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Local Economic Growth and Infant Mortality

Abstract

We show, for the first time, a causal effect of local economic growth on infant mortality. We use geo-referenced data for non-migrating mothers from 46 developing countries and 128 DHS survey rounds and combine it with nighttime luminosity data at a granular level. Using mother fixed effects we show that an increase in local economic activity significantly reduces the probability that the same mother loses a further child before its first birthday.

JEL-Codes: I150, O180.

Keywords: local economic growth, child mortality, nighttime lights.

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1 Introduction

Does economic growth lead to better child health in developing countries? While there is evidence of a positive correlation between economic prosperity and health status for adults in developed countries (Adler et al. 1994, Ettner 1996, Adams et al. (2003)), it is less clear that such a relationship exists for infants and small children in developing countries and, if it exists, what the causal effect of economic well-being on health status is. Recent evidence suggests that the relationship between GDP per capita and height-for-age z scores may be weak to non-existent (Vollmer et al. 2014). In contrast, Aiyar and Cummins (2021) argue that a moderate effect of growth on height-for-age exists, which materializes only over time peaking at age 3 as better off children grow faster.

Even if a positive correlation between economic growth and health status exists, its interpretation is plagued with reverse causality issues – better economic conditions create better health outcomes through better health care, more nutrious diets, and better health-related knowledge, especially the socioeconomic status of parents matters for children (Currie 2009, Almond et al. 2018). But then better health increases human capital accumulation, labor productivity and thus economic outcomes (Alderman and Behrman 2006, Cole and Neumayer 2006, Mary 2018, Miguel and Kremer 2004, Weil 2007). In short, the relationship between health and growth is far from settled.

We make two novel contributions to the debate on this intricate relationship: Our analysis is causal and it is local. We use geo-referenced data of non-migrating mothers to relate the probability of neonatal and infants death of their children to to nighttime luminosity (NTL) in that location and a range of socioeconomic and household characteristics as control variables.

We identify a causal effect by creating a panel of births and infant deaths of all stationary mothers. We use data from 128 Demographic and Health Surveys (DHS) for 46 countries for the period 1992-2013. Although DHS data are cross-sectional, mothers are asked for their complete history of child births and child deaths. That allows us to create a panel and to relate the probability of infant death to the economic conditions at the time of birth in that location. By restricting our sample to non-migrating mothers and by using mother fixed effects we focus on the causal effect of changes in NTL on the probability of infant death for the *same* mother in the *same* location. This avoids sorting effects and controls for all location-specific and mother-specific time-invariant characteristics. We can exclude the usual reverse causality as for each newborn the level of local economic activity is given and the timespan of one year is too short for better health status to affect economic prosperity even if we used contemporaneous NTL. Our identifying assumption is that after controlling for mother fixed effects and a battery of time-variant variables at the child, mother, household, location and national level such as mother's age, gender of the child, conflict, polity2 scores, temperature, precipitation there is no omitted factor correlated with the level of economic activity at the local level.

Second, our analysis is individual and local. Like Vollmer et al. (2014) and Aiyar and Cummins (2021) we use data on individual health outcomes as we cannot assume that changes in economic activity affect all individuals alike (Vollmer et al., 2014, p.e225); yet both contributions - and many more - use GDP per capita as the relevant proxy for the level of economic activity. This assumes that (the change in) economic activity is uniform across locations in a country - a clearly unrealistic assumption given the strong evidence of interregional disparities (e.g. in childundernutrition Khan and Mohanty, 2018) and the theoretical underpinnings through the new economic geography approach If this assumption of equal economic activity across regions is violated, the use of aggregate measures of economic activity can lead to biased estimates of the effect of growth on individual health. The same logic that suggest that the use of individual health data is superior to the use of aggregate health measures (Vollmer et al., 2014, p.e225) implies that the use of local measures for economic activity is superior to the use of aggregate measures such as GDP per capita. Therefore we use nighttime luminosity at the grid level as local measure of economic activity.

We are the first to use NTL in a causal analysis of the growth–health nexus. Amare et al. (2020) is the only other study that relates health outcomes to NTL. They use individual child nutritional data from two different DHS rounds in Nigeria only. Since their data have no panel structure but are repeated cross-sections, they are unable to infer a causal effect of NTL on health outcomes.[1]

NTL data have been shown to be a good proxy for economic activity (e.g., Chen and Nordhaus 2011, Doll et al. 2006, Henderson et al. 2012, Sutton et al. 2007); they have been used for explaining a range of development issues such as the role of pre-colonial ethnic institutions for comparative regional development (Michalopoulos and Papaioannou 2013), ethnic inequality (Alesina et al. 2016), regional favoritism (De Luca et al. 2018, Hodler and Raschky 2014), or microfinance (Brown et al. 2016).

We find that higher NTL reduces the likelihood of infant death significantly: a two-unit increase in NTL, which is equal to the average 10-year increase in NTL in our sample locations, reduces the probability of infant death by 0.11 percentage points, equivalent to 1.7% percent of the mean probability of infant deaths in our sample of 6.6%.

Our analysis speaks to the wider literature on health and growth.[2] Panel studies at the country level, such as Pritchett and Summers (1996), Easterly (1999), Smith and Haddad (2002) or Headey (2013) estimate the correlation of aggregated output variables (mostly GDP per capita) and aggregated health outcomes at the country level. They show that wealthier countries tend to have healthier populations and that economic growth is associated with average health improvements. While being informative, these studies focus on average effects and disregard individual and regional heterogeneity.

A second strand of the literature relates individual health outcomes to individual characteristics and aggregate economic outcomes (e.g., Paxson and Schady (2005), Boyle et al. (2006), Harttgen et al. (2013), Vollmer et al. (2014), Baird et al. (2011)). Even though these studies use individual health data, they use country averages for the variable measuring economic activity,

[1] They assume in their "nearest neighbor approach" that neighboring villages are essentially the same village in order use "village fixed effects" for a regression that analyzes health outcomes of different children from different mothers at different points in time (and space).

[2] For a recent literature review on the effect of economic growth on health see Lange and Vollmer (2017).

which may lead to biased estimates.

