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Saving Lives through Technology

Mobile Phones and Infant Mortality

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Abstract

Digital technologies can expand access to health services to underserved populations. This paper leverages mobile network expansion and survey data spanning two decades to study the impact of access to mobile phones on infant mortality in Africa. Using plausibly exogenous variations in lightning intensity and (sub)regional convergence in mobile penetration as instrumental variables for mobile network expansion, the analysis finds that mobile phones significantly reduce infant mortality. A 10 percentage point increase in mobile coverage is associated with a 0.45 percentage point reduction in infant mortality. Improvements in health knowledge and behavior and health care utilization appear to be plausible channels.

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Saving Lives through Technology: Mobile Phones and Infant Mortality*

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1 Introduction

Digital technologies are revolutionizing traditional methods of delivering information and services to end users. The spread of mobile phone technology is facilitating speedy, cheap and expansive flow of information, thereby creating new opportunities for addressing some of the key challenges that people in the developing world face. This development is especially relevant in the African context where access to physical infrastructure such as roads and health facilities remains very low, limiting citizens' participation in various socio-economic activities. In the last two decades, mobile phone coverage in Africa increased dramatically from an estimated 80 million people in 1999 (Aker and Mbiti, 2010) to over 850 million in 2020 (GSMA, 2020). The widespread use of mobile phones in Africa has fostered creative application of digital technologies in areas such as mobile banking (Jack and Suri, 2014) and health care (Agarwal et al., 2015). These digital tools and applications can significantly improve the coverage, delivery and effectiveness of public health services by facilitating greater access to information, better health knowledge, and improved health service utilization. In fact, recent digital innovations have been instrumental in expanding access to health services in Africa through SMS messaging and a variety of mobile applications. Examples of such initiatives include the "Hello Doctor" app, operational in 10 African countries, which provides free essential health care information, including live group chats and confidential one-on-one text conversation with a doctor.[1]

The potential impact of mobile phone technologies on economic, political and social outcomes has attracted considerable attention in recent years. A growing literature explores the impacts of mobile phone technologies on a range of socio-economic outcomes, including: price dispersion in agricultural markets (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2014), mobile banking (Jack and Suri, 2014), election monitoring, political accountability, government approval, and political mobilization (Aker, Collier and Vicente, 2017; Guriev, Melnikov and Zhuravskaya, 2020; Manacorda and Tesei, 2020; Gonzalez, 2021), learning outcomes (Aker, Ksoll and Lybbert, 2012) and monitoring the spread of infectious diseases (Milusheva, 2020). There is, however, much less work on the health effects of digital (mobile) technologies at scale, with Gonzalez and Maffioli (2020) and Amaral-Garcia et al. (2021) notable recent exceptions.[2]

In this paper, we study the impact of mobile phone technology on infant mortality in Africa,

[1] Other examples include: the "HiDoctor" app which provides free access to health information to Nigerians; the "MomConnect" cellphone application that provides information and advice on maternity to pregnant women in South Africa, and the "Omami (My Child)" app that provides information on immunization dates, growth patterns of children and general infant health tips.

[2] Gonzalez and Maffioli (2020) study the effects of mobile phone coverage in containing the spread of Ebola virus in Liberia, whereas Amaral-Garcia et al. (2021) study the effects of internet diffusion on demand for cesarean section in the United Kingdom. There is, however, an emerging literature that focuses on mobile health (mHealth) applications on specific health outcomes (see Hall, Cole-Lewis and Bernhardt, 2015; Yang and Van Stee, 2019, for review of the literature).

and explore potential mechanisms through which access to mobile phones can improve infant survival. Infant mortality is a key metric of societal health and well-being and its reduction is considered as a marker of social advancement. In that regard, there has been significant progress in reducing infant mortality rates globally, with the number of deaths per 1,000 live births falling from 65 in 1990 to 28 in 2019. Despite this remarkable progress, significant differences remain across regions. As shown in the left panel of Figure 1, Sub-Saharan Africa has the highest rate of infant mortality with 52 deaths per 1,000 live births (UNICEF, 2021). The main causes of the high infant mortality in Africa include: complications during birth, premature birth, and early childhood diseases such as sepsis, pneumonia, diarrhea and malaria, all of which are treatable or preventable (UNICEF, 2017). Poor access to health care facilities in the continent is commonly cited as a major limiting factor in addressing these preventable and treatable diseases.[3]

There are at least three channels through which access to mobile phones can influence child health outcomes. First, it improves access to information on maternal and child care by facilitating communication between end users and health care providers as well as within communities (Amaral-Garcia et al., 2021). Improved access to health information is likely to increase mothers' health knowledge and care seeking behavior.[4] Second, access to mobile phones can facilitate the delivery of public health services through modern applications such as telemedicine and promote health care utilization, especially in areas where physical access to health facilities is lacking (Hall, Cole-Lewis and Bernhardt, 2015; Yang and Van Stee, 2019). Third, expansion of mobile phone (digital) technology can increase household incomes through local economic development and increased productivity, thereby improving the health environment children are born into (Hjort and Poulsen, 2019; Gupta, Ponticelli and Tesei, 2020; Mensah, 2021).[5] Thus, to identify potential channels, we examine the impact of access to mobile phones on proximate determinants of infant mortality that are related to these three mechanisms.

We combine detailed information on the birth and death records of children (born between 1998 and 2016) from the Demographic and Health Surveys (DHS) with a unique dataset on mobile phone coverage spanning across 25 African countries to derive a causal relationship between access to mobile phone services and infant mortality. Specifically, we spatially link the

[3]The relatively poor access to health care services in Africa can be attributed to lack of: (i) physical health infrastructure, (ii) skilled medical professionals, and (iii) alternative sources of public health service delivery. Barriers to accessing health care are particularly acute in rural communities, with some having to travel hours to reach the nearest health facility (Hulland et al., 2019).

[4]A related literature shows that access to information through mobile technology promotes the exchange of information among peers and adoption of agricultural technology (Cole and Fernando, 2020; Fernando, 2021).

[5]Recent studies have shown that mobile technologies have led to higher consumption and lower poverty in African countries (Bahia et al., 2020, 2021; Rodriguez-Castelan et al., 2021).

DHS data with the penetration rates of 2G, 3G, and 4G mobile networks at a 0.1°×0.1° grid cell level.[6] To estimate the causal relationship between mobile phone access and infant mortality, we employ two complementary empirical strategies: two-way fixed effects (TWFE), and instrumental variables (IV).

Our TWFE estimation exploits spatial and temporal variations in the diffusion of mobile networks to estimate the relationship between access to mobile phones and infant mortality. Thus, conditional on plausibly exogenous variations in the roll-out of mobile network coverage, the TWFE would recover the impact of access to mobile phones on infant mortality. However, recent advances in the difference-in-difference (DID) literature have shown that in the presence of heterogeneous and dynamic treatment, the TWFE estimators are likely to yield biased estimates (De Chaisemartin and D'Haultfœuille, 2020*a*,*b*; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). To address this concern, we apply the De Chaisemartin and D'Haultfœuille (2020*a*) estimator, which is robust to the presence of heterogeneous treatment effects.

Aside the issue of heterogeneous treatments and its implications to the TWFE estimates, variations in mobile phone coverage are plausibly endogenous, thus posing a challenge to causal interpretations of our TWFE estimates. There are at least three reasons why expansion in mobile network coverage could be endogenous. First, to maximize revenue, mobile phone operators may prioritize areas with higher (future) economic potential in their expansion plans. Meanwhile, such areas tend to be wealthier, urban, and have improved access to health care with potentially better health outcomes. Second, the timing of mobile network expansion may follow or coincide with provision of other public infrastructure such as health facilities, which are critical for reducing infant mortality. Finally, there are other factors such as income which influence both technology adoption and health outcomes, and may therefore confound the relationship between access to mobile phones and infant mortality. To address this endogeneity concern, we rely on an instrumental variable (IV) approach and employ lightning intensity as an instrument for the rate of mobile network expansion (Andersen et al., 2012; Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2020). Electrostatic waves released during lightning strikes are associated with voltage surges that may destroy the electrical components of digital infrastructure. As a result, the diffusion of digital technologies like mobile phones tends to be slower in areas with high lightning activity (Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2020).

In the African context we study, the use of lightning intensity as instrument for mobile coverage is even more relevant. The incidence of lightning strikes is highest in Africa than anywhere

[6] Mobile penetration rate is defined as the share of people living in an area with cell phone coverage. 2G, 3G, and 4G refers to the second, third and fourth generation mobile technologies, respectively. While the 2G mobile technology supports only voice calls and text messaging, the 3G and 4G supports mobile broadband internet in addition to the functionalities of the 2G networks.

in the world with an average of 17.3 strikes per square kilometer (km^2) per year in Africa compared to an average of 2.9 strikes/km^2 in the rest of the world (Cecil, Buechler and Blakeslee, 2014; Manacorda and Tesei, 2020). Because of the destructive effect of lightning strikes on mobile telephone infrastructure, our instrument is likely to be a strong predictor of the expansion of mobile phone coverage in Africa. Thus, our identifying assumption is that conditional on location and time fixed effects, as well as controls for climate and local economic activity (proxied by nightlights),[7] lightning intensity influences child health outcomes only through its effect on access to mobile phones.

We supplement the main IV analysis with an additional IV strategy that leverages subregional convergence in mobile network penetration induced by harmonization of telecom policies within the subregions of the continent. We instrument for mobile phone coverage in a given location with past mobile phone coverage in similar locations in other countries in the subregion. The motivation for this instrument is the proliferation of subregional associations of telecom regulators and operators whose primary goals are harmonization of telecom policies and facilitation of learning across subregions. This development potentially leads to convergence in telecom network expansion. Again, the exclusion restriction assumption advanced here is that, conditional on the controls,[8] the average mobile penetration rate in other locations in the subregion (outside the country) influences infant mortality only through its effect on mobile phone access. This instrument is similar to Acemoglu et al. (2019) and Acemoglu et al. (2021) who use regional waves in democratization as an instrument for country level democracy. Besides establishing the causal relationship between mobile phones and infant mortality, the granular nature of our data allows us to conduct a range of sub-sample (heterogeneity) analysis by place of residence (urban/rural) and type of the mobile phone technology (2G, 3G, and 4G).

We find that access to mobile phones is associated with significant reduction in infant mortality in Africa. A 10 percentage point (pp) increase in mobile network coverage increases the probability of child survival by 0.45 pp. At the sample mean, this amounts to approximately three avoided deaths per 1,000 live births. Much of this impact is driven primarily by access to 2G mobile network coverage. This is understandable, given that the introduction of mobile broadband internet (3G and 4G) networks is relatively recent in many African countries and coverage remains low. Our estimates are robust to alternative empirical specifications and sampling considerations. Reassuringly, results from the two IV strategies are also qualitatively and quantitatively similar.

[7]These controls absorb potential correlation between the instrument and climatic variables, and local economic development such as infrastructure access and electrification rates that may also influence child survival.

[8]Among the list of controls, we include trade intensity and GDP growth in the subregion to absorb economic shocks in the subregion that could be correlated with mobile network expansion within the subregion as well as health outcomes.

We also find that improvements in mothers' health knowledge, preventive health behavior and health care utilization are potential channels through which access to mobile phones influences infant mortality. For instance, access to mobile phones is associated with increased awareness among mothers on the efficacy of oral rehydration salt (ORS) as treatment for diarrhea. Similarly, access to mobile phones is positively associated with health behaviors such as uptake of insecticide-treated bednets against malaria, and improved sanitation practices. More importantly, we find evidence of a positive association between mobile phone access and utilization of health care: vaccination rates among children and mothers' patronage of formal health care facilities for prenatal care increase with access to mobile phones. The importance of these improved health knowledge, practices and health care utilization in reducing infant mortality is reflected in the fact that we also find evidence of improved short-term health outcomes of children in places with high access to mobile phones.

Overall, this paper provides evidence of significant health dividends from an inclusive digital revolution in Africa. Digital technologies such as mobile phones can play an important role in the effort to reduce easily preventable and treatable infections which are the main causes of infant and child mortality in the region. This points to the need for policy coordination and harmonization across sectors to take advantage of technological complementarities to improve public health outcomes. Our findings can also inform investment appraisals of digital infrastructure in Africa, by uncovering the health impacts of mobile phone technologies, which otherwise would be overlooked, leading to undervaluation of returns from such investments.

