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Storms and infant mortality in the Philippines

Hilde Orderud [a, b, 1]

[a] INVEST Research Flagship Centre, University of Turku, Turku, Finland
[b] Department of Political and Social Sciences, European University Institute, Florence, Italy

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ABSTRACT

Storms are one of the most frequent natural hazards and are expected to become more extreme as climate change proceeds. This paper investigates storms classified as disasters and infant mortality in the Philippines. Data from the Philippine Demographic and Health Surveys from 2003, 2008, and 2017 are combined with data on storms from the Emergency Events Database (EM-DAT) and the Geocoded Disasters Dataset. Storms included in EM-DAT are disasters with human and economic impact on the population. The lagged and immediate impact of storms are considered by including disasters occurring from five years prior to birth to two months after birth. The data are analysed with linear probability models and mother fixed-effects. The results show limited or no association between storms and infant mortality, which reflects a positive overall development in the Philippines over recent years. Improvements in disaster management systems are likely to have made communities and households more resilient.

1. Introduction

Storms were the second most frequent disaster type globally between 2000 and 2019 and affected 727 million people in this period [1]. As the sea surface temperature rises, more extreme storms are expected in the future [2,3]. Damages and losses as a consequence of natural hazard related disasters vary across countries, and are often explained by differences in hazard probability, exposure, vulnerability, and resilience [4–6]. Disasters will seldom affect an entire country equally; more frequently we observe regional disasters where some parts of the country remain unaffected [6]. Populations living in affected areas may face tremendous difficulties, with adverse impact on morbidity and mortality, as well as on property and their overall livelihoods [7–10]. Well-coordinated disaster management systems are of great importance both before, during and after a disaster, where targeted disaster relief has the potential to alleviate the negative disaster impact [11,12].

The Philippines is a lower-middle-income country located in a storm prone geographical corner of the world, and experiences an average of 22 typhoons every year, of which 6–7 are severe [13]. Storms consist of a wide variation of disturbances in the atmosphere with strong winds, often accompanied by thunder, lightning, heavy rainfall, and a temporary rise in sea level [10,14]. Storms in this paper also include typhoons, which change names according to where they originate.[2] Despite improvements in infant mortality (death before 12 months of age) from 35 per 1000 live births in 1998 to 21 per 1000 live births in 2017 in the Philippines, within-country inequalities in child mortality still exist [15,16 17]. Storms might play a role in these inequalities in child mortality [16],

E-mail address: hilde.orderud@utu.fi.

[1] Postal address: INVEST Research Flagship Centre, Department of Social Research, 20014 University of Turku, Finland. Postal address2: Department of Political and Social Sciences, European University Institute, Via della Badia dei Roccettini 9, 50014 Fiesole FI, Italy.

[2] Cyclones are those that occur in the Indian Ocean and South Pacific, hurricanes originate in the Western Atlantic and Eastern Pacific, while typhoons occur in the Western Pacific [14].

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though previous literature exploring the association between storms and infant mortality in the Philippines has indicated conflicting results with no association [18] and an increase in female infant mortality [19].

Storms have in previous research been shown to have a negative impact on birth outcomes such as low birth weight and fetal deaths after storm exposure in utero [20,21], but studies focusing on infant mortality per se are limited. One study found an increase in post-neonatal mortality after one major storm in Brazil [21] and one study found an increase in female infant mortality after storm exposure the previous year in the Philippine context for children born between 1979 and 2008 [19]. In this study, I investigate whether exposure to storms classified as disasters in the child's first two months of life and up to 60 months pre-birth has an impact on infant mortality for Philippine children born between 2000 and 2015. Storm measures according to frequency and number of affected people are analysed at the sub-national level. Data on more than 27,000 births from the 2003, 2008, and 2017 Philippines Demographic and Health Surveys (DHS) are merged with province-level data on the disasters from the Emergency Events Database[3] (EM-DAT) and the Geocoded Disasters Dataset[4] (GDIS). I use linear probability models to identify the potential association between storms and infant mortality. In addition, I apply mother fixed-effects designs to control for stable unmeasured characteristics that may affect infant mortality and bias estimates of the effects of the selected storms. These analyses contribute to a limited but growing literature on infant mortality and storm exposure pre-birth in low- and lower-middle-income countries. Specifically, this paper adds to earlier research in the Philippine context by including more recent data and better accuracy of the timing of the storm exposure. More knowledge on storms and child health outcomes is essential to ensure targeted adaptation and mitigation measures in a world in which climate change and storms will continue to threaten population health.

2. Background

Infant mortality reflects children's and communities' access to basic healthcare and is often an indicator of the socioeconomic development of a country or community [11,22–25]. The immediate and long-term effects of storms can have an impact on children and their families, where a difficult living situation could lead to lower chances of infant survival.

The immediate impacts of storms can generate a challenging environment, in which pregnant women and their households might suffer from a lack of clean water and nutrition, as well as insufficient housing and access to public services [26]. Various health impacts such as injury or death, easier transmission of infectious diseases, increased psychological stress, exacerbation of existing conditions, and malnutrition are likely in disaster contexts [9,26,27]. The immediate consequences of storms might therefore lead to unfavourable living conditions and an increased likelihood of adverse health outcomes, unless appropriate warning systems and immediate disaster relief are in place.

The long-term consequences of storms can be damaging and harmful for both individuals and societies in the months and possibly years after the disaster, when the affected populations may suffer alterations in livelihood, income, educational attainment, mortality risks, and other health effects, as well as potential displacement from permanent homes [9,10,28,29]. Socioeconomic resilience is strongly linked to poverty, and a household's consumption losses and recovery time will vary according to socioeconomic status and the resources available to the household [30]. For example, populations along the western coast of the Pacific Ocean, such as that of the Philippines, are especially vulnerable since many depend for their livelihoods on agriculture and fishing [31,32]. Economic shocks in low-income contexts can lead to an increase in infant mortality [25], when households are forced to make difficult trade-offs as they prioritise their spending of limited financial resources, in such a way that may have a negative impact on the care of infants. Baird et al. [25]suggest that it is the economic conditions around birth that matter the most for infant survival, rather than shocks in the in utero period or when a child is closer to one year of age. Additionally, as pointed out by Brenner [22], there is a maximum of one year lag following an economic downturn for perinatal mortality (still births and early neonatal deaths), while for post-neonatal mortality (deaths between 1 and 12 months of age) there is a minimum lag of three years and maximum of five years. However, the paper by Brenner linking economic downturns and mortality has been criticised by various other researchers (e.g., [33–35]). The question of whether adverse economic change has an impact on infant mortality (including neonatal and post-neonatal mortality) has yielded conflicting results, and it seems to be strongly related to the methodology applied and the context, where research on high-income countries has been most prominent [34,35].

