance probability is 10%, which is associated with a return period of 10 years. In this way, we label each DHS cluster by return period, and classify all clusters into three mutually exclusive bins: the ">10 Years" subgroup includes clusters that have a return period larger than 10 years or clusters that have never been exposed before, which represent regions that are rarely affected by tropical cyclones. Similarly, the "2-10 Years" group includes clusters that have a return period larger than 2 years and smaller than 10 years, and the "1-2 Years" subgroup includes clusters that have experienced frequent exposure annually or biennially. Moving from ">10 Years" to "1-2 Years", the clusters are more and more frequently exposed to tropical cyclones, and we estimate the heterogeneity in effect size across these different locations. In addition to the main analysis, we also perform a robustness analysis using different choices of return period bins: "1-5 Years," "5-20 Years," and ">20 Years," utilizing the same methodology.

We use the average baseline enrollment rate as an indicator of the degree to which education is prioritized. For each DHS cluster, we calculate the average enrollment rate throughout the study period and categorize it as 'low', 'middle', or 'high' based on whether it falls within the lower, middle or upper third, which corresponds to an average enrollment rate lower than 0.77, between 0.77 and 0.92, or higher than 0.92.

To identify the disparities in effects, we categorize tropical cyclone exposure according to the intensity of exposure or the distance from exposure to examine how effects vary. We also examine heterogeneity in child sex, urban/rural, baseline education rate, and return period by interacting these variables with the binary variable of tropical cyclone exposure to estimate the effects for each subgroup. Taking child sex as an example, we introduce an interacting term that combines binary tropical cyclone exposure D_i with dummy variables representing child sex, as shown in the following formula.

$$Y_{ict} = \sum_s \beta_s (I_s D_i) + \delta_c + \gamma_{co,t} + \epsilon_{ict}$$

In this equation, I_s is a dummy variable to determine whether the child i falls into the bin s (female or male). The coefficients β_s provide the marginal effect of the tropical cyclone separately for each gender. For sex heterogeneity, we control fixed effects at both the cluster-sex level and country-year-sex level, considering that the baseline trends among boys and girls can be very different S3. For urban/rural, baseline education rate, and return period, we use the same fixed effects that control at both the cluster level and the country-year level, consistent with the main model specification.

Calculating no schooling attributable to tropical cyclones

We use the estimated effect size for primary school enrollment (by sex and return period) to calculate the total count of children who did not enroll in primary school due to tropical cyclones. We assume the same effect size across all LMICs that have encountered tropical cyclones (not limited to DHS survey sites), accounting for the different return periods. To estimate the total number of affected children, we first compute the return period of tropical cyclones with a wind speed of 33 m/s for each grid cell, which we then use to assign an effect size. Next, we calculate the total number of children who did not enroll in primary school in each year y for each location i using the following equation:

$$N_{i,t,s} = C_{i,t,s} \times \mathbf{1}_{\mathrm{TC}_{i,t}} \times E_{i,s}$$

Here, $C_{i,t,s}$ represents the count of preschool-age children (boys or girls, represented by s) on the grid i during the year t. We calculate the number of children affected between 2000 and 2019, covering a 20-year period that is limited by the availability of population age and gender data from Worldpop (*17*). The dummy variable $\mathbf{1}_{\mathrm{TC}}$ indicates whether the grid i was exposed to tropical cyclone winds of 33 m/s or greater in year t, and $E_{i,s}$ represents the estimated effect size for each grid based on its return period and child sex. The total number of children affected by tropical cyclones between 2000 and 2019 is therefore the sum of $N_{i,t,s}$ in all locations and over the 20-year period.

References for Methods

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Supplementary Methods

Measurement errors in tropical cyclone exposure

Measurement errors in tropical cyclone exposure come from several sources. First, data on the outer radius of tropical cyclones (R_{34}) are only accessible from 2002 onward. For earlier storms lacking documented R_{34} in IBTrACS, we estimate the complete wind profile based on R_{max}, despite the higher uncertainties associated with R_{max}. To quantify this uncertainty, we analyze recent storms where both R_{34} and R_{max} are available. We show that in cases where tropical cyclone size data are of high quality, the wind profiles estimated from R_{max} closely match those estimated from R_{34} across a spectrum of storms, from Tropical Storm to intense Category 4 storms (Figure S13a-e). Only in cases where the storms have atypical structures, such as a strong storm with a compact inner region but also spreading out with a large outer circulation (characterized by a relatively larger R_{34} but smaller R_{max}), there is a noticeable deviation between the two profiles (Figure S13f). In such cases, the wind profiles generated based on R_{max} can underestimate the extent of the strong wind region, leading to an underestimate of areas experiencing wind speeds of 33 m/s or above, which we identify as exposed regions.

Second, for privacy concerns, the central point of the populated area of each cluster has been displaced by up to 2 km in urban clusters, 5 km in 99% of rural clusters, and 10 km in a random sample of 1% of rural clusters, according to the DHS official. We analyze the magnitude of uncertainties and note that this displacement would result in a measurement error ranging between 2-5 m/s, and at no more than 10 m/s even during extremely high wind conditions (not shown).