Our paper contributes to three strands of the literature. First, it contributes to the literature on the effects of new infrastructure, more specifically mobile phones and related digital infrastructure, on various socio-economic outcomes (Jensen, 2007; Aker and Mbiti, 2010; Aker, 2010; Aker, Collier and Vicente, 2017; Jack and Suri, 2014; Guriev, Melnikov and Zhuravskaya, 2020; Manacorda and Tesei, 2020). Our study adds new insights to the public health impacts of digital technologies in general and mobile phones in particular. Much of the existing studies on the health impacts of mobile technologies focuses on mobile health (mHealth) interventions (via, for instance, text messaging and dedicated health apps) and specific health outcomes using survey data (Hall, Cole-Lewis and Bernhardt, 2015; Yang and Van Stee, 2019). While several studies examine the impact of new infrastructure on a range of welfare outcomes, there is little empirical evidence that links access to mobile phone technology to infant health outcomes, and particularly infant mortality.[9]

[9]This literature primarily focuses on transport infrastructure such as roads, railways, air networks and bridges (Faber, 2014; Campante and Yanagizawa-Drott, 2017; Donaldson, 2018; Asher and Novosad, 2020; Asher, Garg and Novosad, 2020; Brooks and Donovan, 2020; Jedwab and Storeygard, 2021) and electricity infrastructure (Dinkelman, 2011; Lipscomb, Mobarak and Barham, 2013; Allcott, Collard-Wexler and O'Connell, 2016). A closely related literature to this paper studies the impact of mobile phone coverage and broadband internet on productivity and

Second, it contributes to the literature on the range of policy interventions that have succeeded in reducing infant mortality. Some of the early interventions include expansion of public health services (Miller, 2008; Wüst, 2012), clean water and sewerage infrastructure (Alsan and Goldin, 2019) and sanitation interventions (Watson, 2006) in the United States and Europe in the late 19^{th} and early 20^{th} century. In recent times, several interventions in developing countries, including water sector liberalization in Argentina (Galiani, Gertler and Schargrodsky, 2005) and clean water programs in Mexico (Bhalotra et al., Forthcoming) have led to reductions in child mortality. These are relatively large and expensive interventions, and lack of fiscal space in many African countries may limit their viability. Mobile phones and related digital technologies hold a strong promise to provide cheaper alternatives to reduce infant mortality in an environment characterized by low health care service penetration. This paper adds to this burgeoning evidence of potential policy options.

Finally, it contributes to the literature on early childhood exposure to environmental, infrastructure, policy and political shocks (see Almond and Currie, 2011; Almond, Currie and Duque, 2018, for a review of the literature). While this literature is well developed, there is a distinct lack of evidence on the effects of early childhood exposure to digital infrastructure on infant and child health. Our paper provides new evidence on the impacts of exposure to mobile technology at the time of birth on infant health. Our findings can inform the design of public health interventions in child and maternal health care in a manner that exploits the potential cost advantages of mobile phone based health services and their greater reach.

The rest of this paper is structured as follows. The next section describes the data used in the paper. Section 3 presents the empirical strategy followed by discussion of our results in section 4. In section 5, we discuss potential mechanisms of our findings. Section 6 presents robustness checks, while section 7 concludes the paper with a summary of findings.

2 Data

This paper uses granular data on mobile network expansion and individual-level health outcomes (birth record) data between 1998 and 2016 complemented with data on lightning strikes, nighttime lights, temperature and precipitation to evaluate the effects of access to mobile phones on infant mortality. We discuss the various datasets in more detail below.

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incomes (Akerman, Gaarder and Mogstad, 2015; Hjort and Poulsen, 2019; Zuo, 2021) and adoption of specific mobile services such as mobile money (Jack and Suri, 2014) or mobile extension services (Cole and Fernando, 2020; Fernando, 2021).

2.1 Mobile Phone Network Data

Our mobile network data comes from Collins Bartholomew,[10] a digital mapping provider which compiles network data provided by national mobile operators under the Global System for Mobile Communications Association (GSMA) – the global association of mobile operators, as well as coverage maps constructed using open source data on cell phone towers from `opencellid.org`.[11] This database has been widely used in studies evaluating the impact of mobile technologies in developing and advanced economies (e.g., Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2020; Mensah, 2021).

The database provides granular data on the coverage maps at a 1 km × 1 km spatial resolution for three generations of mobile technologies: 2G, 3G and 4G. The main differences between these generations of mobile technologies relate to the ability to support broadband internet transmission. While the 3G and 4G enable mobile broadband internet in addition to cellular voice and short-messaging systems (SMS), the 2G technology does not support mobile broadband internet. Further, the deployment of 3G and 4G in Africa is a much recent phenomenon. The 3G, for instance, was deployed in the later part of 2006 while 4G was not available until mid-2010s. As a result, our data on 2G network coverage spans the period 1998 to 2018, while 3G and 4G coverage spans the period 2007-2018 and 2014-2018, respectively.

Using the spatial coverage of the respective mobile technologies, we compute mobile phone penetration rates at $0.1° \times 0.1°$ ($\approx$ 11 km × 11 km) grid cell level. Mobile penetration rates are defined as the share of the population at our grid cell level covered by the network.[12] This measures the percentage of the people living in a grid cell with potential access to mobile services. Thus, for our $0.1° \times 0.1°$ grid cell, mobile coverage rate in a given grid cell with K underlying 1 km × 1 km grid cells is computed as follows (see: Guriev, Melnikov and Zhuravskaya, 2020):

$$\text{Mobile Coverage} = \frac{\sum_{k=1}^{K} \text{Population}_k \times \mathbb{1}(\text{Covered by Network})}{\sum_{k=1}^{K} \text{Population}_k} \tag{1}$$

where $\mathbb{1}$(Covered by Network) turns one if a grid cell k is covered by mobile network and 0 if otherwise. Using this formula, we compute the yearly coverage rates for 2G, 3G, and 4G. In the remainder of this paper, the term *Mobile Coverage* represents the maximum coverage rate for all available networks, i.e., 2G, 3G, 4G. Figures 1, 2 and 3, show the trends in coverage rates in Africa at the sub-national level between 1999 and 2018. These figures clearly show remarkable expansion of 2G mobile technologies while progress on 3G technologies seems to be a slow and

[10] https://www.collinsbartholomew.com/mobile-coverage-maps/

[11] The latter is helpful to address potential under-reporting by telecommunications companies.

[12] Data on population density were obtained from https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev01.

recent phenomenon.

To establish that our mobile coverage measure significantly predicts actual mobile phone usage, we regress mobile phone ownership dummy and indicators for usage of specific mobile phone services on our mobile coverage variables. In Table 1, we present results of this exercise – the correlation between mobile coverage rates and uptake of mobile phone services – using data from the Demographic Health Surveys (DHS). Across all panels, we observe a strong and positive correlation between the mobile coverage rates and ownership of a mobile phone, use of mobile money for financial transactions and mobile broadband internet usage. These findings provide support to the use of our coverage data to evaluate the effect of mobile phones on health outcomes.

2.2 Health Outcomes Data

The health outcomes data come from the DHS and span 25 countries in Africa, of which 23 are in Sub-Saharan Africa.[13] The DHS datasets are collected using standardized questionnaires, with some adaptations based on country specific needs. To allow comparability across countries and over time, the DHS program standardizes variable names and definitions, and cleaner and consistent datasets are released to users as “recodes".[14] The Integrated Public Use Microdata Series (IPUMS) compiles these country level datasets into consolidated multi-country data. We extract key variables on infant mortality, health seeking behavior and health care utilization at the child and the household level from the IPUMS repository.

The DHS surveys consist of three core questionnaires: the household, women's and men's questionnaires. We rely on information from the first two in this paper. The household questionnaire covers household roster, age and gender of household members, relationship status with household head, education and place of residence. The women's questionnaire collects information on mother's characteristics including age, marital status and education; reproductive behavior including dates and survival status of all births, pregnancies and fertility preferences, knowledge and use of family planning methods; antenatal, delivery and postnatal care; breastfeeding and children's nutrition; children's health including immunization, vitamin A supplementation, and recent occurrences of fever, diarrhea and cough.

Due to the fact that the DHS data are repeated cross section often collected in 5-6 year intervals[15] and differences on the start of the surveys across countries and the regularity with which

[13] The countries included in our sample are: Benin, Burkina Faso, Burundi, Cameroon, the Democratic Republic of Congo, Côte d'Ivoire, Egypt, Ghana, Guinea, Kenya, Lesotho, Madagascar, Malawi, Mali, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Tanzania, Uganda, Zambia and Zimbabwe.

[14] see: https://dhsprogram.com/data/Data-Processing.cfm.

[15] In some cases, the gap between consecutive surveys could be 1 or 2 years as in Senegal or more than 10 years as in Benin, Côte d'Ivoire and Tanzania.

they were conducted, the number of data rounds in our analysis sample are not balanced across countries. Among countries in our sample, some were surveyed only once (Chad, Madagascar, Morocco, Mozambique and Niger) and others were surveyed multiple times, with Senegal (6 times) and Egypt (5 times) surveyed most frequently. Our final sample consist of children born between 1998 and 2016. An important feature of the DHS data is that all sample households are geo-referenced, which permits merging the data with other datasets.[16]

2.3 Additional Datasets

The paper also relies on lightning intensity, temperature, precipitation and nighttime lights data. Our data on lightning intensity comes from NASA's LIS/OTD Gridded Lightning Climatology Dataset.[17] This dataset is a satellite based measure of the lightning activities around the world. Specifically, it measures the average lightning intensity between 1995 and 2010 at a $0.5° \times 0.5°$ spatial resolution.[18] From this dataset, we compute the average lightning intensity at our $0.1° \times 0.1°$ grid cell level and use it as an instrument for mobile network coverage. See section 3 for details on the rationale. Data on annual average temperature and total precipitation come from the ERA5 Global Reanalysis Database by the Copernicus Climate Change Service.[19]

To control for changes in the level of local economic development, we include data on nighttime light intensity otherwise referred to as nightlights. Since the pioneering work by Henderson, Storeygard and Weil (2011, 2012), satellite data on nightlights have been widely used in the economics literature as a proxy for economic activities particularly in countries with scant data. The nightlights data are primarily produced by NASA.[20] The nightlights data are available from 1992 to present. However, there is one key constraint to using time series data on nightlights over this period: inconsistencies in the measurement of light intensity between 1992 and 2012, and 2013 to present. The nightlights data from 1992 to 2012 were produced by NASA's Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS). However due to technological advancement and aging of DMSP/OLS satellites, NASA introduced the Visible

[16]To protect the confidentiality of respondents, the geo-located data are randomly displaced 0-2 kilometers in urban areas and 0-5 kilometers in rural locations within the appropriate administrative locations (admin 2 level for surveys after 2008 and regional boundaries for the pre-2008 period). Since the displacements are randomized both for distance and direction, our regression parameters are unlikely to be affected. In fact, Perez-Heydrich et al. (2016) show that estimates from merging the DHS data to raster data on the basis of the displaced GPS coordinates are unbiased for 1-5 km buffers in urban areas and 1-10 km buffers for rural areas for moderate to high spatial autocorrelation in the data measured from the raster data, which is the case for our mobile coverage data.

[17]see: https://ghrc.nsstc.nasa.gov/uso/ds_docs/lis_climatology/LISOTD_climatology_dataset.html.

[18]Other prominent studies using this dataset include Andersen et al. (2012); Manacorda and Tesei (2020).

[19]https://cds.climate.copernicus.eu/cdsapp#!/home.

[20]https://earthdata.nasa.gov/learn/backgrounders/nighttime-lights

Infrared Radiometer Suite (VIIRS)[21] satellites to measure nighttime light intensity around the world. To address the inconsistencies in the two sets of data and allow analysis of the nightlights data over a long time horizon, Li et al. (2020) have produced a global harmonized nightlights data from 1992 to 2018 by harmonizing the inter-calibrated night time lights data from the DMSP satellites and a simulated DMSP-like night time lights data from the VIIRS satellites.[22] Using this harmonized data, we compute the sum of nightlight intensity for each grid cell-year as a proxy for the level of economic activities in the grid cell. Table 2 presents the summary statistics of the main variables used in the analysis.

Finally, to explore the potential direct impacts of lightning strikes on other confounders such as access to and quality of health services, we use the spatial database of health facilities in Africa by Maina et al. (2019). The database includes health facilities managed by the public health sector and covers 50 countries and 98,745 facilities. We supplement these data with the IPUMS Performance Monitoring for Action (PMA) data on health facilities which track the performance of a sample of health centers in 9 Sub-Saharan Africa countries between 2017 and 2019. We use data from 6 countries whose data contains facility geo-coordinates (Burkina Faso, Côte d'Ivoire, Ethiopia, Kenya, Niger and Uganda).