Third, micro-level studies use personal or household income to explain individual health outcomes (e.g. Case et al. (2002), Currie and Stabile (2003)), but they disregard changes in environmental variables. Yet, these are crucial for the growth-health nexus. Individual pollution exposure does not depend on individual household income, but on the level of economic activity around the place of residence; access to piped water depends predominantly on the water infrastructure in a locality, access to health care on the local health facilities (health posts, clinics etc.). Empirical evidence supports this argument. Weil (2014) shows that health improvements in the last centuries can be attributed to the public health environment. This includes access to clean water, appropriate sanitation or medical technology in health facilities. Using DHS data for Tanzania – and after controlling for individual wealth – Khan et al. (2005) find that living in a poor neighborhood is associated with worse health outcomes and lower service utilization rates. Li et al. (2012) examine the relationship between urbanization and human health in China using nighttime luminosity data and find that higher levels of urbanization are linked to higher rates of chronic diseases. Bruederle and Hodler (2018) demonstrate that nighttime lights can serve as a proxy for human development at the local level. Their analysis uses environmental variables for survey locations and human development variables are aggregated at the location level; thus they disregard individual characteristics and thereby individual heterogeneity. Their analysis provides interesting correlations, but cannot establish causality; for instance it is possible that healthier people cluster in regions of higher economic growth and thus the estimated effect of growth on health may be biased. We complement their analysis by focusing on mothers that did not move and explain variations in mortality of children *of the same mother* by variations in local economic activity.

The paper is structured as follows: Section 2 describes the dataset, defines all variables used and explains how the average nighttime lights were derived. Section 3 illustrates the empirical approach. Section 4 presents the main findings. We first show correlations of contemporaneous health measures for children (height-for-age, weight-for-age, anemia etc.) with economic development and then focus on infant mortality in a panel setting. Section 5 contains extensions and robustness checks and Section 6 concludes.

2 Data

In our dataset we combine Demography and Health Survey (DHS) data from 46 developing countries with nighttime light satellite data from the National Oceanic and Atmospheric Administration (NOAA). In each DHS, a nationally representative sample of women between age 15 and age 49 is interviewed. The women were asked to provide information about health outcomes for their children and numerous individual and household variables mainly related to health, fertility and education. DHS are designed as repeated cross-section datasets; households and individuals are not tracked over time. Almost all information collected pertain only to the survey year. Our first data set therefore comprises a battery of relevant health outcomes for children (height-for-age, weight-for-age, hemoglobin levels etc.) and relates those to a range of child, parental and household characteristics, nighttime luminosity and other locational factors and national variables such as the political system, precipitation, temperature and GDP per capita and time and country FE. In this analysis we only look at children currently living in the surveyed household, based on repeated cross-sections.

Even though the DHS are not designed as panels they contain information on the complete birth history of all women interviewed and, if applicable, date of deaths of their children, which allows to create a panel of mothers. Each observation is the year of birth of a child that any given mother has born and whether this child has passed away within the first year of their lives. The geo-reference provided by the DHS allows us to assign to each DHS survey location the respective nighttime light value for any given year. For the panel analysis we assign each child the nighttime light value of its birth year. The availability of nighttime lights from 1992 to 2013 restricts our sample to mothers with children being born in that period of time.

We further restrict the sample to children that were born in the survey location. This is necessary because we only know where children/households live at the time of the survey, but have no detailed information on where they lived before, making it impossible to assign the correct NTL value for mothers who migrated after the birth of their children. Moreover, this restriction avoids sorting effects, which would make identifying causal effect impossible. The DHS provides data on how long a household has lived in the current location which allows us to restrict the sample to children born in the survey location. Because mothers in our sample are stationary, the mother fixed effects capture also time-invariant characteristics of the location.

We thus use all DHS surveys with geo-referenced data conducted after 1993 and for which information on time of residency is available. Our final sample consists of 128 different survey rounds conducted in 46 developing countries. Our main sample of non-migrating mothers contains 40,914 survey locations with a total of 769,128 observations. All countries and the respective DHS surveys are summarized in Table A1.

2.1 Health measures

We study the effect of growth on health using infant mortality (and neonatal and child mortality) as indicator for health quality because it is the only variable in the DHS that allows for a panel analysis and thereby for a causal analysis. Unlike other data, DHS data provide a exceptionally large geographical coverage and at the same time georeferenced data. Thus a geographically encompassing, yet localized and causal analysis of the growth-health nexus needs to follow the strategy that we have chosen.

The use of child-related health variables, however, has additional advantages. First, children are the most vulnerable part of the population; an improvement of their health has the most direct effect on well-being of the population and it has effects throughout the life cycle of the individual. Second, child health measures are usually preferred over adult health measures in the context of growth effects on health due to their relatively high sensitivity. Child health indicators, child mortality in particular, are still strong indicators for health of the population in general (Reidpath (2003)).

2.1.1 Contemporaneous Measures of Child Health

To show the association between local economic outcome and health we make use of all health measures that the DHS provide. We use the anthropometric measures weight-for-age, height-for-age and weight-for-height, which are standardized measures indicating if a child is growing 'normally' as defined by WHO standards. Following the WHO growth standards and a large literature (see e.g. Vollmer et al. 2014, Harttgen et al. 2013 or Headey 2013) we construct indicators for underweight, stunting and wasting as our final measures of health. These indicators are equal to one if the respective value of weight-for-age, height-for-age and weight-for-height is at least two standard deviations below the 'norm', defined by the WHO.[3] We use the birth weight as a further anthropometric measure in our analysis.

Other health measures include the hemoglobin level of children and whether the children suffer from anemia. Since many children in the developing world suffer from low hemoglobin levels and anemia (Kassebaum 2016, Pasricha et al. 2010), we interpret increases in the hemoglobin levels and reductions in incidents of anemia as a health improvements. Moreover, women were asked whether their children have had fever, cough, or diarrhea in the last two weeks. We create dummy variables that are one if they answer affirmatively and zero otherwise.

