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Tropical cyclones and fertility: New evidence from developing countries[☆]

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ABSTRACT

Does exposure to tropical cyclones affect fertility? This paper addresses this question by constructing a panel dataset from geolocated micro-data about the fertility history of mothers along with their local exposure to tropical cyclones for a sample of six developing countries for the 1985–2015 period. We then estimate the causal effect of tropical cyclone shocks on women's likelihood of giving birth. We find evidence that tropical cyclone exposure has a significantly negative effect on motherhood. A cyclonic wind exposure between 60 and 117 km/h (resp. at least of 118 km/h) decreases the probability of giving birth by 7.8 (resp. 7.0) points a year after exposure. We also observed that the magnitude of the effect varies with the degree of cyclonic exposure associated with the mothers' living environment and the number of children ever born. In particular, the fall in the likelihood of giving birth is lower for mothers living in cyclone-prone areas and for those who already have children. Alternative specifications of our baseline model provide further insights: (i) recent past exposure to cyclones was associated with a lower decrease in fertility when exposed once again; and (ii) no evidence of non-linearities was observed in the effect.

1. Introduction

Evidence about the consequences of exposure to cyclonic systems at the individual level is still scarce (Anttila-Hughes and Hsiang, 2013). This lack of comprehensive micro-studies, which could be supported by strong data requirements, leaves many questions unanswered, especially how households reorganize their lives after being impacted by tropical cyclones. Exposure to tropical cyclones along with the associated destruction has the potential to impose high costs on households.¹ The micro-impacts of such adverse shocks are probably stronger in countries with weak institutional ways of coping, as is probably the case in developing countries (Dessy et al., 2019). In this context, children living in the household often play a specific role. They actively contribute to daily activities such as caring for siblings or grandparents, contributing to household chores, or directly participating in the labor market (Banerjee and Duflo, 2007, 2011) and Finlay (2009).² In light of this, parents' decision to have children is likely to be altered, both

positively and negatively, after exposure to a shock such as a tropical cyclone (Sellers and Gray, 2019). As a first piece of evidence, the data used in this paper show that 12% of women who have been exposed to cyclonic systems give birth the calendar year after the exposure compared with 19% for those who have not been exposed. Our paper therefore addresses the following question: does exposure to tropical cyclones causally impact fertility?

Understanding how households adjust their behavior after being exposed to adverse weather shocks such as tropical cyclones is of interest to researchers and policymakers alike, especially in the context of climate change that is expected to modify the frequency and intensity of tropical cyclones in the near future (IPCC, 2019; Knutson et al., 2020). However, the direction of these behavioral changes in terms of fertility is *a priori* unclear from both a theoretical and empirical perspective. In theoretical models such as those of Finlay (2009), P ortner (2014), and Dessy et al. (2019), the direction of the post-disaster decision to have children ultimately depends on assumptions about the benefits and costs associated with children. Empirical findings are

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(H. V er emes).

¹ These costs could relate to household income, livelihood, crop yields, assets, and loss of life.

² Banerjee and Duflo (2011) and Finlay (2009) indicate that in the absence of insurance mechanisms, children's contributions to households may substitute for standard insurance and allow them to smooth consumption over time.

³ According to Noy and duPont IV (2018) a natural disaster could be viewed as the interaction between a natural hazard and an exposed and vulnerable population (or assets) Given this definition, a non-exhaustive list of natural disasters include earthquake, flooding, landslide, tropical cyclones or tornado.

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inconclusive: (Nobles et al., 2015; Nandi et al., 2018), and Finlay (2009) found an increase in family size after a natural disaster, whereas a fall was identified by Evans et al. (2010), Pörtner (2014), Davis (2017), and Norling (2022). Given the inconclusive nature of these studies, it is still an open empirical question as to whether natural disasters affect fertility.³ The main goal of this paper is to rigorously establish the direction and magnitude of the causal effect of tropical cyclones on women's likelihood of giving birth using high-resolution data relating to their true exposure to tropical cyclones on the ground.

Most studies exploring the effect of natural disasters on fertility mainly focus on earthquakes. However, their results probably cannot be extended to the case of cyclonic events for at least two reasons. First, the macro-literature has shown that the consequences of natural disasters on economic growth are not identical for all types of disasters Fomby et al. (2013) and Felbermayr and Gröschl (2014). We can therefore conjecture that the magnitude or even the direction of the effect would differ for fertility depending on the type of natural disaster (Norling, 2022). Second, empirical studies on earthquakes mainly adopt a "one-event" approach by studying the fertility response after an earthquake shock of high intensity Finlay (2009), Nobles et al. (2015) and Nandi et al. (2018). Although the causal effect observed in these studies is undisputed, they do not consider variability in terms of the degree of exposure, the magnitude of the disaster event, or the existence of possible intensification effects. The database constructed here allows us to investigate such issues.

We first begin by presenting a simple theoretical framework of parents' decisions about fertility. The model thus developed, inspired by the works of Ranjan (1999), Finlay (2009), and Norling (2022), is used to frame the discussion and development of the empirical model. In particular, three working assumptions about post-cyclone fertility responses are derived from the model. The first suggests that after an adverse shock such as tropical cyclone exposure, the likelihood of giving birth is expected to fall in part because of a negative income effect. The second investigates the heterogeneous response of fertility for mothers living in cyclone-prone areas and those living in non-prone areas. In this respect, the model suggests that the former group is less sensitive to cyclone shocks. Finally, the third working assumption relates to the response of fertility after tropical cyclone exposure with respect to the number of children ever born. More specifically, the model suggests that the post-cyclone response in terms of fertility is independent from the number of children ever born.

We draw on two main databases to provide empirical evidence for our research questions. We first exploit 14 waves of the Demographic and Health Survey (DHS) from six countries, namely Bangladesh, Cambodia, the Dominican Republic, Haiti, Madagascar, and the Philippines.⁴ This cross-sectional household survey has several practical advantages for the issue at hand: it is nationally representative, has a large number of observations, contains information about individuals' characteristics, and provides geographic information about the location of households. In addition, the DHS includes the full fertility history of each woman interviewed together with detailed information about her geographic location. The second database used here is the Tropical Cyclone Exposure Database (TCE-DAT) of Geiger et al. (2018). This worldwide database provides high-resolution information about the wind field profile of more than 2,700 cyclonic systems, including 484 that made landfall in the six developing countries examined in this paper during the 1985–2015 period. By merging the geographic information of these two databases along with the fertility history of the DHS, we construct a panel data model that allows us to retrieve the tropical cyclone exposure of a given woman in a given year for the entire study period. The relationship between changes in tropical cyclone wind speed exposure and the likelihood of women giving birth

is then examined by means of fixed-effect regressions. In this manner, our panel reduced-form model has numerous advantages, since only a minimal set of assumptions is imposed.⁵

Our main empirical results can be summarized as follows. First, we can respond affirmatively to the abstract's question and our first working assumption: exposure to tropical cyclone wind speed does indeed impact fertility. Our panel setup indicates that the direction of the effect is negative. The point estimate suggests that a cyclonic wind exposure between 60 and 117 km/h (resp. higher than 117 km/h) leads to a 7.8-point (resp 7.0-point) fall in the probability of giving birth 1 year after exposure. Second, our baseline estimates show that the causal effect of wind speed exposure depends on the degree of cyclonic exposure associated with the mother's living environment. The likelihood of giving birth decreases less in cyclone-prone areas, suggesting that people adapt their behavior to the level of cyclonic risk. Third, the magnitude of the fall in fertility also depends on the number of children ever born, a result that is not in line with the insight of our theoretical model. Specifically, in the data we find that mothers with at least two children are much more likely to reduce their fertility after a cyclone than women with no children. Lastly, we refine the nature of the relationship between cyclonic exposure and fertility. In particular, we find evidence of the following: (i) recent past exposure to cyclones is associated with a lower decrease in fertility when exposed; and (ii) no evidence of non-linearities is observed in the causal effect. Overall, our results are estimated to be robust to other measures of tropical cyclone exposure and several changes in terms of the sample restriction and/or empirical specification.

Our paper draws on at least three strands of the economic literature. First, by merging spatially geolocated micro-data with weather variables, our paper forms part of a new but flourishing body of literature that studies the effect of weather shocks on socioeconomic variables (e.g., Deschênes and Greenstone (2011), Kudamatsu et al. (2012), Anttila-Hughes and Hsiang (2013), Barreca et al. (2018), Dessy et al. (2019), Sellers and Gray (2019), Marchetta et al. (2019) and Norling (2022)). We contribute to this research by focusing on the effect of a specific weather variable, namely tropical cyclones, on fertility. Second, our paper contributes to the literature on how households respond after an adverse event (e.g., Morduch (1995), Banerjee and Duflo (2007) and Alam and Pörtner (2018)) by exploring how they react to a cyclonic event that induces the loss of property, crops, and livelihoods. Further, in developing countries, having children enables households to smooth their consumption over time. We thus add to this body of literature by providing evidence for six developing countries regularly subjected to tropical cyclones. Finally, our paper makes an important contribution to the literature on the effect of natural disasters on fertility. To the best of our knowledge, four comparable papers to our own focus on cyclonic events.⁶ First, Evans et al. (2010) investigate how the fertility rate in US counties responds to storm advisories, finding that low-severity advisories are associated with a positive fertility effect, while high-severity advisories are associated with a negative effect. Second, Pörtner (2014) examines the effect of hurricane risks and shocks in Guatemala. He exploits cross-sectional and historical data about hurricane occurrences and finds a negative association between fertility and tropical cyclone exposure at the municipal level. Third, Davis (2017) employs rainfall data as a measure of tropical cyclone exposure and observes that high levels of rainfall in Nicaraguan municipalities are associated with increased

⁵ First, the panel allows us to alleviate problems relating to omitted variables by fully controlling the individual and time fixed effects. Second, insofar as tropical cyclone exposure can be viewed as (quasi-)random, exploiting year-to-year variations in wind speeds experienced by inhabitants on the ground allows us to identify their causal effects.

⁶ Other papers on the post-fertility effect of earthquakes are discussed in Section 4.1.

⁴ The choice of these DHS waves along with the countries studied in this paper is guided by data requirements (see also Section 3.1).

fertility. Fourth, [Norling \(2022\)](#) investigates how fertility responds to disasters in Africa, finding that fertility is negatively associated with disasters. Our paper overcomes many of the problems associated with these four papers, since our panel setup alleviates concerns relating to the unobserved heterogeneity of mothers. We rely on a measure of tropical cyclone exposure, namely wind speed, which is directly related to its physical intensity and destructiveness.⁷ Furthermore, we investigate the heterogeneity dimension with respect to the degree of cyclonic exposure in the mother's living environment and the number of children ever born.

The roadmap of this paper is as follows. Section 2 presents some theoretical elements about fertility and natural disasters as a whole.⁸ Section 3 details the data used in the empirical analysis. Section 4 develops our econometric framework and discusses identification assumptions. Section 5 presents the results. Finally, Section 6 provides the conclusions.

2. Theoretical background

2.1. Economic theory on fertility

Theoretical models explaining fertility are based on the quality–quantity model first developed by [Becker \(1960\)](#), [Mincer \(1963\)](#), and [Willis \(1974\)](#) along with its subsequent extensions.⁹ In general, the model environment considers a representative household that maximizes utility over consumption, the quantity of children, and their quality. The budget constraint is comprised of labor income, benefits and costs associated with children and their education, and the interest gained from saving. [Becker \(1993\)](#) assumes that with increasing income, the demand for child quality increases disproportionately with child quantity. This produces an inverse relationship between income and fertility. In these models, particular focus is given to education as an investment in human capital ([Becker, 1992](#); [Azarnert, 2006](#); [Lee and Mason, 2010](#); [Pörtner, 2014](#); [Vogl, 2016](#)).