3 Empirical Strategy

3.1 Two-Way Fixed Effects

We start our estimation by implementing the following fixed effects model characterizing the probability that an infant i born in a grid cell g, year y and month m dies before her first birthday.

$$Y_{igym} = \alpha_g + \alpha_1 Coverage_{gy} + \alpha_2 X_{igy} + \alpha_y + \alpha_m + \epsilon_{igym} \tag{2}$$

where Y_{igym} is a measure of infant mortality, defined as a dummy variable equal to 1 if a child died within the first 12 months of birth and 0 if otherwise. We also estimate variant specifications where we define infant mortality at one and six months after birth. α_g represents grid cell fixed effects, which capture any time-invariant differences across spatial units, $Coverage_{gy}$ captures local (grid cell level) mobile coverage and X_{igy} is a vector of child and mother characteristics, as well as other community (grid cell) characteristics that may affect infant mortality. These include mothers' age, education and marital status indicators for urban/rural status of

[21] https://ngdc.noaa.gov/eog/download.html

[22] see Li et al. (2020) for details and access to the dataset using https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_data_from_1992-2018_at_the_global_scale/9828827/2.

the place of residence, precipitation, temperature and nightlight intensity. α_y and α_m represent birth year and birth month fixed effects, respectively. The mobile coverage information for each grid cell is calculated as the share of the population in each grid cell living in areas covered by mobile network in each year, weighted by population density in each underlying 1 km × 1 km grid cell. If mobile network expands exogenously or as a function of time-invariant characteristics of different areas, α_1 would identify the causal effect of mobile phone coverage on infant mortality.

Recent advances in the DID literature have shown that in the presence of treatment heterogeneity and temporal dynamics in treatment effects, the TWFE estimator specified in equation (2) is likely to yield biased estimates (De Chaisemartin and D'Haultfœuille, 2018, 2020*a*,*b*; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). The issue stems from the fact that the average treatment effects (ATE) of the TWFE estimator is a weighted average of group-time level ATEs. Since some of weights associated with the groups can be negative, the overall ATE can also be negative even if the ATEs of the respective groups are positive, resulting in biased estimates (De Chaisemartin and D'Haultfœuille, 2020*b*). To address this concern, we probe the robustness of our TWFE estimates by using the De Chaisemartin and D'Haultfœuille (2020*a*) estimator, which is robust to the presence of heterogeneous treatment effects.

Aside from the challenges associated with the heterogeneity and temporal dynamics in treatment effects, causal interpretation of the TWFE estimates requires strong assumptions as mobile network expansion may happen endogenously. For example, mobile phone operators may prioritize high economic potential areas in their expansion plans. Similarly, mobile network expansion may follow or coincide with expansion of other infrastructure, including health facilities, that are crucial for reducing infant mortality. While our fixed effects specification absorbs time-invariant features and differences across space, potential time-varying factors correlated with expansion of mobile networks remain a threat to the identification strategy spelled out in equation (2).

3.2 Main IV Approach

Following recent practices in the literature, we employ an instrumental variables (IV) approach to circumvent potential endogeneity of mobile network expansion. As in Andersen et al. (2011); Manacorda and Tesei (2020); Guriev, Melnikov and Zhuravskaya (2020), we employ spatial variations in the frequency of lightning strikes as an instrument for mobile network expansion and mobile coverage. Lightning strikes are shown to predict the speed of mobile network expansion. More specifically, lightning strikes lead to the destruction of electrical and digital infrastructure used in mobile technology, which increases the cost of mobile network operators and potentially reduces the rate of adoption in areas characterized by high frequency of lightning strikes (Andersen et al., 2011, 2012). Given that lightning strikes affect mobile network infrastructure in a peculiar way that may not disrupt other infrastructures, they can serve as valid instruments for mobile network coverage thereby allowing evaluation of the causal impacts of access to mobile phones (e.g. Andersen et al., 2011; Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2020).

Thus, we estimate the following 2SLS specification to identify the causal impact of mobile coverage on infant mortality. The first-stage specification in equation (3) characterizes mobile coverage (associated with each grid cell in a given year) as a function of lightning frequency interacted with time dummies to allow non-linear trends in mobile coverage as well as other additional controls described in equation (2):

$$Coverage_{gy} = \beta_g + \beta_1 Lightning_g \times T_y + \beta_2 W_{gy} + T_y + \epsilon_{gy} \tag{3}$$

where all terms except the instrument, $Lightning_g \times T_y$, and W_{gy} are as defined in equation (2). $Lightning_g$ denotes the average number of lightning strikes in a grid cell between 1995 and 2010 and W_{gy} stands for all the other controls described in equation (2). Note that the instrument is an interaction between the spatial variation in lightning frequency and non-linear year dummies, which reflects potential differential trends in mobile coverage between areas with varying lightning frequency. If the temporal trends in network coverage for each grid cell remain the same over time, one can assume and impose a linear time trend instead of differential time trend.

Using the first-stage specification in equation (3), we estimate the second stage equation characterizing infant mortality as a function of predicted mobile network coverage. In this setting, the 2SLS estimates would capture the causal impact of mobile coverage on infant mortality if intensity of lightning strikes affect infant mortality only through its impact on digital and phone infrastructure. This assumption is expected to hold at least in our conditional regressions, after controlling for other factors through which lightning frequency may affect infant mortality. For instance, our exclusion restriction assumption is unlikely to hold if lightning slows the pace of electrification, and even reliability of electricity supply, as access to electricity affect health outcomes through several ways including, but not limited to, income and health care delivery. To alleviate this concern, we control for nighttime light intensity, as nightlights are highly associated with electricity consumption. Secondly, in Section 6.4, we show that lightning intensity is uncorrelated with the access to health facilities, and the operation of health facilities. Moreover, concerns about the direct effect of lightning on infant mortality is tempered by the fact that lightning-induced mortality rates are almost negligible in most parts of the world. In fact, the probability of being struck by lightning is 1 in 500,000,[23] thus making lightning an unlikely source of infant mortality in the study area. These factors provide support to the plausibility of our exclusion restriction assumption.

Further, although the peculiar feature of lightning strikes make them plausible instruments that mostly affect digital infrastructure, they may also interact with climatic variables (e.g. rainfall and temperature) and other infrastructure that can affect infant mortality independently. Thus, we control for climatic variables, including annual rainfall and temperature. We also control for other mother and grid cell level characteristics, including degree of urbanization.

We also explore the potential mechanisms through which access to mobile phones can reduce infant mortality. Access to mobile network coverage is likely to increase mothers' and households' access to information relevant to improve children's health and reduce infant mortality. Thus, we focus on examining the impacts of mobile network coverage on mothers' knowledge, health seeking behavior and children's health. For this purpose, we compile several proximate child and mother level health outcomes that affect infant mortality. These include mothers' prenatal and postnatal health care utilization, mothers' knowledge of health care related issues, children's vaccination records and health status.

To probe the robustness of our empirical specifications, we estimate alternative specifications which control for grid cell as well as country fixed effects. We also consider alternative definitions in constructing our sample. Our baseline sample considers all birth records that mothers report. This sample may suffer from recall biases, especially for older cohorts. Thus, we use a sample of infants focusing on those born in the five years preceding the surveys. Another potential concern is selective migration of mothers to areas that are expected to receive access to mobile phones. To show that our results are not driven by potential biases induced by selective migration, we conduct additional sub-sample analysis on children born to mothers who lived in their current place of residence long before the birth of a child. Furthermore, we also explore the relative impacts of the functionality of the various mobile phone technologies by estimating separately, the impact of 2G and 3G/4G connectivity on our outcomes.

Infants living in the same area are likely to share similar observable and unobservable factors including various services and infrastructure. This may generate spatial correlation in the error terms among infants living in the same grid cell. Thus, we cluster standard errors at grid cell level.

[23] (see: https://www.cdc.gov/disasters/lightning/victimdata.html#:~:text=Lightning%20is%20one%20of%20the,greater%20risk%20for%20being%20struck.)

3.3 Alternative IV Approach

So far, our main IV analysis exploits variations in lightning strikes as an instrument for mobile network penetration. The exclusion restriction behind this IV strategy is that conditional on the wide array of controls, and location and time fixed effects, lightning intensity influences health outcomes such as infant mortality only through access to mobile phones. While this assumption is highly plausible, there are counter arguments that lightning could influence general technology adoption such that places with high lightning activities will have slower technology adoption which could ultimately influence average income levels and possibly health care delivery, thus affecting the outcome variable through channels other than access to mobile phones.

In this section, we implement an alternative IV strategy that exploits plausibly exogenous variations in mobile penetration in other countries in the same subregion induced by harmonization of telecom policies within the subregion as an instrument. This instrument is in the spirit of Acemoglu et al. (2019) and Acemoglu et al. (2021) who used regional waves in democratization as instrument(s) for democracy in analyzing the impact of democracy on economic growth and citizens support for democratic institutions, respectively.

Two main factors motivate this instrument. The first relates to harmonization or regionalization of telecom policies. Given the relatively underdeveloped state of the telecom sector in Africa, many subregional economic blocs in Africa have associations of national telecom regulators[24] to facilitate learning and policy harmonization among member countries with the aim of accelerating the pace of access to digital infrastructure to promote sustainable development (Kessides, Noll and Benjamin, 2009).[25] The presence of these regional regulator unions affects telecom policies in member states in several ways. For instance, it could trigger a wave of telecom reforms, particularly among member states with underdeveloped telecom sector, thereby opening up the sector for competition. In addition, a key goal of these regional bodies is the harmonization of telecom policies. These activities have implications on access and pricing. For instance, ECOWAS, the regional economic bloc in West Africa, announced in 2019 the elimination of roaming charges within the West African subregion effective January 2020.[26] The Central

[24] Examples include the West African Telecommunications Regulators Assembly (WATRA), Assembly of Telecommunication Regulators of Central Africa (ARTAC), Association of Regulators of Information and Communications for Eastern and Southern Africa (ARICEA), and Communication Regulators' Association of Southern Africa (CRASA).

[25] For instance, WATRA and Economic Community of West African States (ECOWAS) have over the past decades been working towards harmonization of telecom policies as well as implementing cross-border connectivity projects in the subregion (Kessides, Noll and Benjamin, 2009).

[26] see: https://www.ghanaweb.com/GhanaHomePage/business/No-more-roaming-charges-ECOWAS-citizens-to-enjoy-local-rates-on-calls-Ursula-788905; https://itweb.africa/content/G98YdqLY3AZvX2PD; https://www.ecowas.int/ecowas-member-states-reaffirm-commitment-to-the-effective-implementation-of-the-ecowas-regulation-on-roaming/

African Economic and Monetary Community (CEMAC)[27] also followed with the announcement of eliminating of roaming charges for voice, SMS, and internet in member states starting 2022. The construction of submarine fiber-optic cables linking Africa and the rest of the world that brought high-speed internet to African countries was largely stimulated by subregional telecom associations that worked with a consortium of private investors in the construction of the infrastructure.

Secondly, subregional associations of telecom operators and the presence of multinational telecom operators in multiple countries in the subregion can also facilitate learning and sharing of business ideas, and operational strategies that can stimulate convergence in telecom network expansion within the subregion.[28] These factors suggest that access to digital infrastructure such as mobile phones is likely to be correlated within subregions, as countries are likely to anchor their access targets on current and projected access rates in other countries in the subregion. In other words, we argue that the average mobile phone penetration rates within a subregion is a strong predictor of penetration rate in a given country. Leveraging this idea, we instrument mobile phone penetration rate in a country using lagged (past) average mobile penetration rate in other countries in the subregion. However, we note that significant rural-urban access gaps exist in many countries and these gaps persist even at the subregional level and, thus, incorporate these nuances in the construction of our instrument.[29]

Therefore, we adapt the approach of Acemoglu et al. (2019) and Acemoglu et al. (2021), and define $I_{c(g)} = \{c^{'} : c^{'} \neq c, R_{c'} = R_c\}$ as the set of grid cells in countries whose mobile phone access (coverage) rates influence the penetration (coverage) rates in similar grid cells g in country c in the same region R. Grid cells are sorted into five groups based on population quintiles, and grid cells in the same quintile are classified as similar. The intuition behind this population grouping is that population or market size is a key factor influencing the expansion of mobile networks. Densely populated communities have higher chance of having connectivity relative to areas with low population, all else equal. Therefore, the penetration rates in grid cells of similar population size in other countries in the same subregion are likely to be good predictors of mobile penetration rates in a given grid cell. Using these sets, our instrument is defined as follows:

[27] It consists of Cameroon, Congo, Gabon, Chad, Equatorial Guinea and the Central African Republic.

