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a thesis

by

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Abstract

This thesis contains three self-contained papers on issues of policy relevance for developing countries in the areas of health and political economy.

In the first paper, by using the exogenous measure of physical intensity of natural disasters, I study the impacts of natural disasters on child mortality. Cross-country data on a global scale is employed to examine the impacts of both geophysical and meteorological disasters on under-5 mortality rates, using the difference-in-differences, and dynamic panel method. Overall, disasters have no discernible effects on mortality. Once the income levels of countries are considered, disasters are found to affect the children only in low-income countries, and the effects are persistent. The results are indicative of a lower GDP and vaccination rates amongst children, along with increased maternal mortality and disease incidences in low-income countries as a plausible explanation.

In the second paper, by using rainfall as a proxy for agricultural income, I study the effects of income shocks on under-5 mortality at a sub-national level, using the difference-in-differences method. Rainfall is found to have a positive relationship with agricultural output in developing countries, thereby justifying the use of rainfall as a proxy for agricultural income. Results reveal that rainfall shocks lead to small, but statistically significant increases in mortality overall. However, the low-income group of countries that are primarily reliant on agriculture are affected the most due to rainfall fluctuations. Districts that lie downstream to dams that may have access to reservoir water are insulated from

the vagaries of rainfall. Results remain robust to the consideration of various relevant issues such as selective fertility, selective migration, and measles immunization rates, along with various other robustness tests. Concerns addressed in the first and second essays may be worse in developing countries, generally, due to rampant inequality and the role that institutions play in exacerbating it.

In the third paper, I study the rent-seeking behaviour exhibited by politicians in a developing world context. By using the constituency data from Indian state elections, the thesis shows that powerful politicians engage in distributive politics in their elected constituencies. In this study, the focus is on the leaders of state governments i.e. chief ministers in India. Using nightlights as a proxy for local economic activity, we identify that during the tenure of chief ministers, their elected constituencies see a statistically and economically significant increase in nightlight activity. Results are driven by non-birth regions of chief ministers, confirming that the effect in play is political expediency, rather than ethnic favoritism.

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Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Signature

Author: Sundar Ponnusamy Date: November 17th, 2021

Dedication

To my brother and mentor Senthil, in Heaven,

And to my beautiful family, to whom I owe everything.

Chapter 1

Introduction

Improving the child health is a major policy concern, especially in the developing world context. Even though the young population (aged 0–14 years) constitute only 28% of the global population (WDI, 2019), more than 80% of the global illnesses and casualties registered are due to global climate changes and the resulting income fluctuations attributable to children (WHO, 2009). In an era when global warming is a major phenomenon and global climate is changing at a pace more rapid than most scientific forecasts (IPCC, 2018), it becomes essential to understand its consequences on child health. Unfortunately, the number of studies using reliable measures that focus on the effects of climate change (especially on the consequences of natural disasters) and income fluctuations (due to weather changes) on child health is limited.

In the first two papers of this thesis, I focus on two different factors that can have a major influence on child health – natural disasters due to rising global warming, and income fluctuations due to rainfall shocks, and their effects on child mortality. In identifying the effects of extreme weather events, key problem researchers have faced is the lack of exogenous measures of natural disasters. A similar type of problem is prevalent in the studies that analyzed the effect of income shocks on health due to the existence of a feedback loop between the two (Gallup and Sachs 2001; Deaton 2002). Higher-income leads to better health outcomes; this, in turn, leads to enhanced income opportunities. Hence, there is a reverse causality concern which leads to biased estimates if traditional measures to income such as GDP per capita are used to measure income fluctuations. I overcome these issues generally encountered in the previous studies by applying an exogenous measure of natural disasters in the first paper, and rainfall as quasi-random shocks to agricultural income in the second paper.

In the final paper of the thesis, I examine the rent-seeking behaviour exhibited by politicians in a developing world context. A role of politicians is to act as a countervailing force to mitigate the effects of negative extremities arising due to market failures, natural events, and so on. However, instead of acting in the public interest, politicians might engage in distortionary activities based on their self-interest. This can come in the form of the misallocation of public resources to their favoured districts or constituencies to boost their future electoral prospects (Golden and Min 2013; Hodler and Raschky 2014). Along with identifying the effects of natural disasters, and income shocks on child mortality, this thesis also examines the distortionary behaviour exhibited by politicians.

In the first paper, I examine the effects of natural disasters on under-5 mortality at a global cross-country level, using panel data on 92 countries. Child mortality data from UNICEF (2019) is used as the outcome variable. Most studies have relied on natural disaster data from the EM-DAT index. However, this index suffers from endogeneity issues due to the self-reported nature of the damage from disasters by the respective countries (Hsiang and Jina, 2014). Moreover, disasters in poor countries are less likely to be reported than disasters in the developed countries, which makes this index less suitable for analyzing disasters' impacts in the developing world context (Felbermayr and Gröschl, 2014). To identify the impacts of disasters more precisely, I rely on the GeoMet (geophysical and meteorological) database developed by Felbermayr and Gröschl (2014), which contains information on the physical intensity of six different types of disasters, that provides a variation that is plausibly exogenous to economic or societal outcomes.[1] Results reveal that, overall, there is no discernible effect of disasters on child mortality. However, once income levels of countries are taken into consideration, disasters lead to a significant increase in mortality only in low-income countries. Some key findings are – one standard deviation increase in the disasters cause an additional 6.77 deaths per 1000 live births; effects are found to be persistent, extending beyond the disaster year. Democratic institutions suffer less than non-democracies. Worsening of vital outcomes such as a lower GDP and vaccination rates, along with increases in maternal mortality and

[1] Geo-Met data provides information on six different types of individual disasters–earthquakes, storms and hurricanes, floods, droughts, volcanic eruptions, and extreme temperatures at the country level. GeoMet data also provides a weighted index constructed as a weighted average of all six disasters, adjusted for their standard deviations, and weighted by the country size.

children receiving diarrheal treatment are identified as potential transmission mechanisms in low-income countries. Results remain robust to various tests employed. To conclude, natural disasters are found to have severe impacts only on children in poor countries.

In the second paper, I analyze the effects of income fluctuations on under-5 mortality, at a sub-national level, using panel data on 94 developing countries. A newly available data for child mortality at the district level (second-level administrative unit) from Burstein et al. (2019) is applied. A majority of the population in developing countries relies upon agriculture as the means on livelihood (Jayachandran, 2006) and thereby relies upon rainfall. Due to scarcity of agricultural output data at a sub-national level, I rely on macro-level data on the agricultural output to first establish the relationship between rainfall and agricultural output. Then, by using rainfall shocks as the proxy for agricultural income, I examine the effects of income shocks on child mortality. Findings reveal that better rainfall years lead to a decrease in child mortality and drought periods lead to an increase in child deaths, overall. Once the income classification of countries are considered, low-income countries are affected the most. I also find that the districts that lie downstream to dams that may also have access to stored reservoir water during drought periods suffer less from negative income shocks. These results are not driven by wealthier states (first-level administrative units), allaying any endogeneity concerns. Effects of rainfall fluctuations are found to be persistent, for up to three years following the shock. To summarize, children in poor countries are affected significantly due to rainfall fluctuations and the provision of water resources acts as a potential mechanism to alleviate the effects of droughts.

In the third paper, I test whether there is evidence of redistributive politics in Indian state election settings, by considering nightlights measured from outer space as a proxy for local economic activity (Henderson et al., 2012). I test whether leaders of state governments i.e. chief ministers (CMs) engage in distributive politics towards their elected constituents, under a difference-in-differences setup. The elected constituency of the CMs act as treated units, while everything else as control units. I find evidence that CM constituencies during their tenure experience a 13% increase in luminosity compared with the untreated constituencies, however, no such effect is seen in the years leading to a CM tenure or post-tenure. Contrary to the existing literature, I find that the effects are driven by non-birth constituencies of CMs, providing us an insight on the mechanism at play is political expediency rather than ethnic favouritism as shown in Hodler and Raschky (2014). The neighbours that also align with national parliamentary constituencies (federal constituencies), which share a strategic value are the ones to experience increases in nightlight activities. These results indicate that powerful politicians not necessarily involve in distributive politics based on their ethnic background, rather the future electoral benefits might also be a motivating factor. As children in poor countries are identified to suffer the most due to natural disasters and rainfall shocks in the first two papers, the third paper provides evidence that politicians might redirect resources based on their self-interest and away from the people in need.

The remainder of the thesis is organized as follows. The second chapter investigates the effects of natural disasters on child mortality for a global set of developing and developed countries, while also discussing some of the potential transmission mechanisms. The third chapter examines the effects of rainfall shocks on child mortality for a set of developing countries and also investigates the role of water infrastructure in alleviating the detrimental effects of droughts. In the fourth chapter, I analyze the rent-seeking behaviour exhibited by powerful politicians in a developing world context. The final chapter of the thesis concludes by providing a summary of the thesis' findings and respective contributions to the literature along with relevant policy issues.

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Chapter 2

Natural Disasters and Missing Children[†]

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Contribution to the Paper	I came up with the topic after performing a detailed literature review. Then collected the data and performed the analysis and written the manuscript. I had full-pledged guidance from my panel which helped me improve the work vastly from the initial stages.		
Overall percentage (%)	100%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	10/3/2021

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

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ii. permission is granted for the candidate in include the publication in the thesis; and

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Please cut and paste additional co-author panels here as required.

Abstract

Using an exogenous measure of natural disasters based on physical intensities, I examine their impact on child mortality. I find that children, mostly, in poor countries are affected — a one standard deviation increase in the natural disaster index leads to an additional 6.77 deaths per 1,000 live births in the disaster year. The impact is long lasting, extending beyond the disaster year. I provide suggestive evidence of the potential mechanisms driving these effects, namely, lower GDP and vaccination rates among children, along with an increased maternal mortality and disease incidence in low-income countries due to disasters. Using an endogenous measure of disasters based on damage records from insurance data leads to severe underestimation of the disaster impact. The results are robust to the use of mortality rates from multiple sources, different functional forms, and an extensive dynamic panel specification as well as various other tests.

Keywords: Natural disasters; child mortality; environmental costs

JEL Classification: J13, Q54

2.1 Introduction

Natural disasters are a growing phenomenon across the world, and with global temperatures predicted to increase by around 1.5 degrees over pre-industrial era levels in the coming decades (IPCC, 2018), weather-related disasters will become more frequent if current trends persist (NASA 2005; Van Aalst 2006). While the young population (aged 0–14 years) constitutes only 28% of the total world population,[1] children account for more than 80% of illnesses and the resulting casualties among those affected due to natural disasters (WHO, 2009). Climate-induced risks not only make children more vulnerable, but also threaten to impede a country's development, with the possibility of undoing the improvements made in child health and well-being in recent decades (WHO 2010; UNICEF 2015). Despite the urgent need to understand the effects of disasters on child health, studies focusing solely on children are still lacking (Helldén et al., 2021), while the existing evidence is either mixed or inconsistent (Jeffers and Glass 2020; De Oliveira et al. 2021). In this study, I examine the potential impact of natural disasters (both geophysical and meteorological) on under-5 mortality rates (children aged 0–5 years; hereafter U5MR) in different economic and institutional settings. I also explore some of the potential mechanisms behind this effect.

Previous studies on the effects of natural disasters on child health have primarily focused on individual disasters in a single-country context, such as droughts in Zimbabwe (Hoddinott and Kinsey, 2001), forest fires or tsunamis in Indonesia (Jayachandran 2009; Lépine et al. 2021), hurricanes in the United States (Currie and Maya, 2013) or heat waves in India (Banerjee and Maharaj, 2019). Existing studies at the global level have generally focused on economic growth (Felbermayr and Gröschl 2014; Hsiang and Jina 2014), with limited evidence on the impact of disasters on child mortality on a large scale.[2] Moreover, most studies have used the Emergency Database (EM-DAT) index constructed using damage records from insurance data or news stories. A major drawback of this index is that it suffers from an endogeneity issue due to self-reported disaster counts

[1] Based on data from WDI (2019) for the year 2010.

[2] Kudamatsu et al. (2012) focuses on the effects of rainfall shocks on infant mortality for a group of African countries.

and losses (Hsiang and Jina, 2014) as well as sample selection problems (Felbermayr and Gröschl, 2014), since disasters in high-income countries (HICs) have a higher chance of being reported than those in poor countries, making the prior estimates less precise. By overcoming these issues, this study makes three major contributions to the literature. First, I study the impact of natural disasters on child mortality on a large scale, for a global set of developed and developing countries. Second, I use the database of physical intensities of all disasters developed by Felbermayr and Gröschl (2014), which provides a variation that is plausibly exogenous to economic or societal outcomes. Finally, I focus on the potential mechanisms behind the impact of the disasters.

To measure the U5MR, the outcome variable of interest, I source mortality data from UNICEF (2019), which provides national-level mortality estimates. A panel dataset of 92 countries for 1979–2010 is used.[3] To measure disasters, I rely on the GeoMet database developed by Felbermayr and Gröschl (2014), which contains information on the physical intensity of six types of individual disasters along with two (unweighted and weighted) indices constructed as an aggregate of all the individual disasters. Considering natural disasters as natural experiments (once the geographical factors of the respective countries are controlled for), I employ a linear specification to measure the effects of natural disasters on child mortality, while allowing for a set of control variables commonly used in the literature. Based on the findings, aggregate-weighted disaster indices have no discernible effects on mortality rates for the overall sample.

Low-income countries (LICs) do not face a higher magnitude of disasters than middle-income countries (MICs) or HICs.[4] However, once I consider the income classification of countries (based on the World Bank's (2010) classification), it is clear that the children, mostly, in LICs are affected—a one standard deviation (henceforth, SD) increase in the weighted disaster index leads to a 4.37% increase in the U5MR (i.e., an additional 6.77 deaths per 1,000 live births in the disaster year). On the contrary, disasters have limited or no effect on children in MICs and HICs.[5] Based on individual disaster intensities,

[3]As a robustness check, I employ child death data from three additional sources: WDI (2019), the WHO (2017), and Rajaratnam et al. (2010).

[4]Refer to the summary statistics of the GeoMet index in Table 2.5 (rows 4–6) in the appendix.

[5]This corroborates some previous findings in the literature. For example, Burgess et al. (2013) note

storms and earthquakes have significant adverse impacts on child mortality in LICs. In contrast, estimates based on the endogenous EM-DAT index (a measure of disasters based on damage records from insurance data) are only one-third of the estimates based on the GeoMet index for LICs, stressing the importance of using exogenous measures of disasters to estimate their impacts more precisely.

Not only the income levels of institutions, but also their political status may play a role. While better-quality institutions proxied by their democratic status are found to have robust and positive effects on economic growth (Doucouliagos and Ulubaşoğlu 2008; Acemoglu et al. 2019), ambiguity exists in the relationship between democracies and child mortality. For example, Navia and Zweifel (2000) show that child mortality is lower in democracies than in autocracies, whereas Ross (2006) argues that the political status of a country does not affect child mortality. Therefore, to provide insights into the role of institutional quality, I examine the effects of disasters in democracies and non-democracies. The findings suggest that autocracies suffer the most.

Further, several studies have identified that in-utero shocks suffered during the fetal stage lead to cognitive and developmental defects among children later (e.g., Barker 1995; Deschenes et al. 2009; Almond and Currie 2011; Simeonova 2011; King et al. 2012). Therefore, I also examine the long-run effects of natural disasters on child mortality in LICs by testing the effects of lags of disasters on contemporaneous child deaths. The findings suggest that the effects of disasters are long term, extending for up to four years following the disaster. This provides some evidence on children's exposure to extreme events in their fetal stage, or the destruction of local infrastructure and the resulting long-term consequences that might be at play. I also examine the effects of aggregate disasters at its various percentiles on the U5MR. It is evident that larger disasters result in higher child mortality in LICs.

Finally, I explore some of the potential mechanisms that might explain why natural

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that weather shocks have a large effect on income in developing countries, where large proportions of the population are reliant on agriculture. In health literature, Kudamatsu et al. (2012) shows that income shocks increase infant mortality in African countries, whereas Banerjee and Maharaj (2019) estimates that high temperature shocks during in-utero stage leads to higher infant deaths in rural India, where the majority of income is derived from agriculture.

disasters have a negative impact on children in LICs. First, I examine the effects of disasters on macro-level GDP per capita (data from WDI (2019)), which might affect a country's ability to provide health resources to the public during need (Kim, 2013). The estimated results suggest that disasters are negatively associated with macroeconomic activity only for LICs.[6] The second mechanism I explore is the effect on other health-related measures, such as maternal mortality, child vaccination rates, and children receiving diarrheal treatment, which are strong predictors of the overall state of the public health system as well as child health (WHO 2005; Levine and Rothman 2006). Disasters are associated with the worsening of these vital outcomes only in LICs. Natural disasters are also found to be linked to the spread of communicable diseases in LICs; however, the estimates are to be taken with caution because of the small sample size. The main results for LICs, that is, the effects of disasters on the U5MR, remain robust to conditioning on various health-related covariates such as immunization rates, maternal mortality, public health expenditure, fertility rates, and drinking water accessibility. Other related issues such as selective fertility and migration concerns are also addressed later.

A minor contribution of this study is the exploration of secondary effects of disasters. Internal displacement in the aftermath of disasters,[7] and the resulting lack of access to public health facilities and water resources, along with the outbreak of communicable diseases are some of the key contributors of secondary impacts (Callaghan et al. 2007; Watson et al. 2007; Murthy and Christian 2010; Kouadio et al. 2012). In this study, by using mortality data from Rajaratnam et al. (2010), in which deaths from large disaster years (at least one death per 10,000 population) are replaced with the mean of empirical measurements, I examine the impact of disasters to identify the secondary effects. Results suggest that a one SD increase in the weighted disaster index leads to a 1.90% increase in child deaths in LICs. Therefore, the secondary effects of disasters account for over 40% of the total impact in the disaster year.[8]

[6] These results are in line with Felbermayr and Gröschl (2014), who finds that natural disasters have strong negative effects in poor countries.

[7] For example, around 30.7 million people (accounting for nearly 75% of the total internal displacement) were internally displaced in 2020 due to natural disasters (IDMC, 2020).

[8] I also perform an additional robustness exercise by controlling for the past lags in the dependent variable, subject to a standard, linear dynamic panel model. To account for any potential bias in the

The closest paper to the current study is by Kahn (2005), who shows that poor countries suffer more direct deaths due to natural disasters, and democracies provide a shield. However, there are some major differences between Kahn (2005) and this study. First, instead of direct deaths in a general population, I focus on the mortality rates of children by accounting for both secondary and long-term effects. Second, I use an exogenous measure of natural disasters that takes due care of the selection bias inherent in the EM-DAT index used in the Kahn's work. Third, I provide insights into potential mechanisms behind the impacts of natural disasters. There is limited evidence on the impact of natural disasters on the mortality rates of children at the global, cross-country level, using an exogenous measure of natural disasters. This question is important especially in an era of increasing natural disasters, as it is vital to understand who will be affected the most.

The remainder of this paper is organized as follows. Section 2.2 details the relevant literature, Section 2.3 describes the data and estimation method, Section 2.4 presents the results and Section 2.5 concludes.

2.2 Literature Review

There is a widespread agreement that greenhouse emissions due to human activities will have drastic effects on the future generations through channels such as increases in the global temperatures, rising sea levels and a higher frequency of natural disasters (Deschenes et al. 2009; Currie and Deschenes 2016). Children are one of the most vulnerable groups in a society and therefore more likely to be severely affected due to the climate change (Currie and Deschenes, 2016). While children constitute more than 80% of the illnesses due to the climate change (WHO, 2009), the Currie study further notes that children in the developing countries (henceforth, DCs) will suffer the most as 85% of the world's youth lives in DCs.

A growing recent literature in public health focuses on the effects of disasters on various child health outcomes. Hoddinott and Kinsey (2001) in their early and well-

estimates, I employ the GMM estimator developed by Arellano and Bond (1991). Results remain robust to the consideration of GMM specifications as well. To conserve space, the detailed discussion on the methodology and findings are provided in the online appendix.

cited work have shown that 1994-95 droughts in Zimbabwe have resulted in severe child stunting among the children aged 12-24 months old. Whereas Kudamatsu et al. (2012) have noted that negative rainfall shocks led to an increase in infant mortality, based on a group of 28 African countries, and increases in malarial incidences and malnutrition are potential channels. Children exposed to 1997-98 extreme floods in Ecuador during the third trimester are found to be highly likely to be born with lower birth height and weight (Rosales-Rueda, 2018). And in a most recent work, Lépine et al. (2021) identified the 2004 Indian ocean tsunami to have increased the under-5 mortality in the medium run.

On the effects of extreme temperatures on child health, Deschenes and Moretti (2009) found that heat and cold waves led to an immediate increases in mortality in the US, especially the effects due to extreme cold waves are long lasting. Several studies have also focused on the in-utero temperature shocks and child health. In the study by Banerjee and Maharaj (2019), heat waves during pregnancy are found to be responsible for around 2 deaths per 1000 live births, the set of effects only seen in rural India where infrastructure facilities are lacking. Likewise, in rural Colombia, even moderate heat waves during pregnancy are found to reduce the birth weight of newborns by around 4.1 grams (Andalón et al., 2016). Whereas, forest fires in late 1997 in Indonesia that led to an increase in the air pollution are found to be responsible for around 15,600 missing children based on the 2000 Indonesian census (Jayachandran, 2009).

In a strand of literature on the effects of cyclones on child outcomes: Anttila-Hughes and Hsiang (2013) uses Filipino household level data and finds that typhoons are responsible for around 13% of the overall infant mortality in Philippines in the post-disaster year. The Anttila-Hughes study further adds that the post-disaster year deaths outnumber the immediate deaths by 15-to-1, therefore it is essential to focus on the long-run effects of disasters as well. Likewise, Currie and Maya (2013) by using data on millions of individual birth records shows that children exposed to hurricanes during pregnancy have a higher chance of developing abnormal health conditions such as being on ventilator for 30 minutes longer and also more likely to develop meconium aspiration syndrome

(MAS). While there are few studies that have focused on the effects of geophysical disasters (earthquakes) on maternal stress and birth outcomes (Torche 2011; Kim et al. 2017; Menclova and Stillman 2020), evidences on child mortality are very limited. Chen et al. (2016) using the case of Haitian earthquake have noted that internal displacement is a major cause of the increase in infant mortality, and the children that are displaced and living in camps suffer the most.

Exposure to disasters in the previous month have also been found to cause increases in various illnesses such as diarrhea, fever, and several other respiratory issues, among the under-5 children in rural India (Datar et al., 2013). Not only the physical health, disasters have been found to cause major detrimental effects on other outcomes as well. Children exposed to disasters are found to display adverse mental health outcomes compared with the unexposed children (Becker-Blease et al., 2010). These effects on mental health are not just short-term. Using data from the US, Maclean et al. (2016) identifies that children who were exposed to natural disasters by age five display mental health disorders at their adult stage. In a strand of related literature, using individual level data from Latin America, Caruso (2017) finds that in-utero and young children are the most vulnerable to disasters and they suffer long-lasting effects such as lower human capital accumulation, worse health outcomes and also owns lower amount of assets when they are adults. Therefore, the effects of disasters can be persistent.

A major common factor associted with the above mentioned studies is, majority of them focus on individual disasters in a single country context. While there are some studies on a global scale on the disaster effects on economic growth, evidences on child health is seriously limited, especially using exogenous measures of natural disasters. This is also the major contribution of this study as I investigate the impacts of disasters for a global set of developed and developing countries, by using an exogeneous measure of disasters that contains information on the physical intensities of individual disasters. I also show that using endogenous measure of disaster can lead to a severe under-estimation of disaster's impacts. Considering that only a handful of studies explore the mechanisms behind the effects of disasters, I also focus on potential channels behind the disaster impacts in this study.

2.3 Data and Estimation Method

2.3.1 Data

The outcome variable of interest is the U5MR, expressed as the number of child deaths per 1,000 live births for a given year in log form. Mortality rates are sourced from UNICEF (2019) for 92 countries for the period 1979–2010.[9] Owing to the incomplete nature of vital registration systems, the number of child deaths in a country needs to be estimated using various other sources (French, 2016). To address this data scarcity issue due to a lack of administrative data, the UN Inter-agency Group for Child Mortality Estimation (UNIGME) estimates child mortality rates for a set of countries globally for UNICEF, the World Health Organization (WHO), and the World Bank.[10] Moreover, child death data from alternative sources, such as Demographic and Health Surveys, and Multiple Indicator Cluster Surveys, may be subject to issues such as sampling error and recall bias as well as methodological biases in extracting mortality rates from birth histories, especially for developing countries. Therefore, to correct for the inherent bias, modeling approaches are applied by UNIGME (2018) to smooth out irregularities.[11]

To enhance the credibility of the analysis, along with data from UNICEF (2019), I use data on mortality rates from three additional sources: WDI (2019), WHO (2017), and Rajaratnam et al. (2010). The mortality rates from these four sources are highly correlated with each other in the range of 0.991–0.999.[12] Moreover, the data from Rajaratnam et al. (2010) can be particularly useful for isolating the secondary effects of disasters, as the mortality rates for large disaster years (at least one death per 10,000

[9] Refer to A1 in the online appendix for the list of countries used in this study.

[10] If the current age-specific mortality rates prevail, they can also serve as an indicator of the probability that a new-born will die before reaching the age of five in a country (WDI, 2019), hence suggesting the current health status of a country.

[11] Along with the median rates that provide contemporaneous child deaths per 1,000 live births for a given year, UNICEF (2019) also provides 90% uncertainty bounds to account for any error in the mortality data. For the main analysis, median rates are used. As a robustness test, I use lower and upper bounds as well. A detailed discussion is provided later.

[12] Levine and Rothman (2006), Strulik (2004), French (2016), and Jamison et al. (2016) are some of the studies that have used mortality rates from these sources.

population) are considered to be mortality shocks, and replaced with the mean of the empirical measurements in the year of the shock.

The main goal is to identify the impact of natural disasters on child mortality. To measure natural disasters, I rely on the relatively new comprehensive database, which is also an exogenous measure of natural disasters, developed by Felbermayr and Gröschl (2014). Most studies that have analyzed the effect of natural disasters on developmental outcomes have used the EM-DAT database developed by the Centre for Research on the Epidemiology of Disasters. One of the main problems with the EM-DAT data is that the disaster counts and losses are self-reported, which means the quality of prior estimates that have used the EM-DAT index is affected by endogeneity (Hsiang and Jina, 2014). Moreover, disasters have a higher probability of being reported from HICs than LICs; therefore, there is selection bias inherent in the EM-DAT index (Felbermayr and Gröschl, 2014). And the nature that the EM-DAT index has been measured might be responsible for some of the empirical puzzles, therefore a comprehensive database of physical intensity measures might be required to establish the causal effects (Noy 2009; Cavallo et al. 2013).

To address these issues, Felbermayr and Gröschl (2014) created the GeoMet database containing the physical intensity of six types of natural disasters, namely, earthquakes, volcanic eruptions, storms, floods, droughts, and temperature extremes (heat/cold waves), recorded by geophysicists or meteorologists from 1979 to 2010. Along with information on individual disasters' physical intensities, the GeoMet data also provide two disaster intensity indices constructed as an aggregate of the individual disasters.[13]

One is a simple unweighted sum of disaster intensity measures, while the other is a weighted index constructed using the inverse of the SD of a disaster type within a country over all the years as precision weights. The weighted index ensures that no single disaster dominates the movement of the entire disaster index, which is preferable. Moreover, as the impact of natural disasters can differ by country size, both the indices (and the individual disaster intensities) are scaled by the size of the land area.[14]

[13]Refer to Felbermayr and Gröschl (2014) for a detailed description of the indices' construction.

[14]I also examine the direction and magnitude of the bias in the estimates when the endogenous EM-DAT index is used. Along with the physical intensity of disasters, Felbermayr and Gröschl (2014) provide the counts of disasters from the EM-DAT index weighted by country size.

Table 2.1: Summary Statistics

Variable	Mean	Standard Deviation	Source	Description
Panel A: Main Variables of Interest				
Under-5 Mortality Rates$_{i,t}$	63.50	66.32	UNICEF	Under-5 Mortality Rates, expressed as, the number of child deaths per 1000 live births
Disaster Index, Unweighted$_{i,t}$	0.013	0.020	GeoMet Data	Sum of disaster types scaled by land area.
Disaster Index, Weighted$_{i,t}$	0.012	0.023	GeoMet Data	Sum of disaster types weighted by the country-specific inverse of standard deviations by land area.
Floods$_{i,t}$	0.003	0.007	GeoMet Data	Positive difference in the total monthly precipitation over the average rainfall of the entire available time period (1979-2010).
Droughts$_{i,t}$	0.011	0.081	GeoMet Data	One, if precipitation in three months in a row, or at least in 5 months a year is 50% below long-run monthly precipitation mean, zero otherwise, by land area.
Storms$_{i,t}$	0.003	0.004	GeoMet Data	Max. wind speed in knots by land area.
Earthquakes$_{i,t}$	0.002	0.003	GeoMet Data	Max. Richter scale by land area.
Absolute Temperature$_{i,t}$	0.006	0.030	GeoMet Data	Max. absolute difference in monthly temperature from long-run monthly mean, by land area.
VEI$_{i,t}$	0.009	0.050	GeoMet Data	Max. Volcanic Eruption Index by land area
Disaster Index, Weighted$_{i,t}$	0.00097	0.0021	EM-DAT Data	Count of all disasters in EM-DAT index, weighted by land area.
Panel B: Control Variables				
ln GDP per capita$_{i,t-1}$	8.213	1.361	PWT (7.0)	GDP per capita, PPP.
ln Population$_{i,t-1}$	9.529	1.241	PWT (7.0)	Total Population in thousands.
Polity Index$_{i,t-1}$	2.935	6.525	Polity IV (2010)	Polity scores range between -10 to +10.
Trade Openness$_{i,t-1}$	0.704	0.333	WDI (2019)	Imports plus exports over GDP.
Interest Rate$_{i,t-1}$	0.008	0.026	WDI (2019)	Real interest rate.
Domestic Credit$_{i,t-1}$	0.616	0.448	WDI (2019)	Domestic credit in banking sector (share of GDP).
Gross Capital Formation$_{i,t-1}$	0.052	0.201	WDI (2019)	Gross capital formation (share of growth).
Foreign Direct Investment$_{i,t-1}$	0.026	0.052	WDI (2019)	Foreign direct investment, net inflows (share of GDP).
Inflation$_{i,t-1}$	0.048	0.365	WDI (2019)	Inflation, Consumer prices.
Current Account Balance$_{i,t-1}$	-0.027	0.066	WDI (2019)	Current account balance (share of GDP).
Panel C: Other Outcome Variables				
Maternal Mortality$_{i,t}$	216.55	292.82	WDI (2019)	number of women who die from pregnancy-related causes per 100,000 live births.
Measles Immunization Rate$_{i,t}$	75.36	23.39	WDI (2019)	% of children (aged 12-23 months) who received measles vaccine before twelve months or anytime before the survey.
DPT Immunization Rate$_{i,t}$	76.24	24.26	WDI (2019)	% of children (aged 12-23 months) who received DPT vaccine before twelve months or anytime before the survey.
Diarrheal Care$_{i,t}$	32.08	19.12	WDI (2019)	% of under-5 children who received ORS package in the two weeks preceding the survey.
Communicable Diseases$_{i,t}$	25.05	23.41	WDI (2019)	Cause of death, by communicable diseases and maternal, prenatal and nutrition conditions (% of total)
Sanitation$_{i,t}$	39.89	33.16	WDI (2019)	People using at least basic sanitation services (% of population).
Safe Drinking Water$_{i,t}$	73.97	26.91	WDI (2019)	People using safely managed drinking water services (% of population).
Public Health Expenditure$_{i,t}$	3.370	2.138	WDI (2019)	Domestic general government health expenditure (% of GDP).
Urban Growth$_{i,t}$	2.658	2.046	WDI (2019)	Urban population growth (annual %).

Note: Table provides summary statistics for the entire sample of 92 countries. Panel A contains descriptive measures for the main outcome variable of interest (U5MR), and the independent variables of interest. Panel C provides information for other outcome variables used in the mechanism analysis.

Refer to Table 2.1 for the summary statistics and a short description of the child mortality variable, individual and aggregate disaster indices, and other related variables for the overall sample.

Finally, to identify the potential mechanisms, I examine the effects of disasters on various macro-level economic and health indicators, such as GDP per capita, maternal mortality, measles and DPT vaccination rates, children receiving diarrheal care (percentage of under-5s who received the ORS package), the spread of communicable diseases, sanitation proxied by the percentage of population with basic handwashing facilities including soap and water, the percentage of population with access to drinking water, public health expenditure (as a percentage of GDP) and urban population growth. All the variables are sourced from WDI (2019) and enter the regression in log form.

In this study, I analyze the impact of both the aggregated (unweighted and weighted) disaster indices and the individual disaster intensities on the mortality rates of children. Based on the literature, I control for the following variables in the main analysis: log GDP per capita, population, trade openness, polity index, interest rates, domestic credit, gross capital formation, foreign direct investment, inflation, and current account balance. As a robustness check, I condition on health-related variables, such as maternal mortality, immunization rates, public health expenditure, fertility rates, and drinking water accessibility.

2.3.2 Methodology

In the baseline estimation, I follow a simple, parsimonious model to estimate the effects of disaster, as follows:

$$Y_{it} = \alpha D_{it} + \beta X_{i,t-1} + \delta_i + \delta_t + \theta_i \times t + \eta_{it}, \tag{1}$$

Y_{it} refers to the log of under-5 mortality rates (U5MR). D_{it} is either the aggregated disaster index (unweighted or weighted) or the individual disaster intensities. To include the unobservable differences in the mortality rates between countries due to the different geographies or institutions, I control for the country-fixed effects, δ_i. To consider the common non-linear trends and period-specific shocks, I control for the year-fixed effects, δ_t. Moreover, each country may follow a specific trend due to country-specific health or economic policies. Therefore, I also allow for country-specific trends $\theta_i \times t$ in the specification. $X_{i,t-1}$ refers to the time-varying controls and are in the lag form to avoid reverse causation. η_{it} includes time-varying unobservable shocks to mortality rates.[15]

Considering that an exogenous measure of natural disasters is used in this study,

[15] As a robustness test, I use different specification forms of Equation 1: an elasticity model (both the mortality rates and the disaster index in the log form), a standard growth specification (mortality rates in growth form), and, finally, standardizing the disaster variable. The results remain robust in all cases and are provided in the online appendix.

Equation 1 is sufficient for consistently identifying the effects of disasters on child health (Wintoki et al., 2012), once the geographical factors and the state of the public health system of a country are accounted for. As a robustness exercise, I control for the past lags of the mortality rates in the specification, subject to a linear dynamic panel model. To account for any potential biases in the linear dynamic panel estimates, I employ the GMM estimator developed by Arellano and Bond (1991), while also performing necessary stationarity tests. The results remain robust to these alternative specifications as well. To conserve space, the detailed description of the methodology, potential biases inherent in the linear dynamic panel estimates, and the discussion of the findings are provided in Section A2.5 in the online appendix.

2.4 Results

2.4.1 Baseline Results

Employing a linear specification as outlined in Equation 1, I examine the effect of both the unweighted and weighted disaster indices on the U5MR, using all the countries as a whole, initially. Columns (1) and (2) in Table 2.2 contain the results for the unweighted disaster index, whereas the remaining columns provide the results for the weighted disaster index. Irrespective of the type of index used, the coefficients of disaster indices on the U5MR remain positive but insignificant. Based on the conditional specification in column (2), one standard deviation increase in the unweighted disaster index equates to a 2.32% increase in the U5MR, that is, 1.47 additional deaths per 1,000 births.[16] However, the unweighted disaster index in the first two columns does not take into account the weights of individual disasters. Next, I examine the effects of the weighted disaster index in the rest of the columns.

Column (3) provides the results for the weighted disaster index without any control or country-specific trend, whereas in column (4), I control only for country-specific trends.

[16] The percentage change for a one standard deviation increase in the disaster is calculated using the standard formula: $[(e^{\beta * SD}) - 1] * 100$ i.e., $[(e^{1.146*0.020}) - 1] * 100$ equating to 2.32%. Refer to column (2), Table 2.2 for the estimated beta coefficient (β) and Table 2.1 for the summary statistics of the unweighted disaster index for the overall sample. The estimated effect of 2.32% is equivalent to 1.47 additional deaths per 1,000 live births based on the mean under-5 mortality rates from Table 2.1.

In the last column, I control for both covariates and trends. Compared with the first two columns, the coefficients of the weighted disaster index in columns (3)–(5) are larger in magnitude, but statistically insignificant. Based on column (5), a one standard deviation increase in the weighted disaster index equates to a 2.81% increase in the U5MR, that is, 1.78 additional deaths per 1,000 births.[17] Later, I also control for some health-related covariates as a robustness check. The detailed discussion is provided in Section 2.4.7.