Other extensions of the model explore the demand for children as a demand for insurance ([Pörtner, 2001](#)). This “risk-insurance” hypothesis supposes that in harsh poverty conditions, children function as a kind of generalized insurance against an uncertain future, with this insurance function being one of the main explanations of the high fertility rate ([Cain, 1983](#); [Robinson, 1986](#)). The insurance strategy can derive from the number of children and their risk of death. Generally analyzed in the context of the demographic transition ([Becker, 1992](#); [Schultz, 1997](#); [LeGrand et al., 2003](#); [Doepke, 2005](#); [Azarnert, 2006](#)), some studies focus on the impact of mortality as a shock ([Norling, 2022](#)). The increase in fertility in response to expected future child mortality is also known as the “hoarding” effect. In models where mortality is stochastic and parents wish to preserve a certain number of children, the “hoarding” effect occurs. If fertility is chosen sequentially, there is also a “replacement” effect: parents may condition their fertility decisions on the survival of previously born children ([Doepke, 2005](#)).

The insurance strategy can also derive from the uncertainty of expected future income ([Ranjan, 1999](#); [Pörtner, 2001](#)). This uncertainty notably occurs in the labor market ([Kreyenfeld, 2010, 2015](#); [Hanappi](#)

⁷ More specifically, [Pörtner \(2014\)](#) employs historical records, [Evans et al., 2010](#) use advisory data, and [Norling \(2022\)](#) relies on the Emergency Events Database, worldwide data known to be subject to several biases ([Botzen et al., 2019](#)).

⁸ Given the scarce literature on the specific effect of tropical cyclones on fertility, we sometimes broaden the spectrum by considering natural disasters as a whole. However, given the specific characteristics of tropical cyclones and the associated damage, they may simply be viewed as a natural disaster with the broader literature as a relevant departure point. In this respect, exposure to tropical cyclones and natural disasters are synonymous.

⁹ The interested reader may refer to [Schultz \(1997\)](#) for a review of these extensions.

[et al., 2017](#)). More recently, many studies have analyzed the link between uncertainty and fertility, especially in the context of economic recessions in developed countries.¹⁰ The underlying argument of these studies is that greater uncertainty about future prospects will encourage couples to postpone and possibly to forego childbearing altogether, because this irreversible investment has long-term consequences on resources ([Aassve et al., 2021](#)). In this context, aggregate fertility seems pro-cyclical over the business cycle¹¹ ([Sobotka et al., 2011](#); [Gozgor et al., 2021](#)). This finding is also shown by [Ranjan \(1999\)](#) with a two-period stochastic model of fertility that takes into account the perceived uncertainty about future income. Finally, other works introduce the perception of uncertainty (or risk aversion) to explain fertility variations, showing that at times of heightened uncertainty, risk-averse individuals will postpone childbearing more than risk lovers ([Schmidt, 2008](#); [Hofmann and Hohmeyer, 2013](#)). [Vignoli et al. \(2020\)](#) propose a conceptual framework for studying fertility decisions under uncertain conditions based on expectations and “experience”.

2.2. Impact of natural disasters on fertility

Based on the literature on the determinants of fertility, some authors explore the impact of natural disaster shocks on fertility, mostly adopting an empirical perspective ([Finlay, 2009](#); [Evans et al., 2010](#); [Pörtner, 2014](#); [Nobles et al., 2015](#); [Nandi et al., 2018](#); [Dessy et al., 2019](#)), or ([Norling, 2022](#)). They examine the meaning and magnitude of the potential impact of natural disasters on fertility and sometimes explore potential explanatory factors. Empirical evidence about the effect of natural disasters and, more generally, weather anomalies on fertility is mixed.

The positive impact can be explained by the replacement effect, the insurance mechanism relating to income uncertainty or a fall in the opportunity cost of having children. The replacement effect (or “hoarding” effect) is examined by [Nobles et al. \(2015\)](#) in the context of the Indian Ocean Tsunami in 2004 or by [Nandi et al. \(2018\)](#) for the 2001 Gujarat earthquake in India. [Finlay \(2009\)](#) studies the insurance mechanism and argues that children can be used to smooth consumption over time. More precisely, she shows how fertility can increase after a disaster if and only if the benefit associated with children is higher than the cost of taking care of them. In the model of [Dessy et al. \(2019\)](#) for drought in Madagascar, an exogenous decrease in labor market productivity has two opposing effects on the opportunity cost of children.¹² On the one hand, it decreases the foregone income of women when they spend time out of the labor market to care for children. On the other hand, the income effect renders each additional child more costly. [Dessy et al. \(2019\)](#) assume that the former prevails over the latter.¹³ [Sellers and Gray \(2019\)](#) observe the same result for climate shocks relating to temperature and precipitation where the reduction in the opportunity cost of having children (especially in rural areas) is the main driver of the increase of fertility.

Other empirical evidence nevertheless points to the negative effect of natural disasters on fertility. [Skidmore and Toya \(2002\)](#) study the impact of climatic disasters in 89 countries. Adopting a macro perspective, they find a positive effect on economic growth but a negative impact on fertility. In the special case of tropical cyclones, [Berlemann and Wenzel \(2018\)](#) observe a positive impact on fertility in low-income countries but a negative effect for countries with high levels of development. This

¹⁰ The interested reader may refer to [Aassve et al. \(2021\)](#) or [Sobotka et al. \(2011\)](#) for a review.

¹¹ This result can be nuanced as in the work of [Buckles et al. \(2021\)](#).

¹² The opportunity cost of an additional child is also known as the shadow price. In what follows, both terms are used interchangeably.

¹³ Another reason based on more psychological factors is that motherhood is a means of coping after an emotionally traumatic experience ([Carta et al., 2012](#)).

negative impact may at least partly be explained by conjunctural (Lindstrom and Berhanu, 1999) and psychological factors (Arnberg et al., 2011). The negative effect of natural disasters or climate anomalies on fertility has also been found in micro-economic studies. Thiede et al. (2022) emphasize that climate exposure affects mothers' reproductive outcomes but only in specific locations and for specific subgroups. This heterogeneous impact underscores the need to consider specific groups within a given population. For the United States, Evans et al. (2010) also observe some heterogeneity with an increase in fertility for low-category hurricanes but a decrease for high-category hurricanes. The negative effect can also be explained by an increase in the opportunity cost of having children, for instance if people have to engage in reconstruction activities, (Kochar, 1999; Evans et al., 2010; Alam and Pörtner, 2018; Berlemann and Wenzel, 2018; Norling, 2022) or by the uncertainty caused by the disaster shock (Davis, 2017; Pörtner, 2014; Wang et al., 2022).

2.3. Theoretical model proposition

This subsection develops a model regarding parental decisions about fertility. The model environment involves two periods. The household has utility in both periods but experiences some uncertainties about outcomes in period 2 (Pörtner, 2014). The overall utility U of the household is the sum of utility in period 1 (U_1) and the expected utility in period 2 ($E(U_2)$):

$$U = U_1 + E(U_2)$$

In each period, the household receives utility from consumption of a general good c . In the utility function, we consider the log of consumption to have a diminishing marginal utility of consumption such that $U_1 = \ln(c_1)$ and $U_2 = \ln(c_2)$ (Finlay, 2009). The household budget constraint indicates that income from period 1 Y_1 is spent by consuming c_1 and by supporting the cost k of raising ever-born children n_1 . In period 2, the budget constraint differs. We assume that children born in period 1 contribute positively to household income wn_1 , with $w > 0$. This new income supplements the income received in period 2 Y_2 . The expenditure of period 2 is similar to that of period 1:

$$Y_1 = c_1 + kn_1$$

$$Y_2 + wn_1 = c_2 + kn_2$$

Following (Ranjan, 1999), we assume that income in period 2 varies with probability.¹⁴ Thus, the expected utility of period 2 depends on the probability of exposure to natural disasters λ in period 2. We model exposure to natural disasters (or cyclones) as income loss, because these events have the potential to destroy homes and reduce the economic value of assets such as buildings, land, or crops, which is particularly relevant in developing countries where agricultural activities are still predominant. In the event of an adverse shock, we assume that income decreases by a quantity equal to δY_2 with $\delta \in [0, 1]$. Assuming an absence of intertemporal discounting and saving, the household can choose the number of goods and children to have in each period to maximize an additively separable utility function of the following form:

$$U = \ln(Y_1 - kn_1) + \lambda[\ln(Y_2(1 - \delta) + wn_1 - kn_2)] + (1 - \lambda)[\ln(Y_2 + wn_1 - kn_2)] \quad (1)$$

Let us now focus our discussion on the first-order condition with respect to the optimal number of children to have in period 2. The latter can be written as follows:

$$\frac{\partial U}{\partial n_2} = 0 \Leftrightarrow n_2 = \frac{Y_2(1 - \delta(1 - \lambda)) + wn_1}{k} \quad (2)$$

¹⁴ Although (Ranjan, 1999) assumes that income increases with probability 1/2 and decreases with probability 1/2, we take probability as a parameter between 0 and 1.

The comparative statics of Eq. (2) informs us about the direction of the effect of a given parameter on the number of children to be born in period 2. Regarding the share of income loss due to the occurrence of an adverse event such as a cyclone δ , we obtain:

$$\frac{\partial n_2}{\partial \delta} = \frac{-(1 - \lambda)Y_2}{k} < 0 \quad (3)$$

An increase in the amount of lost income has a negative incidence on fertility, which leads us to the first working assumption to be tested in the empirical analysis:

Working assumption 1: All else being equal, after an adverse shock such as a tropical cyclone, the likelihood of motherhood is expected to fall.

It may be interesting to compute the functional form of the derivative of (3) with respect to the probability of being exposed λ . Indeed, we cannot exclude the fact that the effect of cyclonic exposure on motherhood depends on the degree of exposure for people living in the most exposed areas. The latter is written as:

$$\frac{\partial^2 n_2}{\partial \delta \partial \lambda} = \frac{Y_2}{k} > 0 \quad (4)$$

Given that the number of children is a decreasing function as the share of income loss, the positive sign of (4) indicates that n_2 decreases less in the areas more frequently exposed to the disaster. Our second working assumption to test empirically is as follows:

Working assumption 2: All else being equal, in cyclone-prone areas, the sensitivity of fertility to cyclonic exposure is lower.

Finally, our data allow us to investigate whether post-cyclone fertility depends on the presence of children ever born in the household. In the model, the derivative of (3) with respect to n_1 is thus:

$$\frac{\partial^2 n_2}{\partial \delta \partial n_1} = 0 \quad (5)$$

Consequently, our theoretical framework implies that the number of children to be born in period 2 after tropical cyclone exposure is not related to the number of children born in period 1. Our third working assumption is as follows:

Working assumption 3: All else being equal, the post-cyclone fertility response does not depend on the number of children ever born.

These three working assumptions will frame our empirical results. Section 5 aims to provide an empirical response to these three assumptions.

3. Empirical background and data

3.1. Demographic and health survey

Our primary source of micro-data about female fertility is the DHS of cyclone-exposed countries. The DHS is a series of cross-sectional surveys performed approximately every 5 years. The survey is generally conducted by national institutes of statistics with the technical and financial support of international institutions. For each phase of the DHS, a nationally representative sample of women aged from 15 to 49 years is interviewed. Detailed information is collected about the women's sociodemographic (e.g., household composition, education level, number of children, household well-being) and health characteristics (e.g., infant mortality, nutritional practices, malaria prevalence, contraceptive use). Among the broad range of information available in the DHS, we exploit the mother's fertility history in depth. This retrospective record allows us to retrieve information about the children's year of birth and sex or the women's age at childbirth. Based on this fertility history, we construct a panel dataset of women and define a

binary variable to indicate whether or not a woman gave birth during a given year.

Let us now describe in further detail the sample selection of the DHS, because it has important implications on the design of our empirical study. The sample of each DHS wave is a two-level stratified random sample. At the first level, the country's territory is divided into thousands of clusters with a number of clusters being randomly selected.¹⁵ At the second level, for each cluster selected at the first level, around 30 households are randomly chosen. The geographic information used to locate the women is taken from the first-level selection. In particular, for each selected cluster, the data producer provides geographic information about its centroid. However, to ensure the confidentiality of the selected households, the data producer does not provide the exact latitude and longitude of the cluster's centroid but instead randomly displaces the actual location within a 2 (or 10) km radius in urban (or rural) areas. We then combine information about the cluster's location with tropical cyclone data to retrieve the wind speed exposure experienced by inhabitants on the ground.

