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The Epidemic Effect: Global Governance Institutions Mitigate the Effects of Epidemics*

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Abstract

Epidemics can have deleterious effects on economic development except mitigated through global governance institutions. We examine the effects of sudden exposure to disease on economic outcomes using evidence from the African meningitis belt. Meningitis shocks reduce economic activity and child health outcomes in periods when the World Health Organization (WHO) does not declare an epidemic year. These effects are reversed when the WHO declares an epidemic. We find evidence that the influx of disaster aid in response to WHO declarations may partly explain the results. We document an increase in World Bank health projects approved and funded during epidemic years.

JEL classification: I15, I18, I24, H84, J16, O12

Keywords: Epidemic, Disease, Meningitis, Night Lights, Human Capital, Aid, WHO, World Bank

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1 Introduction

The virulence and human cost of the COVID-19 pandemic and other epidemics in the past few decades have re-ignited policy discussions around strategies to mitigate the economic burden of infectious disease. While previous research has investigated the economic burden of disease, the mechanisms that underlie the effects of epidemics on economic outcomes are less well understood. When countries are declared nationally epidemic by global health governance organizations based on some threshold of cases, the influx of disaster aid and financing efforts following the epidemics may increase economic activity, with resultant positive effects on development. Our work provides key insights into this epidemic effect.

In this study, we ask two questions: (i) how do epidemics of infectious disease impact economic activity and human capital development? And (ii) what roles, if any, do global health governance institutions play in mitigating these impacts? Exploiting quasi-random exposure to meningitis shocks and epidemic years in the African meningitis belt, we assemble data on meningitis cases, epidemics, the flow of World Bank health spending, economic activity and child health outcomes to investigate the effects of ostensibly redistributive institutions on the economic burden of epidemic disease. The meningitis belt consists of about 23 countries in Africa, extending from Senegal to Ethiopia and making up over 700 million individuals, that are frequently exposed to meningitis epidemics as shown in Figure 1a. The epidemic[1] form of meningitis is caused by the bacterium *Neisseria meningitidis* and is characterized by an infection of the meninges or the thin lining covering the brain and spinal cord. Direct transmission is through contact with respiratory droplets or throat secretions from infected individuals (LaForce et al., 2009; García-Pando et al., 2014). Infection is associated with fevers, pain, reduced cognitive function, and in the worst cases, permanent

[1]Where epidemics are defined in the SSA context as greater than 100 cases per 100,000 population nationally within a year by the World Health Organization (WHO) (LaForce et al., 2009).

disability and long-term neurological damage and death. Young children and adolescents are particularly at risk of infection and epidemics can be very costly for households, with households in the belt spending up to 34% of per capita GDP on direct and indirect costs stemming from meningitis epidemics (Colombini et al., 2009; Akweongo et al., 2013).

We exploit quasi-random variation in district level exposure to meningitis shocks and exogenous variation in the announcement of an epidemic year to examine these effects using a panel regression framework. Our meningitis shock variable is constructed from a new dataset, assembling mean weekly meningitis cases per 100,000 population for districts across eight countries in the belt from 1986 to 2008. The shock variable is an indicator that equals one if the z-score for meningitis is above a district's long term mean, following the definition of epidemics outlined by the World Health Organization (Organization, 2020)[2]. We verify the validity of our design by showing that relevant institutional and geographic characteristics are balanced across districts with higher versus lower likelihoods of experiencing meningitis shocks.

The results show that meningitis shocks or high, unexpected levels of meningitis significantly reduce economic activity on average by 6.5% . The effect is nonlinear, with meningitis shocks increasing economic activity during years declared by the World Health Organization (WHO) as epidemic years and reducing economic activity during non-epidemic years. A meningitis shock during a non-epidemic year decreases economic activity by up to 14.2%, while the announcement of an epidemic year reverses the negative effect, increasing it by up to 2.9%. We find similar results for child health outcomes, with unexpected, high meningitis exposure during epidemic years reducing the incidence of stunting and underweight outcomes in children born during the epidemic year. Children born in meningitis shock areas during

[2]The World Health Organization defines an epidemic as "the occurrence in a community or region of cases of an illness clearly in excess of normal expectancy. The number of cases indicating the presence of an epidemic varies according to the agent, size, and type of population exposed, previous experience or lack of exposure to the disease, and time and place of occurrence." (Organization, 2020).

a year declared an epidemic year are 6.6 percentage points (pp) less underweight and 7.6 pp less stunted than their non-epidemic year peers. Overall being born in a meningitis shock district during an epidemic year reduces the current incidence of being underweight by 2.3 pp, versus an increase in the incidence of being underweight of up to 4.3 pp for children born in meningitis shock districts in years not declared epidemic years. Similarly being born in a meningitis shock district during an epidemic year reduces the current incidence of being stunted by 3 pp, versus an increase in the incidence of being stunted of up to 4.6 pp for children born in meningitis shock districts in years not declared epidemic years.

We find some evidence for crowd-out of routine vaccination during epidemic years. Children born in meningitis shock districts during a declared epidemic year experience a 12% reduction in their total vaccinations received, while their peers born in shock districts during non-epidemic years experience an 8% increase in total vaccinations received relative to the sample mean.

We show that a primary mechanism explaining the heterogeneity in results and the reversal of the negative effect of meningitis shocks on economic activity and child health outcomes during declared epidemic years is the influx of disaster aid when the WHO announces an epidemic year, which may offset the negative income shock from increased direct and indirect costs resulting from the epidemic. We document an increase in World Bank health aid projects approved and funded during declared epidemic years. The funding epidemic effect is redistributive, with funds flowing away from non-health to health sector projects. We find evidence of imperfect targeting of World Bank health aid, due to relatively long approval processes for projects. Areas that receive more health aid have higher economic activity. In the absence of the epidemic effect, meningitis shocks can depress GDP growth rates by between 2%- 4.3%.

We conduct a number of robustness checks on our results. We provide evidence that selective migration does not appear to be driving our results. To address potential bias concerns regarding error in the measurement of our meningitis shock variable, we use an instrumental variables strategy. Motivated by work from epidemiology and public health which links large gatherings of people at the Hajj, a Muslim pilgrimage to Mecca that all Muslims are expected to undertake at least once during their lifetimes, to outbreaks of meningitis (Lingappa et al., 2003; Shafi et al., 2008; Yezli et al., 2016); and a related literature in economics linking cultural practices to health outcomes (Almond and Mazumder, 2011), we hypothesize that districts with large shares of Muslims who happen to be attending the Hajj at the beginning of a meningitis outbreak cycle, may not experience meningitis shocks. The timing of the Hajj is quasi-random and varies yearly according to the Islamic calendar. A combination of social distancing from lowered numbers of people in districts around the Hajj at the beginning of an outbreak cycle, and increased mandatory vaccination rates for Hajj travelers from the meningitis belt at Mecca (Yezli et al., 2016) could significantly decrease infection rates over the course of the cycle (Shafi et al., 2008). Following the predictions of the epidemiological literature, we construct a novel instrument that uses (i) the share of the district that is Muslim interacted with (ii) an indicator that equals one if the Hajj happens to fall at the beginning of a meningitis cycle in a given year[3].

We show that our instrument robustly predicts the meningitis shock variable. Districts with a larger share of Muslims potentially departing for Hajj at the beginning of an epidemic cycle have a lower likelihood of being meningitis shock areas. To address possible concerns around the exclusion restriction, we conduct a number of falsification tests, including examining the direct effect of our instrument on our economic outcomes. The results show that our instrument does not directly affect economic activity.

We add to several distinct literatures. First, our work is related to the economics

[3]The beginning of the cycle in meningitis belt countries is January, with cases peaking in March or April and receding in June. We discuss the epidemiology of the disease in further detail in Section 2.

literature on the economic burden of infectious disease, and the effects of early life shocks on human capital outcomes (Acemoglu and Johnson, 2007; Adhvaryu et al., 2019; Almond, 2006; Bleakley, 2007; Bloom and Mahal, 1997; Oster, 2005; Jayachandran and Pande, 2017; Dupas and Robinson, 2013). These studies show that infectious disease can affect a wide range of outcomes, including school enrollment, performance and attainment (Bleakley, 2007; Archibong and Annan, 2017), and labor market outcomes (Almond, 2006; Gould, Lavy, and Paserman, 2011; Bhalotra and Venkataramani, 2015), among others.

We also contribute to work in economics, political science and social epidemiology on the role of redistributive institutions and domestic policy in managing the effects of epidemics of infectious disease (Adda, 2016; Chigudu, 2020, 2019; Farmer, 1996, 2001; Geoffard and Philipson, 1996; Krieger, 2001; Leach, Scoones, and Stirling, 2010; Philipson, 1999; Youde, 2017; Copeland et al., 2013). We expand these literatures by providing quantitative estimates of the role of global and domestic redistributive institutions in managing the impacts of epidemics of infectious disease. We also add to the literature on the importance of domestic policy around social distancing in flattening epidemic curves and reducing the severity of outbreaks (Copeland et al., 2013; Fenichel, 2013).

Our work also contributes to the economics literature on the role of aid in development (Alesina and Dollar, 2000; Burnside and Dollar, 2000; Easterly, 2006; Nunn and Qian, 2014; Bräutigam and Knack, 2004). While a robust literature has found mixed results on the benefits of foreign aid for development (Burnside and Dollar, 2000; Moyo, 2009), a more recent literature has noted that health aid may have positive impacts on human capital outcomes particularly in asset constrained regions (Odokonyero et al., 2015; Kotsadam et al., 2018; Gyimah-Brempong, 2015; Miguel and Kremer, 2004; Bandiera et al., 2019; Ndikumana and Pickbourn, 2017). Our paper provides quantitative evidence of the barriers to targeting disaster aid and adds to the evidence of partial crowd-out that may occur, in areas like routine vaccination, when disaster aid increases in response to epidemics of infectious disease (Bloom, Canning et al., 2004; Deserrano, Nansamba, and Qian, 2020; Aldashev, Marini, and Verdier, 2019).

The rest of the paper is organized as follows. Section 2 provides a brief background on the epidemiology and costs of infectious disease, with a focus on meningitis epidemics. Section 3 describes the data. Section 4 outlines our empirical strategy. Section 5 presents results on the effects of meningitis epidemics on our economic and child health outcomes. Section 6 provides quantitative estimates of the role of World Bank aid as a potential mechanism explaining the results. Section 7 explores selective migration and other inference as alternative explanations underlying the results. Section 8 concludes.

2 Epidemics and the Epidemiology of Infectious Disease: Evidence from the Meningitis Belt

The World Health Organization defines an epidemic as "the occurrence in a community or region of cases of an illness clearly in excess of normal expectancy. The number of cases indicating the presence of an epidemic varies according to the agent, size, and type of population exposed, previous experience or lack of exposure to the disease, and time and place of occurrence." (Organization, 2020). Recent epidemics have had costly human capital impacts including: the Ebola epidemic in West Africa which resulted in an estimated[4] 28,600 cases and 11,325 deaths, the 2015 Zika epidemic in the Americas, the 2016 dengue epidemic worldwide which resulted in 100 million cases and 38,000 deaths, and most recently, the COVID-19 pandemic, resulting in over 80 million cases and more than 1 million deaths as of December 2020 (Bloom and Cadarette, 2019; Lai et al., 2020).

Although a robust literature in social and economic epidemiology has investigated the

[4]Likely underestimated according to Bloom and Cadarette (2019).

economic implications of an increased burden of infectious disease, relatively fewer studies have examined the role of domestic and international health institutions in managing the effects of epidemics (Acemoglu and Johnson, 2007; Adda, 2016; Almond, 2006; Archibong and Annan, 2017, 2019; Deaton, 2003; Jayachandran and Lleras-Muney, 2009). Social epidemiologists in particular have emphasized the importance of ex-ante and ex-post redistributive efforts in health in determining the economic effects of epidemic disease, with studies showing that regions with better and more equitable ex-ante health infrastructure and more, and more equitable distribution of ex-post funding may be able to better manage the effects of epidemics of infectious disease (Farmer, 1996, 2001; Geoffard and Philipson, 1996; Chigudu, 2020; Leach, Scoones, and Stirling, 2010; Bloom, Canning et al., 2004).

A growing literature in economics has highlighted the potential role of targeted redistribution of resources in alleviating the negative effects of infectious disease (Bleakley, 2007; Bandiera et al., 2019; Adhvaryu, Fenske, and Nyshadham, 2019; Adda, 2016; Miguel and Kremer, 2004). While previous studies have examined the impacts of health interventions in targeted randomized control trial settings, there remains relatively little work investigating the role of global health governance institutions in alleviating negative externalities from epidemics of infectious disease (Youde, 2017). We investigate the effects of these institutions in mitigating epidemics caused by one of the most virulent and understudied infectious diseases in the world, meningococcal meningitis in the African meningitis belt.

2.1 The Meningitis Belt

Meningococcal meningitis is a disease so endemic in the sub-Saharan Africa (SSA) region, that an entire swathe of 23 countries from Senegal to Ethiopia, making up over 700 million individuals, has been labelled the 'meningitis belt' due to frequent exposure to meningitis epidemics as shown in Figure 1a[5]. The epidemic[6] form of the disease is caused by the bacterium *Neisseria meningitidis* and is characterized by an infection of the meninges or the thin lining covering the brain and spinal cord. Infection is associated with fevers, pain, reduced cognitive function, and in the worst cases, permanent disability and long-term neurological damage and death. The WHO estimates that about 30,000 cases of the disease are reported each year, with figures rising sharply in regions during epidemic years[7].

The WHO also states that meningococcal meningitis can have high fatality rates, up to 50% when left untreated[8]. Although vaccines have been introduced to combat the spread of the disease since the first recorded cases in 1909 for SSA, effectiveness of the vaccines has been limited due to the mutation and virulence tendencies of the bacterium (LaForce et al., 2009)[9]. The periodicity of epidemics in the belt differs by country, with epidemic waves in the meningitis belt occurring every 8 to 12 years on average by some estimates (Yaka et al., 2008). Young children and adolescents are especially at risk of infection (Zunt et al., 2018).