2.4.2 Samplewise Analysis

One of the focuses of this study is to identify whether the income level and status of a political institution play any role in the impact of natural disasters. Therefore, I split the sample into seven categories and provide the results for the samplewise analysis in Table 2.3. Column (1) contains the baseline results. Columns (2) and (3) present the results for developing (non-OECD) countries and industrialized (OECD) countries, respectively. Columns (4)–(6) provide the results for the countries classified based on their income level (low, middle, high), according to the World Bank's 2010 classification of countries by income.

Better-quality institutions (i.e., democracies) have an efficient allocation of resources in the marketplace and are more responsive to public demand in various significant areas, such as health, justice, and long-run economic growth, as discussed by Baum and Lake (2003). Moreover, political accountability is much higher in democracies, and governments take a proactive approach to counteracting the negative impact of disasters, resulting in fewer deaths (Kahn, 2005). Therefore, to investigate the hypothesis of a negative correlation between the quality of institutions and child mortality, I next analyze the effects of disasters by the political status of countries. To classify countries as democracies or autocracies, I rely on the new democracy indicator developed by Acemoglu et al. (2019), constructed using information from several sources. The results for democratic

[17]For the remainder of the paper, I use only the weighted disaster index for the reason outlined in the Data section as well as for brevity. Moreover, the data for gross capital formation, interest rates, domestic credit, and current account balance are missing for some years. Therefore, these variables are linearly interpolated using the 'ipolate' command in the 'Stata' software to include the missing values and to optimize the available data. As shown in columns (3)–(5) of Table 2.2, dropping the control variables has a negligible effect on the coefficients of the disaster index.

Table 2.2: Effect of Natural Disasters on the U5MR: Baseline Analysis

	(1)	(2)	(3)	(4)	(5)
Unweighted Disaster Index$_{i,t}$	0.799	1.146	-	-	-
	(0.663)	(0.769)	-	-	-
Weighted Disaster Index$_{,i,t}$	-	-	1.162	1.183	1.206
	-	-	(1.064)	(1.077)	(0.994)
ln GDP per capita$_{i,t-1}$	-	-0.099	-	-	-0.098
	-	(0.058)	-	-	(0.058)
Gross Capital Formation$_{i,t-1}$	-	-0.001	-	-	-0.001
	-	(0.017)	-	-	(0.017)
Polity Index$_{i,t-1}$	-	-0.001	-	-	-0.002
	-	(0.002)	-	-	(0.002)
ln Population$_{i,t-1}$	-	0.015	-	-	0.015
	-	(0.011)	-	-	(0.011)
Trade Openness$_{i,t-1}$	-	-0.039	-	-	-0.039
	-	(0.034)	-	-	(0.034)
Interest Rate$_{i,t-1}$	-	0.126	-	-	0.123
	-	(0.110)	-	-	(0.110)
Domestic Credit$_{i,t-1}$	-	-0.028	-	-	-0.028
	-	(0.029)	-	-	(0.029)
Foreign Direct Investment$_{i,t-1}$	-	0.110	-	-	0.111
	-	(0.210)	-	-	(0.210)
Inflation$_{i,t-1}$	-	0.023**	-	-	0.024**
	-	(0.009)	-	-	(0.009)
Current Account Balance$_{i,t-1}$	-	-0.125	-	-	-0.128
	-	(0.141)	-	-	(0.141)
Controls	No	Yes	No	No	Yes
Country-specific Trends	No	Yes	No	Yes	Yes
Observations	2,750	2,657	2,750	2,750	2,657
Number of Countries	92	92	92	92	92

Note: ** and *** denote significance at the 5% and 1% level, respectively. All the regressions control for both country- and period-fixed effects. Standard errors are clustered at the country level.

and non-democratic countries are provided in the last two columns of Table 2.3.

In Table 2.3, Panel A contains the results for the weighted aggregate disaster index and Panel B the results for the individual disaster intensities. The coefficients of the control variables are suppressed for brevity. As shown in column (1) of Table 2.3, the weighted disaster index has a positive, but insignificant effect on the U5MR; whereas out of the six individual disaster intensities (in Panel B), earthquakes have a significant detrimental effect on the U5MR. Once I divide the sample into OECD and non-OECD countries, the results for earthquakes are seen to be primarily driven by developing countries, with the coefficient being significant at the 1% level, whereas the impact of disasters on industrialized countries is smaller and insignificant. This shows that income channels may play a vital role here.

To explore the role of income channels further, I analyze the impact on countries grouped by their income. The results in columns (4)–(6) indicate that under-5s in LICs suffer the most, whereas the effect of disasters on the U5MR in MICs and HICs is close to zero. These findings corroborate some of the earlier studies that identified the effects of weather shocks to be adverse in developing countries (Kudamatsu et al. 2012; Burgess et al. 2013; Banerjee and Maharaj 2019). To interpret the coefficient in column (4), Panel A – a one SD increase in the weighted disaster index leads to a 4.37% increase in the U5MR for LICs.[18] Using the mean value of the dependent variable for LICs from Table 2.5 in the appendix, this equates to an additional 6.77 deaths per 1,000 live births in the disaster year.[19] Based on the last two columns, autocracies suffer the most (column (7)), while the effect of disasters for the democratic group of countries is negligible (column (8)). The results based on the political regimes of countries are in line with Navia and Zweifel (2000), who finds that better-quality institutions have lower child mortality. The results remain robust to conditioning on several health-related covariates as well, as discussed in Section 2.4.7.

[18] I perform a wild cluster bootstrap exercise for LICs that produces p-values correcting for the small number of clusters (Cameron and Miller, 2015), by using 'boottest' command in Stata by Roodman et al. (2019). The p-value of the weighted disaster index for LICs is 0.024 under this small sample robust inference exercise subject to 999 replications, providing further evidence of detrimental effects of disasters in LICs.

[19] To ensure that the results are not driven by any individual country for LICs, I drop one country at a time. The estimated effects of one SD increase in the disasters are in the range of 3.77%-4.87%, with all the p-values remaining under 5%. I also use the unweighted disaster index, instead of the weighted index, and examine the effects of the former on child mortality for LICs. A one-SD increase in the unweighted disaster index causes a 3.32% increase in the U5MR, i.e., an additional 5.15 deaths per 1,000 live births, with the estimate significant at 1%.

Table 2.3: Effect of Natural Disasters on the U5MR: Samplewise Analysis

	Baseline	Non-OECD	OECD	Low Income	Middle Income	High Income	Autocracies	Democracies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:								
Weighted Disaster Index$_{i,t}$	1.206	2.157	-1.621	7.131***	-0.011	-0.174	6.827***	-0.154
	(0.994)	(1.277)	(2.870)	(1.337)	(1.654)	(1.143)	(2.064)	(0.741)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73
Panel B:								
Individual Disaster Intensities$_{i,t}$								
Flood$_{i,t}$	-0.405	-0.231	-1.738	-0.121	-0.344	-0.527	-1.460	-0.315
	(0.554)	(0.607)	(1.865)	(1.951)	(1.649)	(0.315)	(1.294)	(0.393)
Drought$_{i,t}$	0.059	0.081	-0.165	-0.235	-0.021	0.058**	0.062	0.040
	(0.057)	(0.062)	(0.177)	(0.251)	(0.127)	(0.022)	(0.108)	(0.053)
Storms$_{i,t}$	4.635	5.277	-4.413	6.592***	-2.219	5.607	5.737	1.469
	(2.872)	(3.401)	(9.066)	(1.815)	(7.029)	(4.648)	(3.629)	(3.477)
Earthquake$_{i,t}$	12.011***	15.819***	2.427	17.969***	12.800	1.204	27.795***	0.800
	(4.186)	(5.028)	(6.541)	(3.933)	(10.239)	(4.725)	(7.104)	(4.300)
High Temperature$_{i,t}$	-0.208***	-0.189**	-0.048	-0.027	-0.268	-0.276***	0.078	-0.258
	(0.059)	(0.079)	(0.313)	(0.131)	(0.426)	(0.071)	(0.079)	(0.056)
Volcanic Activity$_{i,t}$	-0.106	-0.118	-0.329	-2.067	-0.085	-0.378	0.080	-0.045
	(0.063)	(0.076)	(0.271)	(1.926)	(0.082)	(0.306)	(0.162)	(0.043)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73

Note: ** and *** denote significance at the 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level.

Findings based on the individual disaster intensities in column (4) of Panel B indicate that earthquakes and storms drive the results in LICs. To provide a quantitative interpretation, a one SD increase in earthquake (storms) intensity leads to a 3.1% (2.16%) increase in the U5MR.[20] At their mean values, earthquakes (storms) result in an increase of 2.73% (1.99%) in the U5MR. At their 95th percentiles, earthquakes (storms) result in an increase of 4.22% (5.42%) in child mortality. Therefore, larger the magnitude of disaster impact, higher the effects on child mortality. The results for individual disaster intensities are also in line with some of the earlier work that noted that storms and earthquakes have a major detrimental effect on child health (Anttila-Hughes and Hsiang 2013; Currie and Maya 2013; Chen et al. 2016). To summarize the results, once I account for the income classification of countries, only LICs suffer in terms of child mortality due to natural disasters. In addition, the quality of political institutions matters in alleviating the detrimental impact of disasters on child health.[21]

A major problem associated with the GeoMet disaster index is that while the weighted disaster index takes into account the land size of the country, it does not take into account the population exposed to disasters. Even though the size of the population is already controlled for in the specifications, there could still be a bias in the impact of disasters due to the uncertainty in the size of the population exposed. To provide some insights into the heterogeneity in the impact of disasters based on the potential population exposure, I examine the effect of disasters in the group of LICs sorted by their median population (data from WDI (2019)). Based on the results, a one SD increase in the intensity of the weighted disaster index has an effect of 3.28% (6.32%) increase in the U5MR, in the below (above) median countries by population, with both the estimates being significant at the 5% level. Therefore, disasters have a larger effect in low-income countries with a higher

[20]For LICs, a one SD increase in earthquakes (storms) weighted by the land area is 0.0017 (0.0032). Refer to the last column in Table 2.1 for a short description of the variables. Using estimated coefficients of earthquakes and floods from Table 2.3, and the above reported SDs, estimated effects of the two disasters are calculated in percentages. Refer to Footnote 16 for a short description of the calculation.

[21]It is interesting to note that heat waves lead to a small reduction in mortality (1.17% decrease for one SD increase in extreme temperatures) in the HICs (Column (7), Panel B). This also indicates that extreme cold waves result in a higher child mortality, findings that are in line with Deschenes and Moretti (2009) who notes that extreme cold temperatures are responsible for 0.8% of average annual deaths in the US.

population count. I use population density instead of the total population for robustness, and the findings remain unchanged, i.e., the group of LICs with higher population density (above median) are affected the most.[22] These analyses provide some suggestive evidence into the impact of disasters based on the potential population exposure.

2.4.3 Using the EM-DAT Index

I examine the effects of disasters measured by the endogenous EM-DAT index to identify the direction of any bias. Along with the Geo-Met index, Felbermayr and Gröschl (2014) also provides the EM-DAT index scaled by the size of land area. To conserve space, the results are provided in Table A2, online appendix. While the estimates of disasters remain positive for LICs in column (4), Table A2, they become insignificant with higher standard errors. A one standard deviation increase in the EM-DAT disaster index leads to an increase of 1.6% in the U5MR, a severe underestimation compared with the estimates from the Geo-Met index.[23]

Compared with the 4.37% increase in child mortality for a one-SD increase in the weighted GeoMet index, the effects based on the EM-DAT index are only one-third in size. Compared with the estimates based on the unweighted GeoMet index (refer to Footnote 19), the magnitude of the EM-DAT index is only half. This signifies the need to use disaster indices without endogeneity or selection issues to identify the impact of disasters more precisely. Results from column (7) suggest that autocracies experience significant child deaths as a result of disasters if the EM-DAT index is used. Later, I analyze the impact of disasters measured by the GeoMet index (and also the EM-DAT index) on child mortality subject to a dynamic panel specification. To conserve space, the detailed discussion is provided in the online appendix.

[22] I also test the effect of disasters on the U5MR by using the lower and upper 90% uncertainty bounds of mortality rates from UNICEF (2019), instead of the median rates that have been used so far. The effects of the disaster index are 4.27% and 4.77%, respectively, for a one-SD increase in the disaster, with the estimates being significant at the 1% level.

[23] Refer to Table 2.5 in the appendix for the summary statistics of the EM-DAT index by countries' income classification.

2.4.4 Secondary Effects of Disasters

Next, to ensure that the estimates of natural disasters on child mortality are not sensitive to the use of data from other sources, I verify the results using data from three additional sources: WDI (2019), WHO (2017), and Rajaratnam et al. (2010). As shown in Table A3, online appendix, the results remain qualitatively robust for LICs (refer to column (4)).

Panel D of Table A3 contains results when the mortality rates from Rajaratnam et al. (2010) are used. As explained in the Data section, immediate deaths for large disaster years are replaced with the mean of the empirical measurements in this dataset by Rajaratnam et al. (2010). Therefore, the estimates for LICs are smaller, with a 1.90% increase in the U5MR (column (4), Panel D) for a one-SD increase in disasters, in comparison with the estimates based on the other three sources. As the immediate disaster deaths are replaced in this dataset, the 1.90% increase for LICs provides some suggestive evidence on the secondary effects of disasters, i.e., the effects extend beyond immediate deaths. Compared with the earlier findings for LICs from Table 2.3 (a total effect of 4.37%), the secondary effects account for over 40% of the total disaster impact. This set of analysis provides some insight into the magnitude of the secondary effects of disasters.

Next, I test the impact of disasters based on the interaction between the political status and income classification of countries. To conserve space, the results along with a short description of the findings are provided in the online appendix. The results for the gender-specific analysis and several other robustness tests, such as using different functional forms, controlling for conflict incidences, and issues of selective fertility and selective migration, are also discussed in Sections A2.1–A2.3 in the online appendix.

2.4.5 Detrimental Effect of Disasters at Different Percentiles

Larger disasters are more likely to create significant damage to economic activities and infrastructure (Felbermayr and Gröschl, 2014), which may translate into substantial impacts on child mortality. To investigate this hypothesis, I quantify the detrimental effects of disasters at its different percentiles on the U5MR for LICs and plot them as a graph in Figure 2.1.[24] Based on the graph, the 70th percentile of the disaster (which is also the mean value of the weighted disaster index for LICs) has an effect of 3.63% on the U5MR (i.e., an additional 5.62 deaths per 1,000 live births). Larger disasters have a much bigger impact on child mortality; for example, at the 95th percentile, disasters have an effect of 12.88% on the U5MR, an additional 19.94 under-5 deaths per 1,000 live births.

The curvilinear effect of disasters observed for the U5MR in Figure 2.1 is in line with Felbermayr and Gröschl (2014), who show that the effects of disasters on economic growth are non-linear, with larger disaster years leading to greater economic losses. This can result from the stronger non-linear association between the direct losses in assets and physical intensity of disasters, or the association between asset and output losses. For example, if larger disasters lead to a significant destruction of public health facilities or an enormous internal displacement of people, then there would be higher mortality as well. As a robustness test, I extend Equation 1 to include a non-linear (quadratic) specification of the weighted disaster index, and the results remain robust.[25]

2.4.6 Are the Effects of Disasters Long-Term?

Natural disasters not only affect children but also fetuses, which may have long-term consequences (Barker 1995; Almond and Currie 2011). The destruction of local infrastructure can also be a contributing factor. To identify whether the effects are long term, I analyze the effects of up to four lags of the disasters on the current U5MR for LICs, along with the contemporaneous disaster variables. The results of the long-run effects for the weighted disaster index and three of the individual disasters are shown in Figure 2.2.[26]

[24]Using the estimated coefficient of disasters for LICs from Panel A in Table 2.3 and the realizations of disasters at its different percentiles, the effects of disasters are identified at five percentile intervals for LICs and plotted as a graph.

[25]The coefficients of the linear and quadratic terms are both positive and jointly significant at the 1% level. For brevity, the results are not provided.

[26]Since the impact of droughts, high temperatures, and volcanic eruptions on the U5MR are close to zero, the results are not provided in the graphical format. However, coefficient estimates for the weighted disaster index and individual disasters for the long-run analysis are provided in Table A6, online appendix.

Figure 2.1: Detrimental Effects of Disasters

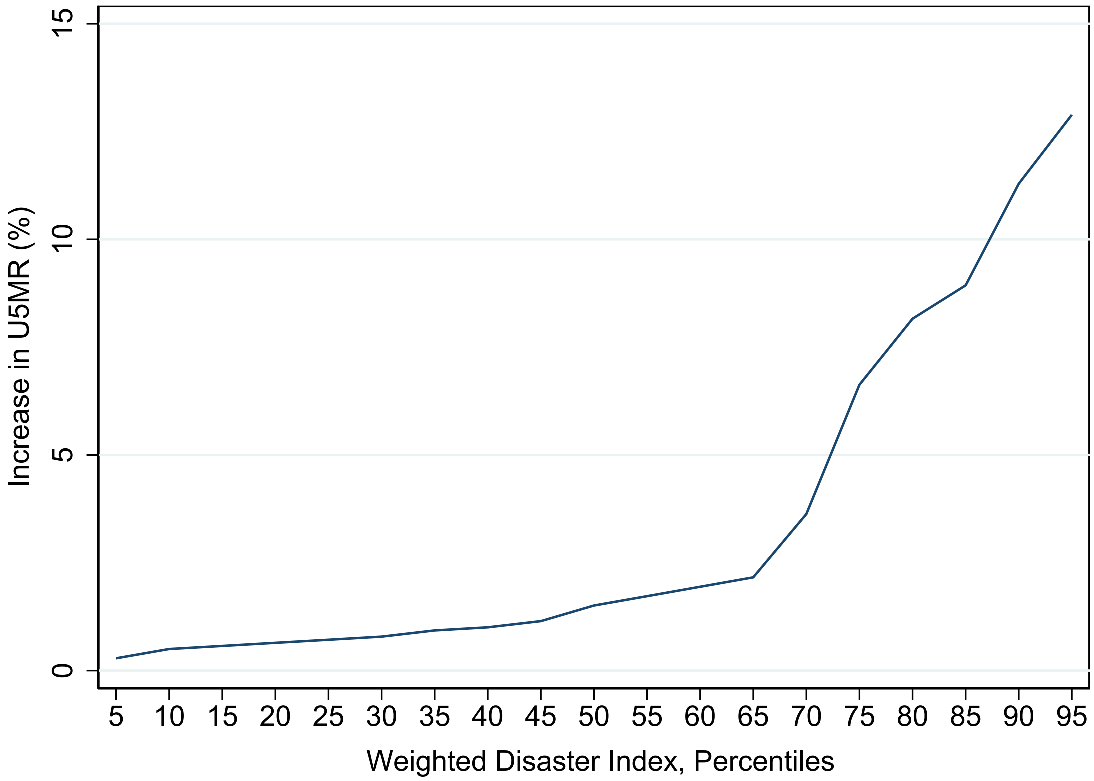
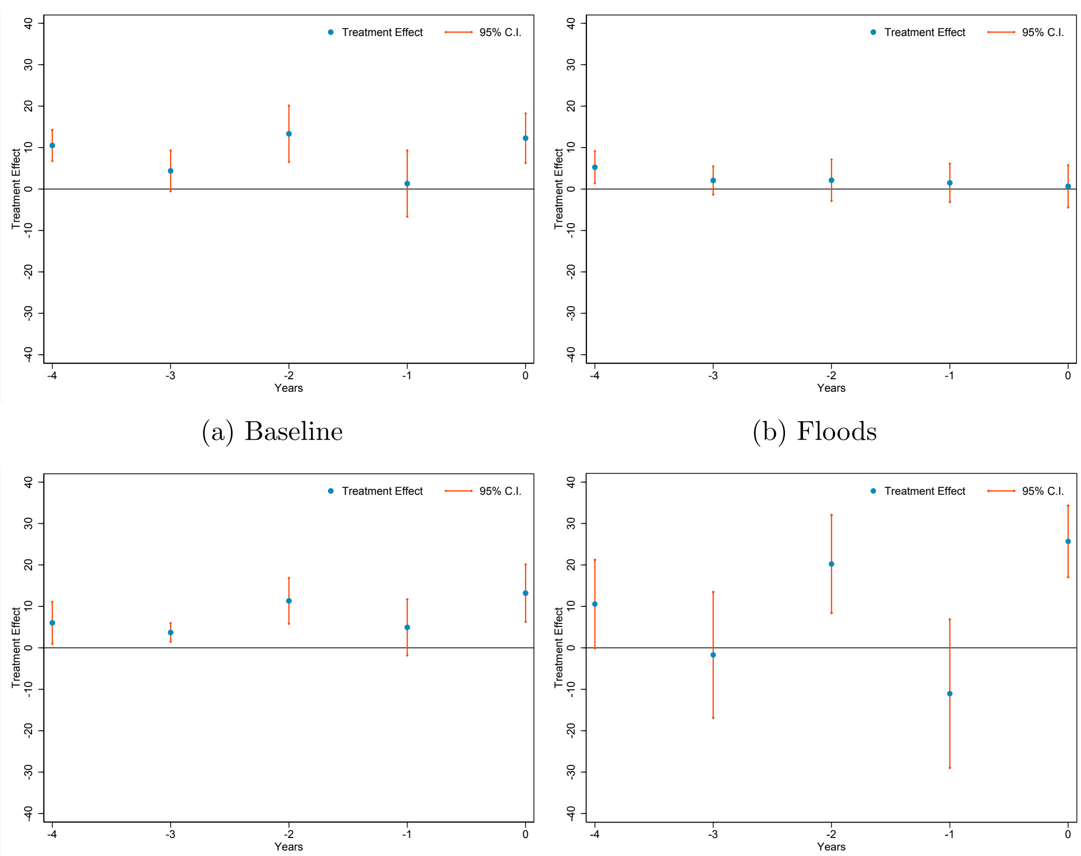


Figure 2.1: A plot of the estimated effects of the weighted disaster index at different percentiles on the under-5 mortality rates for low-income countries. Estimates as of column (4), Panel A, of Table 2.3.

Figure 2.2a indicates that the effects are not just short term. Up to four lags of the disasters are found to have a positive effect on child mortality. A distinct feature of the figure is that the effect of the first lag of the disaster is close to zero. The null effect may be due to the "build back better" hypothesis, in which old and outdated healthcare facilities are replaced with newer capital (Cuaresma et al., 2008), leading to a lower mortality rate in the year immediately following the disaster. Alternatively, it could be due to disaster relief funds or the extra healthcare resources allocated to areas affected by disasters in the short run (Skidmore and Toya, 2002), which lead to lower mortality rates in the year after the disaster. Once the relief fund runs out, or the extra healthcare resources are no longer available, the detrimental effect of further lags are observable.[27]

[27]This temporary (1–2 years) increase in output after disasters is generally observed in construction industries (Belasen and Polachek 2008; Hsiang 2010), but it is still unclear whether the effects have long-run effects on the broader economy (Hsiang and Jina, 2014).

Figure 2.2: Effect of Natural Disasters on the U5MR: Long-Run Effects



(a) Baseline

(b) Floods

(c) Storms

(d) Earthquakes

Figure 2.2: A plot of the lagged effects of disasters over a 5-year period (including the year 0), for low-income Countries. Estimates of Table A6 from the online appendix.

The results for the individual disaster intensities in Figures 2.2b–2.2d suggest that storms and earthquakes have major impact. While the effects of the lags of storms are always positive, the effects of earthquakes are negative for the first and third lags. Even then, the sum of the coefficients of the level and lags of earthquakes remains positive, indicating their long-term negative consequences. I perform a joint distribution test on the lags (and the levels) of the disaster variables (for the weighted disaster index, storms, and earthquakes), and in each case, the variables are jointly significant. These results are in line with Anttila-Hughes and Hsiang (2013), who finds that post-disaster infant mortality due to typhoons in Filipino households outnumbers the immediate child deaths significantly.

2.4.7 Potential Transmission Mechanisms

In this section, I explore some of the potential channels through which disasters might affect child mortality. I analyze the impact of disasters on various macro-level health and economic variables that can impact child health, as explained in the Data section. Table 2.4 provides the results for the three subgroups of countries classified by their income levels, along with the mean of the outcome variables.

First, I explore the impacts on macro-level per capita GDP, which can act as a proxy for a country's ability to provide public health resources to meet public demand (Kim, 2013). The results in column (1) of Table 2.4 suggest that disasters affect poor countries the most, whereas the effects are insignificant or have a wrong sign for the other subgroups. Improvement in maternal health is one of the United Nations Millennium Development Goals (WHO, 2005). Therefore, I focus next on maternal mortality, which may also be indicative of the current health status of a country. The results in column (2) indicate that disasters have major detrimental effects on maternal mortality in both LICs and MICs; however, the effects are identified to be significant only for LICs.

Next, I examine the impact of disasters on other health outcomes such as child vaccination rates and disease incidences (see columns (3)–(6) in Table 2.4). The measles immunization rate is a single measure that can act as a proxy for the overall state of the public health system in a country, as it is correlated with other immunization rates (Levine and Rothman, 2006). Along with the measles vaccination rate, I use the DPT vaccination rate, which measures the percentage of children aged 12–23 months who were immunized before 12 months or any time before the survey. In the sample, the measles and DPT vaccination rates are highly correlated with each other, with a correlation coefficient of 0.8425. The results in columns (3) and (4) suggest that disasters have a negative effect on both the vaccination rates, with a significant effect observed for the DPT immunization rates in column (4) for LICs. However, for the other two income groups, I do not observe a statistically significant or a meaningful relationship as the estimates are

Table 2.4: Natural Disasters and U5MR: Potential Transmission Channels

	GDP	MM	Measles	DPT	Diarrhea	Comm.Dis.	Sanitation	Dr.Water	Health Exp	Urb.Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: LICs										
Weighted Disaster Index$_{,i,t}$	-4.709**	2.769**	-3.697	-12.304**	56.804***	300.738***	-12.541	-1.024	-0.995	-3.116
	(1.980)	(1.350)	(4.919)	(5.748)	(15.814)	(97.599)	(8.859)	(1.677)	(2.880)	(4.413)
Mean Dependent Variable	6.491	642.47	57.569	55.344	28.097	57.009	22.731	30.630	1.456	4.525
Observations	529	370	492	501	118	36	90	198	198	522
Number of Countries	18	18	18	18	18	18	16	18	18	18
Panel B: MICs										
Weighted Disaster Index$_{,i,t}$	4.266	0.775	3.977	4.702	10.960	-12.925	-0.172	-0.376	2.959**	6.611
	(2.409)	(1.632)	(4.261)	(3.111)	(8.951)	(10.484)	(0.100)	(0.242)	(1.226)	(5.395)
Mean Dependent Variable	8.019	176.552	75.248	75.501	34.212	24.479	69.576	61.478	2.548	2.956
Observations	1,307	923	1,258	1,279	228	90	52	495	495	1,248
Number of Countries	45	45	45	45	43	45	14	45	45	45
Panel C: HICs										
Weighted Disaster Index$_{,i,t}$	-0.629	-1.390	-0.364	-1.743	-	13.256	-	0.045	0.458	-1.509
	(1.037)	(1.227)	(1.228)	(1.235)	-	(14.874)	-	(0.045)	(1.082)	(4.349)
Mean Dependent Variable	9.788	9.567	86.902	90.712	-	5.729	-	93.651	5.873	0.983
Observations	821	581	772	790	-	57	-	302	313	751
Number of Countries	29	29	29	29	-	29	-	29	29	29

Note: ** and *** denote significance at the 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level. LIC refers to the low-income group of countries, MIC stands for middle-income countries, and HIC refers to high-income countries.

either insignificant or contain a wrong sign. Likewise, disasters are also associated with a higher percentage of children receiving diarrheal care, as well as an increase in the spread of communicable diseases in LICs, as shown in columns (5) and (6). However, this set of results must be considered with caution because of the small sample size. The findings in columns 3–6 are also in line with Datar et al. (2013), who observed that the probability of immunization decreased while the incidences of diarrhea and other illnesses increased among under-5 children exposed to a natural disaster in rural India in the preceding month.

In columns (7) and (8), I test the effects of disasters on the percentage of people with access to basic sanitation and safe drinking water facilities. While the estimates are found to be negative for both LICs and MICs, the effects are rather imprecise. However, LICs suffer the most. Owing to the insufficient sample size, some of these results are unavailable for HICs. In column (9), I assess the impact on public health expenditure (as a percentage of GDP). As the estimated effects remain negative and insignificant for LICs in column (9), public health expenditure sees an increase for both MICs and HICs due to disasters, albeit insignificant for HICs. These results might be indicative of the lack of resources in LICs, and therefore, the inability of governments to increase the funding required to meet the public demand. As household income and expenditure are found to decrease in the periods of natural disasters (Bui et al., 2014), it might be essential to increase public health expenditure during crises. Finally, testing the impact of disasters on urban population growth, I do not observe any discernible effects, as evident from the last column.

I also examine the robustness of the results for LICs in Table 2.3 by conditioning on various health-related covariates, such as immunization rates, maternal mortality, public health expenditure, and fertility rates. While the estimated effects of disasters remain qualitatively robust, a detailed description of the findings is provided in Section A2.4 in the online appendix to conserve space. For brevity, relevant findings such as the gender-specific analysis, role of the political status–income level interaction on child mortality, various robustness tests, and other relevant issues, such as selective fertility and migration concerns, are also presented in the online appendix.

2.5 Conclusion

Global temperature is predicted to rise by around 1.5 degrees in the coming decades, which would increase the frequency of natural disasters (IPCC 2007; IPCC 2018). While the majority of children live in developing countries, the population in DCs is likely to be affected the most due to such disasters (Currie and Deschenes, 2016). The lack of access to health infrastructure is likely to exacerbate the disaster impact in these countries. Understanding the impact of natural disasters on child mortality at a global level is compelling, and this study contributes to the literature by exploring the same.

Using an exogenous measure of natural disasters, I identify the impact of disasters on the mortality rates of children aged 0–5 years. I examine whether the income or political status of institutions play any role, while also focusing on the persistent effects of disasters, and the potential mechanisms behind their impact. The findings indicate that disasters have no discernible effects on child mortality for a set of countries grouped together. Although LICs do not face more disasters than MICs or HICs, the results indicate that children, mostly, in LICs suffer—a one standard deviation increase in the intensity of the weighted disaster index leads to an additional 6.77 deaths per 1000 live births; among the individual disasters, storms and earthquakes affect the most; while the effects of disasters are long-term, better-quality institutions are found to suffer less from disasters. Various transmission mechanisms, such as lower macro-level GDP and child vaccination rates, along with an increase in maternal mortality and disease incidences due to disasters, might explain the findings regarding LICs.

In the era of global climate change and the accompanying increase in natural disasters, understanding the most affected groups is vital. In this study, I provide evidence that children in LICs suffer the most, while also providing insight into some of the potential mechanisms. Even if we completely switch to clean energy sources or stop emitting greenhouse gases right away, detrimental effects of global warming will continue for a few decades (NASA 2007; Stager 2012). Considering that poor countries which also lack access to better health infrastructure are likely to be affected the most, support from developed countries and global organizations could be crucial in combating the effects of climate change in the short run. Developing countries should also focus on optimal channeling of resources for the efficient management of disaster impacts. On the other hand, adaptive policies to tackle the effects of climate change may amplify, rather than dampen, the disaster effects (Anttila-Hughes and Hsiang, 2013). Hence, it is essential for the enaction of necessary policies to drastically reduce greenhouse emissions at a global level in the immediate future. However, a few limitations remain in this study. More credible estimates can be attained when disaster data (especially meteorological) at a subnational level become available. Moreover, susceptibility of a country to the frequency of future disasters is a potential avenue for further research.

Appendix

Table 2.5: Summary Statistics

Variable	Mean	Std. dev.	Source	Description
U5MR, Low	154.83	64.22	UNICEF	Under-5 mortality rate rates, for Low Income Countries.
U5MR, Middle	60.38	44.91	UNICEF	Under-5 mortality rate rates, for Middle Income Countries.
U5MR, High	9.72	9.51	UNICEF	Under-5 mortality rate rates, for High Income Countries.
Disaster Index, Weighted, Low $_{i,t}$	0.005	0.006	GeoMet-Data	Sum of disaster types weighted by country specific inverse of standard deviations by land area, for Low-Income Countries.
Disaster Index, Weighted, Middle $_{i,t}$	0.010	0.015	GeoMet-Data	Weighted GeoMet Disaster Index, for Middle-Income countries.
Disaster Index, Weighted, High $_{i,t}$	0.020	0.035	GeoMet-Data	Weighted GeoMet Disaster Index, for High-Income countries.
Disaster Index Weighted, Low $_{i,t}$	0.00112	0.0029	EM-DAT-Data	Count of all disasters in the EM-DAT index, weighted by land area, for Low-Income Countries.
Disaster Index Weighted, Middle $_{i,t}$	0.00091	0.0019	EM-DAT-Data	Weighted EM-DAT Index, for Middle-Income countries.
Disaster Index Weighted, High $_{i,t}$	0.00097	0.0018	EM-DAT-Data	Weighted EM-DAT Index, For High-Income countries.

Note: U5MR refers to under-5 mortality rates.

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Online Appendix (Not for Publication)

Natural Disasters and Missing Children

A2 Summary of the Results

A2.1 Gender-specific Analysis

Using data from the World Health Organization (WHO) on gender-specific under-5 mortality rates (henceforth, U5MR), I perform a gender-specific analysis. Results are provided in Table A4. Panel A of the table provides the baseline estimates irrespective of gender, for comparison, whereas panels B and C provides the results for boys and girls, respectively. Based on column (4), Panel A, one standard deviation (henceforth, SD) increase in the disaster index leads to 5.46% increase in U5MR for LICs.[1] Whereas the effect of the disaster on girls is 5.70% as opposed to the effect on boys of 5.25% in LICs for a similar increase in the disaster index. Therefore, there are no significant gender differences in responses to the disasters.

A2.2 Political Status–Income Level Interaction

While LICs lack access to resources compared with wealthier nations (Peters et al., 2008), the population in autocracies experience state intervention in the economy and a less responsive public sector to public demand in terms of health and education (Baum and Lake, 2003). These factors can translate into significant adverse consequences on child health in response to natural disasters. Therefore, to identify whether the interaction between the income level and political status of institutions plays a role, I group countries based on their income level and democratic status and provide the results in Panel A of Table A7. High-income group of countries (henceforth, HICs) are excluded from this analysis as the non-democratic HIC subgroup contains only four countries.

The results in columns (1)–(3) imply that LICs suffer generally, but the effect of disasters on non-democratic LICs (5.19% increase in U5MR for a one SD increase in the disaster intensity) is more than twofold than in democratic LICs (2.08% increase in

[1] The percentage change for one standard deviation increase in the disaster is calculated using the standard formula: $[(e^{\beta * SD}) - 1] * 100$ i.e.$[(e^{8.858*0.006}) - 1] * 100$ equating to 5.46%. Refer to Panel A, Table A4 for the beta coefficient, and Table A1 in the main text (appendix) for the summary statistics of the disaster index for LICs. I follow a similar procedure to calculate the percentage effects for the remainder of the online appendix, wherever noted.

U5MR). For middle-income countries (henceforth, MICs), the null results of disasters on the U5MR observed in Table 2.3 from the main text are driven primarily by democratic countries (Column 5, Table A7). Once the association between the income level and democratic status of institutions is considered, disasters are found to have an adverse effect on the under-5s in non-democratic MICs, albeit statistically insignificant, refer to column (6). The results show that autocracies suffer more than democracies, even in MICs.

Next, I examine a potential mechanism that could provide some insights into why the quality of institution matters by examining the role of official aid received by recipient countries (data from WDI (2019)) in alleviating the effects of disasters. As the public sector is less responsive to public demand in autocracies (Peters et al., 2008), in the absence of a binding policy commitment, the mere expectation of official aid sufficiently increases rent-seeking behavior and reduces productive public spending among recipients (Svensson, 2000). As shown in Panel B of Table A7, official aid (level and first lag) has little to no effect on democratic LICs and MICs (columns (2) and (5)).[2] However, for non-democratic LICs and MICs (columns (3) and (6)), the cumulative effect of the level and first lag of aid is positive, providing suggestive evidence of inefficient management of the aid received by autocracies.

A2.3 Further Robustness Tests

Considering that the effects of disasters are identified to be significant only for the low-income group of countries, I perform various robustness tests for LICs to ensure that the significance of results observed in column (4), Panel A, Table 2.3 in the main text remains robust. A short description of the results is provided below:

A2.3.1 Income Classification of Countries

Countries are classified into different income levels based on the World Bank's 2010 classification. If low-income countries change categories over the sample period considered,

[2] The cumulative effect of the level and first lag of official aid on child mortality is close to zero or negative for democratic LICs and MICs.

this may lead to some endogeneity issues. Therefore, by using the World Bank's historical list of countries classified based on different income levels for the period 1987–2010, I check whether low-income countries have shifted income groups. Except for the Kyrgyz Republic, the rest of the LICs remains in the same group, whereas removing the Kyrgyz Republic from the sample does not affect the results.

