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TROPICAL CYCLONES AND FERTILITY : NEW EVIDENCE FROM DEVELOPING COUNTRIES

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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 tackles this question by constructing a panel dataset from geolocated microdata about mothers' fertility history along with wind field data generated by tropical cyclones hitting a sample of six developing during the 1985-2015 period. Using panel, we estimate the causal effect of tropical cyclone shocks on women's likelihood of giving birth. We find evidence that the effect of tropical cyclone exposure on motherhood is significantly negative. In particular, being exposed to a wind speed cyclone shock decreases the probability of giving birth by 2.6 points a year after exposure. We also find that the magnitude of the effect varies with the degree of cyclonic exposure associated to mother's living environment and to the number of children ever born. Alternative specifications of our baseline model provide further insights, as we find: i) a persistent effect of tropical cyclone shocks in the sense that we do not have evidence of any reversal effect, ii) that recent past exposures to cyclones is associated with a lower decrease in fertility when exposed and iii) no evidence of non-linearities in the effect. The estimated effect is shown to be robust when using alternative formulations of our baseline empirical model.

Keywords: Fertility, Tropical cyclone, Developing countries

JEL classifications: J13, O12, Q54, C23

1 Introduction

Evidence about the consequences of exposure to cyclonic systems at the individual level is still scarce (Anttila-Hughes & Hsiang, 2013). The lack of comprehensive microstudies, which could be explained by strong data requirements, leaves many questions unanswered, in particular how households reorganize their lives after being impacted by tropical cyclones. Exposure to tropical cyclones along with the associated destruction has the potential to induce high costs to households in terms of incomes, livelihoods, crop yields, assets, and loss of life. Arguably, it is likely that the micro-impacts of such adverse shocks are stronger in countries with almost inexistent institutional ways of coping, as is probably the case for developing countries (Dessy et al., 2019). In this context, households have the incentive to diversify their activities, and children often play a particular role within households (Banerjee & Duflo (2007), Banerjee & Duflo (2011)). They actively contribute to daily activities by, for example, caring for siblings or grandparents, participating in housework chores, and even sometimes directly participating in the labor market (Finlay, 2009).[1] In light of this, parents' decision to have children is probably altered after being affected by a tropical cyclone (Sellers & 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 to 19% for those who have not been exposed. Our paper therefore addresses the main following question: Does exposure to tropical cyclones causally impact fertility?

Understanding how households adjust 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 fecundity is *a priori* unclear from both a theoretical and empirical perspective. In theoretical models such as those of Finlay (2009), Pörtner (2014), and Dessy et al. (2019), the direction of the post-disaster decision ultimately depends on assumptions about the benefits and costs associated with children. Empirically, an increase in family size after a natural disaster was found by Nobles et al. (2015), Nandi et al. (2018), and Finlay (2009), whereas a fall was identified by Evans et al. (2010), Pörtner (2014), Davis (2017) and Norling (2022). Given the inconclusive nature of the previous studies, the issue of whether natural disasters affect fertility is still an open empirical question. The main goal of the paper is to rigorously establish the direction and magnitude of the causal effect of tropical cyclones on women's likelihood of giving birth when using high-resolution data on the true exposure to tropical cyclones experienced on the ground.

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

While previous studies exploring the effect of natural disasters on fertility mainly focus on earthquakes, it is likely that their results cannot be extrapolated to the case of cyclonic events. First, the macro-literature has shown that the consequences of natural disasters on economic growth are not identical for all kinds of disasters (Fomby et al. (2013), Felbermayr & Gröschl (2014)). We can therefore conjecture that the magnitude or even the direction of the effect may also be different 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), Nandi et al. (2018)). Although the measurement of a causal effect in these studies is undisputed, they do not consider variability in the degree of exposure, the magnitude of the disaster events or the existence of possible intensification effects. The database constructed here allows for the investigation of such issues.

We first begin by presenting a simple theoretical framework of parents decisions about fertility. The model developed, inspired by the works of Ranjan (1999), Finlay (2009) and Norling (2022), is employed to frame the discussion and the development of empirical model. In particular, three working assumptions about post-cyclone fertility responses are derived from the model. The first one suggests that after an adverse shock, such as an exposure to cyclones, the likelihood of fertility is expected to fall. The second one investigates the heterogeneous response of fertility for mothers living in cyclone prone areas and those living in non-prone area. In that respect, the model suggests that the former group should be less sensitive to cyclone shock. Finally, the third working assumption is about the response of fertility after an exposure to cyclones with respect to the number of children ever born. More specifically, the model suggests that 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) of six countries, namely Bangladesh, Cambodia, Dominican Republic, Haiti, Madagascar and the Philippines.[2] This cross-sectional household survey has several practical advantages for the issue at hand: it is nationally representative, has a large number of observations, and provides information about individuals' characteristics. In addition, the DHS includes the full fertility history of each woman interviewed together with detailed information about their 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 on the six developing countries during the 1985-2015 period examined in this paper. By merging

[2]The choose of this DHS wave and the one of countries studied in this paper is guided by data requirements.

the geographic information of these two databases along with the fertility history of the DHS, we construct a panel data model in which we retrieve the tropical cyclone exposure of a given mother in a given year for the entire study period. The relationship between changes in tropical cyclone wind speed exposure and the female likelihood of giving birth is then examined by means of fixed effect regressions. In doing so, our panel reduced-form model has numerous advantages, since only a minimal set of assumptions is imposed.[3]

Our main empirical results can be summarized as follows. First, we can affirmatively respond to the abstract's question and to 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 tropical cyclone shock of a standard deviation magnitude, leads to a fall of 2.6 points in the probability of giving birth a year after exposure. Second, our baseline estimates then show that the causal effect of wind speed exposure depends on the degree of cyclonic exposure associated to the mother's living environment. In cyclone prone areas, the likelihood of giving birth decrease less. Third, the magnitude of the fall in fertility also depends on the number of children ever born since mothers with at least two children are much more likely to reduce their fertility after a cyclone than mother with no child. In a last step, we take advantage of the continuous nature of the wind speed variable together with the possibility of estimating models with more lags to refine the nature of the relationship between cyclonic exposure and fertility. In particular, we find i) a persistent effect of tropical cyclone shocks in the sense that we do not have evidence of any reversal effect, ii) that recent past exposure to cyclones is associated with a lower decrease in fertility when exposed and iii) no evidence of non-linearities in the causal effect. Overall, our results are estimated to be robust to other measures of tropical cyclone exposure and to several changes concerning sample restriction and/or the empirical specification.

Our paper is related to at least three strands of the economic literature. First, by merging spatially geolocated micro-data with weather variables, our paper is part of a new but flourishing body of literature that studies the effect of weather shocks on socioeconomic variables (e.g., Deschênes & Greenstone (2011), Kudamatsu et al. (2012), Anttila-Hughes & Hsiang (2013), Barreca et al. (2018), Dessy et al. (2019), Sellers & Gray (2019), Marchetta et al. (2019), 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 examining how households respond after an adverse event (e.g., Morduch (1995), Banerjee & Duflo (2007), Alam & Pörtner (2018)). Indeed, in developing countries, having

[3] 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 enables us to identify their causal effects.

children enables households to smooth their consumption over time. Thus, studying how households react to a cyclonic event that induces the loss of property, crops, and livelihoods allows us to contribute to the debate on how they respond to a cyclone shock. We add to this body of literature by providing evidence for six developing countries regularly threatened 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.[4] First, Evans et al. (2010) investigate how the fertility rate in US counties responds to storm advisories. They found 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 data along with historical data about hurricane occurrences and finds a negative association between fertility and tropical cyclone exposure at the municipal level. Third, Davis (2017) exploits rainfall data as a measure of tropical cyclone exposure and observes that high levels of rainfall in Nicaraguan municipalities are associated with an increase in fertility. Fourth, Norling (2022) investigates how fertility responds to disasters in Africa and find that fertility is negatively associated to disasters. Our paper overcomes many of the problems associated with these four papers, since our panel setup alleviates concerns related to the unobserved heterogeneity of mothers. We rely on a measure of tropical cyclone exposure that is directly related to its physical intensity and destructiveness.[5] Furthermore, we investigate heterogeneity dimension with respect to the degree of cyclonic exposure of 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. 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.

[4]Other papers focusing on the post-fertility effect of earthquakes are discussed in subsection 4.1.

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

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.[6] 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, the 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 to child quantity. This produces an inverse relationship between income and fertility. In these models, a particular focus is given to education as an investment in human capital (Becker, 1992; Azarnert, 2006; Lee & 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 constituting one of the main explanations of the high fertility (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 when an increase in fertility occurs in response to the expected future mortality of children. 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 come from on the uncertainty of expected future income (Ranjan, 1999; Pörtner, 2001). This uncertainty can occur in the labor market (Kreyenfeld, 2010, 2015; Hanappi 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.[7] The underlying argument of these studies is that greater uncertainty about future prospects will encourage couples to postpone and possibly forego childbearing altogether, because it involves an irreversible investment with long-term consequences on resources (Aassve et al., 2021). In this context, the aggregate fertility seems pro-cyclical over the

[6] The interested reader can refer to Schultz (1997) for a review of these extensions.

[7] The interested reader can refer to Aassve et al. (2021) or Sobotka et al. (2011) for a review.

business cycle[8] (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 and show that at times of heightened uncertainty, risk-averse individuals will postpone childbearing more than risk lovers (Schmidt, 2008; Hofmann & Hohmeyer, 2013). Vignoli et al. (2020) propose a conceptual framework for the study of 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 have explored the impact of natural shocks on fertility. They examine the meaning and magnitude of the potential impacts of natural disasters on fertility as well as the potential explanatory factors. Empirical evidence about the effect of natural disasters and, more generally, weather anomalies on fertility is mixed. The studies are primarily concerned with poor countries. In this way, most of the time, the occurrence of a natural disaster is modeled as an exogenous shift in labor income.[9] The first-order conditions associated with the maximization of household utility reveals that the desired number of children is chosen up to the point where the satisfaction obtained from an extra child equates to its opportunity cost.[10]

The positive impact can be explained by either the replacement effect or the insurance mechanism relating to income uncertainty. The replacement effect (or "hoarding" effect) is examined by Nobles et al. (2015) on the impact of Indian Ocean Tsunami in 2004 or by Nandi et al. (2018) on the earthquake in India in 2001. Finlay (2009) studies the insurance mechanism and argues that children can be used to smooth consumption over time. More precisely, she shows that 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 increase in labor market productivity has two opposite effects on the shadow price of an additional child. On the one hand, it increases the foregone income of women when they spend time out of the labor market to care for children. On the other hand, an income effect renders each additional child cheaper. Dessy

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

[9] In developing countries, this variation in income corresponds to the realization of labor productivity (in the agricultural sector) at the beginning of each period.