The epidemiology of the disease is complex[10]. Direct transmission is through contact with respiratory droplets or throat secretions from infected individuals(LaForce et al., 2009; García-Pando et al., 2014). The bacteria can be carried in the throat of healthy human

[5]The WHO lists 26 countries in total as being at risk for meningitis epidemics, including Burundi, Rwanda and Tanzania (Organization, 2018).

[6]Where epidemics are defined in the SSA context as greater than 100 cases per 100,000 population nationally within a year by the World Health Organization (WHO) (LaForce et al., 2009).

[7]Source: http://www.who.int/mediacentre/factsheets/fs141/en/

[8]http://www.who.int/mediacentre/factsheets/fs141/en/

[9]The most recent vaccine MenAfriVac has been available in meningitis belt countries since 2010 and has been found to be effective against serogroup A, the strain of the bacterium most frequently associated with epidemics in the belt (Karachaliou et al., 2015). There has been a reduction in serogroup A cases in many countries since the introduction of the vaccine with the vaccine hailed as a success. Concerns have been raised about waning herd immunity over the next decade especially if the vaccine does not become part of routine childhood vaccinations; and an increase in serogroup C cases has been noted in other regions more recently prompting concerns about more epidemics from other serogroups of the bacterium (Karachaliou et al., 2015; Novak et al., 2019). There is currently no vaccine that prevents against all serogroups of *Neisseria meningitidis* (Yezli et al., 2016).

[10]Meningitis epidemics are similar to the COVID-19 pandemic in that they are both spread through contact with respiratory droplets or throat secretions of infected individuals. An important difference is that COVID-19 is caused by a virus while meningitis epidemics are caused by a bacterium.

beings, and, for reasons not completely understood, subdue the body's immune system, facilitating the spread of infection through the bloodstream to the brain following a 3 to 7 day incubation period (Basta et al., 2018; Organization, 2018)[11].

Although epidemic incidence is often associated with higher wind speeds, dust concentrations and lower humidity and temperatures that come with the onset of the dry, Harmattan season in SSA, the mechanisms of transmission are not fully understood[12] (LaForce et al., 2009; García-Pando et al., 2014). The Harmattan season generally extends from October till March, with the harshest part of the season in the first few months from October to December (Perez Garcia Pando et al., 2014). The epidemic curve, as shown in Figure 2, generally follows a sinusoidal pattern in the meningitis belt; cases typically begin in the first month of the year in the dry season in January, and peak around March, with the case load declining rapidly with the onset of the rainy season in June (Lingani et al., 2015).

Documented data on health expenditure of countries in the meningitis belt show that households spend a significant portion of their incomes on direct and indirect costs stemming from meningitis epidemics (Colombini et al., 2009; Akweongo et al., 2013). In Burkina Faso, Niger's neighbor in the meningitis belt, households spent some $90 per meningitis case- 34% of per capita GDP- in direct medical and indirect costs from meningitis infections during the 2006-2007 epidemic (Colombini et al., 2009). In households affected by sequelae, costs rose to as high as $154 per case. Costs were associated with direct medical expenses from spending on prescriptions and medicines[13] and indirect costs from loss of caregiver income (up to 9 days of lost work), loss of infected person income (up to 21 days of lost work) and

[11] The WHO estimates that between 10% and 20% of the population carries textitNeisseria meningitidis in their throat at any given time, with carriage rate spiking in epidemic years (Organization, 2018).

[12] The season is characterized by hot, dry northeasterly trade winds blowing from the Sahara throughout West Africa; dust particles carried by the Harmattan winds make the mucus membranes of the nose of the region's inhabitants more sensitive, allowing nasal and throat secretions to spread more easily and increasing the risk of meningitis infection (Yaka et al., 2008).

[13] Vaccines and treatment are technically free during epidemics, however information asymmetry among health care workers and shortages of medicines often raise the price of medication (Colombini et al., 2009).

missed school (12 days of missed school) (Colombini et al., 2009). Evidence from prepaid private health expenditures[14] in twenty meningitis belt countries between 1995 and 2008 shows a significant increase in private health spending during epidemic years (Table A1). Meningitis epidemics are a notable negative income shock to households in the belt.

3 Description of Data: Economic Activity, Child Health, and World Bank Aid

We combine data from multiple sources for eight countries in the meningitis belt where data on meningitis cases, economic activity and child human capital outcomes were available, namely: Benin, Burkina Faso, Cameroon, Ghana, Mali, Nigeria, Niger and Togo, shown in Figure 1b. As of 2019, five (Benin, Burkina Faso, Mali, Niger and Togo) of these eight countries are classified as low-income by the World Bank, while three (Nigeria, Ghana and Cameroon) are classified as low-middle income countries. Estimates of health spending as a share of GDP and the share of external spending in health expenditure for study countries relative to the Africa and world averages are shown in Figure A3[15].

Within the study countries, per capita health spending is relatively low at \$47 on average, equivalent to 5% of per capita GDP and lower than both the Africa (5.6%) and world (10%) averages. Government spending per capita on health is also quite low at \$11 and equivalent to 1.1% of per capita GDP versus 1.3% for the Africa average and 7.4% for the world mean. Out of pocket spending on health is relatively high at around 50% of health spending in study countries, and higher than the Africa average (36%) and the world average (19%). External spending as a share of health expenditures is relatively high at 19%, similar to the Africa average (20%)[16]. Further detail on the data is provided in the

[14]Prepaid private spending includes private insurance and non-governmental agency spending (Dieleman et al., 2017)

[15]Estimates from 2016 data, the most recent complete dataset available.

[16]Compared to, for example, 0.64% for India and 0.38% for Latin-America and the Caribbean over the

summary statistics table in Table 1.

3.1 Meningitis Cases

We assemble district level records of mean weekly meningitis cases per 100,000 population from the World Health Organization from 1986 to 2008 for countries in the meningitis belt in SSA with available data as shown in Figure 1b[17].

Epidemic years of meningitis are declared by the WHO in the sample when the national average incidence of meningitis is above 100 cases per 100,000 population. Table 1 shows that on average, there were 6 meningitis cases per 100,000 for the district/year in our study sample, with significant variability both across and within countries and years as shown in Figure A1. Following the WHO definition of epidemics as "cases of an illness clearly in excess of normal expectancy", we define a' local' epidemic, meningitis shock, variable, as a measure of 'outside of normal expectancy" meningitis events at the district level. The meningitis shock variable is an indicator that takes on a value equal to one if meningitis cases in a given year is above the district's standardized long-term mean. In other words, the meningitis shock variable equals one if the z-score relative to the district's long term mean of weekly meningitis cases per 100,000 population is greater than zero. The average share of districts classified as meningitis shock districts is around 0.36 as shown in Table 1.

same time period. Complete data on external spending for the entire world sample is not available for the 2016 year.

[17] District level weekly cases of meningitis case per 100,000 population are available from 1995 to 1999 for 28 districts in Benin, 1996 to 1999 for 30 districts in Burkina Faso, 1997 to 1998 for 10 districts in Cameroon, 1996 to 1998 for 138 districts in Ghana, 1989 to 1998 for 80 districts in Mali, 1986 to 2008 for 34 districts in Niger, 1995 to 1997 for 116 districts in Nigeria and 1990 to 1997 for 59 districts in Togo as shown in Figure A1 in the Appendix. These make up a dataset of district level meningitis cases of 495 districts across the 8 countries.

3.2 Night Lights

Following previous literature using night light density as a proxy for economic activity (Henderson, Storeygard, and Weil, 2011; Michalopoulos and Papaioannou, 2013), we use data on night light density from the National Oceanic and Atmospheric Administration (NOAA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) to measure economic activity in the absence of detailed micro-level income estimates for the study countries. Night light density data from the NOAA is available from 1992, and we use data from 1992-2008 to match meningitis case data from our study region. Since a notable fraction of the district level observations take on the value of zero, following previous literature, we use the log of night light density, adding a small number (ln (0.01+ LightDensity)) as our measure of night light density. The log transformation allows us to use all observations and account for outliers in the luminosity data (Michalopoulos and Papaioannou, 2013).

3.3 Child Health

To examine the effects of epidemics on child health outcomes, we use geocoded data from the birth recode (BR) of the Demographic and Health Surveys (DHS) for various years for the 8 countries. The DHS data are nationally representative cross-sectional household surveys that provide information on the demographic characteristics of individuals within households. For the BR sample, women aged 15-49 are individually interviewed to gather information on every child ever born to the woman. For each of the women interviewed, the BR has one record for every birth[18].

For births within the past five years at the time of each survey, the DHS data contains

[18] The BR of the DHS, including important geocoded information on the location of households or household clusters, is available for 1996, 2001 and 2012 for Benin; 1999, 2003 and 2010 DHS for Burkina Faso; 2004 and 2011 DHS for Cameroon; 1998, 2003, 2008 and 2014 DHS for Ghana; 1996, 2001, 2006 and 2012 DHS for Mali; 1992 and 1998 DHS for Niger; 2003, 2008 and 2013 for Nigeria; and 1998 and 2013 for Togo.

information on child anthropometric outcomes including the weight for age z score (WFA z) and height for age z score (HFA z), vaccinations, and mortality status - whether child is alive or dead and age at death if dead. Combined with the district level meningitis cases, this gives a dataset of nationally representative individual level data of births from 1992 to 2014 covering 14 DHS surveys across the 8 countries.

The WFA z and HFA z reflect factors that may affect a child's health in utero, at birth and/or after birth. Higher values are generally associated with favorable health conditions (Jayachandran and Pande, 2017). A child is considered underweight with a WFA z of less than -2.0 while a child is considered stunted with a HFA z of less than -2.0. 38% of children in the sample are underweight while 36% are stunted. Finally, we examine child vaccination rates for routine vaccines. We collect available information on BCG (tuberculosis), polio, DPT (diphtheria, pertussis and tetanus) and measles vaccination as well as a total of all vaccinations[19]. 61% and 42% percent of children in the sample received BCG and measles vaccination respectively. Of the 3 doses of polio and DPT vaccinations required, children received an average of 1.45 and 1.38 doses respectively. The average total number of vaccines received by children in the sample was 3.83 out of a maximum of 8 vaccines as shown in Table 1. Note that the recommended schedule for routine vaccination of children by WHO standards is at birth for BCG and with the first dose at birth for Polio as shown in Table 2. The recommendation is near birth for DPT (first dose at 6 weeks). This is in contrast with the recommendation for measles which may be taken much later after birth (at 9 months) (Organization, 2019).

3.4 World Bank Aid Data

To examine the relationship between epidemics and global governance health interventions/initiatives, we use geocoded data on World Bank funded projects in the International

[19]There is no information on meningitis vaccination rates in the DHS.

Bank for Reconstruction and Development (IBRD) and International Development Association (IDA) lending lines by sectors from AidData (AidData, 2017)[20]. This data contains the location and sectors of World Bank funded projects between 1995 and 2014 as shown in Figure 1c. Projects are classified by the World Bank as belonging to up to 5 sectors, such as: health, central government administration, general public administration, other social services, railways, and roads and highways. The amount of 'aid' or loans and grants (in 2011 USD) committed and disbursed for each project is also reported. A subset of these projects is given an independent evaluation grade (IEG) or project outcome rating based on measuring the extent to which the major relevant objectives of the project were achieved, or are expected to be achieved, efficiently (Ika, Diallo, and Thuillier, 2012).

This rating is on a six-point scale ranging from highly unsatisfactory (1) to highly satisfactory (6)[21]. We limit our sample to the subset of projects approved between 1986 and 2008 to match the duration of our meningitis case data. Summary statistics in Table 1 show that while on average around $56 million is committed to projects approved during our study years, only 12% of projects are health projects, where we define a project as being in the health sector if any one of its 5 sector categories correspond to health. The average committed for health projects is relatively lower at around $6 million per year. The average duration of these projects is around 6 years, while their average IEG rating is 3.98, or around 4 or "moderately satisfactory".

[20]This dataset is the only publicly available microlevel dataset on aid projects for our study region. We explore the effects of epidemic declarations on Official development assistance (ODA) aid from the Organisation for Economic Co-Operation (OECD) at the country level for 20 countries in the meningitis belt from 1995 to 2008 in Appendix A.1.

[21]In detail: "Highly Unsatisfactory"="1", "Unsatisfactory"="2", "Moderately Unsatisfactory"="3", "Moderately Satisfactory"="4", "Satisfactory"="5", "Highly Satisfactory"="6".

4 Empirical Strategy

We propose two identification strategies to explore the effects of epidemics on economic outcomes and their linkages with the influx of disaster aid. The main specification is an OLS panel regression framework. As a robustness check, we use a shift-share instrumental variable (IV) approach, described in Section 7.

4.1 Sources of Variation

We exploit two sources of variations: one is the variation created when countries are declared (nationally) epidemic based on the aggregate distribution of meningitis cases-"Epidemic Year"- which may be exogenous to observed district-level realizations of meningitis, and the other is a "Meningitis Shock" reflecting unusually high cases of meningitis at the district level. In practice, we explore two constructions for "Meningitis Shock": one reflecting the district-level meningitis z-scores- i.e., district meningitis positive deviations from their long-run average, and the other capturing the district's meningitis positive deviations from their long-run (moving) average. We present the results from the z-score specification in the main text[22].

The intuition behind defining meningitis shock in these ways, as stated earlier, follows the WHO definition of an epidemic, such that an individual district may be experiencing epidemic levels of meningitis cases relative to its expectation, but the national average does not rise to the level that the WHO chooses to declare a country-wide epidemic. We note two interesting features of our variations. First, there is significant variation in meningitis cases within country-districts, with no obvious trends in meningitis cases. Second, our "Meningitis Shock" measures are uncorrelated with district-level observables as shown in the balance table estimates discussed in Section 4.2.1, and thus, unlikely picking up any endogenous

[22]The results from both constructions are qualitatively similar, and tables are available upon request.

differences between districts and likely capturing exogenous variations from un-anticipated exposure to meningitis outbreaks.