Supplementary tables

Table S1: Basic statistics of exposed and unexposed sample

Characteristic	**Exposed**		**Unexposed**	
	N	**N = 325,006**	**N**	**N = 4,689,631**
sex	325,006		4,689,631	
male		158,230 (49%)		2,293,675 (49%)
female		166,776 (51%)		2,395,956 (51%)
total years of schooling	325,006	7.75(4.83)	4,689,631	7.00(4.90)
education attainment	325,006		4,689,631	
no education		37,488 (12%)		918,106 (20%)
incomplete primary		61,535 (19%)		604,596 (13%)
complete primary		28,826 (8.9%)		384,520 (8.2%)
incomplete secondary		100,113 (31%)		1,768,334 (38%)
complete secondary		38,916 (12%)		439,277 (9.4%)
higher		58,128 (18%)		574,798 (12%)
wealth index	312,318		4,595,974	
poorest		53,876 (17%)		944,153 (21%)
poorer		62,629 (20%)		982,747 (21%)
middle		66,806 (21%)		933,990 (20%)
richer		67,366 (22%)		874,202 (19%)
richest		61,641 (20%)		860,882 (19%)
place of residence	325,006		4,689,631	
rural		197,000 (61%)		3,247,500 (69%)
urban		128,006 (39%)		1,442,131 (31%)

* n (%); Mean(SD)

508 # Supplementary figures

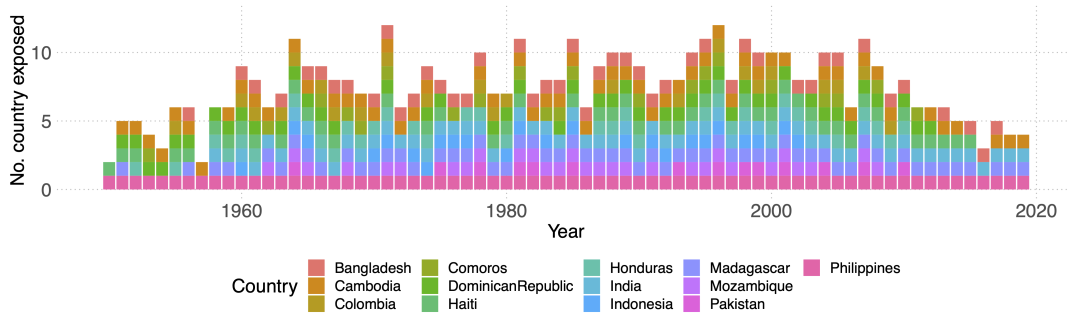

Figure S1: **Variation in TC exposure by country and year.** The bar plot shows the number of countries exposed to tropical cyclones each year. Each country is represented by a color block. We observe substantial variations in the tropical cyclone exposure, with some years seeing only half of the study countries being affected, and some countries exposed yearly while others are exposed only a handful of times during the study period.

Figure S2: **Distribution of total years of schooling by country.** The distribution of each country is estimated based on the population of individuals aged 22 or above at the time of the survey. For all countries except the Philippines, a significant number of people did not enroll in primary school and did not have a formal education. The distribution of total years of schooling in each country is highly determined by the length of each stage within the education system, where a significant portion of the population does not pursue secondary education following the completion of primary education, especially seen in countries such as Colombia, Honduras, Indonesia, Pakistan, etc.

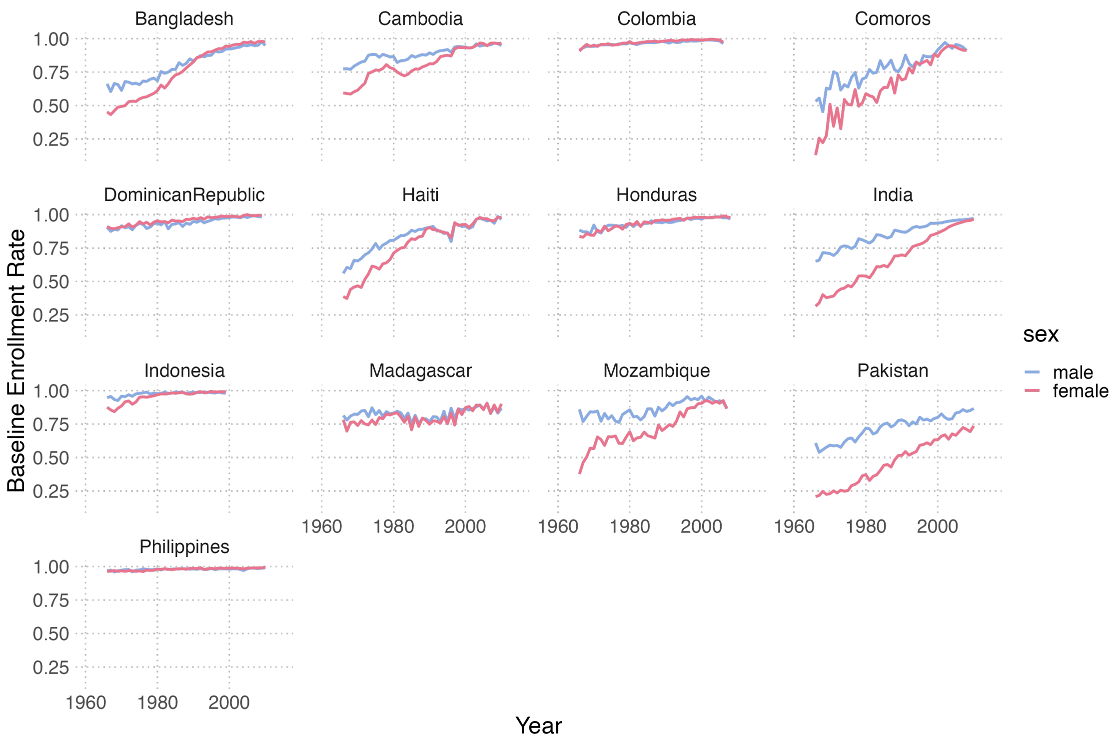

Figure S3: **Baseline primary school enrollment rate for both genders over the years by country.** The enrollment rate is calculated for each calendar year based on the population who were aged 6 in that specific year. For all countries, we observe a steady improvement in enrollment rate for both boys and girls. However, there exists a huge gap between boys and girls, in countries such as India, Mozambique and Pakistan. The Philippines stands out as unique, with a primary school enrollment rate as high as 0.96 even as early as the 1960s.

