THE TRUE COST OF CONFLICT: THE IMPACT OF LEFT-WING EXTREMISM ON CHILD AND ADOLESCENT MORTALITY IN INDIA

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Abstract

Armed conflict exacts a heavy toll on people around the world. India has suffered from numerous armed conflicts with one of the most devastating ones being Left-Wing Extremism (LWE). LWE has killed thousands of people every year since the 1960s. The toll this conflict had exacted on children has not been directly studied. Using household level data from the 2019-21 Demographic and Health Survey (DHS) in addition to district level violence data compiled from the Armed Conflict Location Event Database (ACLED), this thesis examines the mortality risk associated with conflict in India. The empirical strategy employed by this thesis is a binary logistic regression with child and under-18 mortality as dependent variables. The results show that LWE increases the likelihood of both child and under-18 mortality. However, the models also showed that mortality risk could be effectively reduced through improved water access, housing, and health coverage.

KEYWORDS: (Child Mortality, Armed Conflict, Naxalism, Left-Wing Extremism, India)
JEL CODES: (I15, H75, H56)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

Signature

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1. Introduction

Across the world approximately one in six children are affected by armed conflict (Save the Children International, 2022); it destroys homes, kills loved ones, and worst of all, robs children of their futures. Armed conflict plays a major role in driving global child mortality; in 2021 alone, over 5 million children under the age of 5 and another 2.5 million people between the ages of 5-24 died around the world (UNICEF, 2023). The causes of these deaths are manifold but most of them could have been prevented with better access to healthcare, nutrition, and education – the provision of which are all impacted by armed conflict.

Despite being globally prevalent there is no universal definition for what constitutes armed conflict, and it is subject to much debate in academia. The definition adopted by the International Committee of the Red Cross states that armed conflict is fighting between states, protracted armed violence between government authorities and organized armed groups, or violence between organized armed groups (Stewart, 2003). This paper adopts a broad definition of conflict based on the methodology used by the Armed Conflict Location Event Database (ACLED), which divides armed (violent) conflict into four categories: battles, remote violence, violence against civilians, and riots (Raleigh & Dowd, 2016).

All types of armed conflict impose significant costs to societies because of two reasons. Firstly, there are direct impacts such as the destruction of economic assets, loss of life, and reduced investment. The second factor, constituting significant long-term problems for societies affected by conflict, is the opportunity cost of dedicating scare resources towards violent activities. These expenditures come at the expense of other projects that could boost living standards and economic activity.

Even with this framework, the true costs of conflict are immeasurable given the far-reaching toll they exact on children. Children and adolescents are particularly vulnerable to the impacts of conflict as they have a higher likelihood of dying due to injury, skipping lifesaving immunizations, or missing out on adequate nutrition (Shenoda et al., 2018). Their long-term well-being is further compromised by higher rates of school absences; over 240 million children and adolescents around the world experience disruption to their education due to armed conflicts today (UNESCO, 2022).

India is no stranger to armed conflict. It has fought multiple wars against its neighbors, continues to respond to various internal strifes, and faces countless terrorist threats. One particularly violent conflict that has plagued the country for decades is its Left-Wing Extremist (LWE) insurgency. This conflict was described as "the single biggest internal security challenge ever faced by India" by its former Prime Minister, Manmohan Singh (The Economist, 2006). Since the 1960s, Indian police, paramilitary, and armed forces have faced off against a LWE insurgency. At its peak, thousands of people died every year, including combatants, civilians, and most tragically, children (Pletcher, n.d.). The true cost of this conflict on children has not been holistically researched; existing government data shows that the states most affected by LWE have some of India's highest infant mortality rates (MoHFW, 2022). However, given the vast differences in socio-economic characteristics across India's states, it is challenging to draw conclusions from a cross-state comparison.

Directly comparing different instances of armed conflict around the world – or even across Indian states – would obscure many regional and time-dependent factors that may contribute to child mortality. To avoid this bias, this thesis utilizes district level survey data from the Indian National Family and Health Survey (NFHS) in a single year to determine whether armed conflict in India impacted the likelihood of households experiencing a child or adolescent death.

This thesis further focuses on an ongoing Left-Wing insurgency in Central and Eastern India, analyzing whether districts impacted by this type of violence are susceptible to higher rates of child mortality. By comparing the impact of armed conflict across households in districts that share similar socio-economic characteristics, such as nutrition access, schooling, and immunization rates, this thesis aims to isolate the impact of armed conflict on the well-being of children in the region.

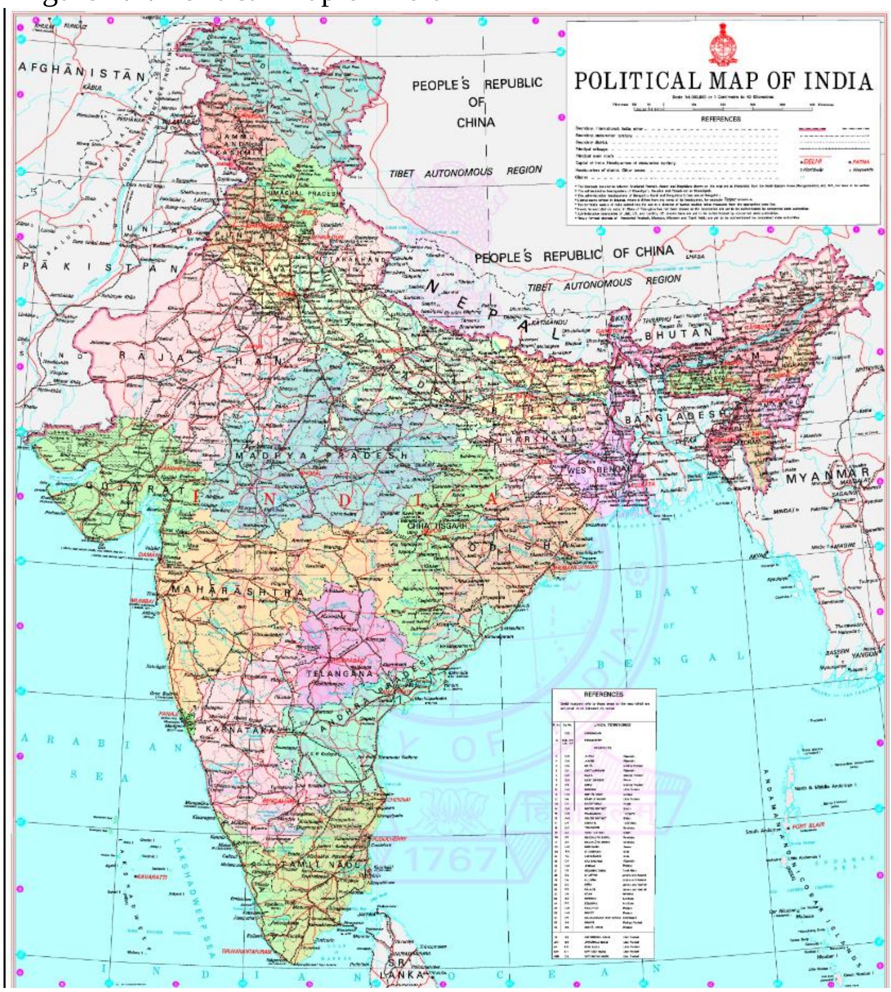
The remainder of this thesis is broken down into six sections. Section 2 provides background information on India, the conflicts it faces, and the evolution of Left-Wing Extremism (LWE) in the country. Section 3 reviews the literature describing the mechanisms that impact child mortality. Section 4 outlines the methodology, empirical model and data sources that underpin this thesis. Section 5 examines the results obtained by the binary logistic regression analysis and outlines the validity of the model. Section 6 discusses the wider implications of the findings, as well as the limitations of this analysis. Lastly, Section 7 concludes the thesis, highlighting policy implications and areas for further study.

2. **Background**

India is the world's most populous country, with a population exceeding 1.42 billion people (Unger, 2022). This enormous population comprises of numerous ethnic, religious, and linguistic groups, with over 100 different languages and all major world religions being represented (Greater Pacific Capital, 2020). India is also home to over 700 different tribal groups, accounting for approximately 100 million people – 8% of its total population (IWGIA, 2022). These tribal groups are classified as Scheduled Indian Tribes (SITs) under the Indian Constitution, with the greatest population of indigenous peoples living in the Central and Eastern states of Madhya Pradesh, Chhattisgarh, Jharkhand, Odisha, Andhra Pradesh, West Bengal, and Karnataka (Kaur et al., 2022). India is a federal country that is subdivided into 28 states and 8 union territories (GoI, n.d.). These are further subdivided into over 750 districts, as well as other village, town and city municipalities (CNBC, 2022). India conducts elections for each of these entities at different times, with India's federal election being the world's largest exercise in democracy consisting of close to a billion eligible voters (Vaishnav & Hintson, 2019).