4.2 OLS Specification

We begin with a simple panel regression model linking changes in nightlights, y_{dct}, our measure of local economic development activity, to the two sources of epidemic variations. For other micro or household-level outcomes (let i index an individual) that we investigate, nightlights is replaced with those outcomes accordingly. We estimate for district d in country c and year t:

$$y_{(i)dct} = \alpha \text{Menin. Shock}_{dct} + \beta \text{Epidemic Year}_{ct} + \gamma \underbrace{\text{Menin. Shock}_{dct} \times \text{Epidemic Year}_{ct}} + \mu_d + \delta_{ct} + \epsilon_{dct} \tag{1}$$

where "Meningitis Shock" is an indicator for a district's positive deviations from its long-run average of mean weekly meningitis cases per 100,000 population. "Epidemic Year" is an indicator for whether the WHO declares an epidemic year in a particular country. This specification includes a set of unrestricted within-country district dummies, denoted by μ_d, which capture unobserved differences that are fixed across districts. The country-by-year fixed effects, δ_{ct} control for aggregate changes that are common across countries over time, e.g. aggregate prices, and national policies. In model specifications with current child health as the outcomes, we also include year of birth fixed effects to account for potential life cycle changes across cohorts.

Our key parameter of interest γ is identified by district-level variation in "Meningitis Shock" and variation from whether or not the WHO declares a nation c's year t as epidemic. This provides an estimate of the "epidemic effect" : how meningitis epidemics and the global and national response affect economic activity. Errors are clustered at the district level to allow for arbitrary correlations. We present inference robustness in Section 7.3.

4.2.1 Design and Validity Checks

Our panel OLS framework requires an important identifying assumption:

$$E(\text{Meningitis Shock} \times \text{Epidemic Year} \times \epsilon|\mu, \delta) = 0$$

In words, this says, conditional on the country by year and district fixed effects (and other observed district characteristics), the interaction term for the epidemic effect must be orthogonal to the random error term, ϵ. We conduct two placebo tests below to evaluate the plausibility of this assumption, lending support for identification.

I. Balance Tests: Do relevant factors (before epidemic years) vary evenly between meningitis shock and non-meningitis shock districts? That is, pre-epidemic exposure, are individuals located in meningitis shock districts appropriate counterfactual for those located in unaffected districts. To test this, we estimate simple regressions of the likelihood of being a meningitis shock district, measured as our meningitis shock variable averaged over the years of available data for each district in each country, on a number of geographic and institutional characteristics for each district following the below specification:

$$y_{dc} = \alpha + \xi \mathbf{M}_{dc} + \delta_c + \epsilon_{dc} \tag{2}$$

where $\mathbf{M}_{dc}$ is district d's likelihood of being a meningitis shock district over the study period. We consider various outcomes, y_{dc}, spanning geographic and institutional features, following previous literature on the relevance of these characteristics for development

(Michalopoulos and Papaioannou, 2013; Archibong, 2019).The results in Table 3 show no observable differences in outcomes across districts that experienced more meningitis shocks between 1986 and 2008 and those that did not.

II. Model with Linear Time Trends: To account for other potential unobserved variables that may vary within-country or district-specific characteristics over time, we estimate Equation 3 below:

$$y_{(i)dct} = \alpha \text{Menin. Shock}_{dct} + \beta \text{Epidemic Year}_{ct} + \gamma \underbrace{\text{Menin. Shock}_{dct} \times \text{Epidemic Year}_{ct}} + \mu_d + \eta_t + \phi_d t + \epsilon_{dct} \tag{3}$$

Estimating Equation 3 with district-specific trends is the most flexible version of our OLS specification; it allows our "Meningitis Shock" and non-shock districts to follow different trends that may relate to factors like differences in internal migration patterns that could affect disease transmission. We interpret results from specifications in Equation 1 and Equation 3 in the results presented in Section 5.

5 The Effects of Meningitis Epidemics on Economic Activity and Child Health Outcomes

5.1 Results for Night Light Density

Figure 3 shows a snapshot of our economic activity results using the raw data. Log night light density is higher in meningitis shock districts during a declared epidemic year and lower in those districts during non-epidemic years. The results for night lights and our child health outcomes are summarized in Figure 4.

Table 4 reports estimates from Equation 1 and Equation 3 with the night light density outcome. First, we interpret the results from the country-year FE model. On average, meningitis shocks reduce economic activity, as measured by night light density, by 6.5% as shown in column (1). The effect is nonlinear, as shown in the fully specified models in columns (2). High levels of meningitis shocks increase economic activity by around 17.1% in epidemic years and reduce economic activity by 14.2% in non-epidemic years. The effect of meningitis shocks during epidemic years is effectively reversed, with an increase in economic activity of up to 2.9% in meningitis shock districts during declared epidemic years. The results are nearly identical in the linear time trend specification from Equation 3, and the estimates are largely stable, if slightly underpowered, as shown in columns (3) and (4).

The results are striking, in that although the average effect of meningitis shocks is negative, there is significant heterogeneity in the effects of these shocks depending on whether or not the WHO declares an epidemic year. Given the high share of health expenditure sourced from donor aid in the majority of the study countries as shown in Table A3, a major mechanism explaining this result may be an influx of disaster aid when the WHO declares an epidemic year. We discuss this mechanism in detail in section 6.

5.2 Results for Child Health Outcomes

Table 5 reports estimates from Equation 1 for the current HFA z and WFA z outcomes, current stunting and underweight status, and child immunization and infant mortality outcomes for children born during the study period. Children born in meningitis shock districts during an epidemic year are taller (column (3)) and weigh more (column (1)) than their peers born into meningitis shock but non-epidemic year districts. Children born in high meningitis, meningitis shock, areas during a declared epidemic year are 6.6 percentage points (pp) less underweight and 7.6 pp less stunted than their meningitis shock, non-epidemic year born peers. Overall being born in a meningitis shock district during an epidemic year reduces the current incidence of being underweight by 2.3 pp, versus an increase in the incidence of being underweight of up to 4.3 pp for children born in meningitis shock districts in years not declared epidemic years. The total effect is equivalent to a 2.3 pp and 3 pp reduction in the current incidence of being underweight and stunted respectively for children born in meningitis shock districts in declared epidemic years.

Columns (5) to (9) of Table 5 report estimates for child immunization outcomes, classified by immunizations recommended at or near birth (BCG, polio, DPT) versus immunizations recommended much later after birth (measles) as discussed in Section 3. The results here differ from the earlier results on positive reversals for health in meningitis shock districts during the epidemic year. For child routine vaccination, the results show significant negative effects of meningitis shocks on BCG, DPT and the number of polio doses (i.e. at or near birth) vaccinations, with the signs negative but not significant for measles or non-at/near birth vaccinations. Routine vaccination for BCG is up to 4.7 pp higher for children born in meningitis shock districts during non-epidemic years and, overall, 2.1 pp lower for children born in meningitis shock districts in declared epidemic years (column (5)). A child born in a meningitis shock district during a declared epidemic year is less likely to have all her vaccinations than her peer born in a meningitis shock district during a non-epidemic year as shown in column (9). The size of the effect is a relative reduction of 0.45 vaccinations or a total reduction of around 0.15 vaccines for children born in meningitis shock districts during declared epidemic years- equivalent to a 12% and 4% reduction in relative and total vaccinations respectively relative to the sample mean. The results are reversed for children born in meningitis shock districts during non-epidemic years, who experience an increase in total vaccinations of up to 0.31 vaccines, or an 8% increase in total vaccinations received relative to their epidemic year born peers.

One potential explanation for these vaccination patterns is, following the aid literature that suggests that health aid in response to shocks, may crowd-out routine vaccination, that there is crowd-out of routine vaccines in years declared epidemic years. The effect is particularly strong for vaccines that should be administered at or close to the time of birth[23] (Deserrano, Nansamba, and Qian, 2020; Boone, 1996; Bräutigam and Knack, 2004). There is no significant effect of meningitis shocks during the epidemic year on infant mortality as shown in column (10) of Table 5.

Table 6 shows the results from the model including district specific time trends in Equation 3. The results are robust to the inclusion of district specific time trends and the estimates are largely stable. Based on the results from the district time trends specification, children born in meningitis shock areas during a declared epidemic year are 8.2 pp less underweight and 10 pp less stunted than their meningitis shock, non-epidemic year peers; equivalent to a total reduction in the current incidence of being underweight and stunted of 4.1 pp and 5.6 respectively for children born in meningitis shock districts during declared epidemic years. The vaccine crowd-out estimates are slightly larger in the district time trends model as shown in column (9). Under the trends model, children born in meningitis shock districts during declared epidemic years experience a relative decrease in total vaccinations of -0.72 vaccines (a 20% reduction relative to the mean) versus an increase in total vaccinations of 0.48 (a 13% increase relative to the mean) for their meningitis shock, non-epidemic year born peers.

6 The Role of Health Aid: Evidence from World Bank Projects

Although there are multiple possible mechanisms that could explain the results outlined in Section 5, one key mechanism that may explain both the positive reversal in economic activity and child health outcomes and the crowd-out of routine vaccination results in Section 5.2 is an inflow of disaster aid after the announcement of an epidemic year. To investigate

[23] Which is why we would expect to see no effects for measles, for example, which should be administered at 9 months.

this hypothesis we use aid data from World Bank projects as described in Section 3.4. We estimate and interpret results from the district time trends model in Equation 3 to account for the small sample size and to examine the direct effect of a declared epidemic year on World Bank aid. As a further robustness check, we examine the effects of meningitis shocks on economic activity by the share of world bank aid to see if shock districts that get more World Bank aid have more economic activity than those that received less aid.

6.1 How World Bank Projects are Approved and Funded

To understand the results, it is important to understand how World Bank projects are funded. Although there is very little research on World Bank internal management practices (Ika, Diallo, and Thuillier, 2012), we spoke to numerous officials and employees at the World Bank to get insight on how Bank aid projects are approved and funded. Our research revealed that projects take relatively long times to be approved, with estimates of an average of 7 to 12 months to approve a single project. Projects must go through 'concept approval, final design approval, then final package to Board' before possibly being approved and funded. The shortest amount of time to approve projects in an 'emergency' setting is reported to be around 3 to 4 months. A snapshot of the World Bank project approval process is provided in Figure 5.

What this means is that locations for World Bank health projects are chosen ex-ante relative to the declaration of an epidemic year, and it can be quite sticky and difficult to target specific areas ex-post[24] (Öhler et al., 2017; Duggan et al., 2020). This affects the targeting of health aid, given the relatively small amount of health aid projects funded in the sample (12%), where officials, acting with incomplete incomplete information, are not able to perfectly target health aid to districts or areas that may be most in need during a

[24]Öhler et al. (2017) provide suggestive evidence that projects are targeted geographically by population share, with more populous regions receiving more projects, rather than by poverty status.

declared epidemic year.

6.2 Results: Health Project and Non-Health Funding in Epidemic vs Non-Epidemic Years

Table 7 reports the first set of estimates showing the impacts of meningitis shocks in epidemic and non-epidemic years on the share of World Bank health aid projects approved and funded. When an epidemic year is declared, there is a significant increase, up to 55 pp, in health projects approved in that year as shown in column (1). Column (2) of Table 7 shows that there is no significant difference in health projects approved to meningitis shock vs non-shock districts, which may be explained by the inability to target issues discussed in Section 6.1.

While there is an increase in total dollars committed and disbursed to health projects during epidemic years, as shown in columns (3) and (7) of Table 7, the effect does not significantly differ between meningitis shock and non-shock districts, suggesting lack of targeting, as mentioned previously. The results suggest a redistribution of aid funds from non-health to health projects, with positive, significant signs in epidemic years for the total amount of funds committed and disbursed to health projects, and negative signs on amounts going to non-health projects as shown in columns (5), (6), (9) and (10).

As a further robustness check, we re-estimate the models in Equation 1, interacting meningitis shock with the share of health projects funded to see if meningitis shock districts that receive a greater share of health aid projects see an increase in their economic activity. The results are shown in Table 8[25]. Meningitis shock districts that receive a greater share of health aid projects and more health aid committed and disbursed see an increase in their economic activity as measured by night light density and shown in columns (1)-(3). The effect is driven by health specific aid not non-health aid as shown in columns (4) and (5).

[25] There is not enough power for a triple interaction or split sample approach including the declared epidemic year.

Table 9 shows the effects of a meningitis shock and declared epidemic year on the duration and independent evaluator rating (IEG) of projects started during the epidemic year by health and non-health project classifications. Projects started during a declared epidemic year are 1.2 years shorter in duration than non-epidemic year projects, a 19% decrease in duration of project relative to a mean of 6.4 years as shown in column (1). The duration effect does not differ between shock and non-shock districts (column (2)), providing further evidence for the lack of aid targeting. The duration effect differs for health projects funded during the epidemic year versus health projects funded during a non-epidemic year as shown in column (3). A typical health project funded during a non-epidemic year lasts for 1 year longer, relative to the sample mean. A health project funded during an epidemic year lasts for a shorter period, 1.46 less years, than its non-epidemic year counterpart.

Projects funded during an epidemic year also receive worse ratings, experiencing a reduction of 2 points or a 50% reduction in their rating relative to a sample IEG rating of around 4 as shown in column (4) of Table 9. Qualitatively, based on data descriptions outlined in Section 3.4, this reduction in ratings is equivalent to a project going from a 'Moderately Satisfactory' (4) rating to an 'Unsatisfactory' (2) rating. There is also heterogeneity in the effects of a declared epidemic year on the IEG rating; health projects funded during non-epidemic years rated 0.7 units higher than health projects funded during non-epidemic years, which are rated -5 units lower as shown in column (6).

One explanation for both the shorter durations and poorer ratings of health projects funded during epidemic years could be linked to the emergency nature of the funding and subsequent inability to target aid projects efficiently discussed in Section 6.1. Though there is no publicly available data on the details of the projects approved over the study period, the dataset includes project titles that provide suggestive evidence on the kinds of health and non-health projects funded in declared epidemic vs non-epidemic years. A snapshot of the top

5 titles in each period is provided in Figure 6. Notable is the difference between the epidemic and non-epidemic year health project titles funded. During the epidemic year the top health project titles are ‘health sector and development program’ and ’Economic recovery and adjustment credit (ERAC) project’, while during non-epidemic years, the top project titles are ‘Community action program’, ‘social fund’ and ’health, fertility and nutrition project’, providing strong suggestive evidence of the responsiveness of World bank health funding to epidemic year announcements.