To conduct our research, we apply several restrictions to our sample. First, among all the countries with DHS micro-data, we select only those with a non-zero exposure to tropical cyclones. Second, given the essential nature of the geographic information about the cluster locations, we exclude the DHS waves without geographic information. For the DHS with geographic information, we exclude households living in clusters without exploitable coordinates.¹⁶ Third, as we use retrospective data about women's fertility, we must ensure that a given woman was really exposed to a given tropical cyclone in a given year. To do so, we follow (Kudamatsu, 2012) and Anttila-Hughes and Hsiang (2013) by restricting our final sample to mothers declaring that they have always lived in their current home.¹⁷ It should be noted that for some DHS waves, information about the date of arrival in the current home is missing for all the observations. As we believe that this knowledge about the mother's place of residence is indispensable for our study purposes, we only select DHS waves for which this information is recorded.¹⁸ These restrictions leave us with a sample of six countries, namely Bangladesh, Cambodia, the Dominican Republic, Haiti, Madagascar, and the Philippines.¹⁹ Finally, as we iterate backwards to construct our panel database, we exclude all records for which the woman's age is below the threshold of 15 years.²⁰ This restriction implies that the number of observations per woman depends on her age at the time of the survey, the year of the survey by itself as well as of the year of the first available observation of our meteorological data (see Section 3.2 below).

Table 1 reports a selection of summary statistics at the time of the interview for women aged between 15 and 49 years included in our analysis. In the cross-section, the total number of children per woman was 3.21. The average age at first childbirth was around 20 years. Approximately 25% of women reported having no education, while

¹⁵ For instance, in Madagascar, 285 out of 21,500 clusters were selected for the 1997 phase of the DHS compared with 600 in 2008.

¹⁶ Missing geographic information may be due to (i) inconsistencies in the reported geographic coordinates or (ii) the incapacity of the data producer to access some clusters (ICF Macro, 1998, 2010).

¹⁷ In a robustness check, we relax this assumption (see Appendix E).

¹⁸ The absence of information about the mother's date of arrival in her current home is problematic, even if geographic information about the cluster locations is available. In particular, tropical cyclone exposure could be attributed to a woman when she lived elsewhere at the time.

¹⁹ Overall, we use 14 DHS waves. Details about DHS waves included together with additional information on women and their exposure can be found in Table 7 of Appendix A.

²⁰ For instance, for a woman born in 1973 and aged 35 at the time of the interview in 2008, we build annual records of her fertility from 1988 onwards. This woman thus enters our dataset at the age of 15 with her last record corresponding to the year of the interview.

around 42% reported a level equivalent to primary education at best. This results in a relatively low number of years at school (around 3.5 years). Overall, Table 1 also shows that heterogeneity exists depending on the countries. To complete the picture, we report in Table 7 of Appendix A similar summary statistics for each DHS wave employed in our empirical studies.

3.2. Tropical cyclone data and wind speed exposure

Tropical cyclones are natural atmospheric phenomena that develop mainly in tropical regions. A cyclone is a non-frontal synoptic scale system that rotates clockwise in the Southern Hemisphere and counter-clockwise in the Northern Hemisphere. It is organized around a center of low atmospheric pressure known as the eye, which is bounded by convective clouds that form an eye wall and precipitating spiral bands that wrap around it. This highly convective phenomenon is characterized by strong surface winds. Cyclonic systems are divided into several categories according to the intensity of the associated winds, defined as the maximum wind speed at an altitude of 10 m, averaged over 10 min (except in the United States where it is averaged over 1 min). In this paper, we use the terms tropical system, cyclonic system, and tropical cyclone interchangeably to designate tropical systems of any magnitude.²¹ The wind associated with cyclonic systems can cause severe damage. Tamura (2009)'s study lists the types of damage according to different wind speed thresholds. For instance, maximum 10-minute averaged winds of 90 km/h can damage roof tiles, while above 162 km/h, the load constraints of the main frames of high-rise buildings exceed the elastic limit. The devastating effects of tropical cyclones are mostly due to the strong winds (CCR, 2020).²²

3.2.1. TCE-DAT characteristics

A prerequisite for our empirical study is a measure of wind speed experienced by the population on the ground. As ground station weather data are not reliable at a detailed level for the six developing countries under scrutiny here, we use the worldwide TCE-DAT of Geiger et al. (2018). To produce this database, Geiger et al. (2018) calculate an estimate of the lifetime's maximum surface wind speed at each spatial location (on a $0.1^\circ \times 0.1^\circ$ grid over land) for more than 2,700 landfalling cyclonic systems between 1950 and 2015. As the pre-1980 data records required to compute wind speed are of lower quality, we adopted a cautious approach by placing our cut-off several years after 1980, namely in 1985.²³ The calculation is based on the International Best Track Archive for Climate Stewardship (IBTrACS) archive (Knapp et al., 2010) that contains all the necessary information for a wind field model such as that of Holland (1980), which is widely used in studies on the evaluation of risks associated with the landfalling of tropical cyclones (Peduzzi et al., 2012). Geiger et al. (2018) implement the revised hurricane pressure-wind model of Holland (2008) in which the maximum surface wind speed W in m s^{-1} (for a given pixel)²⁴ at radial

²¹ We nevertheless acknowledge that three classes of cyclonic phenomena exist. First, a tropical depression has a wind speed of less than 63 km/h. Second, a tropical storm is between 63 and 117 km/h. Third, above 117 km/h, it is called a tropical cyclone in the Indian Ocean and the South Pacific, a hurricane in the North Atlantic and the North-East Pacific, and a typhoon in the North-West Pacific.

²² Using post-cyclone insurance data, CCR (2020) finds that the vast majority of insurance claim payments are due to wind speed as opposed to rainfall, landslides, or storm surges.

²³ Geiger et al. (2018) indicate that data records are sometimes incomplete or of poor quality before the early 1980s. We confirm that using data since 1981 (the first available date for the rainfall variable in our econometric specification) has no incidence on the main message of this paper. Corresponding results are available upon request.

²⁴ For simplicity, we do not add an index to designate pixels.

Table 1
Sample mean for a selection of women’s characteristics.
Source: DHS and authors’ own calculations.

Variable	Sample mean	Bangladesh	Dominican Republic	Haiti	Cambodia	Madagascar	Philippines
Woman’s age	26.80	26.48	26.88	26.85	27.55	26.25	26.52
Woman’s age at first birth	20.12	17.59	19.60	20.62	20.89	18.93	21.73
Woman’s age at first marriage	18.25	14.89	17.83	19.90	19.10	15.29	20.59
Number of children	3.21	2.77	2.67	3.38	3.45	3.85	3.02
Year of education	3.43	3.01	4.03	3.52	3.10	2.65	3.89
No education	0.25	0.47	0.05	0.35	0.35	0.40	0.03
Primary education	0.42	0.31	0.46	0.41	0.54	0.48	0.26
Secondary education	0.24	0.18	0.32	0.23	0.11	0.11	0.41
Tertiary education	0.09	0.04	0.16	0.01	0.01	0.01	0.29
Observation	58 653	4401	12 512	10 611	10 860	10 190	10 079

Notes: Statistics are computed on the cross-section of 58,653 women included in our analysis after applying the sample restrictions described in Section 3.1.

Table 2
Summary statistics of the weather variables for the DHS clusters during the 1981–2015 period.
Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors’ own calculations.

	No. of exposures	No. of exposures $W \in [60, 118[$	No. of exposures $W \geq 118$	Wind speed when $W > 0$	Rainfall	Temperature
Mean	7.40	6.20	1.20	93.50	19.00	25.60
Standard deviation	7.30	6.00	1.60	32.20	8.10	1.90
Min.	0.00	0.00	0.00	61.20	1.90	16.40
Percentile 1%	0.00	0.00	0.00	63.50	5.60	18.30
Percentile 5%	0.00	0.00	0.00	64.60	8.40	22.30
Percentile 10%	0.00	0.00	0.00	65.80	10.50	23.40
Percentile 25%	2.00	1.00	0.00	71.60	13.60	25.00
Percentile 50%	6.00	5.00	1.00	84.30	17.50	25.90
Percentile 75%	9.00	8.00	2.00	99.00	22.90	26.90
Percentile 90%	19.00	16.00	4.00	138.40	29.70	27.70
Percentile 95%	24.00	20.00	5.00	166.10	34.30	28.10
Percentile 99%	29.00	25.00	6.00	212.60	45.60	28.50
Max.	34.00	33.00	9.00	293.70	72.50	29.10

Notes: The first three column represents the statistics relative to the distribution of the total number of cyclonic exposures in the cross-section of clusters. Other columns report the statistics relating to the distribution of wind speed exposure, rainfall, and temperature in the panel of cluster-year pairs. For the wind speed column, summary statistics are computed only for non-zero cluster-year pairs as in Elliott et al. (2015). Wind speed corresponds to the maximum wind speed experienced and is expressed in km/h. Rainfall corresponds to the cumulative precipitation over a year and is expressed in hundreds of millimeters. Temperature is the annual average temperature expressed in Celsius degrees.

distance r from the center of a given cyclonic system is defined as follows:

$$W = \left(\frac{b_s}{\rho e} \Delta p \left(\frac{r}{r_m} \right) \right)^{0.5}, \tag{6}$$

where ρ is the surface air density in kg m^{-3} , e the base of natural logarithms, and Δp the pressure drop at the cyclone center in hPa as a function of r and r_m (radius of maximum winds). Parameter b_s depends on Δp , the temporal intensity change in pressure, the absolute value of the latitude, and the tropical cyclone’s translational speed. Further details on the development of the parametric equation of b_s can be found in Holland (2008). In addition to the wind field model in Eq. (6), Geiger et al. (2018) calculate a translational component multiplied by an attenuation factor (ratio between the tropical cyclone’s center and the radius of maximum wind). The translational wind speed decreases with the distance from the cyclonic system’s center, which is taken into account to provide more realistic estimates of wind speed on the ground. To our knowledge, no other publicly available dataset is available from a ground weather station or remote sensing measurement that covers the whole territory of Madagascar with a spatial resolution higher than $0.1^\circ \times 0.1^\circ$. This is the main reason why we decided to use the wind speed estimate calculated by Geiger et al. (2018).²⁵

²⁵ The dataset is referenced as Geiger et al. (2017) and is available at <https://dataservices.gfz-potsdam.de/pik/showshort.php?id=escidoc:2387904>.

Table 2 and the bar plot of Fig. 1 provide the summary statistics for the cyclonic exposure of the clusters investigated in this paper. The first three columns of the table report the characteristics of the distribution of the number of exposures to cyclonic systems in the cross-section of DHS clusters, while the other columns include the characteristics of the distribution of wind speed, rainfall, and temperature in the panel of cluster-year observations. In the panel, 21.0% of our pairs of cluster-year observations experienced at least one cyclonic exposure during the 1981–2015 sample period. The mean number of exposures to cyclonic systems by cluster was 7.4. Exposure to wind speed falling in the $[60, 118[$ interval is more frequent as its mean number of exposure is of 6.2. Given that the standard deviation of exposure frequency is approximately equal to its mean, the number of exposures by clusters is quite heterogeneous. Thus, 11% of clusters were never exposed to cyclones during the period under consideration, whereas the top 10% of clusters were exposed at least 19 times over the 1985–2015 sample period. Given the nature of our empirical approach, such heterogeneity in the exposure of clusters is worth investigating because it creates within variations that may be explored by our panel-fixed effect regressions. Let us now explore the profile of wind speed exposure generated on the ground. To do so, we focus on the DHS clusters when exposure is non-zero.²⁶ The average wind speed exposure during the 1985–2015 period is 93.5 km/h with a standard deviation of 32.2. The minimum exposure to wind speed is 61.2 km/h in the data. As expected, this value is close to 60 km/h, which is the minimum threshold above

²⁶ In doing so, we follow (Elliott et al., 2015).

