The aerial bombing of Cambodia and health in the very long run

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Abstract

We study the long-run impacts of local area exposures to US bombing in Cambodia on health outcomes among those residing in these locations many years later. Our study is separate from those that focus on the impact of being exposed to bombings as a child; rather, we study how conflicts can map to health outcomes for future generations. Using a wide range of geo-coded data and a spatial regression discontinuity adapted to many boundaries, we find that the long-term health impacts of past bombings vary significantly by location, depending on whether the bombs still influence activities today. We find that in areas where pre-bombing soil was infertile, harder ground, and unexploded ordinance (UXO) is less likely, local area exposure to past bombing has positive effects on health, indicated by higher Height-for-age Z-scores, a decreased likelihood of being underweight or suffering from anemia. In contrast, fertile areas, softer ground, where bombs were more likely to fail and UXO remains a threat show either null or harmful effects. We then utilize numerous data sources to show that local economic development and improved access to health facilities are likely mechanisms explaining the positive effects in low UXO locations today. In regions free from the dangers of UXO, significant investments in economic activities and healthcare infrastructure have mitigated the negative effects of past bombing, even improving health outcomes post-conflict. However, in areas where UXO remains a threat, development has been hindered, and negative impacts persist. Our results overall offer an important lesson that while conflicts can be harmful, their impacts on future generations can be mitigated through investments in the post-conflict era, as long as remnants of war no longer remain.

Keywords: Cambodia, bombing, conflict, health, economic development
JEL-Codes: I10, I15, I18

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1 Introduction

A vast number of under-developed countries have been or are currently exposed to extensive amounts of explosive ordinance through conflict.[1] While exposure to conflict can inflict lasting harm to individuals particularly through affecting health outcomes such as height-for-age, life expectancy, weight, and fertility (Sonne & Nillesen n.d., Duque 2017, Islam et al. 2017, 2016, Akbulut-Yuksel 2017, Akresh et al. 2012), it is less clear how conflicts shape local area development in the long-run and the subsequent consequences on the well-being and health for the local populace. Some evidence indicates long-term harm to local development post-conflict (Abadie & Gardeazabal 2003, Yamada & Yamada 2021), whereas others have shown positive long-term effects as a result of re-vitalization (Davis & Weinstein 2002, Miguel & Roland 2011, Strauss & Thomas 2008). Recently, however, new attention has been drawn to how locations can continue to be shaped through the prevalence of unexploded ordinance (UXO) and the ability, or inability, to clear these remnants of war (Lin 2022). Whether land remains dangerous or not, may control the extent to which local populations can recover and through this impact the well-being and health of future generations.

To address these questions, we leverage a wide range of contemporary and historical data from Cambodia, a still developing nation with extensive exposure to explosive ordnance from US bombing campaigns during the late 1960s and early 1970s. We draw on individual-level health data among women over thirty years post-bombing from the Cambodian Demographic and Health Survey (DHS), spatial information on US airstrike missions, multiple historical data sources we digitize on pre-bombing demographics and transportation networks, and contemporary data on economic outcomes and healthcare infrastructure. Based on US bombing data provided by Yale University (Cambodian Genocide Program), we identify areas profoundly impacted by the bombing, which we call "bombing areas", and establish bombing boundaries dividing regions subjected to destructive bombings from those that were not.[2]

Identifying the effect of residing in these locations is complex because bombing sights may have been selected on pre-bombing characteristics that also associate with health many years later, while instrument designs may lack suitable randomness. To overcome this challenge, we employ a spatial regression discontinuity design (RDD), similar to those in Dell (2010), Dell et al. (2018), with the latitude and longitude of household locations as running variables. We compare individuals on two sides of the bombing boundaries that we constructed and show our design passes a range of checks around the core RDD

[1]The Indochina War, primarily centered in Vietnam, was the heaviest bombardment in history, with the United States dropping over 7.5 million tons of ordnance from 1964 to 1973 in the Indochinese peninsula, far surpassing the tonnage used in World War II and the Korean War (Clodfelter 1995, Miguel & Roland 2011).

[2]We leverage a method from epidemiology that draws grids across Cambodia preserving the spatial clustering of strikes. We discuss this in more detail in Section 3.

assumptions.[3]

Before turning to estimate the consequences on health outcomes, we first separate bombed locations between those likely exposed to higher or lower degrees of UXO by drawing on Lin (2022). Lin demonstrates with extensive ethnographic fieldwork that fertile, soft soil is where bombs were less likely to detonate on impact. We confirm this empirically by matching location-specific, pre-bombing soil fertility data with modern-day data on casualties due to remnants of war. In our RDD, soil fertility is independent of residing in a bombed location but strongly predicts a higher likelihood of present-day casualties in these locations. Thus, today bombed areas with fertile, soft soil are more likely to still be shaped by this past bombing exposure, whereas infertile, harder ground locations are more likely safe for re-development. Based on this, we look at our results on health in aggregate and split by locations with high or low soil fertility.

