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EVIDENCE FROM MADAGASCAR**

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Tropical Cyclones and Fertility : New Evidence from Madagascar *

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Abstract

Does exposure to tropical cyclones affect fertility? This paper tackles this issue by exploiting geolocated microdata from the Malagasy Demographic and Health Survey together with wind field data generated by tropical cyclones hitting Madagascar during the 1985-2009 period. The mothers' fertility history available in the microdata allows us to construct a panel dataset indicating if a mother gave birth during a given year and if she has been exposed to a tropical cyclone. By means of panel regressions, that allows a full control of unobserved heterogeneities, we then estimate the causal effect of tropical cyclone shocks on female likelihood of giving birth. We find evidence that the effect of tropical cyclone exposure on motherhood is significantly negative. In particular, being exposed to wind speed of 100 km/h implies a fall in the probability of giving birth of 25.6 points in the current year together with further decline of 5.9 and 2.0 points respectively one and two years after being exposed. Alternative specifications of our baseline model provide further insights. First, we find mixed evidence of intensification effects. Second, we find no evidence of non-linearities in the effect. Third, the negative effect is stronger before 1998. Fourth, the effect of tropical cyclone on motherhood is persistent since in an extended model estimated coefficients are significantly negative up to seven years after being exposed. The estimated effect is shown to be robust to the use of alternative formulation of the wind speed variable but also to an alternative treatment of geolocated data.

Keywords: Fertility, Tropical cyclone, Madagascar

JEL classifications: J13, O12, Q54, C23

1 Introduction

The macroeconomic consequences of tropical cyclones, or more generally natural disasters, have been the subject of intense debates. Certain studies (e.g. [Skidmore & Toya \(2002\)](#), [Hallegatte et al. \(2007\)](#) or [Crespo Cuaresma et al. \(2008\)](#)) find that natural disasters may have a positive impact on national income as they could trigger a wave of “Schumpeterian” creative destruction, namely opportunities to update and adopt more productive new technologies. In contrast, other studies (e.g. [Noy \(2009\)](#) or [Felbermayr & Gröschl \(2014\)](#)) find that natural disasters have a negative impact on the economy because the destruction they entail is detrimental at least in the short run. This lack of conclusive evidence is in part the consequence of a controversy in the way exposure to natural disasters is measured ([Noy \(2009\)](#) or [Cavallo et al. \(2013\)](#)).¹ In what concerns tropical cyclones, each study measuring the exposure of a given spatial unit by the wind speed experienced at the surface find that they do reduce output in the short-term ([Strobl \(2011\)](#), [Strobl \(2012\)](#) or [Elliott et al. \(2015\)](#)) and even in the long-term ([Hsiang & Jina, 2014](#)). While the economic literature now contains many papers studying the macroeconomic effects of tropical cyclones, evidence about their impacts on individuals’ life remains scarce. This lack of comprehensive micro-studies, which could be explained by strong data requirements, leaves many questions unanswered. In particular, those related to how households reorganize their lives after being impacted by a tropical cyclone. With the present paper, we fill part of this void by constructing a unique Malagasy panel dataset combining household geographic location, female fertility history and wind speed exposure. This allows us to study the effect of tropical cyclone shocks on the decision of having children.

Understanding how households adjust after an adverse shock is of interest for researchers and policy makers alike, especially in a context of global warming that is expected to modify the frequency and the intensity of tropical cyclones in a near future ([IPCC \(2019\)](#) or [Knutson et al. \(2020\)](#)). In the context of a developing country like Madagascar, children actively contribute to the household by, e.g., providing care to siblings or grandparents or participating in housework activities and even sometimes by directly participating in the labor market ([Banerjee & Duflo \(2011\)](#) or [Finlay \(2009\)](#)). Furthermore, in such a risky environment, when access to insurance mechanisms is difficult and when many households face uncertainties in several aspects of daily life, children’s contributions may substitute for standard insurance and allow households to smooth consumption over time ([Banerjee & Duflo \(2011\)](#), [Finlay](#)

¹Many studies have used economic and human damages due to disaster from the EM-DAT dataset. The use of this dataset is accompanied by at least two limitations. First, data on economic damages are collected from different sources and the quality of reporting changes over time ([Strobl, 2012](#)). Second, monetary damages is likely to be correlated with output, namely the dependent variable in a growth regression ([Felbermayr & Gröschl, 2014](#)).

(2009) or Pörtner (2014)). As having an extra child could be viewed as the outcome of a trade-off between the costs and the benefits associated to children, the destruction associated to a negative weather shock, such as a tropical cyclone, probably induces behavioral changes regarding the choice of increasing the family size. Until now, very little is known about the dominant driving forces shaping the post-cyclone fertility behavior.

While existing studies examining the effect of natural disasters on fertility mainly focused on earthquakes, it is likely that their results cannot be extrapolated to the case of cyclonic events. First, the macro-literature have shown that the consequences of natural disasters on economic growth are not identical for all kinds of disasters (Fomby et al. (2013) or Felbermayr & Gröschl (2014)). We can therefore conjecture that the magnitude or even the direction of the effect could also be different for fertility depending on the kind of the natural disaster. Second, empirical studies on earthquakes mainly adopt a “one-event” approach studying fertility response after an earthquake shock of high intensity (Finlay (2009), Nobles et al. (2015) or Nandi et al. (2018)). While there is no issue about the causative nature of the effect unveiled by these studies, they cannot however observe any variability in the frequency or the magnitude of the disaster events as well as the existence of possible intensification effects. The database we construct allows to investigate such issues.

We make use of two main databases in our investigation. We first exploit the 1997 and 2008 waves of the Malagasy version of the Demographic and Health Survey (DHS). This cross sectional household survey has several practical advantages for the problem at hand: it is representative of the Malagasy population, it contains a large number of observations and it provides information about individuals’ characteristics. In addition, the DHS provides the full fertility history of each woman interviewed together with detailed information about their geographic location. The second database we employ is the Tropical Cyclone Exposure Database (TCE-DAT) of Geiger et al. (2018). This worldwide data provides high resolution information about the wind field profile of more than 2,700 cyclonic systems among which 59 threatened Madagascar during the period under scrutiny in this paper. By merging the geographic information of these two databases, together with the fertility history of the DHS, we construct a panel data in which we recover, for the 1985-2009 period, the tropical cyclone exposure of a given mother in a given year. 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 framework has many advantages since only a minimal set of assumptions is imposed. First, having a panel allows us to overcome threats related to omitted variables by means of a full control of individual and time fixed effects. Second, insofar as being exposed to 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. In addition, the panel's structure can be used as a distributed lag model allowing us to investigate whether the effect of tropical cyclone shocks is contemporaneous or builds over time.

Our main results can be summarized as follows. First, our set of regressions indicate that the control for individual and time fixed effects is important. More specifically, models that fail to isolate their effects show a different impact of tropical cyclones on motherhood. This further suggests that the decision of increasing the family size is highly correlated with both mothers' and annuals' unobserved components. Second, our panel setup indicates a negative impact of tropical cyclone exposure on the likelihood of giving birth. The point estimate suggests that a tropical cyclone shock of mean magnitude, namely approximately 100 km/h in our sample, induces a fall of 25.6 points in the probability of giving birth in the current year together with further declines of 5.9 and 2.0 points one and two years after being exposed. Exploiting the distributed lag nature of our model, we further estimate that the cumulative effect of such a shock is a reduction of 33.4 points in the likelihood of giving birth. Third, the estimation of alternative versions of our baseline model allows more nuanced insights. In particular, we find i) mixed evidence about the existence of a potential intensification mechanism, ii) no evidence of non-linearities in the causal effect, iii) a stronger effect for years before 1998 and iv) that the effect of tropical cyclone shocks is persistent since in an extended model estimated coefficients are significantly negative up to seven years after being exposed. Our results are estimated to be robust to the use of other measures of tropical cyclone exposure and to an alternative merging of geolocated data.

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 related to a new, but flourishing, literature that aim to study the effect of weather shocks on socioeconomic variables (e.g. [Deschênes & Greenstone \(2011\)](#), [Kudamatsu et al. \(2012\)](#), [Anttila-Hughes & Hsiang \(2013\)](#) or [Barreca et al. \(2018\)](#)). We add to this literature by focusing on the effect of a specific weather variable, namely tropical cyclones, on fertility . Second, our paper is part of the literature examining how households respond after an adverse event (e.g. [Morduch \(1995\)](#), [Banerjee & Duflo \(2007\)](#) or [Alam & Pörtner \(2018\)](#)). Indeed, as in a developing country context having children enables household to smooth their consumption over time, studying how they react to a cyclonic event inducing loss of properties, crops and livelihoods enables us to contribute to the debate on how households respond to a shock. We further add to this literature by providing evidence for an understudied country, namely Madagascar. Finally, our paper provides an important contribution to the literature studying the effect of natural disasters on fertility. To the best of our knowledge, three are the papers closest to us as they

focus on cyclonic events.² First, [Evans et al. \(2010\)](#) investigate how US counties fertility rate respond to storm advisories. They find 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 risk and shocks in Guatemala. He exploits a cross sectional data together with historical data about hurricane occurrence and find a negative association between fertility and tropical cyclone exposure at the level of municipalities. Third, [Davis \(2017\)](#) exploits rainfall data as a measure of tropical cyclone exposure and finds that high level of rainfall in Nicaraguan municipalities are associated with an increase in fertility. Our paper overcomes many issues of these three papers since our panel setup allows to alleviate concerns related to mothers' unobserved heterogeneity. Furthermore, we rely on a measure of tropical cyclone exposure that is directly related to its physical intensity and destructiveness while [Pörtner \(2014\)](#) employs historical records and [Evans et al. \(2010\)](#) advisory data.