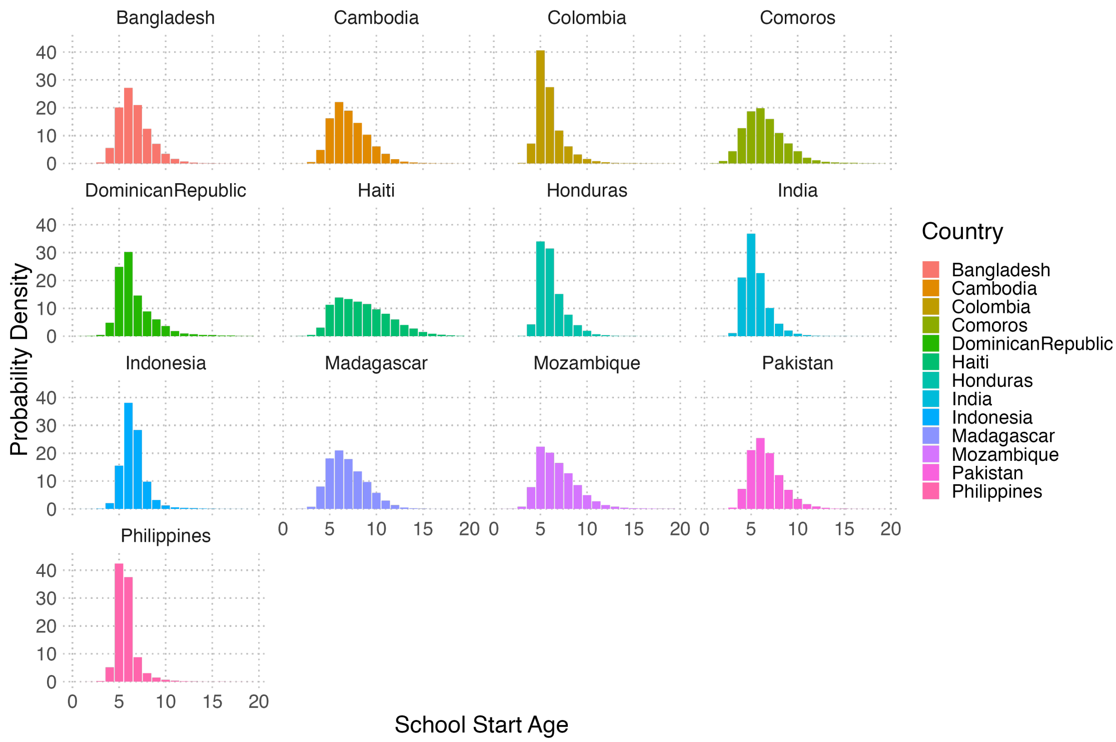

Figure S4: **Distribution of primary school start age by country.** The distribution of school start age in each country is estimated based on the population of individuals who were still attending school at the time of the survey. We determine the age at which these children began their education by subtracting their years of schooling from their age, which represents the distribution for the entire population. Children typically start school at the age of 5 or 6, with the majority enrollment occuring between age 5-7, however we also observe a much broader range of starting ages extending to the age of 15. In some countries, pre-primary education is considered the initial stage of primary education, and as a result the earliest observed age for starting education can be 3 years old in our samples.

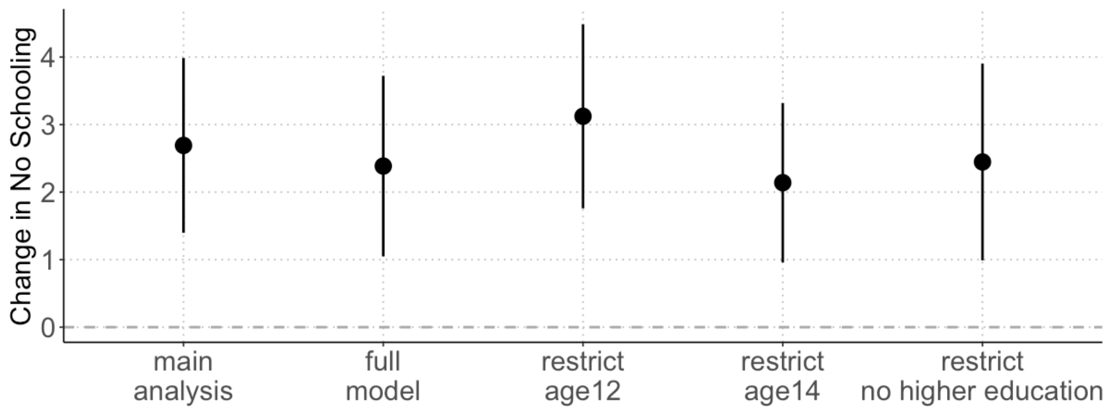

Figure S5: **Robustness of main estimates.** The effects of tropical cyclones on primary school enrollment in the main text is shown with label 'main analysis'. The binary estimate of effects, derived from samples restrict to individuals aged 12 or 14 and older at the time of survey (as opposed to age 10 for the main analysis), is labeled as "restrict age 12" and "restrict age 14", respectively. The model that includes a large set of additional covariates is referred to as the 'full model', which controls child sex, urban/rural, household wealth index (represented as quantile), and annual ambient air temperature at 2m. Binary estimates derived from samples limited to individuals whose highest educational attainment is primary or secondary are labeled as "restrict no higher education". We show that the main estimates are robust to these sensitivity analyses.