[10] The opportunity cost of the additional child is also known as the shadow price. In what follows, we use both terms interchangeably.

et al. (2019) assumes that the former prevails over the latter.[11] Sellers & Gray (2019) observes the same result for climate shocks (temperature and precipitation) where the reduction in the opportunity cost of having children (especially in rural areas) is the main driver of the fertility effect. Finally, for hurricane Cohan & Cole (2002) found a net increase of birth rate due to post-disaster family restructuring.

Skidmore & Toya (2002) study the impact of climatic disasters in 89 countries and finds a positive effect on economic growth but a negative impact on fertility. This negative impact can be explained, at least in part, by conjunctural (Lindstrom & Berhanu, 1999) and psychologic factors (Arnberg et al., 2011). Indeed, recent studies have shown that natural disaster or climate anomalies have a negative impact on fertility under certain circumstances. Thiede et al. (2022) emphasizes that climate exposure affects reproductive outcomes but only in specific locations and populations, with this heterogeneity underscoring the need to consider socioeconomic and environmental factors. More specifically, for cyclones, Berlemann & Wenzel (2018) showed a positive impact on fertility in low-income countries but a strong and significantly negative effect for countries with high levels of development. For the United States, Evans et al. (2010) found an increase in fertility for hurricanes of low severity, while severe tropical storms led to a decrease in fertility. The negative effect can also be explained by the increase in the opportunity cost of having children (Kochar, 1999; Evans et al., 2010; Alam & Pörtner, 2018; Berlemann & Wenzel, 2018; Norling, 2022) or by the uncertainties caused by the disaster shock (Davis, 2017; Pörtner, 2014; Wang et al., 2022).

Despite the underlying uncertainty assumption, few studies incorporate it explicitly. Pörtner (2014) differentiates between risk and shock variables. Risk represents the percentage probability of a hurricane occurring in a given year for each area, whereas shock is the number of cyclones experienced by a woman during her fertile period.[12] Pörtner (2014) finds that shock leads to a decrease in fertility, while the risk increases fertility for the households with land. [13] In the literature that uses theoretical models, (Finlay, 2009; Pörtner, 2014; Marchetta et al., 2019; Norling, 2022) integrate uncertainty in the evolution of income (that depends on the investment in education) in the decision to have children.

2.3 Theoretical model proposition

This subsection develops a model regarding parental decisions about fertility. The model environment has two periods. The household has utility in both periods but experiences

[11] Another reason based on more psychological factors is the fact that motherhood is a way to cope after an emotionally traumatic experience (Carta et al., 2012).

[12] More specifically, this is "the number of cyclones between the year the woman enters her fertility period (taken to be 15 years) and her 29th year or the survey year, whatever is first" (Pörtner, 2014).

[13] Pörtner (2014) also includes the effect of shock and risk on education.

some uncertainties about outcome 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 of 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 obtain 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 is different. 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:

$$\begin{aligned} Y_1 &= c_1 + kn_1 \\ Y_2 + wn_1 &= c_2 + kn_2 \end{aligned}$$

Following Ranjan (1999), we assume that income in period 2 varies with probability.[14] So, the expected utility of period 2 depends on the probability of exposure to natural disasters λ in period 2. 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 how many goods and children to have in each period to maximize a global 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:

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

The comparative statics of equation (2) informs us about the direction of the effect of a given parameter on the number of children to be born in period 2. With respect to the share of

[14] However, although Ranjan (1999) assumes that income increases with probability 1/2 and decreases with probability 1/2, we assume here that probability is a parameter between 0 and 1.

income loss due to the occurrence of an adverse event such as a cyclone δ, we obtain:

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

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

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

Then, 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 that the effect of cyclonic exposure on motherhood depends on the degree of exposure of people living in the most exposed areas. The latter is written as:

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

Given that the number of children is a decreasing function in the share of income loss, the positive sign of (4) indicates that n_2 decreases less in areas that are 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 if 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:

$$\frac{\partial^2 n_2}{\partial \delta \partial n_1} = 0 \tag{5}$$

Consequently, our theoretical framework implies that the number of children to be born in period 2 after 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 the development of our empirical results. Section 5 aims to provide an empirical response to these 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 countries exposed to cyclones. The DHS is a series of cross-sectional surveys that is conducted approximately every 5 years. The DHS is generally conducted by the national institute of statistics and benefited from 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 were interviewed. From these women, detailed information was collected about their sociodemographic (e.g., household composition, education level, number of children, household well-being) and health characteristics (e.g., infant mortality, nutritional practices, malaria prevalence, use of contraceptives). 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 gender or the women's age at childbirth. From this fertility history, we construct a panel dataset of women and define a binary variable to indicate whether a woman gave birth or not during a given year.

Let us now describe in further details 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 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 were randomly chosen. The geographical information that we use to locate the women comes from the first-level selection. In particular, for each selected cluster, the data producer provides geographical information about its centroïd. However, to ensure the confidentiality of the selected households, the data producer does not provide the exact latitude and longitude of the cluster's centroïd but 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 information about tropical cyclones to retrieve the wind speed exposure experienced by inhabitants on the ground.

To conduct our research, we apply some restrictions to our sample. First, among all countries with DHS microdata, we first select those with a positive exposure to tropical cyclones. Second, given that the geographical information about cluster locations is essential, we exclude DHS' wave without geographic information. For the DHS with geographical information we exclude households living in clusters without exploitable coordinates.[16] Third,

[15]For instance in Madagascar, 285 clusters among 21,500 were selected for the 1997 phase of the DHS compared to 600 in 2008.

[16]Missing geographical information are due to i) inconsistencies in the reported geographic coordinates and ii) the incapacity of the data producer to access some clusters (ICF Macro (1998), ICF Macro (2010)).

as we use the retrospective data about mothers' fertility, we need to ensure that a given woman has been really exposed to a given tropical cyclone in a given year. To do so, we follow Kudamatsu (2012) and Anttila-Hughes & Hsiang (2013) by restricting our final sample to mothers declaring that they have always lived in their current home.[17] It should be observed that for some DHS' waves, information about the arrival in the current home is simply missing for all observations. As we believe that having knowledge about the residence of the mother is mandatory for our purpose, we select waves of DHS for which this information is recorded.[18] These restrictions leave us with a sample of six countries namely Banglasdeh, Cambodia, Dominican Republic, Haïti, Madagascar and Philippines.[19] Finally, as we iterate backwards to construct our panel database, we drop all records for which the mother's age is below the threshold of 15.[20]

Table 1 reports a selection of summary statistics. In our final sample, the total number of children per woman was 3.22, while the birth frequency was 17%. The average age at first childbirth was equal to approximately 20 years. Approximately, 23% of women reported having no education, while around 43% reported, at best, a level equivalent to primary education. This results in a relatively low number of years at school (around 3.5 years).

3.2 Macroeconomic context

Table 2 presents macroeconomic statistics for 2015 for the six countries that make up our sample.[21] 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 the effects in our model.

The six countries included in our sample had more than 320 million people in 2015. The majority have a population density higher than the global average (57 inhabitants per km^2). Bangladesh and the Philippines are particularly populous, with 157 million and 103 million inhabitants, respectively. Given the smaller area of Bangladesh (147,630 km^2), it has a density

[17] In a robustness check, we relax this assumption (see Appendix C).

[18] Having no information about the arrival of the mother in the current home is problematic even if geographical information about cluster locations is available. In particular, one could attribute an exposure to a woman whereas she actually leaves elsewhere.

[19] Overall, we employ 14 waves of DHS. DHS waves used in this paper are: for Bangladesh waves IV and V, for Cambodia waves IV and V, for Dominican Republic wave V, for Haïti waves IV, V and VII, for Madagascar waves III and V, and for Philippines waves IV, V and VII.

[20] For instance, for a woman born in 1973 and aged 35 in 2008 at the time of the interview, we build annual records of her fertility from 1988. This woman enters the our dataset when she is 15 and her last record correspond to the year of the interview.

[21] These statistics are mainly from the World Bank (`https://data.worldbank.org/`. The HDI data comes from the UNDP (UNDP, 2016) and the EVI data comes from FERDi (`https://ferdi.fr/en/indicators/a-retrospective-economic-vulnerability-index`)

Variable	Sample mean
Mother's age	26.80
Mother's age at first birth	19.92
Mother's age at first marriage	18.68
Number of children	3.22
% of birth	0.17
Years of education	3.56
No education (in %)	0.23
Primary education (in %)	0.43
Secondary education (in %)	0.25
Tertiary education (in %)	0.09

Table 1: Sample mean of a selection of women's characteristics.
Sources: DHS and authors' own calculations.
Notes : Statistics are computed on a sample of 58653 women. The "% of birth" correspond to the frequency of birth once the panel is constructed.

of 1,213 inhabitants per km², making it one of the 10 most densely populated countries on the planet. Both 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). Haiti and the Dominican Republic both have a population of about 10,500 inhabitants, although the territory of the latter is almost twice the area (27,750 vs. 48,670 km²), thus resulting in its lower population density (215). Finally, Cambodia and Madagascar have lower population densities (87 and 43) due to their large territories, particularly Madagascar with 587,295 km². In most of these countries, their population growth rates are higher than the global rate of 1.2 births per 100,000 inhabitants . Madagascar has the highest population growth rate with 2.6 compared with rates between 1.2 and 1.7 births per 100,000 inhabitants for the five other countries.