Despite India's established democracy and expansive state, it is currently considered a middle-income country with a per capita GDP of $2277 (The World Bank, 2022). India is one of the world's fastest-growing economies with an average growth rate of 6.15% between 2006 and 2023 (GoI, 2022). Even though India is the world's fifth-largest economy, with a real GDP of over $3.5 trillion dollars, it still suffers from high rates of poverty, disparities in access to necessities, and many preventable deaths (Armstrong, 2022). In spite of raising 415 million people out of poverty in the period between 2006 and 2015 (PTI, 2022), India still has a poverty rate of 16.4% – approximately 220 million people (University of Oxford, 2022). India's poverty reduction can be attributed to its rapid economic growth, as well as its numerous government programs such as a national subsidized food staples program and a guaranteed work scheme for the rural poor.

Figure 2.1: Political Map of India



Source: Survey of India – Department of Science and Technology

The benefits of India's rapid economic growth and poverty reduction are not evenly spread, with vast regional differences in GDP per capita and standards of living. Most of India's poorest states are in the Central, Eastern, and North-Eastern regions, whereas India's wealthiest states are those on the Western and Southern coasts (Ray, 2021). This geographic disparity of wealth is caused by various factors, including the spread of different industries that operate in different states. India's Western and Southern states have seen a much larger boom in manufacturing, services, and technology-related industries (Bandyopadhyay, 2013); India's other states have remained reliant on extractive industries such as natural resources and agriculture. Despite some convergence between wealthy and poorer states (Cashin & Sahay, 1996), these economic disparities have translated into different levels of investment across communities, child mortality, and armed conflict.

2.1 The Evolution of Child Mortality in India

India has one of the highest under-5 infant mortality rates (IMR) in the world; in 2019, along with Nigeria, India contributed to almost a third of global child mortality (W.H.O., 2020). Between 1990 and 2019, India's overall under-5 IMR fell by 4.5% year over year (Press Trust of India, 2020). Despite significant progress, most recent estimates from 2021 place India's IMR at 31 deaths per 1000 live births – over 700,000 children, which is more than anywhere else in the world (UNICEF, n.d.). The burden of this tragedy is borne unequally across states, with some states performing significantly worse than their peers, whereas others outperformed expectations. In the period between 2015 and 2019, some states such as Mizoram, a relatively small economic actor in India's North-East, saw drastic falls in their IMR from 32 to 3 deaths per 1000 live births. Other states like Chhattisgarh remained stagnant above the national average at 40 deaths per 1000 live births. Madhya Pradesh continued to have India's highest IMR in 2019 with 47 deaths per 1000 live births, an 8% decrease from 2015 (P.I.B., 2022).

The decline in India's overall IMR can be attributed to numerous factors, including expanded access to healthcare, better nutrition, and improved education. India's economic growth has allowed it to massively invest in its public health provision. One study found that an increase in public health expenditure by 1% of a state's GDP led to infant mortality decreasing by 9 deaths per 1000 live births (Barenberg et al., 2017). This additional funding enabled the rollout of the National Rural Health Mission (NRHM) to meet the needs of underserved rural communities. This program established numerous new clinics and trained a cadre of health workers (ASHA workers) (Basu, 2017). Furthermore, changes in cultural norms, such as those around male preference, have also led to significant improvements in IMR in certain states (Ghosh, 2012). The Ministry of Health and Family Welfare has a list of nine key programs that it began implementing to meet the Millennium Development Goals which include universal immunizations, capacity building of health workers, as well as an online tracking system to check the health of each mother and child in the country (P.I.B., 2014). Various initiatives undertaken by different levels of government, as well as the private and nonprofit sectors, have all played a crucial role in the continuous year-over-year decline. Although the efficacy of each of these schemes differs greatly, the overall result has still been impactful.

2.2 The History of Left-Wing Extremism (LWE) in India

Since its independence in 1947, India has had to contest with different armed movements including multiple wars against its neighbors – China and Pakistan – in addition to internal strife such as tensions in the regions of Kashmir and the North-East. One of the most consequential and long-running threats that India faces is Naxalism. Officially known as Left-Wing Extremism (LWE), Naxalism is an insurgency that has affected numerous Central and Eastern Indian states. The term Naxalite originates from the name of Naxalbari, a town in West Bengal that was the center of a failed peasant uprising (Pletcher, n.d.). Naxalism, and many LWE movements claim to represent the most downtrodden members of Indian society, including tribal peoples and members of the Dalit community that have been at the lowest rung of India’s social and economic ladder.

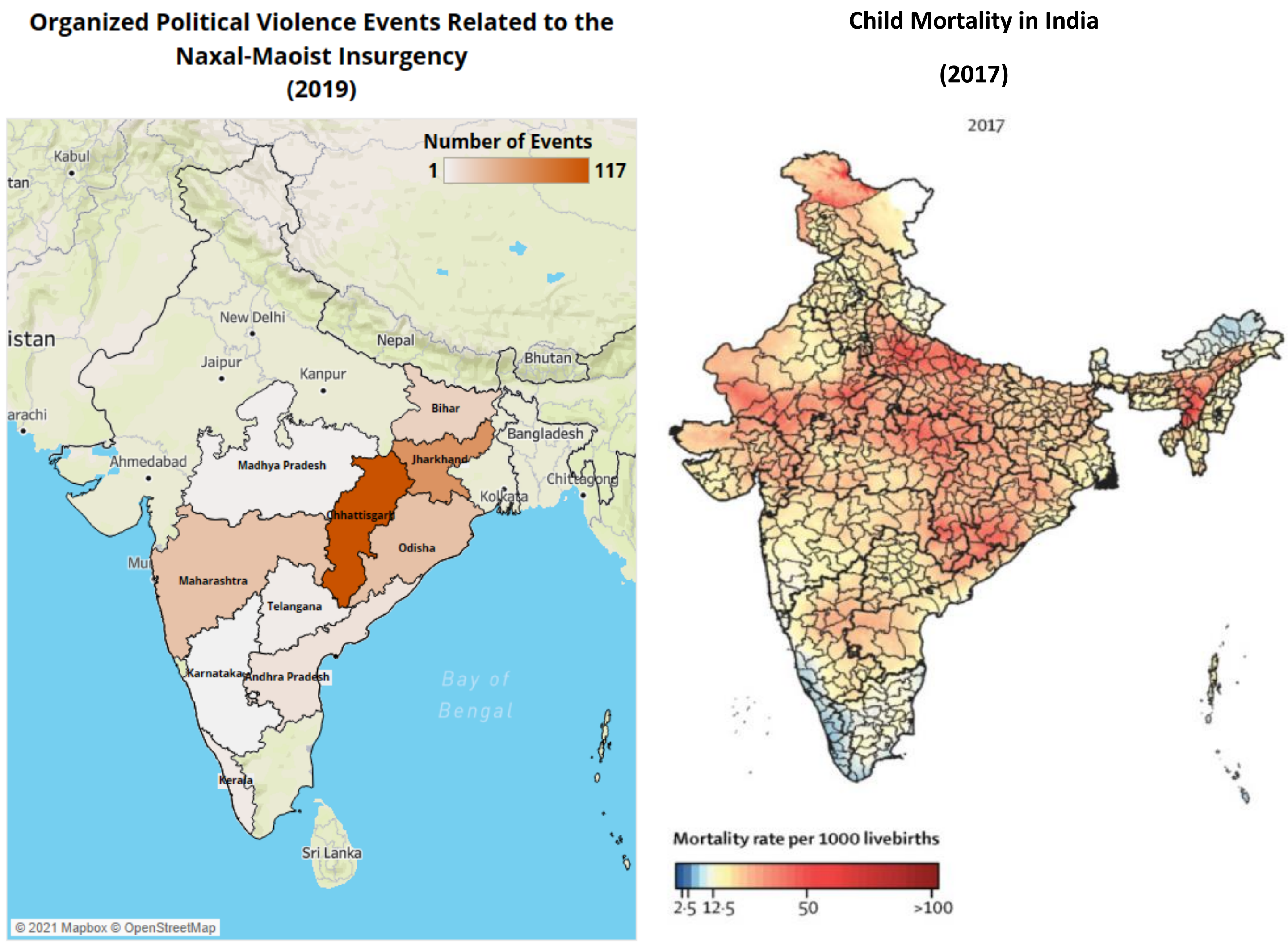
The exact commencement of this conflict is hard to pin down, but the ideological foundations of the movement can be linked to groups splintering away from the Communist Party of India – Marxist (CPI(M)) in 1968 that followed the failed Naxalbari uprising of 1967 (Karat, 2009). The founding principles behind the Naxal movement in India can be attributed to Charu Majumdar's Historic Eight Documents. These documents laid out that the Indian State was a bourgeois institution and denounced mainstream communist parties that agreed to operate within the framework of the Indian constitution (Karat, 2009). Given these factors, Majumdar called for a people's war to overthrow the Indian State (Singhal & Nilakantan, 2016).