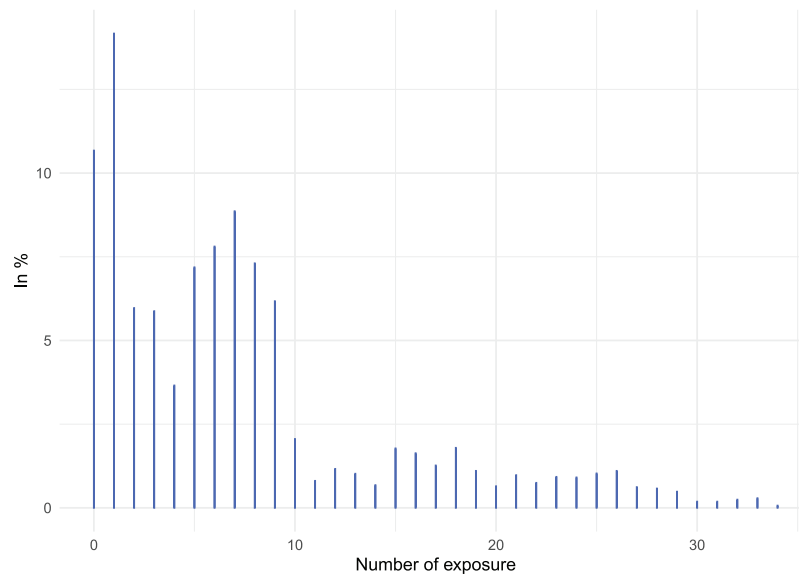


Fig. 1. Distribution of cyclonic exposure experienced by DHS clusters (1981–2015).

Notes: Cyclonic exposure is measured by the total number of exposures to cyclones by clusters during the 1981–2015 sample period. This distribution is computed from the cross-section of clusters.

Source: DHS, TCE-DAT (Geiger et al., 2018), and authors’ own calculations.

which (Geiger et al., 2018) record cyclonic exposure. Again, there is substantial heterogeneity in our sample insofar as 10% of clusters were exposed to tropical cyclones with wind speeds above 138.4 km/h. The maximum wind speed recorded during our sample period was 293.7 km/h, with this extreme wind speed being due to Haiyan, one of the most severe phenomena ever observed in the Philippines. For illustrative purposes, Fig. 2 plots the spatial distribution of the mean of annual maximum wind speeds for the six countries of our sample during the 1985–2015 period. It emerges that the Philippines has the highest exposure to cyclonic wind speed, especially in the north of the country. Madagascar has the second highest exposure, particularly its north-east coast, which is regularly threatened by tropical cyclones. Among the countries studied here, Bangladesh, Haiti, and the Dominican Republic have a wind speed exposure that falls in the middle of distribution. Finally, north-east Cambodia has a similar exposure to the three aforementioned countries, although some parts of the country appear to be less prone to this natural phenomenon.

3.2.2. Other weather data

Although we mainly focus on the impact of tropical cyclone exposure on motherhood, we include two other weather variables in our analysis, namely annual rainfall and mean temperature. Their inclusion is intended to avoid noises due to the shared secular changes that might be correlated with tropical cyclone exposure. Our rainfall variable comes from the Climate Hazards group InfraRed Precipitation with Stations (CHIRPS) dataset constructed by Funk et al. (2015). When constructing this dataset, Funk et al. (2015) combine ground station and satellite information to obtain high-resolution (0.05° × 0.05°) gridded data. Concerning temperature, we use the updated worldwide gridded climate dataset of the Climate Research Unit (CRU) of the University of East Anglia (Harris et al., 2014). This dataset nevertheless has a lower resolution than that of CHIRPS, since it is available at 0.5° latitude/longitude grid cells. The last two columns of Table 2 report the univariate statistics of rainfall and mean temperature.

4. Empirical framework

4.1. Estimated equation

Our empirical strategy involves estimating different versions of the following baseline model:

$$y_{itac} = \beta^{W^1} \times W_{i,t-1}^1 + \beta^{W^2} \times W_{i,t-1}^2 + \beta^R \times R_{i,t-1} + \beta^T \times T_{i,t-1} + \mu_i + \eta_t + \alpha_a + u_{itac} \tag{7}$$

The outcome of interest, namely y_{itac} , is a binary variable equal to one if mother i of age a living in cluster c gives birth in year t and zero otherwise. Given that y_{itac} is dichotomous, we rely on a linear probability model.²⁷ In Eq. (7), β^k with $k \in [W^m, R, T]$ with $m \in [1, 2]$ are coefficients to be estimated. Our main weather variable of interest corresponds to the tropical cyclone wind speed exposure W of woman i in year $t - 1$. The latter is measured by two dummies. The first one, $W_{i,t-1}^1$, is equal to one when maximum wind speed is higher than 60 km/h and lower than 118 km/h. The second one, $W_{i,t-1}^2$, is set to one when maximum wind speed is at least of 118 km/h.²⁸ We also include as controls two other weather variables: annual rainfall R expressed in hundreds of millimeters and annual land surface mean temperature T measured in Celsius degrees in $t - 1$. We justify the inclusion of these two variables as an attempt to lessen the issues arising from the omitted variables. In the event of correlations or shared secular changes among the weather variables, studying the impact of a specific weather variable in isolation could be problematic (Dell et al.,

²⁷ This practice is standard in the empirical literature dealing with dependent dichotomous variables in a panel setup (Anttila-Hughes and Hsiang, 2013; Kudamatsu, 2012; Kudamatsu et al., 2012). In particular, it is well known that the incidental parameter problem complicates the estimation of panel models with fixed effects. In contrast to linear models, it is not possible to remove fixed effects with the traditional within transformation. Moreover, estimating them directly leads to biased estimates of all parameters (see also Wooldridge, 2010) or (Croissant and Millo, 2018) for more details).

²⁸ We also consider an alternative specification in which exposure to tropical cyclones is continuous and measured in kilometers per hour (km/h).

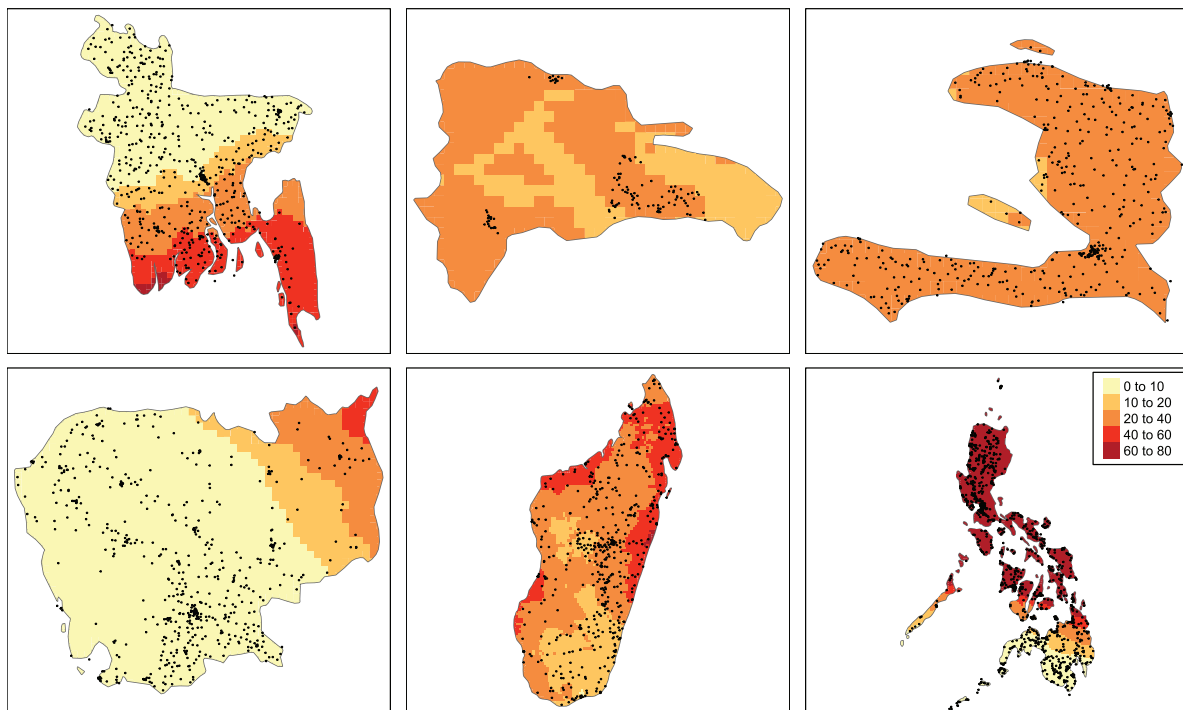


Fig. 2. Mean of wind speed exposure (1980–2015).

Notes: The dots of each panel correspond to cluster coordinates of the last DHS wave used for each country. From the top left to the bottom right, there is Bangladesh, the Dominican Republic, Haiti, Cambodia, Madagascar, and Philippines.

Source: DHS, TCE-DAT (Geiger et al., 2018), and authors' own calculations.

2014).²⁹ We include woman fixed effects μ_i to control for unobserved and time-invariant characteristics that could potentially affect women's likelihood of childbearing.³⁰ In a flexible manner, we also account for year-specific components shared by all women using year fixed effects η_t . Their inclusion ensures that the relationship of interest can be identified from idiosyncratic shocks. We also include woman's age fixed effects α_a controlling for the fact the women's decisions to have babies could differ at different ages. Finally, u_{itac} is the error term. Given the sampling design of the DHS surveys, we follow (Abadie et al., 2017), while standard errors are clustered at the first-level sample selection to allow for any correlation of the error term over time and space within each DHS cluster.

Our estimation of women's likelihood of giving birth mainly controls for weather-related variables. Two main arguments support this choice. First, control variables themselves should not be outcomes of weather-related variables (Dell et al., 2014). As an example, let us take household income as an additional control variable.³¹ In this case, we cannot exclude the fact that it is also an outcome of cyclonic wind speed. Consequently, if a model includes income, then the estimated

coefficient on wind speed would not capture its total net effect on fertility, because income can be written as a function of wind speed. Second, when adding control variables such as income, we may encounter an endogeneity problem. Specifically, we could argue that income has an effect on fertility, but we could also conjecture that fertility explains, at least in part, women's income.³² This is the well-known reverse causation problem, which leads to the introduction of a selection bias in the estimation of the income-related coefficient as well as the other estimated coefficients in the model. Given these two arguments, we believe that the parsimonious model of Eq. (7) remains a relevant departure point. In doing so, our empirical model can unveil the true net effect of cyclonic wind speed (or the total effect) on women's likelihood of giving birth.

4.2. Identifying assumption

Insofar as fixed effects are included in Eq. (7), variables are expressed as deviations from the individual and temporal sample means (Croissant and Millo, 2018). Our identification emphasizes year-to-year variations in levels from the observed means. As a consequence, the fixed effect coefficients associated with wind speed exposure may be interpreted as the impact of tropical shocks on women's probability of giving birth.

The main assumption used to identify the causal effect of tropical cyclones on fertility is randomness in an individual's exposure. Being exposed to cyclonic systems can be viewed as (quasi-)random insofar as the formation of cyclonic systems in addition to their precise trajectories and magnitude are stochastic and thus difficult to predict. When they occur, tropical cyclones generate recognizable wind speeds of high magnitude that impact large spatial units (quasi-)randomly so that inhabitants living in these areas are exposed to them, while those

²⁹ In particular, it is arguable that the tropical cyclone exposure of a given spatial unit may be correlated with its surface temperature or rainfall level. In this respect, Hsiang (2010) finds that each additional Celsius degree in a country's local surface temperature is associated with a 9.36 km/h increase in local wind speed in the Caribbean basin countries.

³⁰ These unobserved factors may be the (time-invariant) preference of women to have a large family. Their preference may also be rationalized by emphasizing the opportunity cost of taking care of children. Women's more limited options in the labor market probably increase the opportunity cost of spending time in labor market activities, thus leading them to have more children and devote more time to childrearing.

³¹ Note that the construction of our panel data does not allow us to retrieve an income variable, because we mainly rely on the mothers' fertility history. Such information is thus not available.

³² Similar problems could arise for variables such as education level, years of education, school dropout, labor market participation, and so on.