Aside from the Dominican Republic, these countries are among the poorest on the planet. Madagascar is the poorest country included in the study, with GDP per capita of USD 1,508. Haiti, Bangladesh, and Cambodia have a per capita income between USD 2,935 and 4,217. Philippines has a higher per capita income of USD 7,123. However, the per capita income of the Dominican Republic is much higher compared with the other countries in the group, being USD 14,565 or twice that of the Philippines. A high proportion of the population in these countries lives below the poverty line. Indeed, the poverty headcount ratio at USD 3.65 a day as a percentage of the population is 92.4% for Madagascar, which is the poorest country.[22] Next, more than half of the population in Bangladesh and Haiti live below the

[22]For this indicator, we chose 2012, because this year has the most complete data, with the exception of

Variables	Bangladesh	Cambodia	DR	Haiti	Madagascar	Philippines
Demographic						
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
Economic and poverty						
GDP per capita	4217	3412	14565	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
Indicators of development						
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

Table 2: Macroeconomic indicators.

Sources: World Bank, UNDP and FERDI.

Notes: DR stands for Dominican Republic. Density is measured as the number of people per km^2, GDP per capita is in USD in Purchasing Power Parity, PHR correspond to the Poverty headcount ratio in USD per day in % of population for 2012, 2016.

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 has a better rate than the world rate with 14.3%. Thus, the Dominican Republic is clearly 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, it 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%). The development indicators provide support to the economic data. Indeed, the human development index (HDI) places the six studied countries between 99th and 163rd place in the world 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).

To focus on birth, we may explore two indicators: the "total fertility rate" which represents the number of children that would be born to a woman if she were to live to the end of

Bangladesh, whose closest year is 2016, and Cambodia, for which this indicator is not available.

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. For the total fertility rate, Haiti, the Philippines, and Cambodia also have a higher rate than the world rate (2.5), while Dominican Republic and Bangladesh have a lower rate. Finally, the birth rate in all these countries is higher than the global value (19.1), because the population is young and of reproductive age.

Finally, let us look at the economic vulnerability index (EVI) defined by the Committee for Development Policy of United Nations. The IVS aims to measure the structural vulnerability of developing countries resulting from the magnitude of shocks and exposure to shocks **??**. 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. The Philippines and Bangladesh have an equivalent score of 24.59 and 24.28, although the Philippines 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.

3.3 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 rotating clockwise in the Southern Hemisphere and counter-clockwise in the Northern Hemisphere. It is organized around a center of low atmospheric pressure called 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 characterised by strong surface winds. Cyclonic systems are divided into several categories, according to the intensity of the associated winds (defined as the maximum speed of the wind 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 systems, cyclonic systems, and tropical cyclones interchangeably to designate tropical systems of any magnitude.[23] The wind associated with cyclonic systems can thus cause severe damage. Some are listed by Tamura (2009)'s study according to wind speed thresholds. For instance, maximum 10-minute averaged winds of 90 km/h can damage roof tiles, while above 162 km/h, the constraints of the main frame of high-rise buildings exceed the elastic limit. The devastating effects of

[23] We however acknowledge that there are three classes of cyclonic phenomena. First, if the wind speed is less than 63 km/h, it is called a tropical depression. Second, between 63 and 117 km/h, it is called a tropical storm. 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, or a typhoon in the North-West Pacific.

tropical cyclones mainly come from strong winds (CCR, 2020).[24]

3.3.1 TCE-DAT caracteristic

A prerequisite for our empirical study is a measure of wind speed exposure experienced by the population on the ground. As it is not possible to rely on weather ground station data at a detailed level in the context of the six developing countries under scrutiny here, we exploit 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 $0.1° \times 0.1°$ grid over land) for more than 2,700 landfalling cyclonic systems between 1950 and 2015. As the quality of data records resuired to compute wind speed is lower before 1980, we choose a cautious approach by placing our cut-off several years after 1980, namely in 1985.[25] The calculation is based on the International Best Track Archive for Climate Stewardship (IBTrACS) archive (Knapp et al., 2010), which contains all the information necessary for a wind field model such as that of Holland (1980) that is widely used in studies on the evaluation of the 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)[26] at radial distance r of 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 equation (6), Geiger et al. (2018) calculated 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

[24] CCR (2020) collect post-cyclone insurance data and find that the vast majority of insurance claim payments are due to wind speed rather than rainfall, landslides, or storm surges.

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

[26] For simplicity, we do not add an index to designate pixels.

wind exposure on the ground. To our knowledge, there is no other publicly available dataset from a ground weather station or remote sensing measurement covering the whole territory of Madagascar with a spatial resolution higher than $0.1° \times 0.1°$. This is the main reason why we decided to use the wind speed estimate calculated by Geiger et al. (2018).[27]

Table 3 and the barplot of Figure 1 show summary statistics about cyclonic exposure of clusters under scrutiny in this paper. Overall, 21.0% of our pairs of cluster-year observations experienced a positive wind speed exposure. Over our sample period, the mean number of exposures to cyclones was of 7.4. Given that the standard deviation of exposure frequency is approximately equal to its mean, the number of exposures by clusters is quite heterogenous. Thus, 11% of clusters were not exposed at all to cyclones. In Figure 2 these clusters are represented by the yellow part of each map. Looking at the top of the distribution, we observe that 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 investigated because it creates within variations that could be explored by our panel fixed effect regressions. Let us now take a look on the profile of wind speed exposure generated at the surface. To do so, we now focus on DHS clusters when exposure is non-zero.[28] The average wind speed exposure during the 1985-2015 period is 93.5 km/h with a standard deviation of 32.2. 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. Observe that the maximum wind speed recorded during our sample period is 293.7 km/h. This extreme wind speed is due to Haiyan, one of the most severe phenomena that passed over Philippines. For illustrative purposes, we plot in Figure 2 the field of annual maximum wind speeds for the six countries belonging to our sample during the 1985-2015 period. It appears that exposure to cyclonic wind speed is the highest in Philippines especially at the north of this country. Then, Madagascar is the second country with the highest exposure. In particular, the north-east cost of the country is regularly threatened by tropical cyclones. Among the countries studied here, Bangladesh, Haiti and Dominican Republic have a wind speed exposure falling in the middle of distribution. Finally, the north east of Cambodia has a similar exposure as the three quoted countries but the other parts of the county appears to be less prone to be exposed to such a natural phenomenon.

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

[28] In doing so, we follow Elliott et al. (2015).

	Nb. of exposure	Wind speed	Rainfall	Temperature
Mean	7.40	93.50	19.00	25.60
Standard deviation	7.30	32.20	8.10	1.90
Min.	0.00	61.20	1.90	16.40
Percentile 1%	0.00	63.50	5.60	18.30
Percentile 5%	0.00	64.60	8.40	22.30
Percentile 10%	0.00	65.80	10.50	23.40
Percentile 25%	2.00	71.60	13.60	25.00
Percentile 50%	6.00	84.30	17.50	25.90
Percentile 75%	9.00	99.00	22.90	26.90
Percentile 90%	19.00	138.40	29.70	27.70
Percentile 95%	24.00	166.10	34.30	28.10
Percentile 99%	29.00	212.60	45.60	28.50
Max.	34.00	293.70	72.50	29.10
Observation	7,626			

Table 3: Summary statistics of weather variables for the DHS clusters during the 1981-2015 period.

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.

Notes: 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 and is expressed in Celsius degrees. For the wind speed, summary statistics are computed only for non-zero cluster-year pairs.

3.3.2 Other weather data

Although our main focus is on the impact of tropical cyclone exposure on motherhood, we include two other weather variables in our analysis, namely rainfall and mean temperature. Their inclusion is meant to avoid noises due to the shared secular changes that might be correlated with tropical cyclone exposure. Our rainfall variable comes from the 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 ($0.05° \times 0.05°$) 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 3 report the univariate statistics of rainfall and mean temperature.

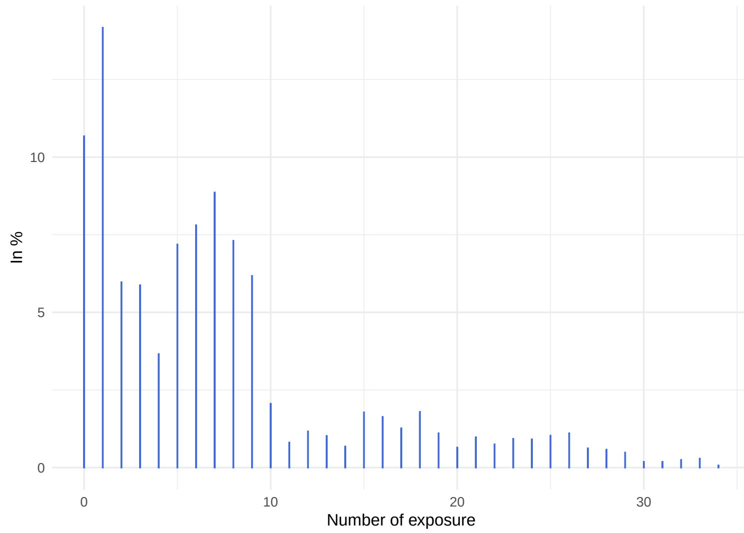

Figure 1: Distribution of cyclonic exposure experienced by DHS clusters (1981-2015).
Sources: DHS, TCE-DAT (Geiger et al., 2018), and authors' own calculations.

4 Empirical framework

4.1 Estimated equation

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

$$y_{itcv} = \sum_{l=1}^{L} \left(\beta_l^W \times W_{i,t-l} + \beta_l^R \times R_{i,t-l} + \beta_l^T \times T_{i,t-l} \right) + \mu_i + \eta_t + \theta_v + \alpha_c + u_{itcv} \qquad (7)$$

Where i indexes a given woman, t a given year, and c a given cluster. The outcome of interest, namely y_{itc}, is a binary variable equal to one if mother i from country c living in cluster v gives birth in year t and zero otherwise. Given that y_{itcv} is dichotomous, we rely on a linear probability model. [29] In equation (7), β_l^j with $j \in [W, R, T]$ 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 $t-1$ measured in kilometers per hour (km/h). 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

[29] Such a practice is standard in the empirical literature dealing with dependent dichotomous variables in a panel setup (Anttila-Hughes & 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 & Millo (2018) for more details).