LWE in India has evolved since this time, adding many groups to their fold, and rallying under the banner of the Communist Party of India – Maoist, an outlawed political and militant group (Karat, 2009). LWE is responsible for the deaths of thousands of people across India, with a report by the Indian Ministry of Home Affairs highlighting that the conflict has claimed 12,000 lives between 2000 and 2018 (Times of India, 2018). The scope of Naxal attacks have included targeted killings of politicians, destruction of infrastructure, ambushes of security force personnel, and at times, the indiscriminate killing of civilians.

In response to LWE, the Indian government states that it is using a holistic approach utilizing "security, development, ensuring rights and entitlements of local communities, improvement in governance and public perception management" (GoI, 2023). Notable security operations conducted by the Indian military and paramilitary forces include Operation Steeplechase (1970s) and a series of recent operations that have been coined as Operation Green Hunt (2009 – present) (Pubby, 2009). The Indian government monitors the presence of LWE across regions and publishes a list of "affected districts" that will receive support under the Security related Expenditure (SRE) Scheme (P.I.B., 2019). At its peak LWE affected hundreds of districts across 22 of India's 28 states, however, as per most recent data, LWE affects 90 districts in 11 states (P.I.B., 2019), which are colloquially referred to as the 'red zone' or 'red corridor'.

2.3 Intersection Between Left Wing Extremism and Child Mortality

Figure 2.2: Maps Comparing Left Wing Extremism and Child Mortality in India



Source: Left – Armed Conflict Location Event Database (ACLED), Right – Indian State Level Disease Burden Initiative, The Lancet

Figure 2.2 shows the presence of LWE events in 2019 and child mortality per 1000 live births in each district in 2017. The most LWE impacted states in the left panel are Chhattisgarh, Jharkhand, and Odisha. The right side of the panel shows India's child mortality rates in 2017.

There is a strong cluster of high child mortality districts clustered in the states of Chhattisgarh, Jharkhand, Madhya Pradesh, and Odisha which overlap with states experiencing LWE conflict.

There are also some high child mortality districts in states and administrative districts that are not connected with LWE. These include districts in the states of Uttar Pradesh and Rajasthan, as well as in various states in the North-East – Tripura, Meghalaya, and Assam. Uttar Pradesh and Rajasthan are highly populous states that are economically less developed than the average Indian state outside of key urban areas. These states have higher rates of communicable diseases and lower education levels which contribute to their higher child mortality burdens (Agarwal & Agarwal, 1987). North-Eastern states suffer due to their remoteness and conflict pressures originating from cross-border spillovers and tribal violence. The remoteness of this region lowers overall access to facilities such as toilets, drinking water, and cooking fuels which all play a role in increasing child mortality (Dinachandra et al., 2015).

3. Literature Review

The effects of armed conflict on child mortality have been widely studied. The list of reasons includes the targeting of children and school infrastructure by combatants, reduced access to healthcare services such as immunizations and routine checkups, and increased disease burdens through lower quality living standards and nutrition which over-burdened health systems are unable to cope with. Other factors, such as the type of conflict , are also a key indicator in how children are impacted. Inter-state conflicts lead to higher neonatal mortality, while intra-state conflicts (civil wars) lead to higher rates of child mortality (Ali & Adan, 2013).

The United Nations Security Council has what it calls the six grave violations against children that occur during war: the killing and maiming of children; the recruitment or use of children in armed forces and armed groups; attacks on schools or hospitals; rape or other grave sexual violence; the abduction of children; and the denial of humanitarian access for children (UNICEF, 2022). This literature review examines factors associated with the above categories that impact child mortality. Armed conflict affects children through direct and indirect channels. Direct impacts refer to the targeting and use of violence towards children themselves, while indirect mechanisms consider the consequences of being denied access to basic human necessities. Additionally, there are some determinants entirely disconnected from conflict that impact child mortality that are explored in this section.

3.1 The Direct Impacts of Conflict on Child Mortality

Conflict has a direct impact on child mortality as children may interact with combatants or become caught in crossfires. Research analyzing Combat Support Hospital (CSH) admissions in Iraq and Afghanistan showed that children made up half of the admitted non-combatants to these hospitals and that gunshot and explosive wounds accounted for 76.3% of admissions

(Creamer et al., 2009). Moreover, research of admittees to CSH showed that there was a higher likelihood of a pediatric patient dying despite similar injury severity to adults. The authors attribute this finding to multiple factors including a lack of pediatric-specific resources and training in these hospitals (Borgman et al., 2012).

During numerous conflicts, different groups have been known to use schools and other educational institutions as military bases as they are often one of the larger built structures in conflict areas. Direct armed involvement in schools makes these institutions a target for opposing forces which may increase the risk of children becoming collateral damage. A study by The Global Coalition to Protect Education from Attack identified 70 countries where attacks on schools occurred between 2009 and 2013. 30 of these instances represented a pattern of deliberate attacks (Petersen, 2014). Moreover, setting up of bases near or in schools facilitates the recruitment of child soldiers. Due to the proliferation of small arms, their relative ease of use, and the low costs of maintaining child soldiers, various armed groups around the world have employed child soldiers extensively (UNICEF, 2001). In one instance, an armed group in Uganda, the Lord's Resistance Army, consisted of over 90% child soldiers (Levy, 2007). In the Indian context, India as a state is a signatory to the Optional Protocol on the Involvement of Children in Armed Conflict, which binds states to not use child soldiers in conflict (U.N.. Unfortunately, numerous non state actors have been known to recruit child soldiers as young as 6. Naxal groups have been known to use child soldiers in multiple Indian states (Singh, 2015). As recently as 2016, the bodies of child soldiers were found by security forces after a skirmish (Mahaseth et al., 2022).

Between the years of 2005 and 2020, UNICEF verified that 93,000 children were recruited into armed conflict globally; a figure that they believe to be an underestimate of the true scale of the problem (UNICEF, n.d.). The recruitment of child soldiers can also occur outside of schools. In many cases the breakdown of caregiving and familial structures forces children to voluntarily join combatant groups as a means of finding solidarity, support, and protection. Despite not being the ideal soldier, children are much cheaper to maintain during a conflict than an adult, further incentivizing their use. Sadly, this fact has resulted in the abductions of numerous children in Naxal affected areas (Mahaseth et al., 2022).

The effects of direct child mortality are also very gendered with factors such as sexual violence playing a huge role in worsening girls' outcomes in conflict zones. One in six children living in conflict zones live in proximity to a site where sexual violence was used by one of the conflicts' belligerents. Sexual violence against children is used as a tactic by armed groups to boost cohesion amongst members and accustom recruits to violence. This strategy is more commonly employed by groups that utilize child soldiers(Sapiezynska, 2021), bringing to light the strong correlation between the recruitment of child soldiers and the weaponization of sexual violence in armed conflict. Sadly, in LWE affected areas, militias on both sides of the conflict have perpetrated sexual violence as a weapon of control (Manecksha, 2016).

Child mortality is likely to remain elevated even after the conclusion of conflict as remnants of the conflict such as landmines and other explosives can be discovered. Children may confuse these explosives for toys or something benign. The UN estimates that there are approximately 100 million unexploded landmines which place children in over 80 countries at risk of death or grievous injury (Watts, 2009). The International Red Cross notes that in many conflict regions, over a third of all landmine casualties are women and children (Doswald-Beck et al., 1995). The remoteness of many of these landmines and the prohibitive cost of demining continue to make them a pervasive threat in numerous regions.

3.2 The Indirect Impacts of Conflict on Child Mortality

Armed conflict denies children access to essential resources. Factors that affect child mortality and welfare indirectly include the willingness and ability of a society to invest in healthcare services, provide adequate nutrition, and ensure schooling. Conflict reduces the likelihood of women and children accessing healthcare services and lifesaving treatment as healthcare facilities struggle to operate either due to intentional targeting or collateral damage. Between 2016 and 2020 (Safeguarding Health in Conflict, 2021). Such transgressions are committed by both state and non-state actors, which proves problematic as most states are signatories to the Geneva Convention which dictate protocols governing the use of force during armed conflict.

Armed conflicts, by damaging health infrastructure and depleting human resources, further impact child health by reducing the uptake of life-saving immunizations which can lead to higher rates of communicable diseases in war-torn communities. Depending on the capacity of the state, and the nature of the conflict, in some instances, the added resources invested into a conflict-affected region may lead to an uptick in immunization rates if the conflict is considered a low-intensity one (Østby et al., 2019). However, in most cases, conflicts lead to declines in access to immunizations and the spread of disease. One study found that 16 countries account for 67% of polio and 39% of measles cases. These countries experienced sudden drops in immunization coverage at the onset of conflict, leading to pockets of low coverage and disease outbreaks (Grundy & Briggs, 2019). Lower rates of immunization threaten to increase child mortality as children are often the most susceptible to communicable diseases.