7 Measurement, Selective Migration and Inference

7.1 Measurement Error: Instrumental Variable Estimates

The results presented in Table 4 and Table 5 suggest that meningitis shocks have heterogeneous effects on economic development, reducing economic outcomes in non-epidemic years and vice versa. The OLS estimates of the effect of meningitis shocks on economic outcomes may be biased if there is some measurement error in our meningitis shock variable. As a further robustness check and to address this concern, we present results using an instrumental variables strategy. A plausible instrument will predict exposure to meningitis shocks but will not affect economic activity, except through the meningitis shock measure.

Following the research in epidemiology and public health on the role of the Islamic Hajj in meningitis outbreaks (Lingappa et al., 2003; Shafi et al., 2008; Yezli et al., 2016), and a related literature in economics linking cultural practices to health outcomes (Almond and Mazumder, 2011), we construct an instrument that is the interaction between two components: (i) the share of the district that is Muslim interacted with (ii) an indicator that equals one if the Hajj happens to fall at the beginning of the meningitis cycle in January in a given year[26].

[26]We present results from robustness checks reconstructing the instrument using the peak versus the

The share of the district that is Muslim is based on mothers' responses to the religion question in the DHS women's sample and is averaged over all years for each district. Although sampling is not based on religion, the Muslim share is stable across individual survey years, with correlation coefficients ranging from 0.65 to 0.98 ($p < .001$) across study countries[27]. The intuition here, from the epidemiological literature, is that since the timing of the Hajj is quasi-random and varies yearly according to the Islamic calendar, districts with large shares of Muslims who happen to be attending the Hajj at the beginning of a meningitis outbreak cycle, may not experience meningitis shocks. A combination of social distancing from lower numbers of people in districts around the Hajj at the beginning of an outbreak cycle, and increased mandatory vaccination rates for Hajj travelers from the meningitis belt at Mecca (Yezli et al., 2016) could significantly decrease infection rates over the course of the cycle (Shafi et al., 2008).

To conclusively test the social distancing hypothesis, we need data on the numbers of people traveling on Hajj from each area. While figures on the exact numbers of people leaving for Hajj, also called pilgrims, from each country over the study period are not publicly available, obtainable evidence from Niger, a meningitis belt country that is 99% muslim and one of the poorest countries in the world, ranking 189 out of 189 countries on the United Nations Human Development Index (HDI), are informative. In Niger, an average of 0.05% of the population, just over 4000 people each year, travelled for Hajj between 1968 and 2013, with pilgrims leaving for around three weeks for Hajj (Archibong and Annan, 2019; Pérouse de Montclos, 2017)[28]. These trips were often subsidized by governments with large muslim populations, with entire ministries created to regulate the Hajj pilgrimage, which

beginning of the meningitis cycle in Table A4 in the appendix.

[27]Correlations are based on the two most recent years of data for each country, to alleviate concerns of fewer observations in earlier years.

[28]Since the 1990s, Saudi Arabia has issued quotas on the number of visas allowed from each country for Hajj travel. For example in 2010, over 12,000 people travelled for Hajj in Niger. The Hajj visa quota for Niger in that year was 15,000 (Pérouse de Montclos, 2017).

gave poor residents the opportunity to travel on Hajj (Pérouse de Montclos, 2017)[29].

A question that arises, given these figures on Hajj travelers, is 'what share of the population would need to leave on Hajj for social distancing to reduce the likelihood of a meningitis shock in a district?' Although there is no epidemiological consensus on this, some figures on the number of meningitis cases in an epidemic may be helpful. For example, Niger had its worst epidemic in 22 years between 1986 and 2008 in 1995 (Mohammed, Iliyasu, and Habib, 2017). During the 1995 epidemic in Niger, there were 43,203 recorded cases of infection, with a national infection rate of 490 per 100,000 population[30]. With an infection rate of 0.49% during the worst epidemic recorded in Niger's recent history, if, in some counterfactual case, 0.05% of the population had left for Hajj at the beginning of the epidemic curve in January, that figure, equivalent to 10% of meningitis cases during the 1995 epidemic, may have been significant enough enough to flatten the epidemic curve and reduce the likelihood of districts experiencing a meningitis shock[31].

This is plausible since the intensity of an infectious disease is measured by its reproduction number, i.e. the expected number of cases generated by one case, which is negatively correlated with social interactions. In epidemiology, this finding is supported when the transmission of contagious diseases are considered via changes in contact networks which can arise due to human responses to disease, such as a reduction in social contacts (Funk et al., 2009). Such epidemiological models have shown that social distancing can be effective at reducing the rate of transmission of disease in an epidemic (Glass et al., 2006). Social distancing, combined with the fact that returnees from the Hajj would have received mandatory menin-

[29]For example, the Commission Nationale du Hadj (CNH) in Cameroon in 2003 and Comissariat a l'organisation du Hadj et de la Oumra (COHO) in Niger in 2013 or the National Hajj Commission of Nigeria in 2006 which replaced Nigerian Pilgrims Commission boards going back to 1958. (Pérouse de Montclos, 2017).

[30]Authors' estimates from WHO data.

[31]Additionally, cultural practices around frequent hand-washing and ritual cleansing for Hajj travelers may further work to limit the spread of disease over this period (Long, 1979).

gitis vaccinations, per regulations in Saudi Arabia, contributing to herd immunity on their return home, may then work to reduce the likelihood of districts with high muslim populations experiencing meningitis shocks (Yezli et al., 2016). Further details on the Hajj and the instrument are provided in Section A.2 in the Appendix.

Panel A of Table 10 presents the first stage estimates for the Share Muslim x Hajj interaction instrument. The instrument significantly predicts meningitis shocks, with an F-stat greater than 10 across all specifications. The model in column (3) with an F-stat of 35.9 appears to provide the most predictive power so following the literature, we interpret the second-stage results in column (3) of Panel B (Staiger, Stock et al., 1997). Panel B of Table 10 presents the second stage estimates for night light density as the dependent variable[32]. The IV results qualitatively support the OLS results for night light density. Meningitis shocks increase night light density overall by 8% in declared epidemic years in the IV specification in Column (3) of Panel B versus a 62% decrease in economic activity in non-epidemic years. The corresponding OLS estimates are a 2.9% increase in epidemic years versus a 14.2% decrease in economic activity in non-epidemic years. The difference in the magnitude of the IV estimates could suggest measurement error in the meningitis shock variable, where the shock indicator is an imperfect proxy for unexpected exposure to high levels of meningitis in our sample. We provide further discussion and evidence of instrument validity in Appendix A.2.

7.2 Selective Migration

To what extent does migration rationalize our results? We investigate the possibility that unhealthy individuals (i.e., with low WFA z, low HFA z, etc) might have moved from areas

[32]Since the only years in the sample for which Hajj falls in January at the beginning of the outbreak cycle are 2005 and 2006 as shown in Table A3, we are unable to estimate child health outcomes with the instrument. There are no countries in the sample which have both complete meningitis data and DHS data on children born in Hajj years.

affected by meningitis to unaffected areas and as a result, unaffected areas experience low economic activity relative to the affected areas. The dual, though prima facie less plausible, statement is that more "healthy" individuals might have moved from areas unaffected by meningitis to the affected areas and as result, unaffected areas experience low economic activity. Thus, instead of assuming limited (selective) internal migration between districts for identification, we relax this assumption and examine it as an alternative explanation for our results.

7.2.1 Migration Estimates

We evaluate the extent of migration across districts to gauge its likely effects. Because detailed micro data on internal migration over the entire sample period (1986 to 2008) is absent, we provide estimates based on the ACMI (aggregate crude migration index) and net migration rate (NMR) values calculated from 1988 to 1992 in Bocquier and Traoré (1998). In the demography literature, ACMI is a widely-used measure of internal migration and captures the share of the population that has changed address averaged over a specified time period. Specifically, the ACMI is a global average based on the specification:

$$CMI_n = \sum_i \sum_{j \neq i} M_{ij} / \sum_i P_i$$

where M_{ij} is the total number of migrants (or migrations) between origin area $i = 1, ...n$ and destination area $j = 1, ...n$; and P_i is the population of each area i at risk of migrating (Bell et al., 2015; Bernard and Bell, 2018). The population assessed here is the population over the age of 15 (Bocquier and Traoré, 1998). The NMR measures the difference between incoming and outgoing migrants in a particular locality.

Table A6 in the Appendix shows the ACMI and NMR (%) values, and indicates extremely low values. Overall, ACMI averages at 0.09 while NMR averages at -0.72%. This means that just 9% of the population report changing their place of residence within their country over the four-year interval (1988 to 1992) with a net movement of -0.72%. The evidence suggests limited internal migration in the study region.

7.2.2 Empirical Test: Role of Selective Migration

To test our conjecture that (selective) migration is not driving the results, we conduct a series of trimming exercises. We begin with the supposition that migration is indeed selective, and then ask "what level of such selective migration would be needed to make our results insignificant?". We reclassify the districts as either meningitis affected (if the observed meningitis cases are above the sample average) or unaffected (if the observed meningitis cases are below the sample average) year to year. We then trim the outcomes using different migration rates in increments of 5%. That is, we recursively drop the top 5%, 10%, 15%, ... of the data with the highest outcomes- reflecting the most healthy individuals or highest economic activity- only in the meningitis affected districts. In each step, we re-estimate our baseline model, and continue the process until the effects for our main interaction term,"Meningitis shock x Epidemic year", become insignificant.

Figure 7 shows the results. We focus on two main outcomes, nightlights and WFA z[33]. WFA z correlates strongly with the other child health outcomes (a simple regression of WFA z on the other health outcomes shows large and significant correlations, $p < 0.01$). As shown, for WFA z, a selective migration rate of 60% is required to render our effects insignificant. For nightlights, a selective rate of either 95% (OLS estimates) or 35% (shift-share IV estimates) is needed. The coefficient signs remain unchanged across all specifications. Our trimming exercise results suggest that migration would have to, differentially, rise by at least 35% to explain the results, which is very unlikely given the empirical evidence in Section 7.2.1.

[33]The results are consistent and available for other outcomes upon request.

This evidence is consistent with the fact that most of the districts are rural where (selective) migration may be difficult to achieve. The results are consistent with other papers showing a lack of selective migration in developing country settings (Bazzi et al., 2016).

7.3 Inference Robustness

Inference for our main analyses is based on the robust cluster (i.e., district) estimator, which allows for arbitrary correlations at the district-level. We examine the sensitivity of the results to alternative inference procedures by reporting additional standard errors using (i) robust but unclustered data which adjusts for arbitrary heteroskedasticity, (ii) the wild-clustered bootstrap, and (iii) the two-way clustering (i.e., district and time) which accounts for the possibility that errors may be either spatially or serially correlated. The wild cluster bootstrap is clustered at the district-level and derived from running 1000 replications in each instance.

Results are displayed in Tables A7 and Table A8 in Appendix A.3[34]. Inference (p-values) are similar across the various procedures. For our main interaction term and the "Meningitis shock" variable, significance is replicated consistently at conventional levels. This is also true for the "Epidemic year" variable, except under the two-way clustering procedure where the estimate is insignificant at the 10% level. Overall, the baseline results on inference show robustness to different procedures.

To examine the effects of arbitrary changes in the designation of the epidemic year (e.g. designated the following year $t+1$ as the epidemic year instead of the correct year t) on the economic outcomes, we re-estimate the model in Equation 1 using arbitrary epidemic year designations. The results in Table A9 show no significant effects of erroneous epidemic year designations on our economic activity outcome.

[34] We present the results from two main outcomes, nightlights and WFA z, in Appendix A.3. Results are consistent and available for other outcomes upon request.

8 Concluding Remarks and Policy Implications

Recent scientific literature have provided evidence that future warming may significantly increase the incidence and alter the geographical distribution of aggregate shocks like epidemics of infectious disease. This may have potentially devastating consequences for global welfare, absent effective redistributive institutions aimed at improving human capital outcomes.

An important contribution of our paper is to provide quantitative estimates of the effects of epidemics of infectious disease on economic and human capital outcomes. We examine the role of disaster aid in determining the distribution of resources following the announcement of an epidemic year. We find that high, unexpected levels of meningitis significantly reduce economic activity on average. The effect is nonlinear, with meningitis shocks increasing economic activity during years declared by the World Health Organization as epidemic years and reducing economic activity during non-epidemic years. A meningitis shock during a non-epidemic year decreases economic activity, while the announcement of an epidemic year reverses the negative effect. We find similar results for child health outcomes, with unexpected, high meningitis exposure during declared epidemic years reducing the incidence of stunting and underweight outcomes for children born during the epidemic year. Children born in meningitis shock areas during a year declared an epidemic year are less underweight and less stunted than their non-epidemic year peers.

The results are robust to extensive controls and instrumenting for meningitis shock using the timing of the Hajj which provides quasi-random variation in social distancing measures essential for flattening epidemic curves. The Hajj strongly predicts meningitis shock districts in areas with high shares of Muslim population and reduces the likelihood of a district experiencing a meningitis shock.

We show that a primary mechanism explaining the heterogeneity in results and the reversal of the negative effect of meningitis shocks on economic activity and child health outcomes during epidemic years is an influx of disaster aid when the WHO declares an epidemic year, which may be enough to offset the decline from increased direct and indirect costs resulting from the epidemic. We document an increase in World Bank health aid projects approved and funded during epidemic years. The epidemic funding effect is redistributive, with funds flowing away from non-health to health sector projects. Areas that receive more health aid have more economic activity.

These results have significant policy implications regarding the role of global governance institutions in mitigating the negative effects of epidemics on economic development. For instance, a simple back of the envelope calculation using estimates from Henderson, Storeygard, and Weil (2011) where a 1% increase in nightlight density increases GDP growth rates by about 0.3% in low and middle income countries, shows that local epidemics like meningitis shocks can reduce GDP growth rates by between 2% and 4.3% in the absence of any inflows of disaster aid; a potential reduction in GDP growth from an average of 6% between 1995 and 2008 in the meningitis belt region by World Bank estimates to an average of 1.7% to 4% over the same period. Further work should be done to quantify the magnitude of the epidemic effect and the role of more efficient targeting in improving the mitigation efforts.