In Section 5.2, we then provide evidence on the health effects for women of residing many years later in local areas bombed in the past and observe positive, beneficial effects.[4] At first glance, these results may seem surprising, but they come into clearer focus once we separate locations by those likely exposed to higher or lower degrees of UXO. The positive effects on health are entirely driven by areas where pre-bombing soil was infertile and thereby UXO is less likely today, while we see some evidence of harmful effects in bombed locations where soil was fertile. Specifically, women living in infertile areas and on the bombing side have 4.5% higher height-for-age Z-scores. They are also 2.5 percentage points less likely to be underweight and 3 percentage points less likely to suffer from severe anemia. Meanwhile, in fertile areas where UXO is more prevalent, we observe null or somewhat negative effects on health. We further show robustness to an extensive set of sensitivity checks giving confidence to the consistency of the evidence.

Next, we turn to explaining these results. It is possible that the re-vitalization of locations having experienced destruction could offer better economic activity and health access but this is only likely where such activity is safe, i.e., the low UXO locations. Of course, at present if the estimated returns to clearing UXO are considered high, then locations may be made safe for development. However, our approach is designed so that comparisons are made among bombing locations independent of factors at the time of bombing likely to make them targeted and potentially better for re-development. Consistent with this, in our design bombing locations are independent of observable dimensions from the time period, such as distance to major railways or roads, soil fertility, agricultural activity, population density, and other measures.

In Section, 6 we bring together wide ranging evidence across data sources and with our empirical design shows that improved economic activity and healthcare infrastructure in bombed locations appear only in infertile, low UXO areas. Particularly, we observe several

[3] It is crucial that outcomes are transformed smoothly as we move in geographic space except for discontinuities at the boundaries due to the long-run effects of local area exposure to bombing. We discuss this in more detail in Section 4.

[4] The DHS health survey focuses on women and it is for this population that we have good health data.

positive effects on economic development in pre-bombing infertile areas, including higher population and market densities, increased household income and family wealth, and greater educational attainment among women. Turning to health accessibility, distances to health facilities are significantly shorter within fertile locations for those on the bombing side, even in the region where health facilities were highly concentrated. Given the fact that the national healthcare system in Cambodia was totally destroyed due to US bombing and the Khmer Rouge Genocide, our findings indicate that areas previously affected by bombing exhibit better healthcare infrastructure development in the post-conflict period. Finally, bombed locations in pre-bombing fertile areas show consistently harmful effects on these outcomes, albeit not always statistically significant. Local exposure to bombing leads to null or even negative effects on economic development, characterized by lower night-time light intensity, reduced market density, and a higher likelihood of families experiencing food shortage.

Altogether, our results contribute to a limited literature on how conflict can shape locations in the long term and create present consequences for residents. We build on observations and important contributions made by Lin (2022, 2024) that provide careful insight into how active UXO practically intrudes on the lives of those living in these areas. Two other recent studies relate to the potential for UXO to create harmful effects in under-developed countries. Both study bombings in Laos from the same period as our study. Guo (2020) instruments locations where strikes were more intense with distance to important bombing centers and find more intensive strikes harm education in the long term. Additionally, Riano & Valencia Caicedo (2024) also leveraging geographic instruments find long-term harm from bombing to individual economic outcomes. With data on UXO accidents, they provide evidence that a high degree of this effect is mediated through the continual presence of UXO. Together their work points to the missed long-term cost of UXO.

Our work shows that the long-term health impacts of past bombing vary significantly across locations, depending on whether the bombs still actively shape activities in the area today. Moreover, we provide robust empirical evidence that our accounting of locations with a greater versus lower propensity for UXO is both accurate and independent of bombing locations within our design, adding to the validity of the heterogeneity we document. The lack of sufficient evidence on measures of present well-being, such as health, obfuscates the true benefit of investments in effectively removing UXO, particularly in poorer countries where the immediate return may be less obvious. Our work suggests that there is scope for re-vitalization to lead to better outcomes and for important benefits on well-being through health and economic activity.

Related literature. Our study adds to existing literature on the long-term impacts of war and human conflicts on health. Most studies in this field have only focused on generations who are directly exposed to conflicts either *in utero* or in their early childhood, less is known about the long-term health impacts on those living in areas that experienced bombing in the past. Numerous papers have found negative health impacts for those directly exposed to conflicts,[5] and a wide range of work also finds similar effects on the next generations whose parents suffer from wars and conflicts.[6] These studies are grounded in the "Fetal Origins Hypothesis", which posits a connection between prenatal environment and the development of future diseases (Barker 1990). Additionally, conflicts also affect subsequent generations because parents' health inputs, family background, and environmental factors are determinants of an individual's health (Strauss & Thomas 2008). However, only a limited number of studies have delved into how conflicts affect human life across multiple generations. Shedding light on this topic, Palmer et al. (2016) conducted research on the influence of bombing intensity on district-level disability in Vietnam and found that the negative effects persisted significantly, even 40 years after the war ended.