2.1.2 Infant mortality

We use *infant mortality*, defined as death within the first 12 months of life, as our primary dependent variable. Infant mortality is preferred over other child health measures, foremost because it allows creating a panel data set retrospectively and thereby identifying a causal effect of development on health (see above). All mothers in the DHS are asked for a complete birth history, including how many births they had in the past and when their children were born, and if they passed away, when their children died. In contrast, anthropometric and other health data can only be compiled for children present at the survey time. Infant mortality is a highly relevant and widely used concept (Paxson and Schady, 2005; Kudamatsu, 2012; Baird et al., 2011), which allows to compare our results to the literature. Unlike anthropometric measures, infant mortality is relatively insusceptible of measurement error and is comparable across different countries and years.

In addition to infant mortality, we use *child mortality*, i.e. death within the first five years, and *neonatal mortality*, death within the first month, as alternative outcome variables. In our final sample 6.64% of the children do not survive the first 12 months, nearly one in eight children dies before reaching their fifth birthday, and 3.3% die in their first month. The variation across different surveys is very substantial. On average, 11.94% of all children from the DHS survey in Mali (survey round from 2001) die before their first birthday, compared to only 1.56% in Armenia (survey round from 2015/16). Similarly, the number of observations between DHS surveys varies considerably.

[3]The results are qualitatively the same if we use the continuous anthropometric measures.

2.2 Economic outcomes

We use satellite collected nighttime lights as a proxy variable for economic output as it is the only variable measuring *local* economic development that is available for the wide range of developing countries (for which we have geo-referenced DHS data). Previous studies (Boyle et al. (2006), Pritchett and Summers (1996) or Vollmer et al. (2014), among others) have relied on country averages such as GDP per capita as the main explanatory variable. As argued above, if individual health outcomes are explained by country averages of GDP per capita, differences in economic activity within a country are disregarded, which have been shown to be substantial (Khan and Mohanty (2018)). This may lead to wrong conclusions. We have argued that only an approach that combines individual health data with local economic variables provides a nuanced and accurate picture of the economic development–health nexus.

The use of nighttime luminosity data has recently become an accepted approach to measuring local economic activity, especially in the context of developing countries for which reliable subnational data are notoriously unavailable (e.g. Hodler and Raschky, 2014; Alesina et al., 2016; Lessmann and Seidel, 2017; Henderson et al., 2012). The nighttime lights are globally available on a yearly basis for 1992 - 2013 and measure light intensity on a scale from 0 to 63 in $\frac{1}{120}$°grids.[4] Even though nighttime lights may not be a perfect proxy for local economic development, they have been shown to be a quite reasonable proxy (Mellander et al. (2015), Bruederle and Hodler (2018)). Moreover, there is no other variable available that provides a consistent measure of economic output across developing countries for a longer time period. We use the Global DMSP-OLS Nighttime Lights Time Series (Version 4) from 1992 - 2013.

Geo-referenced DHS surveys provide coordinates of all survey locations. To obtain the respective level of economic development, we calculate the average nighttime light value within a 10 km circle for each survey location in a given year. For contemporaneous child health measures we use the 10 km radius average NTL values for that location and year, for the panel of non-migrating mothers we use the value for the survey location and the birth year of the respective child.

The DHS provide geo-references for the centers of each survey location (cluster) only. There is no information where exactly each household is located. The distances from the surveyed households to the center of the cluster consequently vary, especially because the clusters sizes are different. Furthermore, to ensure the confidentiality of all respondents, DHS locations are randomly displaced between 0 and 2 kilometers for urban clusters and between 0 and 5 kilometers for rural clusters, with 1% of randomly assigned rural clusters being displaced between 0 and 10 km. This makes the georeference necessarily somewhat inaccurate. Our relatively large circle ensures that the actual household location falls within the circle, it should also capture the area that is relevant for child health (in terms of local income, health-related infrastructure, and pollution levels).

Figure 1 displays the unconditional correlation between average nighttime lights and infant mortality. Each circle depicts a different DHS survey round with the size of the circles

[4] A $\frac{1}{120}$ °grid approximately equals a 0.8x0.8 km^2 area at the equator.

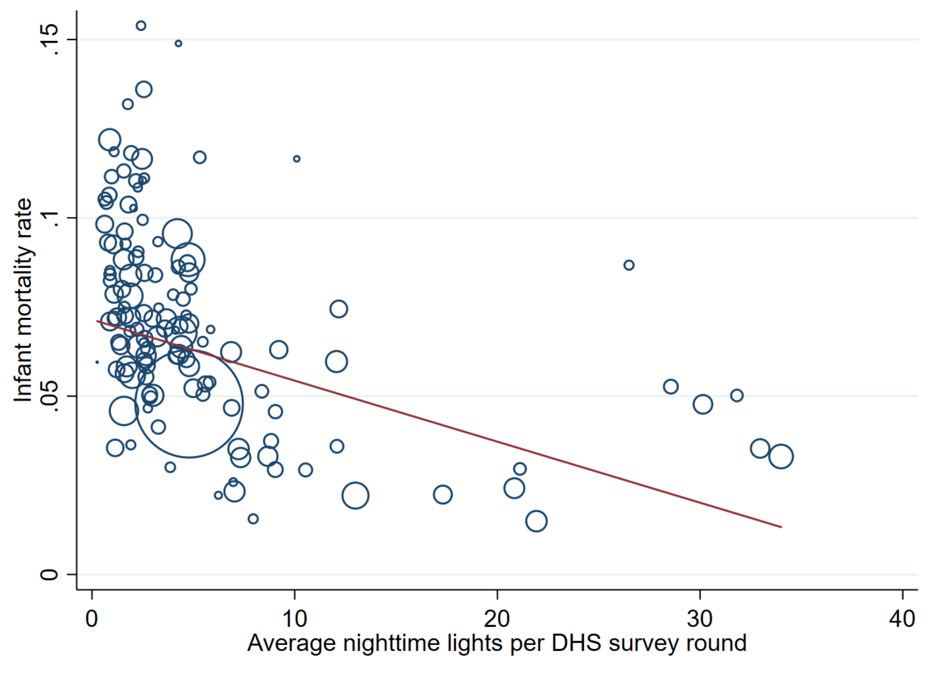

Figure 1: Infant mortality and nighttime lights

representing the number of observations in the respective survey. The graph clearly shows a negative relationship between infant mortality and economic development, but also a substantial variation of infant mortality for given ranges of NTL, especially at the lower end of the NTL distribution.