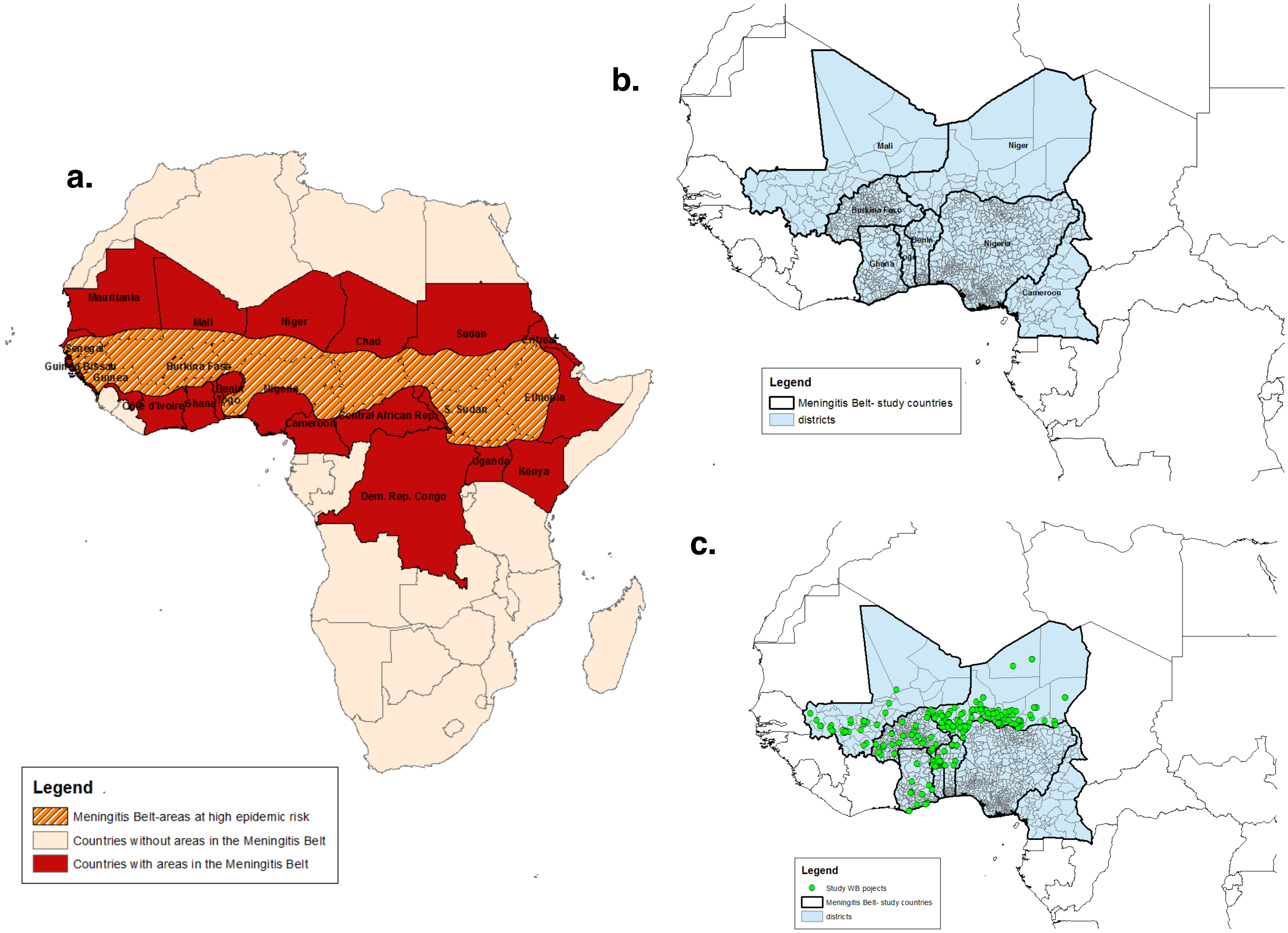


Figure 1: Countries in the African Meningitis Belt (a), with districts in study region (b) and locations of World Bank aid projects for countries and districts in study region over study years (c)

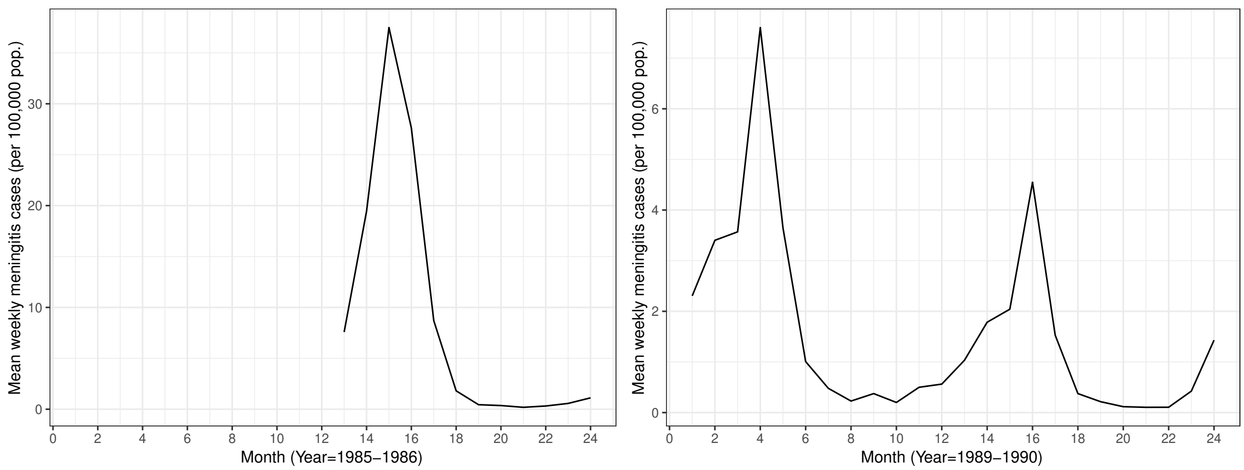


Figure 2: Meningitis Epidemic Curves (Niger)

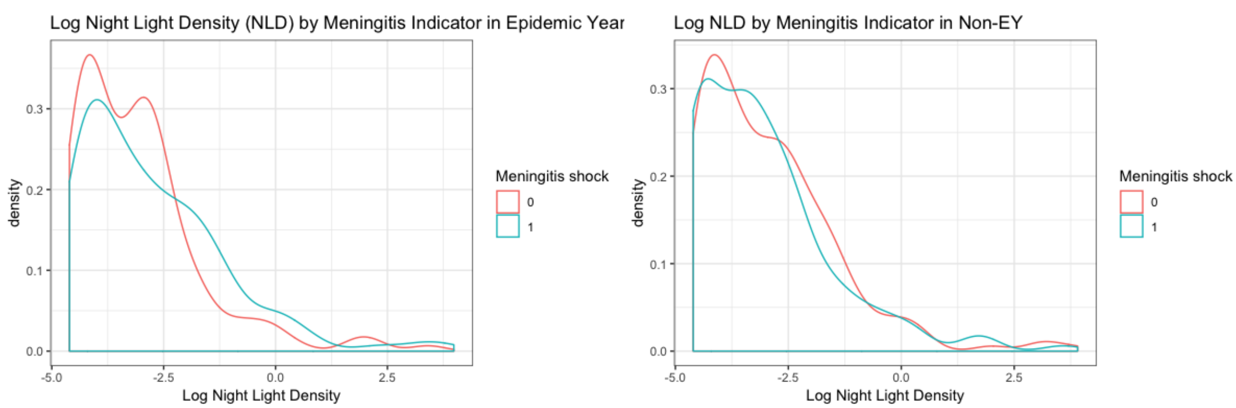


Figure 3: Stochastic dominance: Log night light density is higher in meningitis shock districts during declared epidemic year (EY). Lower in non-epidemic years

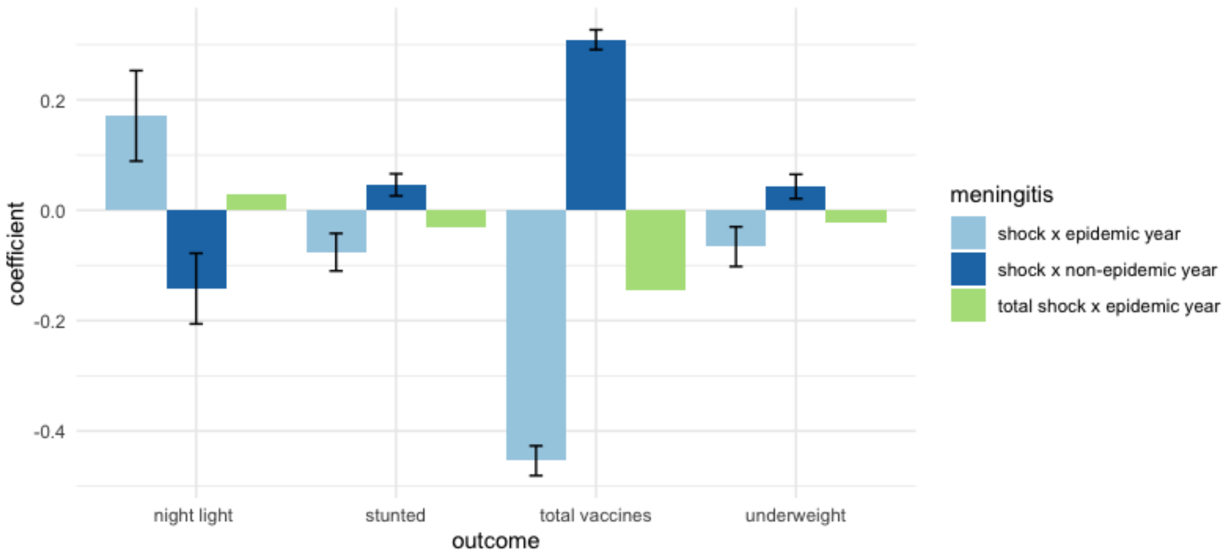


Figure 4: More economic activity, Less stunting and underweight children currently, if born in high meningitis shock districts but year was declared an epidemic year. In high shock, non epidemic year districts, lowered economic activity, and more stunting and underweight. Potential crowd-out of routine vaccines during epidemic years

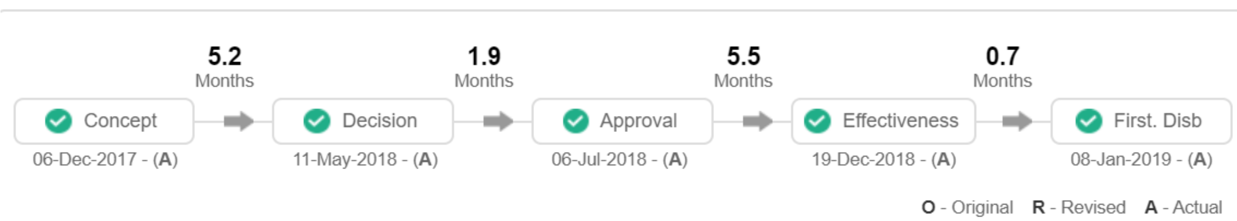


Figure 5: World Bank project approval example snapshot

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
			District Level Night Light Data		
Meningitis Shock (Z)	1,141	0.36	0.48	0.00	1.00
Meningitis Cases (/100,000)	1,220	6.35	13.34	0.00	145.19
Epidemic Year	1,329	0.39	0.49	0	1
Log Night Light Density	1,329	−2.74	1.71	−4.61	3.98
Share Muslim	1,302	0.75	0.36	0.00	1.00
Share Muslim x Hajj	1,302	0.05	0.22	0.00	1.00
			DHS Child Level Data		
Infant Mortality	16,486	0.38	0.49	0.00	1.00
WFA z	17,401	−1.54	1.33	−5.99	5.72
HFA z	17,401	−1.47	1.63	−6.00	5.89
Underweight	17,401	0.38	0.48	0.00	1.00
Stunted	17,401	0.36	0.48	0.00	1.00
BCG	22,401	0.61	0.49	0.00	1.00
Nos. Polio	22,422	1.45	1.31	0.00	3.00
Nos. DPT	22,323	1.38	1.34	0.00	3.00
Measles	21,979	0.42	0.49	0.00	1.00
Nos. Total Vacc.	21,806	3.83	3.33	0.00	8.00
			World Bank Project Level Data		
Health Project	556	0.12	0.33	0	1
Comm. Total, USD	556	55,657,922	28,851,034	5,302,687	238,620,908
Comm. Health, USD	556	6,068,739	17,204,611	0	68,215,861
Comm. Non-Health, USD	556	49,589,183	33,754,342	0	238,620,908
Disb. Total, USD	547	47,585,463	26,440,235	1,987,862	310,653,294
Disb. Health, USD	547	5,503,057	15,818,254	0	61,602,090
Disb. Non-Health, USD	547	42,082,406	30,213,919	0	310,653,294
Project Duration	547	6.117	1.412	1.000	11.000
IEG Outcome	301	3.98	1.24	1.00	6.00

Table 2: WHO recommended vaccination schedule

	Vaccine	Diseases	Age
1	BCG	tuberculosis	at birth
2	Polio (OPV)	polio	at birth, 6, 10, 14 weeks
3	DPT	diphtheria, pertussis, tetanus	6, 10, 14 weeks
4	Measles	measles	9 months