The remainder of this paper is as follows. Section 2 is a preliminary describing the Malagasy context and its tropical cyclone climatology. Section 3 presents in details the data we use in the empirical analysis. Section 4 develops our econometric framework and discusses identification assumptions. Section 5 presents the results. Finally, section 6 concludes.

2 Background

2.1 The climatology of tropical cyclones in Madagascar

Tropical cyclones are natural atmospheric phenomena. According to [Camargo & Hsiang \(2015\)](#), they are considered as the most destructive natural disaster a socioeconomic system may face. A cyclone can be defined as a large, organized systems of winds (driven by convective processes) that rotate around a center of low atmospheric pressure ([Bobrowsky, 2013](#)).³ Tropical cyclones are associated with high speed winds that can be indeed very destructive. According to the works of [Tamura \(2009\)](#), wind speeds above 72 km/h can already damage shutters whilst above 90 km/h tiled roofs can already suffer damages. In case of extreme wind speeds, tropical cyclone can cause severe damage as well as total destruction of properties, buildings, crops or agricultural areas. However, impacts of tropical cyclones do not only depend on wind speeds. Given the combination of low-pressure center and wind-induced sea

²Other papers focusing on the post-fertility effect of earthquakes are discussed in subsection 4.1.

³Depending on the basin they are originated, these systems receive different names ([Bobrowsky, 2013](#)). They are called hurricanes in the North Atlantic and northeastern Pacific basins; typhoons in the northwestern Pacific basin and cyclones in the north Indian basin, the southwestern Pacific, in the southeastern as well as in the southwestern Indian basins and the Australian region.

waves, cyclones are also associated with storm surges, heavy rainfall and landslides (Camargo & Hsiang (2015) or Peduzzi et al. (2012)). Damages and the magnitudes of other hazards related to tropical cyclones, though not perfectly, are all correlated with the wind strength of the system (Haiyan et al. (2008) or Jordan & Clayson (2008)).

Separated by the Mozambique channel and located at 350 km of the south-eastern coast of Africa, Madagascar, the fourth biggest island on Earth, extends from $11^{\circ} 57'S$ to $25^{\circ} 30'S$ and from $43^{\circ} 14'E$ and $50^{\circ} 27'N$. In what concerns tropical cyclones' activity, Madagascar is part of the South-West Indian Ocean (SWIO) basin which is under the responsibility of the Regional Specialized Meteorological Center (RSMC) of La Réunion. Unlike other basins, tropical systems are considered tropical cyclones when they reach a maximum sustained wind speed of 116 km/h. Below such level, they are not labelled as a tropical cyclone but rather as tropical storms when their maximum sustained speed is above 63 km/h and tropical depressions when the sustained speed is below the 63 km/h threshold.⁴ It should be observed that tropical systems that reach the category of tropical cyclones are further classified according to the Saffir-Simpson scale in categories 1 to 5 depending on their maximum sustained wind speeds. The climatology of cyclonic activity in the SWIO has been extensively studied in Leroux et al. (2018). They show that, in an average year, about 9.7 tropical systems are observed within the basin and the half generates wind speeds that allows to characterize them as tropical cyclones. The cyclonic activity of the SWIO so represents about 11% of global cyclonic activity which is almost equal to the cyclonic activity generated in the North Atlantic.

Figure 1 depicts the trajectory of all cyclonic systems that threatened Madagascar during the 1985-2009 period. As shown in the figure, the cyclonic activity around Madagascar has been considerable during this period. Given its large size, the island has been concerned by 59 cyclonic systems during our sample period (Geiger et al., 2018). As cyclonic systems mainly move southwestward in the SWIO, the eastern coast of Madagascar has been hit by many cyclonic systems. The international disaster database (EM-DAT)⁵ is a natural departure point to have a first idea of damages related to tropical cyclones in Madagascar. During these 24 years, four million of people have been affected while around 780,000 have been recorded as homeless after a passing tropical cyclone. Overall, the death toll due to tropical cyclones amounts to 1,534 people.

⁴In this paper, we interchangeably use the terms tropical systems, cyclonic systems and tropical cyclones to designate tropical systems of any magnitude.

⁵The data is freely available on the following website: <https://www.emdat.be/>.

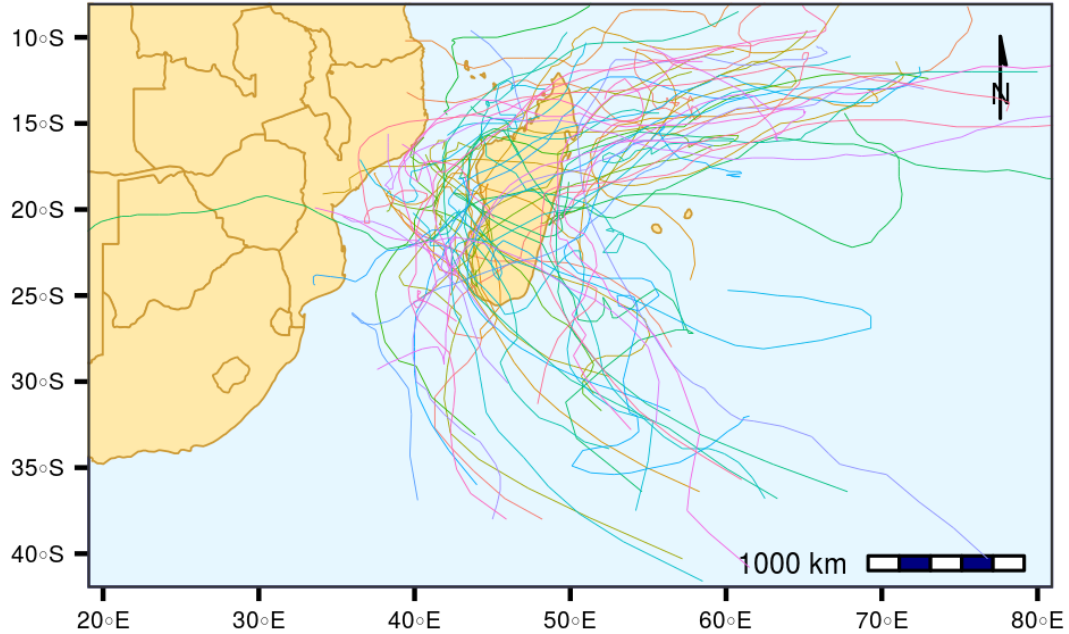


Figure 1: Trajectories of tropical cyclones making landfall on Madagascar.

Sources: Knapp et al. (2018), Geiger et al. (2017) and authors' own representation.

Notes: Selected cyclonic systems are from Geiger et al. (2017) data. Trajectories of cyclonic systems are extracted from Knapp et al. (2018).

2.2 The socio-economic context of Madagascar

Madagascar is one of the poorest countries in the world. According to ICF Macro (2010), per capita income was of only 347 USD in 2007.⁶ A vast proportion of the 20 million of Malagasy people is poor. In particular, 80% of Malagasy people is defined as “extremely” poor as they lived under the poverty line of 1.25 USD per day per person measured at the 2005 purchasing power parity (PPP) exchange rate (World Bank, 2015). The Human Development Index of the United Nation Development Programme was 0.479 in 2005.⁷ As indicated by Nordman et al. (2016), the Malagasy economy is very sensitive to external shocks such as exchange rate fluctuations or natural disaster shocks as well as internal shocks as political crisis. Such features suggest that some years are entangled with very specific characteristics that may have an impact on the parents' decision of having babies. Including time fixed effects in panel regressions could therefore be relevant (see also section 4).

An important share of the Malagasy population is young and of reproductive age. In particular, the half of the population was under 20 in 2008 (ICF Macro, 2010). According to ICF Macro (2010), the Total Fertility Rate (TFR) in Madagascar amounted to 5.2 children

⁶We choose this statistic because the sample period studied in this paper ends in 2009.

⁷See also <https://www.undp.org/>

per woman in 2003 and to 4.8 in 2008. Despite a slight fall, the Malagasy TFR remains almost twice larger than those observed in other developing countries (Pörtner, 2017). With a birth rate of 33‰, Madagascar has one of the highest population growth in the world (Hernández-Correa, 2012). In the context of developing countries, the timing of birth is indicative of women ability to control their fertility. In Madagascar, a woman gives birth for the first time very early since 32% of women aged of 15-19 have already at least one child (ICF Macro, 2010). The timing between two pregnancies is also a relevant statistic because the time elapsed between two births could have an incidence on the health of the child as well as the one of its mother. In that respect, ICF Macro (2010) indicates that 23% of births take place in a time interval of 24 months or less. Given the poor population living in Madagascar and the high birth rate, studying the effect of tropical cyclone strikes on the probability of giving birth is relevant. In particular, such an investigation is indicative of how poor households with many children adjust family size after an adverse size.

3 Data

3.1 The Demographic and Health Survey

Our primary source of micro-data about female fertility comes from the Malagasy version of the DHS. The DHS is a serie of cross sectional surveys conducted in Madagascar roughly every five years between 1992 and 2009. However, as the geographical information we exploit to locate the households are missing for the 1992 and 2004 phases, we exclude them from our analysis. The DHS is conducted by the Malagasy national institute of statistic. As many national DHS, each Malagasy DHS has benefited from the technical and financial supports of many international institutions such as the ICF Macro, the United States Agency for International Development (USAID), the United Nations International Children’s Emergency Fund (UNICEF) and so on. For each phase of DHS, a nationally representative sample of women aged of 15 to 49 were interviewed. From these women detailed information about socio-demographic (such as household composition, education level, number of children or household well-being) and health characteristics (such as infant mortality, nutritional practice, malaria prevalence or use of contraceptive) are collected. Among the wide range of information available in the surveys, we exploit in depth the mother’s fertility history. This retrospective record allows us to recover information about children’s year of birth and gender or woman’s age when giving birth. From this fertility history, we construct a panel dataset of women and we define a binary variable indicating whether the woman gave birth or not during a given year.