Variations in NTL intensity may capture local changes in household income, which in turn may affect nutritional status and access and affordability of health care; they may also capture changes in local public (health) infrastructure such as access to clean water and proper sanitation, primary health care facilities, and in ambient pollution levels.

2.3 Control variables

We use individual and environmental factors as control variables in our analysis. In the first analysis with contemporaneous measures for child health (weight-for-age, hemoglobin levels, anemia, occurrence of fever etc.) as left hand side variables we use as controls at the individual child level gender of the child, age of the child, age squared, its position in the birth order,[5] age of the mother and its squared term, education of the mother measured by the years of schooling and its squared term, dummies for rural residence and for a female household head, the age of the household head, and the number of children under 5 in the household.

Local environmental variables include precipitation, temperature, both as annual averages, and conflict intensity in the area to account for climatic and socioeconomic factors (in addition to the level of economic activity). All data are taken from the PRIO dataset, which offers grid data for 1946-2014 on a global level. Controlling for environmental variables, such as rainfall, is

[5]It is measured as integer value, but we alternatively included dummies for first born child, second born, third born etc., which did not alter the results in any significant way.

crucial, because they could have a direct effect on health outcomes and be related to economic output at the same time. The same is true for temperature or conflict. Moreover, it has been shown that conflict has a significant influence on child health (see Akresh et al. 2012 or Mansour and Rees 2012). We measure the intensity of local conflict by the number of casualties in the grid cell in the previous year.[6]

Control variables at the national level comprise the democracy-autocracy (polity2) score of the Polity IV database measuring the degree of democracy (Marshall et al. (2019)) and the log of GDP per capita in constant US$ 2011 from the Penn World Tables. The POLITY data base is the most widely used data base to describe the political regime, especially the competitiveness in the country's CEO recruiting, and it is consistent over time.

In the panel analysis of non-migrating mothers, since we use mother-fixed effects, we need not (and cannot) control for variables that are only available for the collection period. We include all important determinants of child health that are available in the DHS for all time periods of our mother panel. On the individual level we control for gender of the child, birth order, if the birth was a multiple birth and mother's age at the time of birth. Since we include only mothers that did not migrate, mother fixed effects capture not only mothers' characteristics, but also time-invariant locational factors.

Table A2 summarizes the descriptive statistics of all variables used in the study. To address potential reverse causality issues we use all locational and national variables lagged by one year.[7]

3 Empirical approach

To test for the relationship between child health and economic development we estimate two main regression models. The first model explains contemporaneous health outcomes for children living in the surveyed household. The regression equation is:

$$\text{Health Outcome}_{ihltc} = \beta \ Nightlight_{lt-1} + \mathbf{X'}_{ihlct}\gamma + \delta_c + \delta_t + \epsilon_{ihtlc} \tag{1}$$

where we regress the nighttime light values of each survey location l in $t-1$ on the health outcomes of a child i, living in household h in country c surveyed in year t. $\mathbf{X}$ is a vector of control variables that contain individual, household, location and national controls. All locational and national controls are lagged. We expect nighttime lights to be positively associated with health outcomes throughout all health measures. We furthermore include country and year fixed effects to capture differences between countries and shocks common to all individuals in a given year, respectively. Unfortunately, since we can only use the variation between children, but have no variation over time for children, we cannot clearly identify a causal effect with this

[6] We have also used a conflict dummy variable that is one if the household to which the child belongs is in a conflict zone in the child's birth year and zero otherwise. This did not change our results.

[7] Current year values for rainfall and temperature could be argued to be more meaningful than lagged values. Our estimations yield the exact same results in terms of direction and significance and very similar magnitudes when using contemporaneous values for rainfall and temperature.

approach.

In the second set of regressions we use the complete birth history of women and, by applying mother fixed effects, focus on the within–mother variation for our identification. We thus seek to understand whether the probability of infant death changes for the same mother if economic conditions change at the local level.

$$\text{Infant death}_{mtlc} = \beta \ Nightlight_{lt-1} + \mathbf{X'}_{mlt}\gamma + \delta_m + \delta_c + \delta_t + \epsilon_{mtlc} \quad (2)$$

In this set of regressions, every unit of observation is a child being born in year t, by mother m living in location l in country c. Infant death is an indicator whether the child died within the first 12 months. The coefficient β measures the relationship of interest between economic development in the year preceding the birth in the surroundings of the survey location and the probability of the child dying in the first 12 months. We expect that economic growth has a positive net impact on child health and thus that β is negative.

Again, we include country and birth year fixed effects to account for country specific time-invariant factors or common shocks to all births in the same year. Birth year dummies also capture medical technological progress. The identifying assumption is that nighttime lights are not correlated with any confounding factors, once accounted for mother fixed effects, country and year fixed effects and our control variables.

It is likely that observations for households in the same survey location – villages or neighborhoods – are correlated due to similar geographical, economic, social or other unobservable factors. To account for possible cluster sampling we use standard errors clustered at the survey locations in all regressions. We also lag all explanatory variables in order to account for possible reverse causality. We use neonatal and child mortality as alternative endogenous variables.

4 Main results

Table 1 presents the results of the first set of regressions described in the empirical approach section (eq. 1). We regress contemporaneous health measures of children living in a household surveyed by the DHS on nighttime lights, our variable of interest, and the set of controls described above. We use an inverse hyperbolic sine function transformation of nighttime luminosity. We prefer the inverse hyperbolic sine function because it solves for the highly skewed distribution of NTL in levels and is, other than the logarithm, defined for 0 and thus avoids to arbitrarily add a randomly chosen constant to NTL values. Furthermore, it yielded the best AIC and BIC values and the highest R^2.[8]

Higher local economic activity is consistently associated with higher anthropometric values – higher nighttime luminosities are significantly associated with lower probabilities of being un-

[8]The differences in the information criteria are small across specifications. Using NTL in levels and ln(NTL +0.01) does not alter our results. Regressions with levels and log of NTL are reported for eq. 2 in the robustness checks section.

derweight, stunting and wasting .[9] The magnitudes are however relatively modest. An increase in nighttime lights by 10% is associated with an decrease in the probability of underweight by roughly 0.13 percentage points. Similarly, the association is 0.15 and 0.04 for stunting and wasting.