The provision of water, sanitation, and hygiene – commonly referred to by the acronym WASH – is another challenge during times of armed conflict. WASH facilities are sometimes targeted by combatants, while diversion of resources away from public service delivery also contributes to worse health outcomes for people living in regions dealing with armed conflict. This lack of investment leads to the spread of communicable diseases. A UNICEF report notes that “in fragile countries, children under the age of five are 20 times more likely to die due to diarrheal diseases than to violence” (English & Alhattab, 2021; Als et al., 2020). In the nine countries reviewed by the report, over 48 million people lacked access to potable water and sanitation services. Moreover, attacks on infrastructure decrease the ability of vulnerable groups to access these resources and worsens the disease burden in these communities.

Coming back to the issue of education, the lack of access to schooling impacts children’s nutritional access and their personal hygiene habits. Many skills taught in schools improve a child’s health outcomes, such as reinforcing oral hygiene habits, handwashing, and social skills such as shoe wearing (Sarkar, 2013). Children may not grasp these vital life skills due to being away from school during periods of armed conflict, increasing their vulnerability to various communicable diseases. Armed conflict is also strongly associated with children under-5 being underweight, having severe rates of anemia, and stunting (Dahab et al, 2020; Sumbele et al., 2020). Schools play a significant role in providing nutrition to students in India as children are provided with meals at school through the mid-day meal scheme (The World Bank, 2007). Being away from schools, in addition to the general challenges faced by families in acquiring food, leads to children having significantly fewer calories and inadequate macro-nutrients, resulting in negative impacts on their health.

3.3 Other Factors Impacting Child Mortality

Beyond the impacts of conflict, various biological and social factors impact child mortality. These include family and parental characteristics, genetics, environmental conditions, in addition to other complications associated with the child's birth.

A family's wealth with respect to other households in the region is a strong predictor of child mortality. In other studies of DHS data, such as in Ghana, wealth status had a significant impact on child survival (Lartey et al., 2016). This finding has been reported in different settings, including in India, where analysis of DHS data showed that across all survey periods family wealth had a significant impact on child mortality (Chalasani & Rutstein, 2014). While family wealth in absolute terms is strongly linked to conflict, relative household wealth is less correlated with it. Another family variable which plays an important role in child mortality is the marital status of parents. Children born to single parents have a much higher risk of mortality compared to their counterparts from two-parent households (Remes et al, 2011). This relationship only holds for monogyny – the practice where a man only has a single wife. Children who are born in households that practice polygyny have higher rates of child mortality (Ekholuenetale et al., 2020).

There are many genetic and biological factors that impact child mortality including the presence of certain disease-causing mutations to their alleles (variations in an individual's DNA) and birth complications. Examples of hereditary illnesses caused by mutated alleles include cystic fibrosis and sickle-cell anemia (David & Collins, 2007). Children that are born before they are due (pre-term births) suffer from much higher rates of child mortality (Callaghan et al., 2006). A second birth complication associated with higher child mortality is the type of delivery; some studies show a connection between children that are born using cesarean section delivery and increased child mortality risk (Xie et al., 2015). There are numerous biological factors that have been studied that increase child mortality risk. The main complicating factor is that a lot of this data is not collected widely due to costs and impracticality. The models later in this paper do not explore genetic or biological factors due to the impacts these variables would have on overall sample size.

Environmental factors that impact child mortality include air pollution and altitude. Air pollution comprises of exposure to particulate matter (PM) through indoor and outdoor sources. Children in households with solid fuel use, or in regions with higher PM levels, face higher child mortality risks (Stevens et al., 2008). High altitudes are another factor which increases a child's risk death from respiratory infections and hypoxemia (Niermeyer et al., 2009).

This literature review will guide the model construction process in Section 4. Not all the mentioned mechanisms will be utilized in the model due to challenges with data availability and incompatible datasets.

4. Theory and Methodology

This section explores the rationale for the thesis' empirical strategy, exploring why the binary logistic regression approach was the best choice for the model. It then details the model with a description of each variable used in the models. This section lastly covers the data used, including the sources and steps taken to clean the data.

4.1 Theory

To determine which factors predict the likelihood of child mortality occurring in a particular household, this paper runs multiple binary logistic regressions with child or under-18 mortality as the dependent variable. Logistic regressions enable the probabilistic modelling of binary variables – in our case child/under-18 mortality. As both dependent variables are binary in nature, the empirical models show the odds of whether a child (or person under the age of 18) died in a particular household.

Numerous papers have employed logistic regressions when analyzing DHS data to show which factors impact child mortality. Previous papers have examined the relationship between malnutrition and child mortality in India, maternal education and vaccination rates, as well as antenatal care (Khare et al., 2017; Raza & Khan, 2014; Lakshmanasamy, 2021; Rockli et al., 2016). This type of analysis has also been conducted across multiple countries on different dependent variables. In Sub-Saharan Africa, DHS data was used to identify characteristics which increased prevalence of anemia (Tesema et al, 2021). DHS datasets lend themselves well to this type of analysis as many of the questions asked tend to be binary or categorical in nature. This limits the number of continuous variables that could support an Ordinary Least Squares (OLS) regression.

The binary logistic regressions in this thesis show us the odds ratio associated with each independent variable impacting child/adolescent mortality. We consider both child and adolescent (under-18) mortality as these groups are particularly vulnerable to different factors associated with conflict. Children under the age of five are particularly vulnerable to communicable diseases and other illnesses. Pneumonia, diarrhea, and malaria alone accounted for 30% of childhood deaths in 2019 (UNICEF, 2021). As established in the literature review, children in conflict zones have reduced access to treatment and safe living conditions which make them more prone to catching and succumbing to such ailments.

Adolescents (people under the age of 18) have very different mortality risks from children under the age of 5. Adolescent deaths are more likely to be linked to interpersonal violence, accidental injury, or conflict than to communicable diseases (GBD 2019 Adolescent Mortality Collaborators, 2021). Combatants are likely to target this group when it comes to recruiting child soldiers. Furthermore, attacks on educational institutions would have a greater impact on this group as they may face additional risk of mortality or choose to not go to school as a risk avoidance mechanism.

These factors influenced the decision to run two models on child and under-18 mortality. The datasets further lent themselves to utilizing a binary logistic regression to identify household level risk. This allowed use of the entire DHS India household dataset.

4.2 Empirical Models

This thesis analyzes the effect of 19 independent and control variables on two dependent variables – child and under-18 mortality. The regression analysis for these models was built using STATA© and Microsoft Excel ©. The independent variables are constant across the two models.

Model 1: Logistic regression for child mortality

$$\text{childmortality} = \alpha_0 + \alpha_1 \text{ frequency} + \alpha_2 \text{ sumoffatalities} + \alpha_3 \text{ naxalviolence} + \alpha_4 \text{ accesstowater} + \alpha_5 \text{ waterquality} + \alpha_6 \text{ handwashing} + \alpha_7 \text{ hospitaltype} + \alpha_8 \text{ healthinsurance} + \alpha_9 \text{ wenttoschool} + \alpha_{10} \text{ internet} + \alpha_{11} \text{ anemia} + \alpha_{12} \text{ iodizedsalt} + \alpha_{13} \text{ fathereducation} + \alpha_{14} \text{ mothereducation} + \alpha_{15} \text{ maritalstatus} + \alpha_{16} \text{ familywealth} + \alpha_{17} \text{ caste} + \alpha_{18} \text{ housetype} + \alpha_{19} \text{ sanitation} + \epsilon$$

Model 2: Logistic regression for under-18 mortality

$$u18mortality = \alpha_0 + \alpha_1\, frequency + \alpha_2\, sumoffatalities + \alpha_3\, naxalviolence + \alpha_4\, accesstowater + \alpha_5\, waterquality + \alpha_6\, handwashing + \alpha_7\, hospitaltype + \alpha_8\, healthinsurance + \alpha_9\, wenttoschool + \alpha_{10}\, internet + \alpha_{11}\, anemia + \alpha_{12}\, iodizedsalt + \alpha_{13}\, fathereducation + \alpha_{14}\, mothereducation + \alpha_{15}\, maritalstatus + \alpha_{16}\, familywealth + \alpha_{17}\, caste + \alpha_{18}\, housetype + \alpha_{19}\, sanitation + \epsilon$$

Table 4.1: Overview of Variables Used in Empirical Models.