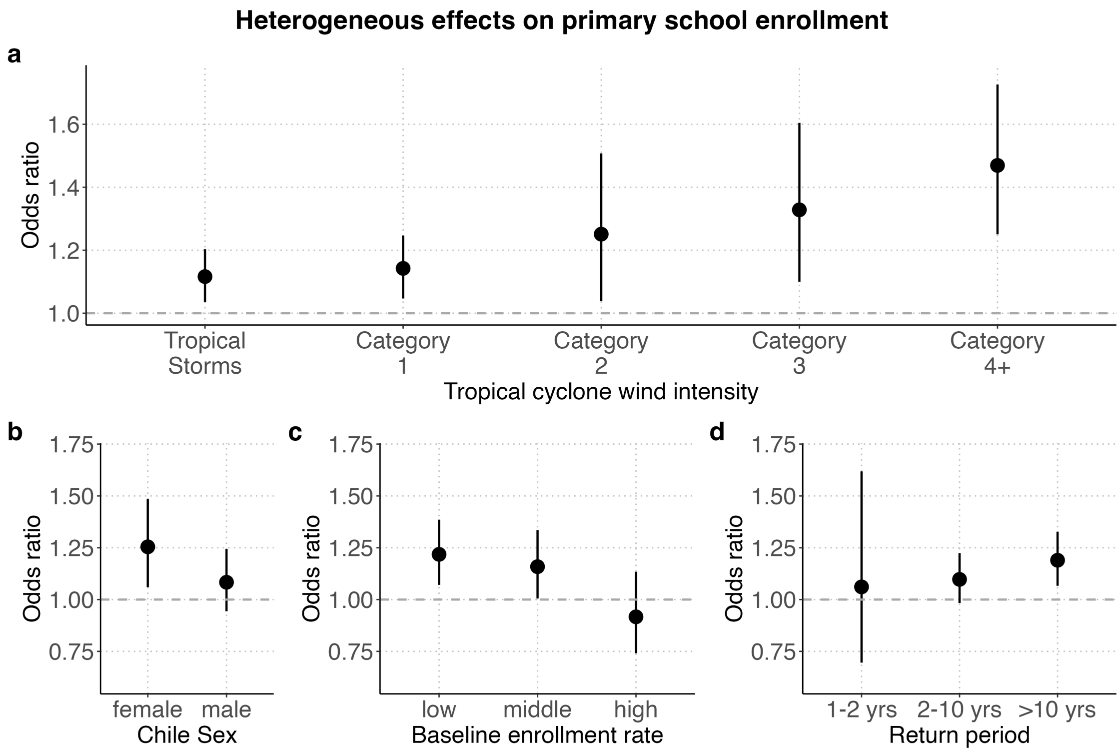

Figure S6: **Effects of tropical cyclone exposure on primary school enrollment estimated using logistic regression.** We estimate the effects of tropical cyclone exposure on primary school enrollment using fixed effect generalized linear model with logit link function. The model controls for cluster fixed effects and country-year fixed effect, same with main model specification. The effects are expressed in odds ratio, where a negative odds ratio represents a lower likelihood of primary school enrollment, compared with no exposure. We observe similar estimates and relationships as in the main analysis, where the effects attenuate with stronger wind intensity, and are more pronounced among school-age girls, in areas with less frequent exposure, and in communities where education is less prioritized.