Increases in NTL reduce the probability of anemia, fever and diarrhea, but increases the probability of cough. It increases birth weight and hemoglobin levels. For eight out of nine health indicators we find a significantly positive association of child health with economic development as measured by NTL.[10]

Table 1: The effect of economic development on various health measures

VARIABLES	(1) Underweight	(2) Stunting	(3) Wasting	(4) Anemia	(5) Hemoglobin	(6) Birth Weight	(7) Fever	(8) Cough	(9) Diarrhea
Asinh(Nightlight)	-0.0126***	-0.0149***	-0.00358***	-0.00851***	0.307***	4.533***	-0.00427***	0.00528***	-0.00158***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.051)	(1.174)	(0.001)	(0.001)	(0.001)
Observations	540,523	525,630	549,538	215,327	215,327	350,202	770,990	779,119	784,963
R-squared	0.118	0.092	0.038	0.156	0.203	0.047	0.055	0.070	0.042
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Unit of observation is a child living in a surveyed household. The dependent variables are denoted in each column. Nightlight measures average light intensity within a 10 km circle of DHS survey location. We use the inverse hyperbolic sine function of nighttime lights. Control variables are male, age, age squared, birth order, mothers age, mothers age squared, mothers education, mothers education squared, rural, female household head (HHH), age of HHH, number of children under 5 in HH, precipitation, temperature, casualties (due to conflict), polity2 and GDP p.c. at PPP. Standard errors are clustered at the DHS location. *** p<0.01, ** p<0.05, * p<0.1

These results show a stable correlation of children's health status and economic activity – healthier kids live in brighter spots – and thus corroborate earlier findings derived at the national level for local measures of economic activity. Like earlier studies, these cross-section regressions are not a causal analysis, since they may suffer from reverse causality and sorting issues. For instance, healthier people may migrate to more prosperous areas (making them even more prosperous). This is the consequence of the nature of the data – DHS provide repeated cross-section data only.

In the mother panel that we create we ask the causal question how does the likelihood of each newborn child to reach its first birthday increase compared to its siblings if economic prosperity has increased in the meantime? We have no sorting effects as we are only looking at stationary mothers and there is no reverse causality as for each newborn the level of local economic prosperity is given. Moreover, the timespan of one year is too short for better health status to affect economic prosperity even if we used contemporaneous NTL. This is even more so for neonatal death rates. Still, in the baseline we use lagged NTL.

Results of the panel regression are given in Table 2. We start by regressing NTL and control variables on infant death in (1) and sequentially add fixed effects. We report the full results with all control variables shown in Table A3. Economic prosperity is significantly associated with (the transformed) intensity of nighttime luminosity in our first model with only control variables but no fixed effects included. An increase in NTL by 10% is associated with a decline in the probability of infant death by 0.055 percentage points. This effect is significant at the

[9] Using the weight-for-age, height-for-age and weight-for-height z-scores yields similar results: children living in brighter areas have higher weight-for-age, weight-for-height and height-for-age z-scores.

[10] The increased incidence of coughing could be caused by higher air pollution.

1 % level; it remains at the same significance level and size if we include time fixed effects (model 2), which suggests that technological progress did not have a sizable effect on infant mortality rates. Including country fixed effects reduces the highly significant effect of NTL by approximately a third pointing towards substantial cross-country differences as discussed above (model 3). In model 4, our preferred specification, we include mother fixed effects. The negative effect of NTL on infant mortality remains significant at the 5% level (p=0.013) and of the same magnitude. Increases in nighttime luminosity cause a statistically significant improvement of children's prospects to live through their first birthday.

A ten percent increase in NTL decreases the probability of infant death on average by about 0.04 percentage points in our preferred specification (4). At first glance, this effect seems to be small. Yet, since many locations have relatively low values of NTL, the average ten percentage increase in NTL is relatively small in absolute units of luminosity. Put differently, a one standard deviation increase at the sample mean decreases the probability of infant death by 0.37 percentage points (which is approximately six percent of the average infant mortality). However, in contrast to the previous small percent change interpretation, a one standard deviation increase in NTL (11.38 units) seems to be large given the range of NTL from 0 to 63. We therefore use a 2 unit-increase in NTL for the interpretation of the magnitude of the effect: This 2-unit increase is equivalent to the average 10-year increase in NTL of all DHS location in our sample (or less than 18 percent of a standard deviation in NTL). An increase of 2 units in NTL decreases the probability of infant death by 0.11 percentage points at the sample mean. This equals roughly 1.7% of the total probability of infant death, which is a moderate average effect.

The effect is substantially more pronounced in darker survey locations due to the nonlinearity of the inverse hyperbolic sine function. This can be exemplified with two observations from our sample. The second child of a 25-year old mother from Kenya with 6 years of education, born in 1993 in a rural DHS cluster in Meru county, a county located in the center of Kenya, has a predicted probability of dying before its first birthday of about 10.09%. According to our estimations, a two-unit increase in NTL would reduce this probability by approximately 0.47 percentage points to 9.62%. This equals a reduction of about 4.7% of the total probability. In comparison, a child with comparable characteristics (second child, mother being 25 years old at birth with 6 years of education), born in a cluster close to Medellín, Colombia in 1994, is expected to have a 6.54% probability of infant death. Since the location is much brighter already, compared to the child in rural Kenya, a 2-unit increase in NTL is estimated to affect the probability of infant death by only 0.015 percentage points.

In specification (5) we focus on neonatal death rates i.e. the share of children dying within their first month. Similar to the coefficient on infant death, the effect of nighttime lights on neonatal death is negative and significant, but somewhat smaller in size. A two-unit increase in NTL at the sample mean decreases the probability of neonatal death by 0.07 percentage points (compared to 0.11 for infant death).

The effect of NTL on child mortality has a similar magnitude as on infant mortality, even though the effect is significant only at the 10% level. This lower significance level is not surprising since the probability to reach the fifth birthday is affected not only by NTL in the year preceding the birth, but also by NTL for up to five subsequent years.