Variable Name	Variable Description	Source (and original variable name)
childmortality	Binary variable which indicates whether a child (under the age of 5) died in the household in the survey period	DHS (sh92)
u18mortality	Binary variable which indicates whether a non-adult (under the age of 18) died in the household in the survey period	DHS (sh92)
frequency	The number of violent attacks recorded in a district in the survey period	ACLED
sumoffatalities	The total number of deaths associated with violent conflict in a district in the survey period	ACLED
naxalviolence	Dummy variable indicating whether violent conflict in the district corresponded to Naxal violence	Ministry of Home Affairs (GoI)
accesstowater	Dummy variable indicating whether the house had access to water on premises	DHS (hv204)
waterquality	Dummy variable indicating whether the house practiced any water purification method	DHS (hv237)

handwashing	Dummy variable indicating whether soap or another detergent was present in the house	DHS (hv232)
govthospital	Categorical variable indicating whether members of the household typically accessed public, private, or alternate methods of care when ill	DHS (sh73)
healthinsurance	Dummy variable indicating whether at least one usual member of the household was covered by a health insurance scheme	DHS (sh71)
wenttoschool	Dummy variable indicating whether eligible members of a household attended school	DHS (hv123)
internet	Dummy variable indicating whether the house had an internet connection	DHS (sh50n)
anemic	Dummy variable indicating whether any child in the household had anemia (of any severity)	DHS (hc57)
salt	Dummy variable indicating whether the house consumed salt that had been fortified with iodine	DHS (hv234a)
fathereducation	Categorical variable indicating the father's schooling – either no education, primary, secondary, or higher	DHS (hv106)
mothereducation	Categorical variable indicating the mother's schooling – either no education, primary, secondary, or higher	DHS (hv106)
maritalstatus	Categorical variable indicating whether the parents in a household are married, divorced, widowed, or never-married.	DHS (hv115_01)
familywealth	Categorical variable indicating whether the wealth bracket that household falls into with respect to state averages – either poorest, poorer, middle, richer, or richest	DHS (sv270s)
caste	Categorical variable indicating the caste category that the household belonged to – either scheduled caste, scheduled tribe, other backward caste, or none	DHS (sh49)
housetype	Categorical variable indicating whether the house structure was permanent, semi-permanent, or temporary in nature	DHS (shnfhs2)
sanitation	Categorical variable indicating whether drainage in household is closed, open, a soak pit, or not present	DHS (sh46)

4.3 Data

4.3.1 Data Sources

The data for this study comes from three different sources: standardized Demographic and Health Survey (DHS program, 2021) data, the Armed Conflict Location Event Database India dataset (ACLED, 2021), and an Indian Government Ministry of Home Affairs press release

(P.I.B., 2019). The timeframe for the data used was between 2019 and 2021, coinciding with the survey period of India NFHS-V (DHS phase VII), however, final regressions only consisted of data from 2019.

Demographic and Health Survey (DHS) Data: The primary dataset used to construct variables associated with child mortality and household welfare is the 2019 National Family and Health Survey (NFHS-V). This is a survey conducted by the Indian Ministry of Health and Family Welfare to assess numerous characteristics associated with population demographics, health, and nutrition. There have been 5 NFHS rounds conducted; the first took place in 1992-93. USAID provides technical assistance for the NFHS program, allowing for the data collected to be standardized under the DHS framework. All NFHS data can be accessed through the DHS program website and follows the universal coding structure utilized in DHS questionnaires around the world. A DHS phase takes up to two and a half years to implement from questionnaire design, surveying, and analysis (DHS program, n.d.). NFHS-V surveyed 636,699 households, including 724,115 women and 101,839 men (NFHS-V, 2021). DHS datasets are recoded to focus on different groups, such as individuals, couples, and households, to help answer different questions. To access the most data, this analysis used the DHS' household recode dataset. After filtering to include relevant districts and survey data from 2019, there were 208,281 household observations used in the regression analysis.

Armed Conflict Location Event Database (ACLED) Data: The dataset used to obtain the number of instances of armed conflict, as well as their severity, was the ACLED dataset on India. This dataset contained a detailed list of every recorded instance of conflict in India between 2016 and 2021. The ACLED dataset contains disaggregated incident information on political violence, demonstrations, and select related non-violent developments around the world

(ACLED, 2022). ACLED researchers provide weekly updates on instances of conflict by reviewing reports from selected sources that include vetted social media accounts, government sources, news media, and NGOs (ACLED, n.d.). After filtering the type of events to include only those which were violent in nature and fell into the relevant time frame, those which occurred in 2019, this dataset included 6823 unique observations of violent events.

Government of India (GoI), Ministry of Home Affairs Press Release: To further corroborate the ACLED dataset, an official government press release from 2019 was used to confirm districts impacted by Naxal/LWE violence. The press release, put out on the 5th of February 2019, contained a list of 90 districts in 11 states that were impacted by LWE (P.I.B., 2019). These districts were matched to districts in the DHS and ACLED datasets.

4.3.2 Data Cleaning and Variable Construction Process

Taking different datasets and merging them to conduct further analysis required multiple steps of data cleaning. The main challenge in merging the three data sources was inconsistencies with district names. India has over 700 districts with new ones being added over time. Each of these districts have different names in multiple languages, which result in different transliterations into English. To match these districts, the DHS dataset's district names were used as a default. Districts were then renamed in the other data sources to match their counterparts in the DHS dataset.

The next step of the data cleaning process included variable selection. As the DHS dataset recorded over 6000 data points for each household, it was crucial to select the relevant questions which would support the construction of variables determined by the literature review. The ACLED dataset also came with numerous qualitative observations which were not relevant to the analysis which had to be dropped. The ACLED dataset recorded each instance of conflict in India. These were sorted by district and conflict type.

The *childmortality* dependent variable was constructed using DHS variables SH92u and SH92n. The SH92 question relates to the age of death of an individual in a household. SH92u is the unit of measurement, either in days, months, or years, while SH92n is the corresponding number. If the units associated with SH92n were either months or days, they were used to generate the *childmortality* variable as these units were only used until an individual turned 6 years of age. If the value of SH92n associated with months was greater than 60, that instance of mortality would not count towards *childmortality*. As the DHS records up to 5 deaths in a household, these steps were repeated five times for SH92n_1 through SH92n_5. The result is a binary variable that recorded whether a child under the age of five years died in the household.

The *u18mortality* dependent variable was calculated in a similar manner to *childmortality*. DHS variables SH92u and SH92n were used and if the unit associated with an individual's mortality was either days or months, that instance would automatically be recorded. In addition to this, if the unit of SH92u was in years, the *u18mortality* variable would account for that if the associated SH92n number was equal to or less than 18. These steps were repeated five times for SH92n_1 through SH92n_5 to record all deaths in the household. The result is a binary variable that recorded whether an individual under or equal to the age of eighteen years died in the household.

ACLED data was used to construct the first two conflict-related independent variables. The *frequency* variable was constructed to record the number of times that a district experienced a violent event. The *sumoffatalities* variable was made by summing all the fatalities recorded with each of these violent events. Lastly, the ACLED database gives a list of actors that identified which districts suffered from LWE/Naxal violence.

The presence of Naxal Violence in a district was verified using the Ministry of Home Affairs press release which listed the 90 districts that faced Naxal violence. The *naxalviolence* dummy variable verified whether districts announced in the press release matched with the DHS SHDIST variable. Any districts that were mentioned in the brief were coded with a 1 while all other districts were coded with a 0. Once the *frequency*, *sumoffatalities*, and *naxalviolence* variables were created, the datasets were merged by district name. The remaining variables were then constructed using data points from solely the DHS dataset.

The *accesstowater* binary variable was constructed using DHS variable HV204 reports the time taken to access a water source. One of the responses to the question was whether there is a source of water on the household's premises. The *accesstowater* variable takes this input and transforms the answer so that if the response to HV204 was "on premises" the variable will indicate that they have water on site. For households that have to travel to fetch water this variable was coded 0. The related *waterquality* variable looked at DHS variable HV237 which asked whether drinking water was treated by any method prior to consumption. If the household treated their water the variable was coded 1, else, it was coded as 0. In addition to this, household hygiene practices were considered with the *handwashing* variable. This dummy variable tracks whether a house made use of soap or some other detergent while washing their hands, with a 0 indicating that they did not, and 1 indicating that they did.

The *govthospital* variable, derived from DHS SH73, looks at whether members of the household usually go to a public or private medical practice when they become ill. DHS SH73 asked people which type of institution they typically visit when ill. For government facilities, govthospital was categorized as public, whereas private clinics, camps, and hospitals were categorized as private. Any self-treatment was categorized as other. The base case for this variable was a private practice so the regression output shows changes that would occur if the household accessed public or alternate care instead. In addition to considering the type of institution, the model also explores whether households had access to *healthinsurance* which is a binary variable that was 1 if at least one member in the household had access to any form of insurance, or 0 otherwise. This variable was constructed from DHS variable SH71.

The *wenttoschool* variable is a dummy variable that checks whether a person under the age of 18 attended school. This variable considered DHS variables HB50 and SH23. HB50 states whether a member of the household is under the age of 18. SH23 lists a reason why the person was not in school. For each individual, if HB50 showed that they were under the age of 18 and SH23 listed any reason for them being out of school, the wenttoschool variable was coded as 0. If the person was under the age of 18 and SH23 was blank, the *wenttoschool* variable was coded 1 to represent the individual being in school. These steps were repeated for each individual in the household.