The immediate or long-term consequences of storms can affect a broad range of determinants of infant survival, such as socioeconomic conditions, provision of and access to healthcare services, nutritional and health status of mother and child, and increased infections [36–38]. Research focusing specifically on storm exposure in utero, like typhoons and hurricanes, has indicated negative birth outcomes such as increased probability of labour and delivery complications, abnormal newborn conditions, low birth weight and fetal deaths, often explained by increased maternal stress [20,21]. Adverse birth outcomes could potentially reduce the chances of infants surviving their first year. One study from Brazil found an increase in post-neonatal mortality after in utero hurricane exposure [21], while a study from the Philippines showed an increase in female infant mortality in the year following a typhoon [19], though this study did not specifically focus on the in utero period. Whether storm exposure will have the most severe impact on infant survival after birth, during the in-utero period, or before conception is unclear, and will most likely depend on the pre-disaster level of determinants related to infant survival as well as the severity of the storm.

Better systems for both storm warnings, disaster mitigation and response can make families and households more resilient, and potentially lead to a better environment for pregnant women and their children. Storms might lead to the release of both national and international aid, depending on context and severity. While economic shocks can result in reduced chances of infant survival, this

[3] Emergency Events Database: https://www.EM-DAT.be/.

[4] Geocoded Disasters (GDIS) Dataset: https://sedac.ciesin.columbia.edu/data/set/pend-gdis-1960-2018.

negative impact has shown to be countered by increased development aid per capita which is often directed towards factors related to infant mortality, such as food aid, health care, control of infectious diseases, and female education [11,12]. The literature is not consistent, however, since other studies have shown no impact of aid on development [39] and limited child health gains [40]. Since both poverty and development are associated with infant mortality, there might be cases where aid does not stimulate the affected area sufficiently to reduce infant mortality. The transition from immediate aid to long-term development aid, also known as the humanitarian-development nexus [41,42], could potentially lead to a gap of assistance to the affected population. This underlines the importance of a well-coordinated disaster response system to ensure adequate and timely support which is sustained in the long run.

2.1. Setting: the Philippines

Most natural hazards happen in Asia, and the Philippines is the fourth most disaster affected country in the world [1]. In addition to frequent natural hazards, the Philippines is also highly vulnerable to the effects of climate change. Also, the south of the country has a history of conflict and instability, where government forces and various Moro resistance groups have been in dispute for decades [43,44]. The Philippines' topography varies greatly, with a long coastline, mountainous regions and more than 7000 islands. There are 81 provinces and three major island groups, Luzon, Visayas and Mindanao, of which primarily northern Luzon and the eastern Visayas are particularly prone to storms. The geographical region where the Philippines is located has the highest frequency of tropical cyclones in the world, and the country has therefore continuously strived to develop its disaster management infrastructures and resources [13]. Thus, after the devastating Typhoon Haiyan in 2013, there was further development with improved communication and coordination, resulting in mitigated impacts on the population [13]. The improved disaster risk reduction and management in the Philippines over the past decade have contributed to several laws, policies, and plans on disaster management, and as of September 2021 the Senate is working on legislation to form the Department of Disaster Resilience [13]. However, despite a comprehensive system of disaster risk reduction and management in place, there is still room for improvement. The approach of reducing the risk by enforcing relocation from the high-risk coastal areas, such as in Tacloban after Typhoon Haiyan in 2013, has been criticised as it can lead to difficulties especially for the poorer urban population [45]. The Philippines has an advanced social protection system to help poor households manage risks and shocks, but suggestions for further improvements have included identifying those at risk of falling below the poverty line and taking into account the aspect of wellbeing losses to strengthen the socioeconomic resilience of communities [30,46].

Previous research from the Philippine context has presented limited and inconsistent results on the association between storms and infant mortality. A report by Monsod and Monsod [18] found a strong correlation between infant mortality and type of climate. However, the results did not show a statistically significant correlation between the frequency of typhoons and infant mortality [18]. Anttila-Hughes and Hsiang [19] investigated the impact of typhoons on economic and health outcomes in Philippine households between 1979 and 2008. They found no evidence of a rise in infant mortality during or immediately following typhoon exposure, but typhoons caused infant mortality to rise the calendar year after the storm. Interestingly, the impact shows a substantial increase in female mortality, which they explain by typhoon-induced economic losses and the following household decisions [19]. Considering the various measures and results from the previous literature which has focused on outcomes for children born from 1979 to 2008, the main contribution from this study is to include more recent data up to 2015, which captures the latest developments in infant mortality. Additionally, where previous research has investigated the yearly impact [19], this study explores disaster exposure up to 60 months prior to birth by including both month and year of the storm and the child's birth. This allows for a better accuracy of the timing of the storm exposure when estimating infant mortality.

3. Data and analysis

3.1. Demographic and Health Surveys

Nationally representative data from the Philippine DHS conducted in 2003, 2008, and 2017 are analysed in this paper. Data on demographic variables such as mortality and fertility are collected retrospectively. In this study children born between 2000 and 2015 are included in the analyses. DHS are household surveys, with accurate data on a range of indicators related to maternal and child health, as well as other socioeconomic indicators [47]. The data used in this paper consist of information from women of reproductive age ranging from 15 to 49 years and have one record for every child born to interviewed women.