[28] Examples of such bodies include the Southern Africa Telecommunications Association (SATA), and the East African Communications Entities Organisation (EACO).

[29] To address these gaps countries often set specific targets particularly aimed at increasing connectivity in rural areas. For instance, countries often mandate telecom operators to achieve certain targets for mobile phone or internet penetration in rural communities, as part of spectrum license allocations. Such policies can be adopted by member countries in a subregional regulator association, and hence over time trends in the gap could evolve along a similar pattern in a subregion. A good example is the so-called "Universal Service Obligation" that countries in the various subregions have adopted which mandates Telcos to achieve universal coverage of at least 2G network within a stipulated time.

$$Z_{c(g)y} = \frac{1}{I_{c(g)y}} \sum_{c'(g) \in I} P_{c'(g)y} \tag{4}$$

where $P_{c'(g)y}$ represents the mobile penetration rate at the grid cell level in other countries in the same subregion in year y. Essentially, $Z_{c(g)y}$, represents the predicted mobile penetration that a person living in grid cell g in country c at time y would have faced if she lived in a similar area in a different country in the same subregion in a given year.

Using lagged values of the predicted mobile coverage in similar locations in the subregion as instrument for mobile penetration, we estimate a 2SLS with the corresponding first stage equation specified as:

$$Coverage_{gy} = \gamma_g + \gamma_1 Z_{c(g)y-1} + \gamma_2 W_{gy} + \psi_y + \omega_{gy} \tag{5}$$

Thus, in the context of our study, equation (5) amounts to instrumenting the mobile coverage rate available in a place where a child was born in a given year with average coverage rate faced by children born in similar locations in other countries in the subregion in the previous year.

Obviously, the exclusion restriction advanced here is that conditional on the grid cell fixed effects, time fixed effects, and an array of controls, past mobile coverage rates in similar grid cells in the subregion affect health outcomes of children only through mobile coverage. This assumption breaks down if coverage rates in subregion are driven by underlying subregional economic or political trends that could also affect child health outcomes. For instance, if economic shocks within the subregion influence mobile penetration while at the same time influencing health outcomes such as infant mortality, then our exclusion restriction may not hold. Similarly, channels such as trade among countries in the subregion can operate to violate our exclusion restriction assumption. To address these concerns, we estimate additional specifications where we control for economic shocks that affect other countries in the subregion. Specifically, following Acemoglu et al. (2019), we construct spatially weighted GDP growth and Trade (as percentage of GDP) of neighboring countries in the subregion.[30]

4 Results and Discussion

To establish that our outcome variable, infant mortality rate, is strongly associated with mobile coverage rate, we start by showing simple correlation between average infant mortality rate and mobile penetration by DHS survey round. The results in Figure 4 indicate that there is a strong

[30]For each country, we compute the average real GDP growth and trade (export + import) (as percentage of GDP of other countries) in the subregion weighted by the inverse distance between the country and each of the countries (neighbors) in the subregion.

negative relationship between the two variables, with correlation of -0.56. We then present our main results estimated using the three alternative methods: Two-Way Fixed Effects, the De Chaisemartin and D'Haultfœuille (2020*b*) approach and instrumental variable regressions. The section concludes with some heterogeneity analysis.

4.1 Two-Way Fixed Effects

We first present results from a fixed effects model using the specification in equation 2 to assess the impact of mobile phone penetration on infant mortality. Results are shown in Table 3. In this analysis, we exploit two main sources of variation: in columns 1 and 2 we use within grid cell variations in mobile network coverage, while in columns 3 and 4 we exploit within country variations. Our specifications of interest are columns 2 and 4 which include the full set of child, mother and community controls. The results show that a 10 percentage point (pp) increase in mobile network coverage is associated with a 0.03 pp increase in the probability that a child survives her first birthday. Relative to the sample mean, this corresponds to about a 4.4 percent decline in infant mortality.

We also estimate a flexible function that allows us to identify nonlinear relationship between mobile phone coverage and infant mortality at varying levels of network penetration as shown in Figure 5. The results suggest that at all coverage levels, mobile phone coverage is associated with lower levels of infant mortality. The results also suggest that greater mobile phone network penetration, especially above the 40% rate, is associated with increasingly lower probabilities of infant mortality, though these estimates are not statistically different from each other. That is, we find no threshold effects that would suggest sharp shifts in the impacts of mobile phone access on infant mortality around certain network penetration rates. Despite the strong association between mobile phone coverage and infant mortality, these estimates do not represent the causal impact of mobile phone coverage on infant mortality, mainly because mobile network expansion may evolve endogenously and, thus, correlate with other determinants of child health and survival.

4.2 TWFE with Heterogeneous Treatment Effect

As highlighted earlier, one concern with TWFE estimates is that they are likely to be biased if the group-time level average treatment effects are heterogeneous and dynamic. To assess the robustness of our results to this issue, we first explore the presence of negative weights in our TWFE estimates using the approach in De Chaisemartin and D'Haultfœuille (2020*b*). Specifically, using the `twowayfeweights` package in Stata by De Chaisemartin and D'Haultfœuille (2020*b*) to estimate the weights associated with the group-time level ATEs in our fixed effects regression, we find that 65 percent of the average treatment effect on treated (ATT) have positive weights, while 35 percent receive a negative weight.[31] The sum of the negative weights is equal to -0.33, suggesting that our results in Table 5 may be biased.

To explore extent to which these negative weights affect our baseline results, we employ the De Chaisemartin and D'Haultfœuille (2020*a*) estimator which is robust to heterogeneous treatment effect.[32] Following Adema, Aksoy and Poutvaara (2022), we implement the estimation as follows. First, to ensure that we have sufficient number of control groups at every time a group switches into treatment, we group the already treated grid-cells into bins using the baseline coverage rates. Treatment effects are then calculated within each bin by comparing the outcomes of grid-cells that obtained first treatment with control grid-cells with similar baseline coverage rates. This requires an appropriate definition of control groups within each bin. Second, since mobile coverage rate is continuous and most grid-cells have recorded some increase in coverage during our sample period, we define a stable control group based on year-on-year changes in coverage rate. The treatment threshold for first time switch is set at 5 percent increase in mobile coverage rate such that grid-cells with increases in coverage rate of less than 5 percent are considered control group. This allows sufficient control groups within each bin. Third, we drop all grid cells that experienced at least a 5 percent decline in year-on-year mobile coverage rate. The exclusion ensures that only grid-cells experiencing monotonic change in coverage rates are used for the analysis. The resulting treatment effect is the weighted average of bin-specific treatment effects.

The results of the De Chaisemartin and D'Haultfœuille (2020*a*) estimator are shown in Figure 6, which also allow us to indirectly test whether the parallel trends assumption holds. Figure 6 shows changes in infant mortality rates before and after a grid cell experiences mobile network connectivity. Prior to treatment, we find that infant mortality trends are generally similar in treated grid cells relative to control grid cells, which gives us confidence that the parallel trends assumption plausibly holds. The post treatment effects are negative and statistically significant from time $t+2$ onward, confirming the earlier results that access to mobile phones is associated with decline in infant mortality rates that are economically and statistically significant.

4.3 Main IV Results

To causally estimate the impact of mobile phones on infant mortality, we use the 2SLS framework outlined in section 3, where we exploit plausibly exogenous variations in lightning inten-

[31] In all, there are 86,348 ATTs of which 56,215 are positive and 30,133 are negative.

[32] This estimator is preferred to variant estimators like the Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) estimators, as it allows for continuous treatment variable, as in the case of our treatment which varies between 0 and 1.

sity as an instrument for mobile phone penetration.

Figure 7 summarizes the first-stage relationship between our instrument and mobile coverage expansion rates. We adopted a flexible non-linear specification by interacting lightning intensity with year dummies. This captures potential non-linearity in the relationship, which cannot be captured by a linear time trend. Full estimation results are presented in Table 4. As expected, the results generally show a negative relationship between lightning strikes and the diffusion of mobile network coverage. The coefficients of the interaction between the lightning intensity and time dummies are negative and statistically significant for most years with the exception of some coefficients for more recent years which are statistically insignificant. This is more clearly shown in Figure 7, which suggests that the negative effects of lightning strikes on the spread of mobile communication technologies declines over time. This evidence provides support to the choice of a flexible nonlinear specification in estimating the relationship between lightning strikes and mobile network coverage. This is intuitive because mobile operators are likely to deploy defensive technologies as such innovations become available and cheaper over time. As shown in Table 4, these findings are robust to controlling for a variety of fixed effects. The first-stage F statistics ($F \approx 20$), a measure of the strength of the instrument, exceeds the conventional benchmark (Stock, Wright and Yogo, 2002) — an indication that our instrument(s) is a good predictor of the spatial and temporal dynamics in mobile network coverage in the study area.

Turning our attention to the 2SLS estimates, Table 5 presents the second-stage IV results on the causal impact of mobile phones on infant mortality. As in the case of the OLS (Table 3), we estimate four specifications alternating between grid cell fixed effects and country fixed effects with and without controls for child, mother and community characteristics. Starting with column 1, we find that a 10 pp increase in mobile network coverage increases the probability of child survival by 0.48 pp. The point estimates reduces slightly to 0.45 after adding controls for child, mother and community characteristics in column 2. The results remain qualitatively similar but larger in columns 3 and 4 where we impose a less strict specification (using country instead of grid cell fixed effects).

The 2SLS estimates are sizeable and significantly larger than the OLS estimates. This is not surprising given that the 2SLS estimates the local average treatment effect (LATE), i.e., the impact for those cases where the instrument (lightning strikes) changes mobile coverage rate while the OLS quantifies the average treatment effect for the entire population. Thus, in the presence of heterogeneous sample and varying response to lightning strikes, children born in areas responsive to lightning strikes are likely to be those who benefit more from access to mobile phone coverage than the full sample of infants in our data. Furthermore, the OLS estimates can be biased in either direction, depending on the correlation between omitted relevant variables and mobile network expansion. Given the nature of our instrument, which is expected to be (at least conditionally) independent of these omitted variable of interest, we base much of our interpretation on the IV estimates.

We next focus our attention on the interpretation of the magnitude of our findings. Our estimates suggest that moving from a place of no mobile coverage to full coverage is associated with approximately 4.5 pp decrease in the probability of a child dying before her first birthday. This is equivalent a 66 percent ($(4.5/6.8)\times100$) decrease in infant mortality rate at the sample mean. Relative to the current infant mortality rate in Africa, this amounts to 34 ($(4.5/6.8)\times52$) lives saved per 1,000 live births. The effect size is comparable to Benshaul-Tolonen (2018), who finds that mining activities are associated with a 50 percent decrease in the infant mortality rate in Sub-Saharan Africa.

4.4 Alternative IV Results

Table 6 presents the first and second stage results from the IV regression using the alternative instrument which is based on lagged subregion mobile coverage. Columns 1-2 and 5-6 are analogous to columns 1-4 in Table 5. In columns 3 and 6, we include spatially weighted GDP growth and trade to account for potential economic shocks in the subregion.

The top panel of the table presents the first stage regression results, which show a strong positive correlation between mobile coverage rates in a given country and lagged subregional mobile coverage. The F-statistics of the excluded instruments are sizable with a minimum of 43.8, thus confirming the relevance and strength of the instrument.

The lower panel presents the 2SLS estimates of the impact of mobile coverage on infant mortality. Reassuringly, the estimates are qualitatively and quantitatively similar to the baseline 2SLS estimates in Table 5, albeit the former are slightly higher. For instance, in our preferred specification (column 2), the estimates using the predicted coverage rate at the subregional level as instrument suggest that a 10 pp increase in mobile coverage reduces infant mortality rate by 0.6 pp compared to a 0.45 pp reduction in Table 5 (column 2) which relies on variations in lightning intensity as instrument. The estimates remain robust in column 3, where we control for economic shocks at the subregional level. In columns 4-6, where we exploit within country variations in mobile coverage, we lose statistical significance when we include individual, mother, and community controls (column 5) and subregional controls (column 6).

Overall, results from the two IV strategies yield estimates that are quantitatively and qualitatively comparable impacts. This provides confidence that our estimates point to the causal impact of mobile phones on infant mortality. In the rest of the paper, we rely on the lightning intensity measure as instrument in estimating the effects of mobile network coverage on the various outcomes.