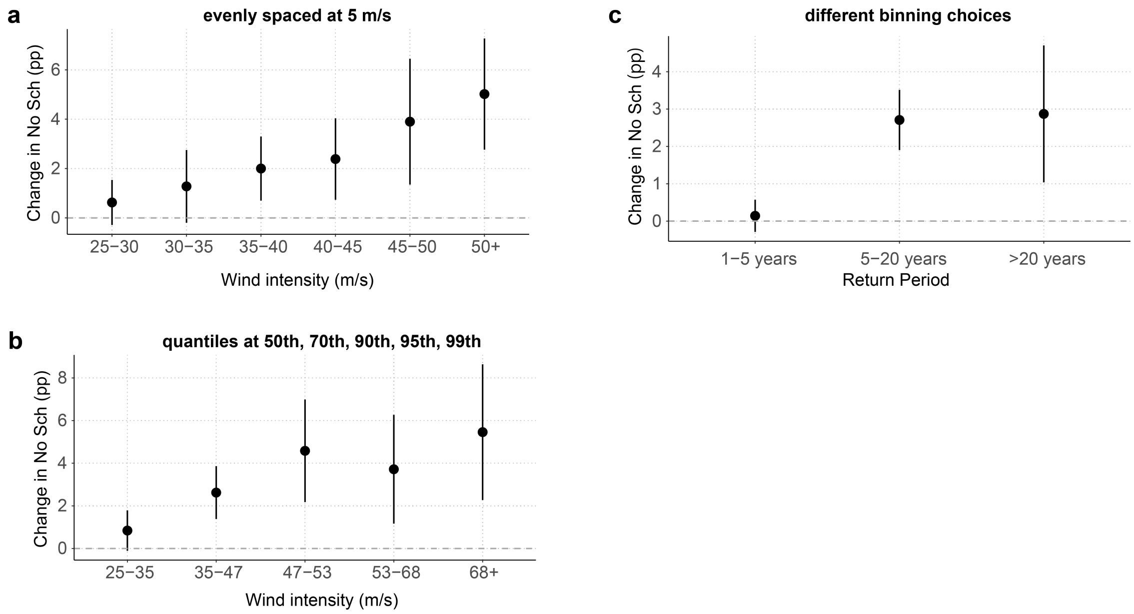

Figure S7: **The heterogeneous effects observed in exposure intensity and level of adaptation are robust to binning choices.** In panel (a-b), we show that the overall shape of the estimated response remains consistent across different choices of tropical cyclone wind binning, when (a) the wind is evenly spaced at 5 m/s or (b) binned to selected quantile cutoffs. In panel (c), we show that the heterogeneity analysis of the return period is robust to the binning choice of 1-5 years, 5-20 years, and >20 years.

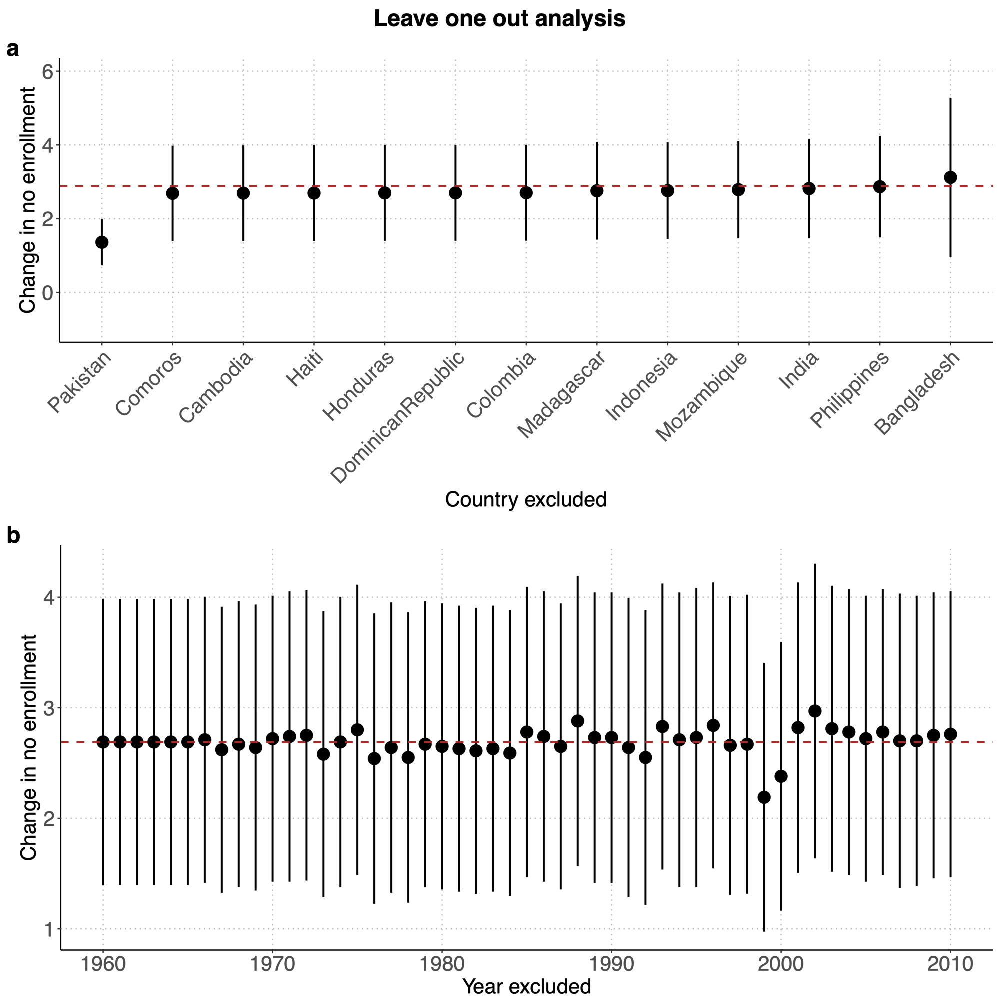

Figure S8: **Binary estimates after exclusion of each country or each year individually**. We show the sensitivity of our binary estimate by running the primary specification while excluding observations for (a) each country individually and (b) each year individually. By removing each country, we observe a variation in the main effect ranging from 1.4 to 3.1 pp. By removing each year, we observe a variation in the main effect ranging from 2.2 to 3.0 pp. The results indicate that our findings are consistent regardless of the country included and are not dominated by a single year. The red dashed line in each panel represents the binary estimate reported in the main text (2.7 pp).