By examining the health outcomes of populations living in areas affected by past bombing in Cambodia, we address the open question on how conflicts shape local health outcomes in the long run. War and conflicts may have indirect repercussions on human life through the destruction of infrastructure such as hospitals, schools, and food systems and widespread environmental devastation (Levy 2002, Palmer et al. 2019). These events also affect economic wealth and macro-level public health, which can be attributed to the economic and health effects across generations (Ghobarah et al. 2003). However, post-war investments in public healthcare, infrastructure, and human capital accumulation have the potential to gradually mitigate and cancel out negative shocks (Strauss & Thomas 2008). Adverse health effects may be fully alleviated after multiple generations as a region strives to restore its pre-war conditions (Devakumar et al. 2014).

Our work is also related to a considerable body of literature examining the long-term effects of conflicts on regions' status quo. Several papers have found results consistent with conflict trap theory, indicating the long-run negative impacts of external shocks relative to the ex-ante condition (Abadie & Gardeazabal 2003, Yamada & Yamada 2021, Harada 2022, Lin 2022). However, some studies observe contrasting results and provide empirical support for neoclassical growth theory, suggesting that economies can return to a balanced growth trajectory and attain a steady-state level (Davis & Weinstein 2002, Miguel & Roland 2011). Meanwhile, Schumpeter's creative destruction theory considers external shocks as opportunities for economic growth (Aghion & Howitt 1990), as demonstrated by Hornbeck & Keniston (2017), who showed that the destruction of outdated buildings caused by the 1872 Boston Fire led to significant development afterwards.

In Cambodia, the impact of conflict varies significantly depending on the current

[5] A variety of work finds that exposure to conflicts and external shocks leads to lower birth weights (Camacho 2008, Mansour & Rees 2012, Maric et al. 2010), lower height-for-age scores among children (Sonne & Nillesen n.d., Duque 2017, Islam et al. 2017), lower adult height (Akresh et al. 2012, Akbulut-Yuksel 2014), overweight likelihood (Akresh et al. 2023), or reduced life expectancy (Akresh et al. 2012)

[6] The evidence of negative health impacts on the second generation is found in Britain (Emanuel et al. 1992), Denmark (Eriksson et al. 2005), and Cambodia (Moyano 2017, Islam et al. 2017).

presence of UXO. If remnants of war are no longer present, regions previously affected by past bombings demonstrate better health outcomes. Consistent with this we also find here better economic growth and healthcare development post-conflict. However, bombing-affected areas with a high risk of UXO experience either null or worse outcomes relative to non-bombed areas.

In the following section, we provide a historical overview of the US bombing campaign in Cambodia. Section 3 discusses the data and the construction of bombing areas and bombing boundaries. Section 4 presents our empirical strategy and assumptions behind this framework. Section 5 reports results, Section 6 examines different mechanisms that potentially shed light on our results and Section 7 concludes the paper.