Table 3

Main regression results.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	(1)	(2)	(3)	(4)
Max. wind $\in [60, 118[$ in $t - 1$	-7.6185*** (0.1317)	-7.7960*** (0.1335)	-8.2838*** (0.1602)	-8.4298*** (0.1626)
Max. wind ≥ 118 in $t - 1$	-6.7236*** (0.2147)	-6.9664*** (0.2129)	-7.1503*** (0.2976)	-7.4140*** (0.3019)
Max. wind $\in [60, 118[$ in $t - 1 \times$ Prone	-	-	1.9229*** (0.2557)	1.8329*** (0.2553)
Max. wind $\geq 118 \times$ Prone	-	-	1.3882*** (0.4136)	1.4043*** (0.4147)
Rainfall in $t - 1$	-	0.2142*** (0.0150)	-	0.2130*** (0.0150)
Temperature in $t - 1$	-	0.7365*** (0.2452)	-	0.7866*** (0.2468)
Observations	1,025,443	1,025,443	1,025,443	1,025,443

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual and woman's age fixed effects. The term "Prone" refers to a dummy equal to one when the mother lives in a village exposed to cyclones at least 10 times during the 1985–2015 period. Rainfall in hundreds of millimeters, and temperature in Celsius degrees.

living in non-affected areas are not. We nevertheless acknowledge that some areas are more likely to be exposed to tropical cyclones, and as a result, the total effect on fertility may vary depending on the level of risk. We also consider this possibility by introducing a heterogeneity dimension into our empirical analysis (see also Section 5).

Two issues potentially relate to the randomness of tropical cyclones, both of which are linked to the ability of meteorologists to forecast their occurrence. Indeed, meteorologists have made substantial progress in forecasting the seasonal frequency of tropical systems (Klotzbach et al., 2019). Furthermore, it is now possible to forecast a tropical cyclone a few days before landfall. From our point of view, this forecasting has almost no incidence on our identification strategy, because our focus is on year-to-year variations. In particular, although seasonal forecasts have a higher predictive power, the year-to-year variations in tropical cyclone wind speed at a given spatial unit are largely unpredictable for scientists and thus for the inhabitants potentially affected by tropical cyclones. Regarding short-run forecasting, it implicitly assumes that all inhabitants living in areas threatened by a cyclonic system have perfect access to information (by means of a radio, television, or newspaper). However, this is certainly not the case in developing countries. Nevertheless, it is probable that important information about the occurrence of tropical cyclones circulates through other channels such as social networks, so we cannot totally exclude the fact that individuals would engage in actions to protect their homes and livelihoods or evacuate. These issues have several repercussions on the interpretation of our results. More specifically, the estimated effect could be viewed as the effect of tropical cyclone shocks after households engage in adaptive behaviors (if any). However, despite such behaviors, inhabitants cannot overcome all the negative effects of tropical cyclones, meaning that a perceptible degradation in their living environment may affect their decision to have children. Insofar as year-to-year variations in the exposure to tropical cyclone shocks are (quasi-)random, our reduced-form panel framework imposes relatively few identifying assumptions while ensuring a causative interpretation.

5. Results

This section presents the results obtained by estimating the econometric model detailed in the previous section. All estimations were made with the R software (R Core Team, 2019) using tools provided by the "fixest" package.³³

³³ Details about the `fixest` package can be found via the following link: https://cran.r-project.org/web/packages/fixest/vignettes/fixest_walkthrough.html.

5.1. Main results

5.1.1. Fertility response to cyclone shocks

Table 3 reports the regression results of the alternative estimations of Eq. (7). To see how the inclusion of controls for temperature and rainfall alter the results, we sequentially add both of them to columns (2) and (4).

Columns (1) and (2) report the results of a model with exposure to wind speed captured by the two dummies previously described. These models show the negative impact of cyclonic system wind speed on women's likelihood of giving birth. The estimated relationship is consistently negative regardless of the inclusion of controls for temperature and rainfall. In the model of column (2), being exposed to cyclonic wind speed between 62 and 118 km/h induces a fall of about 7.8 points in women's likelihood of giving birth in $t + 1$. An exposure to cyclonic wind speed of at least 118 km/h decrease the probability of giving birth by 7.0 points. The alternative specification of the baseline empirical model consisting in employing the wind speed as a numerical variable measured in km/h in place of the two dummies confirms the negative incidence of cyclones on motherhood.³⁴ Finally, others sensitivity checks which consist of changing our sample restriction by including mothers who have migrated, by splitting the sample into two sub-periods or by excluding never-exposed clusters, do not change the qualitative or quantitative pattern of our baseline results. As a result, our empirical evidence provides an affirmative answer to our first working assumption.

Empirical evidence for working assumption 1:

Exposure to tropical cyclones reduces the likelihood of motherhood.

5.1.2. Degree of exposure and fertility response to cyclone shocks

To further investigate the nature of the relationship between wind speed exposure and motherhood, in Appendix B, we present the country-by-country regressions. These regressions show that the six investigated countries have the same qualitative pattern: exposure to cyclones reduces the probability of giving birth. However, depending on the country, the quantitative patterns differ substantially. Thus, countries such as Madagascar or the Philippines show the smallest effect. For instance, being exposed to wind speed falling in the $[60, 118[$ interval reduces the probability of motherhood in $t + 1$ by 6.0 points in the Philippines and by 3.9 points in Madagascar. By contrast, countries

³⁴ In particular, Table 10 of Appendix C shows that a wind speed exposure in t equivalent to one standard deviation, namely 38.8 km/h, induces a fall of 2.6 points (38.8×-0.0668) in women's likelihood of giving birth in $t + 1$.

such as Haiti, Cambodia, or the Dominican Republic experience the greatest effects in terms of post-cyclone reduction in fertility. In Haiti, an exposure to cyclonic wind speed higher than 118 km/h in t translates to a 18.8 points fall in the likelihood of having giving birth. In comparison to Madagascar, the fertility response in Haiti is seven times greater. An interesting feature that emerges from the comparison of the country-by-country regressions is that the effect seems higher in the countries least frequently exposed to tropical cyclones.^{35,36}

In columns (3) and (4) of Table 3, we further explore the link between the degree of exposure associated with tropical cyclones and fertility. As Fig. 2 shows, the clusters are exposed to tropical cyclones in a heterogeneous manner. Summary statistics in Table 2 reveal that during our sample period, 10% of villages were exposed more than 19 times, while 25% were exposed less than twice. Even after controlling for fixed effects, it is possible that the effect of cyclonic wind speed on motherhood depends on the degree of exposure and the preparedness of people living in the most exposed villages. We may imagine that women living in the most frequently exposed areas anticipate the higher probability of exposure when making decisions about childbearing. Thus, their response to a cyclone shock could differ from mothers living in non-prone areas. To investigate this issue, we interact wind speed exposure with a dummy equal to one if the village is exposed more than nine times to cyclonic systems during the sample period of our study.³⁷ We refer to these clusters as cyclone-prone areas. Coefficients associated with this model specification can be found in the last two columns of Table 3. Again, the inclusion of controls for temperature and rainfall does not alter the qualitative and quantitative causal effect of wind speed exposure on motherhood. However, in these models, the coefficients β^{W^1} and β^{W^2} capture the effect of wind speed exposure for mothers living in non-prone areas. Compared with models of columns (1) and (2), the coefficient is higher in columns (3) and (4). All else being equal, exposure to cyclonic wind speeds below (resp. above) 118 km/h decreases the probability of having children by 8.4 points (resp. 7.4 points). The interaction term of the two dummies for wind speed with the dummy for cyclone-prone areas confirms what was previously suggested. Overall, the decrease in the probability of giving birth after a cyclonic exposure is lower. For mothers living in the most exposed areas, the likelihood of giving birth decreases respectively by 6.6 and 6.0 points for exposure below and above 118 km/h.³⁸ This result shows that the fertility response to a cyclone shock is sensitive to the degree of exposure associated with the mother's place of residence and may be seen as a first piece of evidence that people adapt their behavior to their living environment.³⁹ In this sense, our empirical results are in line with our second working assumption.

³⁵ According to the TCE-DAT of Geiger et al. (2018), during the 1985–2015 sample period, Haiti was exposed to cyclones 23 times, Dominican Republic 24 times, and Cambodia 29 times. By contrast, Madagascar and the Philippines were exposed 84 and 284 times, respectively. Consequently, Bangladesh, with a total of 50 exposures, falls in the middle of this distribution.

³⁶ Another interesting feature emerging from Table 9 relates to the magnitude of the effect for the two countries located on Hispaniola island, namely Haiti and the Dominican Republic. Haiti is much less developed than the Dominican Republic (see Table 8). In the theoretical section above, we highlighted that the post-disaster fertility responses could be related to the country's level of development. For Haiti and the Dominican Republic, this does not seem to be the case. Despite their two very different levels of development, the fall in the probability of motherhood is of the same magnitude for cyclonic exposure below 118 km/h. Given that the two countries have a similar level of exposure to cyclones, we may conjecture in this special case that the degree of exposure shapes the post-cyclone fertility response more than the level of development.

³⁷ The number nine corresponds to the 75% percentile of the corresponding distribution (see also Table 2).

³⁸ Each time, the estimated effect in cyclone-prone areas significantly differs from the effect in non-prone areas at the 1% level.

³⁹ Results from columns (3) and (4) of Table 10 further confirm this results.

Table 4

Regression results depending on the number of children ever born. Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	(1)	(2)
Max. wind $\in [60, 118[$ in $t - 1$	-3.2871*** (0.1932)	-3.4531*** (0.1939)
Max. wind ≥ 118 in $t - 1$	-2.9180*** (0.3188)	-3.1103*** (0.3191)
Max. wind $\in [60, 118[$ in $t - 1 \times$ Having 1 child	-0.0620 (0.2639)	-0.1217 (0.2637)
Max. wind $\in [60, 118[$ in $t - 1 \times$ Having 2 children	-4.9263*** (0.2681)	-4.9788*** (0.2677)
Max. wind $\in [60, 118[$ in $t - 1 \times$ Having 3 children	-10.9403*** (0.2403)	-10.9900*** (0.2401)
Max. wind ≥ 118 in $t - 1 \times$ Having 1 child	0.5008 (0.4947)	0.4058 (0.4938)
Max. wind ≥ 118 in $t - 1 \times$ Having 2 children	-4.2787*** (0.4966)	-4.4069*** (0.4968)
Max. wind ≥ 118 in $t - 1 \times$ Having 3 children	-10.5315*** (0.4233)	-10.6470*** (0.4234)
Rainfall in $t - 1$	-	0.2238*** (0.0151)
Temperature in $t - 1$	-	0.0765 (0.2462)
Observations	1,025,443	1,025,443

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual and woman's age fixed effects. The term "Prone" refers to a dummy equal to one when the mother lives in a village exposed to cyclones at least 10 times during the 1985–2015 period. Rainfall in hundreds of millimeters, and temperature in Celsius degrees.

Empirical evidence for working assumption 2:

The fertility response to cyclone shocks depends on the degree of exposure associated with the mother's living environment: in cyclone-prone areas, the likelihood of giving birth decreases to a lesser extent.

5.1.3. Children ever born and fertility response to cyclone shocks

As indicated above, the model of Section 2.3 does not provide a clear message about the post-disaster fertility response with respect to family size. Instead, the model suggests that the post-cyclone fertility response is independent of the number of children ever born. We may nevertheless imagine that the post-cyclone response in terms of fertility would differ depending on the presence of children in the household. The association between children ever born and future fertility is thus worth investigating empirically. Here, we question whether the fertility response to an adverse shock depends on past fertility. To consider this possibility, we run an alternative empirical model in which the two exposure variables interact with dummies indicating the number of children ever born. More specifically, we consider three dummies for mothers who have one, two, or more than two children at the time of the exposure.⁴⁰ The corresponding results are reported in Table 4. It is noteworthy that as observed above, the inclusion of rainfall and temperature does not alter the coefficient associated with cyclonic exposure. The first two rows of the corresponding table can be interpreted as the effect of cyclonic exposure on fertility for women without children at the time of the exposure. The corresponding coefficient is negative for both specifications of the empirical model. We consistently observe negative marginal effects for each interaction term, suggesting that the fall in the likelihood of giving birth after exposure to a cyclonic system is a robust pattern. However, it should be noted that even if it remains negative, the estimated impact of cyclonic exposure is significantly lower for mothers with two children

⁴⁰ In our final sample, 19.4% of women already have one child at the time of the exposure, 16.5% two children, and 30.6% at least three children.

at the time of exposure. Thus, for a wind speed exposure falling in the [60, 118[interval in t , the likelihood of having a child in $t + 1$ decreases by 8.4 points for mothers with two children versus 3.4 points for those without children.⁴¹ For mothers with three children or more the corresponding fall in their likelihood of giving birth in $t + 1$ is equal to 14.4 and 13.8 points for an exposure below and above 118 km/h respectively.⁴² As anticipated, the marginal effect of cyclonic exposure on fertility depends on the number of children ever born, and mothers with a large number of children ever born generally tend to reduce their fertility to a greater extent. However, one of the particularities of our results relates to mothers with only one child for whom the likelihood of motherhood is not different from the one of women without children. This quite puzzling feature could reflect mothers' preference for having at least two children among those who already have one child.