4.5 Heterogeneity

In this section, we explore the potential heterogeneous effects of mobile phone penetration on infant mortality by (i) place of residence (rural vs. urban), and (ii) type of mobile technology (2G and 3G/4G).

Rural-Urban Differences: How does the health effect of mobile phone access differ between rural and urban communities? This is important to our understanding of the channels through which the health impact of mobile phones arise, as well as the impact of existing differences in access to other infrastructure and inequalities in incomes and education. The later may mediate the link between mobile phones and health outcomes. Mobile phones may complement or substitute traditional channels of health information, which may differ between rural and urban communities. Likewise, physical access to health facilities may amplify or dampen the effect of mobile phones on infant mortality depending on the substitute or complementary relationship between mobile phones and proximity to health services.[33] Such disaggregation can also help probe the validity of our instrument and whether the instrument is picking additional effects of complementary infrastructure. For instance, if the instrument affects other health infrastructure, which are likely to differ between rural and urban areas, we expect drastically different results across urban and rural areas.

In Table 7, we estimate separate IV regressions for rural (column 1-4) and urban (5-8) samples. We find that access to mobile phone coverage reduces infant mortality in both rural and urban areas, and the effect sizes are comparable across the two groups. This suggests that our instruments are not picking the impacts of complementary health infrastructure. If anything, the results point to a slightly higher impact in rural areas (for the regressions with country fixed effects). Importantly, these results show that public health benefits of mobile phone expansion accrue to both urban and rural areas. This is an important finding given the urban bias in public health investments and initiatives in Africa.

2G vs 3G/4G Mobile Networks: Next, we examine whether the type of mobile network technology matters for the impact of mobile phones on infant mortality. The current mobile phone network technologies in Africa are 2G technology which supports voice and SMS services, and 3G/4G technologies that support mobile broadband internet in addition to the voice and SMS services. While 3G and 4G coverage in Africa are relatively limited and mostly concentrated in

[33] Admittedly, cell phone coverage may also vary between rural and urban centers. Hence, ex-ante, it may be difficult to predict the differences in the health impact of mobile phones between rural and urban areas.

urban centers, there is extensive 2G coverage in both rural and urban areas. The distinction in the impact of these technologies matters for understanding the feature(s) of mobile phone technology driving health impacts in Africa.

To this end, we use the 2G and 3G/4G coverage rates to separately estimate the effect of the penetration of these respective technologies on infant mortality using our IV framework. Results are shown in Table 8. In columns 1-4, we find negative impact of expansion in 2G network coverage on infant mortality. These effects are economically and statistically significant. Interestingly, the results are identical to the main results which estimates the effect of the combined 2G, 3G and 4G mobile coverage on infant mortality. The effects of 3G/4G coverage are, however, close to zero and statistically insignificant. This suggest that our main results on the impact of mobile phones on infant mortality are primarily driven by expansion of 2G technologies with 3G/4G having little or no role. Again, these findings provides support to the results in Table 7, which suggest that mobile phones affect child health in both rural and urban centers, as unlike 3G/4G, 2G coverage is available in urban as well as rural communities, albeit at varying levels of penetration. We note that 3G/4G technologies were introduced to much of Africa recently and their coverage remains low, which may explain the null finding.

5 Potential Mechanisms

To understand the mechanisms driving the results, we evaluate the effects of mobile phone penetration on a range of proximate determinants of infant mortality, including mothers' health knowledge, mothers' health-seeking and health utilization behavior and immediate determinants of infant mortality, namely child health.

5.1 Health Knowledge

We posit that the dissemination of health information is one of the main channels through which access to mobile phones can affect health outcomes. To test this assertion, we examine the extent to which mobile phone penetration influences health knowledge. Table 9 shows that increase in mobile phone penetration is associated with enhanced health knowledge of mothers. For instance, mothers' knowledge of oral rehydration salt (ORS) as a treatment for diarrhea improves with mobile phone penetration. Likewise familiarity with tuberculosis (TB) and knowledge on whether it is curable also improves with mobile penetration. Conversely, attitudes on keeping contraction of communicable diseases such as TB a secret declines in places with higher mobile phone coverage. These effects are suggestive of a positive health information effect associated with access to mobile phones.

5.2 Preventive Health Behavior

Here, we explore the impacts of access to mobile phones on preventive health care practices, by focusing on the major factors contributing to infant mortality. Malaria being one of the deadly factors contributing to infant mortality in Africa (Kuecken, Thuilliez and Valfort, 2020; Pathania, 2014), changes in mothers' preventive measures against malaria in response to expansion of mobile phone technology would have implications to infant mortality on the continent. Similarly, personal hygiene practices are important factors that affect child health (Freeman et al., 2014), and can be improved by information dissemination through digital tools. Table 10 shows the effects of mobile phone access on use of insecticide-treated bednets, and indicators of good hygiene such as practicing of open defecation and hygienic disposal of children's stool. In relation to the use of bednets, two measures are considered: whether a mother sleeps under bednet (columns 1-2), and whether kids sleep under bednets (columns 3-4). For these outcomes, the results show that mobile network coverage increases usage of bednets by both mothers and children in the household. Though statistical significance varies based on the choice of geographic fixed effect, our results indicate that a 10 pp increase in mobile coverage is associated with 0.7-1.5 pp and 0.3-1.7 pp increase in bednet use by mothers and children, respectively.

In columns 5-8, we also find that mobile network coverage is associated with improved hygienic practices: households are less likely to practice open defecation and more likely to properly dispose off children's stools as opposed to, for example, disposing them in open drains or rivers. A 10 pp increase in mobile coverage is associated with 0-1.4 pp decrease in open defecation and 1.2-4.2 pp increase in hygienic disposal of children's stool. The results in Table 10 are indicative of positive effects of mobile phones on preventive health behavior (attitudes) of people due, potentially, to better information on the implications of these behaviors to health.

5.3 Health Care Utilization

Conditional on access to health facilities, do mobile phones improve the utilization of health care by children and mothers? In Table 11, we examine the effects of access to mobile phones on child vaccination rates. We focus on vaccinations rather than treatments for illnesses because the later could be endogenous to mobile phone coverage whereas children of certain age require vaccines irrespective of their health status. If mobile phones improve health knowledge (information), then we would expect to see higher vaccination rates in communities with high mobile phone penetration. Ultimately, vaccinations are likely to protect against infectious diseases and reduce infant mortality.[34] Table 11 presents robust evidence that this is indeed the

[34] Conversely, mobile phone access can also have a negative effect if it facilitates the spread of anti-vaccination news, thus inducing households to avoid vaccinating their children.

case. As mobile phone coverage rises by 10 pp, vaccination rates for measles and pneumonia vaccines increase by 2.6-2.9 pp and 2.4-5.1 pp, respectively. Likewise, uptake of Vitamin A supplements increases by 4.5-6.5 pp.

We also explore the effects of mobile phones on mothers' utilization of prenatal care. In Table 12, we show that access to mobile phone network increases the probability of mothers receiving prenatal care in a health center. A 10 pp increase in mobile network coverage is associated with 1.7-2.2 pp increase in utilization of prenatal care in a health center. Given the relatively well established link between antenatal care and child health outcomes (Okeke and Abubakar, 2020; Powell-Jackson, Mazumdar and Mills, 2015; Gajate-Garrido, 2013), these results suggest that increase in antenatal care may have been one of the key channels through which mobile phones reduce infant mortality.

5.4 Short-Term Child Health

Here, we focus on immediate causes of infant mortality to more fully establish the links between mobile phones, health knowledge, behavior and utilization and infant mortality. Specifically, we examine the implications of mobile network coverage on short-term child health outcomes such as coughing, diarrhea, and fever. In Table 13, we find a negative relationship between cell phone coverage and the incidence of cough, diarrhea, and fever. In column 1-2, the results show that a 10 pp increase in mobile coverage is associated with a 1-1.4 pp reduction in the probability of a child experiencing cough. In relation to diarrhea (column 3-4), the effect is negative albeit statistically insignificant. In columns 5-6, the effect on the probability of getting fever is also negative and statistically significant (using country fixed effects). A 10 pp increase in mobile network coverage is associated with a 0.7 pp reduction in probability of a child experiencing feverish conditions. These estimates are quite large, amounting to between 28 percent for fever and 55 percent for cough. Overall, the results provide strong evidence of improved short-term child health outcomes due to mobile phone network expansion.

6 Robustness Checks

In this section, we consider alternative scenarios and specifications to examine the robustness of our estimates to alternative explanations and threats to identification.

6.1 Measurement Error in Birth Records

Our main data are constructed using the birth history of mothers matched with spatio-temporal data on mobile phone coverage. Since the birth history data are essentially based on recall, the possibility of measurement error(s) on the exact timing of births can be substantial (Larsen, Headey and Masters, 2019). The data in our baseline analysis covers the full birth history of mothers (covering all births between 1998 and 2016), with the age of children ranging between 0 and 18 years. We match the birth records data with the mobile coverage data based on the year of birth, which may generate errors, especially for birth events farther in the past. Such recall errors/biases in birth records can have important inferential implications (Larsen, Headey and Masters, 2019). To minimize the effect of recall bias on our analysis, we replicate our baseline analysis in Table 5 by restricting the sample to births within five years of the survey (see Table 14).

Both the OLS and IV estimates in Table 14 are qualitatively and quantitatively similar to the baseline estimates in Table 5. This is despite the substantial difference in the sample sizes, where the former sample covers about 1.2 million birth records while the latter covers about half of that. The results provide suggestive evidence that recall bias in the birth history of children by mothers does not have significant effect on our baseline results.

6.2 Alternative Measures of Infant Mortality

Our baseline analyses examine the probability of a child surviving her first birthday. We provide further tests by focusing on two additional measures of infant mortality: (i) child survival through the first month of life, and (ii) child survival through the first six months after birth. Such disaggregation can inform potential channels of the impact of access to mobile phone coverage. More specifically, understanding at which point during infancy much of the impacts are realized would suggest whether the protective role of mobile coverage is highest during the prenatal, neonatal or infancy periods. While we note, in the developmental sense, child health outcomes reflect cumulative impacts up to the point of evaluation, zooming in on specific parts of infancy helps gauge the relative importance of the early few months of life, nonetheless.

Table 15 shows the results from the IV estimation of the effect of mobile phones on infant mortality using two alternative measures of infant mortality: mortality in the first month after birth (column 1-4), and mortality in the first 6 month after birth (column 5-8). In column 1-4, the effect of mobile phones on probability of child survival within the first one month of birth is economically and statistically indistinguishable from zero. However, in columns 5-8, we find robust negative effect (statistically and economically) of mobile phone coverage on infant mortality within the first six months after birth. In Table A1 in the Appendix, we replicate the analysis in Table 15 by restricting the sample to children born within five years prior to the survey and find qualitatively and quantitatively similar results. For instance, these estimations (based on the full and restricted sample) suggest that a 10 pp increase in mobile network coverage increases the probability of surviving the first 6 months of life by about 0.2-0.3 pp. These impacts are relatively lower compared to our main estimates in Table 5, suggesting that much of the protective role of access to mobile coverage is realized in the later parts of infancy.

6.3 The Role of Migration

Here we explore two channels through which potential endogenous migration could affect our results.

Measurement error induced by migration: Since we are measuring the effect of mobile phone connectivity at the survey location on child outcomes using a retrospective measure of mobile coverage, it is possible that children who were born elsewhere (possibly with no mobile coverage) before their parents migrated to the survey location could be regarded as "treated" when in reality, they were not living in the community at the time. To address such miss-classification, we use information on how long the mother has been living in the community and combine it with the birth year of the child to determine whether the child was born in the community. Note that the information on how long a mother has lived in a community is only available for mothers of about half of the children in our sample. Therefore, to classify children as born in the community or not, we rely on the sample of children with complete information on their mothers' duration of residency in the community. Using this information, a child is classified as born in the community if the mother had been living in the community by the year of birth of the child or earlier.

In Table 16 column 1-4, we focus exclusively on the sample of children born in the community and replicate our baseline analysis in Table 5. The results confirm the baseline results that mobile phone penetration has a positive impact on child survival. This provides assurance that our main results are not driven by measurement errors associated with migration of families.

Endogenous migration in response to (expected) mobile network expansion: A second source of concern is that the anticipated arrival of mobile network in a community may induce selective migration into the community. If the arrival of mobile phone coverage induces differential trends in migration, for example, of high skilled or more educated families, changes in infant mortality in the host communities can, to a large extent, be influenced by the type of migrants being attracted to the community, and not necessarily a direct impact of the mobile phones. To rule out this possibility, we impose two restrictions: first, children whose mothers lived in the community at least 3 years before mobile connectivity (Table 16, columns 5-8); and second, children whose mothers lived in the community for at least 3 years before the birth of the child (Table 16, columns 9-12). By doing so, we isolate families whose migration to the community may have been induced by anticipated arrival of mobile phone coverage in the community. Once again, our results are consistent with the baseline findings of a positive impact of mobile phones in reducing infant mortality.