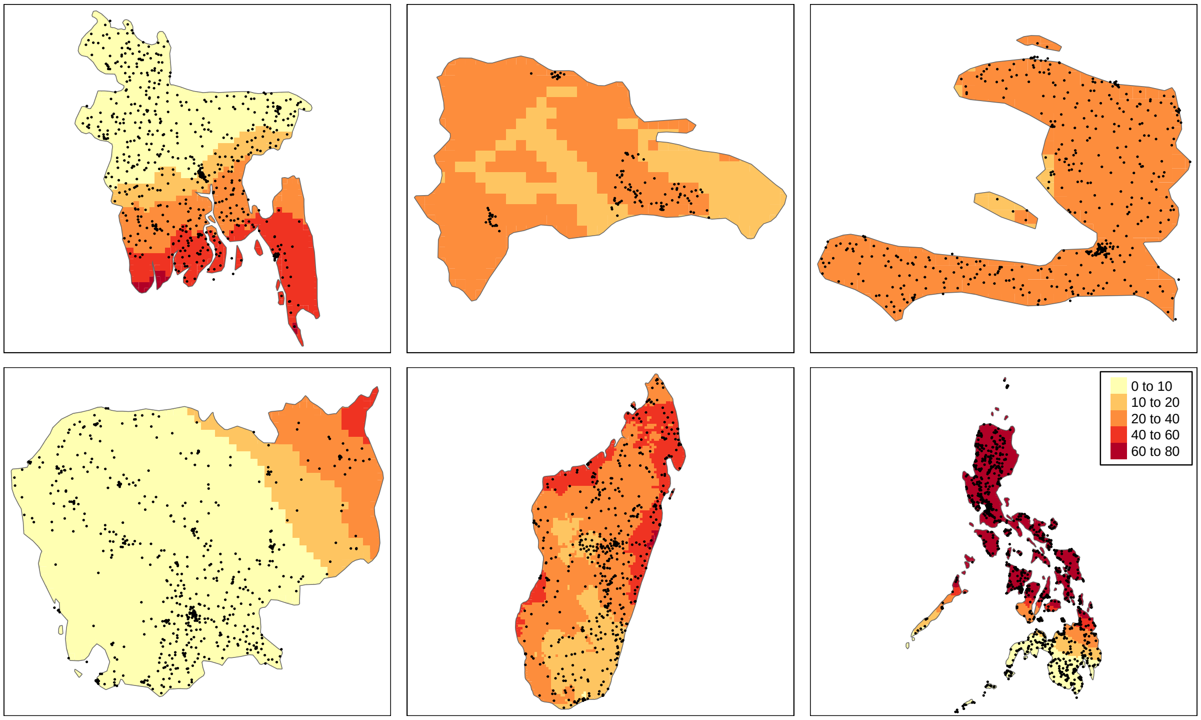

Figure 2: Mean of wind speed exposure (1980-2015)
Sources: DHS, TCE-DAT (Geiger et al., 2018), and authors' own calculations.
Notes: The dots of each panel correspond to cluster coordinates of the last wave of DHS used for each country. From the top-left to the bottom-right we have Bangladesh, Dominican Republic, Haïti, Cambodia, Madagascar and Philippines.

related to omitted variables. If there are correlations or shared secular changes among the weather variables, studying the impact of a weather variable in isolation could be problematic (Dell et al., 2014).[30] In the baseline model, we set $L = 1$ so that the three weather variables enter our model with a one period lag. We also consider the case where $L = 5$ so that each weather variable enters with up to five lags in sensitivity analysis (see subsection 5.2).[31] We include woman fixed effects μ_i to control for unobserved and time-invariant characteristics that could potentially affect women's likelihood of childbearing.[32] We also flexibly account for year-specific components shared by all women using a year fixed effect η_t. Their inclusion ensures that the relationship of interest can be identified from idiosyncratic shocks. We also

[30]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 exposure in the Caribbean basin countries.

[31]As such model reveals that beyond one period, coefficients associated to lags of cyclonic exposure are significant but closer to zero, in the baseline we include only one lag.

[32]These unobserved factors could be the (time-invariant) preference of women to have a large family. Their preference can also be rationalized by emphasizing the opportunity cost of taking care of children. Women's more limited outside 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 their childrearing.

include cluster and country fixed effects θ_v and α_c to capture any unobserved characteristics that plausibly affect women's childbearing behavior at the "village" or the country level. Finally, u_{itcv} 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 u_{it} 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). Let us take household income as an additional control variable.[33] In this case, we cannot exclude 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.[34] This is the well-known reverse causation problem that leads to the introduction of a selection bias in the estimation of the income-related coefficient as well as other estimated coefficients in the model. Given these two arguments, we believe that the parsimonious model of equation (7) remains a relevant departure point. In doing so, our empirical model is able to 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 equation (7), variables are expressed as deviations from the individual and temporal sample means (Croissant & 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 could be interpreted as the impact of tropical shocks on women's probability of giving birth.

The main assumption used on 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 difficult to predict. When they occur, tropical cyclones generate recognizable wind speeds of high magnitude hitting large spatial units

[33] 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 for which such information is not available.

[34] Similar problems could arise for variables such as education level, years of education, school dropout, participation in the labor market, and so on.

(quasi-)randomly so that inhabitants living in these areas experience the exposure, while those living in non-affected areas experience no exposure. We however acknowledge that some areas are more likely to be exposed by tropical cyclones so that the total effect on fertility could vary depending on the level of risk. We also consider this possibility by introducing such a heterogeneity dimension in our empirical analysis (see also section 5).

There are potentially two issues relating to the randomness of tropical cyclones, both of which are related to the ability of meteorologists to forecast the occurrence of tropical cyclones. 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 the occurrence of a tropical cyclone a few days before its landfall. From our point of view, this forecasting nevertheless has almost no incidence on our identification strategy, because our focus is on year-to-year variations. In particular, if seasonal forecasts have a higher predictive power, the year-to-year variations in tropical cyclone wind speed at a given spatial unit largely remains unpredictable for scientists and thus for inhabitants potentially concerned by tropical cyclones. Regarding short-run forecasting, it implicitly assumes that inhabitants living in areas threatened by a cyclonic system have perfect access to the information (by means of a radio, television, or newspaper). This could be not the case in the context of developing countries.Nevertheless, it is probable that important information about the occurrence of tropical cyclones circulates through other channels like people's social networks, so we cannot totally exclude the fact that individuals could engage in actions to protect their homes and livelihood or evacuate. These issues have some 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 degradation in their living environment is perceptible and may affect their decision to have children. Insofar as year-to-year variations in the exposure to tropical cyclones 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.[35]

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

	(1)	(2)	(3)	(4)
Max. wind in $t-1$	-0.0659***	-0.0676***	-0.0784***	-0.0801***
	(0.0014)	(0.0014)	(0.0018)	(0.0018)
Max. wind in $t-1$ × Prone	–	–	0.0305***	0.0304***
	–	–	(0.0025)	(0.0025)
Rainfall in $t-1$	–	0.2001***		0.2029***
	–	(0.0154)	–	(0.0154)
Temperature in $t-1$	–	1.042***	–	0.7866***
	–	(0.2498)	–	(0.2524)
Observations	1,025,443	1,025,443	1,025,443	1,025,443

Table 4: Main regression results.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include woman fixed effect, annual fixed effect, cluster fixed effect and country fixed effect. The term "Prone" refers to a dummy equal to one when the mother leaves in a village that was exposed to cyclone 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.

5.1 Main results

5.1.1 Fertility response to cyclone shocks

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

Column (1) and (2) reports the results of a model with exposure to wind speed being measured by the maximum wind speed generated at the surface. These models show the negative impact of tropical cyclone wind speed shocks on mothers' likelihood of giving birth. The estimated relationship is consistently negative regardless the inclusion of controls for temperature and rainfall. In the model of column (2), a wind speed exposure shock in t equivalent to a standard deviation, namely 38.8 km/h, induces a fall of 2.6 points (38.8×-0.0676) in women's likelihood of giving birth in $t+1$.[36] Alternative specifications of the baseline empirical model, consisting in changing our sample restriction by including mothers who migrate or splitting the sample to consider two sub-periods do not change the qualitative nor the quantitative pattern of our baseline results. As a result, our empirical evidence provides an affirmative answer to our first working assumption.

[36] A similar metric shows that the probability of giving birth for mothers exposed to extreme wind speeds (e.g., 213 km/h), falls by about 14.4 points in the next calendar year.

Empirical evidence on working assumption 1:

Exposure to tropical cyclones does reduce 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 A we present country-by-country regressions. These regressions show that the qualitative pattern is the same for the six countries under scrutiny here: exposure to cyclones reduces the probability of giving birth. However, depending on the country, the quantitative patterns could differ substantially. Thus, countries such as Madagascar or the Philippines are those with the smallest effect. For instance, an extra exposure to wind speed reduce the probability of motherhood in $t+1$ of 0.0452 in Philippines and 0.0271 in Madagascar. By contrast, countries such as Haiti, Cambodia or Dominican Republic experience the highest effects in term of post-cyclone reduction in fertility. In Haiti, and extra exposure to cyclonic wind speed in t translates in a fall in the likelihood of having babies of 0.231. In comparison to Madagascar, the fertility response in Haiti is eight times higher. An interesting feature emerging from the comparison of country-by-country regressions is that the effect seems to be higher in countries least frequently exposed.[37] [38]

In columns (3) and (4) of Table 4, we further explore the link between the degree of exposure associated to cyclonic and fertility. As Figure 2 shows, clusters' exposure to tropical cyclones is quite heterogeneous. Summary statistics of Table 3 unveil that over our sample period, 10% of villages were exposed more than 19 times while 25% were exposed less than two times. Even after controlling for cluster fixed effects, it is still possible that the effect of cyclonic wind speed on motherhood depends on the degree of exposure and preparedness of people living in most exposed villages. We could imagine that mothers living in the most frequently exposed areas anticipate the higher probability of exposure when taking their decision about having babies. Thus, their response to a cyclone shock could be different from mothers living in non-prone areas. To investigate this issue, we interact wind speed exposure

[37] According to the TCE-DAT of Geiger et al. (2018), during the 1985-2015 sample period Haiti has been exposed to cyclones 23 times, Dominican Republic 24 and Cambodia 29. In contrast, Madagascar has been exposed 84 times and Philippines 284. Consequently, Bangladesh, with a number of exposure of 50, falls in the middle of the distribution.