A2.3.2 Controlling for Conflict Incidences

Next, I control for conflict incidences to ensure that the results are not driven due to wars or conflict-related deaths. The threshold for the determination of conflict and wars is determined by the Uppsala Conflict Data Program (UCDP) based on the number of battle-related deaths. If an armed conflict results in at least 25 battle-related deaths, then the UCDP classifies it as a conflict, whereas an armed conflict resulting in at least 1000 battle-related deaths is classified as a war incidence. In the results not shown, coefficient of natural disasters observed for LICs in Table 2.3, main text, remain robust to the inclusion of conflict incidences (both civil conflicts and wars) based on the data from the UCDP.

A2.3.3 Different Functional Forms

I also use various functional forms, such as an elasticity model (both the mortality rates and the disaster index in the log form), a standard growth specification (mortality rates in growth form), and finally, standardizing the disaster index instead of using it in level form. The results remain robust irrespective of the specification applied. Refer to Table A5 for the results.

A2.3.4 Fertility Preferences

A potential concern is that mothers who choose to have children at the time of disasters are selectively different, which might bias the estimates. For instance, a mother's education is a significant determinant of child health (Chen and Li, 2009) and fertility choice (Black et al., 2008). Moreover, increases in household wealth are found to be associated with increases in total fertility, as discussed by Lovenheim and Mumford (2013). Therefore, informed mothers might engage in selective fertility based on the perceived health of the child (Pitt, 1997), which can be affected due to the drop in household income as a result of disasters.

Owing to the lack of fertility preference data at a finer level, I proxy for the mothers' ability to control fertility using the safe contraceptive usage data from WDI (2019).[3] Contraceptive use is essential for fertility-reducing effects (Mamdani et al., 1993) and thereby can help mothers target their ideal family size. While fertility rates are strongly associated with safe contraceptive usage,[4] it is logical to assume that selective fertility is higher in areas with higher contraceptive prevalence rates, as mothers would have increased access to safer contraception methods. Therefore, I examine the effects of disasters on child mortality based on contraceptive prevalence rates subject to Equation 1 in the main text.

The results by contraceptive usage are provided in columns (2) and (3) in Table A8. Column (1) presents the results from column (4) in Table 2.3 for comparison. Disasters affect child mortality in both low and high contraceptive prevalence areas and the estimates in the latter are almost twofold compared with the former. However, the estimated coefficient in column (3) becomes insignificant at conventional significance levels (with a p-value of 0.12), which could be owed to the lower sample size. Therefore, accounting for birth selection bias (if any), the effects of one SD increase in disaster index on child mortality in LICs could be in the range of 3.13%–6.18%, depending on the level of birth selection.

As the next test, I examine the impacts of disasters by macro-level economic activity[5] by analyzing the effects of disasters in LICs based on low and high GDP areas. The last two columns of Table A8 contain the results. The findings suggest that even within LICs,

[3] Contraceptive usage could also be indicative of the overall ability of the government to provide the required resources to the public. For example, contraceptive prevalence rates and macro-level GDP from WDI (2019) have a positive correlation of 0.6482. Therefore the results based on this section should be taken as suggestive evidence only.

[4] The correlation between fertility rates and contraceptive use is -0.762, based on national averages.

[5] This analysis is not solely related to birth selection, but rather a test of the ability of a state to provide the required public health resources to those in demand, as national GDP covers a wide range of economic activities.

the extremely poor countries suffer the most.

A2.3.5 Migration Concerns

Another potential concern is the case of selective migration and that families that migrate due to disasters can be selectively different. For example, if LICs experience a high refugee intake, who are naturally vulnerable, then the estimates of disasters on child mortality for LICs could be upward biased, which is a cause of concern. Instead, if there is an outward migration of a vulnerable group of people from LICs, then the estimates of the disaster index observed in this study are taken to be the lower estimates only. To ensure this, I use data on net migration from WDI (2019), which provides the net total of migrants (number of immigrants minus the number of emigrants) during a period. LICs experience an average of -142,031 emigrants per period, an outward movement of migrants from LICs to other countries, on net. If the majority of families that emigrate consist of at-risk children, then the estimates presented in Table 2.3 in the main text are conservative only.

However, this does not rule out the possibility that the population that emigrates is healthier, which might lead to more at-risk children in the country. This is a serious concern, as it could upward bias the estimates. I address this issue by examining the effects of disasters in countries with high emigration (below median by net migration) compared with low emigration (above median by net migration) following Equation 1 in the main text. Assuming healthier families are the ones that emigrate, in areas where there is higher emigration, there would be a higher proportion of at-risk babies and hence the effects of disasters would also be higher in high emigration areas. In the results not shown, the estimated effects of one SD increase in disasters on child mortality are found to be in the range of 4.6%–5.2% in high and low emigration countries respectively and remains statistically significant at 5%. These estimates remain close to the baseline estimates for LICs from Table 2.3, main text, allaying selective migration concerns.

A2.4 Conditioning on Health-related Covariates

Even after controlling for country-fixed effects, error term in Equation 1 from the main text may contain some time-varying factors that may affect child mortality such as immunization rates, maternal mortality, fertility rates, drinking water accessibility, and public health expenditure. If these variables are also affected by natural disasters, then the coefficient of disasters estimated under Equation 1 can be biased (Mishra and Newhouse, 2009). Therefore, I control for some of these potential confounders next.

Health outcomes such as maternal mortality and measles immunization rates among children are indicative of the overall state of the public health system in meeting public demand (Levine and Rothman, 2006). Likewise, public expenditure on health (as a percentage of GDP) can also be indicative of the degree to which a government focuses on public health. Conditioning on these covariates (entering the regression in log form), I test the robustness of the results for LICs in column (4) of Table 2.3, main text. The coefficients of the weighted disaster index for LICs are provided in the first column of Table A9 for ease of comparison.

In column (2) of Table A9, I control for maternal mortality. While maternal mortality is found to be positively correlated with child mortality, controlling for the former does not have a major effect on the significance or magnitude of the disaster index. In column (3), I condition on the measles immunization rate. Higher vaccination rates are found to be negatively associated with child deaths, thereby entering the regression with the correct sign, however, controlling for immunization rates does not affect the interpretation of the disaster index. In column (4), I control for public health expenditure, which predicts child mortality negatively. Once health expenditure at the macro level is controlled for, the coefficient of the disaster index rises from 7.131 to 11.753. However, we lose around 60% of the observations in column(4) compared with column (1). The significance of the controls is affected once all three covariates are controlled for in the same specification (the last column), but the covariates retain their signs. The estimates of disasters reduce slightly from column (4). In the results not shown, results remain largely unchanged to controlling for the log of fertility rates and the percentage of the population with access to drinking water as well. To summarize, the results for LICs in Table 2.3 remain robust qualitatively to conditioning on various other health-related covariates.

A2.5 Robustness Test: Dynamic Panel Analysis

A2.5.1 Methodology

In an influential work, Grossman (1972) notes that the current health of the population may have an effect on their future health. As countries might involve in various programs to improve the health status of children agreed upon under the MDGs (WHO, 2005), there could be an improvement in the health infrastructure. And the impact of health investments are likely to accumulate over time, which can also affect the stock of the current health capital (Ruhm, 2003). Therefore, I perform an extensive robustness exercise by accounting for these potential dynamics in the mortality rates, following a similar procedure to Acemoglu et al. (2019).[6] I extend Equation 1 in the main text to postulate a dynamic model for mortality rates as follows:

$$Y_{it} = \alpha D_{it} + \sum_{j=1}^{p} \gamma_j Y_{it-j} + \beta X_{i,t-1} + \delta_i + \delta_t + \theta_i \times t + \eta_{it}, \tag{2}$$

Y_{it} is the mortality rate and Equation 2 controls for the p lags of the mortality rates on the right side.[7] The sample contains observations for the period 1979–2010, and t_0 refers to the initial year in the sample. To identify the effect of disasters on mortality using the linear dynamic panel specification (henceforth referred to as the Within estimator) in Equation 2, the standard assumption of sequential exogeneity is imposed i.e. the disaster index and past mortality rates are orthogonal to the current and future shocks to the mortality rates and that no serial correlation exists in η_{it}. Along with the sequential exogeneity assumption, it is also assumed that the mortality rates follow a stationary process (accounting for country and period fixed effects). The stationarity assumption

[6] And if the coefficient of the past lag of the dependent variable is close to one and also significant, then it provides some evidence on the existence of strong dynamics in the dependent variable (Ray and Linden, 2020).

[7] To remove any residual serial correlation in the error term, sufficient lags of the dependent variable must be included (Acemoglu et al., 2019).

ensures that the dynamic panel estimators are consistent. Under the assumptions of stationarity and sequential exogeneity, by using the standard within estimator, Equation 2 can be estimated. Further, I check for stationarity in the mortality rates using the Im et al. (2003) test (henceforth, the IPS test). The IPS test is preferred for this study as it can be applied for unbalanced panels, while also allowing for each panel to have its own autoregressive parameter.

One of the problems with the within estimates based on Equation 2 is the asymptotic bias of order $1/T$ called the Nickell bias when the time dimension T is finite, even if the number of cross-sectional units N (i.e. the number of countries, in this study) goes towards infinity (Nickell 1981; Alvarez and Arellano 2003). Even though each country is observed for nearly 30 times in this study, still there could be some bias, albeit minimal (Judson and Owen, 1999). Also considering that N is not too large in this study, Nickell bias could still be an issue. Therefore, I deal with this potential bias in the next step by implementing the GMM estimator developed by Arellano and Bond (1991) (henceforth, AB estimator), with variables in forward orthogonal deviations (henceforth, FoD, proposed by Arellano and Bover (1995)). The FoD method is more suitable for the unbalanced panels as it does not magnify gaps (Blundell and Bond 1998; Bond 2002; Favara and Imbs 2015) and also works better to remove individual fixed effects, while performing better than the first-difference approach (Hayakawa, 2009). Along with the stationarity test, I perform two further specification tests to ensure that the GMM estimates are consistent. First, I examine the absence of second-order serial correlation in the error term (henceforth, AR(2)), η_{it}. Next, I conduct Sargan test of over-identifying restrictions, which examines the overall validity of the instruments.

However, a drawback associated with the GMM estimator is in the number of moment conditions, as the count rises with the period T in the order of T^2. This leads to a considerably high number of instruments in the model, and, as a result, GMM estimates suffer from an asymptotic bias of order $1/N$ (Alvarez and Arellano, 2003). To avoid this overfitting bias in estimates, I follow Roodman (2009) and collapse the instrument set to take care of the instrument proliferation issue.

It should also be acknowledged that the traditional GMM estimators such as the one used in this study may still have some bias when N is only moderately large (Judson and Owen 1999; Bruno 2005). Moreover, the empirical implementation of the GMM estimators often suffers from poor sample sample properties (p410, Verbeek (2017)). While Equation 2 still serves as a robustness test by accounting for the potential dynamics in the mortality rates, Equation 1 in the main text is the preferred specification due to the above-mentioned reasons. Moreover, considering that an exogenous measure of natural disasters is used in this study, Equation 1 is already sufficient for consistently identifying the effects of disasters on child health (Wintoki et al., 2012), once the geographical factors (country-fixed effects) and the state of the public health system of a country are accounted for. Nevertheless, coefficients of disaster remains closer to each other under both the OLS and dynamic panel method, once the instrument proliferation issue is addressed in the latter. A detailed discussion is provided later.

As the test of stationarity in the dependent variable, I initially performed a test of the unit root by Im et al. (2003), suitable for unbalanced panels such as the one used in this study. Results reject the presence of non-stationarity in the dependent variable comfortably. As an additional test of stationarity, I explicitly allow for unit root (or near unit root presence) in the dependent variable. I follow Acemoglu et al. (2019) and employ the following specification, which is a simple transformation of Equation 2:

$$\Delta Y_{it} = \alpha D_{it} + \sum_{j=1}^{p} \gamma_j{}' \Delta Y_{it-j} + \beta X_{i,t-1} + \delta_i + \delta_t + \theta_i \times t + \eta_{it}, \tag{3}$$

I try the persistence of unit root (or near-unit root) in mortality rates by allowing for different persistence values in the range 0.95–1. This is done by restricting the sum of the coefficients on the lags of mortality, $\sum_{j=1}^{p} \gamma_j$, which accounts for the overall persistence, to the values 0.95, 0.96, 0.97, 0.98, 0.99, and 1. To obtain these models, the left-hand side of Equation 2 is replaced with $Y_{it} - (\sum_{j=1}^{p} \gamma_j) Y_{it-1}$, which implies $\gamma_j{}' = (\sum_{i=0}^{j} \gamma_i) - \rho$ in Equation 3. For example, to allow for a near-unit root persistence of 0.95, a simple transformation on the dependent variable of $Y_{it} - (0.95 * Y_{it-1})$ is applied. And the resulting values are used in place of the dependent variable. Likewise, persistence values of 0.96–

1 are also tried as robustness. This is performed in line with Acemoglu et al. (2019). Therefore, Equation 3 is quite similar to Equation 2, with a simple transformation in the dependent variable. Among these two equations, Equation 3 would be the preferred one in case of non-stationarity. Considering that the presence of stationarity is already rejected as per the Im et al. (2003) test, specification under Equation 3 serves only as a robustness exercise.

A2.5.2 Dynamic Panel Results

Following Acemoglu et al. (2019), I employ an extensive set of dynamic panel specifications by examining the effects of natural disasters on child mortality under two different methods (Within estimator and AB estimator), as explained in the Section A2.5.1. The results of the dynamic panel analysis for the group of low-income countries are provided in Table A10.[8]

Columns (1)–(3) contain the results for the linear dynamic panel, estimated using the Within estimator, under the standard assumptions such as stationarity and sequential exogeneity. To eliminate the serial correlation, within estimators require including many lags of the mortality rates. Therefore, I choose an optimal lag structure by including further lags of the dependent variable until they are insignificant, in line with Acemoglu et al. (2019). In column (1), I include only the first lag of the U5MR and find a substantial magnitude (1.019%), statistically significant at the 1% level with a standard error (robust, heteroskedasticity corrected) of 0.018. To provide an interpretation of the coefficient of disaster, one standard deviation increase in the weighted index leads to 2.40% increase in U5MR.

To identify whether further lags of the dependent variable are required, I add the first two lags of mortality rates in column (2) and up to three lags in column (3). As the third lag of the dependent variable falls insignificant, I do not include further lags. One more point to note is that the sum of the coefficients on the lags included is less than one

[8] Since significant effects are observed only for the LICs based on the income levels, I provide the results under dynamic panel specification only for the LICs to conserve space. In the results not shown, estimates for the baseline (entire sample), MICs, HICs, and for democracies and autocracies remain unchanged qualitatively under the dynamic panel specification as well.

in column (2), therefore non-stationarity (unit root) might not be an issue (Acemoglu et al., 2019), once the required number of lags are controlled for. However, I deal with the potential problem of unit root presence in two different ways. First, I formally test the presence of unit root in the under-5 mortality rates using the Im et al. (2003) (IPS) test. I account for both time trends and lags in the unit-root test, while the number of lags included is based on the respective column. P-values from the IPS stationarity test are reported in the bottom rows of columns (1)-(3), Table A10. Estimated p-values lead to the rejection of the null hypothesis of unit root presence, in all the within estimate specifications. Next, I deliberately allow for the unit root or near unit root presence in the outcome variable following Equation 3. In the results not shown, coefficients of disasters remain statistically significant at 5% levels under both the estimators (Within estimator and AB estimator) and remain closer to the first two rows of Table A10. This exercise bolsters the credibility of the findings, subject to any potential non-stationarity issue. Results under these two tests ensure that non-stationarity is not an issue in this study.

One of the problems with the linear dynamic panel estimates in columns (1)–(3) is the possible Nickell bias, which arises due to the failure of strict exogeneity assumption (Acemoglu et al., 2019). While the bias is found to be minimal when the observed number of time periods is close to 30 (Judson and Owen, 1999), the number of countries in the sample is only moderate. While each country is observed for an average of 29.4 times in this study, there are only 18 countries in the low-income group. Therefore, Nickell bias could still be an issue. To deal with the potential Nickell bias, I use the Arellano and Bond (1991) estimator, which uses the previous lags of the variables on the right side as instruments and applies FoD method proposed by Arellano and Bover (1995).[9] Similar to the within estimators, lags further than two are not required as controls, as evident from the p-value of the third lag of the outcome variable in column (6). Therefore, column (5) is the preferred specification for the AB estimates. Comparing the coefficient estimates of disasters on U5MR in columns (4)–(6) with the first three columns, minor differences

[9]'xtabond2' package in the Stata software is used to perform the GMM-style estimations. Refer to Roodman (2009) for a detailed description.

between the within and AB estimates are observed. Therefore, there is a smaller Nickell bias in the within estimates, however negligible.

I also test formally the presence of the second-order serial correlation (AR2 correlation) and present the results in the bottom rows in columns (4)–(6). The presence of second-order serial correlation is comfortably rejected in all the specifications. However, p-values from Sargan's test of over-identification leads to the rejection of the null hypothesis of instruments' exogeneity at 5% significance levels. While such a finding may cast some doubt on the validity of instruments, the failure of the Sargan test can be attributed to the use of too many moment conditions in the AB estimator, which can reduce the power of the Sargan test significantly (Bowsher, 2002). This instrument proliferation can overfit the endogenous variables and also weaken the test of instruments' joint validity (Roodman, 2009), a common issue encountered in some of the other studies (for example, Agell et al. 2006; Drazen and Eslava 2010; Arulampalam et al. 2012). To address the instrument proliferation issue, I employ an alternate estimator next that reduces the instrument count considerably.

The issue of 'too many moment conditions' is a basic problem with the AB estimator which results in a significantly high number of instruments, in the order of T^2. This leads to an asymptotic bias of order $1/N$ in the AB estimates (Alvarez and Arellano, 2003). To address this problem, I collapse the instrument set following Roodman (2009), which produces a much smaller instrument matrix. Refer to columns (7)–(9) in Table A10 for the results. Similar to the Within and AB estimators, lags further than two are not required, resulting in column (8) being the preferred specification in Table A10.[10] Once the instrument count problem is addressed, the Sargan test fails to reject the null of valid instruments even at 10% significance levels in the last three columns. This implies that the moment conditions are valid, while also providing some confidence in the estimates being consistent.[11] Moreover, the coefficient of the disaster index in column (8) is closer

[10]First two lags of the dependent variable are jointly significant in column (8), even though they are individually insignificant. Therefore, column (8) is treated as the preferred specification.

[11]Lags further than two of the dependent variable and up to 25 lags of the disaster index are collapsed and used as instruments in columns (7)–(9), with the choice of lag length in the latter being mindful of instrument exogeneity, in line with Felbermayr and Gröschl (2014). I perform an additional robustness test by following Acemoglu et al. (2019) and use all available lags in the dependent variable (from t-2

to the coefficient of the disaster from Table 2.3 in the main text – one SD increase in the disaster leads to 4.59% increase in U5MR in the low-income group of countries.

A potential problem with the 'xtabond2' command in the Stata software is that it might produce incorrect estimates if standard instruments are used under forward orthogonal deviations (Kripfganz, 2020). Therefore, I apply the 'xtdpdgmm' stata command from Kripfganz and re-estimate the effects of the disaster as a robustness exercise. Findings remain largely unchanged and instrument validity remains satisfied. Results are provided in columns 1–6 in Table A11. As an additional robustness test, I use one-step system GMM developed by Arellano and Bover (1995) which combines in a system the regression in differences with the regression in levels and can circumvent any finite sample biases. Results remain robust to this alternate estimator as well. Refer to the last three columns in Table A11 for the results. To summarize, results under the dynamic panel specification ensured that natural disasters have strong detrimental effects on under-5 mortality in poor countries.

I also examine the effects of the EM-DAT index under the dynamic panel specification and provided results in Table A12. Based on the preferred specification in column 8 of Table A12, one SD increase in the EM-DAT index leads to a 1.79% increase in U5MR. Therefore, estimates under the EM-DAT index are under-estimated significantly compared with the effects under the Geo-Met index observed in column (8), Table A10.

onwards) and the disaster index as instruments. I identify that some of the lags might not be exogenous when a longer lag length is used. However, the coefficient of the disaster remains closer to column (8), with the estimate being statistically significant at 1%.

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Table A1: Country List

Panel A: HIC					
Australia	Belgium	Canada	Croatia	Cyprus	Czech Republic
Denmark	Finland	France	Germany	Greece	Hungary
Ireland	Israel	Italy	Japan	Netherlands	New Zealand
Norway	Oman	Poland	Portugal	Slovak Republic	Slovenia
Spain	Sweden	Switzerland	United Kingdom	United States	
Panel B: MIC					
Albania	Algeria	Angola	Argentina	Armenia	Azerbaijan
Belarus	Bolivia	Botswana	Brazil	Bulgaria	Cameroon
China	Colombia	Costa Rica	Dominican Republic	Ecuador	El Salvador
Gabon	Guatemala	Honduras	India	Indonesia	Jordan
Malaysia	Mexico	Mongolia	Morocco	Namibia	Nicaragua
Pakistan	Panama	Papua New Guinea	Paraguay	Peru	Philippines
Senegal	South Africa	Sri Lanka	Syria	Thailand	Tunisia
Ukriane	Uruguay	Vietnam			
Panel C: LIC					
Bangladesh	Burkina Faso	Chad	Ethiopia	Haiti	Kenya
Kyrgyz Republic	Madagascar	Mali	Mauritania	Mozambique	Nepal
Niger	Tajikistan	Tanzania	Togo	Uganda	Zambia

Note: HIC refers to High-income countries, MIC refers to middle-income countries and LIC refers to low-income countries.

Table A2: Effect of Natural Disasters (EM-DAT Index) on U5MR: Samplewise Analysis

	Baseline	Non-OECD	OECD	Low Income	Middle Income	High Income	Autocracies	Democracies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Disaster Index$_{,i,t}$	-2.174	-1.829	-4.541	5.288	-7.932	-3.510	8.782**	-3.309
	(4.412)	(5.794)	(3.592)	(4.157)	(5.627)	(2.748)	(4.047)	(2.763)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73

Note: ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level.

Table A3: Effect of Natural Disasters on U5MR: Different Data Sources

	Baseline	Non-OECD	OECD	Low Income	Middle Income	High Income	Autocracies	Democracies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: UNICEF								
Weighted Disaster Index$_{,i,t}$	1.206	2.157	-1.621	7.131***	-0.011	-0.174	6.827***	-0.154
	(0.994)	(1.277)	(2.870)	(1.337)	(1.654)	(1.143)	(2.064)	(0.741)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73
Panel B: WDI								
Weighted Disaster Index$_{,i,t}$	1.182	2.186	-1.754	6.868***	0.050	-0.184	6.776***	-0.353
	(0.971)	(1.232)	(2.875)	(1.383)	(1.546)	(1.140)	(1.996)	(0.781)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73
Panel C: WHO								
Weighted Disaster Index$_{,i,t}$	0.132	0.870	-1.886	8.858***	-0.367	-0.889	6.609***	-0.966
	(0.824)	(0.985)	(2.336)	(1.530)	(0.984)	(0.850)	(1.810)	(0.583)
Observations	1,718	1,293	425	332	881	505	501	1,217
Number of Countries	84	66	21	16	43	25	43	66
Panel D: Rajaratnam et al. (2010)								
Weighted Disaster Index$_{,i,t}$	1.023	1.726	-2.590	3.139**	-0.307	-0.143	6.614***	-0.127
	(0.852)	(1.032)	(2.932)	(1.374)	(1.379)	(1.196)	(2.244)	(0.783)
Observations	2,561	1,878	683	481	1,276	804	904	1,657
Number of Countries	88	68	24	16	45	28	54	71

Note: ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level.

Table A4: Effect of Natural Disasters on U5MR: Gender-Specific Effects

	Baseline	Non-OECD	OECD	Low Income	Middle Income	High Income	Autocracies	Democracies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline								
Weighted Disaster Index$_{,i,t}$	0.132	0.870	-1.886	8.858***	-0.367	-0.889	6.609***	-0.966
	(0.824)	(0.985)	(2.336)	(1.530)	(0.984)	(0.850)	(1.810)	(0.583)
Observations	1,718	1,293	425	332	881	505	501	1,217
Number of Countries	84	66	21	16	43	25	43	66
Panel B: Boys								
Weighted Disaster Index$_{,i,t}$	0.264	0.949	-1.821	8.532***	-0.292	-0.788	6.558***	-0.827
	(0.795)	(0.965)	(2.277)	(1.483)	(0.949)	(0.821)	(1.728)	(0.565)
Observations	1,718	1,293	425	332	881	505	501	1,217
Number of Countries	84	66	21	16	43	25	43	66
Panel C: Girls								
Weighted Disaster Index$_{,i,t}$	0.044	0.832	-1.807	9.241***	-0.364	-0.902	6.837***	-1.065
	(0.847)	(1.013)	(2.255)	(1.592)	(1.052)	(0.840)	(1.884)	(0.588)
Observations	1,718	1,293	425	332	881	505	501	1,217
Number of Countries	84	66	21	16	43	25	43	66

Note: ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level.

Table A5: Effect of Natural Disasters on U5MR: Different Functional Forms

	Baseline	Non-OECD	OECD	Low Income	Middle Income	High Income	Autocracies	Democracies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:								
Dependent Variable: ln $U5MR_{i,t}$								
ln Weighted Disaster Index$_{,i,t}$	0.042	0.049	-0.052	0.057**	-0.004	-0.011	0.064	-0.006
	(0.025)	(0.028)	(0.084)	(0.020)	(0.015)	(0.073)	(0.037)	(0.022)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73
Panel B								
Dependent Variable: Δ ln $U5MR_{i,t}$								
Weighted Disaster Index$_{,i,t}$	0.299	0.479	-0.296	3.762***	0.184	-0.248	2.037	-0.112
	(0.421)	(0.509)	(0.269)	(1.170)	(0.239)	(0.146)	(1.452)	(0.128)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73
Panel C								
Dependent Variable: ln $U5MR_{i,t}$								
Standardized Disaster Index$_{,i,t}$	0.028	0.055	-0.022	0.046***	-0.001	-0.006	0.072***	-0.044
	(0.023)	(0.032)	(0.039)	(0.009)	(0.025)	(0.039)	(0.022)	(0.020)
Observations	2,657	1,963	694	529	1,307	821	978	1,679
Number of Countries	92	72	25	18	45	29	57	73

Note: ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level.

Table A6: Effect of Natural Disasters on U5MR: Long Run Effects

	Weighted Index	Floods	Droughts	Storms	Earthquakes	Temperature	VEI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disaster Index$_{,i,t}$	12.279***	0.661	-0.203	13.194***	25.691***	-0.059	-1.254
	(3.044)	(2.599)	(0.189)	(3.535)	(4.396)	(0.089)	(1.434)
Disaster Index$_{,i,t-1}$	1.317	1.488	-0.281	4.937	-11.049	0.053	-1.931
	(4.067)	(2.359)	(0.137)	(3.459)	(9.132)	(0.080)	(1.173)
Disaster Index$_{,i,t-2}$	13.329***	2.119	-0.238**	11.334***	20.242***	0.115	-1.399
	(3.474)	(2.544)	(0.096)	(2.813)	(6.026)	(0.070)	(1.627)
Disaster Index$_{,i,t-3}$	4.381	2.069	-0.197**	3.706***	-1.706	0.011	-3.002
	(2.506)	(1.736)	(0.083)	(1.141)	(7.739)	(0.074)	(1.531)
Disaster Index$_{,i,t-4}$	10.513***	5.256**	-0.209	6.033**	10.567*	0.004	0.909
	(1.906)	(1.966)	(0.104)	(2.580)	(5.433)	(0.108)	(0.985)
Observations	475	475	475	475	475	475	475
Number of Countries	18	18	18	18	18	18	18

Note: Table provides results for the low-income countries. ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Column (1) provides results for the weighted disaster index. Standard errors are clustered at the country level.

Table A7: Heterogeneity by Polity Status and Income Levels Interaction

	LIC	LIC (Dem)	LIC (Auto)	MIC	MIC (Dem)	MIC (Auto)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Weighted Disaster Index$_{,i,t}$	7.131***	3.882**	7.439***	-0.011	-0.473	2.337
	(1.337)	(1.373)	(2.152)	(1.654)	(0.857)	(2.133)
Observations	529	167	362	1,307	750	557
Number of Countries	18	13	18	45	32	35
Panel B:						
Weighted Disaster Index$_{,i,t}$	6.811***	3.809**	5.973**	-0.552	-0.427	6.742**
	(1.431)	(1.404)	(2.450)	(1.189)	(0.886)	(3.243)
Official Aid$_{,i,t}$	0.058	-0.009	0.088	-0.002	-0.009	0.023**
	(0.036)	(0.019)	(0.066)	(0.009)	(0.015)	(0.010)
Official Aid$_{,i,t-1}$	-0.049	0.010	-0.062	-0.008	-0.013	0.036**
	(0.029)	(0.021)	(0.037)	(0.014)	(0.019)	(0.016)
Observations	529	167	362	1,240	724	516
Number of Countries	18	13	18	45	32	35

Note: ** and *** denote significance at 5% and 1% level, respectively. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. Standard errors are clustered at the country level. LIC(Dem) in column 2 refers to democratic LICs, whereas LIC(Auto) in column 3 refers to nondemocratic LICs.

Table A8: Heterogeneity by Contraceptive use and Macro-level GDP

	Baseline	Low Cont Use	High Cont Use	Low GDP	High GDP
	(1)	(2)	(3)	(4)	(5)
Weighted Disaster Index$_{,i,t}$	7.131***	5.140***	9.992	22.949***	5.793***
	(1.337)	(1.259)	(5.808)	(6.614)	(1.509)
Observations	529	279	250	278	251
Number of Countries	18	9	9	9	9

Note: Table provides results for low income group of countries. ** and *** denote significance at 5% and 1% level, respectively. All the regressions control for both country- and period-fixed effects, along with a set of controls. Standard errors are clustered at the country level. 'Low (High) Cont Use' refers to group of LICs where contraceptive usage is below (above) median. Likewise, 'Low (High) GDP' refers to group of LICs with below (above) median GDP.

Table A9: Robustness Test: Conditioning on Health Related Covariates

	(1)	(2)	(3)	(4)	(5)
Weighted Disaster Index$_{,i,t}$	7.131***	7.437***	8.595***	11.753***	11.409***
	(1.337)	(1.697)	(1.796)	(3.722)	(3.876)
Maternal Mortality$_{i,t}$	-	0.514***	-	-	0.169
	-	(0.162)	-	-	(0.265)
Measles Immunization Rate$_{i,t}$	-	-	-0.106***	-	-0.052
	-	-	(0.021)	-	(0.066)
Public Health Expenditure$_{i,t}$	-	-	-	-0.059	-0.039
	-	-	-	(0.065)	(0.073)
Observations	529	370	492	198	198
Number of Countries	18	18	18	18	18

Note: Table provides results for low income group of countries. ** and *** denote significance at 5% and 1% level, respectively. All the regressions control for both country- and period-fixed effects, along with a set of controls. Standard errors are clustered at the country level.

Table A10: Effect of Natural Disasters on U5MR: Dynamic Panel Analysis

	Within Estimates			Arellano and Bond Estimates			AB Estimates (Collapsed)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weighted Disaster Index$_{i,t}$	3.698***	3.753***	3.827**	3.618***	3.711**	3.796**	7.767***	7.008***	7.133***
	(1.157)	(1.487)	(1.609)	(1.191)	(1.499)	(1.621)	(2.117)	(2.047)	(2.096)
log mortality$_{i,t-1}$	1.019***	2.189***	2.529***	1.015***	2.139***	2.504***	0.769***	1.404	-0.011
	(0.018)	(0.241)	(0.243)	(0.013)	(0.167)	(0.254)	(0.197)	(1.327)	(3.689)
log mortality$_{i,t-2}$		-1.203***	-1.863***		-1.164***	-1.768***		-0.543	2.745
		(0.235)	(0.571)		(0.175)	(0.616)		(1.139)	(6.587)
log mortality$_{i,t-3}$			0.326			0.253			-1.881
			(0.382)			(0.421)			(3.151)
AR(2) Test P-Value				0.422	0.359	0.358	0.331	0.345	0.351
Sargan Test P-Value				0.015	0.024	0.034	0.360	0.238	0.125
Unit Root Test P-Value	0.000	0.005	0.005						
Observations	529	511	493	511	493	475	511	493	475
Number of Countries	18	18	18	18	18	18	18	18	18

Note: Table provides the dynamic panel results for the low-income countries. ** and *** denote significance at 5% and 1% level, respectively. Standard errors robust against heteroskedasticity and serial correlation at the country level are reported in parantheses. All the regressions include a set of controls, country-specific trends, and country- and period-fixed effects. AB Estimates (Collapsed) in columns (7)-(9) refers to specifications in which instrument set is collapsed. Lags further than two of the dependent variable and upto 25 lags of the disaster index are collapsed and used as instruments in columns (7)–(9). Small-sample corrections to the covariance matrix and forward orthogonal-deviations transformation are applied.

Table A11: Effect of Natural Disasters on U5MR: Dynamic Panel Analysis (Robustness Exercise)

	AB Estimates			AB Estimates (Collapsed)			System GMM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weighted Disaster Index$_{i,t}$	4.407***	3.856***	3.917***	5.474**	5.731**	5.891**	8.189***	8.208***	10.063**
	(0.993)	(0.930)	(0.961)	(2.520)	(2.757)	(2.852)	(2.393)	(2.568)	(4.543)
log mortality$_{i,t-1}$	1.017***	2.249***	2.441***	0.765***	1.369	1.049	0.760***	0.516	-3.857
	(0.019)	(0.145)	(0.504)	(0.160)	(0.857)	(2.877)	(0.149)	(1.894)	(12.218)
log mortality$_{i,t-2}$		-1.264***	-1.624*		-0.529	0.439		0.227	7.743
		(0.148)	(0.985)		(0.814)	(5.605)		(1.778)	(20.883)
log mortality$_{i,t-3}$			0.169			-0.659			-3.359
			(0.502)			(2.835)			(9.319)
AR(2) Test P-Value	0.199	0.113	0.125	0.379	0.472	0.529	0.485	0.469	0.910
Sargan Test P-Value	0.001	0.003	0.001	0.442	0.266	0.169	0.750	0.484	0.300
Observations	529	511	493	529	511	493	529	511	493
Number of Countries	18	18	18	18	18	18	18	18	18

Note: Table provides results for low income group of countries. ** and *** denote significance at 5% and 1% level, respectively. Standard errors robust against heteroskedasticity and serial correlation at the country level are reported in parantheses. All the regressions control for both country- and period-fixed effects, along with a set of controls. AB Estimates (Collapsed) in columns (4)-(6) refers to Arellano-Bond specifications in which instrument set is collapsed. Lags further than two of the dependent variable and upto 25 lags of the disaster index are collapsed and used as instruments in columns (4)–(6). The last three columns presents the results for one-step System GMM with orthogonal deviations. Second to tenth lag of the dependent variable and the disaster index are collapsed and used as instruments in columns (7)–(9).

Table A12: Effect of Natural Disasters (EM-DAT Index) on U5MR: Dynamic Panel Analysis

	Within Estimates			Arellano and Bond Estimates			Arellano and Bond Estimates (Collapsed)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weighted Disaster Index$_{,i,t}$	6.881***	5.979***	5.969***	6.759***	5.917***	6.004***	6.147***	6.138***	6.096***
	(0.965)	(0.566)	(0.549)	(0.938)	(0.654)	(0.619)	(1.893)	(1.219)	(1.103)
log mortality$_{i,t-1}$	1.026***	2.147***	2.513***	1.025***	2.139***	2.538***	0.978***	2.022***	1.881***
	(0.019)	(0.177)	(0.268)	(0.011)	(0.167)	(0.142)	(0.039)	(0.169)	(0.517)
log mortality$_{i,t-2}$		-1.154***	-1.879**		-1.164***	-1.959***		-1.081***	-0.753
		(0.168)	(0.658)		(0.175)	(0.443)		(0.172)	(1.173)
log mortality$_{i,t-3}$			0.367			0.402			-0.191
			(0.411)			(0.322)			(0.683)
AR(2) Test P-Value				0.307	0.334	0.341	0.387	0.322	0.327
Sargan Test P-Value				0.123	0.171	0.220	0.051	0.055	0.057
Unit Root Test P-Value	0.000	0.005	0.005						
Observations	529	511	493	511	493	475	511	493	475
Number of Countries	18	18	18	18	18	18	18	18	18

Note: Table provides results for low income group of countries. ** and *** denote significance at 5% and 1% level, respectively. Standard errors robust against heteroskedasticity and serial correlation at the country level are reported in parantheses. All the regressions control for both country- and period-fixed effects, along with a set of controls.

Chapter 3

Rainfall Shocks, Child Mortality and Water Infrastructure[†]

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University of Adelaide

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Name of Principal Author (Candidate)	Sundar Ponnusamy (Meenakshi Sundaram Ponnusamy)		
Contribution to the Paper	I came up with the topic after performing a detailed literature review. Then collected the data and performed the analysis and written the manuscript. I had full-pledged guidance from my panel which helped me improve the work vastly from the initial stages.		
Overall percentage (%)	100%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Abstract

I study the effect of rainfall shocks on child mortality at a sub-national level for a global set of developing countries, using rainfall as a quasi-random shock to agricultural income. I establish that positive (negative) shocks to rainfall lead to a drop (increase) in child deaths overall, based on data for 13,734 districts from 94 countries for the period 2000-2014. Low-income countries (LICs), and countries reliant on agriculture are affected the most due to negative rainfall shocks. In LICs, the impact of negative rainfall shocks is mitigated by around 60% in districts located downstream to dams, an effect predominant among less affluent districts; in addition, the effect of rainfall fluctuations is persistent, lasting for up to three years following the shock. Results remain robust to the inclusion of various controls, to the consideration of relevant issues such as selective fertility and migration, and other robustness tests.