Overall, these robustness exercises corroborate our findings that mobile network access can significantly and meaningfully improve public health outcomes and hence reduce infant mortality.

6.4 Threats to Exclusion Restriction

Finally, our main IV regression relies on the assumption that lightning intensity affects health outcomes mainly through its effect on the diffusion of mobile networks. This assumption is under threat if, for instance, lightning influences the location of health facilities due to potential effects of lightning induced outage spikes and its effects on hospital equipment or even the efficient running of health centers.

In this section, we provide evidence in support of our exclusion restriction by showing the association between lightning intensity and: (i) location of health facilities in Africa, and (ii) operation of health facilities using metrics such as number of days per week for which the facility is operational, and exposure of health facilities to electricity outages. Specifically, in Table A2 we use spatial data on the location of health facilities in Africa matched with lightning intensity to explore the correlation between lightning and the presence (number) of health facility at a $0.1° \times 0.1°$ grid cell level. The results show no statistically significant association between lightning intensity and the probability of having a health facility in a grid cell. Likewise, the results do not show any significant association with the number of health facilities opened in a given location.

Further, in Table A3 we use the IPUMS PMA data on health facilities to assess whether lightning is a good predictor of the performance of health centers surveyed. The main metrics of interest include number of days a health facility is opened per week, and exposure to outages. Once again, the results do not show any statistically significant association between lightning and these outcomes. Aside the statistical insignificance, the coefficients are also close to zero plausibly indicating the lack of relationship between lightning and these outcomes.

Overall, the findings in Table A2 and A3 provide confidence that the threat to our exclusion restriction assumption is likely minimal, hence, the IV estimates reflect the causal impact of mobile penetration on the health outcomes assessed in the paper.

7 Conclusion

Africa has witnessed remarkable progress in reducing infant mortality in the last three decades. Despite this impressive progress, Sub-Saharan Africa is home to the highest infant mortality rates in the world, with poor physical access to health care services commonly cited as a major cause. The recent and rapid expansion of mobile technologies in the continent may present opportunities to avail access to health care services to under-served populations. These potential public health impacts of digital infrastructure remain understudied. Quantifying the potential of digital infrastructure in improving public health outcomes can inform future project appraisals and investments.

In this paper, we examine the impact of expansion of mobile network coverage on infant mortality in Sub-Saharan Africa. We posit that access to mobile technologies can facilitate access to health information and hence improve preventive health behavior and health care utilization. Thus, we explore the impact of access to mobile network coverage on infant mortality as well as proximate determinants of infant mortality. To this end, we compile detailed information on birth and death records of infants from the Demographic and Health Survey (DHS) program and merge these with granular mobile phone coverage data for 25 African countries.

We combine two-way fixed effects (TWFE) and instrumental variables (IV) approaches to estimate the causal relationship between mobile phone access and infant mortality. Our main results come from an instrumental variable approach that exploits variations in lightning strikes as an instrument for mobile phone infrastructure expansion. Recent studies have used this instrument to circumvent potentially endogenous expansion of mobile infrastructure. Lightning strikes are shown to slow down the expansion of mobile technology due to the impact of the electrostatic waves released by lightning on the electrical components necessary for mobile technology (Manacorda and Tesei, 2020; Guriev, Melnikov and Zhuravskaya, 2020). Thus, our main identification strategy relies on the standard instrumental variable assumptions (relevance and validity of the instrument), which we believe hold at least conditional on a long-list of controls that capture climatic conditions and local economic development. To probe the robustness of our results, we also exploit subregional convergence in mobile network penetration induced by harmonization in telecom policies as an additional instrument for mobile network expansion. The rich set of controls and high spatial resolution of our data enable us to conduct a range of heterogeneity analyses and robustness exercises, which also effectively serve to probe the validity of our instruments.

We find that mobile phone coverage significantly reduces infant mortality. A 10 percentage point increase in mobile network coverage leads to 0.45 percentage point reduction in infant mortality. We also show that access to mobile phones improves mothers' health knowledge, preventive health behavior, and health care utilization, which ultimately improve child health. These findings have important implications for informing preventive measures to reduce infant mortality in Africa. The sizeable impacts and public health returns along with other socioeconomic impacts associated with mobile phones may plausibly justify further investments in digital infrastructure in Africa. These findings are particularly useful since health returns are not usually factored into project appraisals associated with investments in digital and related infrastructure. Sub-Saharan Africa remains the least digitally connected part of the world while the region continues to face major public health threats, including high infant and child mortality. The additional public health benefits of mobile network coverage we identify in this paper suggest that an inclusive digital revolution can improve public health service delivery and public health outcomes.

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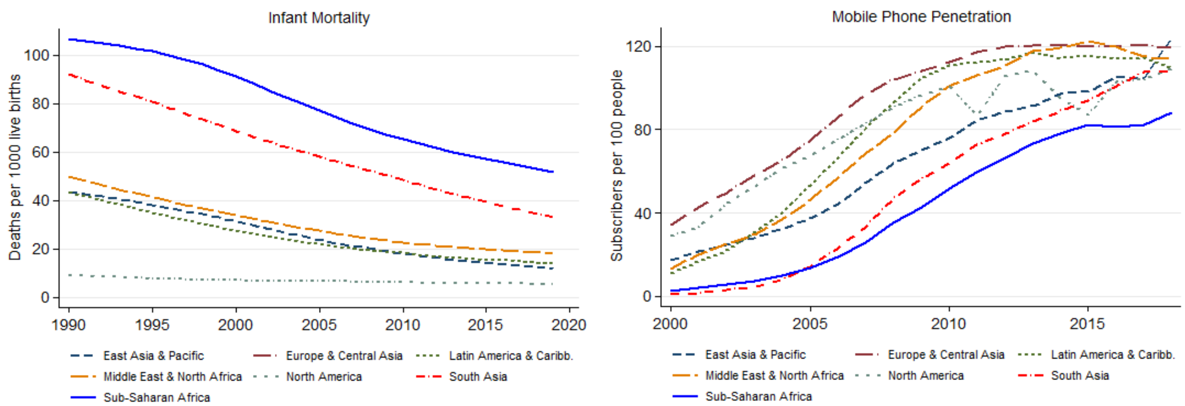
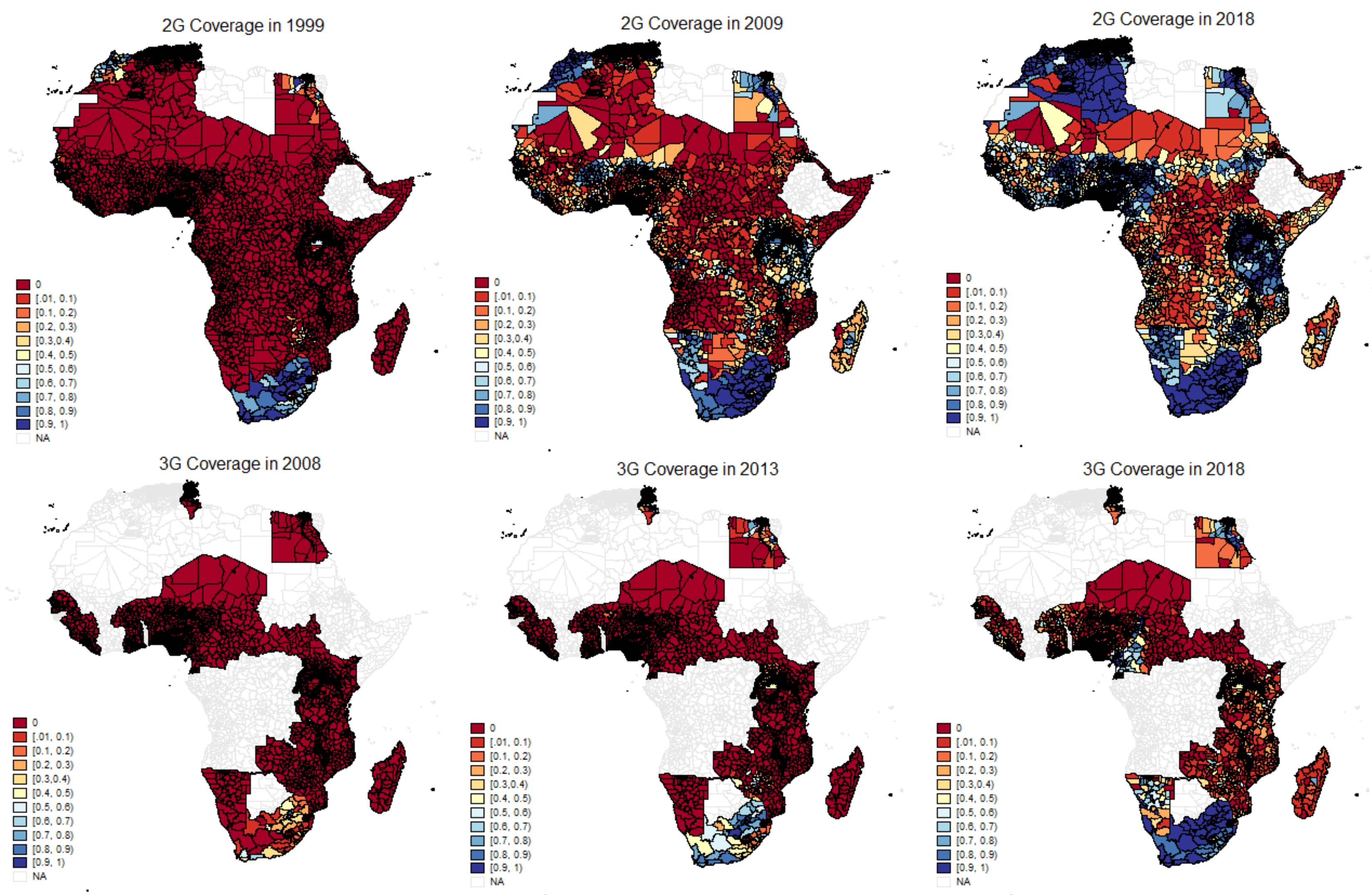
Figures

Figure 1: Regional Trends in Infant Mortality and Mobile Phone Penetration



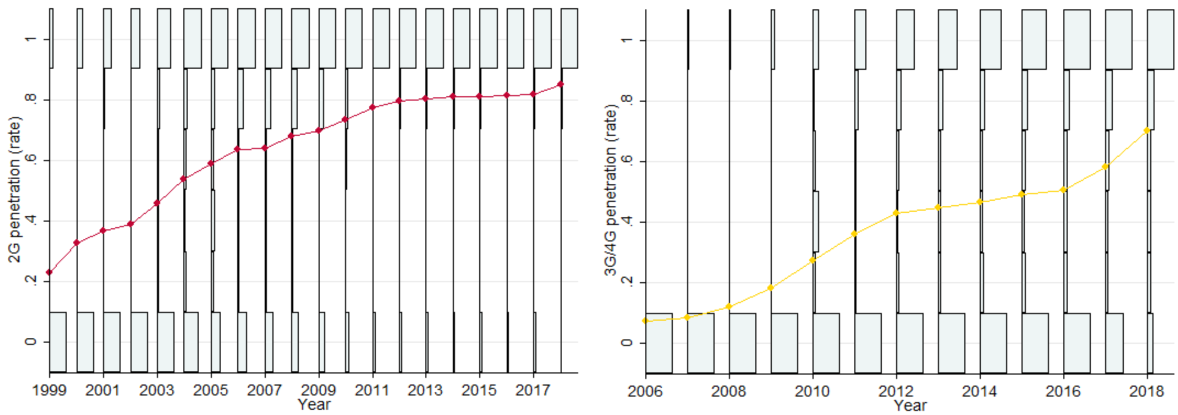
Notes: Authors' construct based on infant mortality data from UNICEF and mobile subscriber data from ITU