[38] Another interesting feature emerging from Table 8 is about the magnitude of the effect for the two countries of the Hispaniola island, namely Haiti and the Dominican Republic. Haiti is much less developed than the Dominican Republic (see also Table 2). In the theoretical section, we highlight that the post-disaster responses of fertility could be related to the country's level of development. For Haiti and the Dominican Republic, it seems to be not the case. Indeed, even with two very different development levels, the fall in the probability of motherhood is of the same magnitude. Given that the level of exposure to cyclones of these two countries is similar, we could conjecture that, in this special case, the degree of exposure is more important in shaping the post-cyclone fertility response than the development level.

with a dummy equal to one if the village were exposed more than nine times to cyclonic systems during the sample period of our study.[39] We refer to these clusters as cyclone-prone areas. Coefficients associated to this model specification can be found in the last two columns of Table 4. Again, the inclusion of controls for temperature and rainfall do not alter the qualitative and the quantitative causal effect of wind speed exposure on motherhood. However, in these models, the coefficient β_1^W now captures the effect of wind speed exposure for mothers living in non-prone area. Compared to models of columns (1) and (2), the latter is higher. All else being equal, an exposure to cyclonic wind speed of one standard deviation size decreases the probability of having children by 3.11 points. The interaction term of wind speed with the dummy for cyclone prone area confirms what has been suggested previously. 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 decrease by 1.93 points for the same level of exposure.[40] Such a result suggests that the fertility response to a cyclone shock is sensitive to the degree of exposure associated to mother's environment. In that sense, our empirical results is in line with our second working assumption.

Empirical evidence on working assumption 2:

The fertility response to cyclone shocks depends on the degree of exposure associated to the mother's living environment: in cyclone prone areas, the likelihood of giving birth reduce less.

5.1.3 Children ever born and fertility response to cyclone shocks

As indicated before, the model of section 2.3 does not deliver a clear message about the post-disaster fertility response with respect to family size. Instead, the model suggest that the post-cyclone fertility response is independent of the number of children ever born. However, depending on the presence of children we could imagine that the post-cyclone response in terms of fertility could be different. The association between children ever born and future fertility is worth investigated empirically. Here, we wonder if the response of fertility to an adverse shock depends on past fertility. To consider this possibility, we run an alternative empirical model in which the exposure variable is interacted with dummies indicating the number of children ever born. More specifically, we consider three dummies for mothers having respectively one child at the time of the exposure, two children or more than two children. Corresponding results are reported in Table 5. It is noteworthy that as before the inclusion of rainfall and temperature does not alter the coefficient associated to cyclonic exposure. The first row of the corresponding table can be interpreted as the effect of cyclonic exposure on

[39] The number of nine correspond to the 75% percentile of the corresponding distribution (see also Table 3).

[40] The estimated effect in cyclone prone area is significantly different from the effect in non-prone area at the 1% level.

	(1)	(2)
Max. wind in $t-1$	-0.0298***	-0.0313***
	(0.0018)	(0.0018)
Max. wind in $t-1$ × Having 1 child	0.0139***	0.0133***
	(0.0024)	(0.0024)
Max. wind in $t-1$ × Having 2 children	-0.0372***	-0.0378***
	(0.0025)	(0.0025)
Max. wind in $t-1$ × Having >2 children	-0.1059***	-0.1063***
	(0.0023)	(0.0023)
Rainfall in $t-1$	–	0.2104***
	–	(0.0156)
Temperature in $t-1$	–	0.4174*
	–	(0.2504)
Observations	1,025,443	1,025,443

Table 5: Regression results depending on the number of children ever born.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include woman fixed effect, annual fixed effect, cluster fixed effect, country fixed effect and controls for rainfall and temperature in $t-1$. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters and temperature in Celsius degrees.

fertility for mothers having no baby at the time of the exposure. The corresponding coefficient is negative for both specification of the empirical model. We consistently witness negative marginal effects for each of the interaction terms suggesting that the fall in the likelihood of giving birth after an exposure to cyclone is a robust pattern. However, it should be observed that, even if it remains negative, the estimated impact of cyclonic exposure is significantly lower for mothers having one child at the time of exposure. Thus, for a cyclonic wind speed shock in t equivalent to a standard deviation, the likelihood of having a baby in $t+1$ decreases by -0.70 point for mothers having one child against -1.21 point for those having no child. For mothers having two children (resp. more than two children) the corresponding fall in mothers' likelihood of having birth in $t+1$ is equal to 2.78 points (resp. 5.34 points).[41] As anticipated, the marginal effect of cyclonic exposure on fertility depends on the number of children ever born and in general mothers with a large number of children ever born reduces more their fertility. However, one of the particularity of our results is about mothers having one child the likelihood of motherhood seems to be less sensitive to cyclonic exposure. This quite puzzling feature could reflect mothers preference for having at least two children for those having already one child.

Empirical evidence on working assumption 3:
The fertility response to cyclone shocks depends on the number of children ever born: mothers with at least two children reduce more their fertility after a cyclone shock.

5.2 Further results

In this subsection, we propose an in-depth analysis to investigate three potential features of the causal effect. First, we estimate a specification to test the existence of non-linearities in the effect. Second, we test whether the negative causal effect depends on mothers' past exposure to cyclones. Three, we include more lags in the baseline model to verify whether the causal effect persists. The results of these alternative estimations are reported in Tables 7 and 6. Note that the study of other heterogeneity dimensions together with robustness checks, which consist of changing the sample or the wind speed variable, are respectively reported in Appendix B and C.

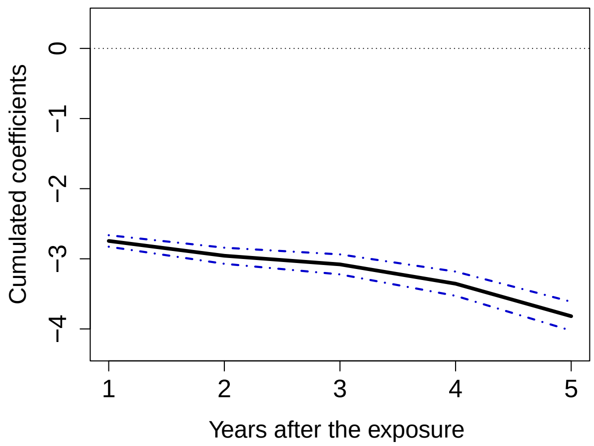

Figure 3: Cumulative effect of wind speed exposure on the likelihood of giving birth.
Sources: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.
Notes: Black solid lines correspond to the cumulative sum of the estimated points, while blue error bands show the associated confidence intervals (at the 5% level of significance). The regression includes mother fixed effects (μ_i), time fixed effects (η_t), village fixed effects (θ_v), country fixed effects (α_c) controls for rainfall (from R_{t-1} to R_{t-5}) and mean temperature (from T_{t-1} to T_{t-5}).

5.2.1 Is the effect persistent over time?

In the baseline model, we include a lag of the exposure variable variable. Here, we reconsider the main specification by adding up to 5 lags of weather variables to the model.[42] The latter model allows us to investigate more precisely the medium-run effects of tropical cyclones on fertility. For illustrative purpose, we depict the cumulative effect of wind speed exposure on motherhood in Figure 3, while the coefficient values are provided in Table 11 of Appendix D.[43]

As shown in Figure 3, the effect of a tropical cyclone shock of one-standard deviation on the likelihood of giving birth persists over time. Furthermore, with a 5-year time frame, we do not observe any strong offsetting behavior, namely a strong positive effect of wind speed exposure for some lags. Table 11 of Appendix D shows that the estimated coefficients are all statistically negative. Exploring the distributed lag nature of this model, Figure 3 indicates that the cumulative effect of extra wind speed exposure amounts to $\sum_{l=0}^{L=5} \beta_l^W = -3.82$.[44]

[41] Each time, the estimated effect associated to the interaction term is significantly different from the effect for mothers having no children at the 1% level.

[42] Rainfall data are only available from 1981. We drop all observations prior to 1986, because it is not possible to obtain 5 lags of the rainfall variable before that year.

[43] We also illustrate the cumulative effects for rainfall and temperature shocks in Figures 4 and 5 of Appendix D.

[44] Regarding the other two weather variables, Figure 4 shows that when accounting for 5 lags, the negative effect of rainfall shocks persists during three years, whereas that of temperature shocks has a hump-shaped behavior.

	β_1^W	ω_1^W	ω_2^W	ω_3^W
Baseline	-0.0676*** (0.0014)			
Intensification	-0.0775*** (0.0020)	0.0085*** (0.0024)	0.0207*** (0.0029)	0.0177*** (0.0027)

Table 6: Alternative specifications: Intensification.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include, rainfall in $t-1$, temperature in $t-1$, as well as the four fixed effects. 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.

Overall, extending the model to include more lags shows that the effect of tropical cyclone shocks has the potential to reduce permanently the probability of motherhood in the medium run as a non-reversal effect is observed.

5.2.2 Intensification mechanism

We now further test the hypothesis that the effect of cyclonic systems on female motherhood builds 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 equation (7), is magnified if the same woman has also been exposed to a 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 such a possibility by interacting wind speed exposure in a given period t with a dummy variable indicating that a given woman i has also been exposed to one, two or more than two tropical cyclones in the last 5 years before the exposure. Our set of dummy variables is denoted as $\tilde{W}_{i,t-l}$. The estimated equation now has the following form:

$$y_{itc} = \beta_1^W \times W_{i,t-1} + \beta_1^R \times R_{i,t-1} + \beta_1^T \times T_{i,t-1} + \sum_{j=1}^{J=3} \left(\omega_j^W \times \tilde{W}_{i,t-1} \right) + \mu_i + \eta_t + \theta_v + \alpha_c + u_{itcv}, \quad (8)$$

where ω_j^W are the parameters to be estimated and j the number of exposure during the past five years. Their interpretations differ from those of β_1^W. The latter corresponds to the effect of wind speed exposure in period $t-1$ on the current likelihood of motherhood. However, the second coefficient, namely ω_1^W, captures a different effect, namely the incremental effect of wind speed exposure on motherhood in period $t-1$ if the woman has additionally been exposed

	$\beta_1^{\tilde{w}^1}$	$\beta_1^{\tilde{w}^2}$	$\beta_1^{\tilde{w}^3}$	$\beta_1^{\tilde{w}^4}$	$\beta_1^{\tilde{w}^5}$	$\beta_1^{\tilde{w}^6}$
Baseline	-0.0676*** (0.0014)					
Non-linearities	-7.9307*** (0.1387)	-7.2436*** (0.2690)	-7.4471*** (0.4420)	-7.4507*** (0.5325)	-6.5088*** (0.7928)	-5.1767** (2.2655)

Table 7: Alternative specifications: Dummies for non-linearities.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include, rainfall in $t-1$, temperature in $t-1$, as well as the four fixed effects. 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.

to only one tropical cyclone during the five past years preceding the exposure. Consequently, the intensification parameters, namely ω_j^W, explore if the effect of a tropical cyclone shock depends on the pattern of previous shocks.