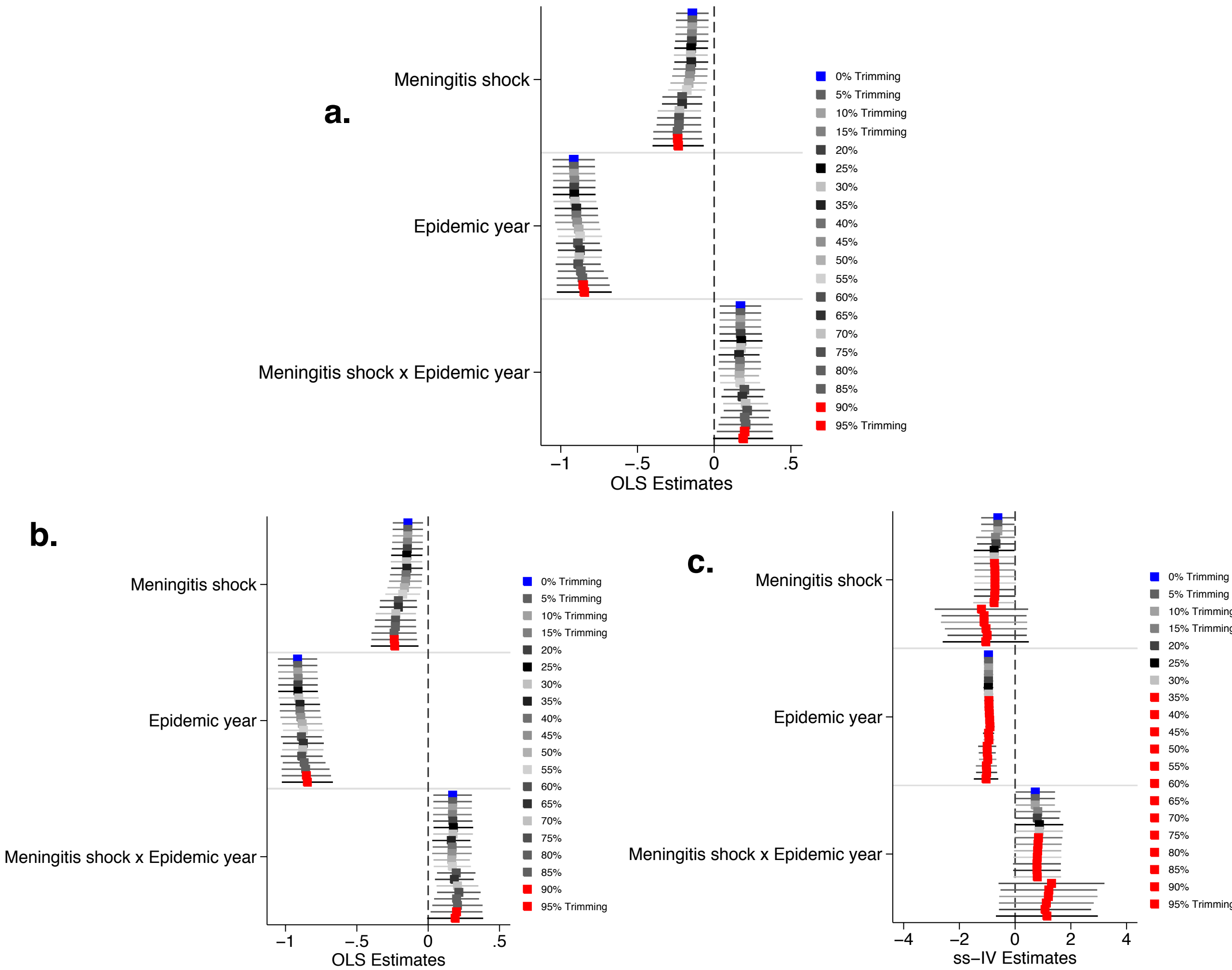
Top 5 WB Project titles by Epidemic year and Health classification	Health project= 0	**Health project=1**
Epidemic year= 0	• Transport sector project • Transport sector program support project • Urban infrastructure rehabilitation project • Transport infrastructure rehabilitation project • Local urban infrastructure development project	• Community action program • Social fund • Health, fertility and nutrition project
Epidemic year=1	• Road Transport project • Pilot private irrigation promotion project • Post-Primary education • Regional Hydropower development project • Village infrastructure project	• Health sector development program • Economic recovery and adjustment credit (ERAC) project

Figure 6: Top 5 World Bank health and non-health projects funded by project title in epidemic and non-epidemic years

Table 3: Balance on geographic and institutional characteristics

	Panel A: Geographic Characteristics					
	Malaria	Land Suitability	Elevation	Access to Rivers	Distance to Sea Coast	Distance to Capital
	(1)	(2)	(3)	(4)	(5)	(6)
Meningitis shock average	−1.680	−0.007	18.696	−0.077	−22.516	−19.465
	(3.214)	(0.081)	(51.375)	(0.339)	(57.331)	(131.928)
Mean of outcome	22.204	0.325	374.821	0.467	128.404	404.695
Observations	242	239	242	242	242	242
R^2	0.576	0.503	0.554	0.094	0.322	0.250
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Geographic and Institutional Characteristics					
	Share Muslim	Pastoral	Centralization Index	Centralization Dummy	Diamond	Petrol
	(1)	(2)	(3)	(4)	(5)	(6)
Meningitis shock average	−0.218	−0.025	−1.182	−0.419	0.009	0.002
	(0.149)	(0.052)	(0.867)	(0.437)	(0.100)	(0.007)
Mean of outcome	0.688	0.026	1.288	0.721	0.012	0.004
Observations	236	764	768	768	242	242
R^2	0.536	0.191	0.078	0.055	0.092	0.025
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions estimated by OLS. Robust standard errors clustered by district in parentheses. Observations at the district level in all specifications except Panel B for the centralization and pastoral outcomes, where observations are districts intersected with Murdock ethnicity regions. 'Meningitis shock average' is the likelihood that a district is a meningitis shock district over the period of study. Land suitability is land suitability for agriculture from FAO data. Elevation is mean elevation in km from the Global Climate database. Distance to capital and seacoast in km. Malaria stability is from the malaria ecology index from Kiszewski et al. (2004). Share muslim is based on DHS data. Access to River is an indicator for whether or not a district has a river running through it. Centralization index is the level of precolonial centralization from Murdock ethnicity data (?) and Centralization dummy is an indicator that equals 1 if the index is greater than 0 (following Archibong (2019)). Pastoralism dummy equals 1 if pastoralism was primary contributor to livelihood in precolonial ethnic region from Murdock data. Petrol and diamond are indicators equal to 1 if the district has recorded deposits of petroleum and diamonds respectively from the PRIO dataset. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.



Notes: Figure plots the distribution of estimates under various trimming values. Regressions (a total of 20) are estimated by OLS. Dependent variable is child health outcome (i.e., weight-for-age WFA z) as described in text in (a) and log night light density in (b) and (c). Meningitis shock is z-score indicator based on district level mean. Models include both district and country-by-year fixed effects. Robust standard errors in parentheses clustered by district. 90% confidence intervals are shown by horizontal lines, separately for each regression. Color codes: blue denotes the baseline model (with no trimming), and red denotes insignificant estimates for the main interaction term- showing the trimming level that interaction term turns insignificant.

Figure 7: Selective Migration Tests: (a) OLS effect of meningitis shock on child health in epidemic vs non-epidemic years with trimming of highest weight-for-age (WFA z) in meningitis affected districts; (b) OLS effect of meningitis shock on economic activity in epidemic vs non-epidemic years with trimming of highest nighlights in affected districts; (c) ss-IV- effect of meningitis shock on economic activity in epidemic vs non-epidemic years with trimming of highest nighlights in affected districts

Table 4: Effect of meningitis shock on economic activity in epidemic vs non-epidemic years (Models: country x year FE and district specific time trends)

	Log Night Light Density			
	(1)	(2)	(3)	(4)
Meningitis shock	-0.075^{**}	-0.065^{*}	-0.142^{**}	-0.142^{*}
	(0.033)	(0.036)	(0.036)	(0.088)
Meningitis shock x Epidemic year			0.171^{**}	$0.159^{\cdot}$
			(0.082)	(0.099)
Mean of outcome	-2.741	-2.741	-2.741	-2.741
District FE	Yes	Yes	Yes	Yes
Country x year FE	No	Yes	Yes	NA
Year FE	NA	NA	NA	Yes
Linear time trends (D)	NA	NA	NA	Yes
Observations	1,141	1,141	1,141	1,141

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district.Two models estimated with country-year FE in columns (1) to (3) and district specific time trends in column (4) as described in text. The Epidemic year coefficient is omitted in the model with country x year FE. The Epidemic year coefficient in column (4) with district time trends is -0.030 and insignificant at conventional levels. Dependent variables are log night light density described in text from 8 African countries from 1992 to 2008. Meningitis shock is Z score indicator based on district level mean as described in text. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level. $\cdot$ Significant near 10 percent level with p 0.1.

Table 5: Effect of meningitis shock on child current weight and height outcomes, at/near birth (bcg, polio, dpt) vs non-at/near birth recommended (measles) child vaccinations, total vaccinations and infant mortality in epidemic vs non-epidemic years (Model: country x year FE)

	Child Weight		**Child Height**		**Child Vaccination**					**Infant Mortality**
	WFA z	Underweight	HFA z	Stunted	BCG	Nos. Polio	DPT	Measles	Total Vaccines	Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Meningitis shock	−0.176**	0.043*	−0.178**	0.046**	0.047**	0.120**	0.118*	0.014	0.309*	−0.009
	(0.081)	(0.022)	(0.079)	(0.020)	(0.018)	(0.060)	(0.061)	(0.037)	(0.166)	(0.018)
Epidemic year	−0.217**	0.061*	−0.543***	0.157***	0.048**	0.164**	0.145	0.113***	0.461**	−0.055***
	(0.101)	(0.036)	(0.126)	(0.037)	(0.022)	(0.075)	(0.091)	(0.041)	(0.216)	(0.019)
Meningitis shock x Epidemic year	0.288**	−0.066*	0.301***	−0.076**	−0.068**	−0.198**	−0.167	−0.024	−0.454*	0.009
	(0.119)	(0.036)	(0.114)	(0.034)	(0.027)	(0.094)	(0.103)	(0.052)	(0.261)	(0.021)
Mean of outcome	−1.583	0.388	−1.476	0.362	0.591	1.375	1.328	0.406	3.674	0.374
Mother's controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,032	15,032	15,032	15,032	19,581	19,606	19,548	19,258	19,151	15,141

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variables are child outcomes described in text from 8 African countries. Mother's controls include mother's age at birth and level of education. Country x year fixed effects (FE) are country x survey year FE. Meningitis shock is Z score indicator based on district level mean as described in text. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 6: Effect of meningitis shock on child current weight and height outcomes, at/near birth (bcg, polio, dpt) vs non-at/near birth recommended (measles) child vaccinations, total vaccinations and infant mortality in epidemic vs non-epidemic years (Model: district specific time trends)

	Child Weight		**Child Height**				**Child Vaccination**			**Infant Mortality**
	WFA z	Underweight	HFA z	Stunted	BCG	Nos. Polio	DPT	Measles	Total Vaccines	Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Meningitis shock	-0.245^{**}	0.041	-0.156^{*}	0.044^{**}	0.065^{***}	0.183^{***}	0.174^{***}	0.035	0.476^{***}	-0.009
	(0.103)	(0.027)	(0.082)	(0.020)	(0.016)	(0.062)	(0.064)	(0.033)	(0.160)	(0.018)
Epidemic year	-0.245^{**}	0.072^{**}	-0.614^{***}	0.174^{***}	0.053^{**}	0.194^{**}	0.174^{*}	0.131^{***}	0.549^{**}	-0.058^{***}
	(0.103)	(0.036)	(0.119)	(0.037)	(0.022)	(0.076)	(0.091)	(0.042)	(0.216)	(0.020)
Meningitis shock x Epidemic year	0.353^{**}	-0.082^{*}	0.388^{**}	-0.100^{**}	-0.092^{***}	-0.293^{***}	-0.259^{**}	-0.067	-0.719^{***}	0.010
	(0.139)	(0.042)	(0.124)	(0.035)	(0.026)	(0.095)	(0.108)	(0.052)	(0.265)	(0.021)
Mean of outcome	-1.583	0.388	-1.476	0.362	0.591	1.375	1.328	0.406	3.674	0.374
Mother's controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends (D)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,032	15,032	15,032	15,032	19,581	19,606	19,548	19,258	19,151	15,141

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variables are child outcomes described in text from 8 African countries. Mother's controls include mother's age at birth and level of education. Linear time trends (D) are district specific time trends. Year FE are survey year fixed effects. Meningitis shock is Z score indicator based on district level mean as described in text. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 7: Effect of meningitis shock and epidemic year on share of World Bank health projects approved and amount committed and disbursed to World Bank projects

	Health Project		**Log Total Committed**				**Log Total Disbursed**			
	Health Project		Comm. Health		Comm. Non-Health		Disb. Health		Disb. Non-Health	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Meningitis shock		0.033		0.580		−0.557		0.734		−0.732
		(0.073)		(1.284)		(1.283)		(1.581)		(1.565)
Epidemic year	0.547*	0.661*	9.750*	11.760*	−10.880*	−12.860**	9.727*	11.910*	−11.160*	−13.350**
	(0.308)	(0.332)	(5.490)	(5.903)	(5.832)	(6.274)	(5.575)	(6.175)	(5.926)	(6.553)
Meningitis shock x Epidemic year		−0.271		−4.805		4.789		−4.959		4.978
		(0.195)		(3.455)		(3.626)		(3.707)		(3.870)
Mean of outcome	0.126	0.164	2.219	2.856	15.097	14.467	2.302	2.991	14.873	14.249
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends (D)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	213	278	213	278	213	269	204	269	204

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variable in columns (1) and (2) is an indicator that equals 1 if the project is classified as a health project as described in text. Dependent variables are log (1+ committed or disbursed amounts)for health and non-health projects in columns (3) to (10) as described in text from study countries. Meningitis shock is Z score indicator based on district level mean as described in text. Epidemic year is an indicator that equals 1 if the year in the study country is declared an epidemic year by the WHO. Linear time trends are district specific time trends. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 8: Effect of meningitis shock on night light density outcomes by World Bank aid share of health projects, and total committed and disbursed aid