The *internet* variable is a dummy for whether a household had access to internet. It was constructed from DHS variable SH50n which tracked whether a household had an internet connection – 1 being Yes and 0 being No. This variable was included to determine whether greater access to information could mitigate any of the child/under-18 mortality risks. This variable was also tested using the linked-ratio test to ensure that it improved the model fit.

Anemia is a dummy variable that was constructed from DHS variable HC57. HC57 records whether a child in the household is anemic and the level of severity – either mild, moderate or severe. If a child recorded any level of anemia the *anemia* variable was coded 1. If a child did not have symptoms of anemia the code was 0. This process was repeated for each child in the household – HC57_1 to HC57_9. The second variable connected to child nutrition is *iodizedsalt*. This dummy variable considers the presence of iodine in salt used in the household which was reported in DHS variable HV234a.

The *mothereducation* variable categorized the level of education that the child's mother received – either none, primary, secondary, or higher. Observations were dropped for respondents who did not know their education level (n=6). DHS variable HV106_02 which looked at highest education level was used. DHS HV101_02 showed the relationship of the selected individual to the head of the household. The *mothereducation* variable assumed that the individual was the mother of the children if the relationship indicated in HV101_02 was the wife. This assumption was made for simplicity but could obscure the relationship in households with multiple mothers. The *fathereducation* variable is categorized in the same way as *mothereducation* – either none, primary, secondary, or higher. Observations were dropped for respondents who did not know their education level (n=514). DHS variable HV106_01 which looked at highest education level was used. The assumption for this variable is that the head of the household is the father to a child. NFHS data typically codes household heads as the main income earner, however, this assumption overlooks non-heterosexual couple households. The base for both variables is set at no education. In addition to parental education levels, the model explored *maritalstatus* of the parents to see whether the type of household a child grew up in impacted their probability of dying. This categorical variable was created by looking at DHS variable HV115_01 which showed the current marital status of the head of the household. Taking the same assumption that the household head was the child's father, the marital status of the family head was taken to be the marital status of the child's parents.

The *caste* variable is a categorical variable derived from DHS variable SH49 which asked households whether they belonged to a protected category (Schedule Caste/Schedule Tribe), another backward class (OBC), or none of the above. The caste variable uses Scheduled Tribe as the base group and compares any changes to child mortality if the group changes. The other major family variable used in the model is *familywealth*. This categorical variable looks at whether a household's wealth quintile determines which households are more likely to suffer due to child mortality.

The *housetype* variable is a categorical variable derived from DHS variable SHNFHS2. This variable looks at whether the dwelling that a family lives in is permanent, semi-permanent, or temporary. The base for this variable is a permanent dwelling, so the model compares what changes would occur if the type of housing changed. A connected variable to the type of housing that households live in is the level of *sanitation*. This categorical variable was derived from DHS variable SH46. It looks at the type of drainage facility available to a household with closed drainage being the base case. The presence of open drainage, soak pits, or no drainage were compared in relation to the base case.

In addition to many variables that were added, other variables were excluded due to concerns with endogeneity. For example, *mosquitonets*, which tracked whether a house made use of mosquito nets to reduce the risk of malaria, was omitted as the use of mosquito nets themselves are highly correlated with variables such as *housetype and familywealth* (Biswas et al., 2010) Moreover, districts that provide better climactic conditions for malaria carrying mosquitoes would see a higher usage of mosquito nets. A model redesign would need to be introduced to change conflict related variables to account for district-level fixed effects in order to introduce this variable.

The *electricity* variable is another example of a dropped indicator variable that is correlated to *housetype*. It is a dummy for whether a household had access to electricity. This variable was omitted after running a linked-ratio test, which determines whether a variable improves the model fit. The linked-ration test showed that the *electricity* variable did not improve model predictive power.

4.3.3 Summary Statistics

Table 4.1 outlines the number of observations, mean, standard deviation, minimum value and maximum value for all of the variables used in the regression analysis. All variables other than *frequency* and *sumoffatalities* are either dummies or categorical variables. Those two conflict related variables are the only continuous variables in the analysis.

Table 4.2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
childmortality	300628	.018	.134	0	1
u18mortality	300628	.021	.144	0	1
frequency	300628	12.591	27.466	0	312
SumofFatalities	300628	2.463	7.541	0	91
naxalviolence	300628	.118	.323	0	1
accesstowater	300628	.749	.434	0	1
waterquality	300628	.51	.5	0	1
handwashing	297832	.69	.463	0	1
govthospital	300628	.639	.506	0	2
healthinsurance	300628	.42	.494	0	1
wenttoschool	300628	.987	.113	0	1
internet	300628	.421	.494	0	1
anemic	300628	.159	.366	0	1
salt	300628	.953	.212	0	1
fathereducation	300628	1.332	1.005	0	5
mothereducation	231820	1.138	.998	0	5
maritalstatus	300568	2.123	.545	0	5
familywealth	300628	2.775	1.399	1	5
caste	277700	2.612	1.163	1	5
housetype	295912	1.828	.963	1	3
sanitation	300628	2.355	1.144	1	4

Table 4.2 provides a matrix of correlation coefficients for all the variables used in the regressions.

Table 4.3 Matrix of correlations

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15	-16	-17	-18	-19	-20	2
(1) childmortality	1																				
(2) u18mortality	0.923	1																			
(3) frequency	-0.01	-0.01	1																		
(4) SumofFatalities	-0	-0.01	0.693	1																	
(5) naxalviolence	0.012	0.014	-0.05	0.086	1																
(6) accesstowater	-0	-0.01	-0	0.02	-0.05	1															
(7) waterquality	-0.02	-0.02	-0.04	-0.03	-0.18	0.183	1														
(8) handwashing	-0.02	-0.02	0.034	0.029	-0.05	0.119	0.171	1													
(9) govthospital	-0.01	-0.01	0.125	0.076	-0.15	0.004	0.096	-0.02	1												
(10) ealthinsurance	-0.01	-0.01	-0.08	-0.1	0.013	-0.06	0.032	-0	0.051	1											
(11) wenttoschool	-0	-0	0.007	0	0.006	0.002	0.016	0.018	-0	0	1										
(12) internet	-0.01	-0.01	0.067	0.036	-0.1	0.096	0.124	0.206	-0.05	-0.03	-0.02	1									
(13) anemic	0.029	0.026	0	0.015	0.014	-0.01	-0.04	-0.04	-0.01	-0.05	0.022	0	1								
(14) salt	-0.01	-0.01	0.029	0.012	-0.04	0.042	0.071	0.093	0.028	-0.01	0.008	0.052	-0.01	1							
(15) athereducation	-0.02	-0.02	0.032	-0	-0.05	0.097	0.18	0.234	-0.04	-0.02	0.051	0.24	-0.03	0.079	1						
(16) nothereducation	-0.01	-0.02	0.02	-0.04	-0.08	0.096	0.22	0.23	0	0.01	0.057	0.223	-0.02	0.084	0.584	1					
(17) maritalstatus	0.003	0.004	-0	-0	-0	0.008	0.008	0.006	0	-0	0.001	0.002	-0	-0	0.004	0.011	1				
(18) familywealth	-0.02	-0.03	0.054	0.007	-0	0.189	0.115	0.347	-0.16	0.013	0.033	0.451	-0.06	0.083	0.405	0.391	0.003	1			
(19) caste	-0	-0.01	0.125	0.129	0.05	0.076	-0.07	0.066	-0.16	-0.07	0.008	0.074	-0.03	0.018	0.1	0.081	0.008	0.221	1		
(20) housetype	0.023	0.028	-0.04	-0.05	-0.02	-0.05	-0.08	-0.2	0.124	-0.04	-0.02	-0.17	0.057	-0.04	-0.2	-0.18	-0.01	-0.48	-0.23	1	
(21) sanitation	0.009	0.013	0.094	0.039	-0.04	-0.17	-0.07	-0.2	0.133	0.03	-0.02	-0.12	0.04	-0.04	-0.17	-0.16	-0	-0.38	-0.16	0.24	1

Note: All highlighted cells indicate collinearity over 30%.

5. Results and Analysis

This section contains the results of the regression analysis of Model 1: Child Mortality, Model 2: Under-18 Mortality, as well as the results of different tests run to assess the credibility of the models.