Table 2: The effect of economic development on various health measures

VARIABLES	(1) Infant Death	(2) Infant Death	(3) Infant Death	(4) Infant Death	(5) Neonatal Death	(6) Child death
Asinh(Nightlight)	-0.00547***	-0.00537***	-0.00354***	-0.00364**	-0.00220**	-0.00350*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Observations	769,128	769,128	769,128	769,128	769,128	606,340
R-squared	0.028	0.029	0.032	0.364	0.365	0.408
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes	Yes
Women FE	No	No	No	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within a 10 km circle of DHS survey location. We use the inverse hyperbolic sine function of nighttime lights. Control variables are birth order, gender, mothers age at birth, multiple birth, polity2, casualties (due to conflict), precipitation and temperature. Standard errors clustered at the DHS location *** p<0.01, ** p<0.05, * p<0.1

The positive effect of local economic development on child health is in line with findings of other studies that use aggregated measures of economic development and find small to moderate effects of growth on health (e.g. Pritchett and Summers (1996), Boyle et al. (2006), Vollmer et al. (2014) or Baird et al. (2011), Aiyar and Cummins (2021)). However, our results are causal, have a very encompassing coverage and they pertain to local economic development and variations on death rates for children of the same mother.

Our findings highlight the importance of *local* economic conditions on health beyond national averages as we have controlled for GDP per capita at the national level in all of our regressions. They are thus more accurate than regressions that use only national GDP per capita as measure of economic prosperity. Local economic conditions matter.

5 Extensions and robustness checks

In this section we test whether our results are heterogenous across different groups or locations, we test whether a recall bias may have affected our results and we report on various further robustness checks.

5.1 Heterogeneity

In the baseline regressions in Table 2 we implicitly assume that the effect of an additional unit of nightlight is homogeneous for all individuals and survey clusters. The effect could however depend on individual or cluster characteristics. We test this in Table 3 by including interaction terms of nighttime luminosity with the variables that may give rise to heterogeneous effects. We amend our preferred specification (model 4 in Table 2) with these interaction terms; the baseline specification is repeated in column (1) for comparison.

Table 3: Heterogeneity

VARIABLES	(1) Baseline	(2) Gender differences	(3) Rural differences	(4) Ethnic Frac.	(5) Gini	(6) PolityIV	(7) GDP
Nightlight	-0.00364**	-0.00286*	-0.00295	0.000650	-0.00598	-0.00377**	-0.00544***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.012)	(0.001)	(0.002)
Nightlight x Male		-0.00150***					
		(0.000)					
Nightlight x Rural			-0.000997				
			(0.003)				
Nightlight x Ethn. Frac.				-0.00710			
				(0.005)			
Nightlight x Gini					2.33e-05		
					(0.000)		
Nightlight x Polity2						6.81e-05	
						(0.000)	
Nightlight x GDP							0.00170
							(0.001)
Observations	769,128	769,128	769,128	663,282	82,014	769,128	769,128
R-squared	0.364	0.364	0.364	0.365	0.516	0.364	0.364
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Women FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within a 10 km circle of DHS survey location. We use the inverse hyperbolic sine function of nighttime lights. Control variables are birth order, gender, mothers age at birth, polity2, casualties (due to conflict), precipitation and temperature. Standard errors clustered at the DHS location
*** p<0.01, ** p<0.05, * p<0.1

First, we analyze gender differences in the reaction to changes in NTL. We find that the effect of growth on health is about one third stronger for boys. This finding is in contrast to Baird et al. (2011) who find that female infant mortality reacts more strongly to economic shocks than male mortality.[11] Second, we observe no difference in the effect of NTL on infant death between rural and urban areas. We also find no evidence for significantly heterogeneous effects of NTL on infant mortality with respect to the political system, the degree of ethnic fragmentation, inequality, or the level of GDP per capita.

In addition we tested for a wide array of possible differential effects of nightlight that did not yield any significant results and are not reported in Table 3. For instance, we find no difference with respect to the education of the mother or the wealth quintiles of the households.[12] It is important to note, that richer households, more educated women, democratic and less corrupt countries have lower infant mortality rates in absolute terms. We do however find no difference in the effect of local economic growth for these groups.

5.2 Recall bias

A possible recall bias may be a concern as data on child births and possible deaths are only available in retrospect, i.e. mothers may not recall correctly the birth history of their children, including possible deaths of their children. Even though it seems unlikely that mothers have imprecise recollection of their children's birth years and possible deaths we address this issue following a procedure suggested by Paxson and Schady (2005) by excluding births that took

[11]Note that boys have a higher infant mortality than girls, cf. Table A3.

[12]The results for education and wealth are however problematic, because we only have data available for the year in which the survey was conducted - but not for all previous years a mother has given birth. Our non-findings might be driven by this data limitation.

place more than a certain number of years before the survey.

Table 4: Taking recall bias into account

VARIABLES	(1) All births included	(2) ≤20 years	(3) ≤15 years	(4) ≤10 years	(5) ≤5 years
Asinh(Nightlight)	-0.00364**	-0.00483***	-0.00441***	-0.00410*	-0.00880*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)
Observations	769,128	740,330	660,626	471,263	149,304
R-squared	0.364	0.371	0.386	0.432	0.540
Controls	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Women FE	Yes	Yes	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within a 10 km circle of DHS survey location. We use the inverse hyperbolic sine function of nighttime lights. Control variables are birth order, gender, mothers age at birth, polity2, casualties (due to conflict), precipitation and temperature. Standard errors clustered at the DHS location *** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the results of our preferred specification with a sub-sample for only those births that took place no longer than 20, 15, 10 or 5 years ago. There is no clear consensus on how long observations can date back in order for the recall bias to be unproblematic. While Paxson and Schady (2005) propose not to rely on data that date back more than 12 years, Baird et al. (2011) only use observations not older than eleven years. We are agnostic about the correct time span for child births and deaths to be included and run our regressions for different subsamples instead.

The results in Table 4 are straightforward – a recall bias seems not to be an issue in our context. The coefficients in all four additional regression are significant and of comparable size. Unsurprisingly, the significance levels are somewhat lower for the smaller subsamples.