	Log Night Light Density				
	(1)	(2)	(3)	(4)	(5)
Meningitis shock	−0.094*	−0.103*	−0.103*	0.767	−0.153
	(0.058)	(0.061)	(0.061)	(1.578)	(0.310)
Share health	0.055				
	(0.222)				
Comm. health		−0.130			
		(0.117)			
Disb. health			−0.131		
			(0.117)		
Comm. non-health				−0.002	
				(0.006)	
Disb. non-health					−0.002
					(0.007)
Meningitis shock x Share health	0.188*				
	(0.095)				
Meningitis shock x Comm. health		0.009*			
		(0.005)			
Meningitis shock x Disb. health			0.009*		
			(0.005)		
Meningitis shock x Comm. non-health				−0.010*	
				(0.006)	
Meningitis shock x Disb. non-health					−0.007
					(0.006)
Mean of outcome	−3.056	−3.056	−3.056	−3.056	−3.056
District FE	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes	Yes
Observations	147	147	147	147	147

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variable is Log night light density described in text from 8 African countries. Meningitis shock is Z score indicator based on district level mean as described in text. Results qualitatively similar with district specific time trends (D). ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 9: Effect of meningitis shock and epidemic year on duration and independent rating of World Bank aid projects

	Duration and Rating (IEG) of World Bank Projects					
	Duration			IEG		
	(1)	(2)	(3)	(4)	(5)	(6)
Meningitis shock		-0.075			0.091	
		(0.173)			(0.130)	
Health project			1.003***			0.708**
			(0.043)			(0.315)
Epidemic year	-1.214***	-1.366***	-0.969***	-2.042***	-2.165***	0.108
	(0.149)	(0.196)	(0.060)	(0.197)	(0.276)	(0.142)
Meningitis shock x Epidemic year		0.283			0.530	
		(0.443)			(0.484)	
Health project x Epidemic year			-1.462***			-5.004***
			(0.116)			(0.326)
Mean of outcome	6.428	6.402	6.428	3.977	3.976	3.977
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends (D)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	269	204	269	301	204	301

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variables are World Bank project independent evaluation group (IEG) ratings and duration of project outcomes described in text from study countries. Meningitis shock is Z score indicator based on district level mean as described in text. Linear time trends (D) and (C) are district and country level time trends respectively. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table 10: First and second-stage estimates for interacted Share Muslim x Hajj instrument and comparisons with OLS results for night light density

	Panel A: First-Stage Estimates					
	Meningitis Shock					
	(1)	(2)	(3)	(4)		
Share Muslim x Hajj	-15.314^{***}	-17.225^{***}	-17.176^{***}	-16.357^{***}		
	(2.910)	(2.902)	(2.867)	(3.897)		
Epidemic year and Shock x Year Interaction	No	Yes	Yes	Yes		
District FE	Yes	Yes	Yes	Yes		
Country x year FE	Yes	Yes	No	No		
Linear time trends (C)	No	No	Yes	No		
Linear time trends (D)	No	No	No	Yes		
F-Stat of Excluded Instrument	27.69	35.23	35.90	17.61		
Observations	1,114	1,114	1,114	1,114		
	Panel B: Second-Stage 2SLS vs OLS Estimates					
	Log Night Light Density					
		IV			OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Meningitis shock	-0.697^{*}	-0.620^{*}	-0.622^{*}	-0.065^{*}	-0.142^{**}	-0.124^{**}
	(0.420)	(0.364)	(0.365)	(0.036)	(0.036)	(0.060)
Epidemic year		-0.956^{***}	-0.199		-0.916^{***}	-0.010
		(0.099)	(0.148)		(0.083)	(0.054)
Meningitis shock x Epidemic year		0.725^{*}	0.704^{*}		0.171^{**}	0.142^{*}
		(0.431)	(0.421)		(0.082)	(0.073)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	No	Yes	Yes	No
Linear time trends (C)	No	No	Yes	No	No	Yes
Linear time trends (D)	No	No	No	No	No	No
Observations	1,114	1,114	1,114	1,141	1,141	1,141

Notes: Robust standard errors in parentheses clustered by district in all specifications. Meningitis shock is Z score indicator based on district level mean as described in text. Log night light density outcomes described in text from 8 African countries from 1992 to 2008. Linear time trends (C) and (D) are country and district specific time trends respectively. In Panel B, IV estimates from column (1) to (3) and OLS estimates from column (4) to (6). ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

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A Appendix (For Online Publication)

Contents

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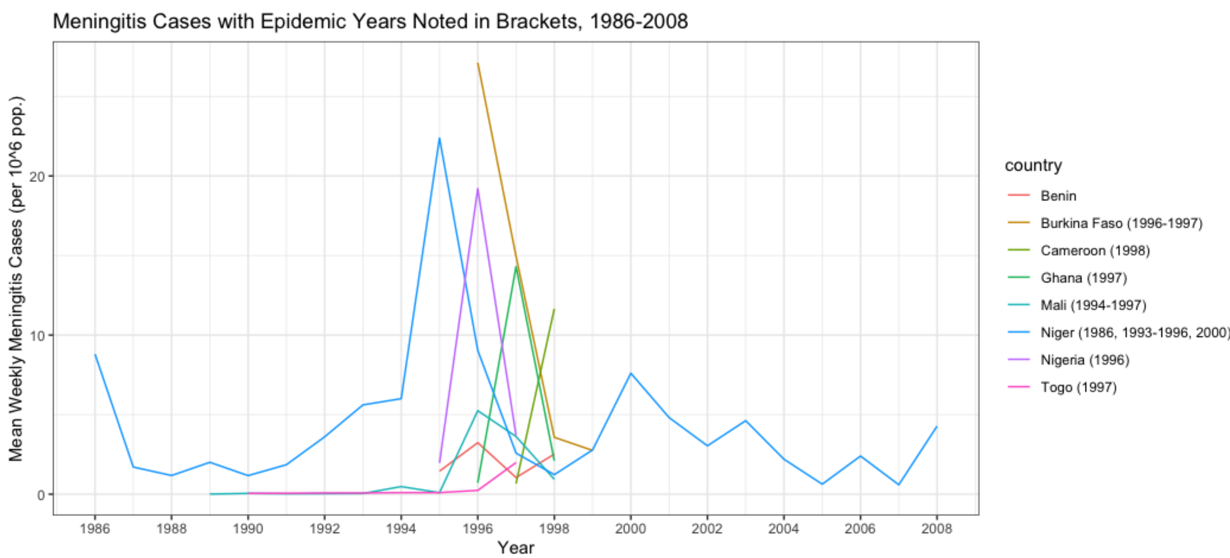

Figure A1: Mean weekly meningitis cases per district over study region, with epidemic years specified in brackets

A.1 Health Expenditures and Aid in the Meningitis Belt

Figure A2 and Figure A3 present health spending statistics for countries in the meningitis belt and study area. Table A1 reports results on the effects of meningitis epidemics on private health expenditures. There is a significant increase in prepaid private health expenditures[35] in the 20 meningitis belt study countries between 1995 and 2008. Domestic government health spending, in contrast, remains unchanged in response to epidemics. This is perhaps unsurprising given that government health spending accounted for just over 23% of health spending among meningitis belt countries, while out of pocket expenditures made up 47%

[35]Prepaid private spending includes private insurance and non-governmental agency spending.

of total health spending as of 2017 by World Bank estimates. Meningitis epidemics are a notable negative income shock to households in the belt. Given that these shocks pose a significant private cost to households and the fact that 20% of health spending in the belt comes from external, donor sources, do these donors/lenders respond with increased financing to belt countries during epidemics?

Table A2 reports results on the effects of epidemics on ODA aid flows committed to meningitis belt countries. There is no effect of epidemic year declarations on total aid committed to belt countries during the epidemic year as shown in column (2). The share of aid committed to health or to infectious disease control in particular is not significantly associated with epidemic year declarations as shown in column (1). On the other hand, epidemic year declarations are strongly positively associated with the total amount committed to infectious disease control and the share of infectious disease spending in total aid committed in the following year as shown in column (3) and column (4) of Table A2. National government donor aid agencies are very slow to respond to epidemics in recipient countries. Additionally, there is no increase in overall aid committed in the following year, suggesting targeted increases in infectious disease spending only and potential crowd-out of non-health spending following an epidemic year.

In contrast, international financial organizations like the World Bank are quicker to respond to epidemic declarations with crisis financing as shown in Table 7. The World Bank funds more health projects during epidemic years, and increases the total amount committed and disbursed to countries during the epidemic year. The results do not show the same lag in funding from the Bank as in the national government donor agencies. There is similar crowd-out, with World Bank aid funding distributing away from non-health projects towards health projects.

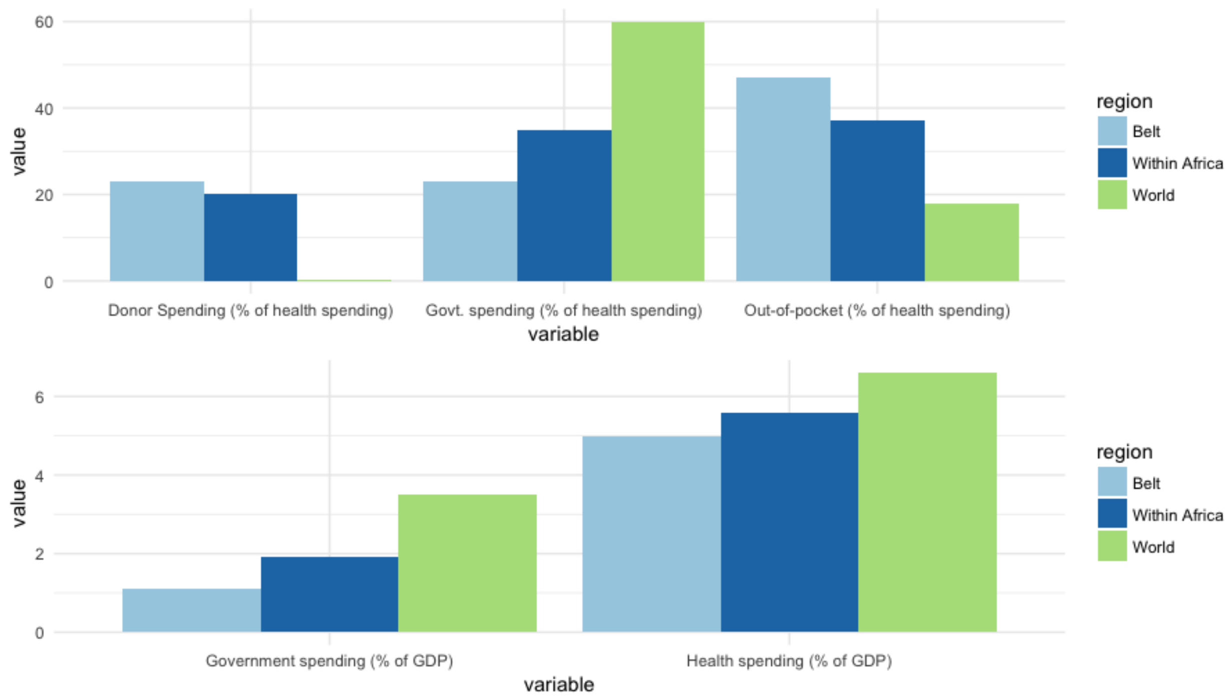

Figure A2: Health spending statistics in meningitis belt region, 2017. Source: World Bank

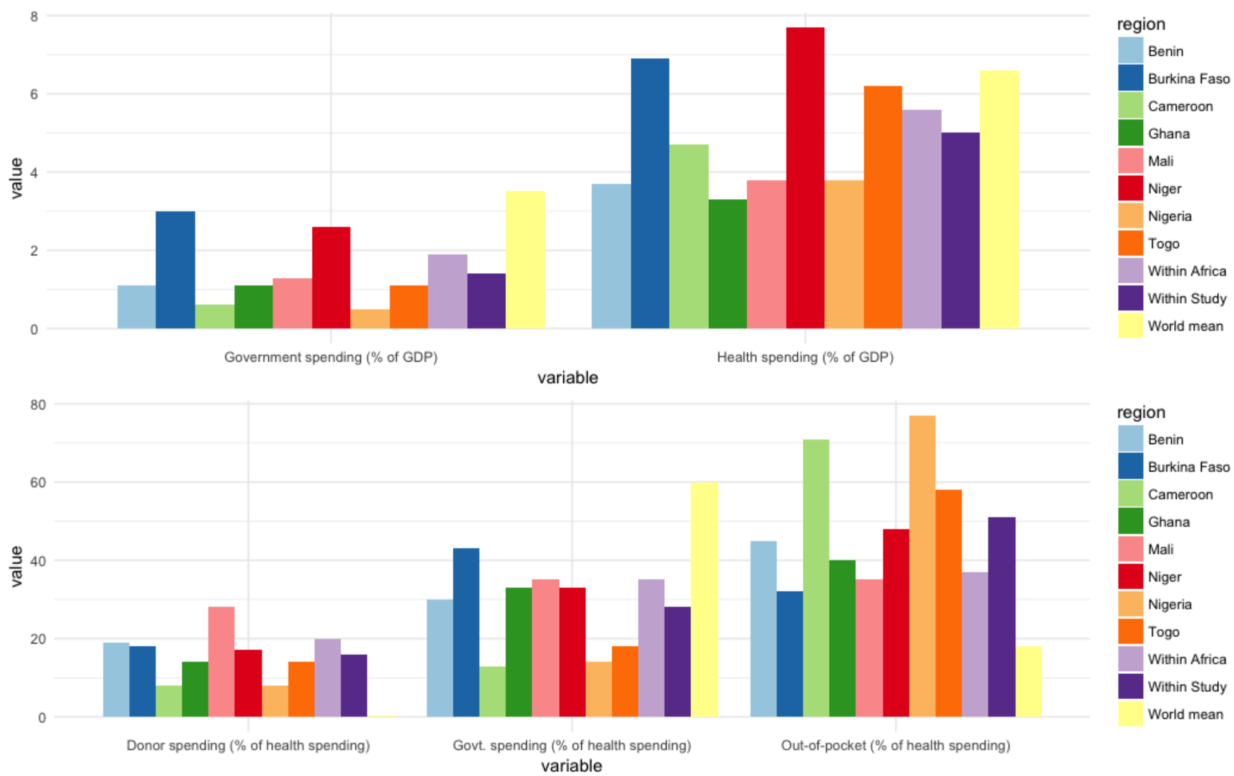

Figure A3: Health spending statistics across study regions, 2017. Source: World Bank