The last row of Table 6 explores the possibility of intensification effects by adding $\tilde{W}_{i,t-1}$ to the model. Overall, there is no evidence regarding the existence of an intensification mechanisms. The three ω_j^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 has also been exposed to tropical cyclones. Let us consider that before the exposure in $t-1$, the mother has been exposed to two tropical cyclones. In this case, the total effect of an extra wind speed exposure amounts to -0.0568 (namely, $\beta_1^W + \omega_2^W$).[45] All in all, the fact that the decrease in the probability of motherhood is lower for exposed mothers in a recent past echoes with the empirical evidence on working assumption 2: regularly exposed mothers appear to be less sensitive to cyclonic shock.

5.2.3 Non-linearities

Our baseline model implicitly assumes that the fertility response to tropical cyclone shocks is linear. However, the literature exploring the effect of weather shocks on economic variables often indicates that the effects are likely to be non-linear. In particular, Emanuel (2011) and Nordhaus (2010) suggest that damage due to tropical cyclones exponentially increases with the level of wind speed experienced on the ground. Despite such suggestions, it is not straightforward when other socioeconomic variables also respond non-linearly to wind

[45] For each coefficient, we check that the total effect is significantly different from β_1^W.

speed exposure, especially in a context when household micro-data is used. To reveal a possible non-linear relationship, we follow a non-parametric approach by breaking wind speed up into bins corresponding to the Saffir-Simpson scale. This approach has two main advantages. On the one hand, it is simple to implement. On the other, it is flexible and does not impose any functional forms on our wind speed explanatory variable. Hence, we construct six dummies equal to one when wind speed falls within the bin and zero otherwise. Specifically, $\tilde{w}_t^1 = 1(W_t \in [62;118[)$, $\tilde{w}_t^2 = 1(W \in [118;153[)$, $\tilde{w}_t^3 = 1(W \in [153;177[)$, $\tilde{w}_t^4 = 1(W \in [177;208[)$, $\tilde{w}_t^5 = 1(W \in [208;251[)$, and $\tilde{w}_t^6 = 1(W \in [251;300[)$.[46] We report the related results in Table 7.

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 to the highest wind speed, namely $\beta_1^{\tilde{w}^6}$ is not significantly different from $\beta_1^{\tilde{w}^1}$. It should also be observed that coefficients' standard errors is increasing with the level of the Saffir-Simpson scale. This indicates that for the most extreme phenomenon the estimated effect between cyclonic exposure and fertility.[47] The linear approximation used in our baseline model appears as a relevant departure point.

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 find both a positive and a negative association between the two phenomena. Given this disparity, our paper sought to respond to this question in the context of six developing countries regularly threatened by cyclonic systems. Our empirical strategy significantly improves the body of knowledge, because we exploit spatially geolocated household micro-data together with weather data that captures true cyclonic exposure at a high-resolution level (Geiger et al., 2018). Merging these two types of spatial data enables us to construct panel data to indicate whether a given mother gives birth in a specific period and whether she was exposed to cyclonic wind speeds. Our panel data allows us to retrieve the causal effect of tropical cyclone wind speed shocks while relying on 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 and fertility are derived, we aim at providing empirical evidence

[46] Implicitly, the first bin $\tilde{w}_t^0 = 1(W_t \in [0;62[)$ serves as reference in the regression.

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

about these important questions. Improving the understanding of the links between cyclones and fertility is imperative in order to build appropriate public policy responses, particularly in poor countries. Our main results indicate that exposure to tropical cyclone wind speeds leads to a fall in the probability of giving birth, in line with the work of Pörtner (2014), Davis (2017), Norling (2022) but in contrast with the work of Cohan & Cole (2002), Hamilton et al. (2009), Evans et al. (2010) or Berlemann & Wenzel (2018). Heterogeneity analyses further suggest that the magnitude of the effect varies with the degree of exposure to cyclones associated to the household's living environment but also to the number of children ever born. First, in cyclone prone areas, the likelihood of giving birth reduce less, which suggests a process of adaptation in exposed populations. In that sense, our finding echoes with conclusions suggesting that human behaviors could adapt to climate change (Casey et al., 2019; Thiede et al., 2022). Second, mothers with at least two children reduce more their fertility after a cyclone shock. This result can also guide the design of public policies to respond to shocks by taking into account the family structure of the territory concerned, which could have an impact on demographic dynamics. Refinements of the main results indicate that the negative effect persists over time, while we find evidence that past exposure to cyclones imply a weaker decrease in fertility. However, 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 do not respond totally to how mothers adjust their fertility when the risk associated with tropical cyclones increases. This issue is of particular importance, since climate change has the potential to alter the frequency, genesis, spatial extent, and characteristics of the most extreme tropical cyclone events (Knutson et al., 2010; IPCC, 2019; Knutson et al., 2020). At this stage, even though our study found a negative response of fertility to cyclonic shocks, we cannot exclude the possibility that fertility could actually increase in response to tropical cyclone risks in the future. This is a further challenge for policy designers as climate change could also alter the opportunity cost of having babies. To deal with is, we believe that policy makers should engage in policies focusing the supply of family planning as well as those influencing the demand for fertility by reducing for instance household poverty and girl's school enrollment. We believe that such investigations could improve our understanding of the mechanisms explaining fertility behavior. This is, however, beyond the scope of this paper, although it is on our agenda for future research.

References

Aassve, A., Le Moglie, M., & Mencarini, L. (2021). Trust and fertility in uncertain times. *Population Studies*, 75(1), 19–36.

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). *When Should You Adjust Standard Errors for Clustering?* Working Paper 24003, National Bureau of Economic Research.

Alam, S. A. & Pörtner, C. C. (2018). Income shocks, contraceptive use, and timing of fertility. *Journal of Development Economics*, 131, 96 – 103.

Anttila-Hughes, J. & Hsiang, S. (2013). Destruction, disinvestment, and death: Economic and human losses following environmental disaster. *SSRN Electronic Journal*.

Arnberg, F. K., Eriksson, N.-G., Hultman, C. M., & Lundin, T. (2011). Traumatic bereavement, acute dissociation, and posttraumatic stress: 14 years after the ms estonia disaster. *Journal of traumatic stress*, 24(2), 183–190.

Azarnert, L. V. (2006). Child mortality, fertility, and human capital accumulation. *Journal of Population Economics*, 19, 285–297.

Banerjee, A. V. & Duflo, E. (2007). The economic lives of the poor. *Journal of Economic Perspectives*, 21(1), 141–168.

Banerjee, A. V. & Duflo, E. (2011). *Poor economics : a radical rethinking of the way to fight global poverty*. Public Affairs.

Barreca, A., Deschenes, O., & Guldi, M. (2018). Maybe next month? temperature shocks and dynamic adjustments in birth rates. *Demography*, 55, 1269–1293.

Becker, G. S. (1960). *An Economic Analysis of Fertility*, (pp. 209–240). Columbia University Press.

Becker, G. S. (1992). Fertility and the economy. *Journal of Population Economics*, 5(3), 185–201.

Berlemann, M. & Wenzel, D. (2018). Hurricanes, economic growth and transmission channels: Empirical evidence for countries on differing levels of development. *World Development*, 105, 231–247.

Bertinelli, L. & Strobl, E. (2013). Quantifying the local economic growth impact of hurricane strikes: An analysis from outer space for the caribbean. *Journal of Applied Meteorology and Climatology*, 52(8), 1688–1697.

Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2), 167–188.

Buckles, K., Hungerman, D., & Lugauer, S. (2021). Is fertility a leading economic indicator? *The Economic Journal*, 131(634), 541–565.

Cain, M. (1983). Fertility as an adjustment to risk. *Population and Development review*, (pp. 688–702).

Carta, G., D'Alfonso, A., Colagrande, I., Catana, P., Casacchia, M., & Patacchiola, F. (2012). Post-earthquake birth-rate evaluation using the brief cope. *Journal of Maternal Fetal Neonatal Medecine*, 25(11), 2411–2414.

Casey, G., Shayegh, S., Moreno-Cruz, J., Bunzl, M., Galor, O., & Caldeira, K. (2019). The impact of climate change on fertility. *Environmental Research Letters*, 14(5), 054007.

CCR (2020). *Evolution du risque cyclonique en Outre-mer à horizon 2050*. Technical report, Caisse Centrale de Réassurance.

Cohan, C. L. & Cole, S. W. (2002). Life course transitions and natural disaster: marriage, birth, and divorce following hurricane hugo. *Journal of family psychology*, 16(1), 14.

Croissant, Y. & Millo, G. (2018). *Panel Data Econometrics with R*. John Wiley & Sons, Ltd.

Davis, J. (2017). Fertility after natural disaster: Hurricane mitch in nicaragua. *Population and Environment*, 4(38), 448–494.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3), 740–98.

Deschênes, O. & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4), 152–85.

Dessy, S., Marchetta, F., Pongou, R., & Tiberti, L. (2019). Fertility response to climate shocks. working paper or preprint.

Doepke, M. (2005). Child mortality and fertility decline: Does the barro-becker model fit the facts? *Journal of population Economics*, 18(2), 337–366.

Elliott, R. J., Strobl, E., & Sun, P. (2015). The local impact of typhoons on economic activity in China: A view from outer space. *Journal of Urban Economics*, 88, 50 – 66.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, (436), 686–688.

Emanuel, K. (2011). Global warming effects on u.s. hurricane damage. *Weather, Climate, and Society*, 3(4), 261–268.

Evans, R., Hu, Y., & Zhao, Z. (2010). The fertility effect of catastrophe: U.s. hurricane births. *Journal of Population Economics*, 23, 1–36.

Felbermayr, G. & Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics*, 111, 92 – 106. Special Issue: Imbalances in Economic Development.

Finlay, J. (2009). *Fertility Response to Natural Disasters The Case of Three High Mortality Earthquakes*. Policy Research Working Paper 4883, The World Bank.