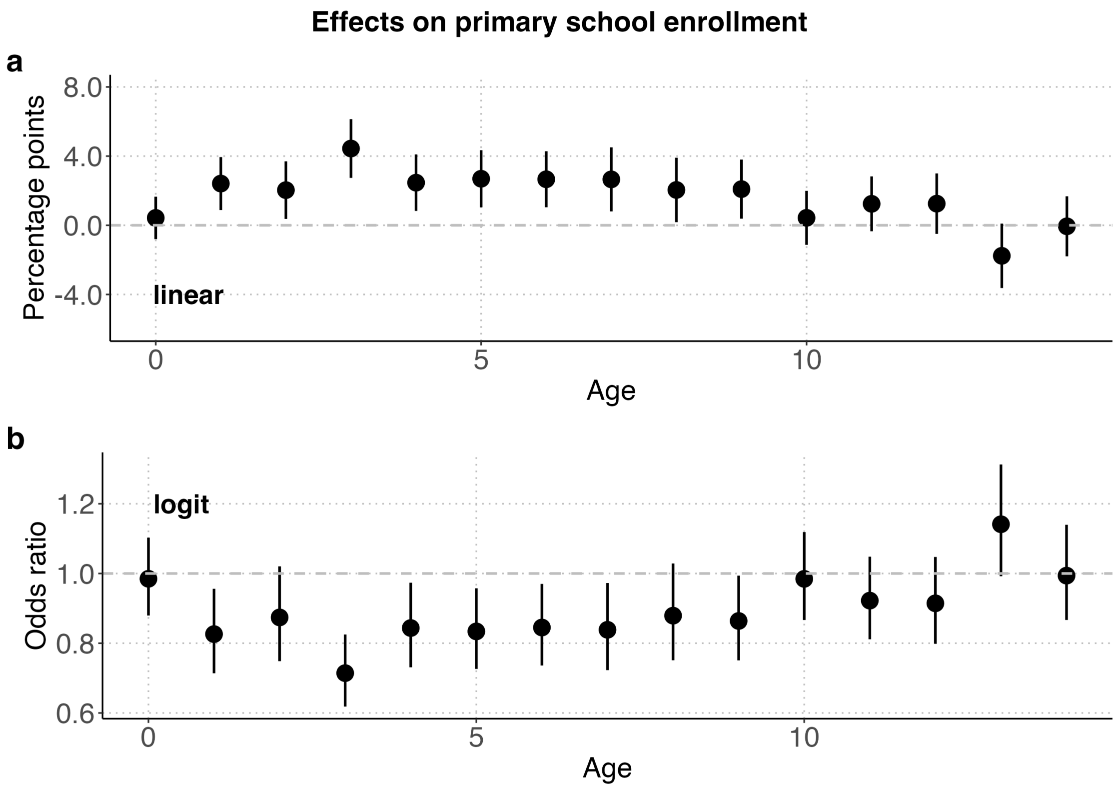

Figure S9: **Effects of tropical cyclone exposure at age 0-14 on primary school enrollment.** Coefficients were generated from fixed effect models which regress whether the child enrolled using a series of binary variables indicating any tropical cyclone exposure from age 0 to age 14, with (a) linear link function and (b) logit link function. These analyses control for fixed effects at cluster and country-year levels, the same as the main model specification. We observe significant effects of tropical cyclone exposure for the early life period of 3 to 9, suggesting that exposure before school start could have an impact on school enrollment. Children who live in LMICs have a wider range of starting ages S4, which partially explains why significant effects can still be observed at the age of 9. We did not observe significant effects of tropical cyclone exposure after the age of 9, which is consistent with the evidence that most enrollments occur before the age of 10.

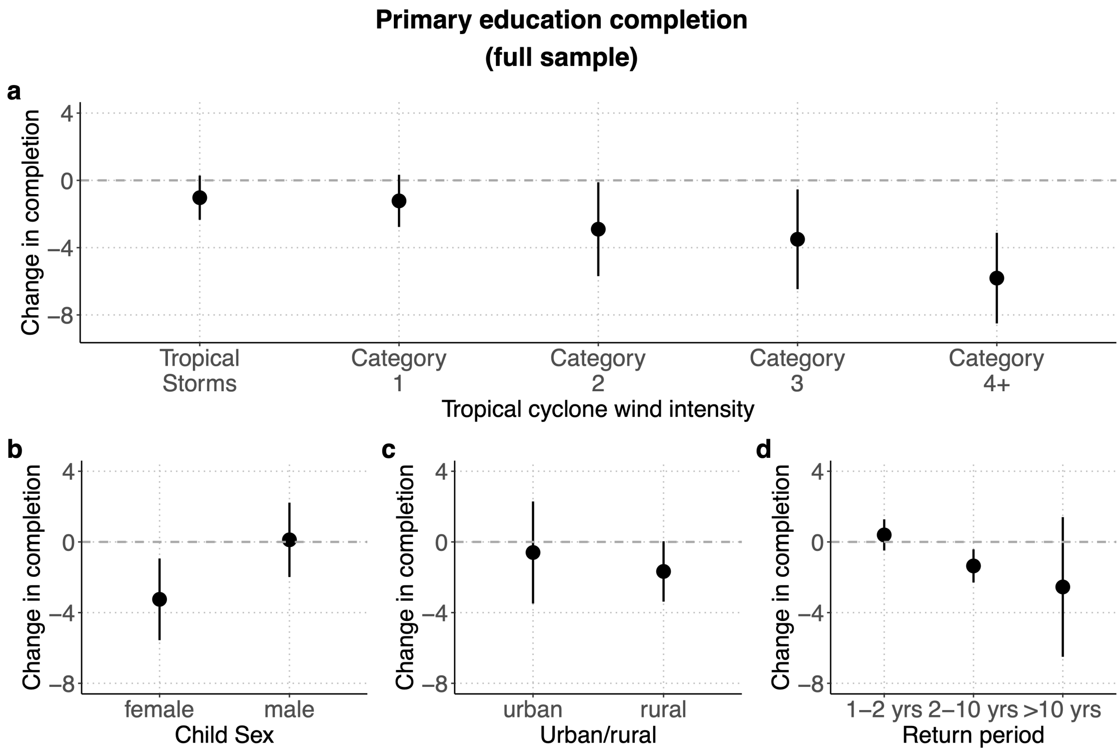

Figure S10: **Results for primary school completion with full sample.** Similar to 2, we show the heterogeneous effects of tropical cyclone exposure on primary school completion by (a) wind intensity, (b) gender, (c) urban/rural, and (4) return period as a measurement of the level of adaptation. We show that the tropical cyclone exposure is negatively related to primary school completion, and the effects are more pronounced when storms are stronger, among school-age girls and in areas that were less frequently exposed.