Empirical evidence for working assumption 3:

The fertility response to cyclone shocks depends on the number of children ever born: mothers with at least two children reduce their fertility more after a cyclone shock.

5.2. Further results

In this subsection, we undertake an in-depth analysis to investigate three potential features of the causal effect. First, we examine whether the negative causal effect depends on womens' past exposure to cyclones. Second, we estimate a specification to test if non-linearities exist in the effect. The results of these alternative estimations are reported in Tables 5 and 6. The study of other heterogeneity dimensions along with robustness checks, which consist of changing the sample or the wind speed variable, are respectively reported in Appendices D and E.

5.2.1. Intensification mechanism

Let us now test the hypothesis that the effect of cyclonic systems on female motherhood increases over time. Indeed, it is possible that the impact of a tropical cyclone shock in a given year t , as revealed by our panel estimate of Eq. (7), is magnified if the same woman was also exposed to another tropical cyclone in the past few years (e.g., in $t - 1$). Similar to Dell et al. (2014), we label this mechanism the intensification effect. We consider this possibility by interacting the two dummies for wind speed exposure in a given period t with another dummy variable, which indicates that a given woman i was also exposed to one, two, or more than two tropical cyclones in the last 5 years before the exposure. We note the corresponding dummy z_{ijt} where j indicates the woman's situation regarding her own exposure to cyclones during the last 5 years. Our set of interacted variables is thus $\tilde{W}_{i,t-1}^m = W_{i,t-1}^m \times z_{ij,t-1}$ with $m \in [1, 2]$. The estimated equation now has the following form:

$$y_{itac} = \beta^{W^1} \times W_{i,t-1}^1 + \beta^{W^2} \times W_{i,t-1}^2 + \beta^R \times R_{i,t-1} + \beta^T \times T_{i,t-1} + \sum_{j=3}^J \sum_{m=1}^M \left(\omega_{j,t-1}^m \times \tilde{W}_{i,t-1}^m \right) + \mu_i + \eta_t + \alpha_a + u_{itac}, \tag{8}$$

where $\omega_{j,t-1}^m$ are the parameters to be estimated. Their interpretation differs from that of β^{W^m} . The latter corresponds to the effect of cyclonic exposure in period $t - 1$ on the current likelihood of motherhood. However, the second coefficient ω_1^W captures a different effect, namely the incremental effect of exposure to cyclones on motherhood in period

⁴¹ Table 11 presents the results when wind speed is measured as a numerical variable and in km/h. We find that for mothers with two children (resp. more than two children) the corresponding fall in their likelihood of giving birth in $t + 1$ after a wind speed shock of a standard deviation magnitude is equal to 2.8 points (resp. 5.0 points).

⁴² Every time, the estimated effect associated with the interaction term significantly differs from the effect for women without children at the 1% level.

$t - 1$ if the woman was exposed to only one additional tropical cyclone in the 5 years preceding the exposure. Consequently, the intensification parameters, namely $\omega_{j,t-1}^W$, explore whether the effect of a tropical cyclone shock depends on the pattern of previous shocks.

The last four columns of Table 5 explores the possibility of intensification effects by adding $\tilde{W}_{i,t-1}^m$ to the model.⁴³ This corresponds to the regression results of Eq. (8) and includes all interaction terms. Overall, there is no evidence for the existence of intensification mechanisms in the case of exposure to wind speed between 60 and 118 km/h. The three $\omega_{j,t-1}^W$ are estimated to be significantly positive. This finding suggests that the impact of wind speed exposure in $t - 1$ is dampened if between $t - 2$ and $t - 6$, the mother was also exposed to tropical cyclones. Let us consider that before the exposure in $t - 1$, the mother was exposed to two tropical cyclones. In this case, the total effect of wind speed exposure is a fall of 6.7 points (namely, $\beta^{W^1} + \omega_2^{W^1}$) in the likelihood of motherhood.^{44,45} Overall, the decrease in the probability of motherhood is lower for mothers exposed in a recent past, which reflects the empirical evidence for working assumption 2: regularly exposed mothers appear to be less sensitive to cyclone shocks.

5.2.2. Non-linearities

The literature exploring the effect of weather shocks on economic variables often indicates that the effects are likely non-linear. In particular, Emanuel (2011) and Nordhaus (2010) suggest that tropical cyclone damage exponentially increases with the level of wind speed experienced on the ground. Nevertheless, this is not straightforward, as other socioeconomic variables also respond non-linearly to wind speed exposure, especially when household micro-data is used. To further investigate a possible non-linear relationship, we add another dummy for wind speed in our econometric model. This approach has two main advantages. First, it is simple to implement, and second, it is flexible without imposing any functional forms on our wind speed explanatory variable. Hence, we construct an additional dummy by splitting W^2 in two bins. The first one $W^{2'}$ is equal to one when wind speed falls within the [118, 153[interval. The second one W^3 is one when cyclonic wind speed is at least of 153 km/h.⁴⁶ We report the related results with all the aforementioned dummies in the estimated equation in Table 6.

Given the standard errors associated with point estimates, we cannot conclude that the post-fertility effect of the tropical cyclone shock is non-linear with maximum wind speeds. In particular, coefficients associated with the highest wind speed, namely β^{W^3} , is not significantly different from $\beta^{W^{2'}}$. It should also be observed that standard errors of coefficients increase with the level of wind speed. This probably indicates a loss of statistical power due to the low frequency of severe cyclones.⁴⁷ Overall, we do not find evidence that for the most extreme phenomenon, the estimated effect between cyclonic exposure and fertility is magnified.⁴⁸

⁴³ Table 12 of Appendix C explores the existence of intensification mechanism with a model using wind speed in place of dummies for exposure.

⁴⁴ For each coefficient, we verify whether the total effect significantly differs from β^{W^1} .

⁴⁵ Regarding an exposure to cyclonic wind at least equal to 118 km/h, it seems that the opposite is observed as coefficients associated to the $\omega_j^{W^2}$ is negative. However, two out of three coefficients are not significant and for the only significant coefficient the total effect ($\beta^{W^2} + \omega_1^{W^2}$) is of the same magnitude than the one of the baseline, namely β^{W^2} .

⁴⁶ Exposure to low wind speed occurs much more frequently than exposure to high wind speed. For instance, 17.7% of the cluster-year observations are exposed to wind speeds between 63 and 117 km/h, whereas only 0.7% are exposed to wind speeds exceeding 177 km/h. Comprehensive statistics about exposure frequency is available upon request.

⁴⁷ To further check the existence of a non-linear model, we run another regression with bins that have the same amplitude. Again, we do not find any significant difference between coefficients associated with the highest and lowest wind speeds. Corresponding results are available upon request.

⁴⁸ The absence of a linear effect of cyclone exposure on the probability of having children indicates that the effect is probably fully realized at

Table 5

Alternative specifications: Intensification.
 Source: Sources: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	Baseline	Model with intensification			
	$\beta_1^{W^m}$	$\beta_1^{W^m}$	$\omega_1^{W^m}$	$\omega_2^{W^m}$	$\omega_3^{W^m}$
Max wind $\in [60, 118]$ in $t - 1$	-7.7960*** (0.1335)	-7.8067*** (0.1740)	0.4848** (0.2322)	1.1033*** (0.2675)	1.2567*** (0.2687)
Max wind ≥ 118 in $t - 1$	-6.9667*** (0.2129)	-5.2426*** (0.3734)	-1.6707*** (0.4952)	-0.6872 (0.6085)	-0.8683 (0.5208)

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual woman's age fixed effects and controls for rainfall and precipitation in $t - 1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees. For the baseline row, we report the value of β_1^W .

Table 6

Alternative specifications: dummies for non-linearities.
 Source: Sources: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	β^{W^1}	β^{W^2}	β^{W^3}
Non-linearities	-7.2473*** (0.1212)	-6.2145*** (0.2415)	-6.5293*** (0.3157)

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees. For the baseline row, we report the value of β_1^W .

6. Concluding remarks

The economic literature is still inconclusive about the direction of the effect of natural disasters on fertility. Theoretical models based on the quantity–quality approach of Becker (1960) as well as empirical estimates observe both a positive and negative association between the two phenomena. Given this disparity, our paper aimed to tackle this issue in the context of six developing countries that are regularly impacted by cyclonic systems. Our empirical strategy significantly improves the body of knowledge, because it exploits spatially geolocated household micro-data along with weather data that captures true cyclonic exposure at a high resolution (Geiger et al., 2018). Combining these two types of spatial data enables us to construct panel data to determine whether a given mother gives birth in a specific period and whether she is exposed to cyclonic wind speeds. Our panel data allow us to retrieve the causal effect of tropical cyclone wind speed shocks while using a minimal set of identifying assumptions (Dell et al., 2014).

After presenting a theoretical model from which three working assumptions about the effect of cyclonic exposure on fertility are derived, we provide empirical evidence about these important issues. Improving our understanding of the links between cyclones and fertility is imperative in order to develop appropriate public policy responses, particularly in poor countries. Our main results indicate that exposure to tropical cyclone wind speeds decreases the probability of giving birth, which is in line with (Pörtner, 2014; Davis, 2017), and Norling (2022) but in contrast with (Cohan and Cole, 2002; Hamilton et al., 2009; Evans et al., 2010), and Berlemann and Wenzel (2018). Heterogeneity analyses further suggest that the magnitude of the effect

moderate wind levels. From our point of view, this is still consistent with our modeling of cyclonic exposure as a negative income shock (see Section 2.3) as the sensitivity of agricultural assets is probably higher than other assets. Consequently, even a moderate exposure to cyclonic systems, says 110 km/h, could induce important income losses for people working in the agricultural sectors. In our final micro data, 67% of households live in rural areas and, given the sample of country considered in this paper, we could imagine that their income depend for a large part on the agricultural sector.

varies with the degree of exposure to cyclones associated with the household's living environment as well as the number of children ever born. First, in cyclone-prone areas, the likelihood of giving birth falls to a lesser extent, thus pointing to a process of adaptation among exposed populations. In this sense, our findings echo previous studies, suggesting that humans can adapt their behaviors to climate change (Casey et al., 2019; Thiede et al., 2022). Second, mothers with at least two children reduce their fertility more after a cyclone shock. This result may help guide the design of public policies in response to shocks by taking into account the family structure in the affected territory, which could also impact demographic dynamics. Further refinements of these main results indicate that past exposure to cyclones leads to a weaker decline in fertility. Nevertheless, our empirical model does not indicate non-linearities in the effect.

The panel estimates proposed in this paper are useful to highlight the fertility response to a tropical cyclone shock. In light of this, our estimates respond only partially to the question of how mothers adjust their family size when the risk of cyclones, namely the degree of cyclonic exposure, increases. This issue is of particular importance, since climate change has the potential to alter the frequency, spatial extent, and characteristics of the most extreme tropical cyclone events (Knutson et al., 2010; IPCC, 2019; Knutson et al., 2020). Combined with the fact that climate change may have an incidence on the opportunity cost of having children, these constitute an additional challenge for public policy makers. To deal with this, we believe that policy makers should promote policies that focus on family planning and influence the demand for children, for instance, by reducing household poverty and increasing girls' education. We believe that such investigations could improve our understanding of the mechanisms that explain fertility behavior. This is, however, beyond the scope of this paper, although it is on our agenda for future research.