5.3 Functional form

This section tests whether our results are affected by the functional form that we use for nighttime lights. As described above, our main specification uses the inverse hyperbolic sine function of nighttime lights. Thus, our results suggest a non-linear effect that grows weaker with increased nighttime lights. In specifications (2) to (4), we use the levels of nighttime light and test for a linear, squared and third order relationship between NTL and infant death. We find a negative and significant coefficient in (2), suggesting an average linear decline in infant death with increased NTL.

The effect is somewhat less significant compared to our baseline specification and of similar magnitude. We find no evidence in favor of a squared relationship in (3) and only a slightly significant coefficient on the third order polynomial in (4). Another possibility is to use the logarithm of nighttime lights plus a small constant, such as for instance used by Michalopoulos and Papaioannou (2013), Michalopoulos and Papaioannou (2014) and Hodler and Raschky

Table 5: Functional form

VARIABLES	(1) Baseline	(2) Levels	(3) Second order	(4) Third order	(5) Logs
Asinh(Nightlight)	-0.00364**	-0.000294*	1.56e-05	-0.000702	-0.00130*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Nightlight squared			-5.86e-06	2.96e-05	
			(0.000)	(0.000)	
Nightlight squared				-4.46e-07*	
				(0.000)	
Observations	769,128	769,128	769,128	769,128	769,128
R-squared	0.364	0.364	0.364	0.364	0.364
Controls	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Women FE	Yes	Yes	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within a 10 km circle of DHS survey location. Different functional forms of nighttime lights are used according to the column description. Control variables are birth order, gender, mothers age at birth, polity2, casualties (due to conflict), precipitation and temperature. Standard errors clustered at the DHS location *** p<0.01, ** p<0.05, * p<0.1

(2014). In (5) we thus use the natural logarithm of NTL+0.01. The results confirm our baseline finding of a negative impact of NTL on infant death, although the coefficient is not as significant as in our baseline specification and the baseline specification outperforms alternative specifications by all usual information criteria.

5.4 Different radii of nighttime lights

In this section we test whether the choice of radius drives our results. In the main specifications, we used the average NTL in a 10 km circle around the georeferenced survey location. As discussed in the data description, this choice was mainly driven by the random displacement of GPS coordinates by the DHS and the area that we considered relevant for the health-relevant infrastructure. Nevertheless, the cut-off distance of 10 km remains to some extent arbitrary. Table 6 shows the results of our preferred specification when using different radii.

We find a significant and negative impact of NTL on infant death irrespective of the radius used for the NTL calculation, although the coefficient on nighttimelight is only significant at the 10% level for 2km radius and not significant at any conventional significance levels for 1km radius (p-value = 0.11). The effect clearly shrinks in size with smaller radii. This is intuitive, because an increase in NTL of a large circle implies a larger increase in economic activity compared to the same average increase of a smaller circle.[13] We conclude that our

[13]As an example, assume that the area of a village cluster equals approximately the area of a 1km circle, but the surroundings in every direction emit no NTL. Then the computed averages are higher for a 1km circle compared to a circle with a larger area. Similarly, the village has to grow more (i.e. emit more NTL) s.t. the average NTL increase by 1 unit compared to a smaller circle.

Table 6: Different radii

VARIABLES	(1) 15km	(2) 10 km - Baseline	(3) 5km	(4) 2km	(5) 1km
Nightlight (t-1)	-0.00594***	-0.00364**	-0.00312**	-0.00185*	-0.00152
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	769,128	769,128	769,128	769,128	769,128
R-squared	0.364	0.364	0.364	0.364	0.364
Controls	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Women FE	Yes	Yes	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within different circles of DHS survey location, denoted by the column description. We use the inverse hyperbolic sine function of nighttime lights. Control variables are birth order, gender, mothers age at birth, polity2, casualties (due to conflict), precipitation and temperature. Standard errors clustered at the DHS location *** p<0.01, ** p<0.05, * p<0.1

main findings are not driven by the size of the circle used for the NTL calculation.

6 Conclusion

Our study analyzes the link between local economic development and individual health outcomes in developing countries. We combine geo-referenced infant mortality data from 128 DHS survey rounds from 46 developing countries with nighttime luminosity as a proxy for local economic activity. To estimate the effect of local growth on health, we compare the probability of infant death among siblings of the same mother in the same location as a response to local economic development.

We make two main contributions to the literature: First, we investigate the effect of *local* economic development on individual health outcomes, rather than just using economic growth at the country level. This novelty is crucial as individual health is affected by local conditions – pollution, health care infrastructure, clean water and proper sanitation infrastructure, etc. – rather than by national averages of these magnitudes. This is particularly important as the heterogeneity of local conditions is very pronounced in many developing countries and thus national averages such as GDP per capita are not very informative. Furthermore, our study is not limited to a specific setup or country but uses a wide array of developing countries. Thus our results should be externally valid and applicable to other developing countries.

Second, by using regressions with mother fixed effects on a panel of non-migrating mothers we are able to identify the causal effect of local growth on infant mortality of children of the same mother. Our study shows that economic growth at the local level causes a moderate and significant decline in infant mortality. An increase in NTL, equivalent to the average increase over one decade, decreases infant mortality by 0.11 percentage points or 1.7% of average mortality in our sample. This suggests that *local* economic growth can substantially contribute to achieving the Sustainable Development Goal (Target 3.2). However, given the still high rates of infant mortality in many developing countries, local economic growth alone cannot bring about the change that is needed: Economic growth per se is not a panacea for the pressing problem of infant and child mortality: it needs to be complemented by measures that ensure equitable access to health care and health-related infrastructure and measures that improve the quality of child health care. Lastly, growth needs to be sustainable in the sense that it limits the environmental costs associated with it.