Fomby, T., Ikeda, Y., & Loayza, N. V. (2013). The growth aftermath of natural disasters. *Journal of Applied Econometrics*, 28(3), 412–434.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, D., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2(150066).

Geiger, T., Frieler, K., & Bresch, D. N. (2017). A global data set of tropical cyclone exposure (TCE-DAT). *GFZ Data Services*.

Geiger, T., Frieler, K., & Bresch, D. N. (2018). A global historical data set of tropical cyclone exposure (tce-dat). *Earth System Science Data*, 10(1), 185–194.

Gozgor, G., Bilgin, M. H., & Rangazas, P. (2021). Economic uncertainty and fertility. *Journal of Human Capital*, 15(3), 373–399.

Hamilton, B. E., Martin, J. A., Mathews, T., Sutton, P. D., & Ventura, S. J. (2009). The effect of hurricane katrina: births in the us gulf coast region, before and after the storm.

Hanappi, D., Ryser, V.-A., Bernardi, L., & Le Goff, J.-M. (2017). Changes in employment uncertainty and the fertility intention–realization link: An analysis based on the swiss household panel. *European Journal of Population*, 33, 381–407.

Harris, I., Jones, P., Osborn, T., & Lister, D. (2014). Updated high-resolution grids of monthly climatic observations – the cru ts3.10 dataset. *International Journal of Climatology*, 34(3), 623–642.

Hofmann, B. & Hohmeyer, K. (2013). Perceived economic uncertainty and fertility: Evidence from a labor market reform. *Journal of Marriage and Family*, 75(2), 503–521.

Holland, G. (1980). An analytic model of the wind and pressure profiles in hurricanes. *Monthly Weather Review*, (pp. 1212–1218).

Holland, G. (2008). A revised hurrican pressure-wind model. *Monthly Weather Review*, (pp. 3432–3445).

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of Sciences*, 107(35), 15367–15372.

ICF Macro (1998). *Madagascar Enquête Démographique et de Santé 1997*. Report, Institut National de la Statistique - INSTAT/Madagascar.

ICF Macro (2010). *Madagascar Enquête Démographique et de Santé 2008-2009*. Report, Institut National de la Statistique - INSTAT/Madagascar.

IPCC (2019). Special report on the ocean and cryosphere in a changing climate. In N. Weyer (Ed.), *In it together: why less inequality benefits all*: In press.

Klotzbach, P., Blake, E., Camp, J., Caron, L.-P., Chan, J. C., Kang, N.-Y., Kuleshov, Y., Lee, S.-M., Murakami, H., Saunders, M., Takaya, Y., Vitart, F., & Zhan, R. (2019). Seasonal tropical cyclone forecasting. *Tropical Cyclone Research and Review*, 8(3), 134 – 149. Special Issue for the 9th WMO International Workshop on Tropical Cyclones.

Knapp, K. R., Kruk, M. C., Levinson, D. H., Diamond, H. J., & Neumann, C. J. (2010). The international best track archive for climate stewardship (ibtracs). *Bulletin of the American Meteorological Society*, 91(3), 363–376.

Knutson, T., Camargo, S. J., Chan, J. C. L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., & Wu, L. (2020). Tropical Cyclones and Climate

Change Assessment: Part II: Projected Response to Anthropogenic Warming. *Bulletin of the American Meteorological Society*, 101(3), E303–E322.

Knutson, T., McBride, J., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J., Srivastava, A. K., & Obersteiner, M. (2010). Tropical cyclones and climate change. *Nature Geoscience*, (3), 157–163.

Kochar, A. (1999). Smoothing consumption by smoothing income: Hours-of-work responses to idiosyncratic agricultural shocks in rural india. *The Review of Economics and Statistics*, 81(1), 50–61.

Kreyenfeld, M. (2010). Uncertainties in female employment careers and the postponement of parenthood in germany. *European sociological review*, 26(3), 351–366.

Kreyenfeld, M. (2015). Economic uncertainty and fertility. *Kölner Zeitschrift für Soziologie & Sozialpsychologie*, 67.

Kudamatsu, M. (2012). Has democratization reduced infant mortality in sub-saharan africa? evidence from micro data. *Journal of the European Economic Association*, 10(6), 1294–1317.

Kudamatsu, M., Persson, T., & Strömberg, D. (2012). *Weather and Infant Mortality in Africa*. CEPR Discussion Papers 9222, C.E.P.R. Discussion Papers.

Lee, R. & Mason, A. (2010). Fertility, human capital, and economic growth over the demographic transition. *European Journal of Population= Revue Europeenne de Demographie*, 26(2), 159.

LeGrand, T., Koppenhaver, T., Mondain, N., & Randall, S. (2003). Reassessing the insurance effect: A qualitative analysis of fertility behavior in senegal and zimbabwe. *Population and Development Review*, 29(3), 375–403.

Lindstrom, D. P. & Berhanu, B. (1999). The impact of war, famine, and economic decline on marital fertility in ethiopia. *Demography*, 36(2), 247–261.

Marchetta, F., Sahn, D. E., & Tiberti, L. (2019). The role of weather on schooling and work of young adults in madagascar. *American Journal of Agricultural Economics*, 101(4), 1203–1227.

Mincer, J. (1963). Market prices, opportunity costs, and income effects. *Measurement in economics*, (pp. 67–82).

Mohan, P. & Strobl, E. (2017). The short-term economic impact of tropical cyclone pam: an analysis using viirs nightlight satellite imagery. *International Journal of Remote Sensing*, 38(21), 5992–6006.

Morduch, J. (1995). Income smoothing and consumption smoothing. *Journal of Economic Perspectives*, 9(3), 103–114.

Nandi, A., Mazumdar, S., & Behrman, J. (2018). The effect of natural disaster on fertility, birth spacing, and child sex ratio: evidence from a major earthquake in india. *Journal of Population Economics*, 31, 267–293.

Nobles, J., Frankenberg, E., & Thomas, D. (2015). The effects of mortality on fertility: Population dynamics after a natural disaster. *Demography*, 52, 15–38.

Nordhaus, W. D. (2006). *The Economics of Hurricanes in the United States*. Working Paper 12813, National Bureau of Economic Research.

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics*, 01(01), 1–20.

Norling, J. (2022). Fertility following natural disasters and epidemics in africa. *The World Bank Economic Review*, 36(4), 955–971.

Peduzzi, P., Chatenoux, B., Dao, H., Bono, A. D., Herold, C., Kossin, J., Mouton, F., & Nordbeck, O. (2012). Global trends in tropical cyclone risk. *Nature Climate Change*, 2, 289–294.

Pörtner, C. C. (2001). Children as insurance. *Journal of Population economics*, 14, 119–136.

Pörtner, C., C. (2014). *Gone With the Wind? Hurricane Risk, Fertility and Education*. Working paper, Seattle University.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Ranjan, P. (1999). Fertility behaviour under income uncertainty. *European Journal of Population/Revue Européenne de Démographie*, 15, 25–43.

Robinson, W. C. (1986). High fertility as risk-insurance. *Population Studies*, 40(2), 289–298.

Schmidt, L. (2008). Risk preferences and the timing of marriage and childbearing. *Demography*, 45(2), 439–460.

Schultz, T. P. (1997). Chapter 8 demand for children in low income countries. volume 1 of *Handbook of Population and Family Economics* (pp. 349–430). Elsevier.

Sellers, S. & Gray, C. (2019). Climate shocks constrain human fertility in indonesia. *World Development*, 117, 357–369.

Skidmore, M. & Toya, H. (2002). Do natural disasters promote long-run growth? *Economic inquiry*, 40(4), 664–687.

Sobotka, T., Skirbekk, V., & Philipov, D. (2011). Economic recession and fertility in the developed world. *Population and development review*, 37(2), 267–306.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from US coastal counties. *The Review of Economics and Statistics*, 93(2), 575–589.

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the central american and caribbean regions. *Journal of Development Economics*, 97(1), 130 – 141.

Tamura, Y. (2009). Wind-induced damage to buildings and disaster risk reduction. In *The Seventh Asia-Pacific Conference on Wind Engineering, November 8-12, 2009, Taipei, Taiwan.*

Thiede, B. C., Ronnkvist, S., Armao, A., & Burka, K. (2022). Climate anomalies and birth rates in sub-saharan africa. *Climatic Change*, 171(1-2), 5.

Vignoli, D., Bazzani, G., Guetto, R., Minello, A., & Pirani, E. (2020). Uncertainty and narratives of the future: A theoretical framework for contemporary fertility. *Analyzing contemporary fertility*, (pp. 25–47).

Vogl, T. S. (2016). Differential fertility, human capital, and development. *The Review of Economic Studies*, 83(1), 365–401.

Wang, Y., Gozgor, G., & Lau, C. K. M. (2022). Effects of pandemics uncertainty on fertility. *Frontiers in Public Health*, 10.

Willis, R. (1974). Economic theory of fertility behavior. In *Economics of the family: Marriage, children, and human capital* (pp. 25–80). University of Chicago Press.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

Appendices

A Country-by-country regressions

	Bangladesh	Haïti	Cambodia	Madagascar	Philippines	Dominican Republic
	(1)	(2)	(3)	(4)	(5)	(6)
Max. wind in $t-1$	-0.0813***	-0.2314***	-0.2044***	-0.0271***	-0.0452***	-0.2392***
	(0.0056)	(0.0062)	(0.0075)	(0.0029)	(0.0022)	(0.0053)
Rainfall in $t-1$	-0.0783	0.2542***	-0.2107**	0.0352	0.0865***	-0.2156***
	(0.0746)	(0.0732)	(0.0912)	(0.0566)	(0.0290)	(0.0661)
Temperature in $t-1$	2.295	0.5763	-3.945	0.4324	4.893***	1.051
	(2.648)	(4.237)	(2.829)	(1.591)	(1.342)	(2.507)
Observations	70,266	184,742	185,876	166,238	187,823	230,498

Table 8: Country-by-country regression results

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include, woman fixed effect, annual fixed effect, cluster fixed effect and country fixed effect. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters and temperature in Celsius degrees.