Keywords: Income shocks; child mortality; dam infrastructure

JEL Classification: H54, J13

3.1 Introduction

In an era of global warming when the temperature is expected to rise by around 1.5 degrees above pre-industrial levels, increases in the intensity and frequency of droughts will be a recurring phenomenon (IPCC, 2018). For developing countries that are generally reliant on agriculture (World Bank, 2018), fluctuations in rainfall imply significant impacts on their income. While the agricultural sector accounts for nearly 80% of the damages due to droughts in developing countries (FAO, 2017), children account for around 80% of the illnesses and casualties due to global climate change (WHO, 2009). By considering rainfall as a quasi-random shock to agricultural income, I examine the impacts of rainfall shocks on child mortality (children aged 0–5 years) in this study under a reduced-form specification. For analysis, I rely upon newly available child mortality data at the second-level administrative unit (district level), for a global set of 94 developing countries from Burstein et al. (2019). In addition, I examine the beneficial effects of water infrastructure in reducing the effects of negative rainfall shocks (henceforth, droughts) on the local population.

The relationship between the loss of income due to rainfall fluctuations and child health in developing countries is well-established in the literature. Droughts are found to be associated with higher infant mortality (Kudamatsu et al., 2012), decreases in the probability of girls' survival rate (Rose, 1999), child stunting (Hoddinott and Kinsey, 2001) and an increased number of malnourished children (Jensen, 2000).[1] While most of the studies focus on a single country context,[2] even fewer studies explore mortality mitigating channels. Trade openness (Burgess and Donaldson, 2010), access to mobile money (Riley, 2018), piped water and sanitation (Rocha and Soares, 2015) and clean drinking water (Lin et al., 2021) are identified as potential risk-reducing channels of

[1] Various other studies have also established the relationship between income shocks and health outcomes (Deaton and Paxson 1998; Case et al. 2005; Baird et al. 2011; Burker et al. 2015; Fenske et al. 2019), as well as the relationship between child health and associated human capital (Bloom and Canning 2000; Weil 2007; Currie et al. 2010; Currie 2009; Smith 2009).

[2] Only a few studies identify the effects of income shocks for a large set of developing countries. Kudamatsu et al. (2012) examines the impacts of droughts on infant mortality for 28 African countries, whereas Baird et al. (2011) focuses on the effects of income shocks on child mortality for 59 developing countries. However, neither of these studies explore mortality mitigating channels, which is a main focus of this paper.

droughts on child deaths. In this study, I establish the overall effects of rainfall shocks on child mortality first, while also disentangling the heterogeneous effects by income classification of countries, and their agricultural reliance. Next, I focus on a relatively unexplored but potentially important mitigating channel – the role of dam infrastructure and examine whether access to reservoir water helps reduce the effect of droughts.

In the role of water provisions on developmental outcomes, Duflo and Pande (2007) in their seminal work shown that districts that are downstream to dams have experienced increases in agricultural productivity along with a reduced vulnerability to droughts. However, the evidence of dam infrastructure on child health is limited and mixed. Chakravarty (2011) shows that children who reside immediately downstream to dams in African countries experience a significant reduction in child mortality. On the other hand, Mettetal (2019) notes that increases in the number of dams in South Africa are associated with increases in infant mortality. While their studies investigate the direct effects of dams' placement on child mortality in African context, I focus on the mitigating role played by dams in alleviating the detrimental effects of droughts in downstream districts that may have access to reservoir water, on a global scale.

Unraveling the causal links between income and adult/child health outcomes has been particularly challenging, due to issues such as omitted variable bias (Currie 2009; Chandra and Vogl 2010; Björkman-Nyqvist 2013) or due to the existence of a feedback loop between income and health (Gallup and Sachs 2001; Deaton 2002). To overcome these issues, several studies have relied on rainfall as exogenous shocks to agricultural income (Miguel et al. 2004; Bohlken and Sergenti 2010; Iyer and Topalova 2014; Shah and Steinberg 2017).[3] As water is the primary input for agricultural productivity, the most direct effect of rainfall is certainly on the agricultural sector. This relationship is well-documented in different parts of the world (Jayachandran 2006; Pandey et al. 2007; Alene 2010).[4] Along with their effects on the agricultural sector, rainfall can also have an

[3] Apart from rainfall, some studies have relied on other measures such as natural disasters (Baez et al. 2007; Heger and Neumayer 2019) and chlorophyll concentration in the ocean (Ludwig and Flückiger 2014; Axbard 2016) as exogenous shocks to income.

[4] As most of the world's poor are reliant on agriculture as a major income source, they are in turn naturally affected by shocks to rainfall Jayachandran (2006). While this effect would be predominant in rural areas due to agriculture being their significant income source, it can also affect urban regions if the

effect on a non-agricultural sector, for example, the energy sector, considering that 34% of the power generation in developing countries is through hydroelectric power and this figure is substantially higher for Africa at 47%, where power generation is reliant on river water (Barrios et al., 2010). Diminished access to electricity owing to lower hydroelectric production during drought periods can also result in worse child health outcomes due to factors such as lack of access to infrastructure (Fay et al., 2007) or food poisoning (Gonzalez-Eiras and Rossi, 2011).

The outcome variable of interest is the mortality rates of children aged 0–5 years (U5MR), expressed as the number of deaths per 100 live births, sourced from Burstein et al. (2019). The dataset contains a total of 13,734 districts from 94 developing countries for the period 2000–2014. Rainfall data from Willmott and Matsuura (2001) is extracted for the sample considered.[5] Initially, I test the effects of rainfall fluctuations on child mortality, subject to a simple, linear specification. The estimates of the effects of the log of rainfall on child mortality suggest that a 10% increase in rainfall leads to a drop of 0.005 percentage points (pp.) in under-5 mortality overall, with estimates being statistically significant at 1% level. Once the income levels of countries are taken into consideration, low-income countries (henceforth, LICs) are affected three-fold (a drop of 0.02 pp.), followed by lower-middle-income countries (henceforth, LMICs) experiencing a drop of 0.004 pp. for a 10% increase in rainfall, statistically significant at 1% level. However, upper-middle-income countries (henceforth, UMICs) remain unaffected by rainfall fluctuations. Based on the geographical location, Sub-Saharan African countries (SSA) are affected the most, especially those that are in the low-income category; whereas based on agricultural reliance, those that are highly dependent on agriculture suffer the most.

Effects of rainfall shocks can be asymmetric i.e. positive shocks to rainfall may lead to a drop in mortality due to the rise in income, whereas negative rainfall shocks can lead to an increase in mortality stemming from the drop in agricultural output. To

effect is too large to cause inflation in food prices Fichera and savage (2015).

[5] Owing to the unavailability of agricultural output data at a sub-national level for a global set of developing countries, I use macro-level agricultural output data from WDI (2010) to test the relationship between rainfall and agriculture. Results suggest a strong correlation between the two, especially in low-income, low-middle-income, and African countries. Detailed discussion is provided in Section 3.4.1.

account for this asymmetric effect, I standardize the rainfall variable to classify shocks as positive or negative.[6] As presumed, positive shocks to rainfall lead to a drop in mortality, whereas negative shocks lead to an increase in child deaths, especially for LICs, agriculture-oriented countries, and African countries.[7]

Next, I examine the role of dam infrastructure in alleviating the detrimental effects of droughts on child health. By using the geo-referenced locations of around 38,000 dams at the global level from GOODD (2020) database and using river streams data from HydroSheds (2006), I identify districts that are located downstream to a dam on a river network which may have access to reservoir water in periods of negative rainfall shocks. If downstream districts are insulated from negative shocks to rainfall, then it provides a basis for investing in water infrastructure to alleviate the negative impacts of droughts, especially in the developing world context where the majority of the population is reliant on agriculture.

Results from dam analysis suggest that districts with upstream dams that may have access to reservoir water are found to experience a higher benefit during positive shocks especially in low-income, lower-middle-income, and African countries. During periods of droughts, it is clear that children in downstream districts from low-income countries are most insulated from vagaries of the weather, with the effects of droughts mitigated by more than 50%. Wealthier states (first-level administrative units) that have higher resources may build more dams, while also being able to provide better healthcare facilities amongst other things. If this is the case, then the estimates suffer from endogeneity bias. To test this, I use nightlights as a proxy for a broad range of economic activities and classify states as wealthy or poor. Results are primarily driven by poorer states, allaying any endogeneity concerns.[8] A detailed discussion is provided in the Results sec-

[6] Following Cole et al. (2012) and Iyer and Topalova (2014), one standard deviation increase in rainfall above the long-run average of a district is classified as a positive shock, whereas a one standard deviation decrease in rainfall below the mean is classified as a negative shock. I also follow Shah and Steinberg (2017) to create an alternative definition of rainfall shocks at the bottom 20th and top 80th percentiles. Results remain robust and detailed discussion is provided in section 3.4.8.

[7] Burstein et al. (2019) also provides mortality data for infants and neonates. Rainfall has a significant impact on the children in these age groups as well. A detailed discussion is provided in Section 3.4.4.

[8] While the analysis based on nightlights help alleviate some endogeneity concerns regarding the ability of states to provide the required health resources, another limitation still remain regarding the placement of dams. Countries might construct dams based on the vulnerabilities of districts, for example, there is a

tion. Moreover, considering that the information on the type of dam is unavailable, these results are taken to be lower estimates.[9] And this analysis provides an understanding of the linkages between the provision of water resources to a better survival rate amongst the children (especially in LICs).

As inequities in income result in a lack of access to education or investment opportunities to the poor (Alesina et al., 2016), a dearth of opportunities may push the poor in higher inequality areas to agriculture for means, which can lead to a higher sensitivity to rainfall fluctuations. Therefore, I examine the effects of rainfall shocks on child mortality in areas classified by their level of income inequality. Following Alesina et al. (2016), I create GINI coefficients representing the income inequality at the first-level administrative unit (henceforth, referred to as 'states') by using nightlight per capita at the district level.[10] Results from income inequality analysis suggest that districts located in higher-inequality regions from a low-income group of countries are most affected due to negative shocks. However, I do not observe a consistent set of results for other income groups. These results indicate that even amongst low-income countries that are primarily agriculture-dependent, areas that suffer from higher-income inequality are affected the most.

Moreover, effects of rainfall fluctuations are found to have persistent effects i.e. up to three lags of rainfall have a significant effect on child mortality, especially a stronger effect that can be observed in LICs. And the cumulative effects are much larger than if only the contemporaneous effects are considered.

Next, I examine the sensitivity of the results subject to various robustness tests. First I investigate a potential bias in the estimates due to the heterogeneity in the treatment effects across time or groups and negative weights being assigned to some of the

chance that dams are constructed in under-developed areas or in mindful of the geographical placement. Using dam placement data based on the geographic characteristics of districts might help address this issue completely.

[9]While irrigation dams are built specifically to assist the downstream districts with access to reservoir water during periods of droughts, recreational dams are not. Therefore, the beneficial effects of the interaction term between the downstream dams and droughts can be downward biased due to the inclusion of recreational dams in the analysis.

[10]While rainfall is a primary determinant of agricultural income (Fichera and savage, 2015), various sources have used nightlights measured from satellite imagery as a proxy for other broad range of economic activities (Henderson et al. 2012; Hodler and Raschky 2014; Khalil et al. 2020).

treated/control pairs (De Chaisemartin and D'Haultfoeuille 2020; Goodman-Bacon 2018). Second, I employ other relevant control variables such as temperature, pollutant concentration, nightlight intensity, and population in the specifications, all at the district level. I also try various sensitivity tests for the main set of results such as using trends at the district-level instead of state-level, using bootstrapped standard errors, clustering standard errors at the state level instead of the district level, using an alternative definition for rainfall shocks, performing analysis by pooling data at the state level, examining the role of malarial incidences and the associated health channel mechanism of droughts, among various other tests. The results remain robust to all exercises employed. Other related issues such as selective fertility and migration that may impose bias in the estimates are also discussed in detail.

As measles immunization rates are used as one of the covariates in the construction of the child mortality estimates by Burstein et al. (2019) and considering that these immunization rates are also indicative of the state of the public health system in a country Levine and Rothman (2006), I explore a potential health channel mechanism of rainfall shocks next. For example, if there is a drop in immunization rates amongst children when rainfall is lower, which can lead to more child deaths, then the perceived income channel mechanism of rainfall shocks on child mortality could indeed be the health mechanism. Owing to the lack of publicly available, measles vaccination rates data at a subnational level, I examine the relationship between rainfall shocks and vaccination rates at a cross-country level. Rainfall fluctuations are found to be positively associated with measles immunization rates amongst the children. Therefore, I analyze this potential health channel mechanism of rainfall shocks through a heterogeneity analysis by above/below median measles vaccination rates. Results provide suggestive evidence that the income channel mechanism is dominant. A detailed discussion is provided in the results section.

This study makes three major contributions to the literature on the income-health nexus. First and foremost, I provide empirical evidence on the effects of income shocks on child mortality for a global set of developing countries. Second, I provide evidence on how the provision of water resources can help dampen the effects of droughts and thereby, provide a better survival chance for the children. Third, I interconnect income inequality to the income-health relationship and provide an understanding of its role in the detrimental effects of income fluctuations on child health, along with considering various other relevant issues such as selective fertility, selective migration, and measles immunization rates in detail. To the best of my knowledge, this is the first study to focus on the role of dams in mitigating the detrimental effects of droughts on child mortality, on a global scale. Understanding the consequences of rainfall fluctuations and potential ways of alleviating their impacts is important especially in an era of increasing global warming and frequent droughts (UN, 2013).

The rest of the paper is organized as follows. Section 3.2 provides the data description, Section 3.3 contains the estimation method, Section 3.4 presents the results and I conclude with Section 3.5.

3.2 Data

The outcome variable of interest is U5MR, that is, the number of children dying before the age of five years, expressed per 100 live births, at the district level for a given year. Panel data for 13,734 districts from 94 countries for the period 2000–2014 is used and the list of countries is provided in Table B1, online appendix.

Owing to the lack of proper birth registration data in developing countries, it is difficult to obtain mortality data even at a national level.[11] Child mortality data at the subnational level is even scarcer for developing countries. This data scarcity problem is alleviated in a recent paper by Burstein et al. (2019) in which the authors have used information on 15.9 million births and 1.1 million child deaths from 467 geo-referenced household surveys to produce mortality estimates at the sub-national level for children aged under five. Burstein et al. (2019) provides two different contemporaneous mortality measures: an unweighted variable that provides information on the total number of child

[11]UN Inter-agency Group for Child Mortality Estimation (UNIGME) produces various mortality estimates at the country level for global organizations such as UNICEF, World Bank, and World Health Organization (WHO). UNIGME employs various modelling approaches to correct for any biases inherent in sources such as Demographic and Health Surveys (DHS), and Multiple Indicator Cluster Survey (MICS) to produce the mortality estimates.

deaths for a district in a given year; and a weighted variable on the probability of dying before the age of five, in a given district and year.[12] In this paper, I rely upon the weighted rates i.e. probability of a child's death, to identify the effect of income shocks on mortality. These probabilities are converted into mortality rates and are expressed as the number of deaths per 100 live births.[13] Focusing on weighted rates is of particular significance as it will help unmask the effects of rainfall shocks in areas with low death counts but higher mortality rates per births, owing to smaller population size.

Considering the scarcity of data on agricultural productivity at a sub-national level for a global set of developing countries, I rely on macro-level agricultural output data to establish the relationship between rainfall and agricultural income. WDI (2010) provides various measures on agricultural output and for this study, I use Value added from agriculture (as % of GDP). As robustness, I also try total value added from agriculture (in constant 2010 US$).[14]

Next, as a measure of exogenous shocks to agricultural income, I rely on the historical rainfall data from Willmott and Matsuura (2001), Version 4.01, which provides gridded, precipitation data at a global level till the year 2014. Monthly rainfall data in millimeters is extracted at the district level by matching weather stations to the centroids of district boundaries, for the period 2000–2014 to identify the average yearly rainfall for a given district.[15] Since there are multiple ways to parameterize rainfall, I employ both a linear and a non-linear specification. Initially, I apply rainfall in log form, and then to identify

[12]To produce a detailed panel dataset on child mortality at the subnational level, Burstein et al. (2019) fits the geostatistical discrete hazards model to a data on 15.9 million births and 1.1 million deaths of children that have occurred since the year 2000, while using ten geospatial covariates to fit the model and also applying different mechanisms to account for any data sparsity. Data on child deaths and births for a given location and year are sourced from either summary birth histories (SBHs) or complete birth histories (CBHs). The resulting dataset provides information on the probability of dying before the age of five and the total number of under-5 deaths that have occurred at each location in a year. See Burstein et al. (2019) for a detailed discussion. Later on, I control for some of these spatial covariates for robustness. A detailed discussion is provided in Section 3.4.8.

[13]Burstein et al. (2019) provides three different measures of U5MR data: mean values and two uncertainty bounds. While I rely upon the mean values for the main analysis, I also use bounds on the mortality rates as robustness tests. The detailed discussion is provided in the Results section.

[14]Value added data on agriculture from WDI (2010) also contains information on two other related sectors – fishing and forestry. Therefore, estimates of rainfall on these measures have to be taken as conservative estimates only.

[15]By linking rainfall data to the sub-national level boundaries shapefile from GADM (2020), monthly rainfall is extracted using ArcGIS software.

the asymmetric effects, I also use a non-linear form following Cole et al. (2012) and Iyer and Topalova (2014). An indicator variable 'positive rainfall shock' takes on a value one if rainfall in a given district is one standard deviation above the long-run average of that district and 'negative rainfall shock' takes on the value one if rainfall is one standard deviation below the long-run mean of a particular district. Table 3.1 provides a summary of the rainfall shocks and under-5 mortality rates.

Table 3.1: Summary Statistics

Variable	Mean	Std. dev.	Source	Description
U5MR, Overall	5.169	4.315	Burstein(2019)	Under-5 mortality rate rates for the entire sample.
U5MR, LIC	10.020	4.067	Burstein(2019)	Under-5 mortality rates for low income countries.
U5MR, LMIC	6.010	4.526	Burstein(2019)	Under-5 mortality rates for lower-middle income countries.
U5MR, UMIC	2.575	1.302	Burstein(2019)	Under-5 mortality rates for upper-middle income countries.
Positive rainfall shock, Overall	0.163	0.369	Willmott and Matsuura(2001)	Equals '1' for positive shocks and '0' otherwise.
Negative rainfall shock, Overall	0.148	0.356	Willmott and Matsuura(2001)	Equals '1' for negative shocks and '0' otherwise.
Positive rainfall shock, LIC	0.164	0.370	Willmott and Matsuura(2001)	Equals '1' for positive shocks and '0' otherwise.
Negative rainfall shock, LIC	0.156	0.363	Willmott and Matsuura(2001)	Equals '1' for negative shocks and '0' otherwise.
Positive rainfall shock, LMIC	0.163	0.369	Willmott and Matsuura(2001)	Equals '1' for positive shocks and '0' otherwise.
Negative rainfall shock, LMIC	0.143	0.349	Willmott and Matsuura(2001)	Equals '1' for negative shocks and '0' otherwise.
Positive rainfall shock, UMIC	0.162	0.368	Willmott and Matsuura(2001)	Equals '1' for positive shocks and '0' otherwise.
Negative rainfall shock, UMIC	0.153	0.359	Willmott and Matsuura(2001)	Equals '1' for negative shocks and '0' otherwise.
Dam-fed district, Overall	0.187	0.389	GOODD(2020)	Equals '1' if a district has an upstream dam and '0' otherwise.
Dam-fed district, LIC	0.223	0.417	GOODD(2020)	Equals '1' if a district has an upstream dam and '0' otherwise.
Dam-fed district, LMIC	0.179	0.384	GOODD(2020)	Equals '1' if a district has an upstream dam and '0' otherwise.
Dam-fed district, UMIC	0.184	0.388	GOODD(2020)	Equals '1' if a district has an upstream dam and '0' otherwise.
Average Temperature	22.51	5.99	Willmott and Matsuura(2001)	Average annual temperature in degree Celcius.
Log Pollutant Concentration	2.71	0.86	Donkelaar(2020)	Log of pm2.5 fine particulate matter.
Log Nightlights	0.250	2.309	NOAA(2020)	Log of average nightlights measured from space.
Average Population	153.173	484.243	CIESIN(2018)	Average population at district level, in 000's.
Polity Index	0.287	0.536	Polity IV (2020)	Rescaled in the range of -1 to +1.
VA from Agriculture, Overall	15.40	9.51	WDI (2019)	as a percentage of GDP.
VA from Agriculture, LIC	26.01	12.71	WDI (2019)	as a percentage of GDP.
VA from Agriculture, LMIC	18.31	7.82	WDI (2019)	as a percentage of GDP.
VA from Agriculture, UMIC	8.84	3.63	WDI (2019)	as a percentage of GDP.
Measles Immunization Rate, Overall	70.67	15.01	WDI (2019)	as a percentage of the total children, aged 12-23 months.
Measles Immunization Rate, LIC	61.18	15.90	WDI (2019)	as a percentage of the total children, aged 12-23 months.
Measles Immunization Rate, LMIC	71.11	13.50	WDI (2019)	as a percentage of the total children, aged 12-23 months.
Measles Immunization Rate, UMIC	79.53	9.48	WDI (2019)	as a percentage of the total children, aged 12-23 months.

Note: U5MR refers to under-5 mortality rates; Overall refers to the entire sample of 94 developing countries; LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. "U5MR, Low" provides the under-5 mortality rates for low-income countries and so on. VA refers to Value Added that provides the net output of a sector after adding up all outputs and subtracting intermediate inputs, based on the definition from WDI (2010).

To understand whether the provision of water resources acts as a channel to deter the negative consequences of health shocks, I identify whether a district is downstream or not, to a dam. GOODD (2020) provides geo-referenced locations of more than 38,000 dams at a global level. Using a line network of all rivers with a 15 arc-second resolution from HydroSheds (2006), dams locations from GOODD (2020) and district-level polygon shapefile from GADM (2020), I find whether a district has a dam upstream or not by using ArcGIS software.[16] Approximately 20% of the districts in the sample are downstream (i.e. dam-fed), whereas a slightly higher percentage of the districts from LICs are dam-fed compared with LMICs and UMICs, refer to Table 3.1. Districts with upstream dams can have additional access to water resources than other districts in the form of stored reservoir water. This access to reservoir water during drought periods can act as a buffer and help mitigate some of the negative consequences to agricultural output, thereby dampen the effect of rainfall fluctuations on child death.

To determine the role of income inequality in the effects of income fluctuations on child mortality, I follow Alesina et al. (2016) and create a GINI index at the state level by using per-capita nightlight activity at the district level. I extract nightlight data from the database maintained by the National Oceanic and Atmospheric Administration (NOAA) for each district and then by using the gridded population data from CIESIN (2018),[17] I find the nightlights per capita. Following Alesina et al. (2016), using per-capita nightlights at second-level administrative units, GINI coefficients for the first-level administrative units are calculated.

Various other factors such as temperature and pollution can have an effect on health outcomes (Deschenes et al. 2009; Landrigan et al. 2017; He et al. 2020). Therefore, I also control for these two variables, along with district-level population for the period considered, as a robustness test. In addition to the precipitation data, Willmott and Matsuura (2001) also provides data on the temperature in degree celcius. By following a similar method as for rainfall, I extract temperature data at the district level. Next, using

[16]Trace Downstream feature in ArcGIS software is used to identify the districts that are located downstream to a dam i.e. dam-fed districts for the 94 developing countries in the sample.

[17]CIESIN (2018) provides gridded population data at five-year intervals. Missing data for the intermediate years are replaced with linear interpolation.

ground-level fine particulate matter data from Van Donkelaar et al. (2020), I measure the pollutant concentration (PM2.5 particulates) for each district. District level population data is from CIESIN (2018).

3.3 Estimation Method

This study employs district level panel data on child mortality and rainfall for the period 2000–2014. In the baseline estimation, I follow a simple, reduced-form model to estimate the impacts of rainfall fluctuations on under-5 child mortality, as below:

$$Y_{ist} = \alpha Rain_{ist} + \delta_{is} + \delta_t + \delta_{ct} + \theta_s \times t + \eta_{ist}, \tag{1}$$

Y_{ist} is the under-5 mortality rates expressed as the number of deaths per 100 live births for district i in state s (first-level administrative units) for a year t.[18] $Rain_{ist}$ is the log of rainfall, the explanatory variable of interest. To control for the unobservable differences in the mortality rates between districts due to the different geographies, I control for the district-fixed effects, δ_{is}. To account for the common non-linear trends and period-specific shocks, I control for the year-fixed effects, δ_t. Similarly, δ_{ct} refers to country x year fixed effects, which controls for any potential shock that might affect all districts in a given country and year. Moreover, each state may follow a specific trend due to the state-specific, health, or economic policies, and therefore, I also allow for the state-specific trends $\theta_s \times t$ in the specification.[19] η_{ist} includes the time-varying unobservable shocks to the child mortality.

However, the effects of rainfall can be asymmetric i.e. while positive shocks to rainfall may lead to better agricultural outcomes and thereby a reduction in mortality, negative shocks to rainfall can have adverse effects through a drop in agricultural income. As the next step, I follow a non-linear model as below:

[18] Burstein et al. (2019) also provides information on child mortality in different age bins – infants and neonates. I also test the effects of rainfall shocks on these two outcome variables. Detailed discussion is provided in the online appendix.

[19] As robustness, I also use district-specific instead of state-specific trends. Results remain unchanged. The detailed discussion is provided in the Results section.

$$Y_{ist} = \alpha_1 Positiveshock_{ist} + \alpha_2 Negativeshock_{ist} + \delta_{is} + \delta_t + \delta_{ct} + \theta_s \times t + \eta_{ist}, \quad (2)$$

Dummy *positiveshock* takes on a value one if the rainfall in a district is one standard deviation above the long-run mean of that particular district; likewise, the variable *negativeshock* takes on a value one if the rainfall is one standard deviation below the long-run mean.[20]

Agricultural income in districts that are downstream to dams may be less affected by droughts due to access to irrigation water, which in turn can dampen the effects of negative shocks to rainfall on child mortality. By identifying dam-fed districts using the location of 38,000 dams from GOODD (2020) database and river networks from HydroSheds (2006), I assess the effect of rainfall shocks in dam-fed districts subject to the following specification from Iyer and Topalova (2014):

$$\begin{aligned} Y_{ist} = \alpha_1 Positiveshock_{ist} + \alpha_2 (Positiveshock_{ist} * downstream_{is}) + \\ \alpha_3 Negativeshock_{ist} + \alpha_4 (Negativeshock_{ist} * downstream_{is}) + \delta_{is} + \delta_t + \delta_{ct} + \\ \theta_s \times t + \eta_{ist}, \end{aligned} \quad (3)$$

In Equation 3, shocks to rainfall interact with the dummy *downstream* that takes on a value one for dam-fed districts i.e. districts with a dam upstream to it and zero if the district has no upstream dam. These dam-fed districts are set to benefit during drought seasons as stored water from reservoirs are channelled through canals and spillways (Biswas and Tortajada, 2001). Therefore, districts with upstream dams should be less susceptible to negative shocks to rainfall. If this is the case, then from a policy-making perspective, the provision of water resources in the form of dams will be an important mechanism to improve child health in periods of adverse economic conditions, a finding

[20] As robustness, I use an alternative definition for rainfall shocks following Shah and Steinberg (2017). Using the standardized rainfall measure, positive shocks take on a value of one, if the standardized rainfall is above the top 80th percentile, and negative shocks as one, if the standardized rainfall is below the bottom 20th percentile. A detailed discussion of the results is provided in the online appendix.

which can help assist foreign institutions (and the recipients) optimally allocate (channel) resources.

3.4 Results

3.4.1 Rainfall and Agricultural Output

Existing literature has well-established the relationship between rainfall variations and agricultural output, and income (Jayachandran 2006, Fichera and savage 2015, Shah and Steinberg 2017). Nevertheless, I examine the impacts of rainfall on agricultural output for the sample considered in this study.[21] As the data for agricultural productivity at the subnational level is unavailable for all developing countries, I use cross-country data on agricultural output to analyze the relationship with rainfall. By using the value added from agriculture, I examine the effects of rainfall shocks on agricultural output at a cross-country level and present results in Table 3.2. Panel A provides the results for the effects of rainfall on value added from agriculture (as a % of GDP) and panel B provides the results for total value added (in constant 2010 US dollars). Both variables are sourced from WDI (2010) and enters the regression in log form, along with the precipitation variable. Along with country fixed effects and year fixed effects, country-specific trends are also controlled for in the specifications, to account for any trends in the dependent variable. Moreover, I also include macro-level GDP per capita (sourced from WDI (2010)) which can account for other economic or technological factors that may impact the agricultural output.

Column (1) contains the results for the entire sample, whereas columns (2)–(4) produces results for the group of countries classified by their income as per the World Bank convention (for the year 2010). Columns (5) and (6) presents results for countries classified by below-median and above-median respectively, by the value of the dependent variable; whereas the last two columns contain results for Sub-Saharan African countries and the rest, respectively. Results from column (1) suggest a strong, positive correlation between rainfall and agricultural productivity, statistically significant at 5% level. Based

[21] Using precipitation data from Willmott and Matsuura (2001), I estimate the average rainfall in each country for the sample considered.

Table 3.2: Effects of Rainfall on Agricultural Output

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent Variable: Log of $VA_{i,t}$(% of GDP)								
$Log\_Rain_{i,t}$	0.093***	0.148**	0.138**	0.007	0.079	0.112***	0.097**	0.089*
	(0.031)	(0.062)	(0.039)	(0.092)	(0.058)	(0.031)	(0.041)	(0.047)
No. of Countries	89	26	36	27	43	46	41	48
Observations	1,278	361	526	391	610	668	574	704
Panel B: Dependent Variable: Log of Total $VA_{i,t}$								
$Log\_Rain_{i,t}$	0.051*	0.091**	0.059*	0.043	0.052	0.063*	0.070*	0.022
	(0.027)	(0.042)	(0.030)	(0.073)	(0.042)	(0.037)	(0.040)	(0.032)
No. of Countries	85	24	35	26	42	43	39	46
Observations	1,209	336	503	370	607	602	539	670

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include country-specific trends, country fixed effects, and period fixed effects. Standard errors are clustered at the country level.

on the income-wise results from columns (2)–(4), the effects of rainfall are much stronger in the low-income group of countries (LICs), followed by low-middle-income countries (LMICs). However, a similar set of results is not observed for the upper-middle-income countries (UMICs). There is also a considerable difference in the magnitude of estimates between panels A and B (for example, the coefficient of the log of rainfall is -0.067 for UMICs in panel A, however, the coefficient becomes positive in panel B), therefore using two different measures to ensure the relationship between agriculture and rainfall is required. As the countries at the lower end of the income spectrum are reliant on agriculture, they, in turn, are affected by rainfall shocks, Jayachandran (2006). Our results suggest the same i.e. in LICs and LMICs, where agriculture is dominant,[22] the effects of rainfall shocks are also significant.

Results from columns (5) and (6) reinforce this evidence i.e. effects are significant in countries where agriculture is dominant (i.e. in above-median countries); Based on the last two columns, African countries are affected the most, owing to their heavy reliance on agriculture.[23] Therefore, this set of analysis suggests a strong, positive correlation between agriculture and rainfall, especially for low-income, low-middle-income, and African countries, ensuring the validity of using rainfall as a proxy for agricultural income in developing countries.

3.4.2 Baseline Results

Now I proceed to test the effects of rainfall fluctuations on under-5 mortality rates using Equation 1. There are a total of 13,734 districts in the sample for the period 2000–2014. The outcome variable is mortality rates expressed as the number of deaths per 100 live births and the independent variable of interest is the log of rainfall. Results for the entire sample of 94 countries are provided in Table 3.3. Tables also provide the mean of the dependent variable for ease of interpretation of estimated coefficients.

[22]Refer to Table 3.1 for the value added from agriculture for the group of countries classified income-wise.

[23]For the sample period considered, value added from agriculture constitutes 22.97% of the total GDP for African countries, whereas, for the rest of the sample, agriculture accounts for only 14.75%. For the African countries that are in the low-income category, this figure increases even higher to 32.15%. Source: Author's calculations.

Column (1) shows the effects of rainfall on U5MR for a specification that accounts for both country-year fixed effects and year fixed effects.[24] Based on the findings, a 10% increase in rainfall leads to a drop of 0.0046 percentage points (pp.) in child mortality, a small but significant effect. Comparing with the mean dependent variable, this equates to a drop of around 0.09% in under-5 mortality. Next, as each state (first-level administrative units) may follow their own health or economic policy, I control for state-specific trends in Column (2). Or each district might be following a specific trend, possibly due to a better/worse micro-level management by local health officials. Therefore, I control for district-specific trends instead of state-specific trends in column (3). Results remain unchanged to the inclusion of either type of trend. Coefficient drops slightly to the inclusion of district-level population in column (4), however, the significance of estimates are unaffected.[25] In column (5), I drop the top 10 percentile of observations i.e. regions with very high child mortality rates to confirm that the results are not driven by areas with poorer child health. As expected, the effect of rainfall drops, however, a strong effect persists. Finally, in column (6), I cluster the standard errors at the state level instead of the district level, as robustness. There is a small increase in the standard error with the coefficient remaining significant at 1% level.

[24]While country-year fixed effects account for any shocks that might affect a particular country in a given year; year fixed effects will control for any shock that might affect all countries in the sample for a specific year.

[25]Mortality rates used in this study are already weighted based on the number of live births. Nevertheless, I control for the district level population to ensure that the effects are not driven by high-population regions. While higher population areas end up with higher mortality, the effect of rainfall is still strong, even though it is slightly lower compared with previous estimates that did not account for the population count, Column (4), Table 3.3.

Table 3.3: Effects of Rainfall on U5MR: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
Log $\mathrm{Rain}_{i,t}$	-0.044***	-0.044***	-0.044***	-0.039***	-0.034***	-0.037***
	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)	(0.012)
Log $\mathrm{Population}_{i,t}$				0.240***		
				(0.042)		
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Trends	No	Yes	No	Yes	Yes	Yes
District Specific Trends	No	No	Yes	No	No	No
No. of Districts	13,734	13,734	13,734	12,838	13,245	13,297
Observations	204,781	204,781	204,781	189,645	184,310	198,782

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level in columns (1)–(5) and at the state level in column (6). The top 10 percentile of the under-5 mortality rates is dropped in column (5).

3.4.3 Heterogeneity across samples

A set of results based on the entire sample will help us identify the effects of income fluctuations on child health, for a global set of developing countries. But, there might be considerable heterogeneity, due to the income levels of countries or their reliance on agriculture, for example. Therefore, I explore the impacts of rainfall fluctuations on child mortality across various country groups, subject to Equation 1. Table 3.4 contains results for sample-wise analysis. Panel A of Table 3.4 contains rainfall in log form, whereas in panel B I try a non-linear specification of rainfall i.e. the type of shock to establish the asymmetric effects.

Column (1) of panel A contains the results for baseline estimates which were discussed earlier. Columns (2)–(4) provides results for countries grouped by their income levels as per the World Bank's convention. As evident, the set of countries that are low in the income spectrum are the ones to suffer the most i.e. low-income countries are affected more than two-fold compared with the baseline estimates, whereas low-middle income countries are affected similarly to the baseline. A 10% increase in rainfall leads to a drop of 0.016 percentage points in U5MR for the LICs, whereas LMICs experience a drop of 0.004 pp. for a similar increase in rainfall. As LICs are the ones to be most reliant on agriculture, they are in turn most affected by rainfall fluctuations, followed by LMICs.[26] However, upper-middle-income countries that are less reliant on agriculture, remain largely unaffected, refer to column (4), Table 3.4.

Next, to confirm the findings, I perform one more set of analysis based on countries' reliance on agriculture. Using data from WDI (2010), I group countries on their share of value-added from agriculture (as a percentage of total GDP). Column (5) provides results for countries that are less reliant on agriculture and column (6) contains results for agriculture-dominant countries.[27] While both groups of countries are affected due

[26] Using upper or lower bounds instead of the mean mortality rates from Burstein et al. (2019) for LICs results in estimates of -0.206 and -0.124 for the log of rainfall respectively, each individually significant at 1%. Results for other specifications also remain robust qualitatively and will be provided on request.

[27] Countries that are below (above) median on value-added from agriculture are classified as less (more) reliant on agriculture. Instead of value-added from agriculture, I also use the share of employment in agriculture (data from WDI (2010)) to perform this analysis. Results remain robust qualitatively and will be provided on request.