5.1 Model Results

Table 5.1: Binary Logistic Regression Output for Model 1 and 2 (Odds Ratios)

	(1)	(2)
VARIABLES	Child Mortality	Under-18 Mortality
Frequency of Conflict Incidents	0.998	0.998**
	(0.00102)	(0.000981)
Sum of Conflict Related Fatalities	1.000	1.001
	(0.00355)	(0.00331)
Naxal Violence in District	1.144**	1.171***
	(0.0597)	(0.0564)
Access to Water On Premises	1.025	1.018
	(0.0426)	(0.0390)
WaterQuality - Treated Before Drinking	0.844***	0.846***
	(0.0330)	(0.0306)
Handwashing Practiced	0.900***	0.893***
	(0.0364)	(0.0333)
Hospital Type (Base = Private)		
Public	0.823***	0.830***
	(0.0320)	(0.0299)
Other	1.008	1.004
	(0.142)	(0.130)
Access to Health Insurance	0.897***	0.915***
	(0.0332)	(0.0313)
Went to School	0.835	0.860
	(0.110)	(0.106)
Access to Internet	1.095**	1.089**
	(0.0445)	(0.0410)
Anemia	1.586***	1.472***
	(0.0651)	(0.0569)
Iodized Salt	0.975	0.983
	(0.0761)	(0.0707)
Father's Education Level (Base = None)		
Primary	0.917	0.904**
	(0.0506)	(0.0455)
Secondary	0.920	0.886**
	(0.0471)	(0.0416)
Higher	0.918	0.885
	(0.0801)	(0.0726)
Don't Know	1.145	0.949

Table 5.1: Binary Logistic Regression Output for Model 1 and 2 (Odds Ratios)

	(1)	(2)
VARIABLES	Child Mortality	Under-18 Mortality
	(0.673)	(0.557)
Mother's Education Level (Base = None)		
Primary	1.010	1.017
	(0.0546)	(0.0503)
Secondary	1.006	0.971
	(0.0494)	(0.0442)
Higher	0.933	0.848
	(0.0973)	(0.0853)
Don't Know	2.413	2.071
	(1.753)	(1.503)
Marital Status (Base = Never married)		
Married	1.813	2.153*
	(0.816)	(0.969)
Widowed	1.676	2.536
	(1.413)	(1.871)
Divorced	-	-
Not Living Together	4.086	4.142
	(4.541)	(4.603)
Family Wealth (Base = Poorest)		
Poorer	1.024	1.030
	(0.0537)	(0.0494)
Middle	0.950	0.935
	(0.0566)	(0.0515)
Richer	0.956	0.976
	(0.0651)	(0.0614)
Richest	0.861*	0.853**
	(0.0728)	(0.0676)
Caste (Base = Schedule Tribe)		
Schedule Caste (SC)	1.035	1.003
	(0.0597)	(0.0531)
Other Backward Class (OBC)	1.066	1.016
	(0.0539)	(0.0472)
None	0.948	0.924
	(0.0565)	(0.0508)
Don't Know	1.346	1.482**
	(0.251)	(0.242)
House Type (Base = Permanent)		
Temporary	1.483***	1.507***
	(0.123)	(0.115)
Semi-Permanent	1.308***	1.352***
	(0.0558)	(0.0534)
Type of Sanitation (Base = Closed Drainage)		
Open Drainage	1.058	1.085*
	(0.0515)	(0.0494)
Soak Pit	1.077	1.074

Table 5.1: Binary Logistic Regression Output for Model 1 and 2 (Odds Ratios)

VARIABLES	(1) Child Mortality	(2) Under-18 Mortality
	(0.0953)	(0.0892)
No Drainage	1.068	1.105*
	(0.0592)	(0.0570)
Constant	0.0113***	0.0113***
	(0.00545)	(0.00539)
Observations	208,281	208,281

seEform in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5.1 provides the odds ratios for the two models along with their associated standard errors in parentheses. The stars accompanying odd ratios represent p-values, explained at the bottom of the table. The left column specifies the regression results for child mortality (under-5) while the right column specifies the results for under-18 mortality. Of particular interest to this analysis are the significant results associated with *naxalviolence* in both models, as well as the significant *frequency* result in model 2. The odds of child mortality in districts with *naxalviolence* are 14% higher than the odds of child mortality in districts without *naxalviolence.* Moreover, under18mortality is 17% higher in districts with *naxalviolence* than those without it. Surprisingly, districts with higher conflict frequency have 0.2% lower odds of under-18 mortality.

There were numerous household and individual variables that showed significant odds ratios in either increasing or decreasing child mortality. *Anemia*, *temporary* and *semi-permanent* housing, and an *internet* connection increased the odds of mortality across both models, while *waterquality*, *handwashing*, accessing *public* hospitals, whether a member of the household had access to *healthinsurance*, and whether a family was from the richest wealth quintile significantly decreased the odds of child mortality.

In both models, *waterquality* – the treatment of drinking water – lowered the odds of mortality compared to households where water was not treated by approximately 15.5%; that figure was 10% for *handwashing.* Households which used a *public hospital* had between 17 and 18% lower odds of experiencing mortality when compared with households that made use of *private hospitals.* Being a member of the *richest* wealth quintile also decreased the odds of mortality when compared to the *poorest* quintile by 14 and 15% for child and under-18 mortality respectively. The under-18 mortality risk further decreased due to the father's education level. Compared to no education, *primary* education decreased the odds of *under18mortality* by 9.6% while *secondary* education decreased the odds of under-18 mortality by 11.4%.

Regarding factors that increased mortality risk, households where at least one of the children had any level of anemia were associated with a 58.6% increase in odds of child mortality and a 47.2% increase in odds for u18mortality compared to households where none of the children were anemic. The type of structure that a family lived in also significantly increased the odds of mortality. In model 1, compared to families that lived in permanent structures, families that lived in *semi-permanent* structures saw a 30.8% increase in *childmortality* while people living in *temporary* dwellings saw a 48.3% increase. Model 2 showed a 35.2% increase in under18mortlatity for people in *semipermanent* structures and a 50.7% increase for those living in *temporary* structures compared to those who lived in *permanent* houses. Furthermore, in both models, households that had access to the *internet* saw an approximately 9% increase in the odds of mortality compared to households that did not have internet access.

People who did not know their caste, the type of drainage, and marriage status also showed some impacts on model 2 (under-18 mortality) alone. The *sanitation* variable results showed that compared to households with closed drainage, those with open and no drainage on premises had 8.5 and 10.5% higher odds of experiencing under-18 mortality. The *maritalstatus* variable showed the largest increase in odds of mortality – 115.3% going from never married to married. However, given that less than 1% of children are born outside of wedlock in India (Chamie, 2017), most child and under-18 deaths would occur in households with married couples. People who did not know their caste had 48% higher odds of under-18 mortality compared to households that identified as Scheduled Tribes. Table 5.2 summarizes the findings mentioned above, showing which of the variables had significant results and the direction they impacted child and under-18 mortality.

Table 5.2: Significant Model Results and Direction

Model 1: Child Mortality		**Model 2: Under-18 Mortality**	
Increased Risk	**Decreased Risk**	**Increased Risk**	**Decreased Risk**
Anemia (***)	Water Quality (***)	Naxal Violence (***)	Water Quality (***)
Semi-Perm House (w.r.t Permanent) (***)	Handwashing (***)	Anemia (***)	Handwashing (***)
Temporary House (w.r.t Permanent) (***)	Public Hospital (w.r.t Private) (***)	Semi-Perm House (w.r.t Permanent) (***)	Public Hospital (w.r.t Private) (***)
Naxal Violence (**)	Access to Health Insurance (***)	Temporary House (w.r.t Permanent) (***)	Access to Health Insurance (***)
Internet Access (**)	Richest Wealth (w.r.t Poorest Quintile) (*)	Internet Access (**)	Frequency (**)
		Don't Know Caste (w.r.t Schedule Tribe) (**)	Primary Father Education (w.r.t No Education) (**)
		Open Drainage (w.r.t Closed Drainage) (*)	Secondary Father Education (w.r.t No Education) (**)

		No Drainage (w.r.t Closed Drainage) (*)	Richest Wealth (w.r.t Poorest Quintile) (**)
		Married Couples (w.r.t Never Married) (*)	
*** p<0.01, ** p<0.05, * p<0.1 w.r.t – with respect to (base variable specified for categorical regressions)			

5.2 Model Performance:

The performance of the model depends on multiple parameters including the goodness of fit, sample size, any confounding variables, and challenges with endogeneity. The model variables do suffer from some multicollinearity, mostly associated with the *familywealth* variable (see Table 4.2). Family wealth is correlated with the education levels of the father and mother, as well as the house structure and sanitation practices. There is also a strong correlation between the frequency of violent incidents and the sum of fatalities associated with them. To check the effect of multicollinearity on the model, Variance Inflation Factors (VIF) were calculated for the entire model and each independent variable. The mean VIF for both models were 3.26, which is not a cause for concern. A general rule of thumb is that variables with VIFs greater than 4 or 5 suffer from some multicollinearity, while those above 10 suffer from serious multicollinearity ("Detecting Multicollinearity...", n.d.). The only variables with a VIF greater than 5 were *wenttoschool* and *anemia*. These variables were still included due to the lack of alternative measures for child education and nutrition.