Appendix

Table A1: Survey years

Country	Years				
Albania	2008				
Angola	2015				
Armenia	2010	2015			
Bangladesh	1999/00	2004	2007	2011	2014	
Benin	1996	2001	2011	2017		
Bolivia	2008					
Burkina Faso	1993	1998/99	2003	2010		
Cambodia	2000	2005	2010	2014		
Cameroon	2004	2011	2018			
Colombia	2010					
Coteivoire	1994					
Dominican Republic	2007	2013				
Egypt	1995	2000	2003	2005	2008	2014
Ethiopia	2000	2005	2011	2016		
Ghana	1993	1998	2003	2008	2014	
Guinea	1999	2005	2012	2018		
Guyana	2009					
Haiti	2000	2005/06	2012	2016		
India	2015					
Jordan	2002	2007	2012	2017		
Kenya	2003	2008/09	2014			
Lesotho	2004	2009	2014			
Liberia	2007	2013				
Madagascar	1997	2008				
Malawi	2000	2004	2010	2015		
Mali	1995/96	2001	2006	2012	2018	
Moldova	2005					
Morocco	2003					
Mozambique	2011					
Namibia	2000	2006/07	2013			
Nepal	2001	2006	2011	2016		
Niger	1998					
Nigeria	2003	2008	2013	2018		
Peru	2000	2004-06	2007/08	2009		
Philippines	2003	2008	2017			
Rwanda	2005	2007	2010	2012	2014	
Senegal	1997	2005	2010/11	2012	2014	
Sierra Leone	2008	2013	2019			
Swaziland	2006					
Tajikistan	2017					
Tanzania	1999	2010				
Timor-Leste	2009	2016				
Togo	1998	2013/14				
Uganda	2000/01	2006	2011	2016		
Zambia	2007	2013/14	2018			
Zimbabwe	1999	2005/06	2010/11			

Table A2: Descriptive Statistics

Variables	(1) Obs	(2) Mean	(3) S.D.	(4) Min	(5) Max
Sample 1: Children living in the household					
Child had fever in last 2 weeks	770,990	0.251	0.434	0	1
Child had cough in last 2 weeks	779,119	0.265	0.441	0	1
Child had diarrhea in last 2 weeks	784,963	0.156	0.363	0	1
Underweight	540,523	0.216	0.412	0	1
Stunting	518,795	0.262	0.440	0	1
Wasting	538,594	0.0741	0.262	0	1
Height for Age Z-score	518,734	-1.083	1.385	-4	4
Weight for Age Z-score	540,460	-0.977	1.284	-4	4
Weight for Height Z-score	538,531	-0.307	1.214	-4	4
Hemoglobin level	195,152	104.6	17.16	1	298
Anemia	195,152	0.347	0.476	0	1
Birth weight	231,020	3,182	604.4	1,500	5,000
Nighttime lights	546,027	8.282	14.66	0	63
GDP per capita (PPP)	546,027	3,894	3,173	500.6	11,785
Mothers age	546,027	28.76	6.810	13	49
HH head is female	546,027	0.162	0.369	0	1
Age of HH head in years	546,027	40.79	13.21	12	99
Number of HH members	546,027	6.934	3.891	1	74
Mother yrs. of education	546,027	4.781	4.795	0	25
Children under five	546,027	2.013	1.178	0	20
Polity2	546,027	2.714	4.830	-9	9
Casualties	546,027	2.258	17.20	0	435
Temperature	546,027	23.77	4.680	-0.256	38.46
Precipitation	546,027	1,123	735.3	1.082	4,451
Birth order	546,027	3.407	2.347	1	18
Male	546,027	0.507	0.500	0	1
Age of child	546,027	1.904	1.406	0	4
Rural	546,027	0.677	0.468	0	1
Sample 2: All births from mothers included					
Infant death	769,128	0.0664	0.249	0	1
Neonatal death	769,128	0.0333	0.179	0	1
Child death	643,326	0.121	0.326	0	1
Nighttime lights	769,128	5.535	11.38	0	63
GDP per capita (PPP)	769,128	3,484	2,643	188.9	10,922
Male	769,128	0.510	0.500	0	1
Mothers age at birth	769,128	26.14	6.553	11	49
Multiple birth	769,128	0.0318	0.175	0	1
Casualties	769,128	26.342	2328.01	0	332,748
Precipitation	769,128	1,181	727.4	0.679	6.12
Temperature	769,128	23.23	5.028	-14.39	38.10
Polity 2	769,128	2.199	5.215	-10	9
Gini Index	160,843	44.566	9.364	27	65.8
Ethn. Fractionalization	666,667	0.587	0.310	0.016	0.89

Table A3: The effect of economic development on various health measures

VARIABLES	(1) Infant Death	(2) Infant Death	(3) Infant Death	(4) Infant Death	(5) Neonatal Death	(6) Child death
Asinh(Nightlight)	-0.00547***	-0.00537***	-0.00354***	-0.00364**	-0.00220**	-0.00350*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Log(GDP)	-0.0197***	-0.0179***	-0.00620**	-0.00619*	-0.00658***	0.0661***
	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)	(0.006)
Birth order	0.00773***	0.00763***	0.00740***	-0.0211***	-0.0119***	-0.0179***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Male	0.0114***	0.0114***	0.0114***	0.0119***	0.00953***	0.0153***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Multiple birth	0.175***	0.175***	0.175***	0.191***	0.143***	0.224***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Mothers age at birth	-0.00258***	-0.00237***	-0.00242***	0.000554	0.000311	-0.00136*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Number of casualties	2.47e-08	1.11e-08	-3.62e-08	1.92e-08	1.22e-07	-5.35e-08
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-1.38e-06**	-1.50e-06***	-2.42e-06***	3.45e-07	1.52e-06	-2.01e-08
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.00103***	0.00111***	2.52e-05	-0.000137	0.000307	0.000904
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Polity2	-0.00166***	-0.00123***	-0.000380***	-9.57e-05	-2.10e-05	0.000572**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	769,128	769,128	769,128	769,128	769,128	606,340
R-squared	0.028	0.029	0.032	0.364	0.365	0.408
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Birth cohort FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes	Yes
Women FE	No	No	No	Yes	Yes	Yes

Note: All variables are regressed on the probability that a child dies before reaching their first birthday. Unit of observation is a child. Nightlight measures average light intensity within a 10 km circle of DHS survey location. We use the inverse hyperbolic sine function of nighttime lights. Standard errors clustered at the DHS location *** p<0.01, ** p<0.05, * p<0.1

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