Table 3.4: Effects of Rainfall on U5MR: Samplewise Analysis

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear Specification								
Log $\text{Rain}_{i,t}$	-0.044***	-0.163***	-0.040***	-0.011	-0.011	-0.078***	-0.142***	-0.028***
	(0.007)	(0.020)	(0.010)	(0.012)	(0.010)	(0.010)	(0.021)	(0.008)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	13,734	1,881	6,309	5,544	6,710	7,024	3,409	10,325
Observations	204,781	28,136	93,689	82,956	100,137	104,644	50,911	153,870
Panel B: Non-linear Specification								
Positive Shock $\text{Rain}_{i,t}$	-0.030***	-0.066***	-0.051***	0.001	-0.002	-0.054***	-0.116***	-0.002
	(0.003)	(0.013)	(0.006)	(0.002)	(0.003)	(0.005)	(0.011)	(0.002)
Negative Shock $\text{Rain}_{i,t}$	0.010***	0.065***	-0.003	0.006***	0.002	0.017**	0.022*	0.005
	(0.004)	(0.012)	(0.008)	(0.002)	(0.004)	(0.007)	(0.012)	(0.003)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

to rainfall fluctuations, the effect on agriculture-reliant countries is more than three-fold compared with the other sample. This re-enforces the findings for different income groups that the LICs and LMICs that are more likely to be reliant on agriculture are being affected the most due to rainfall fluctuations.[28]

Finally, I focus on geographical locations by splitting the sample into two: Sub-Saharan Africa (SSA) and the rest (Non-SSA). Column (7) contains results for African regions and column (8) contains results for non-African countries. It is evident that out of the two groups, African countries are the most affected due to rainfall fluctuations, which can be owed to their heavy reliance on agriculture and thereby on rainfall (Chakravarty, 2011). I also perform a continent-wise analysis, while also focusing on the role of polity status of institutions. A detailed discussion is provided in the online appendix to preserve space.[29]

3.4.4 Assymmetric Effects

So far, a linear specification is used to estimate the effects of rainfall fluctuations. Next, to capture the asymmetric effects, I follow a non-linear specification based on Equation 2 and present the results in panel B, Table 3.4. Rainfall shocks are classified as positive or negative based on the standardized values from the mean, as explained in the Estimation method section. Based on Column (1), positive shocks to rainfall lead to a decrease in U5MR, and negative shocks lead to adverse effects, for the entire sample. Results suggest that a one standard deviation increase in rainfall leads to a 0.03 pp. drop in child mortality (a drop of 0.58%) whereas one standard deviation decrease in rainfall leads to an increase of 0.01 pp. (an increase of 0.193%) in the outcome variable.

Next, I analyze the asymmetric effects for countries grouped by their income levels. Based on columns (2)–(4), Table 3.4, low-income countries are the ones to be affected

[28] Out of 27 UMICs, only four of them are agriculturally dominant; whereas 27 out of 40 LMICs and 25 out of 27 LICs (except for Yemen and South Sudan which are reliant on oil, while value-added from agriculture constituting below 10% of the GDP for these two countries) are agriculturally reliant. Out of 45 SSA countries, 22 belong to the low-income category and five are from the upper-middle-income category. The list of countries by their agricultural dominance will be provided on request.

[29] One of the limitations of the mortality data from Burstein et al. (2019) is the lack of rural/urban indicator or the proportion of village area in a district. While it is preferrable to examine the effects of rainfall shocks in rural areas, it is not possible unfortunately due to the data limitation.

the most, especially by negative shocks. The effect of droughts on LICs is more than three-fold compared to that baseline. For LMICs, while positive fluctuations result in lower mortality, I do not observe any effect for negative shocks.[30] Amongst the developing countries at the higher end of the income spectrum in the sample, i.e. UMICs, positive shocks do not affect U5MR. Surprisingly, negative rainfall shocks lead to an increase of 0.272% in child mortality, statistically significant at 1%.[31]

Columns (5) and (6) in Table 3.4 deconstruct the effects for countries based on their reliance on agriculture. Findings from panel A are reiterated in panel B, i.e. agriculturally dominant countries are highly affected, in terms of both positive and negative shocks. Finally, in the last two columns, I test the effects for SSA and non-SSA countries. Similar to LMICs, African countries are highly affected by positive shocks, however, the effect of negative shocks is small but significant. I also find that African countries that are of the low-income group are highly affected significantly due to rainfall shocks. In the results not shown, a positive shock leads to a decrease of 0.083 pp and a negative shock causes an increase of 0.087 pp in U5MR in low-income African countries, both statistically significant at 1%. Significant effects of rainfall shocks are also observed in the low-income group of countries that are from the non-SSA region and are agriculturally reliant. Therefore, results that have been observed for LICs earlier are not entirely driven by African countries. Findings for non-African regions from panel A are revised in panel B as significant effects are not observed once a non-linear specification is applied. I also analyze the effects of rainfall shocks on infant and neonatal mortality rates using data from Burstein et al. (2019). Results remain qualitatively unchanged i.e. infants and neonates in LICs, agriculturally reliant countries and the African countries are affected the most. A detailed discussion is provided in the online appendix.

[30] A possible reason can be attributed to the high labor mobility out of the agricultural sector to other sectors during the drought periods, which can dampen the effects of droughts (Jayachandran, 2006). While LMICs are still reliant on agriculture with a value-added from agriculture of 18.30%, it is still around 8% lower compared to that of LICs (refer to Table 3.1). This might provide a higher opportunity to secure employment in non-agricultural sectors during weak rainfall seasons, for LMICs. This makes a potential avenue for future research, considering the current data limitations on labor mobility at a sub-national level on a global scale.

[31] Results are driven by upper-middle-income countries that are agriculturally dominant, where positive shocks lead to a drop in child mortality (coefficient of -0.002 and a p-value of 0.183), and negative shocks lead to an increase of 0.39% in child mortality (coefficient of 0.009, statistically significant at 1%).

Along with the income channel mechanism, rainfall can also affect child mortality through diseases mechanism due to higher malarial incidences during periods of heavy rainfall (Ding et al. 2014; Boyce et al. 2016). While the findings so far suggest that positive shocks to rainfall lead to fewer child deaths, if the wet seasons are also accompanied by higher malarial incidences, this can result in more deaths. Therefore the beneficial effects of positive shocks can be mitigated by the higher number of deaths due to malarial incidences which can attenuate the estimates of positive shocks towards zero.[32] Therefore, the beneficial effects of positive shocks to rainfall that have been observed in panel B, Table 3.4 are lower estimates only.[33]

Some of the recent literature has raised concerns in the reliability of the treatment effects under the difference-in-differences (DiD) setting used in this study, where the average treatment effect is also estimated as the pairwise comparisons between earlier and later treated units (Romeo and Sandler, 2021). In this setting, estimates may be subject to bias if the treatment effect is heterogeneous across time or groups and if negative weights are assigned to some of the treated/control comparison pairs (De Chaisemartin and D'Haultfoeuille 2020, henceforth, CH; Goodman-Bacon 2018, henceforth, GB). To ensure that the estimates in this study are not affected due to the negative weights, I employ the most recent testing procedure from CH – 'twowayfeweights' estimation command in Stata, to all the specifications in Table 3.4. Results suggest that negative weights is not a concern as it is almost zero for all the specifications. I examine the robustness of this set of results by applying a computationally demanding 'ddtiming' Stata package from GB. Results remain robust and all four pairwise comparisons for all the specifications in Table 3.4 have positive weights. Therefore, the bias due to negative

[32] If there are higher malarial incidences only during better rainfall years, then malarial cases amongst the children would be lower during drought years which will result in lower child deaths during dry periods. Therefore, a drop in under-5 mortality due to this health mechanism might be offsetting some of the detrimental effects of droughts via the income mechanism in the case for African countries, resulting in a lower magnitude for droughts, refer to Column (7), Table 3.4.

[33] As robustness, I test the effects of rainfall shocks in the African region by high/low-risk countries based on the median malarial incidence levels, by using data on the incidence of malaria (per 1000 population at risk) from WDI (2010). The effects of negative shocks remain equal determinants of child mortality (1.7% in low-risk countries vs 1.9% in high-risk countries). This provides suggestive evidence of a lower bias in the estimates of negative shocks due to malarial incidences.

weights is not a concern in this study.[34]

To summarize the findings, positive shocks to rainfall lead to better health outcomes for children and negative shocks cause detrimental effects overall. Low-income countries that are heavily reliant on agriculture are affected the most, followed by low-middle-income and African countries. However, there are a couple of potential concerns. Mothers who choose to have children during rainfall shock years might be selectively different. There is also an issue of selective migration across districts or even national boundaries. By using contraceptive usage data from WDI (2010) as a proxy for a mother's ability to involve in sex selection, I address the issue of selective fertility. And using net migration data from WDI (2010) and also by pooling data at the state level, I address the issue of selective migration. Results in the main text remain robust to the consideration of both these issues. A detailed discussion is provided in the online appendix, for brevity. I proceed further to examine whether the provision of water infrastructure in the form of dams helps dampen the detrimental effects of droughts on the local population.

3.4.5 Role of Water Provisions: Impact of Dams

For individuals dependent on agriculture and thereby, reliant on rainfall, adverse weather outcomes such as droughts mean a direct hit to their income. Provision of water accessibility during these adverse weather seasons should naturally buffer some, if not the entirety of the adverse consequences.[35] Since the seminal work by Duflo and Pande (2007) on the effect of dams on agricultural productivity, various other studies have also focused on the role of dams on different outcomes. In related literature, Chakravarty (2011) and Mettetal (2019) both test the direct effects of irrigation dams on infant mortality, in a group of African countries and South Africa, respectively. While their studies relate the direct consequences of placement of irrigation dams on infant mortality, I focus

[34] Results for LICs from ddtiming estimation also suggests that, if treated units are compared with the never treated units, estimates of droughts on child mortality is more than two-fold compared with the estimates from Table 3.4. Therefore, the estimated coefficient of droughts in Table 3.4 are to be taken as lower estimates only.

[35] Access to reservoir water may benefit only a part of the district and this may result in imperfect protection against rainfall shocks, Sarsons (2015).

Table 3.5: Effects of Rainfall Shocks on U5MR: Role of Dams Infrastructure

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive Shock $Rain_{i,t}$	-0.023***	-0.056***	-0.041***	0.002	-0.001	-0.044***	-0.103***	-0.002
	(0.003)	(0.014)	(0.005)	(0.002)	(0.003)	(0.005)	(0.012)	(0.002)
Positive Shock $Rain_{i,t}$* 1 if Dam Upstream	-0.033***	-0.037	-0.054***	-0.004	-0.010	-0.059***	-0.036*	0.001
	(0.009)	(0.025)	(0.018)	(0.003)	(0.010)	(0.015)	(0.021)	(0.005)
Negative Shock $Rain_{i,t}$	0.012***	0.078***	-0.000	0.004*	0.004	0.019***	0.031**	0.005
	(0.004)	(0.013)	(0.008)	(0.002)	(0.004)	(0.007)	(0.015)	(0.003)
Negative Shock $Rain_{i,t}$* 1 if Dam Upstream	-0.010	-0.053**	-0.020	0.011**	-0.008	-0.014	-0.028	-0.003
	(0.011)	(0.025)	(0.022)	(0.005)	(0.010)	(0.019)	(0.024)	(0.008)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

on how access to reservoir water affects the effects of rainfall shocks on child mortality in districts that are dam-fed. Presumably, this additional water resource should act as insurance against the negative rain shocks.

Results for the dams analysis as per Equation 3 is provided in Table 3.5. Column (1) produces the estimated coefficients for the baseline. When all countries are grouped as one, a similar set of results for positive and negative shocks as that of column (1) from panel B, Table 3.4 are observed. However, it is clear that dam-fed districts do experience a higher benefit as the interaction term between shocks to rainfall and the indicator variable for districts with upstream dams are negative for both positive and negative shocks, albeit insignificant for the latter. One of the possible reasons for imprecise estimates could be due to the information on the type of dams being unavailable, these coefficients on interaction terms might end up with higher standard errors.[36] However, the presence of dams upstream does benefit those districts with access to reservoir water. This provides some evidence on the provision of water resources and their beneficial impacts, overall.

Next, I focus on the group of countries classified income-wise. While column (2) demonstrates that positive shocks to rainfall almost have a similar effect in LICs as that of column (1), based on the mean dependent variable; the effects of negative shocks are almost three-fold compared with the baseline estimates. It is also evident that the dam-fed districts experience lower mortality both during positive and negative shock periods. Almost 60% of the adverse consequences of negative shocks are averted in districts with upstream dam i.e. a drop of 0.051 pp. from 0.077 pp.[37] Results for LMICs show a similar pattern as that of LICs i.e. dam-fed districts experience the beneficial impacts of water infrastructure during both better rainfall years and drought periods, as evident from the estimated negative impacts on the interaction terms, albeit one of the interaction terms being statistically insignificant. We do not see a similar pattern as that of LICs and

[36] As irrigation dams are built to provide access to reservoir water during droughts; hydroelectric or recreational dams are likely to be built for non-irrigation purposes. Therefore, the beneficial impacts observed for dam-fed districts are to be taken as lower estimates only.

[37] In low-income countries that are agriculturally dominant (countries that are above-median in value-added from agriculture), droughts have a much bigger impact of an increase of 0.11 percentage points on child mortality. However, dam-fed districts do experience a 70% reduction in negative consequences of rainfall shocks, being statistically significant at a 1% level. Results will be provided on request.

LMICs for the group of UMICs. Results based on income levels of countries suggest that building infrastructure in the form of dams is a significant policy mechanism for mitigating the detrimental effects of droughts, especially for LICs that are reliant on agriculture.

A potential concern is that states that are wealthier tend to build more dams, which may also have better resources (such as better hospitals, higher vaccination rates amongst the children, and so on) to insulate districts from income fluctuations. If this is the case, then the results that have been observed for LICs and LMICs will be primarily driven by wealthier states. To address this concern, I identify states' wealth (proxied by nightlight activities) and then test the effect of rainfall shocks in wealthier and poorer states, classified as above- and below-median by nightlight activity, respectively, for both LICs and LMICs. Results are provided in Table B8, online appendix to preserve space. Columns (1) and (4) of Table B8 reproduce results for LICs and LMICs from Table 3.5 for ease of comparison. As evident from columns (2) and (5), results are primarily driven by districts from poorer regions, that are more likely to be agriculturally oriented and less likely to have better access to resources.[38] This robustness test bolsters the credibility of the results.

Columns (5) and (6) in Table 3.5 deconstruct the results for a group of countries based on their agricultural dependence. Similar to the earlier findings, downstream districts in agriculture-oriented countries (column (6)) do experience greater benefits overall, especially during better rainfall years.[39] While shocks to rainfall do not have economically strong effects in countries where agriculture is less prevalent, small beneficial effects from interaction terms are observed.

The last two columns in Table 3.5 provide results for African and non-African regions.

[38]Dam-fed districts from relatively affluent states in LICs also benefit, as evident from column (3). As the beneficial effects from positive shocks are magnified, detrimental effects from droughts are dampened in downstream districts. I also extend this analysis to African countries in low-income groups and a similar set of results are observed i.e. results are not driven by wealthier regions. Results for the latter will be provided on request.

[39]One of the limitations of this part of the analysis is, to accurately estimate the effect of water accessibility on outcomes of interest in agriculturally dominant countries, one has to classify the districts by the type of cultivation methods employed. I leave this for future research owing to data scarcity on cultivation methods (and crop composition) at the sub-national level.

The effects of rainfall shocks are found to be much higher in African regions, findings in line with Table 3.4. While interaction terms are statistically insignificant at traditional levels, almost 90% of the negative shocks' effects are alleviated in dam-fed districts, an economically strong effect.[40] In non-African regions, the presence of dams has some beneficial impacts during drought periods, however, estimates fall insignificant. Therefore, findings from Table 3.5 suggest that dams infrastructure help alleviate the detrimental effects of rainfall shocks on child mortality, especially in low-income countries.

3.4.6 Lagged Effects of Rainfall

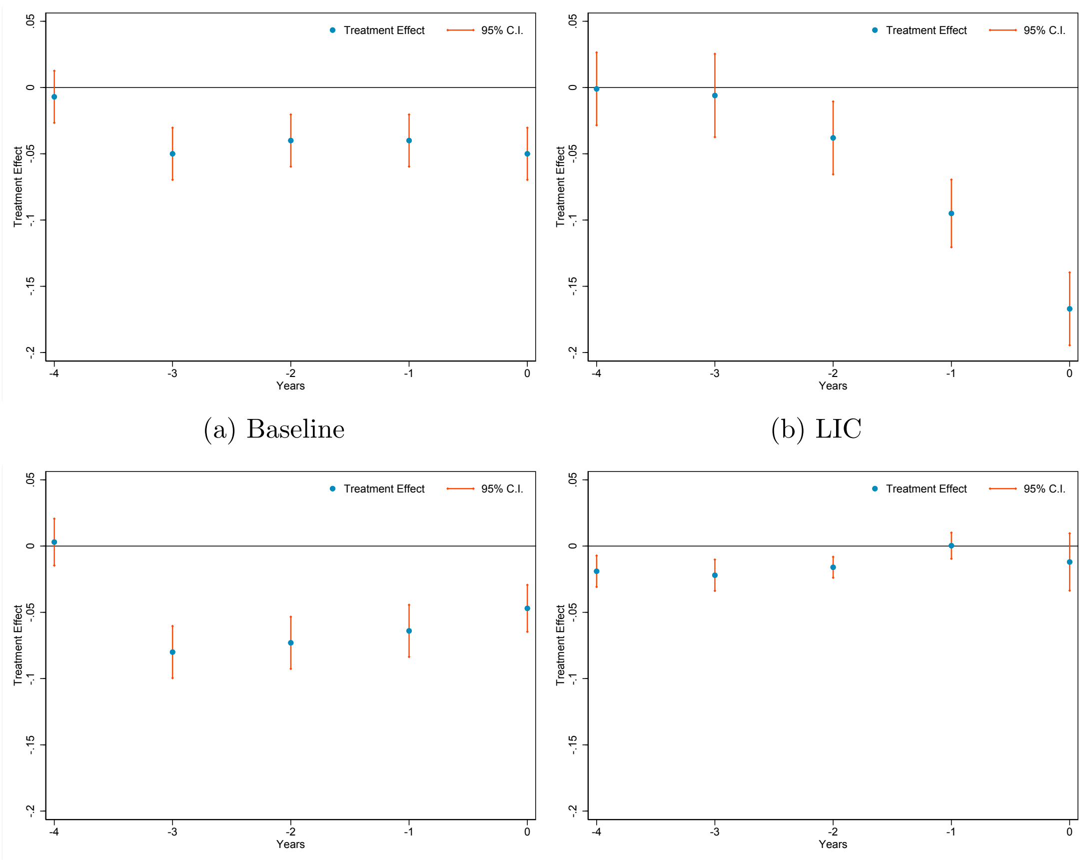
Not only contemporaneous rainfall shocks but previous shocks to rainfall may also affect child mortality. This may result either due to the long-term consequences of income shocks at a macro-economic level (Felbermayr and Gröschl, 2014) or due to an effect on nutritional intake (Ruel et al., 2004) and the associated long-term effects. To examine the persistent effects, I investigate the lagged effects of rainfall (in the log form) on U5MR under a standard dynamic treatment effect specification.[41] The estimated coefficients for each year are presented separately in Figure 3.1, for up to four years of lagged rainfall, along with the contemporaneous rainfall. The figure contains the dynamic effects for the baseline group of countries, along with countries sorted by their income levels.

As evident from Figure 3.1a, up to three lags of rainfall affect child mortality, whereas the coefficient of the farthest lag is not only close to zero but also falls insignificant. This indicates that the effects of rainfall shocks are not only contemporaneous but can be persistent. For the low-income group of countries based on Figure 3.1b, the current rainfall fluctuation has a bigger impact and the effect decreases linearly with further lags. Cumulative effects of the contemporaneous and the lags of rainfall results in a drop of U5MR by 0.031 percentage points for a 10% increase in rainfall, an effect almost two-fold higher in magnitude compared with estimates from panel A, column (2), Table 3.4.

[40] Effect of interaction between negative shocks and dam-fed districts are economically and statistically significant (with a p-value of 0.006) for low-income African countries. Results will be provided on request.

[41] Rainfall is used in the log form and long-run effects are presented in a graphical format for the ease of presentation. I also employ a non-linear specification and the direction of estimated effects of positive/negative rainfall shocks are in line with Table 3.4. Results for non-linear specifications will be provided on request.

Figure 3.1: Lagged Effects of Rainfall on Under-5 Mortality



(a) Baseline (b) LIC

(c) LMIC (d) UMIC

Figure 3.1: Each figure represents the plot of the impact of the four lags of rainfall (in log form) on child mortality, along with the coefficient of contemporaneous rainfall (year 0). -1 refers to the coefficient of the first lag of rainfall, -2 refers to the second lag, and so on. Estimates as of Table B9 in the online appendix. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries.

A similar effect as that of the baseline is also observed for LMICs and UMICs, i.e. effects of rainfall fluctuations are persistent. Surprisingly, once the long-run effects are accounted for, LMICs suffer the most.[42] These sets of results indicate that focusing only on contemporaneous effects will lead to an underestimation of the true impacts of income shocks. Suffering an income blow might lead to an increase in debt or a reduction

[42]Based on the findings for long-run analysis under a non-linear specification, results remain in line with panel B, Table 3.4 i.e. LICs are affected the most. Therefore, the higher beneficial effects obtained for LMICs may be due to account for rainfall shocks in a linear form and once the shocks are considered in a non-linear form, LICs are found to be affected the most. Results will be provided on request.

in the quality of nutritional intake at an individual level which might have long-term consequences and the findings of this study support the same.

3.4.7 Heterogeneous effects by Income Inequality

Income inequality results in persistent disadvantages to certain segments of a society in terms of lack of access to better health and education, disproportionate taxes, and higher crime rates, see Alesina et al. (2016). As income inequality strongly promotes agricultural expansion (Ceddia, 2019) and populations residing in regions with higher inequality lack opportunity in education and employment (Stiglitz, 2012), I presume that the population in low-income equality regions may be heavily reliant on agriculture. This in turn can lead to higher impacts of rainfall fluctuations on agricultural income and thereby significant effects on child mortality. To test the hypothesis, I examine the effects of rainfall shocks on under-5 mortality, subject to the associated inequality levels of the concerned regions. Following Alesina et al. (2016),[43] I create a regional income inequality index using nightlights per capita at the sub-national level using the first year in the sample i.e. the year 2000, as follows:

$$G_s = \frac{1}{n}\left[n + 1 - 2\frac{\sum_{i=1}^{n}(n+1-i)y_{is}}{\sum_{i=1}^{n} y_{is}}\right] \tag{4}$$

G_s is the income inequality index (GINI coefficient) for a first-level administrative unit (state) for the year 2000, n refers to the number of districts within a state, and y_{is} the nightlight per capita in a district i and state s in the year 2000.[44] The Gini coefficient accounts for differences in average income at the state level, as represented by nightlights per capita at the district level. G_s ranges from zero to one, representing the highest level of equality and inequality possible, respectively.

Table 3.6 contains the results for inequality analysis estimated under Equation 2.

[43] Alesina et al. (2016) provides two different measures of inequality index: an ethnic inequality index constructed using the nightlight luminosity within ethnic group boundaries and a regional inequality index based on administrative boundaries. For this study, the latter is used.

[44] As robustness, instead of the year 2000, I use the inequality index constructed for the last year in the sample i.e. for 2014, and perform analysis. Results remain robust and will be provided on request.

Panel A consists of results for the entire sample, whereas the other three panels provide income-wise analysis. Column (1) reproduces results from Table 3.4, panel B for the ease of comparison between the estimates. In columns (2)–(3), I test the effects of rainfall shocks in lower vs higher income inequality areas classified as below and above median using the estimated GINI coefficients. A similar analysis is repeated in the last two columns, however with the 90th percentile as the cutoff.

Based on the median analysis, panel A indicates that either type of rainfall shock has a larger effect in districts within higher inequality states. As evident from panel B, while positive shocks have a higher impact on child mortality amongst districts from low-inequality regions, negative shocks have bigger adverse consequences in higher inequality areas, for LICs. This evidence suggests that not only do the children from low-income equality regions benefit less when tides are in their favor, they are also the ones to be affected the most when the weather fares worse. This can arise due to the lack of opportunity and thereby, possibly lower labor mobility to more productive sectors during droughts. In lower-middle-income countries, while higher inequality regions experience a higher benefit during positive shocks period indicating reliance on rainfall, a consistent set of results as LICs is not observed in terms of negative shocks, whereas rainfall shocks remain both economically and statistically insignificant for UMICs.

Therefore, inequality seems to play a bigger role in low-income countries, based on the median analysis. To test this further, I classify the sample based on the 90th percentile and provided results in the last two columns. While the analysis based on columns (4) and (5) reiterates the findings discussed earlier for panels A and B, effects for LMICs are a bit more consistent once a higher cutoff is used. Results suggest that lower inequality regions are affected less due to rainfall shocks, whereas higher inequality regions are affected the most, even though the coefficient of negative shocks falls low in magnitude and is insignificant. For UMICs, both positive and negative shocks have adverse effects in high inequality regions. To summarize the findings for income inequality analysis, districts within lower equality states from low-income countries are affected the most due to rainfall shocks.

Table 3.6: Effects of Rainfall Shocks on U5MR: Role of Income Inequality

	Baseline	< Median	> Median	< 90th perc	> 90th perc
	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline					
Positive Shock Rain$_{i,t}$	-0.030***	0.000	-0.076***	-0.028***	-0.056***
	(0.003)	(0.003)	(0.006)	(0.003)	(0.014)
Negative Shock Rain$_{i,t}$	0.010***	0.005*	0.011	0.002	0.023*
	(0.004)	(0.003)	(0.008)	(0.005)	(0.014)
No. of Districts	13,734	6,044	5,952	10,704	1,189
Observations	205,418	88,540	87,681	158,741	17,480
Panel B: LIC					
Positive Shock Rain$_{i,t}$	-0.066***	-0.085***	-0.038**	-0.070***	-0.020
	(0.013)	(0.022)	(0.017)	(0.014)	(0.039)
Negative Shock Rain$_{i,t}$	0.065***	0.015	0.056***	0.048***	0.075**
	(0.012)	(0.018)	(0.017)	(0.013)	(0.037)
No. of Districts	1,895	846	850	1,527	164
Observations	28,272	12,504	12,623	22,695	2,432
Panel C: LMIC					
Positive Shock Rain$_{i,t}$	-0.049***	-0.014**	-0.113***	-0.046***	-0.083***
	(0.006)	(0.006)	(0.010)	(0.006)	(0.020)
Negative Shock Rain$_{i,t}$	-0.004	0.023***	-0.035**	-0.006	0.006
	(0.008)	(0.007)	(0.015)	(0.009)	(0.018)
No. of Districts	6,356	3,099	2,767	5,192	614
Observations	93,959	44,994	40,337	76,408	8,923
Panel D: UMIC					
Positive Shock Rain$_{i,t}$	0.001	0.002	0.002	-0.000	0.012
	(0.002)	(0.002)	(0.003)	(0.002)	(0.008)
Negative Shock Rain$_{i,t}$	0.007***	0.007**	-0.000	0.002	0.029***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.010)
No. of Districts	5,620	2,353	2,172	4,022	462
Observations	83,238	33,954	31,809	58,947	6,816

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries.

3.4.8 Robustness Tests

In this section, I examine the sensitivity of the estimates of rainfall to conditioning on various covariates and present the findings. As explained in the Data section, to overcome the scarcity of mortality data at the subnational level, Burstein et al. (2019) applies various modeling techniques to estimate child deaths data, while using ten different geospatial covariates.[45] To verify that the coefficient of rainfall is unaffected by the inclusion of the covariates, I control for some of the variables such as temperature, pollutant concentration, population, and nightlight activities that are publicly available at the sub-national level in Equation 2, all in log form. And I perform heterogeneity analysis by using other covariates that can confound the results such as measles immunization rates and malarial incidences. As these variables are unavailable publicly at a subnational level, I use the cross-country data and perform above/below median analysis.

First, to account for other weather-related factors that may affect child mortality, I include average temperature. I also control for pollution concentration and population to account for other factors that may predict child mortality. Results are provided in Table 3.7. Panel A contains results for the specifications controlling only for the temperature, whereas panel B controls for other variables as well. Even after various other factors that might affect child mortality are controlled for, results for rainfall shocks remain largely unchanged, especially for LICs, LMICs, and African countries.[46]

As the other covariates used in the estimation of mortality rates by Burstein et al. (2019) are unavailable at a sub-national level, they are not directly controlled for in this study. However, I perform heterogeneity tests by using the macro-level data on the covariates such as malarial incidence rates and immunization rates. Analysis by malarial incidences is already discussed in section 3.4.4. As measles immunization rates are highly

[45] Variables used are: travel time to the nearest city, marriage-aged women's educational qualification, the ratio of under-5 children to women in reproductive age (aged 15-49 years), pollutant concentration (PM2.5 particulate matter), total population, urban indicator, nightlight intensity measured from space, the proportion of children aged 12–23 months who had received the third dose of DPT vaccine, malarial incidence rate, and stunting prevalence amongst under-5 children.

[46] Results remain robust to conditioning on nightlight activity measured from space as well. This set of results are presented in the online appendix instead of the main text as nightlights data is missing for several districts – around 45% (40%) of observations are lost for LICs (African countries). Results are provided in Table B10, online appendix. From the table, it is also evident that once nightlight activities are controlled for, significant effects of droughts observed for UMICs in Table 3.4 are not present anymore.

Table 3.7: Effects of Rainfall Shocks on U5MR: With Controls

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Controlling for Temperature							
Positive Shock $\text{Rain}_{i,t}$	-0.030***	-0.067***	-0.053***	0.002	-0.001	-0.057***	-0.115***	-0.002
	(0.003)	(0.013)	(0.006)	(0.002)	(0.003)	(0.010)	(0.011)	(0.002)
Negative Shock $\text{Rain}_{i,t}$	0.011***	0.063***	-0.002	0.006***	0.001	0.018***	0.021*	0.006*
	(0.004)	(0.012)	(0.008)	(0.002)	(0.004)	(0.007)	(0.012)	(0.003)
Log_$\text{Temperature}_{i,t}$	0.069***	1.078**	0.018	0.163	0.230	0.037*	0.048	0.062***
	(0.023)	(0.501)	(0.021)	(0.083)	(0.102)	(0.019)	(0.473)	(0.021)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	13,645	1,873	6,229	5,543	6,692	6,953	3,409	10,236
Observations	202,400	28,040	91,425	82,935	100,119	102,281	50,911	151,489
	Panel B: Controlling for Temperature, Pollutant Concentration and Population							
Positive Shock $\text{Rain}_{i,t}$	-0.035***	-0.069***	-0.058***	0.002	0.000	-0.065***	-0.118***	-0.001
	(0.004)	(0.013)	(0.007)	(0.002)	(0.004)	(0.006)	(0.011)	(0.002)
Negative Shock $\text{Rain}_{i,t}$	0.012**	0.062***	-0.001	0.006**	-0.001	0.020**	0.017	0.006
	(0.005)	(0.013)	(0.009)	(0.002)	(0.004)	(0.008)	(0.013)	(0.004)
Log_$\text{Temperature}_{i,t}$	0.027**	0.996**	-0.009	-0.139**	0.324***	0.006	0.277	0.031***
	(0.013)	(0.492)	(0.012)	(0.062)	(0.103)	(0.012)	(0.523)	(0.011)
Log_PM2.5 $\text{Pollutant}_{i,t}$	0.004	0.111	-0.010	0.013**	-0.016	0.021	0.269***	-0.022**
	(0.012)	(0.074)	(0.019)	(0.006)	(0.011)	(0.018)	(0.072)	(0.011)
Log_$\text{Population}_{i,t}$	0.256***	0.364*	0.436***	-0.049***	0.321***	0.176***	0.938***	-0.017
	(0.049)	(0.205)	(0.082)	(0.018)	(0.076)	(0.060)	(0.156)	(0.031)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	10,981	1,738	5,029	4,214	5,185	5,796	3,128	7,853
Observations	163,046	26,012	74,314	62,720	77,198	85,848	46,859	116,187

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

correlated with all other immunization rates in a country and can act as a proxy for the overall state of the public health system (Levine and Rothman, 2006), I use the measles vaccination rates amongst the children to test a potential health channel mechanism. Findings suggest that rainfall fluctuations predict the macro-level vaccination rates in a country, positively. If increases in rainfall lead to higher vaccination rates, there would be lower at-risk children and therefore lower child deaths. Hence the effects observed so far could be this health-related mechanism, rather than the income channel.

However, further findings reassure that the income channel mechanism is still dominant. A detailed discussion is provided in section B3.2 in the online appendix. Another covariate that has been used in the construction of the mortality rates by Burstein et al. (2019) which can affect our estimates is the mother's education. Using the average secondary schooling completion for the period 2000-14 as a proxy for female education, I perform a heterogeneity analysis. I identify that the group of LICs and African countries that are below the median in female secondary schooling are affected the most. Results will be provided on request.

I perform additional robustness tests for the results provided in Table 3.4 such as bootstrapping the standard errors, performing analysis by pooling data at the state level, clustering standard errors at the state level, fitting equation to both linear and quadratic state-specific trends, using district-level trends instead of state-specific trends, dropping one country at a time to check the sensitivity of results and finally, using an alternate definition of rainfall shocks following Shah and Steinberg (2017). Results remain robust to all the specifications employed and a detailed discussion is provided in the online appendix, along with the set of results, to preserve space.

For brevity, various other relevant findings such as the effect of rainfall shocks on infant and neonatal mortality, heterogeneous effects on child mortality by measles immunization rates, other relevant concerns such as selective fertility and migration, and the results for continent-wise analysis are presented in the online appendix.

3.5 Conclusion

The rate of global climate change is far higher than most scientific forecasts, and droughts will be a frequent phenomenon in the coming decades (UN, 2013). Even though the youth population accounts for only 28% of the global population,[47] owing to adverse consequences of changes in global climate children account for more than 80% of illnesses and deaths (WHO, 2009). Therefore, it is necessary to understand the impacts of these weather disasters and also ways to minimize their adverse impacts. In this study, by considering rainfall as quasi-random shocks to agricultural income, I examine the effects of income fluctuations on U5MR. I use newly available data on this mortality age group from Burstein et al. (2019) at the district level for a global set of 94 developing countries.

As agricultural output data at the sub-national level is scarce, I rely on macro-level data on the agricultural output to reinforce the relationship between rainfall and agriculture, first. Then, I document that child mortality decreases during the periods of positive rainfall shocks and increases during drought periods in developing countries. The large and diverse sample allows identifying the differential impacts of rainfall shocks based on income levels of countries. Low-income countries are the most affected due to rainfall shocks, followed by lower-middle-income countries, and African countries. I also find that child mortality in districts downstream to dams that may have access to reservoir water experience higher benefits during periods of both positive and negative shocks, especially in low-income, and African countries, thereby providing evidence on the mitigating effects of dams infrastructure on the local population. This set of results are not driven by wealthier states (first-level administrative units) that may also have the ability to provide better resources, thereby allaying any endogeneity concerns.

The effects of rainfall are not only contemporaneous, there is evidence of persistent effects for up to three lags of rainfall. I also test the role of income inequality in the effects of rainfall shocks. I find that children in higher inequality regions from low-income countries tend to bear most of the burden during periods of bad weather. The main set of results remain robust to the inclusion of various controls and subject to

[47]Source: Author's calculations based on WDI (2010).

different robustness tests.

In an era of global climate change and the accompanying weather-related disasters (NASA, 2005), understanding the effects of income shocks on the most-affected groups is vital. This study uses finer-level data from a global set of developing countries and shows that children in poor countries are affected the most due to droughts. I also provide evidence that the provision of water resources dampens the negative effects of rainfall on the local population in low-income countries. Droughts will be a frequent phenomenon in the coming decades due to global warming (IPCC, 2018) and even if we completely switch to clean energy sources, the rise in global temperatures will continue for a few decades (NASA 2007; Stager 2012). Considering that poor countries lack resources to provide a better health infrastructure, support of the developed countries and global organizations may be vital to combat the effects of droughts on public health. And the optimal channeling of resources by the recipients may be required for efficient management of the adverse impacts of rainfall shocks. However, one potential limitation remains in this study, in the analysis of the impacts of water infrastructure on local populations. Countries might build dams in mindful of the vulnerabilities of districts and in this case, better quality estimates can be obtained by using geographical characteristics of districts to identify the random placement of dams, that can help isolate more precisely their role in mitigating the effects of droughts on child health.

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Online Appendix (Not for Publication)

Rainfall Shocks, Child Mortality and Water Infrastructure

B3 Supplementary Results

B3.1 Other Mortality Rates

Along with the under-5 mortality data, Burstein et al. (2019) provides the probability of death for infants (children aged below 1 year) and neonates (newborns, less than 28 days old), at the district level. Following a similar approach as for under-5 mortality rates (U5MR), I convert them into infant mortality rates (number of infant deaths per 100 live births) and neonatal mortality rates (number of neonatal deaths per 100 live births).[1] Effects of rainfall shocks are estimated under Equation 2 in the main text and results are provided in Table B2. Panel A contains results for infant mortality rates (henceforth, IMR), whereas panel B provides results for neonatal mortality rates (henceforth, NMR).