The DHS data are collected from a sample of the population and use a two-stage stratified sample design [17]. In the first stage, enumeration areas (survey clusters) are selected. In the second stage, a systematic sample of an average of 20–30 households per cluster is selected. Additionally, these datasets also contain geographic data on the clusters, which contain latitude, longitude, and elevation [47]. A total of 42 clusters without geocoded data were excluded. In a rural area, a cluster can be an entire village (barangay in the Philippines), a part of a village or a group of small villages, while in urban areas a cluster is usually a city block [48]. Clusters are geomasked to protect the respondents' confidentiality. This implies that urban clusters are displaced a distance of up to 2 km and rural clusters are displaced a distance of up to 5 km, and additionally a randomly selected 1 % of rural clusters are displaced a distance up to 10 km [49]. Presumably because of the geomasking, some of the clusters ended up being located in the sea. To identify the province these clusters belonged to, they were relocated inside the nearest land border. A total of 118 clusters were relocated. This leaves a total of 2811 clusters included in the analyses. The geocoded clusters were then identified according to the Philippines' 81 provinces using the software QGIS 3.30.1 and administrative maps.

3.2. The Emergency Events Database

Data from the EM-DAT and the GDIS [50] on storms in the Philippines are used to identify storm exposure according to province, month, and year. EM-DAT is a database on mass disasters from 1900 to the present, and GDIS is a geocoded extension of a selection of EM-DAT disasters between 1960 and 2018. For disasters to be included in EM-DAT, at least one of the following criteria must be fulfilled: 1) 10 people or more died, 2) 100 or more people affected/injured/homeless, or 3) declaration by the country of a state of emergency and/or an appeal for international assistance. This indicates that any storm included in the database has had an impact on the affected population. The dataset covers essential core data such as month and year of the occurrence, in addition to which provinces that were affected by each particular storm. For some of the storms there are severity measures included, such as affected population. Data on storms from 1995 to 2016 are identified, since the analyses focus on storms which occurred up to 60 months prior to birth (the earliest birth included being from 2000) and up to two months after birth (the latest births included are from 2015) (Fig. 1). A total of 139 storms are included in the analysis, where most of these storms affect more than one province. Two storms, one occurring in 2008 affecting two provinces and one occurring in 2017 affecting two provinces, do not report the number of affected people.

The administrative level (province) of each of the DHS clusters was identified by conducting a spatial join with the 81 provinces from the administrative map provided through GADM Maps and Data[5] (Fig. 2). Information for each storm on month, year, and affected population were included in the dataset at the province level.

3.3. Variables

Infant mortality is the dependent variable, coded 1 if the child died before 12 months of age and 0 if it survived the first 12 months. A total of 1330 children who were born less than 12 months prior to the interview were excluded from the analysis, since information on whether they survived until 12 months of age is unknown. Disasters are a frequent cause of displacement within the Philippines, but the majority of people are believed to return to their homes relatively quickly after a disaster, though some remain displaced for years [51]. To ensure that the women (mothers of children analysed) have been living in the indicated province for the storm exposure time of interest, years lived in current location at time of interview, time of interview, and time of birth of the child were used to include only children of mothers located in the same province for the five preceding years before the child was born.

Two independent variables are estimated in the analyses. The first variable is storm frequency as a continuous variable, which counts number of storms in each time period. The second variable is a continuous measure of number of affected people (divided by 100.000 for easier interpretation), which include 137 storms since data on affected population were missing for two of the storms. If more than one storm occurred in the same time period, the storm with the highest number of affected people will be included.

The DHS data and the geographical data on the storms were combined to identify the child's exposure to storms using information on the year and month of their birth, as well as their cluster and province of residence during the interview, and the year and month of each storm in each province. Four time periods were created to measure storm exposure before birth, that is 60-t37 months, 36-25 months, 24-10 months, and 9-0 months prior to birth, in addition to storm exposure from birth to 2 months of age (Fig. 3). Most deaths occur within the first two months of life (mean age at death is 1.87 months), so storms are also included for this period to capture a potential immediate impact. Overall, the time periods are intended to capture the immediate and long-term consequences of storms for infant mortality.

Control variables included in the analyses are birth year of the child, sex of the child, if the child was part of multiple birth, birth order, maternal age at birth, maternal education (no education, primary, secondary, higher), place of residence (urban/rural), and island group (Luzon, Visayas, Mindanao). Maternal education was missing for three of the children.

The final sample analysed consists of a total of 27,336 children born between 2000 and 2015. Descriptive information on the control variables is presented in Table 1.

3.4. Statistical analysis

The statistical analyses are conducted in two steps. In the first step, I estimate linear probability models (LPM) to examine the associations between storm exposure, measured by number of storms (frequency) and number of people affected, and infant mortality for the five time periods of storm-exposure. The linear probability model is linear regression estimated on a binary outcome, infant mortality, with estimates showing the effect of the independent variable, storm exposure, on the outcome on the percentage point scale. Linear probability models are chosen since they allow for estimation of marginal effects, compared to logistic regression which produces group-specific estimates and has a more complex interpretation [52]. Cluster robust standard errors are estimated at province level. I apply three models, where the first model is unadjusted, the second model includes birth year of the child, sex of the child, if the child was part of multiple birth, and birth order as controls, while the third model adds maternal age at birth, maternal education, place of residence, and island group. Controlling for island group captures the differences in infant mortality between the island groups, especially in regard to the ongoing conflict in the southern island group of Mindanao. Conflicts could impact child survival in conflict-prone provinces, as has been identified through previous research on children and armed conflict in other contexts [53,54].

In the second step of the analysis mother fixed-effects are estimated. This model compares storm exposure between children of the same mother and controls for stable unmeasured factors, which, in addition to stable factors in the area of residence, can include stable behavioural traits that may affect the outcomes. Two models are applied, the first is unadjusted, while the second applies time-

[5] GADM Maps and Data: https://gadm.org.