CRedit authorship contribution statement

Idriss Fontaine: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Sabine Garabedian:** Writing – original draft, Supervision, Project administration, Funding acquisition, Formal analysis. **Hélène Vérèmes:** Visualization, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

The authors do not have permission to share data.

Appendix A. Additional summary statistics

See Table 7.

Table 7

Sample mean for a selection of women's characteristics y DHS wave.

Source: Sources: DHS and authors' own calculations.

Units		Woman at the time of the interview									Panel of woman-year observations						
Country and DHS wave	Year	Obs.	Age 1st birth	Age 1st marriage	No. child.	Years educ.	No educ.	Prim. educ	Sec. educ.	Tert. educ.	Age	MW	MW > 0	No. exp.	No. MW € [60, 118[No. MW ≥ 118	Obs.
Bangladesh-III	2000	1,420	17.64	14.87	2.66	3.07	0.53	0.29	0.15	0.04	26.25	16.68	88.50	3.00	2.71	0.30	20,098
Bangladesh-IV	2004	1,554	17.44	14.81	2.79	2.81	0.48	0.30	0.18	0.04	26.52	12.68	90.04	2.74	2.44	0.31	25,019
Bangladesh-V	2007	1,427	17.72	15.00	2.86	3.16	0.40	0.33	0.23	0.05	26.63	15.74	99.02	3.29	2.65	0.65	25,149
Dominican Republic- V	2007	12,512	19.60	17.83	2.67	4.03	0.05	0.46	0.32	0.16	26.88	24.84	94.03	5.31	4.22	1.10	230,498
Haiti-IV	2000	3,376	20.62	19.42	3.38	3.13	0.44	0.40	0.15	0.00	27.87	11.22	95.94	1.97	1.71	0.28	52,478
Haiti-V	2006	3,005	20.58	19.20	3.60	3.35	0.40	0.40	0.19	0.01	27.42	15.17	84.23	3.54	3.33	0.25	54,213
Haiti-VII	2017	4,230	20.66	20.83	3.21	3.85	0.25	0.41	0.32	0.02	25.78	25.91	85.63	6.43	6.00	0.48	78,051
Cambodia-IV	2000	5,937	20.95	19.10	3.42	3.13	0.38	0.52	0.09	0.01	27.86	5.42	81.34	1.11	1.06	0.05	96,294
Cambodia-V	2005	4,923	20.81	19.10	3.47	3.08	0.31	0.56	0.12	0.01	27.21	5.36	84.75	1.27	1.20	0.08	89,582
Madagascar-III	1997	2,450	18.72	16.29	3.89	2.57	0.35	0.50	0.14	0.01	26.72	25.12	105.80	3.29	2.19	1.11	30,788
Madagascar-V	2009	7,740	18.99	14.81	3.84	2.69	0.42	0.48	0.10	0.01	26.14	25.67	102.62	5.17	3.71	1.48	135,450
Philippines-IV	2003	2,480	21.71	20.46	3.02	3.97	0.04	0.31	0.38	0.27	27.34	48.68	98.85	9.59	7.67	1.93	43,563
Philippines-V	2008	2,651	21.72	20.58	3.14	3.99	0.04	0.29	0.39	0.28	27.10	45.77	97.45	10.62	8.64	2.01	51,572
Philippines-VII	2017	4,948	21.74	20.67	2.95	3.80	0.02	0.22	0.45	0.31	25.82	47.21	97.48	11.02	8.92	2.14	92,688
Final sample	–	58,653	20.12	18.25	3.21	3.43	0.25	0.42	0.24	0.09	26.80	23.26	93.13	4.97	4.05	0.94	1,025,443

Notes: Statistics are computed on the sample included in our analysis after applying the sample restrictions described in Section 3.1. Wind speed corresponds to the maximum wind speed experienced and is expressed in km/h. "MW" stands for "maximum wind speed".

Table 8

Macroeconomic indicators.

Source: World Bank, UNDP, and FERDI.

Variables	Bangladesh	Cambodia	DR	Haiti	Madagascar	Philippines
<i>Demographic</i>						
Pop. (in thousands)	157 830	15 417	10 405	10 563	24 850	103 031
Population growth	1.2	1.3	1.2	1.4	2.6	1.7
Area (in km ²)	147 630	181 040	48 670	27 750	587 295	300 000
Density	1 213	87	215	383	43	346
<i>Economic and poverty</i>						
GDP per capita	4217	3412	14 565	2935	1508	7123
Annual GDP growth	6.6	7	6.9	2.6	3.1	6.3
PHR	51.6	–	14.3	58	92.4	34.6
<i>Indicators of development</i>						
HDI score	0.579	0.563	0.722	0.493	0.512	0.682
HDI rank	139	143	99	163	158	116
Total fertility rate	2.1	2.6	2.4	3.1	4.2	3
Birth rate	19.2	22.3	20.6	25.6	32.8	23.2
EVI	24.28	35.26	21.27	28.80	35.31	24.59

Notes: DR stands for the Dominican Republic. Density is measured as the number of people per km², GDP per capita is the purchasing power parity in USD, and PHR corresponds to the poverty headcount ratio in USD per day in % of population for 2012 and 2016.

Appendix B. Country-by-country analysis

B.1. Macroeconomic context

Table 8 presents the macroeconomic statistics for 2015 for the six countries comprising our sample.⁴⁹ We choose this year because the sample period studied in this paper ends in 2015. These statistics allow us to better understand the differences in the magnitude of effects in our model.

The six countries included in our sample had a total population of more than 320 million people in 2015. In the majority, the population density was higher than the global average (57 inhabitants per km²). Bangladesh and the Philippines are particularly populous, with 157 million and 103 million inhabitants, respectively. Given the smaller area of Bangladesh (147,630 km²), its population density of 1,213 inhabitants per km² makes it one of the 10 most densely populated countries on the planet. The Philippines and Haiti also have high population densities, with 346 and 383 inhabitants per km², respectively, although the Philippines has a much larger area (300,000 km²). The Dominican Republic and Haiti both have a population of about 10 million inhabitants, although the territory of the former is almost twice that of the latter (48,670 vs. 27,750 km²), thus resulting in its lower population density (215). Finally, Cambodia and Madagascar have lower population densities of 87 and 43 inhabitants per km², respectively, due to their large territories, particularly Madagascar with 587,295 km². In most of these countries, their population growth rates exceed the global rate of 1.2. Madagascar has the highest population growth rate.

Aside from the Dominican Republic, these countries are among the poorest on the planet. Madagascar is the poorest country included in the study, with a GDP per capita of USD 1,508. The per capita income of Haiti, Bangladesh, and Cambodia ranges between USD 2,935 and 4,217, while the Philippines has a higher per capita income of USD 7,123. By contrast, the per capita income of the Dominican Republic is much higher than the other countries in the group, standing at

⁴⁹ These statistics are mainly taken from the World Bank (<https://data.worldbank.org/>). Human Development Index (HDI) data are taken from the United Nations Development Program (UNDP, 2016), and the Economic Vulnerability Index (EVI) data come from the Foundation for Research and Studies on International Development (FERDI) (<https://ferdi.fr/en/indicators/a-retrospective-economic-vulnerability-index>).

USD 14,565 or twice that of the Philippines. A high proportion of the population in these countries lives below the poverty line. Indeed, as a percentage of the population, the poverty headcount ratio of USD 3.65 per day is 92.4% for Madagascar, which is the poorest country in the sample.⁵⁰ More than half of the population in Bangladesh and Haiti live below the poverty line with 59.3% and 58% of the population, respectively. The poverty headcount ratio in the Philippines is similar to the world rate (32.7%) with 34.6%. Only the Dominican Republic exceeds the world rate with 14.3%. Thus, the Dominican Republic clearly stands above the sample in terms of wealth. We may also draw attention to the wealth difference between the Dominican Republic and Haiti, which share the same island.

These countries are characterized by high but heterogeneous economic growth rates. Indeed, the growth rate is much higher than the world rate (3.1%) for Cambodia (7%), the Dominican Republic (6.9%), Bangladesh (6.6%), and the Philippines (6.3%), while it is equivalent for Madagascar (3.1%) and lower for Haiti (2.7%). Development indicators lend support to the economic data. Indeed, the HDI places the six studied countries between 99th and 163rd place in the global rankings. More precisely, Haiti and Madagascar belong to the group of countries with low human development (< 0.550), while Cambodia, Bangladesh, and the Philippines have medium human development (between 0.550 and 0.700). Only the Dominican Republic is in the high development group (> 0.700).

Focusing on birth, let us explore two indicators: the “total fertility rate”, which represents the number of children born to a woman if she were to live to the end of her childbearing years and bear children in accordance with age-specific fertility rates of the specified year, and the “crude birth rate”, which indicates the number of live births per 1,000 midyear population. These two indicators show the strong birth dynamics in these territories. Madagascar has the highest rates with 4.2 and 32.8, respectively. The total fertility rate is higher rate than the global rate (2.5) in Haiti, the Philippines, and Cambodia, whereas it is lower in the Dominican Republic and Bangladesh. Finally, the birth rate is higher than the global value (19.1) in all these countries on account of the young population of reproductive age.

Finally, let us look at the Economic Vulnerability Index (EVI) defined by the United Nations Committee for Development Policy. The EVI aims to measure the structural vulnerability of developing countries following their exposure to shocks and the magnitude of these

⁵⁰ For this indicator, we chose 2012, because it has the most complete data, with the exception of Bangladesh, whose most complete year is 2016, and Cambodia, for which this indicator is not available.

Table 9

Country-by-country regression results.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	Bangladesh (1)	Haiti (2)	Cambodia (3)	Madagascar (4)	Philippines (5)	Dominican Republic (6)
Max wind $\in [60, 118[$ in $t - 1$	-7.8711*** (0.5243)	-20.0555*** (0.5029)	-16.9176*** (0.6412)	-3.9462*** (0.3543)	-6.0487*** (0.2877)	-18.8681*** (0.4542)
Max wind ≥ 118 in $t - 1$	-8.5338*** (1.3322)	-18.8241*** (0.8752)	-22.3535*** (1.2214)	-2.6892*** (0.4814)	-6.3965*** (0.3827)	-33.1409*** (0.9374)
Rainfall in $t - 1$	-0.0726 (0.0744)	0.0951 (0.0739)	-0.2199** (0.0908)	0.0409 (0.0568)	0.1100*** (0.0293)	-0.2507*** (0.0662)
Temperature in $t - 1$	2.0355 (2.6323)	1.6805 (4.2202)	-4.0677 (2.8561)	0.8754 (1.5790)	4.5630*** (1.3234)	1.7959 (2.5171)
Observations	70,266	184,742	185,876	166,238	187,823	230,498

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees.

Table 10

Main regression results — Wind speed in km/h.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	(1)	(2)	(3)	(4)
Max. wind in $t - 1$	-0.0651*** (0.0014)	-0.0668*** (0.0017)	-0.0775*** (0.0018)	-0.0793*** (0.0018)
Max. wind in $t - 1 \times$ Prone	-	-	0.0305*** (0.0024)	0.0304*** (0.0024)
Rainfall in $t - 1$	-	0.2016*** (0.0150)	-	0.2043*** (0.0150)
Temperature in $t - 1$	-	0.9622*** (0.2429)	-	0.7062*** (0.2453)
Observations	1,025,443	1,025,443	1,025,443	1,025,443

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects and woman's age fixed effects. The term "Prone" refers to a dummy equal to one when the mother lives in a village exposed to cyclones at least 10 times during the 1985–2015 period. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees.

shocks (Guillaumont, 2009). We see that the two most vulnerable countries are Madagascar and Cambodia, with scores of 35.31 and 35.26, respectively. Haiti has a score of 28.80. Although the Philippines and Bangladesh have an equivalent score of 24.59 and 24.28, the former has a more advanced level of development in terms of GDP and HDI. The Dominican Republic is also the least vulnerable country in the sample with a score of 21.27.