The set of results for IMR and NMR are qualitatively similar to that of under-5 mortality rates i.e. low-income countries (LICs), low-middle-income countries (LMICs) and African countries (SSA) are affected the most. While the effects of rainfall shocks on infants and neonates are qualitatively similar to the findings for under-5 children, there are considerable differences in the magnitudes. For example, droughts lead to an increase in U5MR of 0.065 p.p. (or 0.648%), based on column (2), Table 3.4 in the main text. Whereas, droughts lead to an increase of 0.033 p.p. (or 0.509%) in IMR and 0.01 p.p. in NMR (or 0.32%). Therefore, under-5 children are the ones most affected due to weather outcomes, followed by infants and neonates.

B3.2 Measles Immunization Rates

Measles vaccination rates are not only well correlated with all other immunization rates,[2] it also stands as a proxy for the overall state of the public health system (Levine and Rothman, 2006). Therefore, by using measles immunization rates as a proxy for the public health system of a country, I examine the heterogeneous effects of rainfall on under-5 mortality based on vaccination rates, subject to a standard dynamic treatment

[1] The three mortality rates from Burstein et al. (2019) are highly correlated with each other, in the range of 0.9316–0.9751. Source: Author's calculations.

[2] For example, measles and DPT vaccination rates have a correlation of 0.9284, based on data from WDI (2010). Source: Author's calculations.

effect specification. Results are presented in a graphical format in Figure B1, for the groups of countries classified income-wise and also for African countries. If vaccination rates in a country are affected by income shocks (proxied by rainfall), then the perceived income channel mechanism observed so far could indeed be the health channel mechanism i.e. drop in immunization rates due to a lower rainfall can lead to higher child deaths as a result of under-vaccinated children in a country.

Owing to data scarcity on vaccination rates at a sub-national level, I use macro-level data on the percentage of children aged 12-23 months who received the measles vaccination, before 12 months or anytime before the survey, from WDI (2010). Effects of up to four lags of rainfall (in log form), along with the contemporaneous rainfall are tested on immunization rates. Results from Figure B1 suggest that increases in rainfall in previous years leads to an increase in vaccination rates in a country, especially in LICs, LMICs, and African countries, while a stronger effect is observed in LICs and African countries.[3] In the results not shown, I also identify that the results that have been observed in Figure B1 are primarily driven by countries where vaccination rates have been lower.[4] Therefore, if the effects of rainfall shocks on U5MR is solely due to health channel mechanism i.e. as a result of a drop in the immunization rates which can result in more child deaths, then the effects of rainfall shocks on child mortality would be prevalent only in regions where vaccination rates have been lower.

Next, I analyze the effects of rainfall shocks subject to a non-linear specification for countries classified by median immunization rates. Results are provided in Table B3. Lower vaccination rates can lead to more vulnerable children and therefore higher child mortality, as evident from the mean dependent variable. For LICs, droughts are found to have significant effects in both high/low vaccination prevalence regions. While the income channel is still dominant in the case of LICs, the health channel mechanism is also found to be at play as evident from the magnitude of droughts in columns (1) and

[3] I also use a non-linear specification as in Equation 2 in the main text to identify the asymmetric effects of rainfall shocks. Positive shocks lead to an increase in vaccination rates, whereas negative shocks lead to a decrease.

[4] Average vaccination rates in a country are identified for the sample period considered. Results are driven by countries that are below-median in terms of the average immunization rates.

(2). Results for LMICs and African countries do not support the health mechanism hypothesis, as droughts have an effect on child mortality even in regions with higher immunization rates. To summarize the findings, the effects of rainfall shocks are driven by both health and income channels in the case of LICs, and income channel is found to be the dominant mechanism. For LMICs and African countries, the health channel mechanism for droughts is not observed.

B3.3 Fertility Preferences

Mothers who choose to have children during periods of rainfall shocks could be selectively different, which can cause a potential bias in the estimates. As a mother's education is a significant determinant of her child's health (Chen and Li, 2009) and also her fertility preferences (Black et al., 2008), an informed mother might be involved in birth selection depending upon the perceived health status of her child Pitt (1997). Owing to the scarcity of data on fertility preferences at a sub-national level, I proxy for mothers' ability to involve in birth selection with safe contraceptive usage data at the macro-level, from WDI (2010). As contraceptive use is essential for targeting the family size (Mamdani et al., 1993) and due to the presence of strong correlation between fertility and safe contraceptive usage,[5], it is logical to assume that birth selection to be higher in areas with high contraceptive prevalence rates. This can result in a reduced effect of rainfall shocks (and also lower child mortality) due to a lower number of birth of at-risk children in high contraceptive use areas.[6] However, evidence based on this analysis should be taken only as suggestive, as contraceptive usage is correlated with the overall quality of health infrastructure in a country.[7]

I examine the effects of rainfall on child mortality in the group of countries classified by contraceptive prevalence rates and provided results in panel A, Table B4. Mean

[5] Fertility and Safe contraceptive usage have a strong negative correlation of -0.8266. Source: Author's calculations based on data from WDI (2010)

[6] To ensure that the results are not driven due to differences in education, I test the average education amongst females proxied by secondary school enrolment data from WDI (2010). Education is found to be fairly similar across sub-samples within LICs, LMICs, and SSA countries.

[7] For example, safe contraceptive usage and measles vaccination rates have a strong positive correlation of 0.767. The latter can act as a proxy for the overall state of the public health system, Levine and Rothman (2006).

dependent variable and estimated effects of droughts remain almost the same in columns (1) and (2), indicating that selective fertility may not be a major concern in LICs.[8] For LMICs, only positive rainfall shocks are found to have significant effects based on Table 3.4 in the main text and a similar set of results are observed in columns (3) and (4), Table B4 as well. If the birth selection is an issue in LMICs, true estimates of positive rainfall shocks on child mortality would be in the range of 0.57% to 0.93%, statistically strong effects. For African countries, droughts have detrimental effects only in regions with higher contraceptive prevalence, going against the hypothesis of birth selection. However, in the results not shown, droughts are found to have strong, detrimental effects in low-income African countries, where contraceptive usage is also lower.

To summarize, if women's ability to involve in the birth selection is proxied by the availability of access to safe contraceptive usage methods, the estimated bias for low-income countries and low-income-African countries is found to be lower. While fertility preferences could induce bias in estimates for LMICs, a range for true coefficients is provided.

B3.4 Selective Migration

Another potential concern is that families that migrate are selective, which can bias the estimates of rainfall shocks on child mortality. Migration across sub-national boundaries is not a concern in this study, as Burstein et al. (2019) finds that mortality estimates are generally robust to the consideration of migration based on data from six countries in their study. Therefore, I focus on the issue of migration across national boundaries first and then I focus on potential migration across sub-national boundaries.

In the case of international migration, if entry (exit) of refugees is abundant, this can lead to an increase (decrease) in the number of at-risk children in a country, which can upward (downward) bias the estimates of droughts. Using net migration (number of immigrants minus the number of emigrants) data from WDI (2010), I identify that for

[8] A concern is that positive rainfall shocks have beneficial effects on child deaths only in regions with higher contraceptive use, for LICs. It is identified that more than 40% of the sample in column (1) is composed of two oil-dominant countries - Yemen and South Sudan. Once I exclude these countries from the analysis, both the shocks are found to have significant effects. Results not provided.

LICs, LMICs, and African countries, there is an abundant outward movement of people, on net.[9] Assuming that families that emigrate are vulnerable, the estimates of droughts observed in Table 3.4 in the main text for these three groups of countries are to be taken as lower estimates only.

However, there is the possibility that families that emigrate are healthier, which could mean more at-risk children in a country. In this case, if selective migration is a concern, then the effects of rainfall shocks would be driven by the countries where emigration has been higher i.e. below-median (as net migration is negative). Results for migration analysis are provided in panel B, Table B4. Estimated effects of droughts and also the mean dependent variable is fairly similar in both below- and above-median regions in LICs, which goes against the hypothesis that healthier families are the ones emigrating.[10] For LMICs, positive rainfall shocks are found to cause a drop of 0.087 p.p. (or 1.07 percent) in low emigration areas, whereas a decrease of 0.018 p.p. (or 0.47 percent) in higher emigration areas. If selective migration is a concern, true effects of positive rainfall shocks would be in the range of 0.47% to 1.07%, both statistically significant at 1% for low-middle-income group of countries. While positive rainfall shocks have significant effects in the last two columns, estimated effects of droughts do not support the hypothesis of healthier families migrating, as droughts are found to have significant effects only in column (5).

Next, I address the concern of migration across sub-national boundaries. As explained earlier, this is not a major concern in this study as Burstein et al. (2019) identifies the mortality estimates to be generally robust for the consideration of migration data from six countries in their study. However, I address this potential concern by pooling the district-level mortality data to the state level (first-level administrative units) and perform the analysis.[11] Results are provided in panel B, Table B6. If migration occurs across district

[9] Net migration for LICs is -85,816; for LMICs, there is an outward movement of 257,619 and for African countries, there is a net migration of -53,895 people.

[10] There is also a possibility that the health status of families that immigrate and emigrate are similar, which averages out the net effect.

[11] This robustness test also serves another purpose by helping us identify that the results observed for rainfall shocks by using mortality data at the district level are not due to using finer-level data. A detailed discussion is provided later.

boundaries within the same state, then this analysis will help us identify the true effects of rainfall shocks. Results for the baseline, LICs, LMICs (only for positive shocks), agriculturally reliant countries, and African regions in panel B, Table B6 are in line with the estimates from Table 3.4 in the main text, thus estimated effects remain robust qualitatively. Considering the lack of migration data at sub-national levels, the analysis by using the pooled data at the state level help allay some of the migration concerns.

B3.5 Continent-wise Analysis

In this part, I check the effects of rainfall shocks based on the geographical location of countries and also the quality of political institutions and their effects on mortality. Refer to Table B5 for the results. Column (1) contains the results for baseline analysis for ease of comparison. While panel A considers only the shocks to rainfall, panel B also takes into account the role of institutional quality measured by Polity4 scores (rescaled so that it ranges from -1 to +1, which higher scores implying a better institutional quality) on alleviating the impacts from shocks. Based on panel A, while positive shocks have a larger effect in African regions, followed by the Americas; negative shocks seem to affect almost all the regions. While the effect of downward shocks to rainfall is lowest amongst Asian countries; the Americas are the worst-affected. However, results fall imprecise for some of these specifications.

But, once the level of the polity status of respective countries (in the lag form) are controlled for, effects of negative shocks become more prevalent in all the regions, refer to panel B, Table B5. It is also evident that the higher the quality of institutions, the better the benefits from positive shocks to rainfall (except in the case of Middle Eastern countries) and the lower the adverse consequences of negative shocks are. These results suggest that the negative effects of income fluctuations are averted to a large extent in better quality institutions.

B3.6 Additional Robustness Tests

Next, I perform few additional robustness tests for the main set of results established in Table 3.4 in the main text and provided the results in Tables B6 and B7. First, even though the number of clusters in the sample is not small, I bootstrap the standard errors to ensure that the inferences are valid. P-values under bootstrapped procedure is provided in panel A, Table B6. Second, I pool the data and perform the analysis at the state level instead of the district level and provided the results in panel B, Table B6. Along with the explanation provided in section B3.4, this set of results will help ensure that the results in Table 3.4 in the main text are not driven due to using a finer level data. Third, I cluster the standard errors at the state level, instead of the district level to account for the possibility that state health officials might exhibit preferential treatment towards certain districts, which means fewer resources for other districts within the same state. Results for clustering at the first-level administrative unit are provided in panel C, Table B6. Based on the first three robustness tests, estimated effects in Table 3.4 in the main text remain robust qualitatively, especially for LICs, LMICs and African countries.[12] However, the significance of the effect of droughts in UMICs that was observed in Table 3.4 is sensitive to the type of clustering employed and also whether finer-level data is used or not.

Fourth, I control for the lag of the dependent variable to control for the possibility that past mortality may affect the current one. Results are provided in panel A, Table B7. Even after the past mortality rate is accounted for, the significance of rainfall shocks is unaffected for LICs and agriculturally reliant countries, whereas positive shocks to rainfall benefit the children in LMICs and African countries still.[13]

Fifth, I use an alternative definition for rainfall shocks. So far, positive and negative rainfall shocks are defined as one standard deviation above or below the mean, respec-

[12] Droughts have significant impacts in African countries that are of low-income category, and also for non-African, low-income countries, that are agriculturally dependent, when standard errors are clustered at the state level. Results will be provided on request.

[13] African countries that belong to the low-income group are still affected due to droughts, with estimates being significant at 1% level. I also control for up to four lags of the dependent variable for low-income countries that are also agriculturally dependent (by excluding Yemen and South Sudan, two oil-dominant economies). Effects of shocks are still significant. Results not provided.

tively. Now, I follow Shah and Steinberg (2017) and construct rainfall shocks at the top 80th and bottom 20th percentiles.[14] Results are presented in panel B, Table B7. While the effects of rainfall shocks in panel B, Table B7 maintain their significance as that of panel A, Table B6 for LICs, LMICs, UMICs, and agricultural-oriented countries, the magnitude of impacts falls in size. This could be owed to the fact that now shocks are being classified close to the mean of the standardized variable, which leads to a drop in the estimated effects. Nevertheless, qualitative interpretation remains unaffected largely, except for African countries.

I also perform three more tests by using both linear and quadratic state-specific trends; using district-level trends instead of state-level trends and finally, dropping one country at a time to ensure that the results are not driven by any individual country (especially for low-income, and African countries). Results remain robust subject to every test employed and will be provided on request. To summarize, qualitative interpretation of shocks remains largely unaffected for low-income countries and African countries that belong to the low-income category. As LICs are heavily reliant on agriculture, rainfall shocks predict child mortality robustly in this group of countries.

[14]Positive shock takes on a value one if the standardized rainfall variable is above the top 80th percentile, whereas negative shock takes on a value one if the standardized rainfall variable is below the bottom 20th percentile.

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Table B1: Country List

Panel A: LICs					
Benin	Burkina Faso	Burundi	Central African Rep.	Chad	D.R.Congo
Eritrea	Ethiopia	Gambia	Guinea	Guinea-Bissau	Haiti
Liberia	Madagascar	Mali	Mozambique	Nepal	Rwanda
Sierra Leone	Somalia	South Sudan	Syria	Tajikistan	Tanzania
Togo	Uganda	Yemen			
Panel B: LMICs					
Angola	Bangladesh	Bhutan	Bolvia	Cambodia	Cameroon
Cape Verde	Comoros	Ivory Coast	Djibouti	Egypt	El Salvador
Ghana	Honduras	Indonesia	Kenya	Kyrgyztan	Laos
Lesotho	Mauritania	Mongolia	Morocco	Myanmar	Nicaragua
Nigeria	Pakistan	Palestine	Papua New Guinea	Philippines	Congo Republic
Senegal	Sudan	Swaziland	Sao Tome and Principe	Timor Leste	Tunisia
Uzbekistan	Vietnam	Zambia	Zimbabwe		
Panel C: UMICs					
Algeria	Belize	Botswana	Colombia	Costa Rica	Cuba
Dominican Rep.	E.Guinea	Gabon	Guatemala	Guyana	Iran
Iraq	Jamaica	Jordan	Libya	Namibia	Panama
Paraguay	Peru	South Africa	Sri Lanka	Suriname	Thailand
Trinidad and Tobago	Turkmenistan	Venezuela			

Note: LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries.

Table B2: Effects of Rainfall Shocks on Infant and Neonatal Mortality Rates

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Infant Mortality Rates (IMR)							
Positive Shock $Rain_{i,t}$	-0.019***	-0.042***	-0.034***	0.001	0.000	-0.038***	-0.076***	-0.002
	(0.002)	(0.008)	(0.004)	(0.001)	(0.002)	(0.003)	(0.006)	(0.002)
Negative Shock $Rain_{i,t}$	0.009***	0.033***	0.005	0.005***	0.004*	0.013***	0.021***	0.004**
	(0.002)	(0.007)	(0.004)	(0.002)	(0.002)	(0.004)	(0.008)	(0.002)
Mean Dependent Variable	3.641	6.482	4.156	2.095	2.621	4.616	6.669	2.639
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921
	Panel B: Neonatal Mortality Rates (NMR)							
Positive Shock $Rain_{i,t}$	-0.011***	-0.024***	-0.019***	0.001	-0.001	-0.020***	-0.042***	-0.001
	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Negative Shock $Rain_{i,t}$	0.004***	0.011***	0.002	0.004***	0.003***	0.005**	0.009**	0.002**
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)
Mean Dependent Variable	2.012	3.116	2.303	1.308	1.534	2.469	3.288	1.589
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. IMR stands for Infant mortality rates and NMR stands for Neonatal mortality rates. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMICs refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

Table B3: Effects of Rainfall Shocks on Measles Immunization Rates

	LIC (Low)	LIC (High)	LMIC (Low)	LMIC (High)	SSA (Low)	SSA (High)
	(1)	(2)	(3)	(4)	(5)	(6)
Positive Shock $\mathrm{Rain}_{i,t}$	-0.035*	-0.095***	-0.103***	-0.017***	-0.164***	-0.056***
	(0.019)	(0.017)	(0.013)	(0.004)	(0.016)	(0.012)
Negative Shock $\mathrm{Rain}_{i,t}$	0.072***	0.059***	-0.026	0.010**	-0.006	0.053***
	(0.016)	(0.018)	(0.017)	(0.004)	(0.019)	(0.013)
Mean Dependent Variable	10.129	9.927	9.410	3.993	12.939	9.054
No. of Districts	869	1,014	2,341	3,971	1,576	1,838
Observations	12,996	15,143	34,908	58,825	23,494	27,417

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and SSA refers to Sub-Saharan African countries. In panel A, LIC (Low) refers to LICs where the measles immunization rate has been below-median, whereas LIC (High) refers to LICs where the measles immunization rate has been above-median and so on.

Table B4: Effects of Rainfall Shocks on U5MR: Selective Fertility and Migration Concerns

	LIC (Low)	LIC (High)	LMIC (Low)	LMIC (High)	SSA (Low)	SSA (High)
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Selective Fertility					
Positive Shock $Rain_{i,t}$	-0.009	-0.115***	-0.078***	-0.022***	-0.156***	-0.067***
	(0.018)	(0.017)	(0.010)	(0.005)	(0.016)	(0.013)
Negative Shock $Rain_{i,t}$	0.057***	0.076***	-0.009	0.004	-0.007	0.058***
	(0.015)	(0.018)	(0.012)	(0.009)	(0.019)	(0.013)
Mean Dependent Variable	10.103	9.942	8.279	3.894	12.779	8.994
No. of Districts	914	969	3,060	3,252	1,672	1,742
Observations	13,623	14,516	45,241	48,492	24,914	25,997
	Panel B: Selective Migration					
Positive Shock $Rain_{i,t}$	-0.038**	-0.091***	-0.089***	-0.018***	-0.087***	-0.141***
	(0.018)	(0.017)	(0.011)	(0.005)	(0.014)	(0.016)
Negative Shock $Rain_{i,t}$	0.065***	0.067***	-0.006	-0.002	0.035**	0.009
	(0.015)	(0.019)	(0.013)	(0.008)	(0.017)	(0.018)
Mean Dependent Variable	9.892	10.147	8.165	3.842	9.700	12.019
No. of Districts	939	944	3,154	3,158	1,726	1,688
Observations	14,041	14,098	47,021	46,712	25,753	25,158

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC refers to lower-middle-income countries and SSA stands for Sub-Saharan African countries. In panel A, LIC (Low) refers to LICs where safe contraceptive usage has been lower, whereas LIC (High) refers to LICs where contraceptive usage has been higher and so on. In panel B, LIC (Low) refers to LICs where emigration has been lower, whereas LIC (High) refers to LICs where emigration has been higher and so on.

Table B5: Effects of Rainfall Shocks on U5MR: Continent-wise Analysis

	Baseline	Africa	Asia	Americas	Middle-East
	(1)	(2)	(3)	(4)	(5)
	Panel A: No Interaction				
Positive Shock $Rain_{i,t}$	-0.030***	-0.116***	-0.003	-0.007*	0.008
	(0.003)	(0.011)	(0.003)	(0.004)	(0.007)
Negative Shock $Rain_{i,t}$	0.011***	0.022*	-0.008	0.047***	0.033***
	(0.004)	(0.013)	(0.006)	(0.004)	(0.005)
Mean Dependent Variable	5.169	10.847	3.589	2.715	3.634
No. of Districts	13,743	3,414	4,685	2,779	1,389
Observations	204,832	50,911	69,264	40,906	20,738
	Panel B: Polity Interaction				
Positive Shock $Rain_{i,t}$	-0.000	-0.046	0.024***	0.015	-0.001
	(0.006)	(0.032)	(0.006)	(0.009)	(0.013)
Negative Shock $Rain_{i,t}$	0.056***	0.146***	0.037***	0.088***	0.145***
	(0.010)	(0.035)	(0.010)	(0.019)	(0.015)
Politylag *$PositiveShockRain_{i,t}$	-0.045***	-0.106**	-0.039***	-0.031***	0.059*
	(0.009)	(0.048)	(0.009)	(0.012)	(0.032)
Politylag *$NegativeShockRain_{i,t}$	-0.071***	-0.223***	-0.061***	-0.045**	-0.326***
	(0.015)	(0.050)	(0.016)	(0.024)	(0.042)
Mean Dependent Variable	5.169	10.847	3.589	2.715	3.634
No. of Districts	13,533	3,352	4,566	2,775	1,374
Observations	186,721	45,914	62,897	38,002	18,428

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level.

Table B6: Effects of Rainfall Shocks on U5MR: Robustness Tests

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Bootstrapped SEs							
Positive Shock $Rain_{i,t}$	-0.030***	-0.066***	-0.051***	0.001	-0.002	-0.054***	-0.116***	-0.002
	(0.003)	(0.013)	(0.006)	(0.002)	(0.003)	(0.005)	(0.011)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.571]	[0.420]	[0.000]	[0.000]	[0.218]
Negative Shock $Rain_{i,t}$	0.010***	0.065***	-0.003	0.006***	0.002	0.017**	0.022*	0.005
	(0.004)	(0.012)	(0.008)	(0.002)	(0.004)	(0.007)	(0.012)	(0.003)
	[0.000]	[0.000]	[0.553]	[0.010]	[0.563]	[0.024]	[0.097]	[0.123]
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921
	Panel B: Pooling at the State level							
Positive Shock $Rain_{i,t}$	-0.059***	-0.097***	-0.062***	-0.004	-0.010	-0.103***	-0.100***	-0.013
	(0.013)	(0.029)	(0.022)	(0.006)	(0.009)	(0.023)	(0.024)	(0.010)
Negative Shock $Rain_{i,t}$	0.037**	0.156***	-0.024	0.000	0.002	0.053**	0.048*	0.019*
	(0.015)	(0.033)	(0.025)	(0.010)	(0.013)	(0.026)	(0.028)	(0.011)
Mean Dependent Variable	6.364	10.755	6.234	2.845	4.169	7.796	9.846	3.602
No. of States	1,330	349	576	405	644	686	586	744
Observations	18,900	4,951	7,903	5,881	9,066	9,834	8,276	10,534
	Panel C: State Level Clustering							
Positive Shock $Rain_{i,t}$	-0.029***	-0.062**	-0.050***	0.003	-0.000	-0.055***	-0.115***	-0.000
	(0.008)	(0.025)	(0.015)	(0.004)	(0.007)	(0.013)	(0.026)	(0.005)
Negative Shock $Rain_{i,t}$	0.012	0.066***	-0.002	0.005	0.003	0.018	0.022	0.006
	(0.009)	(0.022)	(0.018)	(0.008)	(0.010)	(0.011)	(0.020)	(0.007)
Mean Dependent Variable	5.215	10.036	6.060	2.579	3.422	6.909	10.851	3.297
No. of Districts	13,277	1,885	6,062	5,330	6,448	6,829	3,368	9,909
Observations	198,833	27,817	90,976	80,040	96,615	100,218	50,486	148,347

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level in Panel A and at the state level in Panels B and C. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

Table B7: Effects of Rainfall Shocks on U5MR: Robustness Tests

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Controlling for the Dependent Variable's First Lag							
Positive Shock $\text{Rain}_{i,t}$	-0.014***	-0.013**	-0.026***	-0.000	-0.002	-0.027***	-0.044***	-0.001
	(0.002)	(0.006)	(0.003)	(0.001)	(0.002)	(0.003)	(0.006)	(0.001)
Negative Shock $\text{Rain}_{i,t}$	0.007**	0.020***	0.002	0.009***	0.001	0.010**	0.001	0.008***
	(0.003)	(0.008)	(0.005)	(0.002)	(0.002)	(0.005)	(0.006)	(0.003)
$\text{U5MR}_{i,t-1}$	0.684***	0.819***	0.684***	0.338***	0.736***	0.671***	0.826***	0.374***
	(0.033)	(0.029)	(0.033)	(0.071)	(0.049)	(0.033)	(0.033)	(0.035)
Mean Dependent Variable	5.172	10.031	6.012	2.574	3.391	6.876	10.847	3.293
No. of Districts	13,722	1,878	6,305	5,539	6,704	7,018	3,404	10,318
Observations	190,618	26,213	87,156	77,249	93,240	97,414	47,429	143,189
	Panel B: Alternative Definition of Rainfall Shocks							
Positive Shock $\text{Rain}_{i,t}$	-0.021***	-0.053***	-0.036***	0.003	-0.008***	-0.033***	-0.074***	-0.003
	(0.003)	(0.012)	(0.005)	(0.002)	(0.003)	(0.005)	(0.010)	(0.002)
Negative Shock $\text{Rain}_{i,t}$	0.008**	0.047***	-0.003	0.007***	-0.009**	0.021***	0.013	0.004
	(0.004)	(0.011)	(0.006)	(0.002)	(0.004)	(0.006)	(0.011)	(0.003)
Mean Dependent Variable	5.172	10.031	6.012	2.574	3.391	6.876	10.847	3.293
No. of Districts	13,743	1,883	6,312	5,548	6,714	7,029	3,414	10,329
Observations	204,832	28,139	93,733	82,960	100,144	104,688	50,911	153,921

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries. Columns (5) and (6) sort countries by below- and above-median, respectively, based on value-added from agriculture (as % of total GDP).

Table B8: Effects of Rainfall Shocks on U5MR: Role of Dams Infrastructure, By Nightlight Activity

	LIC	LIC-BM	LIC-AM	LMIC	LMIC-BM	LMIC-AM
	(1)	(2)	(3)	(4)	(5)	(6)
Positive Shock $\text{Rain}_{i,t}$	-0.056***	-0.063***	-0.012	-0.041***	-0.069***	-0.019***
	(0.014)	(0.021)	(0.019)	(0.005)	(0.010)	(0.005)
Positive Shock $\text{Rain}_{i,t}$* 1 if Dam Upstream	-0.037	-0.038	-0.014	-0.054***	-0.084***	-0.027**
	(0.025)	(0.035)	(0.029)	(0.018)	(0.028)	(0.013)
Negative Shock $\text{Rain}_{i,t}$	0.078***	0.084***	0.075***	-0.000	-0.014	0.010
	(0.013)	(0.023)	(0.013)	(0.008)	(0.014)	(0.006)
Negative Shock $\text{Rain}_{i,t}$* 1 if Dam Upstream	-0.053**	-0.078**	-0.035	-0.020	0.002	0.005
	(0.025)	(0.035)	(0.027)	(0.022)	(0.035)	(0.016)
Mean Dependent Variable	10.020	11.795	8.153	6.010	7.621	4.414
No. of Districts	1,883	911	906	6,312	3,165	3,202
Observations	28,139	13,527	13,446	93,733	46,324	46,694

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries and LMIC stands for lower-middle-income countries. LIC(BM) refers to below-median LICs by nightlight activity, whereas LIC(AM) refers to above-median LICs by nightlights, and so on.

Table B9: Effects of Rainfall Shocks on U5MR: Dynamic Treatment Effects

	Baseline	LIC	LMIC	UMIC
	(1)	(2)	(3)	(4)
Log $\text{Rain}_{i,t}$	-0.057***	-0.161***	-0.084***	-0.017
	(0.006)	(0.032)	(0.010)	(0.011)
Log $\text{Rain}_{i,t-1}$	-0.035***	-0.091***	-0.063***	0.005
	(0.005)	(0.022)	(0.010)	(0.004)
Log $\text{Rain}_{i,t-2}$	-0.029***	-0.074***	-0.034***	-0.013**
	(0.006)	(0.013)	(0.012)	(0.005)
Log $\text{Rain}_{i,t-3}$	-0.041***	-0.053***	-0.069***	-0.015**
	(0.006)	(0.013)	(0.010)	(0.006)
Log $\text{Rain}_{i,t-4}$	-0.028	0.016	-0.035***	-0.017**
	(0.012)	(0.016)	(0.010)	(0.005)
Log $\text{Rain}_{i,t-5}$	-0.020	-0.025	-0.020	-0.016**
	(0.010)	(0.017)	(0.010)	(0.005)
Log $\text{Rain}_{i,t-6}$	0.017	0.019	0.020	-0.004
	(0.015)	(0.019)	(0.021)	(0.006)
Log $\text{Rain}_{i,t-7}$	0.009	0.013	-0.020	-0.007
	(0.005)	(0.015)	(0.015)	(0.005)
No. of Districts	13,678	1,894	6,304	5,604
Observations	150,030	20,710	68,438	60,882

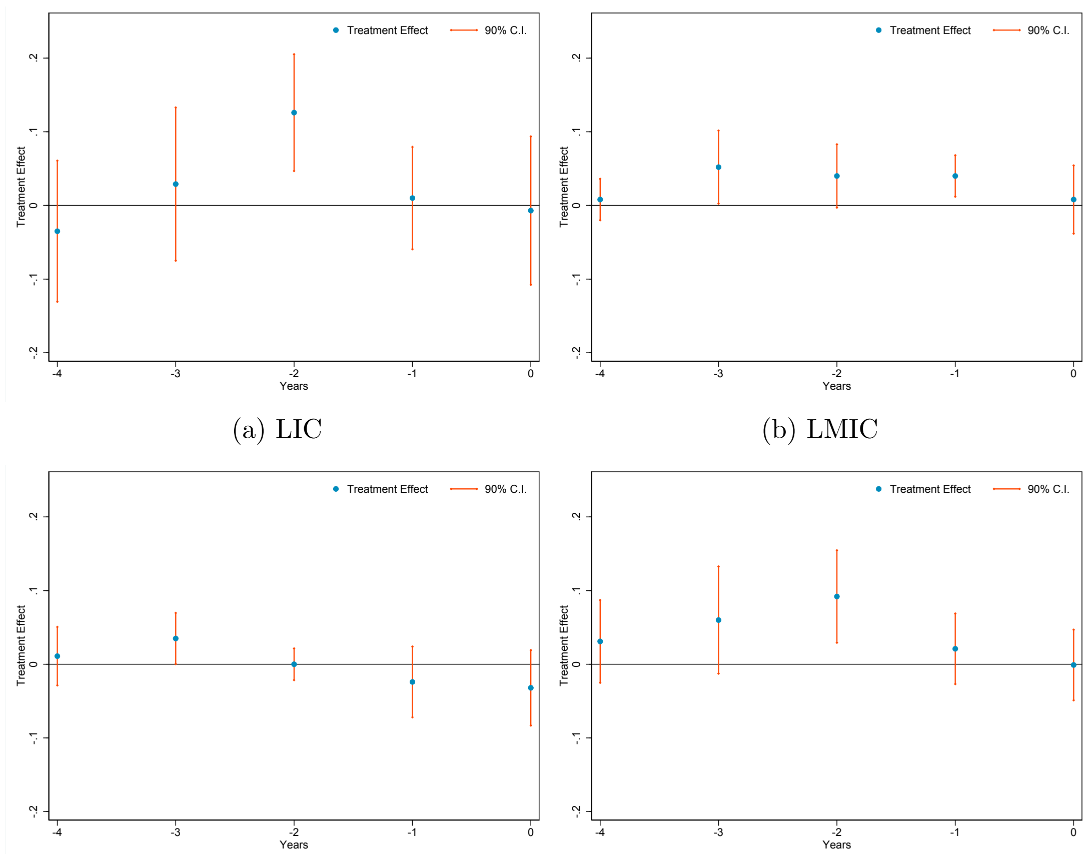
Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period-fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries.

Table B10: Effects of Rainfall Shocks on U5MR: Controlling for Nightlights

	Baseline	LIC	LMIC	UMIC	Low Agri	High Agri	Africa	Non SSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive Shock Rain$_{i,t}$	-0.037***	-0.054***	-0.042***	0.000	-0.003	-0.074***	-0.155***	-0.001
	(0.004)	(0.017)	(0.007)	(0.002)	(0.003)	(0.007)	(0.013)	(0.002)
Negative Shock Rain$_{i,t}$	0.024***	0.028*	0.038***	0.001	0.001	0.044***	0.088***	-0.000
	(0.005)	(0.016)	(0.010)	(0.002)	(0.004)	(0.010)	(0.015)	(0.005)
Log_Temperature$_{i,t}$	0.002	1.918***	-0.068***	-0.114**	0.201**	-0.035	-1.116*	0.037**
	(0.022)	(0.328)	(0.024)	(0.056)	(0.085)	(0.022)	(0.656)	(0.016)
Log_PM2.5 Pollutant$_{i,t}$	-0.006	-0.081	-0.014	0.009	-0.010	-0.001	0.317***	-0.033***
	(0.013)	(0.093)	(0.025)	(0.007)	(0.009)	(0.025)	(0.078)	(0.013)
Log_Nightlight$_{i,t}$	-0.011*	-0.043***	0.013	-0.039***	-0.040***	0.011	0.018	-0.025***
	(0.006)	(0.017)	(0.010)	(0.003)	(0.007)	(0.009)	(0.016)	(0.004)
Log_Population$_{i,t}$	0.186***	0.648***	0.393***	-0.059***	0.134*	0.252***	0.885***	0.006
	(0.052)	(0.236)	(0.113)	(0.019)	(0.069)	(0.075)	(0.232)	(0.030)
Mean Dependent Variable	5.169	10.020	6.010	2.575	3.393	6.869	10.847	3.292
No. of Districts	10,278	1,417	4,689	4,172	5,068	5,210	2,756	7,522
Observations	128,187	14,993	57,023	56,171	66,346	61,841	31,356	96,831

Note: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. All the regressions include state-specific trends, country-year fixed effects, district fixed effects, and period-fixed effects. Standard errors are clustered at the district level. LIC refers to low-income countries, LMIC stands for lower-middle-income countries and UMIC refers to upper-middle-income countries.

Figure B1: Long Run Effects of Rainfall on Mealses Immunization Rates



(a) LIC (b) LMIC

(c) UMIC (d) SSA

Figure B1: Each figure represents the plot of the impact of four lags of rainfall (in log form) on measles vaccination rate amongst children, along with the coefficient of contemporaneous rainfall (year 0). -1 refers to the coefficient of the first lag of rainfall, -2 refers to the second lag, and so on. LIC refers to low-income countries, LMIC refers to low-middle income countries, UMIC stands for upper-middle-income countries and SSA refers to Sub-Saharan African countries.

Chapter 4

Political Favoritism by Powerful Politicians: Evidence from Chief Ministers in India[1]

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Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper, however, names of co-authors appear in alphabetical order in the publication.		
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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Abstract

We study whether in single-member-district legislative systems, powerful politicians engage in political favoritism towards their constituents. The focus is on the chief ministers of Indian state governments. Using night light intensity as a measure of economic activity, we find that a constituency represented by a sitting chief minister exhibits about 13 percentage increase in luminosity relative to all other constituencies. The effect comes predominantly from the cases where the chief minister's constituency lies outside their birth region. Neighboring constituencies, particularly those with strategic political value, also benefit from this windfall, suggesting the mechanism at play is likely to be political expediency rather than in-group favoritism.

Keywords: *Distributive Politics, Ethnic Favoritism, Rent-seeking*

JEL Codes: D72; R11

4.1 Introduction

There is enduring interest among political economists in understanding why some districts or constituencies succeed in receiving a disproportionate amount of distributive benefits. Several explanations have been offered. Golden and Min (2013) summarize 150 studies from around the world classifying them by different hypotheses about the nature of distributive politics. These range from the instrumentalist—i.e., politicians target benefits to those voters whose support is crucial to winning the election, to the rent seeking—i.e., politicians treat distributive benefits as rents to be expropriated for themselves, or their extended selves such as their family, clan or ethnic group.[1]

In a recent study, Hodler and Raschky (2014) provide a detailed cross-country analysis using the birth district of the head of the national government as a proxy for his/her ethnic base. They show that these districts enjoy considerable economic gains compared to other areas. In particular, the estimated effect capturing such rent seeking behavior by powerful politicians is particularly salient in states where democracy is weak or absent. Similarly, using the example of governors of Russian state, Tkachenko and Esaulov (2020) show that in polities with weak institutions, sub-national rulers have considerable discretion in directing/extracting resources. They find that governors who do not have pre-governing local ties in the region demonstrate greater predatory behavior, compared to governors with local ties (insiders). The measure of such predatory behavior is the inefficiency and favoritism in contract allocation for public projects.