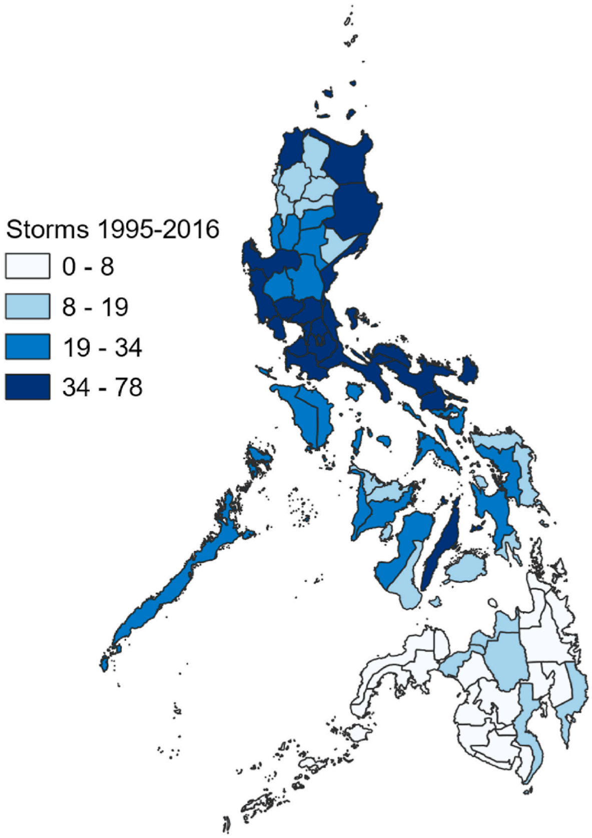

Fig. 1. Storms 1995 to 2016 across provinces in the Philippines as listed in EM-DAT.

varying variables which could vary between children born to the same mother: birth year of the child, sex of the child, whether the child was part of a multiple birth, and birth order. The fixed-effects model is given by

$$y_{ij} = \alpha + \beta_1 storm_{ij} + \beta_2 X_{ij} + \mu_i + \varepsilon_{ij} \tag{1}$$

In the mother fixed-effects model, y_{ij} is the value of the outcome variable for child i born by mother j. $storm_{ij}$ is the independent variable according to the five time periods of storm exposure, and X_{ij} are the control variables. The time-varying control variables are: birth year of the child, sex of the child, whether the child was part of a multiple birth, and birth order. μ_i captures unmeasured province-level characteristics, such as availability of healthcare services, and ε_{ij} is the random error term.

3.5. Sensitivity analysis

Three sensitivity analyses are included. The first two analyses are assessing whether more severe storms are more likely to have an impact on infant mortality. The severity of the storm is estimated by number of affected people. Firstly, model 3 is estimated with a binary storm measure of none or less than 500.000 people affected versus 500.000 or more. This severity measure is selected based on the average number of people affected in each time period, which ranges from 222.923 to 766.192. Secondly, model 3 is estimated with a binary storm measure of none or less than 1 million people affected versus 1 million or more, which is expected to capture more severe storms. These measures will only consider storm exposure if the storm affected a large part of the population, which then could capture the severity of the storm. Finally, a measure of total number of storms from 60 months prior to birth until birth are included, to see whether infant mortality possibly could be affected when mothers are exposed to a high number of disasters in the years preceding birth.

All analyses are conducted with the software QGIS 3.30.1 and Stata 16.1.

4. Results

The association between infant mortality and storms are none or limited when investigating the binary measure of storms (none/one or more) for all exposure periods, though a non-significant lower probability when exposed to one or more storms is shown (Fig. 4). Another binary measure of storm exposure, capturing severity with none or less than 500.000 people versus 500.000 or more affected, show a similar pattern. Also here, a non-significant lower probability of infant mortality in each of the time periods is observed

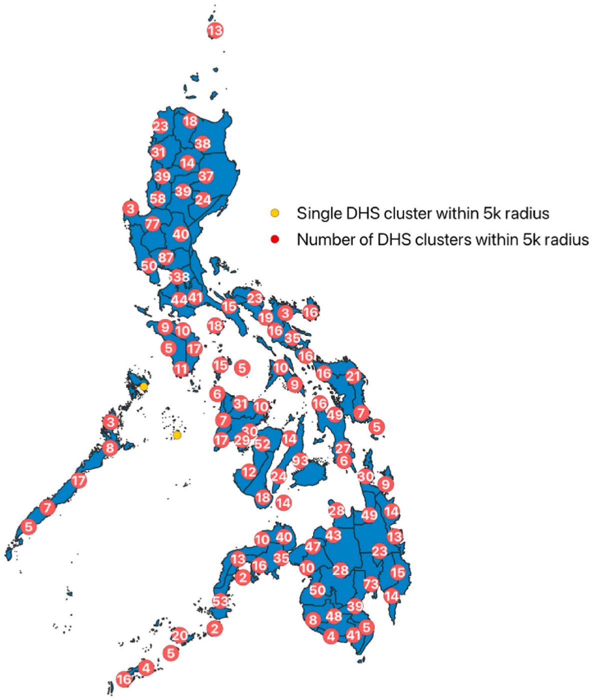

Fig. 2. DHS clusters from survey waves 2003, 2008, and 2017 across provinces in the Philippines presented as clustered points. Numbered red points indicating amounts of clusters within 5-km radius of each other. Yellow points indicating single clusters within 5-km radius.

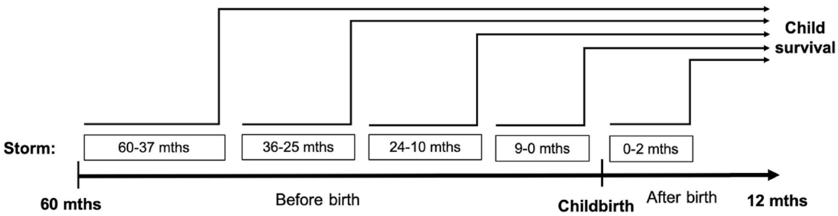

Fig. 3. Illustration of the time periods of storm exposure in time periods up to 60 months prior to birth and 2 months after birth.

when exposed to a severe storm (with 500.000 or more affected). These binary associations point in the direction of no association between storms classified as disasters and infant mortality.

The estimates from the linear probability models show an overall limited or no impact of storm frequency on infant mortality. However, for model 1, without any controls, a significant ($p < 0.05$) decrease in infant mortality of 0.1% point for each additional storm occurring during pregnancy and in the exposure time period up to two months after birth is observed (Table 2). The estimate for storm exposure in the time period from birth up to two months after birth remains also for model 2, but disappears when adding additional controls in model 3. For the second storm variable, with number of people affected, the estimates show no association with the number of affected population and infant mortality (Table 3). In model 1 and 2 the results show a significant ($p < 0.05$) decrease in infant mortality for exposure to storms 25–36 months before birth, but these estimates are showing no measurable size of the impact (−0.000) indicating small coefficients. The significant estimates disappear in model 3, when controlling for maternal age, maternal education, urban/rural place of residence and island group.