To better understand the predictive power of the models, classification statistics and Hosmer-Lemeshow post regression analyses were conducted. The classification statistics for both models show that model 1 (child mortality) was 98.43% correctly classified, while model 2 (under-18 mortality) was 98.16% correctly classified. The Hosmer-Lemeshow test is another goodness of fit test. In both models, the p-values associated with the tests were not statistically significant (0.865 for model 1 and 0.679 for model 2). The null hypothesis is that the models have a good fit; high p-values show that we fail to reject this null hypothesis and can claim that the models have a good fit.

6. Discussion

6.1 Model Implications

The models' findings have significant policy implications for India and beyond when it comes to impacts of conflict, as well as where interventions may have the most success in preventing unnecessary child and adolescent deaths. The most important finding is that Naxal violence in a district increases the likelihood of child and under-18 mortality. This finding highlights the reality that this type of conflict is exacting a steep toll on India's future generation. Further research is required at a local level to ascertain the nuanced mechanisms through which LWE conflict impacts child and adolescent health to better target policy to improve mortality outcomes.

The slightly larger coefficient for Naxal violence in model 2 (under-18 mortality) may also indicate the different mechanisms through which this conflict impacts children and adolescents. This finding may imply that LWE groups or the Indian government may either be targeting adolescents or recruiting them to be combatants which would place them at greater risk of death.

The other relevant finding is that the frequency of conflict events in a district decreases child mortality in a district. While this result is marginal, it may imply that the Indian state is targeting programs and spending additional resources to mitigate the negative outcomes of a conflict in regions that are worst impacted. If that is the case, it may support the Indian governments' holistic approach to tackling conflict. This hypothesis would warrant further analysis to determine whether this result is caused due to more resources and support being sent to areas with higher rates of conflict, rather than more conflict occurring in regions that have greater access to resources.

Other findings from the two models may help guide policy interventions to mitigate high rates of child and adolescent mortality in a district. The fact that having access to clean drinking water, public health care, and a permanent house with sanitation access all reduce mortality risk come as no surprise.

India has recently been investing in numerous national schemes to address these issues. The government of India launched the *Jal Jeevan* mission in 2022 which aims to connect every household in the country to piped drinking water by 2024 (PIB Delhi, 2022). The government is also aiming to expand universal health coverage through the *Ayushman Bharat* scheme that aims to create 150,000 health and wellness centers to boost primary health coverage. This scheme also started the implementation of the world's largest health insurance program – Pradhan Mantri Jan Arogya Yojna. This scheme aims to cover over 500 million people with some insurance cover. India also is undertaking a massive home building push with plans to construct 30 million permanent rural homes by 2024. The efficacy of these schemes varies greatly. Some of them are far behind schedule while others remain underfunded. However, the impacts of such schemes can only fully be understood over a broader time horizon. Regardless of their status, the models suggest that the government should double down on such programs and increase investment in them to reduce child mortality. Such schemes may also address the disparities in mortality outcomes that exist between the richest and poorest households. Presently the wealthiest households have much lower mortality rates compared to the poorest ones, which is a critical factor that needs to be addressed.

Hygiene practices such as hand washing are another area where education can be improved to reduce child and adolescent mortality. Improved information and public health campaigns could result in significant reductions in child mortality risks. Furthermore, ensuring access to adequate nutrition that prevents anemia should also be prioritized. Indian schools' midday meal programs should serve nutritionally fortified foods to ensure that children are able to get an adequate number of calories as well as necessary nutrients.

The only results from the models which are challenging to interpret are those surrounding internet access. India is currently in the midst of a digital transformation with millions of people connecting to the internet for the first time. Ideally, having access to the internet would result in a better-informed population that can access more services from home. On the contrary, the models show that internet access increases mortality risk. This finding may indicate that the internet may be spreading disinformation that worsens mortality outcomes, however, the coefficient is weak – a 1% increase in the odds of mortality in households that have internet access versus those that don't.

6.2 Model Strengths, Limitations, and Methods for Improvement

Model Strengths

The models used in the regression analysis are based on a very large dataset which limits the effect that any outliers may have on the results. Moreover, DHS datasets are widely used and have been the basis for numerous published works. This allows for the reproducibility of the model in different settings. ACLED datasets are also widely used in academia and are one of the standard data sources for research on armed conflict. The broad nature of these datasets as well as the nuanced data points that they capture allow for the models to be locally relevant, while still ensuring external validity.

Model Limitations and Methods for Improvement

Despite the strengths of the model, it suffers from numerous limitations that impact model performance. The main challenge being that the cross-sectional analysis only covers one year – 2019. While DHS data is non-continuous, further studies could run the analysis across different DHS surveys to better understand change over time. Using a single year may bias the results due to time-specific factors that impacted India in 2019. Further datasets would be needed to support this analysis however as there is limited overlap between the ACLED dataset and DHS data. The previous DHS was conducted in 2015 and partly in 2016, whereas ACLED district level monitoring began in 2016 which would prevent us from using this micro-level data to conduct further analysis.

Other Indian state-level surveys may provide further data allowing us to run the model during different time-periods. However, this would require merging additional datasets and further data cleaning given the different methodologies employed by the surveys. Furthermore, data may not be equally built out for all states, limiting the number of variables the model would be able to assess. Along the same lines, another area for improvement would be running a time-series analysis to better capture the change over time. Introducing data across different time periods will also allow for the model to consider lagged variables which would be better predictors of some mechanisms and useful to study policy interventions. These approaches would enable researchers and policy makers to see the impact of policies over time and consider further advanced econometric analyses.

Despite improvements over cross-state or cross-national models, a district level analysis still leaves room for uncertainty. There are other factors that impact child mortality that are not considered by the model. Appending more variables, such as those mentioned in the literature review (such as sexual violence, immunization levels, genetic mutations, and environmental factors), would be beneficial to capturing more of the mechanisms associated with child mortality. Variables surrounding access to adequate nutrition and communicable diseases would address one hole in the model. Any addition of new variables must account for multicollinearity and endogeneity to ensure that the model has the greatest accuracy.

A logistic regression model is subject to some Gauss-Markov assumptions, including: no multi-collinearity, having a sufficiently large sample size, and linearity between logit and independent variables (Ching, 2020). The Alkaike and Bayseian information criteria or a linked-ratio test could be employed to ensure that additional variables being added to the model improve the model. One further test that could be conducted to check the model is the box-Tidwell test which ensures linearity of the model. Furthermore, as we do not have an output such as the R-squared term to determine model fit, the likelihood ratio test could also be performed to check for the probability of omitted variable bias in the model.

One crucial fact is that both the ACLED and DHS observations are geolocated. This information could allow us to analyze conflict at the community level, allowing for an even more localized analysis. Geolocation would allow for the proximity of households to violent events to be factored by utilizing Geographic Information Systems (GIS) to further show direct impact of proximity to conflict on child and adolescent mortality. In the current model, there is no variation in the *frequency* and *sumoffatalities* variables between households in each district. By considering proximity to conflict, a future analysis could introduce variation in the conflict related variables. This adaptation would allow for greater model predictive power as that an analysis would introduce district fixed effects to control for other district specific factors.

In an ideal case, further datasets across years and variation within districts using geolocated incidents of conflict would allow for models to be run with time and district fixed-effects. If conflict related results remain significant in such a model, it will give significant credibility to the impact that they have on child and adolescent mortality in India.

7. Conclusion

Around the world, millions of children are impacted by armed conflict. The literature is clear on the multitude of mechanisms through which conflict exacts a steep toll on children and adolescents. This thesis examines existing literature and develops a model to determine whether conflict, after controlling for confounding factors, has an impact on child mortality and adolescent mortality. Given that India has suffered from multiple long running armed conflicts, the models also considered what many consider to be India's most consequential internal security challenge – Naxalism or Left-Wing Extremist violence.

This thesis shows that districts suffering from Left-Wing Extremist violence faced significantly worse child and adolescent mortality outcomes. In spite of this troublesome finding, the two models used in the analysis offered some pathways to mitigate the risk of child and adolescent mortality. Investing in equitable housing, health infrastructure, and nutrition access all reduce the likelihood of child and adolescent mortality and should be the focus of policy makers.

This thesis adds to the growing literature surrounding the human impacts of conflict. It addresses a gap in quantitative studies on the effect of conflict on child and adolescent mortality in the Indian subcontinent. LWE violence shares many traits with other armed insurgencies which make the findings of this thesis relevant to settings beyond India. Regardless of its findings, this thesis leaves much to be desired in terms of its analysis. Appending more variables, geolocating incidents of conflict, and focusing on a narrower setting may provide meaningful places to extend the research and elucidate upon the toll conflict exacts on people. This thesis will hopefully bring about further discussion and research into this extremely relevant topic.

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