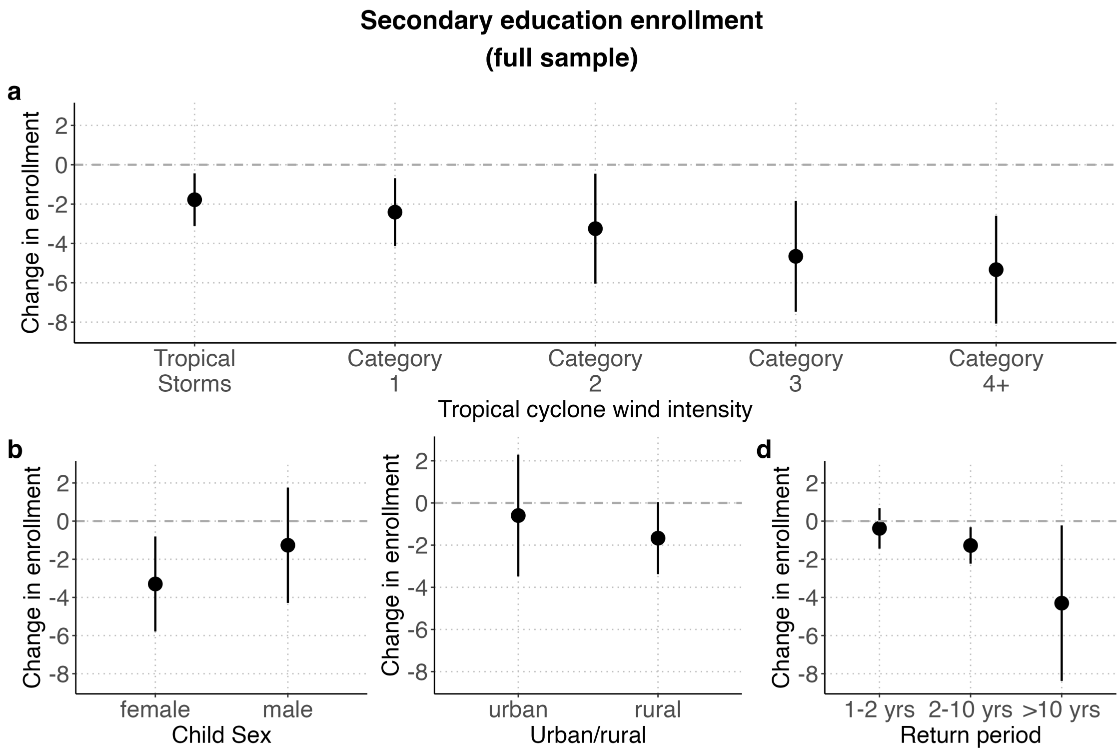

Figure S11: **Results for secondary education enrollment with full sample.** Similar to 2 and S10, we show the heterogeneous effects of tropical cyclone exposure on secondary school enrollment by (a) wind intensity, (b) gender, (c) urban/rural, and (4) return period as a measurement of the level of adaptation. Exposure to tropical cyclones is associated with a decrease in secondary school enrollment, particularly when storms are stronger, among school-age girls, and in areas with less frequent exposure.