Let us now describe in more detail the sample selection of the Malagasy DHS because it has important implications for the design of our empirical study. The sample of each DHS wave is basically a two-level stratified random sample. At the first level, the Malagasy territory is divided into approximately 21,500 clusters and among them a number of clusters is randomly selected. In particular, 285 clusters have been selected for the 1997 phase of the DHS against 600 in 2008. At the second level, for each cluster selected at the first level, roughly 30 households are randomly selected. The geographical information we exploit to locate women comes from the first level selection. In particular, for each selected cluster, the data producer provides geographical information about its centroid. However, to ensure the confidentiality of selected households, the data producer does not provide the exact latitude and longitude of the cluster’s centroid but displaces randomly the actual location within a two (resp. ten) kilometers radius in urban (resp. rural) areas. We then combine information about household’s location with information about tropical cyclones to retrieve the wind speed exposure experienced by inhabitants on the ground. To the best of our knowledge, we are the first to combine such a high resolution geographic information about household location with high resolution information about wind speed exposure.⁸

To conduct our research we apply some restrictions to our sample. First, as the geographical information about clusters’ location are essential, we further drop households living in clusters without exploitable coordinates. Consequently, we are left out with 268 clusters for the 1997 phase of the DHS and 585 for the 2008 phase.⁹ For illustrative purposes, we display in Figure 4 of Appendix A the clusters’ distribution within the Malagasy territory. Second, as we use the retrospective information about mothers’ fertility, we have to make sure that a given woman has been 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 “always” live in their current home. Third, 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.

Table 1 reports a selection of summary statistics by distinguishing the two waves of DHS under scrutiny in this paper. In our final sample, the total number of children per woman is of 3.95 in the 1997 wave of DHS and of 3.70 in the 2008 wave. The average age when giving birth for the first time is approximately equal to 19 years. More than 25% of women report having no education while approximately three quarter reports having, at best, a level equivalent to primary education. This results in a relatively low number of years at school

⁸Anttila-Hughes & Hsiang (2013) have a similar approach than us but they consider a geographical divide of Philippine into only 13 regions.

⁹Missing geographical information are due to i) inconsistencies in geographic coordinates reported and ii) the incapacity of the data producer to go in some clusters (ICF Macro (1998), ICF Macro (2010)).

Variable	DHS-1997	DHS-2008
Mother’s Age	26.45	26.64
Mother’s age at first birth	18.74	19.01
Mother’s age at first marriage	17.79	17.88
Number of children	3.95	3.70
Years of education	2.84	3.07
No education	0.26	0.28
Primary education	0.51	0.50
Secondary education	0.22	0.21
Tertiary education	0.02	0.02

Table 1: Sample mean of a selection of women characteristics.

Sources: DHS and authors’ own calculations.

(around three years). Overall, changes in women characteristics remain marginal between the two surveys.

3.2 Tropical cyclone data and wind speed exposure

A prerequisite for our empirical study is a measure of wind speed exposure experienced by population on the ground. As it is not possible to rely on weather ground station data at a detailed level in the context of Madagascar, we exploit the worldwide TCE-DAT of Geiger et al. (2018). To produce the latter, Geiger et al. (2018) calculated an estimate of the lifetime’s maximum surface wind speed at each spatial location (on a $0.1^\circ \times 0.1^\circ$ grid over land) for more than 2,700 landfalling cyclonic systems between 1950 and 2015. The calculation is based on the The International Best Track Archive for Climate Stewardship (IBTrACS) archive (Knapp et al., 2010) which contains all the information required by a wind field model such as Holland (1980) model, widely used on studies on the evaluation of the risks associated with the landfalling of tropical cyclones (Peduzzi et al., 2012). Geiger et al. (2018) implemented 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)¹⁰ at radial distance r of the center of a given cyclonic system is defined as follows:

$$W = \left(\frac{b_s}{\rho e} \Delta p \left(\frac{r}{r_m} \right) \right)^{0.5}, \quad (1)$$

where ρ the surface air density in $kg.m^{-3}$, e the base of natural logarithms, Δp the pressure drop to the cyclone center in hPa as a function of r and r_m (the radius of maximum winds).

¹⁰For simplicity, we do not add an index to designate pixels.

The 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 (1), [Geiger et al. \(2018\)](#) calculated a translational component multiplied by an attenuation factor (the ratio between the tropical cyclone’s center and the radius of maximum wind). The translational wind speed decrease with distance from the cyclonic system’s center is taken into account to provide more realistic estimates of wind exposure on the ground. To our knowledge, there is no other publicly available dataset of ground weather station or remote sensing measurement covering the whole territory of Madagascar with a spatial resolution higher than $0.1^\circ \times 0.1^\circ$. That is the main reason why we decided to use the wind speed estimate calculated by [Geiger et al. \(2018\)](#).¹¹

Table 2 and the histogram of Figure 2 show summary statistics of wind speed experienced by DHS’ clusters when exposure is non-zero.¹² Overall, 23.8% of our pairs of cluster-year observations experienced a positive wind speed exposure. The average wind speed exposure during the 1985-2008 period is of 103.8 km/h with a standard deviation of 35.3. There is substantial heterogeneity in our sample insofar 10% of clusters have been exposed to tropical cyclones’ wind speed above 150 km/h. Observe that the maximum wind speed observed during our sample period amounts to 259.3 km/h. Such an intense wind speed is due to tropical cyclone Gafilo, which is among the most severe phenomenon observed since 1985 in the Southwest Indian Ocean basin. For illustrative purposes, we plot in Figure 5 of Appendix A the complete wind fields of four selected tropical cyclones that hit Madagascar during the 1985-2009 period.

3.3 Other climatic data

Despite 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 shared secular changes that might be correlated with tropical cyclone exposure. Our rainfall variable comes from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset constructed by [Funk et al. \(2015\)](#). When constructing this dataset, [Funk et al. \(2015\)](#) combine ground station and satellite information to obtain a high-resolution ($0.05^\circ \times 0.05^\circ$) gridded data. In what concerns temperature, we make use of the updated worldwide gridded climate dataset of the Climate Research Unit (CRU) of the University of East Anglia ([Harris et al., 2014](#)). The resolution

¹¹The dataset is referenced as [Geiger et al. \(2017\)](#) and is available at <https://dataservices.gfz-potsdam.de/pik/showshort.php?id=escidoc:2387904>

¹²In doing so, we follow [Elliott et al. \(2015\)](#).

	Wind speed	Rainfall	Mean temperature
Mean	103.8	15.6	21.7
Standard deviation	35.3	6.5	2.8
Min.	63.0	2.0	16.3
Percentile 1%	63.5	3.6	16.7
Percentile 5%	65.3	5.9	17.5
Percentile 10%	67.5	7.7	18.2
Percentile 25%	75.1	11.8	18.9
Percentile 50%	94.2	14.7	21.9
Percentile 75%	125.5	18.5	23.7
Percentile 90%	151.7	24.3	25.6
Percentile 95%	178.1	28.2	26.1
Percentile 99%	214.4	34.9	26.6
Max.	259.3	46.1	27.0

Table 2: Summary statistics of weather variables for DHS’ clusters during the 1985-2009 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 is expressed in hundreds of millimeters per year. Mean temperature is the annual average temperature and are expressed in Celsius degree. For wind speed summary statistics are computed only for non-zero clusters-year pairs.

level of the latter dataset is however lower than the one of CHIRPS since it is available at a 0.5° latitude/longitude grid cells. The last two columns of Table 2 report univariate analyses of rainfall and mean temperature. Histograms of these two variables are depicted in Figures 6 and 7 of Appendix A.

4 Empirical framework

4.1 Estimated equation

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

$$y_{it} = \sum_{l=0}^L \left(\beta_l^W \times W_{i,t-l} + \beta_l^R \times R_{i,t-l} + \beta_l^T \times T_{i,t-l} \right) + \mu_i + \eta_t + \zeta X_{it} + u_{it} \quad (2)$$

Where i indexes a given woman and t a given year. The outcome of interest, namely y_{it} , is a binary variable equal to one if mother i gives birth in year t and zero otherwise. Given that y_{it} is dichotomous, we therefore rely on a Linear Probability Model (LPM). Here, it should be

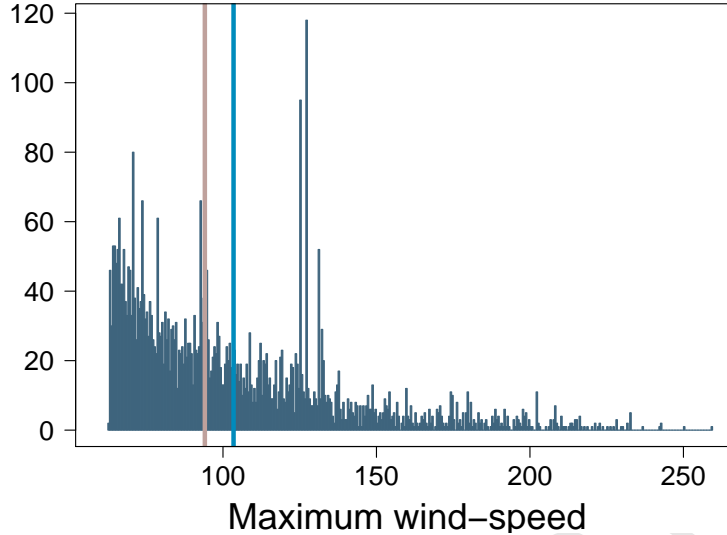


Figure 2: Distribution of maximum wind speed experienced by DHS clusters (1985-2009).