A natural question then arises: can democratic institutions help mitigate such distortionary policies through electoral and political incentives? On the other hand, even in democracies, political power enjoyed by the heads of government gives them considerable influence over a vast array of policy instruments, which can in turn be also targeted towards recipients of their choice. This target may be their own constituency, say, for reasons of ethnic affinity if the constituency represented by the politician has a greater concentration of co-ethnics. Or, it could be due to strong (re)electoral concerns, for in-

[1] Examples of rent seeking as ethnic favoritism by politicians include Kramon and Posner (2013), Franck and Rainer (2012), Kasara (2007), Burgess et al. (2015). Examples of distributive politics for instrumentalist reasons are rather numerous; for signal examples see Dixit and Londregan (1996), Stokes (2005) and Stokes et al. (2011).

stance, when the leader's constituency is viewed as a 'prestige seat', winning it with a handsome margin may be crucial to retaining the position as head of the ruling party.[2] At the same time, to be chosen the leader of the legislative majority, politicians in leadership positions must also win support of other legislators who might represent different interests, compelling them to target benefits to their constituencies, especially if their own reelection prospects are secure. Halse (2016) is a good example of the standard political incentives encountered by a legislator in deciding local public investments. The author finds evidence for the idea that each representative has an incentive to choose projects which concentrate benefits locally but whose costs are spread-out over all districts.

In order to explore these issues, we focus on the world's largest democracy, India. In particular, we focus our attention on Indian state governments and examine the extent of distributive benefits channeled by state government heads towards their electoral constituencies. Our approach has the advantage of holding constant the political and electoral milieu. Furthermore, studying a parliamentary democratic system allows us to shed light on whether constituencies with some non-electoral affinity to the politician, like ethnicity or regional affiliation, tend to gain more or whether such windfalls are more likely to be driven by electoral incentives. The head of the state government, referred to as the Chief Minister (CM), is analogous to the prime minister in the central government, and as such enjoys wide discretionary powers over important decisions at the state level.

We employ a difference-in-differences methodology where the treated units comprise all constituencies whose elected member of legislative assembly (MLA) becomes the CM of the respective State in that electoral cycle. All other constituencies act as the control units.[3] As our measure of local economic activity we use satellite data on night light activity, which we then map to our spatial unit of analysis: an assembly constituency. Our results show close to a 13 percentage increase in night light activity in the CM's

[2]Such prestige seats are a salient feature, particularly in our setting of India. Political parties and individual leaders have long associated themselves with specific constituencies in both Federal and State legislatures in India. One recent prominent example is the 'embarrassment' caused by the loss of the constituency of Amethi by the President of the Indian National Congress (INC), Rahul Gandhi, in the recently concluded Indian General Elections of 2019, a seat that was held by the INC for almost 52 years.

[3]We conduct robustness checks by restricting the set of control constituencies to those which only belong to opposition parties in a given electoral cycle as well.

constituency relative to all other constituencies. Furthermore, we find no evidence of differential trends before treatment, i.e. 'treated' constituencies do not appear to be undergoing increased activity prior to their elected members becoming chief ministers of their respective state.

We unpack this baseline finding by studying the heterogeneity of the effects by the affinity of the CM to their electoral constituency. Following Hodler and Raschky (2014), we proxy ethnic affinity by whether the CM's constituency lies in their region of birth as well. Politicians contesting from their birth districts will likely have more constituents with whom they share ethnic affinity (kinship/clan/caste/sub-caste). Ethnic affinity with their voters can lead to politicians being able to engage in rent seeking behavior without having to face penalty at the polling booth. For instance, Kauder and Potrafke (2015) document the case of SCU (Christian Social Union) politicians in Bavaria who engaged in nepotism in public employment and yet did not suffer lower re-election prospects. If ethnic altruism like concerns are strong then one might expect higher benefits channeled towards these constituencies. On the other hand, politicians are more likely to be guaranteed a higher vote share even without channeling distributive benefits to their constituents if voting takes place along ethnic lines. This is particularly salient in our setting given that ethnic affinity has been shown to play an important role in voters' support of politicians in India (see, for instance, Anderson et al. 2015; Banerjee and Pande 2007). Contrary to the findings in Hodler and Raschky (2014), we find that the estimated treatment effect is concentrated almost entirely in those constituencies that do *not* lie in the birth district of the CM.[4] This suggests that when a CM does not share ethnic affinity with his constituents (a 'non birth CM'), he has to work harder to win their support in seeking his reelection relative to a 'birth CM'. This compels him to transfer more distributive benefits to his constituency relative to the birth CMs.

We explore heterogeneity in our findings along a number of dimensions. The estimated effects are stronger for the CMs of more corrupt States and for constituencies that are primarily rural. This result, while in line with Hodler and Raschky (2014)'s finding that

[4]There are a number of key differences between our setup and the one in Hodler and Raschky (2014), which we outline later in this section.

weak polities exhibit greater *regional* favoritism, need not emanate from *ethnic* favoritism, as we discussed above. We also explore the dynamics in our baseline effects. Although the CM constituencies are developing similar to other constituencies three years prior to treatment, there is a sharp increase in night light activity in the first three years of the chief minister's tenure, which then dissipates toward the end of the term and goes back to zero post-tenure signifying that there are no long term gains in regional development for CM constituencies.

We conduct a similar analysis for the constituency of the opposition leader in the State assembly as well and uncover weak evidence for some form of predatory politics in operation. The constituency that the leader of the main opposition party belongs to seems to fare worse compared to all other non-CM constituencies.

We also explore regional spillovers and document increases in night light intensity at a very local level, largely restricted to the immediate neighbors of the CM constituency. This analysis also provides suggestive evidence of a strategic element in operation in vein of the instrumentalist nature of distributive politics. Among neighboring constituencies, CMs seem to only invest differential funds in those state assembly constituencies that fall in the same Lok Sabha (LS) or federal constituency that the CM's own constituency lies in. India, much like other established democracies, has 'upward' mobility of politicians with individuals starting from the lower level of government and progressing all the way to the federal level, and LS constituency that contains the CM's local constituency would be the obvious choice of the constituency for the CM to contest for higher office from.[5] The patterns of results we find in our spillover analysis is consistent with this hypothesis.

Finally, we undertake a robustness exercise for the parallel trends assumption crucial in difference-in-differences setup. We employ the interactive fixed effects (IFE) framework of Bai (2009), which allows us to relax this assumption by allowing for differential trends in a more flexible way using factor methods. For instance, if there is a federal development program from which constituencies can benefit in heterogeneous ways then

[5] A shining example of this mobility is the current prime minister of India, Narendra Modi, who started as a regional worker of the Rashtriya Swayamsevak Sangh (RSS) and then became the chief minister of Gujarat in 2001, and eventually got elected as the prime minister in 2014. For an analysis of various career trajectories of politicians in different multi-level democratic systems, see Borchert (2009).

such unobservable trends can potentially complicate inference in a standard difference-in-differences setting. The IFE framework helps control for precisely such dynamics. Our baseline analysis passes this check giving credence to the idea that chief ministers are indeed differentially developing their electoral constituencies and unobservable time varying confounders are unlikely to be biasing our estimates.

Our paper contributes to the growing empirical literature looking at political favoritism in the provision of government services and its effect on economic outcomes in different regions and/or institutional contexts. In the context of a representative democracy, the literature looks at the effect of both the incentives as well as ability/power of an electoral district's representative on the share of distributive benefits that a district receives.[6] For instance, Aidt and Shvets (2012) show that legislators facing term limits tend to bring less distributive benefits to their constituents, indicating the role of re-election incentives. Regarding the role of the politician ability, it has been hypothesized, in the context of US Congressional politics, that districts and states represented by more senior politicians or those sitting on influential committees, receive a favorable treatment in delivery of public goods and in location of federally sanctioned projects. For instance, Levitt and Poterba (1999) find that States represented by more senior Congressional members exhibit a higher growth rate, which they treat as an overall measure of favorable policies towards these states.[7] Kramon and Posner (2013) point out that there is a great deal of variation in the incidence of political favoritism in terms of the means used, and to whom the benefits accrue. Several studies, primarily focusing on African countries, have documented instances of ethnic favoritism in specific government policies such as agricultural taxes (Kasara, 2007), health and education (Franck and Rainer, 2012), and road construction (Burgess et al., 2015). Brollo and Nannicini (2012) document favorable treatment received by state-aligned municipalities in Brazil.

[6]A commonly used term for such benefits, particularly in the U.S. context, is pork-barrel spending. The idea that re-electoral concerns are an important motivation for legislators wanting to channel pork-barrel spending to their districts is well understood. However, this term typically has a negative connotation as being wasteful. Distributive benefits is a more generic term and does not have an adverse connotation.

[7]Other examples include Knight (2005) and Knight (2008) which look at the value of being a proposer as well as the bargaining power of legislators more generally in legislative bargaining settings, and Larcinese et al. (2006) and Berry et al. (2010) which look at the distributive powers of Presidents.

In the context of India, Asher and Novosad (2017) show that constituencies represented by representatives belonging to the ruling party receive favorable treatment than those belonging to the opposition. In an interesting paper, Fiva and Halse (2016) show that hometown/land bias is not limited to systems with single member districts, but also occurs in closed list proportional representation systems. While the majority of literature on distributive politics suggests regional/ethnic (often both) favoritism, Fisman et al. (2020), in the case of membership to China's politburo, find evidence of regional/ethnic penalty, i.e., those with college or hometown affiliation with the Politburo members have a 5-9 percentage points lower selection probability. However, the channels of regional favoritism, or a lack thereof, that we are interested in exploring are primarily in the context of democratic systems.

De Luca et al. (2018) extend the framework of Hodler and Raschky (2014), and using data from 140 countries show that the top political leader in a country, for instance the prime minister or president, tend to favor their ethnic homelands in terms of development as measured by night-light activity. However, there are some key differences between those two studies and our analysis here. First, both these papers analyze the existence of potential favoritism shown only by the head of the federal government across a large sample of countries with different political regimes. In contrast, our study focuses at the heads of state governments and sub-national electoral districts and thus studies a similar phenomenon at a much finer level. For instance, our unit of analysis is much smaller in size, about 1/10th in area of the administrative district used in the above studies, and hence we can locate more precisely the recipients of the leaders' favors. This in turn also allows us to uncover important patterns in the spatial spread of political favoritism in and around the home constituency of the chief minister. Second, in our setup the political leader has to be an elected member of their state's local assembly, which makes our work closer to the literature on distributive politics. Nevertheless, a major motivation of the analysis below is to study how ethnic and regional affiliations of elected official might also shape the nature of distributive politics. In this sense, we are combining the above two approaches to studying political/regional favoritism exhibited on part of powerful politicians.

The rest of this paper is organized as follows. Section 4.2 gives a brief institutional background of the Indian political system. Section 4.3 gives details on the data that we employ in our study, followed by section 4.4 that outlines our empirical methodology. Section 4.5 presents the results and Section 4.6 concludes.

4.2 Institutional Context

India has a federal system of government with 29 states and 7 union territories. Each state has a legislature, typically referred to as state/legislative assembly, in which legislators are elected from Local Assembly Constituencies (LACs). The Chief Minister (CM) is the head of the state government, analogous to the prime minister in the central government. State assembly elections are held every five years, but not synchronously with the central elections. There are no term limits for the chief minister.

The Constitution of India provides three lists—State List, Union List, and Concurrent List—which specify the areas that come under the state, central, and joint jurisdiction, respectively. Prominently, the states have the responsibility for making laws, and control the expenditure on items such as police, public health, agriculture, roads, local markets, industrial policy (except for nationally sensitive sectors). Additionally, items such as education and electricity provision also come under State jurisdiction on account of them being on the Concurrent List.

As leader of the ruling majority in the assembly as well as the council of ministers, chief minister is a powerful position in state politics in India. The powers enjoyed by the chief minister arguably give him/her a say in decisions that have distributive consequences over different constituencies that goes well beyond the discretionary funds meant for local area development which are available to all members of the State Assembly (see Asher and Novosad, 2017). It therefore stands to reason that a chief minister would try to use his discretionary powers to either benefit his own constituency and/or the constituencies held by his party members and/or try to divert resources away from those constituencies held by the opposition. The exact nature of such behavior depends on the incentives faced by the chief minister.

There is substantial anecdotal evidence alluding to the existence of such favoritism on the part of chief ministers in India. For example, the constituency of Gorakhpur, from which the newly appointed Chief Minister of Uttar Pradesh (UP), Yogi Adityanath, was elected, received "VIP treatment thanks to a host of allocations in the UP Budget" (Times of India, 2018). The projects included a specialty medical department for the city's medical college, a new 110 kilometer express-way, an auditorium and a new zoo. Similarly, while reporting the budget allocation in the newly formed state of Telangana, the Deccan Chronicle stated, "For those interested in knowing the flagship programmes of the TRS government, there is no need to go around the state. A visit to Chief Minister K. Chandrasekhar Rao's home constituency of Gajwel, is enough to see them all." (Acharyulu and August, 2018).

It is not only the chief ministerial constituencies that may receive a favorable treatment. Important allies and politically valuable constituencies may also be chosen for that purpose. In 2012 the constituency of Chevella in Andhra Pradesh received a '60 million dollars bounty' in terms of various infrastructure projects justified on the basis of long standing political links between the political party of the chief minister and the constituency (Ifthekhar , 2012). On the other hand, there are also claims, mostly by opposition members, suggesting that certain constituencies, particularly those held by opposition party leaders are neglected or that projects previously assigned to them are scrapped or diverted.[8]

While anecdotal evidence is indicative, a more thorough empirical treatment to establish the existence of such political favoritism is important. For instance, one possibility that can explain away the above evidence is the potential for over reporting by news media for anything related to the chief minister's constituency given their salience. Furthermore, much like any ordinary constituency, every chief ministerial constituency also gets an entitled development fund and hence the crucial question is of differential development compared to other constituencies in the state.

[8]See for instance Dwarakanath and August (2018) and Wadhman (2018).

4.3 Data

We compile information from a number of different sources to construct the dataset used in this study. Following a recent stream of literature studying economic growth, especially in developing countries, we proxy local economic development by night-light activity based on satellite imagery. Henderson et al. (2012) was one of the first papers that employed night light data as a proxy for economic activity. Since then a number of studies have used satellite imagery as a measure of local economic development in diverse settings. We extract night light information from the database maintained by the National Oceanic and Atmospheric Administration (NOAA). These data are collected by U.S. Air Force satellites, and the subsequent raw data is then cleaned to reflect light activity which is primarily a result of man-made processes. The NOAA provides annual data at scales of less than 1 square kilometer from 1992 onward. We use ArcGIS to map these data to the level of the local assembly constituency, our primary geographic unit of observation.[9]

Data on electoral characteristics for each local assembly or general assembly constituency comes from the statistical reports compiled by the Election Commission of India. This resource provides information on top two candidates for each constituency, their party affiliations, the margin of victory, and total voter turnout among other measures. Next we hand-collected data on all Chief Ministers (CM) across 17 major Indian States for the period 1992 to 2008.[10] We compile information on the CM's birth region, which in our main analysis corresponds to the local assembly constituency that he or she was born in, the exact dates they remained in power, and their party affiliations. We match these with a candidate characteristic database maintained by the Association for Democratic Reforms (ADR), an independent think-tank that was instrumental in the lead up to the eventual Indian Supreme Court judgment that required candidate affidavits to be publicly available. These affidavits contain information on education, asset details,

[9]We create similar data at the Lok Sabha (Federal constituency) and the administrative district level as well, which we employ for various specification checks.

[10]Due to the reshaping of electoral boundaries, at both the State and Federal level, we cannot extend our sample period all the way to the present.

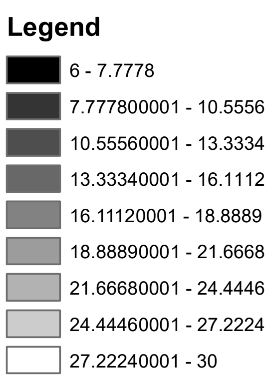
Figure 4.1: Night Light Activity - Maddur, Karnataka

(a) 1997 - 2 years Before Power

(b) 2001 - 2nd Year of Power

(c) 2002 - 3rd year in Power

(d) 2005 - Two Years After Power



and criminal records for all aspirants of electoral office at both the State and Federal level.

Figure 4.1 presents night light activity for a representative constituency: Maddur in the state of Karnataka. Maddur's state member of parliament became the chief minister of Karnataka in 2000. Figure 4.1(a) shows night light activity in Maddur, 2 years before it became a CM constituency. Two years into the term we start seeing a brighter spot in the south east of 4.1(b). This becomes brighter and radiates out in 4.1(c), and then the whole constituency darkens again 2 years after the term of the CM ended as depicted in 4.1(d). In our empirical analysis, we will try to tease out whether this is an actual effect of Maddur being the constituency of the chief minister of Karnataka, and was a recipient of differential resources as a result, or whether this is a result of some pre-existing spurious trend.

4.4 Empirical Methodology

4.4.1 Baseline Specifications

The empirical methodology we use is straightforward. We implement a difference-in-differences style framework with specifications of the following format,

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{cst} + \lambda_c + \lambda_{st} + \varepsilon_{cst} \qquad (1)$$

Our primary measure of economic activity is captured by $log(Nightlight_{cst})$, which is the log of average night light intensity in local assembly constituency c in state s and in year t.[11] A constituency c is considered to be 'treated' in year $t = \tau$, where τ indexes the tenure of the current chief minister of state s and who is elected from c, represented by CM^{τ}_{cst}. We will refer to this constituency as the CM constituency in the subsequent discussion. Constituency specific time-invariant factors are captured by λ_c,

[11] Following the literature, we add 0.01 to our dependent variable to deal with observed intensities of zero in our data. In addition to this, as a robustness exercise we also employ the inverse hyperbolic sine transformation, which is immune to the zero observed value concern (Johnson, 1949; Burbidge et al., 1988). Results are very similar across specifications. The night light measure is top-coded, and hence the data has a limitation in measuring extremely brightly lit areas. Due to this concern, we drop the top 1% of observations by night light activity, although our results are robust to their inclusion.

which controls for the concern that CM constituencies might be prominent constituencies, historically, and can have higher levels of pre-existing economic development. Similarly, λ_{st} is a state x year fixed effect that flexibly controls for potential shocks that might hit all constituencies in a given state and year. Finally, ε_{cst} is the usual error term. We cluster our standard errors at the constituency level.

Because of the staggered nature of state assembly elections in India, chief ministers can be sworn into office at any time during the year. At the same time due to administrative and implementation delays, one would expect lags in the initiation of developmental projects and observing their impact through changes in night light intensity. For this reason, in our baseline specifications CM^{τ}_{cst} takes the values 1 in year $t = \tau$ only if the chief minister takes charge before June, for the first year of tenure ($\tau = \underline{\tau}$), and is 1 for year $t = \tau$ if the CM leaves office after June for the last year of tenure ($\tau = \bar{\tau}$).[12] For most of our analysis, we also implement a lagged version of our treatment variable, motivated by the above cited concerns.[13]

Under equitable distribution of resources across constituencies within a state, γ should be close to zero and statistically insignificant. A positive estimated coefficient γ will provide evidence for preferential treatment of chief ministers to their own constituencies relative to the rest of the state. However, whether one can interpret this coefficient as causal evidence of political bias is subject to standard pitfalls in a difference-in-differences setup: the potential of pre-existing differential trends across CM and non-CM constituencies spuriously manifesting as a treatment effect. For instance, if prospective candidates for the chief minister position differentially contest from areas that were doing worse then γ would underestimate the true effect. Similarly, in the more likely scenario of future CM constituencies trending positively we would spuriously overestimate the true impact. We, therefore, augment equation (1) with various ways of controlling for pre and post spurious effects, closely following the specifications used in Hodler and Raschky (2014). This gives us estimating equations of the following format,

[12] It takes the value 1 for all intervening years, assigning the relevant constituency to the treatment group for the length of the tenure of the chief minister. We conduct robustness tests by defining treatment without imposing this restriction and the results are very similar to the baseline.

[13] This lagged specification is the primary estimating equation in Hodler and Raschky (2014).

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{cst} + \phi_1 \sum_{k=1}^{3} CM^{\tau-k}_{cst} + \phi_2 \sum_{k=1}^{3} CM^{\bar{\tau}+k}_{cst} + \lambda_c + \lambda_{st} + \varepsilon_{cst} \quad (2)$$

Here $CM^{\tau-k}_{cst}$ takes the values 1 up to three years prior to constituency c becoming a CM constituency and ϕ_1 captures whether constituency c was already developing differentially even before coming into power. Similarly, ϕ_2 captures the analogous impact up to three years after the tenure of the chief minister ends for constituency c. If ϕ_1 and ϕ_2 are statistically indistinguishable from zero then this would provide further credence to our estimation strategy in uncovering the differential development undertaken by chief ministers in their own constituencies. In section 4.5.3 we expand on this further and investigate a dynamic treatment effects model, akin to Autor (2003).

4.4.2 Interactive Fixed Effect Specification

The main assumption in difference-in-differences style methodologies is the so-called common trends assumption. Most researchers are concerned whether it holds or not, and we generally see robustness checks that control for potential differential trends across treatment and control in various ways. For instance, our setup in section 4.4.1 is also mindful of this and we flexibly control for potential trends both before and after treatment in various ways in equation (1) and (2). However, one concern that can still complicate inference, and that is not captured by the above specifications, is if a common shock hits the entire system and impacts all units in potentially heterogeneous ways. For instance, in our case if a nation wide development program is launched throughout India with different constituencies benefiting in different ways then it can bias the estimated coefficient measuring our treatment effect. Similarly, macroeconomic conditions would impact individual units differentially engenders similar inference related concerns. While state specific year fixed effects will mitigate some of these concerns, we implement a more formal robustness check in the form of Bai's (2009) interactive fixed effect (IFE) models to explore the sensitivity of our estimates to such potential unobservable shocks.[14] These models assume a more flexible error structure and estimate specifications of the following form,

$$log(Nightlight_{cst}) = \alpha + \gamma CM^{\tau}_{ct} + \lambda_c + \lambda_t + \theta_c f_t + \varepsilon_{ct} \tag{3}$$

where we now add a constituency and a year fixed effect, and instead of using time effects interacted with state fixed effects to capture unobservable trends, we use a more flexible factor structure on the error term. Here f_t is an $r \times 1$ vector of unobserved common shocks and θ_c is an $r \times 1$ vector of factor loadings that captures constituency-specific response to the common shocks. All other variables are defined as in equation (1). As Kim and Oka (2014) explain, the common factors have a purely statistical interpretation and correspond to the principal components of the error term or in our case the 'principal' part of night light activity that is not explained by the included controls. This factor structure provides the added flexibility in IFE models in capturing more general forms of unobserved heterogeneity compared to the commonly used approaches, like unit specific linear time trends, that require *a priori* assumptions.

4.5 Results

4.5.1 Baseline Results

In this section we present our baseline results. We report findings for both a contemporaneous measure of constituency c being a CM constituency as well as its first lag. Column (1) of Table 4.1 presents the estimated effect based on equation (1). We estimate a γ coefficient of 0.1220 ($p < 0.01$), which amounts to a 13 percentage increase in night light intensity for each year a constituency's elected representative in the state assembly is the chief minister of the state.[15] Column (2) then adds controls to detect similar 'impacts'

[14] The literature on panel data with interactive fixed effects has been growing steadily over the past decade. For a theoretical overview of this literature refer to Hsiao (2018). For a more empirically driven summary, especially for difference-in-differences style research designs, refer to Gobillon and Magnac (2016). For an implementation of IFE to an actual empirical problem, refer to Kim and Oka (2014) and Givord et al. (2018).

[15] The percentage effect is calculated in the standard way using the following formula: $100(e^{\beta} - 1)$.

3 years before and 3 years after the constituency became a CM constituency. The baseline estimate falls only slightly to 12.6 percentage, with neither of the added controls being statistically significantly different zero. In column (3), we further test the potential concern of differential trends across CM and non-CM constituencies by adding a linear trend for 3 years prior and 3 years after the CM tenure.[16] The estimated coefficients are close to zero and statistically insignificant. Column (2) and (3) provide evidence that the difference-in-differences strategy provides an adequate setup to explore the treatment effect of interest.[17] The last three columns of Table 4.1 redo the analysis for the lagged measure of CM tenure. We estimate slightly attenuated effects, as expected, but the specification checks in columns (5) and (6) come through again.[18]

The above findings provide evidence for a prevalent differential effect for a CM constituency, however, determining the underlying mechanism for this phenomenon is much harder. For instance, as outlined earlier, chief ministers could have political expediency motivated concerns where they want to maximize their chances of getting re-elected from the same seat. On the other hand, Hodler and Raschky (2014) provide convincing evidence from a cross-country analysis that political leaders exhibit favoritism toward sub-national regions they have an affinity with. In their analysis, they use the birth region of the leader as a measure of this affinity.

Motivated by this finding, we implement a similar analysis to explore whether the same phenomenon can help explain our findings. We collect information on the birth district of each CM in our sample, and split the treated units into two groups: CM constituencies that lie in the birth district of the CM and those that do not.[19] Table 4.2 presents the results from this exercise. In the context of India, we document that

[16]As a robustness exercise, we add a CM constituency specific linear and quadratic time trends for our entire sample period as well. Results are robust to both additions and presented in appendix Table 4.9.

[17]For the analysis in columns (2) and (3), our estimates are not sensitive to the time window chosen to calculate the trends pre and post tenure. We repeat this analysis by varying the window between 4 and 10 years and our estimated coefficient from these specifications remains between 0.110 and 0.119.

[18]We re-estimate our baseline specification without putting in the restriction of defining first year of tenure conditional on oath taking before June. In other words, we treat all constituencies as treated the year a CM is elected from there. The results are slightly attenuated for the contemporaneous specification, due to contamination bias type concerns as expected, but are almost identical for the first lag specification. Specification checks based on variants of equation (2) also pass.

[19]On average there are around 11 to 12 local assembly constituencies in a given district.

a constituency that *does not* lie in the birth district of the chief minister witnesses an average increase of over 20 percentage when its elected member is the chief minister. The analogous effect for those constituencies in the actual birth district is under 5 percentage and statistically insignificant. More importantly, as columns (3) and (6) show, these cannot be explained by differential trends or spurious effects around the tenure of the chief minister across birth and non-birth constituencies.[20] Ethnic favoritism as well as political expediency could be at play in determining the extent of favorable treatment received by CM's constituency. Our results show that in the context of Indian state-level politics, the ethnicity effect is negligible. This raises the possibility of political expediency as an alternative explanation. We find support for this explanation in the form of significantly higher transfers by non-birth CMs. Additionally, we find greater transfers to those neighboring districts, as discussed in section 4.5.4, which lie in the federal constituency, indicating the possibility that the local politician may be investing in cultivating voter support for forays into federal politics. This behavior also suggests political expediency at play.

However, a recent finding in the literature suggests that ethnic favoritism is extremely prevalent across the world, with De Luca et al. (2018) terming it as 'an axiom of politics'.[21] Their main finding shows that political leaders differentially invest in their birth regions regardless of political expediency related concerns. Although they only focus on the head of the federal government in their analysis, their findings do seem to be at odds with our results in the context of India. One possible explanation for the pattern of political favoritism that we uncover is the practice of voting along ethnic/caste lines. Previous literature has documented this in the context of South Asia in general and India in particular (Anderson et al., 2015). Birth regions of chief ministers are likely to coincide with their ethnic home-grounds as well, implying that under a political setup where individuals vote on ethnic lines rather than actual performance, political leaders do not have to invest as many resources in the development of their regions to maximize the likelihood of re-election. In other words, regardless of performance, ethnically aligned

[20] The results presented above are completely robust if we measure night light in per capita terms.

[21] Likewise, Do et al. (2017) document favoritism by powerful bureaucrats towards their clan members.

voters are going to re-elect leaders with similar ethnic background. This equilibrium is likely to not hold for political leaders contesting elections from non-native regions, creating pressure on them to actually enhance regional development to garner votes in subsequent elections.

Before proceeding further, we highlight two important caveats to the analysis offered above. First, following the previous literature, we also assume that a candidate is weakly more likely to belong to the same ethnic group as his electoral district's population if he is born in that district than if he is born outside it. If this assumption is satisfied, one can use whether a candidate was born in his electoral district as a proxy for ethnic affinity with voters. For instance, this is the main ingredient in the approach taken by Hodler and Raschky (2014) and subsequent papers as well. However, one would need much more finely grained data to empirically test this assumption.

Second, we do not model the candidate decision regarding which constituency to run in. Rather, we study the CM's transfer decision conditional on contesting from that district. As long as there are no systematic differences between those who run inside their district or outside their birth district, selection effects are not likely to contaminate our results. For instance, if non-birth CMs are more politically astute they can be selecting constituencies that were already trending up in terms of economic activity, which could spuriously present itself as a positive treatment effect in our analysis. Columns (2) and (3) of Table 4.2 show that there are no statistically significant pre-trends for non-birth CMs and the point estimate is in fact negative. This allays concern that the higher estimated effect in non-birth CM constituency is not likely to be a result of the CMs decision to run from that constituency.

A recent set of papers has raised concerns regarding the estimation of treatment effect parameters in difference-in-differences (DiD) design. For instance, Goodman-Bacon (2018) shows that in such designs the estimating specification, like equation (1) above, is aggregating multiple 2x2 DiD comparisons with the regression assigning different weights across these comparisons. Ideally, we want treated units to be compared only to the never treated units. However, Goodman-Bacon (2018) establishes that when early-treated

Table 4.1: Chief Minister Tenure and Night Light Activity in Own Constituency

	Contemporaneous Specification			First Lag Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.122***	0.119***	0.119***	0.088***	0.078**	0.087**
	(0.033)	(0.044)	(0.044)	(0.032)	(0.036)	(0.037)
Three Years Before	–	- 0.040	- 0.022	–	- 0.056	- 0.020
		(0.047)	(0.042)		(0.044)	(0.035)
Three Years After	–	0.027	0.040	–	- 0.020	- 0.047
		(0.041)	(0.054)		(0.031)	(0.034)
Linear Pre-trend	–	–	- 0.020	–	–	- 0.037
			(0.028)			(0.030)
Linear Post-trend	–	–	- 0.015	–	–	0.029
			(0.022)			(0.020)
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

units serve as 'control' for later-treated units due to change of treatment status of the latter in certain 2x2 comparisons, it can induce biases in the estimated effect. This is particularly problematic when treatment is staggered as in our setting. To allay such potential concerns, we implement his diagnostic procedure and find that in our study the treated vs never-treated comparison gets a 0.996 weight with a slightly higher estimated treatment effect of 0.162 compared to our baseline effect of 0.122.[22] The problematic comparisons, which Goodman-Bacon (2018) calls timing-only, i.e. where both treatment and control groups are treated and the variation comes from a change in treatment status only, get close to zero weights in our setting. This is not surprising, since a vast majority of constituencies never become CM-constituencies hence there always remains a big pool of never treated units in the sample. In other words, our setting does not suffer from the concerns raised in Goodman-Bacon (2018), which gives us more confidence in the validity of our approach.

Finally, it is imperative to discuss the appropriate level of clustering for standard errors in the above employed specifications. Recent work by Abadie et al. (2017) has

[22]We use the Stata command provided by Goodman-Bacon et al., 2019 to perform this part of the analysis. We thank an anonymous referee for pointing us in this direction.

Table 4.2: Night Light Activity by CM's Constituencies and Birth District

	Non-Birth District			Birth District		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.189***	0.195***	0.195***	0.049	0.045	0.049
	(0.054)	(0.070)	(0.070)	(0.030)	(0.042)	(0.041)
Three Years Before	–	- 0.068	- 0.047	–	- 0.014	0.034
		(0.080)	(0.055)		(0.045)	(0.045)
Three Years After	–	0.080	0.095	–	0.003	0.017
		(0.067)	(0.061)		(0.035)	(0.035)
Linear Pre-trend	–	–	- 0.019	–	–	- 0.035
			(0.061)			(0.017)
Linear Post-trend	–	–	- 0.017	–	–	- 0.017
			(0.040)			(0.016)
Observations	54,536	54,536	54,536	54,536	54,536	54,536

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

argued to cluster standard errors at the level at which treatment is administered in the setting at hand. Since this is at the assembly constituency level, the above results and all later specifications follow their advice and cluster at the constituency level. They also argue that clustering at more aggregate levels, say at the state level as argued by Cameron and Miller (2015), for instance, may result in overly conservative confidence intervals. Nevertheless, for the sake of robustness we implement the wild-cluster bootstrap routine, due to the small number of states in India, and present the results in appendix table 4.10. The reported p-values using the wild-cluster bootstrap do not change the substantive conclusions presented in tables 4.1 and 4.2.[23] Results presented in the rest of the paper are also robust to the wild-cluster bootstrap but we do not report them for brevity purposes. In addition to the above, there is a second concern related to appropriate calculation of standard errors: the small number of treatment clusters in our data. We undertake this in section 4.5.6 by implementing a randomization inference routine similar to Conley and Taber (2011).

[23] We use the Stata command boottest developed by Roodman et al. (2019) to conduct this part of the analysis.

4.5.2 Heterogeneity Analysis

4.5.2.1 By State or Constituency Characteristics

In this subsection we undertake a heterogeneity analysis by various characteristics at the state and individual chief minister level. This exercise will help further dissect the estimated preferential treatment shown by chief ministers toward their own constituencies. Table 4.3 presents results for both the contemporaneous and first lag specification but only for our most saturated specification, i.e. specification similar to columns (3) and (6) from Table 4.1. Panel A splits states by whether they are considered to be corrupt or non-corrupt. We use the standard measure in the literature for this designation the so-called BIMAROU index (Fisman et al., 2014). Column (1) estimates that CM constituencies in corrupt states witness a 20.8 percentage ($\gamma = 0.1886$) growth in night light, which is twice the size of non-corrupt states shown in column (3). This finding makes intuitive sense since the baseline estimated effect is not entirely a result of ethical practices and hence one would expect exactly this pattern *a priori*.

We perform a heterogeneity analysis by splitting sample into two subgroups – corrupt and non-corrupt states. Election rigging is more likely to occur in the states where corruption is higher. We find that chief ministers' transfers to their own constituencies where they got elected from is almost two-fold in corrupt states compared with the non-corrupt states, showing evidences of higher favoritism.

Panel B then splits the sample by degree of rurality. We construct our own data driven measure of rurality by geocoding the proportion of area in each CM constituency that comprises of villages. Results show that chief ministers that belong to more rural home constituencies, direct more funds to their areas. This effect is substantial and strongly significant for the first lag specification as well. The results are also robust to perturbations to our 80% threshold for treating a constituency as primarily rural.

Table 4.3: Heterogeneity by State Characteristics

	Contemp	First Lag	Contemp	First Lag
	(1)	(2)	(3)	(4)
Panel A: Corruption	Corrupt States		Non-Corrupt States	
CM Tenure Effect	0.189**	0.119	0.092***	0.074***
	(0.087)	(0.085)	(0.028)	(0.029)
Observations	20,672	19,456	33,864	31,872
Panel B: Percent Rural	Rural > 80%		Rural < 80%	
CM Tenure Effect	0.142***	0.108***	- 0.009	- 0.031
	(0.039)	(0.036)	(0.075)	(0.083)
Observations	47,668	44,864	6,868	6,464

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

4.5.2.2 By Chief Minister Characteristics

Based on a Supreme Court order, starting from 2004 all candidates that aspired for political office had to submit disclosure forms detailing important personal information that the Court deemed important to the electorate. These included pre-election details of financial assets and income, academic qualifications as well as details of any criminal cases or convictions against the candidate. We collect information from these candidate disclosure forms for all chief ministers in our sample. Specifically we construct binary variables for chief ministers with at least a college degree, and whether they have any criminal record prior to filing nomination papers. We also construct continuous variables for overall political experience in years, and for tenure as chief minister as well. Table 4.4 first reproduces results from our baseline specification in column (1). We then interact the four characteristics mentioned above with our baseline treatment variable. Column (2) shows that inexperienced politicians divert slightly more funds to their own constituencies on assuming the position of chief minister, however, the interaction term itself is statistically insignificant. We find a similar results for chief ministers at the start of their tenure as well. We analyze the dynamics of CM tenure in more detail in the next subsection.