The impact of storm frequency on infant mortality for siblings with various storm exposure, mother fixed-effects, is seen to have no impact for most exposure periods (Table 4). There is one exception, where a significant ($p < 0.05$) increase in infant mortality of 0.1% point for storm exposure 37–60 months prior to birth is shown for model 2, when adding birth year, sex, multiple birth, and birth order. For the second storm measure of number of people affected, the mother fixed-effects estimates indicate no association for all exposure periods (Table 5). This is in line with the estimates for number of people affected from the linear probability models.

4.1. Sensitivity analysis

Firstly, the sensitivity analysis explores linear probability models with 500.000 or more affected, showing no significant association on infant mortality neither for the linear probability models nor mother fixed-effects (Appendix, Tables 1–2). Secondly, exploring a storm measure of 1 million or more affected show no significant impact for the linear probability model (Appendix, Tables 1–2). Though, when applying mother fixed-effects on the same storm measure the exposure period 25–36 months prior to birth show a sig-

Table 1
Descriptive statistics (with weights).

Variable	Categories	Mean
Infant mortality	Alive	0.97
	Dead	0.03
Neonatal mortality	Alive	0.98
	Dead	0.02
Birth year of the child	Year	2006.3
Sex of the child	Male	0.53
	Female	0.47
Multiple birth	No	0.99
	Yes	0.01
Birth order	1	0.24
	2	0.21
	3	0.18
	4 or higher	0.37
Maternal age	Years	28.0
Highest maternal educational level	No education	0.02
	Primary	0.27
	Secondary	0.46
	Higher	0.25
Place of residence[1]	Rural	0.59
	Urban	0.41
Island groups	Luzon	0.52
	Visayas	0.19
	Mindanao	0.28
Storms 0–2 mths after birth	None	0.77
	One or more	0.23
Storms 0–9 mths prior to birth	None	0.44
	One or more	0.56
Storms 10–24 mths prior to birth	None	0.35
	One or more	0.65
Storms 25–36 mths prior to birth	None	0.47
	One or more	0.53
Storms 37–60 mths prior to birth	None	0.33
	One or more	0.67

Total sample without weights: 27,336.
[1] Urban/rural residence is predefined in the DHS dataset.

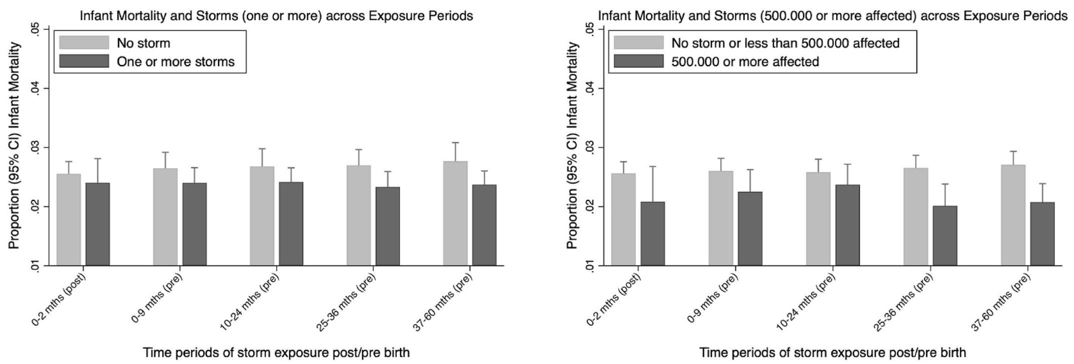

Fig. 4. Proportion of infant mortality across time periods of storm exposure according to no storm or one or more storms, and no storm/less than 500.000 affected or 500.000 or more affected. The range spike plots show 95 % confidence intervals.

nificant decrease ($p < 0.05$) in infant mortality of 0.9% points. Finally, investigating the total number of storms during the 60 months preceding birth show no association with infant mortality for the linear probability model, though when comparing siblings with different storm exposure in the mother fixed-effects model a significant ($p < 0.05$) increase in infant mortality of 0.1% points is observed (Appendix, Tables 3–4).

5. Discussion

The aim of this paper was to investigate the impact of both immediate and lagged disaster exposure on infant mortality by applying linear probability models and mother fixed-effects. The overall results imply limited or no impact of storms on infant mortality for

Table 2
LPM regression results for infant mortality according to storm frequency 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality					
	Model 1		Model 2		Model 3	
	Coeff	(95 % CI)	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (number of storms)						
0-2 mths (post)	−0.001*	(-0.002, −0.000)	−0.001*	(-0.002, −0.000)	−0.001	(-0.002, 0.000)
0-9 mths (pre)	−0.001*	(-0.001, −0.000)	−0.001	(-0.001, 0.000)	−0.000	(-0.001, 0.000)
10-24 mths (pre)	−0.000	(-0.001, 0.001)	0.000	(-0.001, 0.001)	0.000	(-0.000, 0.001)
25-36 mths (pre)	−0.000	(-0.001, 0.001)	−0.000	(-0.001, 0.001)	0.000	(-0.001, 0.001)
37-60 mths (pre)	−0.000	(-0.000, 0.000)	−0.000	(-0.001, 0.001)	0.000	(-0.000, 0.001)
Birth year (child)			−0.001*	(-0.001, −0.000)	−0.001**	(-0.001, −0.000)
Male			Ref.	(−)	Ref.	(−)
Female			−0.007**	(-0.011, −0.003)	−0.007**	(-0.012, −0.003)
Not multiple birth			Ref.	(−)	Ref.	(−)
Multiple birth			0.117***	(0.076, 0.158)	0.122***	(0.079, 0.165)
Birth order (1)			Ref.	(−)	Ref.	(−)
2			−0.006	(-0.012, 0.000)	−0.008*	(-0.015, −0.001)
3			−0.005	(-0.010, −0.001)	−0.009**	(-0.016, −0.003)
4 (or higher)			0.007*	(0.001, 0.013)	−0.001	(-0.008, 0.007)
Mother age at birth					0.000	(-0.000, 0.001)
Education (None)					Ref.	(−)
Primary					−0.012	(-0.027, 0.004)
Secondary					−0.022*	(-0.038, −0.005)
Higher					−0.028**	(-0.045, −0.010)
Place of residence (Rural)					Ref.	(−)
Urban					−0.005*	(-0.010, −0.000)
Island group (Luzon)					Ref.	(−)
Visayas					0.009*	(0.002, 0.016)
Mindanao					0.004	(-0.002, 0.010)
Prob > F	0.0000		0.0000		0.0000	
R-squared	0.0003		0.0112		0.0133	
Root MSE	0.15685		0.15601		0.15586	
Number of observations	27,336		27,336		27,336	

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Weights not applied.

all exposure periods. These findings underline an overall positive development in the Philippines over the recent years, and combined with improved disaster management systems, this may have contributed to better chances of infant survival in the country.