Figure 2: Trends in Mobile Network Coverage in Africa



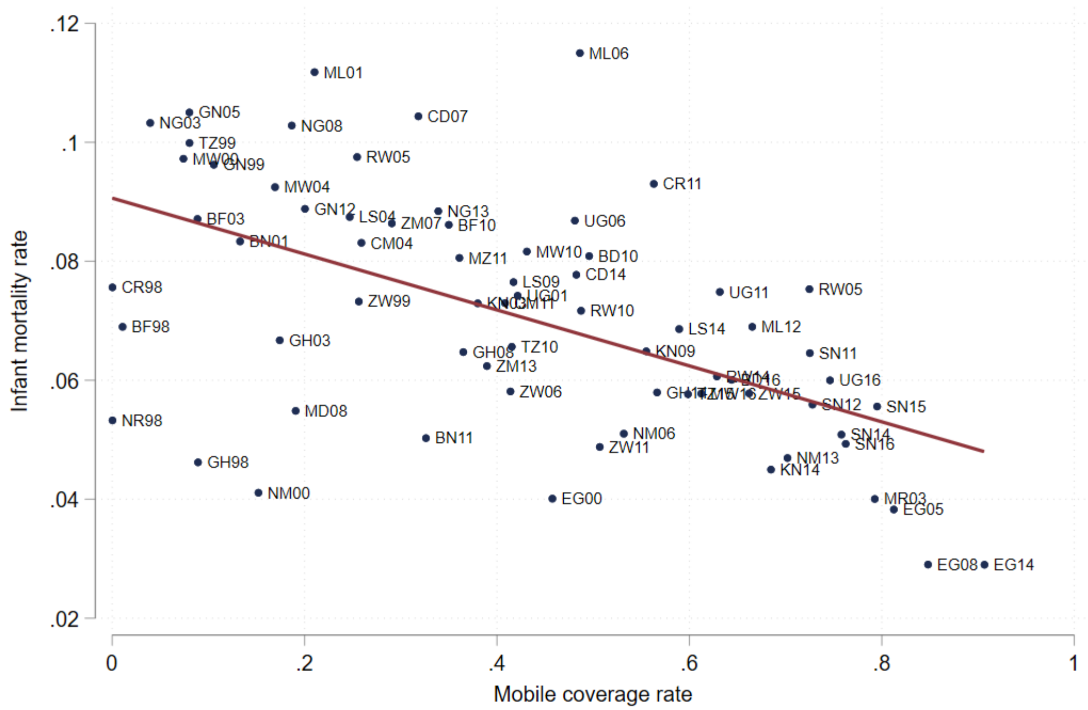
Notes: The figure shows the coverage rate of the 2G and 3G mobile phone networks at the subnational level (second administrative units) over time. Authors' construct based on data from Collins Bartholomew Mobile Coverage Explorer.

Figure 3: Mobile Network Penetration Time



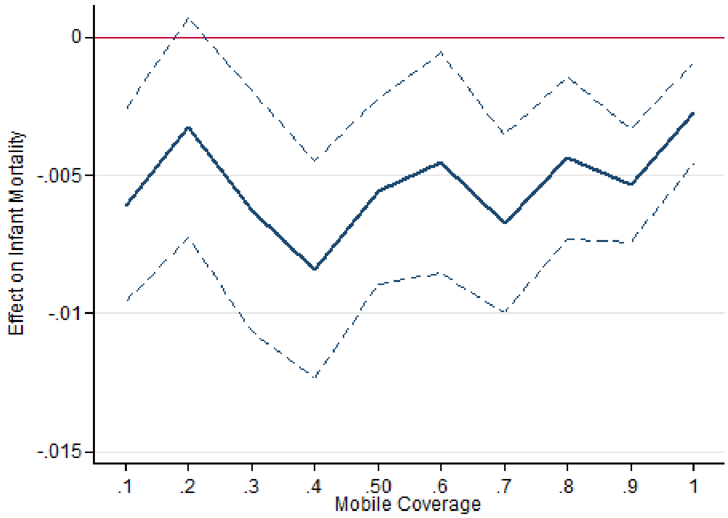
Notes: The figure shows the temporal trends in the coverage rate of the 2G and 3G mobile phone networks in Africa. Authors' construct based on data from Collins Bartholomew Mobile Coverage Explorer.

Figure 4: Correlation between mobile coverage and infant mortality



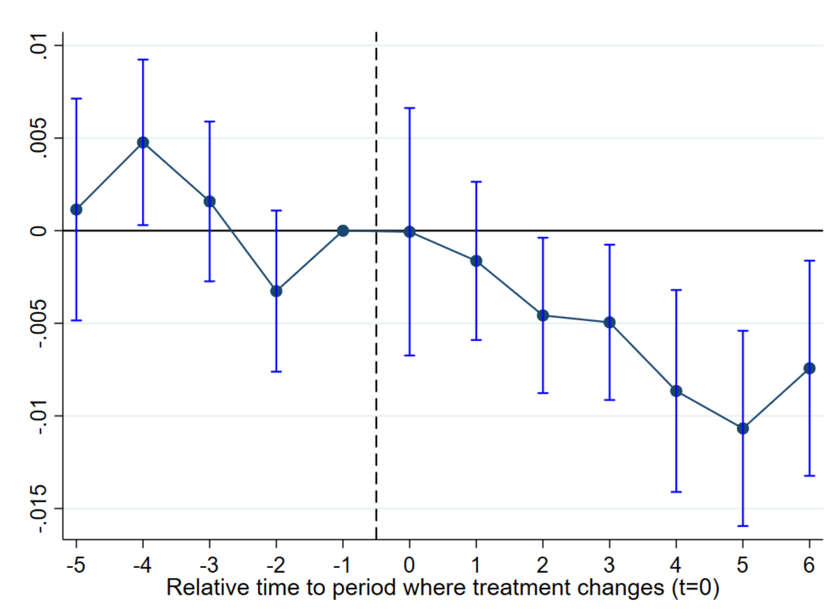
Notes: This graph shows the correlation between mobile phone coverage and infant mortality by country-survey round. Each dot represents DHS survey round, with the first two letters of the point label representing country and the last two numbers survey round.

Figure 5: Association between Mobile Coverage and Infant Mortality



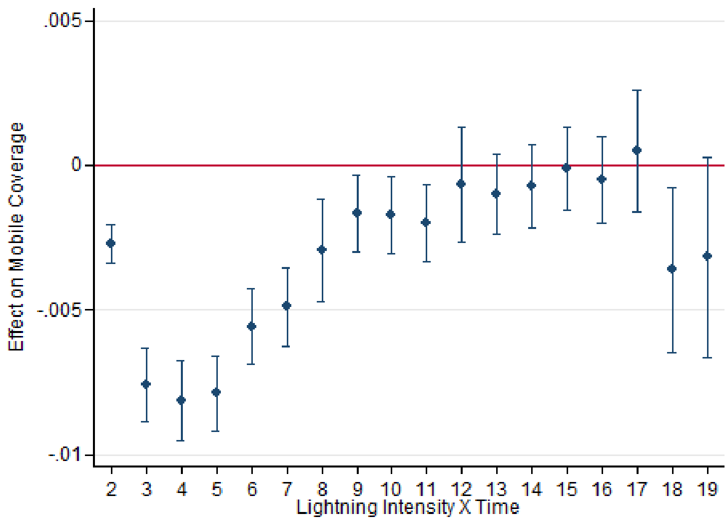
Notes: This graph shows point estimates and 90% confidence intervals of the relationship between mobile network coverage and infant mortality. Estimates are obtained from a regression controlling for child and mother characteristics, log of nightlight intensity, average precipitation and temperature in year of birth, and fixed effects for birth year, birth month, and grid level. Standard errors are clustered at grid level.

Figure 6: Event Study: Mobile Phones and Infant Mortality



Notes: This graph shows point estimates and 90% confidence intervals of the relationship between mobile network coverage and infant mortality based on the De Chaisemartin and D'Haultfœuille (2020*a*) estimator. Standard errors are calculated using 50 bootstrap replications, clustered at the grid cell level.

Figure 7: First Stage Relationship



Notes: This graph shows point estimates and 90% confidence intervals of the relationship between mobile network coverage and lightning intensity interacted with time dummies. Reference time dummy is $t = 1$.

Tables

Table 1: Correlation between Network Coverage and Mobile Uptake

	Owns a Mobile Phone (0/1)		Uses Mobile Money (0/1)		Uses Internet (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage	0.253***		0.256***		0.154***	
	(0.032)		(0.024)		(0.019)	
2G Coverage		0.205***		0.222***		
		(0.063)		(0.034)		
3/4G Coverage						0.256***
						(0.016)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.087	0.084	0.219	0.218	0.071	0.139
Mean dep. var	0.435	0.435	0.441	0.441	0.098	0.139
Observations	96973	96973	42214	42214	96972	56112

Notes: Estimations based on women sample. OLS estimations. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Infant Mortality (12 months)	0.069	0.254	0	1	1352284
Infant Mortality (6 months)	0.052	0.222	0	1	1352284
Infant Mortality (1 month)	0.037	0.188	0	1	1352284
Mobile Coverage	0.501	0.449	0	1	1225184
2G Mobile Coverage	0.501	0.449	0	1	1225145
3G/4G Mobile Coverage	0.087	0.246	0	1	260548
Urban	0.268	0.443	0	1	1352284
Female	0.493	0.5	0	1	1352284
Mothers Years of Schooling	4.111	4.361	0	27	1351766
Twin	0.035	0.183	0	1	1352284
Mothers Age at Birth	26.105	6.569	9	49	1352284
Ln Temperature	3.144	0.165	1.878	3.441	1352284
Ln (1 + Precipitation)	3.371	0.912	0.005	6.275	1352284
Lightning Intensity	16.12	11.961	0.014	152.553	1349927
Measles Vaccination	0.616	0.486	0	1	588599
Pneumonia Vaccination	0.788	0.409	0	1	90759
Vitamin A supplements	0.597	0.491	0	1	552237
Prenatal Care from a Skilled Provider	0.732	0.443	0	1	477357
Mother sleeps under Bednet	0.363	0.481	0	1	587269
Kids sleeps under Bednet	0.435	0.496	0	1	464137
Open defecation	0.232	0.422	0	1	924477
Mother knows ORS	0.775	0.417	0	1	901597
Mother heard of TB	0.9	0.3	0	1	249036
Mother believes TB is curable	0.867	0.339	0	1	181761
TB should be kept a family secret	0.349	0.477	0	1	183251
Owns a Cell Phone	0.447	0.497	0	1	110005
Uses Mobile Money	0.425	0.494	0	1	49209
Uses Internet	0.103	0.304	0	1	110004
Hygienic disposal of stools	0.595	0.491	0	1	535524
Child Coughing	0.24	0.427	0	1	648772
Child has Diarrhea	0.16	0.367	0	1	648946
Child has Fever	0.242	0.428	0	1	648842

Table 3: Mobile Phones and Infant Mortality

	Dep. Var: Infant Mortality (0/1)			
	OLS			
	(1)	(2)	(3)	(4)
Mobile Coverage	-0.003***	-0.003**	-0.012***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No
Country FE	No	No	Yes	Yes
Mean dep. var	0.068	0.068	0.068	0.068
Observations	1225109	1224663	1225184	1224739

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 4: Mobile Phones and Infant Mortality: IV First Stage Regression

	Dep. Var: Mobile Network Coverage			
	(1)	(2)	(3)	(4)
Lightning Intensity				
× $t = 2$	-0.003***	-0.003***	-0.002	-0.002
	(0.000)	(0.000)	(0.002)	(0.003)
× $t = 3$	-0.008***	-0.008***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.002)	(0.002)
× $t = 4$	-0.008***	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
× $t = 5$	-0.008***	-0.008***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 6$	-0.006***	-0.006***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 7$	-0.005***	-0.005***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 8$	-0.003***	-0.003***	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
× $t = 9$	-0.002**	-0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 10$	-0.002**	-0.002**	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 11$	-0.002**	-0.002**	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 12$	-0.001	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
× $t = 13$	-0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 14$	-0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 15$	-0.000	-0.000	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 16$	-0.001	-0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 17$	0.000	0.000	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
× $t = 18$	-0.004**	-0.004**	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)
× $t = 19$	-0.003	-0.003	0.004***	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
Controls	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No
Country FE	No	No	Yes	Yes
First-stage F test	20.367	20.377	20.132	20.248
Observations	1222752	1222306	1222827	1222382

Notes: Dependent variable is the mobile coverage, defined as the share of the population with mobile network coverage. The results shown interaction between lightning intensity and time dummies. Reference period is $t = 1$. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and log of nightlights. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 5: Mobile Phones and Infant Mortality