B.2. Regression results

Appendix C. Alternative specification of the baseline model

See Tables 10–12.

Appendix D. Exploring other heterogeneity dimensions

D.1. Differences in urban–rural areas

According to Kochar (1999), Evans et al. (2010), and Pörtner (2014), the occurrence of a cyclone modifies the shadow price of having an additional child, especially if couples live in areas that are more prone to negative impacts. In developing countries, a large proportion of the population lives in rural areas and depends on agricultural activities. As stressed by Dessy et al. (2019), the characteristics of economic life differ drastically in rural and urban areas. In rural areas, women

Table 11

Regression results depending on the number of children ever born — Wind speed in km/h.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	(1)	(2)
Max. wind in $t - 1$	-0.0273*** (0.0018)	-0.0289*** (0.0018)
Max. wind in $t - 1 \times$ Having 1 child	0.0019 (0.0024)	0.0013 (0.0024)
Max. wind in $t - 1 \times$ Having 2 children	-0.0428*** (0.0024)	-0.0434*** (0.0024)
Max. wind in $t - 1 \times$ Having > 2 children	-0.1004*** (0.0023)	-0.1009*** (0.0023)
Rainfall in $t - 1$	-	0.2125*** (0.0151)
Temperature in $t - 1$	-	0.3646* (0.2436)
Observations	1,025,443	1,025,443

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees.

Table 12

Alternative specifications: Intensification.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	β_1^W	ω_1^W	ω_2^W	ω_3^W
Baseline	-0.0676*** (0.0014)			
Intensification	-0.0679*** (0.0018)	0.0052** (0.0023)	0.0129*** (0.0028)	0.0146*** (0.0026)

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters, and temperature in Celsius degrees.

For the baseline row, we report the value of β_1^W .

contribute actively to agrarian activities, meaning that their labor supply makes an important input to this production activity. By contrast, in urban areas, it is easier for women to diversify their professional activities, as they have greater employment opportunities in the service sector. Thus, women living in urban areas depend less on activities that

Table 13

Exposure to tropical cyclone wind speed for models including heterogeneity dimensions by interaction terms.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	$j = \text{rural}$	$j = \text{low educated}$
Max wind $\in [60, 118[$ in $t - 1$	-7.1107*** (0.1893)	-6.2379*** (0.1683)
Max wind ≥ 118 in $t - 1$	-6.5568*** (0.3166)	-5.7530*** (0.2690)
Max wind $\in [60, 118[$ in $t - 1 \times (j = 1)$	-1.0361*** (0.0019)	-2.6039*** (0.2172)
Max wind ≥ 118 in $t - 1 \times (j = 1)$	-0.6510*** (0.0023)	-2.0749*** (0.3776)
Observations	1,025,443	1,025,443

Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$.

may be negatively impacted by tropical cyclone exposure unlike their rural counterparts engaged in agricultural activities. Consequently, it is likely that the opportunity cost of motherhood and childrearing is less linked to tropical cyclone exposure in urban compared with rural areas. To test this mechanism, we introduce another heterogeneity dimension into our econometric framework using interaction terms. We interact the wind speed variables with a dummy indicating whether the household lives in a rural area.

The econometric model of column (1) of Table 13 shows the corresponding estimates. In rural areas, exposure to tropical cyclone wind speed is associated with a greater decrease in the probability of giving birth. The difference between the estimated marginal effects is significant.

D.2. Differences by education

The last heterogeneity dimension explored here involves interacting wind speed exposure with a dummy that indicates whether the mother has a low level of education at the time of the interview. Indeed, we conjecture that low-educated women have a greater chance of working in the agricultural sector compared with those with a high level of education, meaning that the post-cyclone opportunity cost of having children would be greater for the former. The corresponding regression results are displayed in the second column of Table 13. As anticipated, the reduction in the likelihood of giving birth after a cyclone shock is higher for low-educated mothers. More specifically, the total marginal effect for an exposure to wind speed below 118 km/h is equal to 8.8 points.

Appendix E. Robustness analysis

The panel estimates presented in the main text reveal that a tropical cyclone shock leads to a significant fall in women's likelihood of giving birth. These findings could be sensitive to the different choices regarding the data, model, and specification when estimating the baseline model. To ensure that the main message of this paper holds true, we check the robustness of our results according to five dimensions: (i) alternative formulations of the tropical cyclone variable, (ii) the inclusion of migrant mothers in our final sample, (iii) the sample period, and (iv) the inclusion of never-exposed clusters. The results of these alternative estimations are reported in Table 14.

Tropical cyclone variable. An important robustness check is to establish whether the results are similar when using alternative formulations of the measure of tropical cyclone exposure. We address this issue by considering two other measures of the incidence of tropical cyclones.

Instead of directly using the wind speed experienced by a given spatial unit, many recent papers construct ad-hoc indices of potential destruction (also known as a damage function).⁵¹ The reasoning behind these indices follows (Emanuel, 2011). More specifically, below a certain threshold \bar{W} , wind speed is unlikely to provoke substantial physical damage, so the level of physical destruction could be assumed to be zero. However, once the wind speed generated by the cyclonic system is above \bar{W} , the level of damage increases in a non-linear fashion. To understand how such alternative measures of tropical cyclone exposure affect our conclusion, we run two other checks.

In the first check, we follow a similar strategy as (Strobl, 2012) and construct the following potential destruction index:

$$D_{it} = W_{it}^\zeta \text{ if } W_{it} > \bar{W} \text{ and zero otherwise} \tag{9}$$

When constructing D_{it} , two parameters are of importance, because they shape the functional form: ζ , which corresponds to the parameter that links the maximum surface wind speed to the level of damage, and \bar{W} , which is the threshold above which the level of destruction becomes perceptible. Different values have been proposed for these two parameters, although related empirical evidence is scarce, especially for developing countries. In the US context, Emanuel (2005) suggests that the level of damage can be studied by the cubic value of the maximum wind speed at the surface. By contrast, Nordhaus (2006) suggests that destructiveness increases with the eighth power of maximum wind speed.⁵² Concerning \bar{W} , Strobl (2012) and Bertinelli and Strobl (2013) set it to 177 km/h (value above which a cyclonic system becomes category 3 on the Saffir-Simpson scale), while (Mohan and Strobl, 2017) select a value of 119 km/h (value above which a cyclonic system becomes category 1 on the Saffir-Simpson scale). Without further evidence about these parameters, we choose $\lambda = 3$ as suggested by Emanuel (2005) and Strobl (2011), and we fix $\bar{W} = 93$ km/h as indicated by Emanuel (2011). Column (2) of Table 14 provides the results of this alternative estimation.

In the second check, we follow (Emanuel, 2011) and construct the following index f_{ct} to capture the proportion of damaged property:

$$f_{ct} = \frac{v_{ct}^3}{1 + v_{ct}^3} \tag{10}$$

with

$$v_{ct} = \frac{\text{MAX}(W_{ct} - \bar{W}, 0)}{W^* - \bar{W}}. \tag{11}$$

Where c denotes a cluster and W^* corresponds to the threshold at which half of buildings are damaged. Again, we lack strong empirical evidence when choosing an appropriate value for W^* . Here, as we fix \bar{W} to 93 km/h, we set W^* to 166 km/h, namely the wind speed threshold at which the Regional Specialized Meteorological Center (RSMC) of La Réunion labels a tropical system as "intense". Corresponding results are reported in column (3) of Table 14.

A closer inspection of columns (2)-(3) of Table 14 leads us to make a few comments. First, the qualitative patterns of our results are entirely preserved, since the estimated coefficients for the two different measures of wind speed are all negative. Second, the observed quantitative patterns are broadly consistent with our baseline estimate, even if the non-linear nature of the wind speed variable of the models has some interpretative incidence. Thus, for a level of destruction in

⁵¹ Examples include (Strobl, 2011, 2012; Bertinelli and Strobl, 2013), and Mohan and Strobl (2017).

⁵² In the context of US coastal counties, Strobl (2011) uses an estimate of 3.17 for ζ .

Table 14

Alternative specifications: robustness.

Source: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.

	Baseline (1)	Wind speed variable (2)	(3)	With migrants (4)	Sample period (5)	(6)	Only exposed clusters (7)
$\beta_1^{W^1}$	-7.7960*** (0.1335)	-8.19e ⁰⁶ *** (4.78e ⁻⁰⁷)	-6.6639*** (0.4940)	-6.9615*** (0.0810)	-8.0620*** (0.1818)	-7.4588*** (0.1420)	-7.8894*** (0.1072)
$\beta_1^{W^2}$	-6.9664*** (0.2129)			-6.5696*** (0.1427)	-6.5419*** (0.3085)	-7.2032*** (0.2457)	-7.0865*** (0.1875)
Obs.	1,025,443	1,025,443	1,025,443	1,785,137	526,822	498,621	925,970

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses and adjusted for clustering at the DHS cluster level. All regressions include woman fixed effects, annual fixed effects, woman's age fixed effects and controls for rainfall and precipitation in $t - 1$.

The model of column (1) corresponds to the baseline model. The model of column (2) uses the potential destruction index from Eq. (9) instead of the baseline wind speed variable. The model of column (3) uses the index from Eq. (10) instead of the baseline wind speed variable. The model of column (4) corresponds to the estimation of the baseline estimate for a sample including migrant mothers. The results of columns (5) and (6) correspond to the models for the sample periods of 1985–1997 and 1997–2015, respectively. The results of column (7) correspond to the estimation of the baseline estimate for a sample without non-exposed clusters.

$t - 1$ equivalent to the standard deviation of the damage function, the models of column (3) (resp. column (2)) indicate that a mother is 0.5 points (resp. 0.8) less likely to give birth in t . The negative effects are substantially higher when considering events with extreme wind speeds of 250 km/h. In particular, for this level of exposure, the probability of motherhood falls by 6.1 points (resp. 12.8 points) for the potential destruction index from Eq. (10) (resp. Eq. (9)).

Overall, other measures of tropical cyclone exposure show that our main result does not depend on the choice of the wind speed variable. The two alternative measures used in this section nevertheless have several limitations as they rely on parameters for which the evidence is missing for the six countries studied in the paper (models of columns (2) and (3)). For this reason, our preferred specification directly uses dummies based on the wind speed variable of Geiger et al. (2018).

Sample restriction regarding migration. In the main text, the results are based on a sample of mothers declaring that they had always lived in their current home. We thus restrict our sample to non-migrant mothers to ensure that when iterating backwards, we retrieve only true exposure to cyclones. Indeed, the risk of including migrant mothers is that tropical cyclone exposure may be attributed to a woman who actually lived in a non-affected area at the time of the event. Furthermore, the DHS includes a variable indicating the number of years of residence in the current home. However, as highlighted by Kudamatsu (2012), this declarative variable could be subject to recall bias. For these two reasons, we exclude all migrant mothers from our baseline analysis. One potential pitfall of this sample restriction is that non-migrant and migrant mothers may differ with respect to the observable characteristics. In particular, we may suppose that non-migrant mothers are older than migrant mothers on average. In this robustness exercise, we consider another sample before re-estimating Eq. (7). In addition to non-migrant mothers, we include migrant mothers but only keep the observations since their arrival in their current home. Corresponding results can be found in column (4) of Table 14 and show no significant difference from the baseline estimates of the main text.

Sample period. Implicitly, our baseline model assumes that the estimated effect is averaged over the entire sample under scrutiny. However, it is possible that the decision to have children changes over time. We address this possibility by separately estimating Eq. (7) for two sample periods. The first sample spans the 1985–1997 period, whereas the second begins in 1985 and ends in 2015. Results are respectively reported in columns (5) and (6) of Table 14.

The main insight provided by these alternative panel estimations is that there is no significant difference in the causal effect of wind speed exposure for the two sub-periods.

Excluding non-exposed clusters. As indicated in Fig. 1 some clusters were never exposed to tropical cyclones during the period under scrutiny. Here, we check the sensitivity of our baseline results by estimating a model that excludes these clusters. Corresponding results are reported in column (7) of Table 14, showing that our results are robust to the exclusion of never-exposed clusters.

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