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

Notes: The light blue vertical line represents the mean of the distribution. The light pink vertical line represent the median of the distribution. Maximum wind speeds are expressed in km/h.

mentioned that such a practice is standard in the empirical literature dealing with dependent dichotomous variable in a panel setup (Anttila-Hughes & Hsiang (2013), Kudamatsu (2012) or Kudamatsu et al. (2012)).¹³ In equation (2), β_t^j with $j \in [W, R, T]$ are coefficients to be estimated. Our weather variable of main interest corresponds to tropical cyclone exposure of woman i in year t measured by the maximum wind speed (due to tropical cyclone) W .¹⁴ The latter variable is obtained by merging the clusters' geographic location with maximum wind speeds estimated in (1). As usual in SWIO, the wind speed variable is then expressed in kilometer per hour (km/h). We also include as controls two others weather variables: rainfall R expressed in hundreds of millimeters per year, and annual land surface mean temperature T measured in Celsius degree. We justify the inclusion of these two variables as an attempt to reduce problems related to omitted variables. If there are correlations or shared secular changes among weather variables, studying the impact of a weather variable in isolation could be problematic (Dell et al., 2014). In particular, it is arguable that the tropical cyclone exposure of a given spatial unit may be correlated with its surface temperature or its rainfall level. In that respect, Hsiang (2010) finds that each additional Celsius degree in country's local surface temperature is associated with a 9.36 km/h increase in local wind exposure in

¹³It is well known that the incidental parameter problem complicates the estimation of panel models including fixed effects. In contrast to linear models, it is not possible to removed 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)).

¹⁴For each birth occurring in a given calendar year t , we carefully check that exposure to tropical cyclone wind speed in calendar year t and $t - 1$ occurs at least nine months before the birth.

the Caribbean basin countries.¹⁵ Consequently, the non-inclusion of temperature or rainfall in equation (2) could introduce a bias in β_l^W , because in such a context the coefficient on wind speed exposure could capture the combined effect of the three weather variables. To take into account that some delays could exist between the moment when parents decide to have a baby and the actual occurrence of the birth, we employ a distributed lag model. In our baseline specification, the three weather variables enter our model contemporaneously and up to lag $L = 2$. Doing so, allows us to investigate whether tropical cyclones impact fertility behavior contemporaneously or with some temporal lags.¹⁶ We include woman fixed effects μ_i to control for unobserved and time-invariant characteristics that could potentially affect women likelihood of childbearing. These unobserved factors could be female’s (time-invariant) preference for having a large family. Such a preference concept can also be rationalized by emphasizing the opportunity cost of taking care of children. Women having lower outside options on the labor market probably have a higher opportunity cost of spending time in labor market activities leading them to have more babies and to devote more time to children education. We also flexibly account for year-specific components shared by all women using a year fixed effect η_t . Including such time fixed effects becomes even more relevant in the Malagasy context. For instance, the political crisis that followed the presidential elections of December 2001 triggered a severe economic recession. Arguably, such a time fixed effect may impact the decision of having children. Moreover, the inclusion of these time fixed effects ensure that the relationship of interest are identified from idiosyncratic shocks. X_{it} is a vector of time-varying woman’s characteristics such as age and age squared while ζ is the vector of estimated coefficients associated to these controls. Finally, u_{it} is the usual error term.

In equation (2) the coefficients of main interest are the set of β_l^W . They reveal the effect of wind speed exposure in period $t - l$ on woman likelihood of motherhood in t . A positive sign for β_l^W suggests that wind speed exposure increase woman likelihood of giving birth while a negative sign suggests the opposite. At this stage, it should be observed that current evidence about the effect of natural disasters on fertility is mixed. On the one hand, certain papers as those of Nobles et al. (2015) or Nandi et al. (2018) stress that women have more children after a disaster because they follow a replacement effect behavior due to mortality within the family or within an extended group often called the “community”. Furthermore, in a developing country context, Finlay (2009) suggests that to overcome a negative disaster shock parents are more likely to increase their family size. Indeed, in such a context, children often participate to the labor market or to domestic activities very early so that they could lead to a net increase in household income. Carta et al. (2012) suggest that fertility could help mothers to

¹⁵Hsiang (2010) computes this with a panel setup including country and year fixed effects together with country’s specific trends.

¹⁶We also include up to ten lags of each weather variable in a sensitivity analysis. See subsection 5.2.

overcome the traumatic and stressful experience triggered by the disaster. On the other hand, other papers, as those of [Kochar \(1999\)](#) or [Evans et al. \(2010\)](#), indicate that the opportunity cost of children education increases after a natural disaster. Consequently, parents are likely to postpone the decision of having babies to devote more time to other specific activities, especially reconstruction or working on the labor market. Moreover, natural disasters could trigger a period of uncertainty both in terms of income and in terms of available livelihood ([Davis \(2017\)](#) or [Pörtner \(2014\)](#)). Combined with the fact that couples may anticipate that babies born after a disaster may have worse health outcome ([Pörtner, 2014](#)), it is likely that motherhood decreases after the occurrence of a natural disaster. It should be observed that the estimated β_i^W of equation (2) are silent about the mechanism behind the impact of tropical cyclone exposure on fertility. However, as the direction of the impact is mainly an empirical question, our econometric framework allows us to discriminate between economic mechanisms suggesting a positive response of fertility after the occurrence of natural disasters from those suggesting a negative response.

4.2 Identifying assumption

A first natural option when estimating equation (2) is to employ a standard Ordinary Least Square (OLS) regression by pooling all cross-sections together and without transforming the data. Due to the exogenous nature of tropical cyclone wind speed on our fertility variable, it is unlikely that reverse causation is a concern. Arguably, exposure to wind speed could impact motherhood but the reverse effect seems impossible. However, a pooling model still suffers from the omitted variable bias.¹⁷ In particular, if a correlation exists between women’s unobserved components and their fertility behavior, putting the former into the error term is problematic as it has the potential of leading to inconsistent estimates ([Wooldridge, 2010](#)). That is why, our preferred specification throughout this paper is the one including both types of fixed effects.

Insofar fixed effects are included into equation (2), variables are expressed in deviations from the individual and temporal sample means ([Croissant & Millo, 2018](#)). Our identification so emphasizes year-to-year variations in levels from the observed means. As a consequence, the fixed effect coefficients associated to wind speed could be interpreted as the impact of tropical shocks on woman probability of giving birth.¹⁸ Given the nature of our estimated effect, it is legitimate to raise question about the external validity of our study, especially in a context of anthropogenic warming. Indeed, one could argue that the effect of short-run

¹⁷As recalled by [Dell et al. \(2014\)](#), in a pooling model context increasing the number of control variables does not necessarily reduce the omitted variable bias.

¹⁸It should be observed that the same interpretation holds for temperature and rainfall.

changes of a given weather variable on some economic outcome differs from the effect of a long-run and gradual change in the same weather variable. In particular, economic agents (households, firms or policy makers) may engage in actions aiming to mitigate the negative effect of climate change or to increase their coping capacity. In what concern tropical cyclones, it is expected that climate change would decrease their frequency while it would increase their average intensity and the proportion of cyclonic systems reaching very intense levels (of category 4-5 of the Saffir-Simpson scale) (Knutson et al., 2020). Consequently, it is likely that tropical cyclones would still act as a shock so that the focus on year-to-year variations remains a relevant departure point.

The main assumption we rely on to identify the causal effect of tropical cyclones on fertility is randomness in individual's exposure. Being exposed to cyclonic systems can be viewed as (quasi-)random insofar cyclonic systems' formation but also their exact trajectories and magnitude are stochastic and difficult to predict. When occurring, tropical cyclones generate recognizable wind speeds of high magnitude hitting (quasi-)randomly large spatial units so that inhabitants living in these areas experience the exposure and those living in non-affected areas experience any exposure. There are potentially two issues about the randomness nature of tropical cyclones' exposure and both are related to the progress of meteorologists in forecasting tropical cyclones' occurrence. First, meteorologists have made progress in forecasting the seasonal frequency of tropical systems (Klotzbach et al., 2019). Second, it is now possible to forecast the occurrence of a tropical cyclone a few days before a tropical cyclone's landfall. From our point of view, such possibilities have 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 cyclones' wind speed of a given spatial units remains for a large part unpredictable for scientists and so for inhabitants potentially concerned by tropical cyclones. As regard to short run forecasting, it implicitly assumes that inhabitants living in areas under the threat of a cyclonic system have a perfect access to the information (by means of a radio, television or newspapers). This is however not necessarily the case in the context of Madagascar. In particular, ICF Macro (2010) documents that 54% of female Malagasy listen the radio at least once a week and that only 19% watch television at least once a week. The same statistics amount to 40% and 14% according to ICF Macro (1998). Such statistics suggest that an important proportion of Malagasy people have not a full access to information. Despite this, it remains possible that information about the occurrence of tropical cyclones circulates by means of other channels, such as networks, so that we cannot totally exclude that individuals could engage in action to protect their home and their livelihood or evacuate. Such possibilities have some implications on the interpretation of our results. More specifically, the effect we estimate could be viewed

as the effect of tropical cyclone shocks after households engage in adaptive behaviors (if any). It should be observed that, despite such behaviors, inhabitants cannot overcome all the negative effects of tropical cyclones so that a degradation in their living environment is perceptible and may have a consequence on their decision of having children. Insofar year-to-year variations in the exposition 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 with panel data methods. It also proposes many robustness checks. All estimations have been done with the R software (R Core Team, 2019) by using tools provided by the “plm” package of Croissant & Millo (2008).

5.1 Main results

The Table 3 reports regression results of alternative estimations of equation (2). To see how the inclusion of mother fixed effects μ_i and time fixed effects η_t alter the results, we sequentially add them throughout columns (1)-(4).