Storms, neither measured through frequency nor number of people affected, show any consistent impact on infant mortality when occurring during pregnancy or the two first months of life. This finding is in contrast with previous studies [19–21]. Better disaster management systems in the Philippines in the recent years [13] are likely to have contributed to this. Firstly, one explanation may be timely and accurate storm warnings, which have contributed to saving lives in disaster contexts [55,56]. Secondly, immediate disaster relief might also contribute to much needed support for mothers and children, especially in relation to healthcare, water, and sanitation, which have a positive impact on infant survival [11,36,37]. Immediate disaster relief may also contribute to better food security for the affected population, which potentially could ensure a healthier nutritional status for mother and child. Finally, it is important to highlight that the results capture the positive overall development across time, both in regard to child mortality and socioeconomic conditions. Applying more recent data would therefore reflect this positive development to a larger degree than previous research which analysed children born between 1979 and 2008 [19].

When analysing siblings with different storm exposure, storm frequency shows an increase in infant mortality when exposed 37–60 months prior to birth (Table 4), while storms affecting more than 1 million people show a decrease when exposed 25–36 months prior to birth (Appendix, Table 2). Recurrent storms may not release disaster relief, whereas a single severe storm could be enough to activate the disaster relief system, potentially leading to a positive long-term impact on child survival. A potential boost in the household economy could have a positive impact on infant survival, since this might result in better resources and finances to spend, for example, on healthcare, which is an important determinant of child survival [33,36,37,57]. The decrease in infant mortality for storms occurring 25–36 months prior to birth could reflect the potential delay in the disaster relief and recovery support, where the impact at household level might not be present until months or years after financial support has been released. In some cases, there might also be a delay in the disaster relief, due to bureaucratic processes and challenging systems to operate for the affected population. Storm frequency shows an increase in infant mortality, which could be related to household economy and household priorities of resources when affected by recurrent storms. Several storms within the same time period could potentially create an economic downturn for the household. A minimum lag of three years and maximum of five years in impact on infant mortality after an economic downturn, as suggested by Brenner [22], could be one explanation. The estimated decrease in infant mortality when storms occur two to three years prior to birth could therefore be due to the lagged impact of disaster relief and recovery efforts, while the in-

Table 3
LPM regression results for infant mortality according to number of people affected (continuous) 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality					
	Model 1		Model 2		Model 3	
	Coeff	(95 % CI)	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (affected population)	Ref.	(–)	Ref.	(–)	Ref.	(–)
0-2 mths (post)	−0.000	(-0.000, 0.000)	−0.000	(-0.000, 0.000)	−0.000	(-0.000, 0.000)
0-9 mths (pre)	−0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)
10-24 mths (pre)	0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)
25-36 mths (pre)	−0.000*	(-0.000, −0.000)	−0.000*	(-0.000, −0.000)	−0.000	(-0.000, −0.000)
37-60 mths (pre)	−0.000	(-0.000, 0.000)	−0.000	(-0.000, 0.000)	−0.000	(-0.000, 0.000)
Birth year (child)			−0.001	(-0.001, −0.000)	−0.001*	(-0.001, −0.000)
Male			Ref.	(–)	Ref.	(–)
Female			−0.007**	(-0.012, −0.003)	−0.007**	(-0.011, −0.003)
Not multiple birth			Ref.	(–)	Ref.	(–)
Multiple birth			0.118***	(0.080, 0.166)	0.118***	(0.077, 0.159)
Birth order (1)			Ref.	(–)	Ref.	(–)
2			−0.006	(-0.015, −0.001)	−0.007*	(-0.014, −0.001)
3			−0.005	(-0.016, −0.002)	−0.008*	(-0.014, −0.002)
4 (or higher)			0.007*	(-0.008, 0.007)	0.000	(-0.007, 0.007)
Mother age at birth					0.000	(-0.000, 0.001)
Education (None)					Ref.	(–)
Primary					−0.010	(-0.026, 0.005)
Secondary					−0.019*	(-0.036, −0.002)
Higher					−0.025**	(-0.042, −0.008)
Place of residence (Rural)					Ref.	(–)
Urban					−0.004	(-0.008, 0.000)
Island group (Luzon)					Ref.	(–)
Visayas					0.008*	(0.001, 0.014)
Mindanao					0.002	(-0.004, 0.009)
Prob > F	0.0000		0.0000		0.0000	
R-squared	0.0005		0.0114		0.0133	
Root MSE	0.15684		0.156		0.15586	
Number of observations	27,336		27,336		27,336	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

crease in infant mortality when storm occur three to five years prior to birth could reflect an intensification in hardship conditions when exposed to recurrent storms with a following lagged impact.

The results when comparing siblings with different lagged storm exposure in the five years preceding their births show that those born after more storms had a reduced chance of survival (Appendix, Table 4). A high number of storms could increase the disaster vulnerability of the household and consequently reduce their socioeconomic resilience with each storm they experience. Households barely able to balance their resources on a day-to-day basis might therefore be particularly fragile when faced with several storms, with one additional storm being enough to push the family into poverty. One sibling could therefore be born into a household that is still able to maintain good living conditions, while the next sibling could be born into the household after exposure to few additional storms which potentially could lead to worsening conditions for the family. Households with already limited resources are consequently more vulnerable. Examples of such households may be those which depend for their livelihoods on agriculture, farming, or fishing [31,32]. Populations in especially exposed storm-prone areas might not consider risks from storms as the most significant threat to their lives and livelihoods, but living in such areas could also relate to other risks and vulnerabilities such as lack of access to income-earning opportunities, education, and health care, which is understood as more immediate threats [45]. In the Philippines, the bottom income quintile is more likely to suffer asset losses, but also well-being losses which entail aspects such as socioeconomic resilience and ability to maintain consumption levels [30]. These families and households might therefore require additional support as part of the disaster relief system, especially when faced with several disasters within a period of five years.