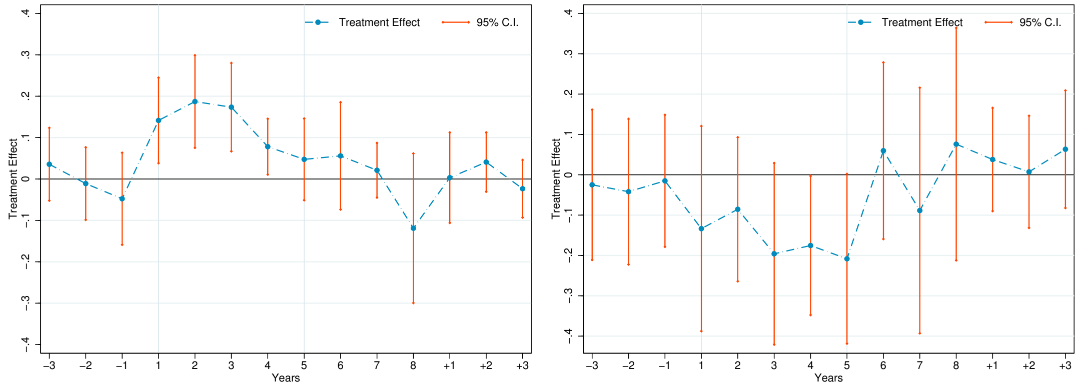
Table 4.4: Heterogeneity by CM Characteristics

	(1)	(2)	(3)	(4)	(5)
CM Tenure Effect	0.122***	0.154***	0.178***	0.103***	0.103***
	(0.033)	(0.052)	(0.062)	(0.038)	(0.036)
CM*Experience	–	−0.011	–	–	–
		(0.014)			
CM*Tenure	–	–	−0.011	–	–
			(0.010)		
CM*College Education	–	–	–	0.051	–
				(0.085)	
CM*Criminal Record	–	–	–	–	0.020
					(0.017)
Observations	54,536	54,536	54,536	54,536	54,536

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

Column (4) provides suggestive evidence that more educated CMs divert more funds to their constituencies. The baseline effect falls to 0.103 or 10.9 percentage with the interaction effect of a college degree being 0.051, although this is statistically insignificant. For politicians, with a criminal record the baseline effect is again few percentage points lower than our main findings, although we don't have enough power to identify the interaction coefficient itself. Overall these results show the existence of some heterogeneity in the estimate effect of preferential treatment of chief ministers shown toward their home constituency, however, because of the small sample number of treated units in these subcategories results are imprecise.

Figure 4.2: Dynamic Treatment Effects of CM Tenure - Overall



(a) Baseline (b) LIC

4.5.3 Dynamic Treatment Effects

In this section we implement a standard dynamic treatment effect specification to unpack how the estimated effect varies by each year of tenure of the chief minister. As is common in the difference-in-differences literature, a by-product of such an exercise is a visualization of the pre-treatment common trends assumption as well (see for instance, Autor, 2003). Figure 4.2 presents the estimated coefficient for each year separately, starting from 3 years before a constituency had its representative elected as the chief minister, and up to 3 years after the tenure of the chief minister.[24] We have only two chief ministers in our sample who remained in power for more than 9 years, we therefore top code years in power to 8. There are three findings worth highlighting in Figure 4.2(a). First, we find no evidence of future CM constituencies growing differentially with respect to the rest of the constituencies in the three years before assuming power. This corroborates our results in the above analysis as well. Second, the estimated treatment effect is concentrated in the first three to four years of the tenure of the chief minister, and diminishes there after. Finally, we find no evidence of long term gains in economic activity after the

[24]We repeat this analysis and implement a complete event-study style difference-in-differences by estimating separate coefficients for every time period, omitting the year before treatment. Appendix Figure 4.5 provides the results from this exercise and as can be seen our CM tenure effects remain robust to this change.

chief minister has gone out of power signifying that chief ministers might be focused on maximizing short term objectives with respect to their re-election bids.

We next explore the existence of any predatory practices undertaken by the chief minister toward their main rivals, in addition to the preferential treatment that they exhibit toward their home constituencies. As mentioned earlier there is substantial anecdotal evidence for this phenomenon with prominent opposition politicians regularly making allegations in this vein against sitting chief ministers. Although it might be difficult to ascertain whom a given chief minister considers their prime rival, one political portfolio that we can consider is the leader of the opposition in the state assembly in each respective chief minister's tenure. The opposition leaders usually are the heads of the second largest political party in the state and in most instances are the main contender for the top position in government for their respective parties. We implement a similar analysis as above for these opposition leaders. Figure 4.2(b) provides suggestive evidence that some form of predatory politics might be at play in our institutional setting. Constituencies that opposition leader are elected from perform similar to the rest pre-treatment but start trending downward moment their representative becomes the opposition leader in the state assembly. Although our point estimates are similar in magnitude to the effect sizes in Figure 4.2(a), but due to a fewer number of opposition leaders in our sample, the coefficients are imprecisely estimated.

4.5.4 Spillovers

There is a substantial literature in economics that has studied the local economic effects of various public policies or other treatment regimes that can induce localized spillovers. While a complete analysis of regional spillovers is beyond the scope of this paper, in this section we provide suggestive evidence of localized effects accruing to areas beyond just the CM constituency itself. For instance, if a CM constituency is getting electrified then power infrastructure might have to pass through nearby constituencies creating the potential of developmental spillovers. Even without these mechanical spillovers, one might expect standard regional fiscal multipliers to manifest in economic growth for

Table 4.5: Chief Minister Tenure and Night Light Activity - Neighboring Areas

	Baseline	15 km	25 km	35 km	District	LS
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect	0.122***	0.088**	0.072	0.060	0.013	0.077***
	(0.033)	(0.036)	(0.062)	(0.064)	(0.030)	(0.024)
Observations	54,536	54,536	54,536	54,536	8,483	6,565

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

neighboring areas as well. On the other hand, CMs might also target broader areas around their constituencies, especially if they are also strategically important.

Feyrer et al. (2017) provide an intuitive and straightforward way of studying potential spillovers when treatment is administered to a given geographic area of interest. In their analysis of the fracking boom in the US, they study local spillovers accruing to areas beyond the county of interest by drawing circles of increasing radii around the centroid of the treated county. In Table 4.5 columns (2) to (4), we implement their approach for our setting. We draw circles, of 15, 25, and 35 km radius from the center of each constituency and calculate night light intensity within these circles. Treatment is defined as the circle whose centroid lies in a CM constituency. We see a slightly smaller estimated effect of around 0.088 percentage points in column (1) which falls to around 0.060 and becomes insignificant for the 35 km radius.[25] In other words, any potential economic spillovers dissipate the farther away we go from the CM constituency.[26]

Another common approach in the literature is to aggregate the spatial unit of analysis to a larger geographic entity and rerun the analysis to check if the effect persists. For instance, Hodler and Raschky (2014); Feyrer et al. (2017) among others. In column (5) we aggregate our data to the administrative district level, which has around 6 to 7 LACs in it. Our estimated coefficient falls close to zero at this level of aggregation. This can imply

[25] We only implement the baseline regression of column (1) of Table 4.1 here since we found no evidence of pre-trends there.

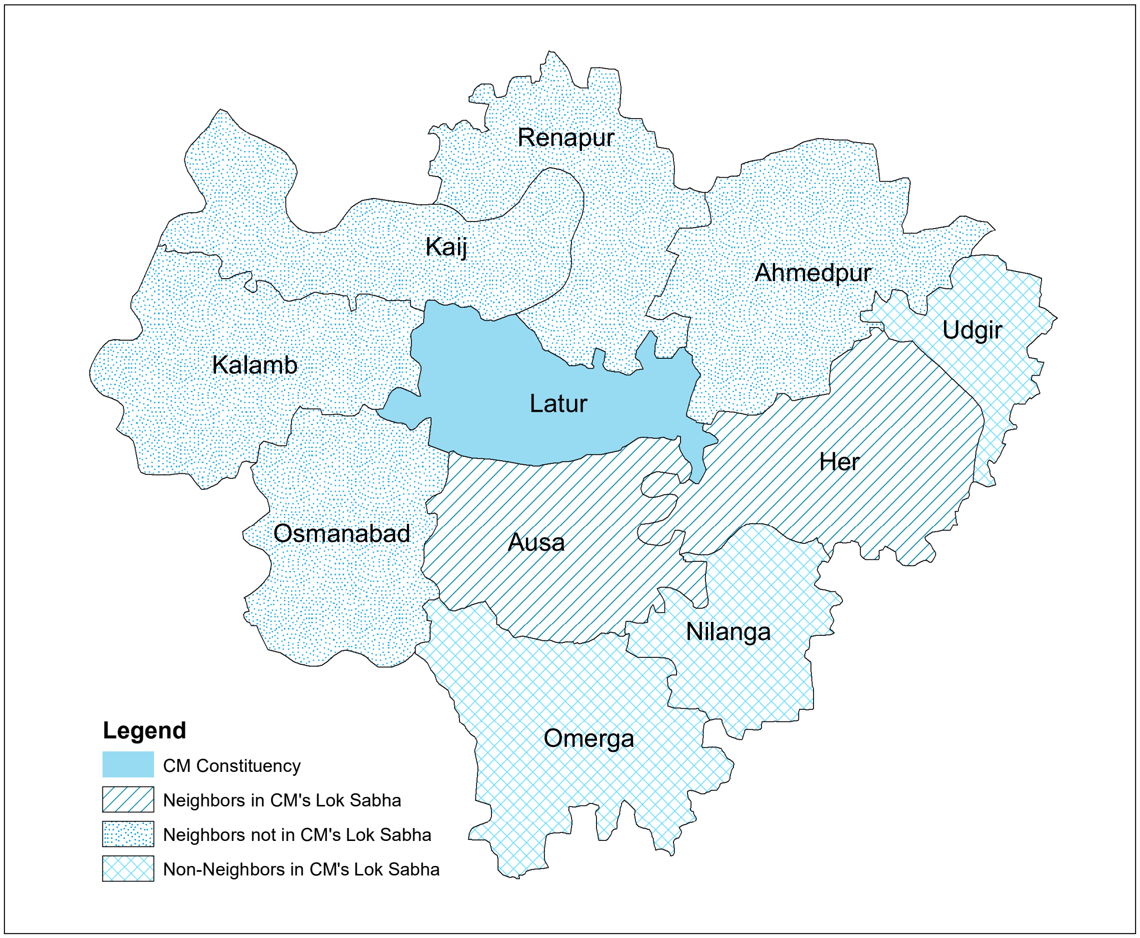
[26] James and Smith (2020) point out that this approach can potentially overestimate spillovers since treated counties in Feyrer et al., 2017 farther away can have inward spillovers to other treated counties hence amplifying the true spillover. We are less likely to suffer from this concern since each state has only one treated or CM constituency. Furthermore, neighboring constituencies of two different treated constituencies across states rarely overlap hence inward spillovers are not likely to intersect either.

two things: 1) either any spillovers that exist are operating at a really local level, i.e. immediate vicinity of the treated constituency, or 2) if politicians are engaging in strategic behavior due to political expediency concerns then they are differentially investing in only those nearby constituencies that can help them politically and this can be difficult to capture with aggregation at the district level since it is an administrative agglomeration. To explore this further, column (6) aggregates the data to the federal constituency level or Lok Sabha (LS), which also contains around 6 to 7 LACs on average, albeit a different mix than the district agglomeration.[27] Here we estimate an effect size of 0.077 ($p < 0.01$) implying that some spillovers do operate beyond just the CM constituency and may have a potential strategic element to them. In the rest of this section, we dig a little deeper into this assertion.

In the above analysis we took the approach to aggregate our analysis to various levels while keeping the CM constituency in the estimation sample. Another alternative approach is to conduct a so-called donut analysis where the treated unit is dropped and units bordering it are considered as the treated zone. For instance, Hornbeck and Keskin (2015) do a similar analysis to study the local economic effect of the availability of a source of groundwater to areas outside the treated area. In our setting this is is visualized with an example in Figure 4.3, where Latur, the constituency of the chief minister of Maharashtra, has seven immediate neighbors. We drop the actual CM constituency from this analysis and then either consider all 7 neighbors as treated units or 'slice' the donut in interesting ways to uncover any heterogeneity in estimated spillovers. Columns (1) and (2) estimate a CM Tenure coefficient of 0.049 ($p < 0.01$) for all neighbors, translating into a 5 percentage increase in night light activity for neighboring constituencies relative to the control constituencies.

[27] This reduces the distinct number of geographic units from around 3200 LACs in our main analysis to 500 federal constituencies here.

Figure 4.3: Neighboring Constituencies to the CM's Own Constituency - Latur



The remaining columns of Table 4.6 try to shed light on the potential mechanism for these spillovers. We first restrict to the Lok Sabha (LS) or federal assembly constituency that a given CM constituency lies in. Next we assign treatment status to only those neighbors of the CM constituency that fall in the same LS. This is shown by the slanted lines constituencies in figure 4.3. Our motivation for this is based on a persistent pattern in the Indian political landscape: a substantial number of chief ministers have career trajectories of moving 'upward' to federal government either as ministers in federal cabinets or as the prime minister itself. If chief ministers have these long term goals, then it would be helpful to strategize and develop areas in potential LS seats that they might contest from in the future. Columns (3) and (4) assign treatment to only these constituencies, among the set of neighbors, and present evidence for precisely such strategic consider-

Table 4.6: Chief Minister Tenure and Night Light Activity - Neighboring Constituencies and Lok Sabha (LS) of CM Constituency

Neighbor Definition	All		Same LS		Different LS		Non-Neighbor Same LS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CM Tenure Effect	0.049**	0.049***	0.071**	0.071**	0.026	0.026	0.001	0.005
	(0.017)	(0.018)	(0.028)	(0.028)	(0.027)	(0.027)	(0.029)	(0.029)
Three Years Before	- 0.006	- 0.021	0.008	0.002	- 0.020	- 0.043	- 0.015	- 0.021
	(0.017)	(0.020)	(0.026)	(0.030)	(0.022)	(0.027)	(0.025)	(0.026)
Three Years After	0.004	0.005	0.005	0.002	0.001	- 0.018	- 0.006	- 0.028
	(0.016)	(0.024)	(0.020)	(0.027)	(0.025)	(0.026)	(0.023)	(0.028)
Linear Pre-trend	–	0.016	–	0.007	–	0.025	–	0.011
		(0.011)		(0.016)		(0.015)		(0.014)
Linear Post-trend	–	-0.001	–	0.004	–	0.023	–	0.027
		(0.013)		(0.013)		(0.015)		(0.016)
Observations	53,635	53,635	53,635	53,635	53,635	53,635	53,635	53,635

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

ations. Neighbors that lie in the same LS constituency witness around a 7 percentage increase in night light intensity, similar to the findings above. However, those neighbor that belong to different LS constituencies (dotted areas in figure 4.3) show an increase of around 2 percentage but this is statistically insignificant.

For completeness, the final two columns of Table 4.6 repeat the analysis for non-neighboring constituencies that lie in the same LS constituency as the CM constituency, the point estimates are close to zero and statistically insignificant. This provides suggestive evidence that chief ministers might be balancing short-term state assembly level gains versus long-term aspirations of running for federal level political portfolios.

4.5.5 State and Federal Cabinet Ministers

Our analysis so far has focused on the constituency of the holder of the highest office in state governments in India. Similarly, as outlined before previous literature has focused on heads of government at the country level. However, there are other important portfolios in parliamentary setups as well, for instance, federal and state cabinet ministers who also might engage in distributive politics. In the Indian setup the federal government appoints around 30 ministers to the cabinet who are responsible for various portfolios. These ministers can either be elected members of the Lok Sabha, the Indian Parliament, or can be unelected. We focus on the elected ministers and repeat the above analysis at the Lok Sabha constituency level. Similarly, state governments also form cabinets where ministers are primarily drawn from the elected assemblies. We hand collected data on federal and state cabinet ministers along with their birth districts and elected constituencies. Our data includes information on 46 state cabinet ministers with portfolios of Home, Revenue and Finance, and 39 federal cabinet ministers.

At the outset, it is not clear whether cabinet ministers are likely to divert funds to their constituencies similar to the CMs. While federal ministers might face similar re-election incentives, they are also likely to be judged for achievements at a much broader level. Similarly, given that one does not have to be an elected member of parliament to become a minister, re-election pressure are likely to be strictly weaker than in the

Table 4.7: Cabinet Minister Tenure and Night Light Activity in Own LS Constituency

	State			Federal		
	(1)	(2)	(3)	(4)	(5)	(6)
Minister Tenure Effect	0.000	- 0.017	- 0.014	- 0.008	- 0.000	- 0.000
	(0.024)	(0.034)	(0.034)	(0.032)	(0.044)	(0.044)
Three Years Before	–	- 0.026	- 0.021	–	0.016	- 0.027
		(0.029)	(0.030)		(0.027)	(0.028)
Three Years After	–	- 0.043	- 0.045	–	0.015	0.018
		(0.036)	(0.033)		(0.044)	(0.046)
Linear Pre-trend	–	–	0.004	–	–	0.040***
			(0.018)			(0.014)
Linear Post-trend	–	–	- 0.001	–	–	- 0.001
			(0.013)			(0.015)
Observations	54,307	54,307	54,294	6,565	6,565	6,565

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

case of chief ministers. Also, the items of expenditure in the State list, over which a CM has discretionary powers, is much more comprehensive than the items of targetable expenditure items controlled by any single state cabinet minister.

Table 4.7 presents results from our baseline specifications implemented at the Lok Sabha level. Here a constituency is considered treated if its Lok Sabha member holds a federal cabinet portfolio. It is immediately evident that these constituencies do not undergo any differential development compared to the control constituencies. The estimated point estimate is close to zero in both the contemporaneous and the first lag specification. However, unlike the CM constituencies there is some evidence that these constituencies had a positive pre-trend before their members became federal ministers. Overall it seems that state CMs are much more likely to divert funds for the development of their own constituencies compared to federal ministers.[28]

[28]It is indeed possible that some other channel of group affinity could explain why chief ministers make significantly more transfers to their electoral constituencies. It will be interesting to examine what other form of group loyalties could be at play in determining transfers. This would require much more fine-grained data on various constituency attributes. We leave this for a future project.

4.5.6 Robustness Checks

4.5.6.1 Randomization Inference

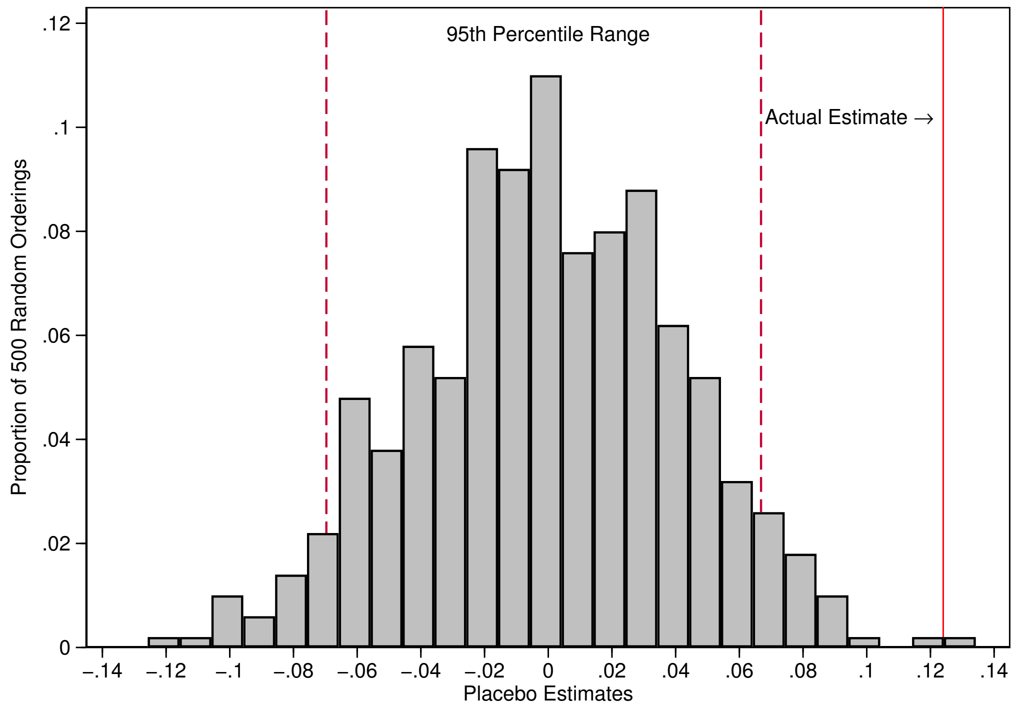
One concern that can plague the above analysis is the validity of our employed statistical inference procedures. So far in the analysis we clustered the standard errors at the constituency level using standard methods. However, recent literature has raised concerns about the validity of standard errors in difference-in-differences studies especially when the number of treated clusters or observations within them are small relative to the sample size. This applies to our setting here as well since each state has only one CM constituency per electoral cycle, resulting in less than 1% of the observations as treated. In this section we implement a randomization inference style procedure following recommendations made in Conley and Taber (2011).[29] The idea here is straightforward: we randomly assign treatment status to control constituencies belonging to the same state, i.e. we treat non-CM constituencies as if they were CM constituencies.[30] These placebo assignments, however, follow the same tenure length as the actual chief minister did for a given state and tenure combination. We then estimate equation (1) based on this randomly ordered dataset and repeat this process for 500 random draws. Figure 4.4 presents the results from this exercise. As is immediately evident, the placebo estimates are centered around zero and our actual estimate (column (1) Table 4.1) is well to the right of the 95th percentile of this distribution. We also repeat this exercise by randomly drawing from only those control constituencies that belong to the political party of the chief minister. Results are similar to Figure 4.4 although the distribution of placebo estimates moves slightly to the right as expected.[31] Overall this exercise provides credence to the conclusion reached in our main analysis that chief ministers are indeed differentially developing their own constituencies and potential concerns about inference procedures are not influencing our findings.

[29] Similar methods of inference are now being applied regularly in the empirical literature, for instance, see Bursztyn and Jensen (2015) for a recent implementation.

[30] The correct CM constituency is part of the sample and hence theoretically can be reassigned treatment status as well in a given iteration.

[31] We do not plot these results for brevity purposes.

Figure 4.4: Permutation Tests: Random Orderings of CM Constituencies



4.5.6.2 Interactive Fixed Effects

As a second robustness check, we next present results from the interactive fixed effects (IFE) specification outlined in section 4.4.2. As outlined there, the IFE models are capable of controlling for more general forms of unobserved heterogeneity by allowing individual constituency to respond differentially to common unobservable shocks. In practice, IFE setups require the researcher to specify the number of factors (r) to be included in the model. While there are statistical tests proposed to inform the optimal number of factors (e.g., Bai and Ng (2002)), there are also concerns regarding the stability of these tests (Onatski et al., 2013). Therefore, applied researchers using these methods generally vary the number of factors included in the model and check for the stability of the parameter of interest across specifications (e.g, Kim and Oka, 2014; Gobillon and Magnac, 2016).

Table 4.8 presents our results from this exercise. We first estimate a standard linear panel data model, which included only constituency and year fixed effects and present results only for the contemporaneous specification. The point estimate in the first column

Table 4.8: Chief Minister Tenure and Night Light Activity - Interactive Fixed Effects

	Standard	Number of Factors				
	0	1	2	3	4	5
CM Tenure Effect, γ	0.138*** (0.037)	0.131*** (0.040)	0.120*** (0.043)	0.120*** (0.040)	0.112** (0.044)	0.114** (0.050)
Observations	54,536	54,536	54,536	54,536	54,536	54,536

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All specifications include an additive constituency fixed effect and a year fixed effect. Standard errors are clustered at the constituency level.

of Table 4.8 is slightly higher compared to our preferred specification in column (3) of Table 4.1. This is expected since the latter assumes a prior structure for differential trends for the CM constituencies as defined in equation (2). The remaining columns in Table 4.8 then vary the factors between 1 to 6. As is evident, our estimated effect is very stable across specifications and is similar to the baseline finds in section 4.5.1. This signifies that our setup is likely capturing the causal effect on local economic development for a constituency whose member of parliament is elected as the Chief Minister as opposed to a differential response to some underlying unobservable common shock.

4.6 Discussion and Conclusion

This paper contributes to the literature on the nature of distributive politics in legislative systems with single member districts. Specifically, we seek to understand whether constituencies represented by powerful politicians get a more favorable treatment relative to other constituencies. We use night light intensity as a measure of development, and show that during the tenure of the chief minister (CM) their home constituencies enjoy on average 13 percent higher night light activity compared to other constituencies. The estimated effect peaks during the second year of a chief minister's tenure but do not persist in the long-run after the CM has left office. These results are not confounded by differential 'pre-treatment' development trajectories for constituencies represented by chief ministers and regular members of state legislative assemblies.

Ethnic affinity between the leader and his/her constituency, for instance proxied by the birth region of the leader, is often cited in the literature as a plausible explanation for such favorable treatment. However, we find that the increased night-light effect is stronger when a CM's constituency lies *outside* his/her birth district. In particular, a constituency that does not lie in the birth district of the chief minister witnesses an increase of over 20 percentage points when its elected member is the CM. The analogous effect for those CM constituencies in their actual birth district is under 5 percentage and statistically insignificant. Thus, while both political expediency as well as ethnic favoritism are at work, it is former that seems to be the dominant effect.[32]

One can conjecture the reasons for our findings. One possibility, consistent with anecdotal evidence, is that a CM's popularity in his/her own constituency is an indicator of their performance or ability, which is then used by the larger party leadership in deciding whether to continue with the chief minister in future. If a CM constituency lies in their birth region, then they may naturally enjoy more popularity given the ethnic affinity. However, when this is not the case, the CMs need to work harder, by providing more benefits, to 'buy' popularity. Similarly, another indication that career concerns rather than ethnic affinity are likely to motivate the CM's choice of distributive policies is evidenced by the fact that among constituencies neighboring their current electoral constituency, those which overlap with the same federal constituency exhibit greater night light activity relative to those which do not. This suggest that the chief minister may be cultivating his/her popularity with an option of entering federal politics in future.

Overall, our results provide evidence that at least in the case of India, ethnic or familial affinity to geographic regions is not a primary determinant of differential allocation of development funds by powerful political leaders. Instead we find mechanisms based on political expediency on part of these leaders as more plausible. These seem to extend

[32] The relative prevalence of ethnic vis-a-vis political favoritism will differ by the quality of democratic institutions. It seems plausible that in countries with low quality of democratic institutions, in which elections can be rigged, politicians engage in ethnic favoritism with impunity, but see no need for political favoritism. As democratic quality improves to a moderate level, ethnic favoritism is crowded out by the need to appease a majority of local constituents using pork-barrel spending. And, as there is further improvement in institutional quality, political favoritism by leaders also gets curbed. The relative prominence of political favoritism over ethnic favoritism that we find seems to be consistent with India having moderately high quality democratic institutions. Note that India scores a 9 out of 10 on the PolityIV Index of democratic institutional quality, the only democracies with a better rank are the "Western" developed country democracies. (See http://www.systemicpeace.org/vlibrary/GlobalReport2017.pdf)

to concerns based in terms of both maximizing the chances of re-election from the same constituency, as well as developing affinity with voters in those regions that are likely to help them climb the political ladder.

Interestingly, we find that the night-light effect tends to be a short-run phenomenon, and no long-run effect on night-light is discernible. This suggests that regional favoritism tends to take the form of short term transfers or policy favors rather than investment in infrastructure or local public goods. The finding that, in the Indian context, politically channeled benefits tend not to be allocated to infrastructure or local public goods provision is well-documented in Asher and Novosad (2017). They conjecture that this may be because the control over local regulatory processes and the ability to remove bureaucratic gridlock provide politicians with a relatively "cheap policy tool" to direct resources to target areas. These cheap policy tools are as easy to take away as they are to give. This fact, combined with a short average duration of CM tenure (under 4 years), could be the driver of our findings. Our findings are also consistent with our view that political expediency is the more dominant explanation of regional favoritism; if transfers were motivated by ethnic affinity, one would expect them to be made in a more long-lasting form.

Although the primary aim in this paper was to test the hypothesis of ethnic favoritism, it is possible that some other channel of group affinity could explain why non-birth CMs make significantly more transfers to their electoral constituencies. It will be interesting to examine what other form of group loyalties could be at play in determining transfers. This would require much more fine-grained data on various constituency attributes.

Finally, while our paper sheds light on transfers by powerful politicians at the state level, it would be interesting to explore whether similar dynamics exist at the local government level as well, such as municipal and village councils. We leave this question for future research.

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Appendix

Figure 4.5: Dynamic Treatment Effects of CM Tenure - All Time Periods

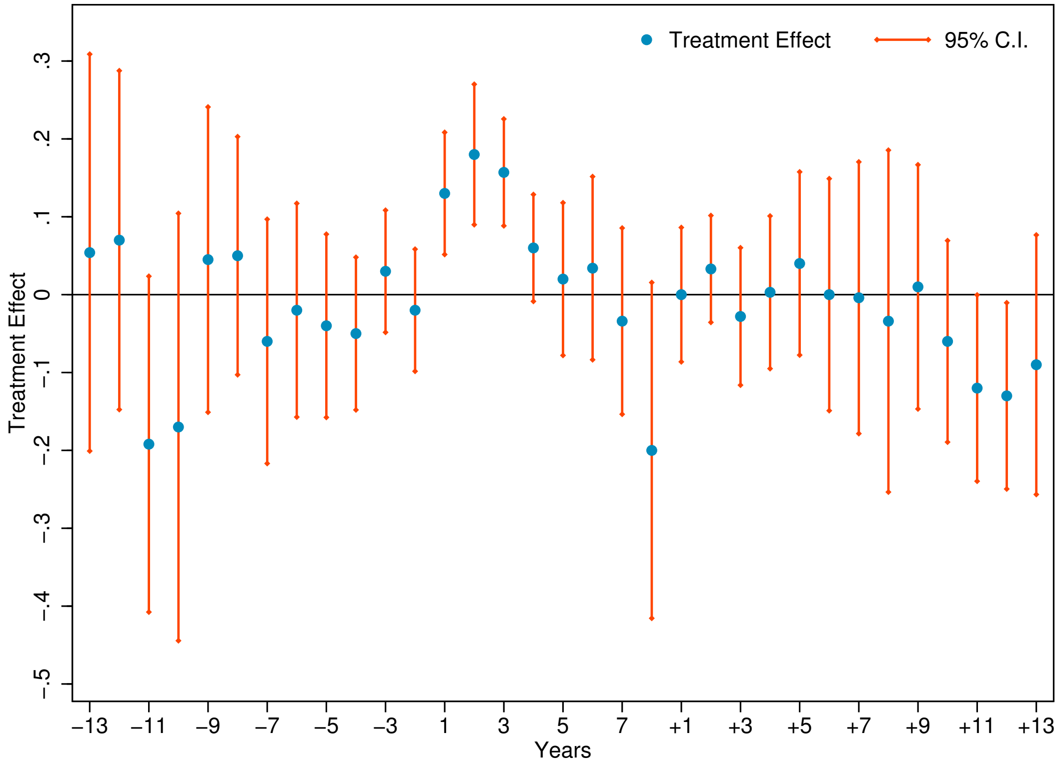

Table 4.9: Chief Minister Tenure and Night Light Activity in Own Constituency - Trends

	Contemporaneous Specification			First Lag Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect, γ	0.122***	0.122***	0.121***	0.088***	0.088**	0.086**
	(0.033)	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)
LAC specific linear trend	×			×		
LAC specific quadratic trend	×	×		×	×	
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All regressions include a constituency, and a state by year fixed effect. Standard errors are clustered at the constituency level.

Table 4.10: Chief Minister Tenure and Night Light Activity - Wild Bootstrap p-values

	Contemporaneous Specification			First Lag Specification		
Panel A: Baseline Results	(1)	(2)	(3)	(4)	(5)	(6)
CM Tenure Effect, γ	0.122***	0.119***	0.119***	0.088***	0.078**	0.087**
	(0.033)	(0.044)	(0.044)	(0.032)	(0.036)	(0.037)
	[0.000]	[0.008]	[0.008]	[0.017]	[0.066]	[0.033]
Panel B: Birth vs Non-Birth	Non-Birth District			Birth District		
CM Tenure Effect	0.189***	0.195***	0.195***	0.049	0.045	0.049
	(0.054)	(0.070)	(0.070)	(0.030)	(0.042)	(0.041)
	[0.000]	[0.010]	[0.009]	[0.147]	[0.298]	[0.284]
Three Years Before	×			×		
Three Years After	×			×		
Linear Pre-trend	×	×		×	×	
Linear Post-trend	×	×		×	×	
Observations	54,536	54,536	54,536	51,328	51,328	51,328

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. (Standard errors clustered at the constituency level following prescriptions from Abadie et al., 2017). [p-values from wild cluster bootstrap at the state level based on Cameron and Miller, 2015)

Table 4.11: Chief Minister Tenure and Night Light Activity in Own Constituency

	Baseline			Control: Power Const			Control: Opposition Const		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CM Tenure Effect	0.122***	0.119***	0.119***	0.069*	0.049	0.046	0.158	0.181**	0.181**
	(0.033)	(0.044)	(0.044)	(0.040)	(0.049)	(0.048)	(0.067)	(0.084)	(0.085)
Three Years Before	–	-0.040	-0.022	–	- 0.050	- 0.008	–	0.001	0.018
		(0.047)	(0.042)		(0.046)	(0.065)		(0.057)	(0.063)
Three Years After	–	0.027	0.040	–	- 0.038	- 0.081	–	0.070	0.090
		(0.041)	(0.054)		(0.066)	(0.095)		(0.056)	(0.074)
Linear Pre-trend	–	–	- 0.020	–	–	- 0.045	–	–	- 0.021
			(0.028)			(0.040)			(0.024)
Linear Post-trend	–	–	- 0.015	–	–	0.058	–	–	- 0.022
			(0.022)			(0.055)			(0.089)
Observations	54,536	54,536	54,536	25,083	25,083	25,083	29,453	29,453	29,453

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. All specifications include an additive constituency fixed effect and a year fixed effect. Standard errors are clustered at the constituency level.

Chapter 5

Conclusion

Child health is one of the primary determinants of human capital development and can potentially decide the future economic status at an individual level, and the quality of labour force and economic growth at a macro-level. While the health status of children has improved over the past few decades overall, developing countries still lag behind in terms of the trends exhibited by developed countries. Various factors such as lack of infrastructure, corruption, informational asymmetry, and inequality have been attributed to this differential trend. Moreover, the growing global warming issue and the resulting weather changes have stacked odds against the Sustainable Development Goals (SDGs) in improving quality of life globally. Therefore, it is essential to understand the consequences of natural disasters and weather changes on child health. In this thesis, I focus on the impacts of disasters and rainfall shocks on child mortality in different economic and institutional settings, to unmask the heterogeneous impacts of extreme natural events. Along with identifying the effects of disasters on child health, I also focus on rent-seeking behaviour exhibited by politicians for their self-interests.

In the first paper, I use exogenous measures of natural disasters based on physical intensities to examine disaster impacts on under-5 mortality. The study finds that while low-income countries do not suffer a similar amount of disasters as middle or high-income countries, only the children in low-income countries are affected due to natural disasters. The effects of disasters last beyond the disaster year, exhibiting persistent behaviour. Non-democracies suffer more than democracies. Negative impacts of droughts on various vital factors such as macro-level GDP, maternal mortality, child vaccination rates, and disease incidences are identified as potential causal mechanisms. When global warming is predicted to continue for decades, this study's findings suggest that amongst children, those born in poor countries who lack access to resilient infrastructure will suffer the most. While this paper used the best sources of data currently available at the cross-country level, more credible estimates can be obtained if data on natural disasters at a finer level is made available in the future.

The second paper studies the impacts of income shocks on under-5 mortality by using rainfall as a proxy for agricultural income and by relying on a new sub-national level data on child mortality. Low-income countries and the group of African countries that are agriculturally reliant suffer the most due to income shocks, followed by the lower-middle-income countries. The effects of income shocks are not just transitory, rather they are persistent, lasting for up to three years. While dam-fed districts that have access to reservoir water suffer less in periods of negative rainfall shocks, children from higher inequality regions from low-income countries suffer the most due to income shocks. The existing studies suggest that droughts will be more prevalent in the coming decades. In this paper, I provide evidence that children in low-income countries bear most of the burden however, the provision of water resources can act as an important channel through which some of the adverse impacts of rainfall shocks can be mitigated. An avenue for future research is the heterogenous effects of rainfall shocks by the type of crops cultivated in districts either at an individual country level or global level.

In the third paper, I focus on the linkage from political to development economics. Using nightlight activities measured through satellite imageries as a proxy for local economic growth, the study tests whether chief ministers (CMs) i.e. leaders of Indian state assemblies engage in favouritism towards their elected constituencies, via an unfavourable distribution of public assets. Based on the findings, chief ministers' constituencies exhibit a 13% increase in the luminosity during their tenure, an effect unobserved during both the pre-and post-tenure of chief ministers. Results are primarily driven by non-birth regions of CMs, evidence of political expediency rather than in-group favouritism. Neighbouring constituencies that align with national federal constituencies, which carry significant political value to CMs also benefit from the windfall. The study provides evidence of distortionary behaviour from politicians in the developing world context.

These studies show that in an era when global warming is a serious issue and when natural disasters and extreme weather events are a frequent phenomenon, children from poor countries suffer significantly. We also provide evidence based on a developing country setting that politicians redirect public resources to their favored elected constituencies for their self-interest, a distortionary behavior which may take resources away from the public in need. Even if we completely switch to clean energy sources in the near future, global warming is expected to continue for a few more decades. Not only the employment of counter-balancing policies under better regimes by developing countries are requisites, necessary support from developed countries, and global organizations, along with the optimal channelling of resources by the recipients are needed for the efficient management of adverse effects of impending extreme events.