Column (1) reports the results of a model without individual and annual fixed effects. It so corresponds to the pooling model. Such a model shows a significantly negative relationship between wind speed exposure in t and $t - 1$ and motherhood in t . For exposure occurring in $t - 2$, we rather witness a positive association. In what concerns the other two weather variables, the model unveils a positive association between rainfall in t and $t - 1$ and fertility in t , while the opposite is observed in $t - 2$. Such a switching behavior is also observed for mean temperature. While the model of column (1) is a natural departure point, it does not account for unobserved heterogeneity, preventing any causative interpretation of tropical cyclone exposure on motherhood.

In columns (2) and (3), we include either individual fixed effects or annual fixed effects. The main finding that stands out from these two columns is about the magnitude of coefficients associated to wind speed. Depending on the fixed effect included in the regression, values of β_t^W change. As an example, let us focus on β_1^W . From an estimate of β_1^W of -0.0593 in model (1), the model of column (2) provides an estimate of -0.0710 while the one of column (3) finds $\beta_1^W = -0.0429$.¹⁹ Such changes indicate that strong correlations exist between mother

¹⁹Differences among estimated coefficients associated to β_1^W of model (1), (2) and (3) are statistically significant at the 5% level.

fixed effects, time fixed effects and the likelihood of giving birth. Given the sensitivity of the results to the inclusion of fixed effects, our preferred specification is the one controlling for individual and time unobserved heterogeneity.²⁰

The last column of Table 3, reports results of the estimation of the complete version of equation (2), namely the one including both kinds of fixed effects to the model. It shows a negative impact of tropical cyclone wind speed shocks on mothers' likelihood of giving birth. The estimated relationship is consistently negative for all lags of wind speed and even for cyclonic events occurring two calendar years before the birth. An extra wind speed exposure in t equivalent to the sample average, namely 103.8 km/h, induces a fall of 25.6 points (103.8×-0.2461) in women likelihood of giving birth in the current year.²¹ Exposure to tropical cyclone shocks of mean intensity in $t - 1$ and $t - 2$ further reduces the probability of having babies in t of 5.9 (103.8×-0.0564) and 2.0 (103.8×-0.0189) percentage points respectively. The distributed lag nature of our empirical model allows us to compute the cumulative effect of tropical cyclones by summing up the three coefficients on wind speed. In the context of our preferred specification $\sum_{l=0}^{L=2} \beta_l^W = -0.3214$, suggesting that following a tropical cyclone shock of mean intensity, the medium-run reduction in the probability of giving birth is of 33.4 points. Overall, the results of column (4) is suggestive that the effect of tropical cyclone exposure on the decision of having children is persistent. We further investigate this issue in subsection 5.2. To our knowledge, we are the first to document such evidence by using detailed information about individual location and wind speed exposure. In what concerns the other two weather variables, the model of column (4) shows a positive significant impact for rainfall shocks occurring in t and for temperature shocks occurring in t , $t - 1$ and $t - 2$.

5.2 Sensitivity

Overall, the panel estimates of the last subsection unveils that a tropical cyclone shock leads to a significant fall in mothers' likelihood of giving birth. These findings could be sensitive to different choices made when estimating the baseline model. To ensure that the main message of this paper holds but also in order to produce more nuanced insights, we check the sensitivity of our results along six different dimensions: i) the use of alternative formulation

²⁰To further motivate this choice, we apply the Lagrange multiplier test. In particular, we test for the presence of individual, time and both kinds of fixed effects. Each time, the tests point toward the presence of fixed effects. As the presence of individual and time fixed effect is not rejected, the model included both of them are our preferred specification.

²¹A similar metric shows that the probability of giving birth for mothers exposed to very extreme wind speed (e.g of 250 km/h), as those generated by Gaflo in 2004, falls of about 61.6 points in the current calendar year.

	(1)	(2)	(3)	(4)
<i>Coefficients on wind speed</i>				
Max. Wind in t (β_0^W)	-0.2053*** (0.0023)	0.2074*** (0.0024)	-0.2436*** (0.0025)	-0.2461*** (0.0026)
Max. Wind in $t - 1$ (β_1^W)	-0.0593*** (0.0022)	-0.0710*** (0.0023)	-0.0429*** (0.0024)	-0.0564*** (0.0025)
Max. Wind in $t - 2$ (β_2^W)	0.0069* (0.0022)	-0.0055*** (0.0023)	-0.0040 (0.0025)	-0.0189*** (0.0026)
<i>Coefficients on rainfall</i>				
Rainfall in t (β_0^R)	0.2954*** (0.0338)	0.2804*** (0.0426)	0.2677*** (0.0421)	0.3996*** (0.0522)
Rainfall in $t - 1$ (β_1^R)	0.0948*** (0.0349)	0.2047** (0.0420)	-0.0022 (0.0438)	0.0580 (0.0507)
Rainfall in $t - 2$ (β_2^R)	-0.2755*** (0.0334)	-0.1826*** (0.0417)	-0.1295** (0.0410)	-0.0248 (0.0498)
<i>Coefficients on mean temperature</i>				
Mean Temp. in t (β_0^T)	-4.0206*** (0.5239)	3.5547 *** (0.6555)	-0.1501* (1.5011)	4.4704 *** (1.6293)
Mean Temp. in $t - 1$ (β_1^T)	-0.4802 (0.5312)	6.5316*** (0.6246)	5.1759 (1.7207)	11.9460*** (1.8447)
Mean Temp. in $t - 2$ (β_2^T)	4.9857*** (0.4801)	12.5595 *** (0.6216)	-4.5409*** (1.5390)	7.1820*** (1.8094)
Mother fixed effects	No	Yes	No	Yes
Annual fixed effects	No	No	Yes	Yes
Observations	155108	155108	155108	155108

Table 3: 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: Significant levels: * 10%, ** 5%, *** 1%. All regressions include women' age and its square. Model of column (1) does not include fixed effects. Model of column (2) only includes individual fixed effects (μ_i). Model of column (3) only includes annual fixed effects (η_t). Model of column (4) includes both individual and annual fixed effects.

of the tropical cyclone’s variable, ii) the sample period, iii) the presence of non-linearities, iv) the presence of intensification mechanism, v) the number of lags and vi) the merging of geolocated data. Results of all alternative estimations are reported in Tables 4, 5 and 6. To facilitate the comparison with the baseline estimate, the first column or the first row of each table repeats estimation results from column (4) of Table 3. Finally, it should be observed that, to save some spaces, Tables 4 to 6 report only estimated coefficients associated to tropical cyclones.²²

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 employed. We tackle this issue by considering three other measures of tropical cyclone incidence.

First, we notice that the economic literature followed different strategies to approach tropical cyclones’ exposure or more generally disaster exposure. In particular, some empirical papers that aim to estimate the impact of a natural disaster on the economy rely on dummy variables (Skidmore & Toya, 2002). This dummy is equal to one if a given spatial unit, typically a country or a region, has been exposed to a disaster during a given period. We so replace our wind speed variables by a dummy for positive tropical cyclone exposure in a given year. Corresponding results are reported in column (2) of Table 4.

More recently, rather than using directly the wind speed experienced by a given spatial unit, many papers construct ad-hoc indexes of potential destruction (also called a damage function).²³ The intuition behind such indexes follow Emanuel (2011). More specifically, below a certain threshold \bar{W} it is unlikely that wind speed provokes substantial physical damages so that the level of physical destruction could be assumed to be zero. However, once wind speed generated by the cyclonic system is above \bar{W} , the level of damages increases but in a non-linear fashion. To understand how such alternative measures of tropical cyclone exposure affect our conclusion, we then run two other checks.

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

$$D_{it} = W_{it}^\lambda \text{ if } W_{it} > \bar{W} \text{ and zero otherwise} \quad (3)$$

When constructing D_{it} , two parameters are of importance because they shape its functional form. On the one hand, λ which corresponds to the parameter relating the maximum surface wind speed experienced to the level of damages. On the other hand, \bar{W} which is the threshold

²²Complete results remain available upon request.

²³Examples include Strobl (2011), Strobl (2012), Bertinelli & Strobl (2013) or Mohan & Strobl (2017).

above which the level of destruction becomes perceptible. Different values of these two parameters have been proposed but empirical evidence about them is scarce, especially for the Malagasy context. In the US context, Emanuel (2005) suggests that the level of damages can be approached by the cubic value of the maximum wind speed observed at the surface. By contrast, Nordhaus (2006) suggests that destructiveness increases with the eight power of maximum wind speed.²⁴ In what concerns \bar{W} , Strobl (2012) and Bertinelli & Strobl (2013) set it to 177 km/h (the value above which a cyclonic system falls in the third category level of the Saffir-Simpson scale) while Mohan & Strobl (2017) select a value of 119 km/h (the value above which a cyclonic system falls in the first category level of the Saffir-Simpson scale). Without further evidence about these parameters, we choose $\lambda = 3$ as suggested by Emanuel (2005) or Strobl (2011) and we fix $\bar{W} = 93$ km/h as indicated by Emanuel (2011). Column (3) of Table 4 shows results of this alternative estimation.

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

$$f_{ct} = \frac{v_{ct}^3}{1 + v_{ct}^3} \quad (4)$$

with

$$v_{ct} = \frac{\text{MAX}(W_{ct} - \bar{W}, 0)}{W^* - \bar{W}}. \quad (5)$$

Where c denotes a cluster and W^* corresponds to the threshold at which half of buildings is damaged. Again, we lack of 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 labeled a tropical system as an “intense” tropical cyclone. Corresponding results are reported in column (4) of Table 4.