Table A1: Reduced Form Relationship Between Epidemic Year and Health Expenditures for Meningitis Belt Countries, 1995-2008

	Panel: Prepaid Private Spending (PPP) and Government Health Spending (GHES)					
	PPP/THE	PPP/GDP	PPP/CAP	GHES/THE	GHES/GDP	GHES/CAP
	(1)	(2)	(3)	(4)	(5)	(6)
Epidemic Year	0.005*	0.0003**	0.455**	0.014	0.001	1.471
	(0.003)	(0.0001)	(0.198)	(0.016)	(0.001)	(1.136)
Mean of outcome	0.038	0.002	2.510	0.285	0.015	22.626
Observations	107	107	107	107	107	107
R^2	0.970	0.938	0.975	0.810	0.827	0.893
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions estimated by OLS. Robust standard errors in parentheses. Observations are 20 meningitis belt countries for which data is available over 1995 to 2008 including: Benin, Burkina Faso, Cameroon, CAR, Cote d'Ivoire, DRC, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Mali, Mauritania, Niger, Nigeria, Senegal, Sudan, and Togo. CAP is per capita. GDP is per GDP in 2015 USD PPP. Country and year fixed effects included in all specifications. Source: Global Burden of Disease Health Financing Collaborator Network. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table A2: Effect of meningitis epidemics on ODA aid flows committed to belt countries, 1995-2008

	Concurrent Spending, t			**Spending, t+1**		
	Infectious/Total	Comm. Total	Comm. Infectious	Infectious/Total	Health/Total	Comm. Total
	(1)	(2)	(3)	(4)	(5)	(6)
Epidemic Year	−0.003	−0.033	0.895***	0.005**	−0.008	−0.153
	(0.003)	(0.091)	(0.331)	(0.003)	(0.010)	(0.100)
Mean of outcome	0.009	20.430	14.446	0.009	0.064	20.420
Observations	78	112	60	60	91	91
R^2	0.609	0.920	0.818	0.557	0.406	0.950
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regressions estimated by OLS. Robust standard errors in parentheses. Observations are 20 meningitis belt countries for which data is available over 1995 to 2008 including: Benin, Burkina Faso, Cameroon, CAR, Cote d'Ivoire, DRC, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Mali, Mauritania, Niger, Nigeria, Senegal, Sudan, and Togo. $ConcurrentSpending$ is same year spending in columns (1) and (2). $Spending, t+1$ is spending in the following year. Comm. Total is log (total committed real (2010) dollars). Comm. Infectious is log (1+ total committed real dollars to infectious disease control). Source: OECD CRS data ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

A.2 Hajj Months and IV Framework, Robustness

We propose a shift-share IV approach, a common strategy for estimating local labor market impacts of migration (Altonji and Card, 1991). This alternative strategy allows us to determine the amount of potential bias from our OLS strategy (bounding the bias), and assess the role of unobserved confounds (e.g., unobserved trends) in inducing bias.

The intuition behind the instrument draws on research in epidemiology and public health on the role of the Islamic Hajj in meningitis outbreaks (Lingappa et al., 2003; Shafi et al., 2008; Yezli et al., 2016), and a related literature in economics linking cultural practices to health outcomes (Almond and Mazumder, 2011). We hypothesize that districts with large shares of Muslims, who happen to be attending the Hajj at the beginning of a meningitis outbreak cycle or epidemic curve, may not experience meningitis shocks. As discussed in Section 2.1, the meningitis outbreak cycle or epidemic curve, shown in Figure 2, generally follows a sinusoidal pattern; cases typically begin in the first month of the year in the dry season in January, and peak around March, with the case load declining rapidly with the onset of the rainy season in June.

A combination of social distancing from lowered numbers of people in districts around the Hajj at the beginning of an outbreak cycle, and increased mandatory vaccination rates for Hajj travelers from the meningitis belt at Mecca could significantly decrease infection rates in a district over the course of the cycle, resulting in a 'flattened' epidemic curve as discussed in Section 4(Yezli et al., 2016; Shafi et al., 2008). Large numbers of Muslims leaving for Hajj at the beginning of an epidemic cycle could, thus, reduce the likelihood of a district experiencing a meningitis shock.

The validity of such shift-share instrument has been explored in previous work (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2018). We discuss concerns for identification below. Specifically, our instrument interacts variation in Muslim shares with variation in the Hajj calendar month as follows:

$$\text{Share Muslim x Hajj}_{dct} = \sum_{n=1}^{N} s_{ndc} \times h_t \tag{4}$$

where s is the share of the district's population n that is Muslim interacted with h, an indicator that equals one if the Hajj happens to fall at the beginning of a meningitis outbreak cycle in January in a given year t. Meningitis Shock (and its interaction with epidemic year) in Equation 1 is replaced with their predicted versions derived based on the instrument. While our instrument is a standard instance of shift-shares, our innovation comes from finding an interesting and context-relevant shift- Islamic Hajj- that plausibly influences the distribution of meningitis.

A.2.1 Design and Validity Checks

I. Exogeneity (identifying assumption): For causal interpretation of the impact of the "epidemic effect" , the instrument for meningitis must be orthogonal to characteristics that are correlated with nightlights and child health, conditional on county by year and district fixed effects:

$$E(\text{Meningitis Sh}\widehat{\text{ock} \times} \text{Epidemic Year} \times \epsilon | \mu, \delta) = 0$$

While the exclusion restriction is not directly testable, we conduct placebo tests, documenting that the Hajj variation is uncorrelated with nightlights[36].

II. Validity of the Hajj (shift)-Muslim (share) instrument: Previous researchers have

[36]Child health outcomes omitted as not estimable due to lack of data over the Hajj time period. Results are in Table A4 in Appendix A.2.

demonstrated that if the "shares" are endogenous, then the shifters can provide exogeneity provided the Hajj shocks are not correlated with shocks to nightlights other than meningitis (Borusyak, Hull, and Jaravel, 2018). First, this seems plausible based on our placebo tests for identification in Equation 2.

Second, we construct another instrument, (Share Muslim $\times$ $Hajj_{dct})^2$, in addition to the baseline instrument, and then conduct an over-identifying test on the null hypothesis that the estimated impact of the epidemic effect on nightlights are statistically not different from each other. We fail to reject this over-identifying test for validity (Hansen's J statistic, $p > 0.67$), indicating that the results are generated by Hajj shocks that are plausibly uncorrelated with shocks in nightlights.

Table A3: Hajj Months, 1986-2008

	year	hajj month
1	1986	august
2	1987	august
3	1988	july
4	1989	july
5	1990	july
6	1991	june
7	1992	june
8	1993	june
9	1994	may
10	1995	may
11	1996	april
12	1997	april
13	1998	april
14	1999	march
15	2000	march
16	2001	march
17	2002	february
18	2003	february
19	2004	february
20	2005	january
21	2006	january
22	2007	december
23	2008	december

Table A4: Reduced form estimates interacted Share Muslim x Hajj instrument at start (January) vs peak (March) of epidemic curve

	Meningitis Shock				Log Night Light Density			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Muslim x Hajj (Jan)	−15.314***	−15.755***			10.675	8.738		
	(2.910)	(3.644)			(7.825)	(9.118)		
Share Muslim x Hajj (March)			0.016	1.032**			−0.024	0.359***
			(0.118)	(0.437)			(0.086)	(0.125)
Mean of outcome	0.318	0.318	0.318	0.318	−3.096	−3.096	−3.096	−3.096
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	No	Yes	No	Yes	No	Yes	No
Linear time trends (C)	No	No	No	No	No	No	No	No
Linear time trends (D)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,114	1,114	1,114	1,114	1,302	1,302	1,302	1,302

Notes: Regressions estimated by OLS. Robust standard errors in parentheses clustered by district. Dependent variables are Meningitis shock is Z score indicator based on district level mean as described in text in columns (1)-(4) and log night light density described in text from 8 African countries from 1992 to 2008 in columns (5)-(8). Linear time trends (C) and (D) are country and district specific time trends respectively. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table A5: Placebo tests for Hajj month's exogeneity (=First-Stage)

	Meningitis Shock				
	(1)	(2)	(3)	(4)	(5)
Share Muslim x Hajj	-17.230^{***}			-23.140^{***}	-16.520^{***}
	(2.902)			(4.606)	(2.749)
Share Muslim x Hajj m+1		3.426		13.450^{**}	
		(3.729)		(5.289)	
Share Muslim x Hajj m+1			8.353		6.138
			(7.393)		(7.397)
Controls: Epi year +					
Menin. Shock x Epi year	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,141	1,109	1,104	1,109	1,104

Notes: Regressions are estimated by OLS. Dependent variable is Meningitis shock, a z-score indicator based on district level mean as described in text. Models include both district and country-by-year fixed effects. Robust standard errors in parentheses clustered by district. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level based on clustered standard errors in parentheses.

A.3 Migration and Inference Robustness

Table A6: Internal Migration Statistics for Selected Countries in the Meningitis Belt, 1988-1992, Source: Bocquier and Traore (1998)

Country	ACMI (4-yr avg)	NIMR (%)			
		Capital city	Principal towns	Secondary towns	Rural
Burkina Faso	0.03	1.86	0.29	-0.79	-0.09
Cote d'Ivoire	0.16	0.43	-2.24	-2.74	0.99
Guinea	0.05	1.21	-1.94	-2.14	-0.04
Mali	0.09	0.85	0.31	0.23	-0.19
Mauritania	0.08				
Senegal	0.12	0.5	0.36	-0.6	-0.25
Niger	0.06	-0.06	0.91	-0.22	-0.04
West Africa (8)	0.09	0.8	-0.39	-1.04	0.06
Sample years	1988-1992	1988-1992	1988-1992	1988-1992	1988-1992

Notes: ACMI is the aggregate crude migration intensity ratio described in the text. NIMR is the net internal migration rate in percentages. It is calculated for each region. Regional classification of 'principal' or 'secondary' towns differs for each country and is based on population size. For Niger, principal towns are regional capital cities, and secondary towns are all remaining settlements of over 5000 people (Beauchemin and Bocquier, 2004).

Table A7: Inference Robustness: Effect of meningitis shock on economic activity in epidemic vs non-epidemic years

	Log Night Light Density			
	Clustered SE (D)	Robust SE	Wild cluster-bootstrap (D)	Two-way clustered SE (D, Y)
	(1)	(2)	(3)	(4)
Meningitis shock	-0.142^{**}	-0.142^{***}	-0.142^{**}	-0.142^{**}
	(0.036)	(0.043)		(0.058)
	[0.028]	[0.001]	[0.021]	[0.016]
Epidemic year	-0.916^{***}	-0.916^{***}	-0.916	-0.916^{***}
	(0.083)	(0.110)		(0.037)
	[0.000]	[0.000]	[0.170]	[0.000]
Meningitis shock x Epidemic year	0.171^{**}	0.171^{***}	0.171^{**}	0.171^{**}
	(0.082)	(0.062)		(0.077)
	[0.037]	[0.006]	[0.029]	[0.028]
Mean of outcome	-2.741	-2.741	-2.741	-2.741
District FE	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes
Observations	1,141	1,141	1,141	1,141

Notes: Regressions estimated by OLS. Dependent variable is log night light density described in text from 8 African countries from 1992 to 2008. Meningitis shock is z-score indicator based on district level mean as described in text. Alternative standard errors reported in parenthesis. p-values are reported in brackets. Reported p-values for wild bootstrap clustered at either one- or two-ways and derived from running 1000 replications. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table A8: Inference Robustness: Effect of meningitis shock on child health (weight-for-age WFA z) in epidemic vs non-epidemic years

	WFA z			
	Clustered SE (D)	Robust SE	Wild cluster-bootstrap (D)	Two-way clustered SE (D, Y)
	(1)	(2)	(3)	(4)
Meningitis shock	-0.176^{**}	-0.176^{***}	-0.176^{**}	-0.176^{*}
	(0.081)	(0.042)		(0.104)
	[0.030]	[0.000]	[0.028]	[0.093]
Epidemic year	-0.217^{**}	-0.217^{***}	-0.217^{**}	-0.217
	(0.101)	(0.056)		(0.247)
	[0.032]	[0.000]	[0.045]	[0.379]
Meningitis shock x Epidemic year	0.288^{**}	0.288^{***}	0.288^{**}	0.288^{**}
	(0.119)	(0.061)		(0.121)
	[0.017]	[0.000]	[0.027]	[0.018]
Mean of outcome	1.583	1.583	1.583	1.583
District FE	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes
Observations	15,032	15,032	15,032	15,032

Notes: Regressions estimated by OLS. Dependent variable is child health outcome (i.e., weight-for-age WFA z) described in text from 8 African countries from 1992 to 2008. Meningitis shock is z-score indicator based on district level mean as described in text. Alternative standard errors reported in parenthesis. p-values are reported in brackets. Reported p-values for wild bootstrap clustered at either one- or two-ways and derived from running 1000 replications.. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.

Table A9: Placebo tests for Epidemic year's exogeneity

	Log Night Light Density				
	(1)	(2)	(3)	(4)	(5)
Meningitis Shock	-0.142^{**}	-0.044	-0.0474	0.118^{**}	-0.124^{**}
	(0.064)	(0.033)	(0.029)	(0.056)	(0.049)
Meningitis shock x Epidemic year	0.171^{**}			0.202^{**}	0.181^{**}
	(0.082)			(0.093)	(0.084)
Meningitis shock x Epidemic year t+1		-0.049		-0.098	
		(0.070)		(0.083)	
Meningitis shock x Epidemic year t+ 2			-0.034		-0.046
			(0.098)		(0.101)
Mean of outcome	-2.741	-2.741	-2.741	-2.741	-2.741
District FE	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,141	1,141	1,141	1,141	1,141

Notes:Regressions are estimated by OLS. Dependent variable is log night light density described in text from 8 African countries from 1992 to 2008. Meningitis shock is z-score indicator based on district level mean as described in text. Models include both district and country-by-year fixed effects. Robust standard errors in parentheses clustered by district. ***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level based on clustered standard errors in parentheses.