I acknowledge that this study has limitations. First, the analyses cover storms at the provincial level and do not account for differences between sub-provinces, potentially resulting in measurement errors in storm exposure. Storm impact is investigated at the province level, so storms which affected a high number of people are likely to capture a larger share of the province population and could indicate the severity of the disaster. The frequency measure would possibly indicate a heavy impact on provinces when the frequency is high, but here it is also likely that the preparedness level is high. Secondly, despite including various measures of storm exposure, all measures suffer from various inaccuracies. Other studies investigating storm impact on infant mortality have used damages after one major hurricane [21] or average yearly windspeed with a better accuracy of the geographical path of the storm [19]. This paper, however, focused on repeated storms and used a better accuracy of the timing of the storm exposure by including month and year, though only with a geographical accuracy at province level. Identification of a more precise measure of storms is recommended for future research, including better precision of geographical impact, severity, and timing. Finally, the Philippines is not

Table 4
Mother fixed-effects results for infant mortality according to storm frequency 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality			
	Model 1		Model 2	
	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (number of storms)				
0-2 mths (post)	−0.002	(-0.003, 0.000)	−0.001	(-0.003, 0.001)
0-9 mths (pre)	0.000	(-0.001, 0.001)	0.000	(-0.001, 0.002)
10-24 mths (pre)	0.000	(-0.001, 0.002)	0.001	(-0.001, 0.002)
25-36 mths (pre)	−0.001	(-0.002, 0.001)	−0.000	(-0.002, 0.001)
37-60 mths (pre)	0.001	(-0.000, 0.002)	0.001*	(0.000, 0.002)
Birth year (child)			0.001	(-0.000, 0.002)
Male			Ref.	(–)
Female			−0.008**	(-0.014, −0.003)
Not multiple birth			Ref.	(–)
Multiple birth			0.134***	(0.078, 0.189)
Birth order (1)			Ref.	(–)
2			−0.015***	(-0.023, −0.007)
3			−0.024***	(-0.036, −0.013)
4 (or higher)			−0.035***	(-0.050, −0.019)
Prob > F	0.3346		0.0000	
Within	0.0003		0.0103	
Between	0.0002		0.0000	
Overall	0.0000		0.0027	
N(observations/groups)	27,336/14,165		27,336/14,165	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

Table 5
Mother fixed-effects results for infant mortality according to number of affected people (continuous) 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality			
	Model 1		Model 2	
	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (affected population)	Ref.	(–)	Ref.	(–)
0-2 mths (post)	−0.000	(-0.000, 0.000)	−0.000	(-0.000, 0.000)
0-9 mths (pre)	0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)
10-24 mths (pre)	0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)
25-36 mths (pre)	−0.000*	(-0.000, −0.000)	−0.000	(-0.000, 0.000)
37-60 mths (pre)	−0.000	(-0.000, 0.000)	0.000	(-0.000, 0.000)
Birth year (child)			0.001*	(0.000, 0.003)
Male			Ref.	(–)
Female			−0.008**	(-0.014, −0.002)
Not multiple birth			Ref.	(–)
Multiple birth			0.134***	(0.079, 0.189)
Birth order (1)			Ref.	(–)
2			−0.015***	(-0.023, −0.007)
3			−0.024***	(-0.035, −0.012)
4 (or higher)			−0.035***	(-0.050, −0.019)
Prob > F	0.3400		0.0000	
Within	0.0004		0.0101	
Between	0.0001		0.0000	
Overall	0.0003		0.0031	
N(observations/groups)	27,336/14,165		27,336/14,165	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

only prone to storms, but suffers also from other natural hazard related disasters such as floods and earthquakes, which can have an impact on the results. Though, being a lower-middle income country on a trajectory of positive progress towards becoming a higher-middle income country [13], may also imply a higher level of resilience and protection against severe negative outcomes of disasters than that which could be expected in a low-income context.

6. Conclusion

This study investigated the potential immediate and lagged impact of storm exposure on infant mortality. A positive trend of development in the Philippines across time along with well-coordinated disaster management systems are likely to be reflected in the limited associations between storms and child survival as presented in this paper. As climate change proceeds, more extreme storms can be expected, hence adequate disaster relief systems combined with climate change adaptation are essential to protect vulnerable populations. Future research should further explore the possible association between disaster relief and infant mortality, as well as possible disaster policy implications that may have contributed to the limited impact of storms on infant mortality in recent years. Additionally, whether in-utero exposure could have had an impact on infant survival for children born prior to 2000 would be worth exploring in more detail, preferably with more accurate spatial and severity storm measures.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

This paper used publicly available data from Demographic and Health Surveys (DHS) and data on storms available from the Emergency Events Database and from the Geocoded Disasters Dataset.