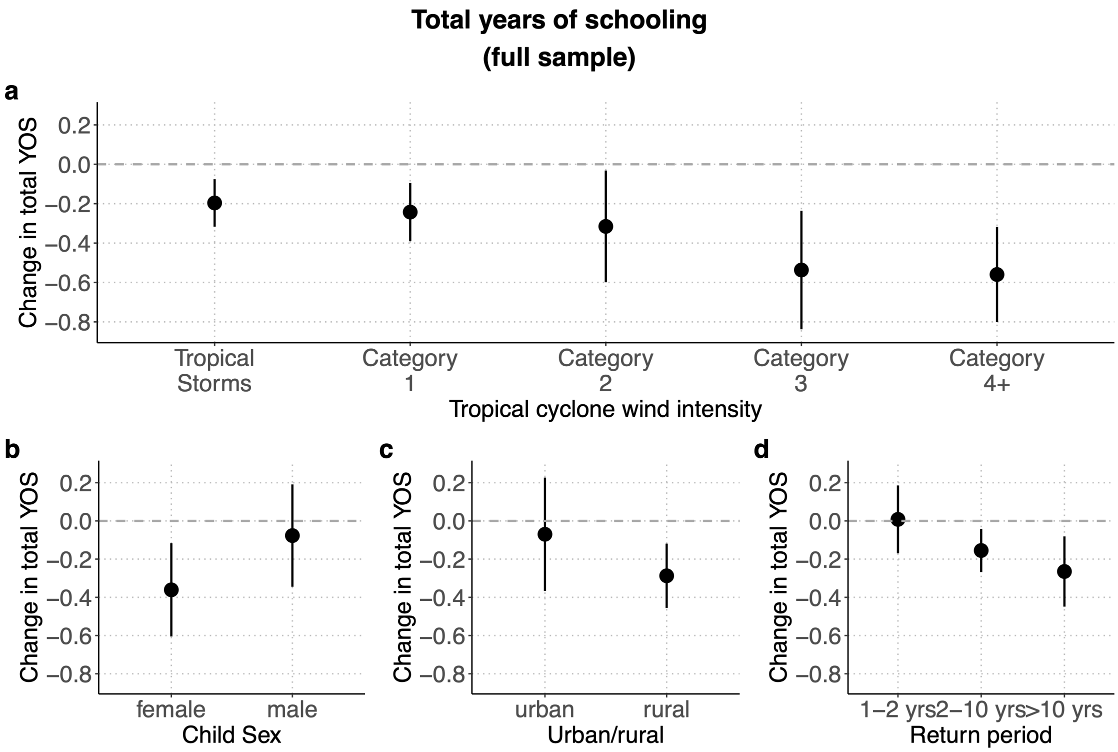

Figure S12: **Results for total years of schooling with full sample.** Similar to Fig. 2, we show the heterogeneous effects of tropical cyclone exposure on total years of schooling by (a) wind intensity, (b) gender, (c) urbanity, and (4) return period as a measurement of the level of adaptation. Exposure to tropical cyclones of Tropical Storm level is associated with a decrease in total years of schooling of 0.2 years. This effect triples to 0.6 years if exposed to Category 4 or more intense storms. The effects are more pronounced among girls compared to boys, particularly in rural areas and in regions that experience less frequent exposure to tropical cyclones.

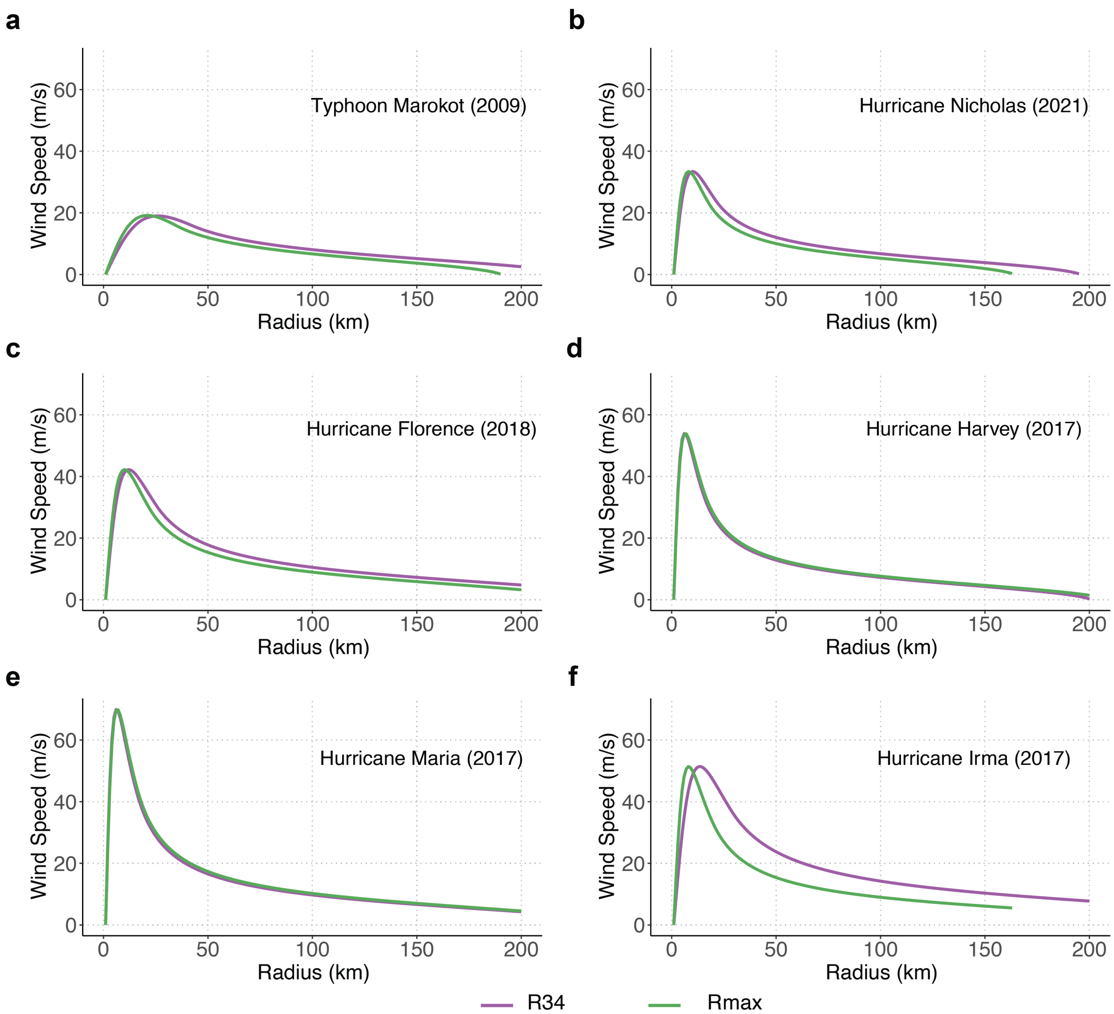

Figure S13: **Measurement errors in tropical cyclone exposure.** We quantify uncertainties in the identification of tropical cyclone exposure by comparing the azimuthally averaged wind profile estimated from R_{34} and R_{max}, using recent storms as case studies. We show that the wind profiles estimated from R_{max} closely match those estimated from R_{34} in a broad spectrum of storms with varying intensities (subplots a-e). Only in cases where storms exhibit atypical structures, such as Hurricane Irma (2017) which has a compact inner region but also expands with a broad outer circulation, is there a noticeable deviation between the two profiles (f).