	Dep. Var: Infant Mortality (0/1)			
	IV			
	(1)	(2)	(3)	(4)
Mobile Coverage	-0.048***	-0.045***	-0.054***	-0.057***
	(0.008)	(0.008)	(0.014)	(0.014)
Controls	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No
Country FE	No	No	Yes	Yes
First-stage F stat	20.367	20.377	20.132	20.248
Mean dep. var	0.068	0.068	0.068	0.068
Observations	1222752	1222306	1222827	1222382

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 6: Mobile Coverage and Infant Mortality: Alternative Instrument

	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage Regression: Dep. Var: Mobile Coverage					
Subregional Mobile Coverage ($t-1$)	0.135***	0.135***	0.128***	0.789***	0.499***	0.500***
	(0.018)	(0.018)	(0.019)	(0.017)	(0.058)	(0.058)
	IV: Dep. Var: Infant Mortality (0/1)					
Mobile Coverage	-0.063***	-0.061***	-0.068***	-0.023***	-0.003	-0.003
	(0.021)	(0.021)	(0.023)	(0.003)	(0.004)	(0.004)
Controls	No	Yes	Yes	No	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Subregional Ctrls	No	No	Yes	No	No	Yes
Birth-Year	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	No	No	No
Country FE	No	No	No	Yes	Yes	Yes
First-stage F stat	55.837	55.841	43.846	2060.643	74.943	74.326
Mean dep. var	0.067	0.067	0.067	0.067	0.067	0.067
Observations	1090675	1090299	1090299	1090794	1090418	1090418

Notes:The top panel shows the first stage regression results where the dependent variable is the mobile phone coverage in a grid cell in a given year of birth. The instrument is the average mobile phone coverage in similar grid cells (communities) in other countries in the same subregion in the previous year. The bottom panel presents the second stage IV results where the dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlights. Climate Ctrls include the log of temperature and precipitation at grid cell level. Subregional Ctrls include the first lags of the spatially weighted average of Trade % of GDP and real GDP growth in the subregion. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level ; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 7: Mobile Coverage and Infant Mortality: Rural vs Urban

	Dep. Var: Infant Mortality (0/1)							
	Rural				Urban			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile Coverage	-0.036***	-0.033***	-0.050***	-0.055***	-0.035***	-0.033***	-0.040***	-0.034***
	(0.011)	(0.011)	(0.016)	(0.018)	(0.010)	(0.010)	(0.009)	(0.009)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat	26.168	26.161	25.753	24.301	11.598	11.538	10.255	10.940
Mean dep. var	0.073	0.073	0.073	0.073	0.056	0.056	0.056	0.056
Observations	870494	870245	870562	870313	352240	352043	352265	352069

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 8: 2G vs 3G Mobile Coverage and Infant Mortality:

	Dep. Var: Infant Mortality (0/1)							
	IV							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2G Mobile Coverage	-0.048***	-0.045***	-0.054***	-0.057***				
	(0.008)	(0.008)	(0.013)	(0.014)				
3G/4G Mobile Coverage					0.010	0.008	0.001	-0.001
					(0.010)	(0.010)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat	20.397	20.408	19.890	20.235	25.759	25.757	32.034	33.406
Mean dep. var	0.068	0.068	0.068	0.068	0.050	0.050	0.050	0.050
Observations	1222713	1222267	1222788	1222343	260154	260081	260198	260126

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 9: Mobile Coverage and Health Knowledge

	Know ORS(0/1)		Heard of TB (0/1)		Believes TB is curable (0/1)		TB should be kept secret (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile Coverage	0.202***	0.206***	0.086	0.767***	0.334***	0.545***	-0.473**	-0.068
	(0.026)	(0.031)	(0.059)	(0.194)	(0.101)	(0.180)	(0.221)	(0.120)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	No	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Survey-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F stat	22.940	18.934	3.714	3.297	3.574	2.056	2.175	2.279
Mean dep. var	0.788	0.788	0.902	0.902	0.868	0.868	0.348	0.348
Observations	815915	815916	240428	240429	175662	175671	177096	177100

Notes: Controls include urban dummy, age of the mother, years of schooling for mother, and log of nightlights. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level

Table 10: Mobile Coverage and Health Behavior

	Mother Sleep under bednet (0/1)		Kids sleep under bednet (0/1)		Open defecation (0/1)		Hygienic disposal of kids stools (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile Coverage	0.154***	0.066	0.025	0.174***	0.001	-0.140**	0.122*	0.422***
	(0.048)	(0.058)	(0.069)	(0.063)	(0.021)	(0.057)	(0.064)	(0.080)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	No	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Survey-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F stat	10.495	9.660	11.452	9.217	22.673	20.709	13.498	10.193
Mean dep. var	0.356	0.356	0.430	0.430	0.222	0.222	0.617	0.617
Observations	538045	538081	416197	416211	838188	838189	448775	448802

Notes: Dependent variables: a dummy equal to 1 if the mother sleeps under mosquito bed net and 0 if other wise (column 1-2); a dummy equal to 1 if the children under age 5 in the household sleep under mosquito bed net and 0 if other wise (column 3-4); a dummy equal to 1 if the household practises open defecation and 0 if otherwise (column 5-6); a dummy equal to 1 if households disposes children stools in a hygienic manner and 0 if otherwise (column 7-8). Controls include urban dummy, age of the mother, years of schooling for mother, and log of nightlights. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level
** Significant at 5 percent level
*** Significant at 1 percent level

Table 11: Mobile Coverage and Vaccination

	Measles		Pneumonia		Vitamin A	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage	0.292***	0.266***	0.512***	0.244	0.649***	0.445***
	(0.053)	(0.061)	(0.191)	(0.156)	(0.126)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Religion FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F stat	28.598	17.875	10.427	6.695	22.815	11.415
Mean dep. var	0.624	0.624	0.791	0.791	0.611	0.611
Observations	491673	491774	77238	77240	458326	458381

Notes: Dependent variable is a dummy equal to 1 if the child is vaccinated against the respective illness and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.

* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level

Table 12: Mobile Coverage and Health Care Utilization

	Prenatal Care in Health Center	
	(1)	(2)
Mobile Coverage	0.223***	0.168**
	(0.067)	(0.072)
Controls	Yes	Yes
Climate Ctrls	Yes	Yes
Grid FE	Yes	No
Country FE	No	Yes
Birth-Year FE	Yes	Yes
Birth-Month FE	Yes	Yes
Religion FE	Yes	Yes
First-stage F stat	11.555	7.967
Mean dep. var	0.756	0.756
Observations	358837	358929

Notes: The dependent variable is a dummy equal to 1 if a women with a birth in the last 5 years received antenatal care from a skilled provider for the most recent birth 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and distance to nearest health facility. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level

Table 13: Mobile Coverage and Child Health

Dep. Var:	Cough (0/1)		Diarrhoea (0/1)		Fever (0/1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage	-0.102***	-0.137***	-0.005	-0.014	-0.019	-0.069***
	(0.025)	(0.025)	(0.016)	(0.015)	(0.026)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Survey-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	No	Yes	No	Yes	No
Country FE	No	Yes	No	Yes	No	Yes
First-stage F stat	26.417	23.024	26.458	23.035	26.440	23.016
Mean dep. var	0.247	0.247	0.160	0.160	0.245	0.245
Observations	572379	572404	572514	572538	572471	572495

Notes: Estimates are obtained from IV regressions. Dependent variables are measures of short term health conditions of a child: a dummy equal to 1 if the child experienced cough during the past four weeks prior to the survey and 0 if otherwise (columns 1-2); a dummy equal to 1 if the child experienced diarrhoea during the past two weeks prior to the survey and 0 if otherwise (columns 1-2); a dummy equal to 1 if the child experienced fever during the past 4 weeks prior to the survey and 0 if otherwise (columns 1-2); Controls include gender of the child, age of child, urban dummy, age of the mother, log of nightlight intensity, and mother's years of schooling . Climate controls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level

Table 14: Mobile Coverage and Infant Mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dep. Var: Infant Mortality (0/1)							
	Children born within 5 years prior to the Survey							
	OLS				IV			
Mobile Coverage	-0.004**	-0.004**	-0.010***	-0.004***	-0.061***	-0.062***	-0.063***	-0.066***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.011)	(0.011)	(0.013)	(0.014)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat					22.500	22.503	17.637	18.754
Mean dep. var	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
Observations	609253	608994	609335	609077	608061	607802	608143	607885

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 15: Mobile Coverage and Infant Mortality: Alternative Measures of Mortality

Dep. Var:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Infant Mortality 1 month (0/1)				Infant Mortality 6 months (0/1)			
	IV							
Mobile Coverage	0.003	0.006	0.003	0.005	-0.014**	-0.011	-0.018**	-0.019**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat	20.367	20.377	20.132	20.248	20.367	20.377	20.132	20.248
Mean dep. var	0.036	0.036	0.036	0.036	0.051	0.051	0.051	0.051
Observations	1222752	1222306	1222827	1222382	1222752	1222306	1222827	1222382

Notes: In column 1-4, the dependent variable is a dummy equal to 1 if the child died within first one month of birth and 0 if otherwise. In column 5-8, the dependent variable is a dummy equal to 1 if the child died within first six month of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table 16: Mobile Coverage and Infant Mortality: Role of Migration

	Dep. Var: Infant Mortality (0/1)											
	Child born in comm				Mom lived in comm before Mobile Connectivity				Mom lived in comm before birth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mobile Coverage	-0.022*	-0.021*	-0.034**	-0.037**	-0.020*	-0.019*	-0.023	-0.031*	-0.021*	-0.021*	-0.036**	-0.040**
	(0.011)	(0.011)	(0.016)	(0.016)	(0.012)	(0.011)	(0.016)	(0.016)	(0.012)	(0.012)	(0.016)	(0.016)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat	20.367	24.353	14.779	14.940	22.871	22.889	12.960	13.760	23.385	23.366	14.221	14.558
Mean dep. var	0.036	0.068	0.068	0.068	0.071	0.071	0.071	0.071	0.067	0.067	0.067	0.067
Observations	499596	499333	499684	499422	402214	401996	402322	402104	445657	445426	445764	445534

Notes: Dependent variable is a dummy equal to 1 if the child died within first 12 months of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

A Online Appendix

A.1 Robustness Checks

Table A1: Mobile Coverage and Infant Mortality: Robustness checks

Dep. Var:	Infant Mortality 1 month (0/1)				Infant Mortality 6 months (0/1)			
	IV							
	Sample: Children born within 5 years prior to the Survey							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile Coverage	-0.006	-0.006	-0.004	-0.003	-0.027***	-0.027***	-0.029***	-0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Climate Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	No	No	Yes	Yes	No	No
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F stat	22.500	22.503	17.637	18.754	22.500	22.503	17.637	18.754
Mean dep. var	0.033	0.033	0.033	0.033	0.045	0.045	0.045	0.045
Observations	608061	607802	608143	607885	608061	607802	608143	607885

Notes: In column 1-4, the dependent variable is a dummy equal to 1 if the child died within first one month of birth and 0 if otherwise. In column 5-8, the dependent variable is a dummy equal to 1 if the child died within first six month of birth and 0 if otherwise. Controls include gender of the child, birth-order, a dummy equal to 1 if child was a twin and 0 if otherwise, age of mother at birth, urban dummy, years of schooling for mother, and the log of nightlight intensity. Climate Ctrls include the log of temperature and precipitation at grid cell level. Standard errors clustered at grid-cell level in parenthesis.
* Significant at 10 percent level; ** Significant at 5 percent level ; *** Significant at 1 percent level

Table A2: Lightning and Location of Health Facilities

	Health Facility (0/1)	# of Health Facilities
	(1)	(2)
Lightning Intensity	0.002	0.004
	(0.002)	(0.005)
Population Density	0.119***	0.516***
	(0.040)	(0.179)
Country FE	Yes	Yes
R-square	0.245	0.264
Mean dep. var	0.137	0.262
Observations	302827	302827

Notes: Standard errors are clustered at country level.
* Significant at 10 percent level; ** Significant at 5 percent level;
*** Significant at 1 percent level

Table A3: Lightning and Operation of Health Facilities

	# Days Open per week		Experience outage		Outage lasting more than 2hrs	
	(1)	(2)	(3)	(4)	(5)	(6)
Lightning Intensity	0.00003	0.00381	-0.00226	-0.00072	-0.00009	-0.00106
	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
Controls	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility Open Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.25218	0.39396	0.19075	0.24546	0.15301	0.17110
Mean dep. var	6.15696	6.23193	0.20356	0.12066	0.27507	0.18968
Observations	2026	1328	2024	1326	2014	1318

Notes: Controls include, nightlights, population density, and mobile network coverage. Standard errors are clustered at grid cell level.
* Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level