Inspection of columns (2)-(4) of Table 4 leads to some straightforward comments. First, the qualitative patterns of our results are entirely preserved since estimated coefficients on the three different measures of wind speed are almost all negative. Second, the quantitative patterns observed are broadly consistent with our baseline estimate even if the non-linear nature of the wind speed variable of models of columns (3) and (4) has some interpretative incidence. Thus, for a level of destruction in t equivalent to the mean of the damage function, the models of column (4) (resp. column (3)) indicates that a mother is 0.5 points (resp. 1.0) less likely to give birth in $t + 1$. The negative effects are sharply higher when considering events generating extreme wind speeds of 250 km/h. In particular, for such a level of exposure, the probability of motherhood falls of -5.3 points (resp. -13.8 points) for the index of potential

²⁴In the context of US coastal counties, Strobl (2011) proposes an estimates of 3.17 for λ .

	Baseline	Wind speed variable		Sample period		Merging	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Coefficients on wind speed</i>							
β_0^W	-0.2461*** (0.0026)	-28.8878*** (0.2839)	$-5.02e^{-06}$ *** ($1.01e^{-07}$)	-44.9245*** (1.1576)	-0.2672*** (0.0040)	-0.2407*** (0.0035)	-0.2727*** (0.0026)
β_1^W	-0.0564*** (0.0025)	-6.3773*** (0.2782)	$-7.93e^{-07}$ *** ($9.42e^{-08}$)	-5.7713*** (1.0620)	-0.0926*** (0.0044)	-0.0524*** (0.0033)	-0.0641*** (0.0025)
β_2^W	-0.0189*** (0.0026)	-2.8768*** (0.2853)	$-7.37e^{-09}$ ($9.73e^{-08}$)	0.1740 (1.1074)	-0.0156*** (0.0048)	-0.0311*** (0.0032)	-0.0191*** (0.0026)
Obs.	155108	155108	155108	155108	67297	72361	155108

Table 4: 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: Significant levels: * 10%, ** 5%, *** 1%. All regressions include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (R_t , R_{t-1} and R_{t-2}) and mean temperature (T_t , T_{t-1} and T_{t-2}), women' age and its square.

The model of column (1) corresponds to the baseline model. The model of column (2) is the one using dummy variables in place of the baseline wind speed variable. The model of column (3) is the one using the index of potential destruction of equation (3) in place of the baseline wind speed variable. The model of column (4) is the one using the index of equation (4) in place of the baseline wind speed variable. Columns (5) and (6) respectively correspond to the estimation of the baseline estimate for years before and after 1998. The model of column (7) is the one using pixels within a circle of 20 km radius from the centroid of each cluster to compute wind speed exposure, rainfall and temperature.

destruction of equation (4) (resp. equation (3)). As regard to the use of a dummy variable, the model of column (2) suggests that being exposed to a tropical cyclone reduces likelihood of childbearing of 28.97 points in t , 6.4 in $t + 1$ and 2.9 in $t + 2$.

Overall, the use of other measures of tropical cyclone exposure shows that our main result does not depend of the choice of the wind speed variable. The three alternative measures used in this section have however many limitations since either they do not exploit the variability generated by W_{it} (model of column (2)), or they rely on parameters for which evidence is missing in the context of Madagascar (models of column (3) and (4)). That is in part why, our preferred specification is the one that directly uses the wind speed variable of Geiger et al. (2018).

Sample period Implicitly, our baseline model assumes that the estimated effect is an average over the entire sample under scrutiny. However, it is possible that the decision of

having children changes over time. We address this possibility by estimating equation (2) for two sub-periods. The first one spans the 1985-1997 period while the second one the 1998-2008 period. Results are respectively reported in columns (5) and (6) of Table 4.

The main insight of these alternative panel estimations is as follow: before 1998 tropical cyclone exposure in t and $t - 1$ has a stronger effect on women likelihood of pregnancies than after 1998. For instance, being exposed to tropical cyclone shocks of mean intensity in t decreases the likelihood of giving birth in $t + 1$ of 9.6 points before 1998 against 5.4 after 1998. Overall, considering alternative sample periods is suggestive that the decision of having children is less related to tropical cyclone exposure in recent years.

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	$\beta_0^{\tilde{w}^1}$	$\beta_0^{\tilde{w}^2}$	$\beta_0^{\tilde{w}^3}$	$\beta_1^{\tilde{w}^1}$	$\beta_1^{\tilde{w}^2}$	$\beta_1^{\tilde{w}^3}$	$\beta_2^{\tilde{w}^1}$	$\beta_2^{\tilde{w}^2}$	$\beta_2^{\tilde{w}^3}$
<i>Baseline</i>		-0.2461*** (0.0026)			-0.0564*** (0.0025)			-0.0189*** (0.0026)	
<i>Non-linearities</i>	-23.1100*** (0.4463)	-24.4418*** (0.8232)	-26.0676*** (1.4778)	-5.1615*** (0.4185)	-3.0598*** (0.7373)	-3.8503*** (1.3438)	-3.3737*** (0.4214)	-0.2578 (0.7848)	1.1091 (1.3796)

Table 5: 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: Significant levels: * 10%, ** 5%, *** 1%. All regressions include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (R_t , R_{t-1} and R_{t-2}) and mean temperature (T_t , T_{t-1} and T_{t-2}), women' age and its square. For the baseline row, we respectively reports values of β_0^W , β_1^W and β_2^W .

Merging of geolocated information The available information about household location is displaced up to ten kilometers from the exact cluster’s position (see also subsection 3.1). Up to now, we extract weather information only from the pixel in which centroid’s clusters belongs. We test the robustness of our results to this choice. In particular, from each centroid coordinate we draw a circle of 20 km radius and we compute the mean of each weather variable using pixels within the circle. We then use these averaged values as independent variables in equation (2). Corresponding results are shown in column (7) of Table 4.

Using this alternative merging has almost no incidence on the results. In particular, point estimates of β_t^W are not statistically different from the baseline.

Non-linearities Our baseline model implicitly assumes that the fertility response to tropical cyclone shocks is linear. However, the literature examining the effect of weather shock on economic variables often indicates that effects are likely to be nonlinear. In particular, Emanuel (2011) or Nordhaus (2010) suggest that damages exponentially increase with the level of wind speed experienced at the ground. Despite such suggestions, it is however not straightforward that other socioeconomic variables also respond non-linearly to wind speed exposure, especially in a context when household microdata is used. Here, in order to reveal a possible non-linear relationship, we follow a non-parametric approach by breaking wind speed up into four bins. Such an approach has two main advantages. On the one hand, it is simply to implement. On the other hand, it is flexible and does not impose any functional forms to our wind speed explanatory variable. We so construct three dummies taking one when wind speed falls within the bin and zero otherwise. Specifically, $\tilde{w}_t^1 = 1(W_t \in [100; 149[)$, $\tilde{w}_t^2 = 1(W \in [150; 200[)$ and $\tilde{w}_t^3 = 1(W \in [200; 300[)$.²⁵ We report related results in Table 5.

Given standard errors associated to point estimates, we cannot conclude that the post-fertility effect of tropical cyclone shock is non-linear in maximum wind speed. The linear approximation we use in our baseline model appears as a relevant departure point.

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 (2), is magnified if in past years (e.g. in $t - 1$), the same woman has also been exposed to a tropical cyclone. As Dell et al. (2014), we call such a 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 in the last five years, a given woman i has also been exposed to at least two tropical cyclones. Our set of dummy variables are denoted as $\tilde{W}_{i,t-l}$. The

²⁵Implicitly, the first bin $\tilde{w}_t^0 = 1(W_t \in [0; 99[)$ serves as reference in the regression.

	β_0^W	β_1^W	β_2^W	ω_0^W	ω_1^W	ω_2^W
<i>Baseline</i>	-0.2461*** (0.0026)	-0.0564*** (0.0025)	-0.189*** (0.0026)	- -	- -	- -
<i>Intensification</i>	-0.2468*** (0.0026)	-0.0550*** (0.0026)	-0.0179*** (0.0026)	-0.0087 (0.0092)	-0.0289*** (0.0087)	-0.0093 (0.0090)

Table 6: Alternative specifications – Intensification mechanisms

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: Significant levels: * 10%, ** 5%, *** 1%. All regressions include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (R_t , R_{t-1} and R_{t-2}) and mean temperature (T_t , T_{t-1} and T_{t-2}), women’ age and its square.

estimated equation has now the following form:

$$y_{it} = \sum_{l=0}^L (\beta_l^W \times W_{i,t-l} + \beta_l^R \times R_{i,t-l} + \beta_l^T \times T_{i,t-l}) + \sum_{l=0}^L (\omega_l^W \times \tilde{W}_{i,t-1-l}) + \mu_i + \eta_t + \zeta X_{it} + u_{it}, \quad (6)$$

where the ω_l^W are parameters to be estimated. Their interpretations are different from those of β_l^W . For instance, let $l = 0$ so that we are interested in interpreting β_0^W and ω_0^W . The first estimated coefficient, namely β_0^W , corresponds to the effect of wind speed exposure in period t on current likelihood of motherhood. However, the second one, namely ω_0^W , captures a different effect because it is the incremental effect of wind speed exposure on motherhood in period t if, in addition the woman has been exposed to at least two tropical cyclones between $t - 1$ and $t - 5$. Consequently, the intensification parameters, namely ω_l^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 $\tilde{W}_{i,t-1-l}$ to the model. Overall, evidence about intensification mechanisms is mixed. The three ω_l^W are estimated to be negative. Nevertheless, estimated coefficients are significant only for $t - 1$. Such a finding suggests that the impact of wind speed exposure in $t - 1$ is magnified if between $t - 2$ and $t - 6$ the mother has also been exposed to at least two tropical cyclones. In such a case the total effect of wind speed exposure amounts to -0.0839 (namely, $\beta_1^W + \omega_1^W$). Our model does not provide sufficient statistic power to conclude about the existence of such intensification for events occurring in t and $t - 2$.