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Appendix

Table 1
LPM regression (model 3) results for infant mortality according to affected population (binary) 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality			
	500.000 or more affected		1 mill or more affected	
	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (binary)	Ref.	(–)	Ref.	(–)
0-2 mths (post)	−0.001	(-0.008, 0.006)	−0.002	(-0.011, 0.007)
0-9 mths (pre)	0.002	(-0.002, 0.006)	0.004	(-0.000, 0.009)
10-24 mths (pre)	0.003	(-0.002, 0.008)	0.004	(-0.001, 0.009)
25-36 mths (pre)	−0.001	(-0.006, 0.004)	−0.005	(-0.010, 0.000)
37-60 mths (pre)	−0.002	(-0.007, 0.004)	−0.004	(-0.009, 0.002)
Birth year (child)	−0.001**	(-0.001, −0.000)	−0.001**	(-0.001, −0.000)
Male	Ref.	(–)	Ref.	(–)
Female	−0.007**	(-0.011, −0.003)	−0.007**	(-0.011, −0.003)
Not multiple birth	Ref.	(–)	Ref.	(–)
Multiple birth	0.118***	(0.077, 0.159)	0.118***	(0.078, 0.159)
Birth order (1)	Ref.	(–)	Ref.	(–)
2	−0.007*	(-0.014, −0.001)	−0.007*	(-0.014, −0.001)
3	−0.008*	(-0.014, −0.002)	−0.008*	(-0.014, −0.002)
4 (or higher)	0.000	(-0.007, 0.007)	−0.000	(-0.007, 0.007)
Mother age at birth	0.000	(-0.000, 0.001)	0.000	(-0.000, 0.001)
Education (None)	Ref.	(–)	Ref.	(–)
Primary	−0.010	(-0.026, 0.005)	−0.011	(-0.026, 0.005)
Secondary	−0.019*	(-0.036, −0.002)	−0.019*	(-0.036, −0.002)
Higher	−0.025**	(-0.042, −0.008)	−0.025**	(-0.042, −0.008)
Place of residence (Rural)	Ref.	(–)	Ref.	(–)
Urban	−0.004*	(-0.009, −0.000)	−0.004*	(-0.008, 0.000)
Island group (Luzon)	Ref.	(–)	Ref.	(–)
Visayas	0.008*	(0.001, 0.016)	0.007*	(0.000, 0.014)
Mindanao	0.003	(-0.004, 0.010)	0.002	(-0.005, 0.008)

(*continued on next page*)

Table 1 (*continued*)

Variables	Infant Mortality			
	500.000 or more affected		1 mill or more affected	
	Coeff	(95 % CI)	Coeff	(95 % CI)
Prob > F	0.0000		0.0000	
R-squared	0.0133		0.0136	
Root MSE	0.15586		0.15584	
Number of observations	27,336		27,336	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

Table 2
Mother fixed-effects (model 2) results for infant mortality according to people affected (binary) 0–2 months after childbirth, and 0–9, 10–24, 25–36, 37–60 months prior to childbirth.

Variables	Infant Mortality			
	500.000 or more affected		1 mill or more affected	
	Coeff	(95 % CI)	Coeff	(95 % CI)
Storm exposure childbirth (binary)	Ref.	(–)	Ref.	(–)
0-2 mths (post)	−0.003	(-0.014, 0.007)	−0.007	(-0.019, 0.005)
0-9 mths (pre)	0.005	(-0.002, 0.012)	0.008	(-0.001, 0.016)
10-24 mths (pre)	0.001	(-0.006, 0.008)	0.003	(-0.004, 0.010)
25-36 mths (pre)	−0.004	(-0.012, 0.003)	−0.009*	(-0.016, −0.001)
37-60 mths (pre)	−0.002	(-0.009, −0.005)	−0.003	(-0.010, 0.004)
Birth year (child)	0.001	(-0.000, 0.002)	0.001*	(0.000, 0.002)
Male	Ref.	(–)	Ref.	(–)
Female	−0.008**	(-0.014, −0.002)	−0.008**	(-0.014, −0.003)
Not multiple birth	Ref.	(–)	Ref.	(–)
Multiple birth	0.134***	(0.079, 0.189)	0.135***	(0.080, 0.190)
Birth order (1)	Ref.	(–)	Ref.	(–)
2	−0.015***	(-0.023, −0.007)	−0.015***	(-0.023, −0.007)
3	−0.024***	(-0.035, −0.012)	−0.023***	(-0.035, −0.012)
4 (or higher)	−0.034***	(-0.050, −0.019)	−0.034***	(-0.050, −0.019)
Prob > F	0.0000		0.0000	
Within	0.0101		0.0106	
Between	0.0000		0.0000	
Overall	0.0031		0.0034	
N(observations/groups)	27,336/14,165		27,336/14,165	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

Table 3
LPM regression (model 3) results for infant mortality according to number of storms 0–60 months prior to childbirth.

Variables	Infant Mortality	
	LPM	
	Coeff	(95 % CI)
Storm exposure childbirth	Ref.	(–)
60-0 mths (pre)	0.000	(-0.000, 0.001)
Birth year (child)	−0.001**	(-0.001, −0.000)
Male	Ref.	(–)
Female	−0.007**	(-0.011, −0.003)
Not multiple birth	Ref.	(–)
Multiple birth	0.118***	(0.077, 0.159)
Birth order (1)	Ref.	(–)
2	−0.007*	(-0.014, −0.001)
3	−0.008*	(-0.014, −0.002)
4 (or higher)	0.000	(-0.007, 0.007)
Mother age at birth	0.000	(-0.000, 0.001)
Education (None)	Ref.	(–)
Primary	−0.010	(-0.026, 0.005)
Secondary	−0.019*	(-0.036, −0.002)

(*continued on next page*)

Table 3 (*continued*)

Variables	Infant Mortality	
	LPM	
	Coeff	(95 % CI)
Higher	−0.025**	(-0.042, −0.007)
Place of residence (Rural)	Ref.	(–)
Urban	−0.005*	(-0.009, −0.000)
Island group (Luzon)	Ref.	(–)
Visayas	0.009*	(0.002, 0.016)
Mindanao	0.004	(-0.002, 0.010)
Prob > F	0.0000	
R-squared	0.0133	
Root MSE	0.15586	
Number of observations	27,336	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

Table 4
Mother fixed-effects (model 2) results for infant mortality according to number of storms 0–60 months prior to childbirth.

Variables	Infant Mortality	
	500.000 or more affected	
	Coeff	(95 % CI)
Storm exposure childbirth (binary)	Ref.	(–)
60-0 mths (pre)	0.001*	(-0.000, 0.001)
Birth year (child)	0.001	(-0.000, 0.002)
Male	Ref.	(–)
Female	−0.008**	(-0.014, −0.003)
Not multiple birth	Ref.	(–)
Multiple birth	0.134***	(0.079, 0.189)
Birth order (1)	Ref.	(–)
2	−0.015***	(-0.023, −0.007)
3	−0.024***	(-0.035, −0.013)
4 (or higher)	−0.035***	(-0.050, −0.019)
Prob > F	0.0000	
Within	0.0101	
Between	0.0000	
Overall	0.0027	
N(observations/groups)	27,336/14,165	

Notes: *p < 0.05; **p < 0.01; ***p < 0.001. Weights not applied.

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