B Exploring others heterogeneity dimensions

B.1 Differences in urban-rural

According to Kochar (1999), Evans et al. (2010), and Pörtner (2014), the occurrence of a cyclone modifies the shadow price of having an extra child, especially if couples live in areas that are more likely to be negatively impacted. In developing countries, a large share 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 contribute actively to agrarian activities, meaning that their labor supply is an important input of this production activity. By contrast, in urban areas, it is easier for women to diversify their activities, as they have greater employment opportunities in the service sector. Thus, in urban areas, women depend less on activities that may be damaged by tropical cyclone exposure unlike their rural counterparts engaged in agricultural activities. Consequently, it is likely that the opportunity cost of motherhood and raising children is less linked to tropical cyclone exposure in urban than in 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 if the household lives in a rural area.

The econometric model of column (1) of Table 9 show the corresponding estimates. Being exposed to tropical cyclone wind speed is associated with a greater decrease in the probability of giving birth in rural areas. The difference between the estimated marginal effects is significant.

	j = rural	j = low educated
Max. wind in $t-1$	-0.0614***	-0.0519***
	(0.0019)	(0.0016)
Max. wind in $t-1 \times (j=1)$	-0.0096***	-0.0279***
	(0.0023)	(0.0021)
Observations	1,025,443	1,025,443

Table 9: Cyclonic wind speed exposure for models including heterogeneity dimensions by interaction terms.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include, rainfall in $t-1$, temperature in $t-1$, as well as the four fixed effects.

B.2 Differences by education

The last heterogeneity dimension that we explore involves interacting wind speed exposure with a dummy that indicates if the mother has a low level of education at the time of the interview. Indeed, we could conjecture that low-educated women have a greater chance of working in the agricultural sector compared to those with a high education level so that post-cyclone opportunity cost of having children could be higher. Correspond regression results are displayed in the second column of Table 9. As anticipated, the reduction in the likelihood of giving birth after a cyclone shock is higher of about 50% for mothers with a low level of education. More specifically, the total marginal effect amounts to 0.0798.

C Robustness analysis

Overall, the panel estimates presented in the main text reveal that a tropical cyclone shock leads to a significant fall in mothers' likelihood of giving birth. These findings could be sensitive to different choices when estimating the baseline model. To ensure that the main message of this paper holds true, we check for the robustness of our results along five dimensions: i) alternative formulations of the tropical cyclone variable, ii) the sample period, iii) the merging of geolocated data, iv) the inclusion of migrant mothers in our final sample, and v) the inclusion of cluster-specific time trends. Results of these alternative estimations are reported in Table 10.

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

More recently, rather than directly using the wind speed experienced by a given spatial unit, many papers construct ad-hoc indexes of potential destruction (also known as a damage function).[48] The reasoning behind such indexes follows Emanuel (2011). More specifically, below a certain threshold $\bar{W}$, it is unlikely that wind speed provokes substantial physical damage so that 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 though 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 one, we follow a similar strategy as Strobl (2012) and construct the following index of potential destruction:

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

When constructing D_{it}, two parameters are of importance, because they shape its functional form: λ, which corresponds to the parameter relating the maximum surface wind speed experienced to the level of damages, and $\bar{W}$, which is the threshold above which the level of destruction becomes perceptible. Different values of these two parameters have been proposed, although empirical evidence about them 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

[48] Examples include Strobl (2011), Strobl (2012), Bertinelli & Strobl (2013), and Mohan & Strobl (2017).

destructiveness increases with the eighth power of maximum wind speed.[49] Concerning $\bar{W}$, Strobl (2012) and Bertinelli & Strobl (2013) set it to 177 km/h (the value above which a cyclonic system becomes category 3 on the Saffir-Simpson scale), while Mohan & Strobl (2017) select a value of 119 km/h (the 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 10 shows 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

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

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 threshold of wind speed at which the RSMC of La Réunion labels a tropical system as "intense". Corresponding results are reported in column (3) of Table 10.

A closer inspection of columns (2)-(3) of Table 10 leads to a few comments. First, the qualitative patterns of our results are entirely preserved, since 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 models has some interpretative incidence. Thus, for a level of destruction in $t-1$ equivalent to the standrad deviation of the damage function, the models of column (3) (resp. column (2)) indicates 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 such a level of exposure, the probability of motherhood falls by 6.1 points (resp. 12.8 points) for the index of potential destruction of equation (10) (resp. equation (9)). Regarding the use of a dummy variable, the model of column (2) suggests that being exposed to a tropical cyclone reduces the likelihood of childbearing by 28.97 points in t, 6.4 points in $t+1$, and 2.9 points in $t+2$.

Overall, the use of other measures of tropical cyclone exposure shows that our main result does not depend on the choice of the wind speed variable. The three alternative measures

[49] In the context of US coastal counties, Strobl (2011) uses an estimate of 3.17 for λ.

used in this section nevertheless have many limitations, since they either do not exploit the variability generated by W_{it} (model of column (2)) or rely on parameters for which the evidence is missing in the context of Madagascar (models of columns (3) and (4)). For this reason, our preferred specification directly uses the wind speed variable of Geiger et al. (2018).

	Baseline	Wind speed variable		With migrants	Sample period	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^W	-0.0676***	$-8.19e^{06}$***	-6.6639***	-0.0607***	-0.0666***	-0.0658***
	(0.0014)	($4.78e^{-07}$)	(0.4940)	(0.0010)	(0.0022)	(0.0019)
Obs.	1,025,443	1,025,443	1,025,443	1,785,137	526,822	498,621

Table 10: Alternative specifications: Robustness.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include mother fixed effects (μ_i), time fixed effects (η_t), country fixed effects (α_c) cluster fixed effects (θ_v) controls for rainfall (R_{t-1}) and mean temperature (T_{t-1}).

The model of column (1) corresponds to the baseline model. The model of column (3) uses the index of potential destruction of equation (9) instead of the baseline wind speed variable. The model of column (3) uses the index of equation (10) instead of the baseline wind speed variable. The model of column column (4) corresponds to the estimation of the baseline estimate for a sample including migrant mothers. Results of columns (5) and (6) correspond to the models for the sample periods 1985-1997 and 1997-2015, respectively.

Sample restriction regarding migration In the main text, we present the results based on a sample of mothers who declared that they had always lived in their current home. We restrict our sample to non-migrant mothers to ensure that when iterating backwards, we retrieve only the true exposure to cyclones. Indeed, the risk when including migrant mothers is that cyclone exposure may be attributed to a woman who actually lived elsewhere at the time of the event. Furthermore, the DHS includes a variable that indicates the number of years of residence in the current home. However, as highlighted by Kudamatsu (2012), this declarative variable could be subject to a recall bias. For these two reasons, we exclude all migrant mothers in 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 equation (7). In addition to non-migrant mothers, we include migrant mothers but keep only the observations after their arrival at their current home. Corresponding results can be found in column (4) of Table 10 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 equation (7) for two sample periods. The first sample spans the 1985-1997 period, while the second one begins in 1985 and ends in 2015. Results are respectively reported in columns (5) and (6) of Table 10.

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

D Model with 5 lags

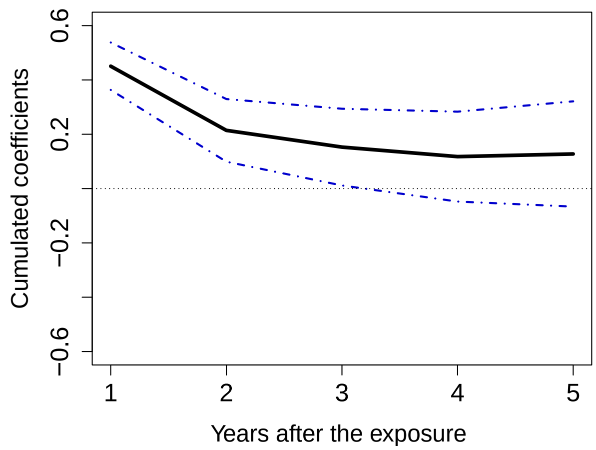

Figure 4: Cumulative effect of rainfall shocks on the likelihood of giving birth.

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.

Notes: Black solid lines correspond to the cumulative sum of the estimated points, while blue error bands show the associated confidence intervals (at the 5% level of significance). The regression includes mother fixed effects (μ_i), time fixed effects (η_t), village fixed effects (θ_v), country fixed effects (α_c) controls for rainfall (from R_{t-1} to R_{t-5}) and mean temperature (from T_{t-1} to T_{t-5}).

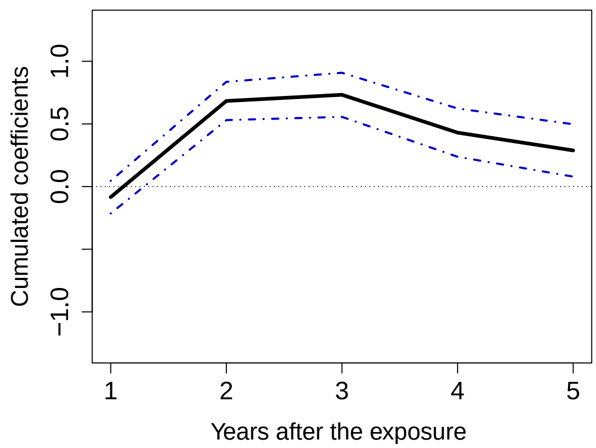

Figure 5: Cumulative effect of temperature shocks on the likelihood of giving birth.
Sources: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014), and authors' own calculations.
Notes: Black solid lines correspond to the cumulative sum of the estimated points, while blue error bands show the associated confidence intervals (at the 5% level of significance). The regression includes mother fixed effects (μ_i), time fixed effects (η_t), village fixed effects (θ_v), country fixed effects (α_c) controls for rainfall (from R_{t-1} to R_{t-5}) and mean temperature (from T_{t-1} to T_{t-5}).

	β_1^W	β_2^W	β_3^W	β_4^W	β_5^W
Baseline	-0.0676***	-	-	-	-
	(0.0014)	-	-	-	-
Five lags	-0.0707***	-0.0054***	-0.0032***	-0.0071***	-0.0119***
	(0.0015)	(0.0012)	(0.0012)	(0.0012)	(0.0013)

Table 11: Alternative specifications: Varying the number of lags.

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.

Notes: Significance levels: * 10%, ** 5%, *** 1%. Robust standard errors are in parentheses, adjusted for clustering at the DHS cluster level. All regressions include rainfall in $t-1$, temperature in $t-1$, as well as the four fixed effects. Maximum wind speed is measured in km/h, rainfall in hundreds of millimeters and temperature in Celsius degrees.

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