Number of lags In the baseline model, we include up to two lags of each weather variable. Here, we reconsider the main specification by adding up to ten lags of weather variables into

the model.²⁶ The latter model allows us to investigate more precisely the medium to long-run effects of tropical cyclones on fertility. For illustrative purpose, we display the cumulative effect of wind speed exposure on motherhood in Figure 3 while values of the coefficients are left as an appendix material (see Table 7 of Appendix B).²⁷

As shown in Figure 3, the effect of tropical cyclone shocks on the likelihood of giving birth persists over time. Furthermore, with a time window of ten year we do not observe any strong offsetting behavior, namely a strong positive effect of wind speed exposure for some lags. The Table 7 of Appendix B shows that estimated coefficients are statistically negative up to lag $l = 7$. Exploring the distributed lag nature of that model, Figure 3 indicates that the cumulative effect of an extra wind speed exposure amounts to $\sum_{l=0}^{L=10} \beta_l^W = -0.560$.²⁸ In what concerns the other two weather variables, Figures 8 show that when accounting for ten lags, the negative effect of rainfall shocks is persistent while the one of temperature shocks act mainly the first four year after the exposure. Overall, extending the model to allows the inclusion of more lags shows that the effect of tropical cyclone shocks has the potential to reduce the probability of motherhood in the medium to long run.

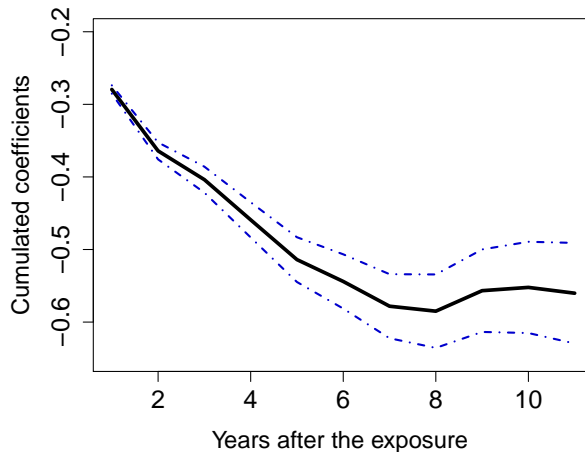


Figure 3: Cumulative effect of wind speed exposure on the likelihood of giving birth.
Sources: DHS, TCE-DAT of Geiger et al. (2018), CHIRPS dataset of Funk et al. (2015), CRU dataset of Harris et al. (2014) and authors' own calculations.
Notes: Black solid lines correspond to the cumulative sum of the points estimated, blue error bands are confidence intervals (at 5% degree of significance) associated. The regression include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (from R_t to R_{t-10}) and mean temperature (from T_t to T_{t-10}), women' age and its square.

²⁶As rainfall data is available only from 1981, we drop all observations prior to 1991 because it is not possible to obtain ten lags of the rainfall variable before that year

²⁷We also display in Figures 8 and 9 of Appendix B the cumulative effects for rainfall and temperature shocks.

²⁸The lower bound (at a 95% degree of confidence) of this estimate is -0.629 while the upper bound is -0.490.

6 Discussion

6.1 Interpreting the evidence

As discussed in subsection 4.1, empirical evidence about the effect of cyclonic systems, or more generally natural disasters, on fertility is mixed. Some papers find a positive impact and explain it by either the replacement effect (Nobles et al. (2015) or Nandi et al. (2018)) or by the fact that motherhood is a way to cope after an emotionally traumatic experience (Carta et al., 2012). In contrast, others studies find a negative effect and explain it by uncertainties generated by the disaster shock (Davis (2017) or Pörtner (2014)) or the increase in the opportunity cost of having babies (Kochar (1999) or Evans et al. (2010)). By taking advantage on a unique panel dataset combining household geographic location, female fertility history and wind speed exposure, our empirical study points toward a negative effect. We are not saying that replacement effect does not exist nor that motherhood is not viewed as a manner to recover after tropical cyclone shocks in Madagascar but our empirical study suggests that they are not the dominant driving forces behind post-disaster motherhood. In contrast, our reduced-form econometric framework is indicative that tropical cyclone shocks modify household living environment in a manner that is likely to alter the timing of the decision of having children.

Given our results, a legitimate question is about the true nature of the post-disaster decision of having babies. Indeed, the negative causal impact we observed could be either an unintended consequence of tropical cyclone shocks or a deliberate decision of postponing fertility. It is however difficult to provide a clear answer to such an issue with our panel data because we do not observe contraceptive prevalence or the frequency of sexual intercourse over time. Furthermore, exploiting the DHS cross section, in which such information is available, could also be unsatisfactory because it prevents us to control for individual and time fixed effects. Consequently, as an attempt to fix ideas, we turn to the economic literature. In that respect, three papers could be enlightening. First, Hernández-Correa (2012) finds that Malagasy women experiencing adverse shocks are more likely to use contraceptive such as pills or condoms. However, as Hernández-Correa (2012) exploits a cross-section, its results is potentially affected by the presence of unobserved heterogeneity. Second, a recent empirical study of Alam & Pörtner (2018) allows us to have a more comprehensive view of the mechanism at work after a negative shock. From Tanzanian panel data that allows for a full control of individual unobserved heterogeneity, their conclusions are twofold. On the one hand, the likelihood of pregnancies decreases after an income shock.²⁹ On the other hand, a crop loss induces a statistically significant increases in the use of contraceptives. Third, exploiting

²⁹The income shock of Alam & Pörtner (2018) corresponds to an accidental crop loss.

a panel dataset of women in Uganda, [Abiona \(2017\)](#) finds that an unanticipated rainfall shock increases the likelihood of using contraceptives for childbirth control. Taken together, these three studies suggest that adverse shocks increase the demand for contraceptive so that the decision to postpone motherhood can be viewed as deliberate. We however agree that such a conclusion should be further confirmed by other empirical studies that ideally observe contraceptive use over time and control for unobserved heterogeneity.

6.2 Concluding remarks

By taking advantage on a unique opportunity to match geolocated household micro-data with wind field data generated by cyclonic systems, we construct a panel dataset that allows the investigation of the effect of exposure to tropical cyclones shocks on motherhood. Contrary to what has been found for earthquakes, our empirical model points toward a negative effect of tropical cyclone shocks on mothers' likelihood of giving birth. We also find that such effects are not only contemporaneous but also persistent.

The empirical evidence emerging from this paper is suggestive that the occurrence of tropical cyclone shocks acts as an adverse shock generating uncertainties and increasing the opportunity cost of taking care of children. However, the panel data we constructed does not allow us to provide a definitive answer about the true nature of the decision of postponing fertility. On this specific topic, we still need further empirical evidence especially in a country where fertility rates remain high. The investigation of such issues would be probably enlightening. They are, however, beyond the scope of this paper and are on our agenda for futures researches.

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Working paper

Appendices

A Additional figures

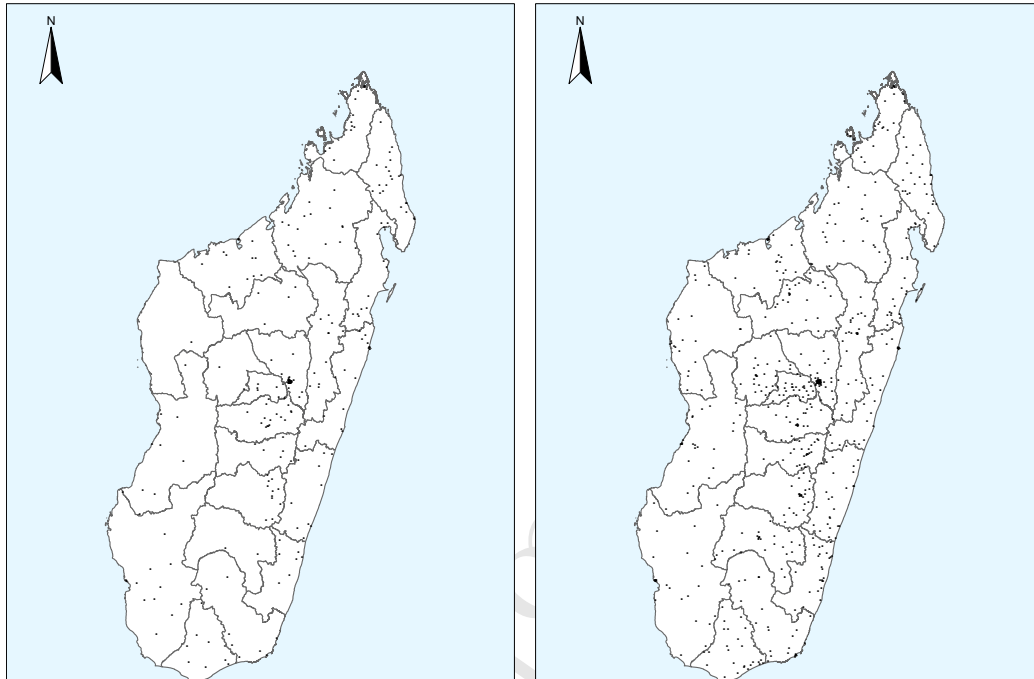
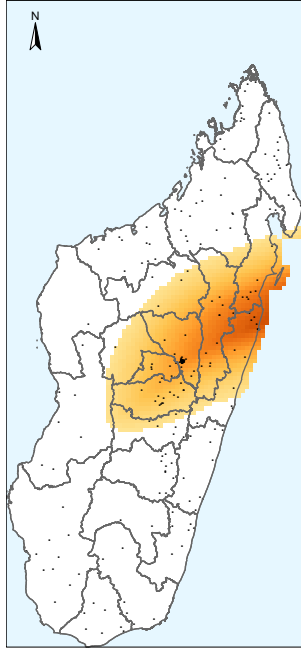
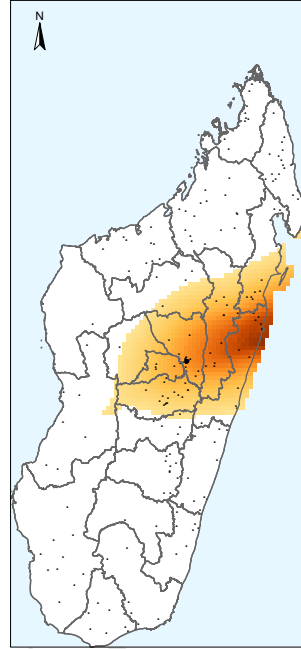


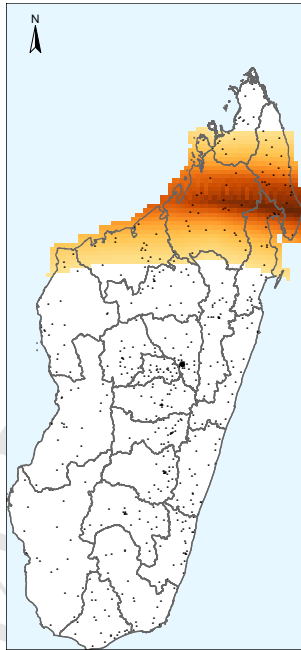
Figure 4: Distribution of DHS clusters - DHS-1997 (left) and DHS-2008 (right).
Sources: DHS and authors' own representation.



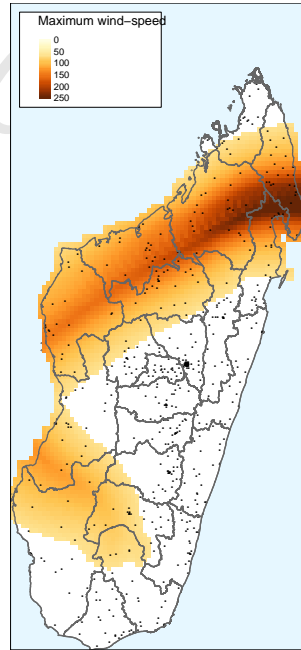
(a) Honorinina (1986)



(b) Geralda (1994)



(c) Hudah (2000)



(d) Gafilo (2004)

Figure 5: Wind fields of four selected tropical cyclones making landfall on Madagascar.

Sources: DHS, TCE-DAT of Geiger et al. (2017) and authors' own representation.

Notes: Wind speeds correspond to the maximum wind speed observed for a given pixel. Wind speeds are expressed in km/h. For panel (a) and (b), clusters selected for the 1997 phase of the DHS are displayed. For panel (c) and (d), clusters selected for the 2008 phase of the DHS are displayed.

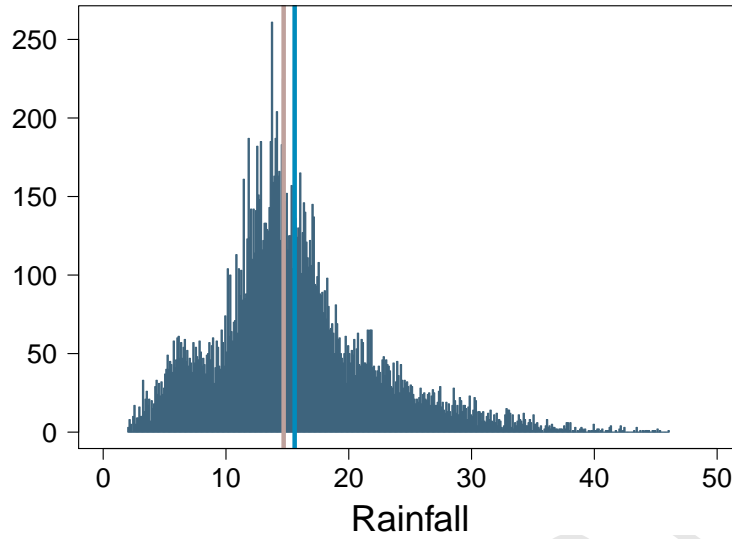


Figure 6: Distribution of rainfall experienced by DHS clusters (1985-2009).

Sources: DHS, CHIRPS dataset of [Funk et al. \(2015\)](#) and authors' own calculations.

Notes: The light blue vertical line represents the mean of the distribution. The light pink vertical line represent the median of the distribution. Rainfall is expressed in hundreds of millimeters per year.

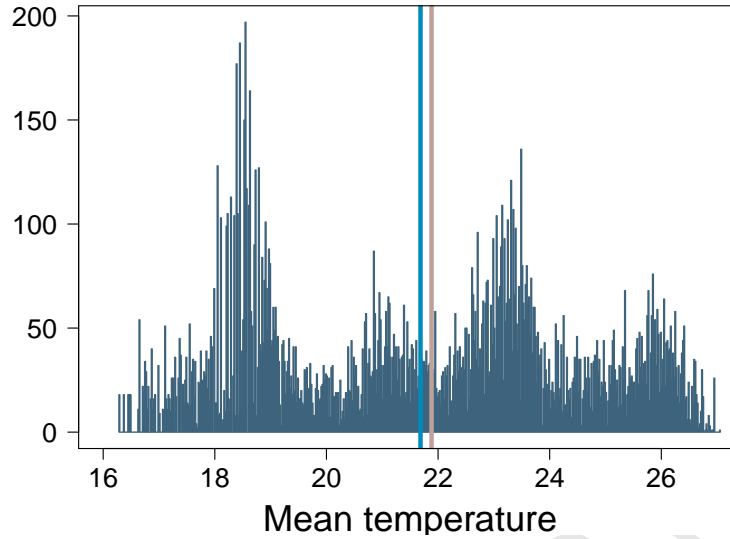


Figure 7: Distribution of mean temperature experienced by DHS clusters (1985-2009).

Sources: DHS, CRU dataset of [Harris et al. \(2014\)](#) and authors' own calculations.

Notes: The light blue vertical line represents the mean of the distribution. The light pink vertical line represent the median of the distribution. Mean temperature is the annual average temperature and is expressed in Celsius degree.

B Model with ten lags

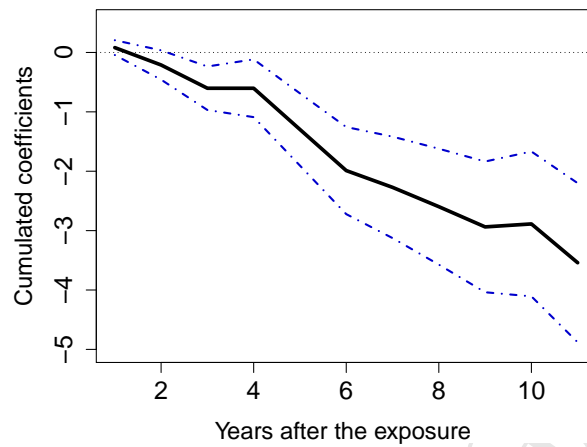


Figure 8: Cumulative effect of rainfall shocks on the likelihood of giving birth.

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 points estimated, blue error bands are confidence intervals (at 5% degree of significance) associated. The regression include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (from R_t to R_{t-10}) and mean temperature (from T_t to T_{t-10}), women' age and its square.

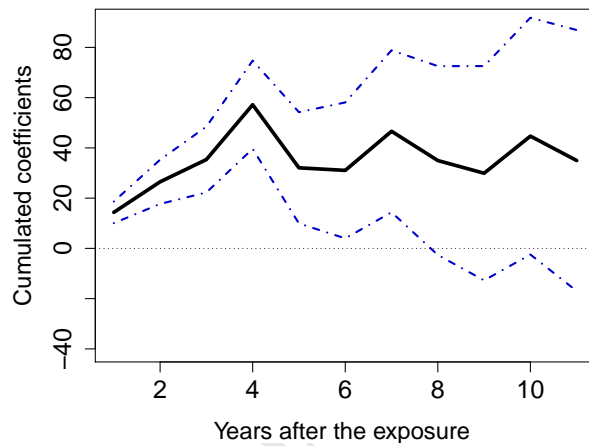


Figure 9: Cumulative effect of temperature shocks on the likelihood of giving birth.
Sources: DHS, TCE-DAT of [Geiger et al. \(2018\)](#), CHIRPS dataset of [Funk et al. \(2015\)](#), CRU dataset of [Harris et al. \(2014\)](#) and authors' own calculations.
Notes: Black solid lines correspond to the cumulative sum of the points estimated, blue error bands are confidence intervals (at 5% degree of significance) associated. The regression include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall (from R_t to R_{t-10}) and mean temperature (from T_t to T_{t-10}), women' age and its square.

	β_0^W	β_1^W	β_2^W	β_3^W	β_4^W	β_5^W	β_6^W	β_7^W	β_8^W	β_9^W	β_{10}^W
<i>Baseline</i>	-0.2461*** (0.0026)	-0.0564*** (0.0025)	-0.0189*** (0.0026)	-	-	-	-	-	-	-	-
<i>Up to ten lags</i>	-0.2795*** (0.0029)	-0.0846*** (0.0030)	-0.0396*** (0.0032)	-0.0554*** (0.0032)	-0.0548*** (0.0034)	-0.0301*** (0.0033)	-0.0341*** (0.0034)	-0.0069** (0.0033)	0.0282*** (0.0032)	0.0045 (0.0031)	-0.0080* (0.0033)

Table 7: Alternative specifications – Varying 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: Significant levels: * 10%, ** 5%, *** 1%. All regressions include mother fixed effects (μ_i), time fixed effects (η_t), controls for rainfall and mean temperature (for the same number of lags as the wind speed variable), women' age and its square.

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