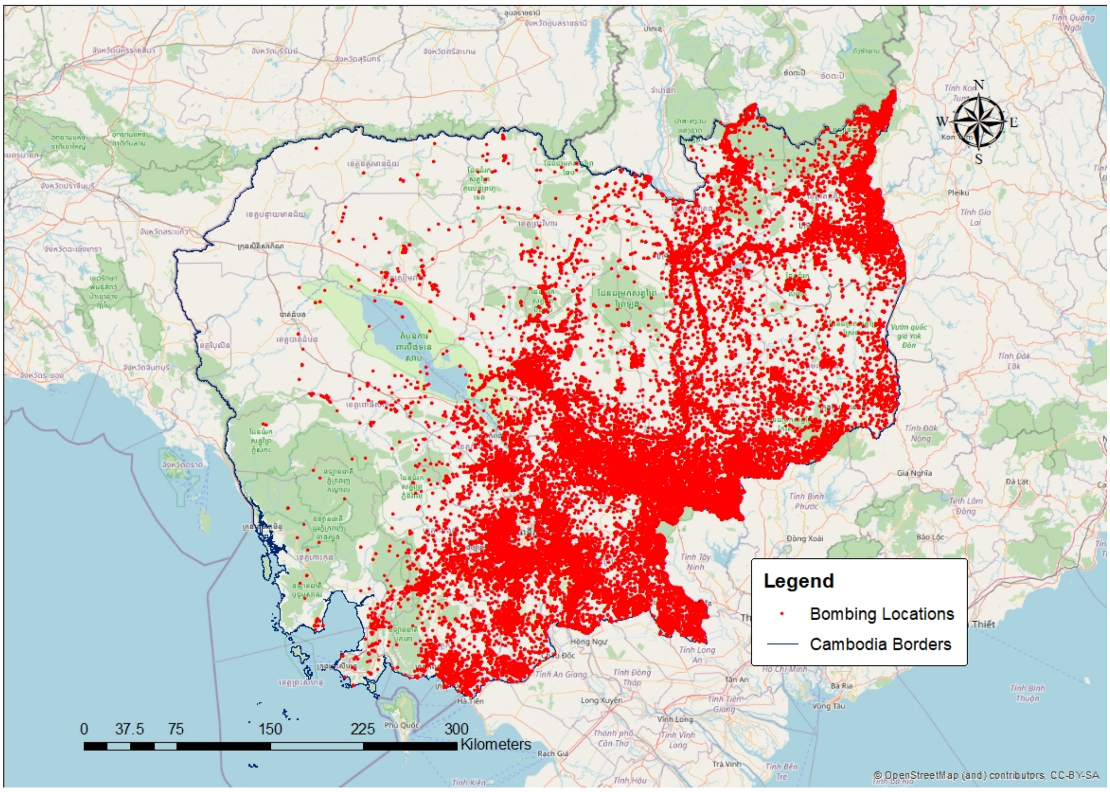
2 Historical background

Over the last century, Cambodia experienced a sequence of events, including colonisation, civil wars and genocide (Rany et al. 2012, Chandler 2018). After a 90-year period of French protectorate and colonization from 1863-1953, independence was established in the country at the Geneva Conference on November 9th, 1953. Following a coup d'état on 18 March 1970, Prince Sihanouk, who was leading the country at the time, was deposed by the Lon Nol Government. This event triggered a civil war within the country lasting until 1975. In April 1975, the Khmer Rouge, led by Pol Pot, took control of the country, marking the end of the civil war and the beginning of a period often referred to as genocide. During this time, approximately 1.7 million people were tragically lost due to executions, punishment, exhaustion, illness, and deprivation. The Khmer Rouge regime persisted until 1979 when a new government was established with the support of Vietnamese forces. However, political instability still remained in the country until the establishment of the UN protectorate over Cambodia in 1991 at the Paris Peace Conference (Rany et al. 2012, Chandler 2018).

During 1965-1975, the country suffered from the spill-over of Vietnam-American War with carpet bombing. Cambodia is historically recognized as the most heavily bombed country (Owen & Kiernan 2006). Beginning in 1965, under the Johnson administration, Cambodia was subjected to extensive bombing aimed at disrupting supply lines and destroying Communist bases. After the coup in 1970, the bombing campaign of the U.S. military forces was not only to eradicate Vietnam Communist forces but also to support Lon Nol's regime in the internal civil war. Funding for the war was halted in 1973 when the U.S. Congress became aware of Nixon's deception regarding the military campaign (Owen & Kiernan 2006).

Data from Yale University (Cambodian Genocide Program) reveal that 2,757,107 tons of munitions were dropped on 115,273 bombing sites in Cambodia. This amount of bombing far exceeded the amount dropped by the Allies during World War II - around 2 million tons in total (Owen & Kiernan 2006). Most of the bombing sites were located

Figure 1: Bombing sites targeted in Cambodia



Notes: Red dots give the location of bombing sites between October 1965 and May 1975. Data provided by Yale University (Cambodian Genocide Program). Map overlaid on OpenStreetMap base map and drawn on ArcGIS.

in Eastern Cambodia close to Vietnam's borders, as depicted in Figure 1. The previously estimated number of casualties caused by this campaign was between 50,000 and 150,000 citizens, yet it is alleged that aerial bombings caused the death of 600,000 Cambodians (Ear 1995), not to mention other consequences such as starvation and displacement. The bombing and conflict also had significant impacts on health in Cambodian with the reduction in life expectancy and poor nutritional outcomes (Moyano 2017).

Bombing also poses indirect threats to people's livelihoods through the presence of unexploded ordnance. Unexploded ordnance (UXO) denotes military ammunition or explosive devices that have not functioned as they should be, often known as Explosive Remnants of War (ERW). Ariel bombs that failed to explode are categorized as UXOs (Martin et al. 2019). In Cambodia, decades of armed conflicts, including the U.S. aerial bombing, the Vietnamese invasion in 1979, and civil wars in the 1970s and 1980s, have deeply contaminated the country with landmines and UXO (Martin et al. 2019).[7] Cam-

[7]It is critical to distinguish between landmines and UXO in Cambodia. Extensive minefields were laid by the Khmer Rouge, the Royal Cambodian Armed Forces (RCAF), the Vietnamese military and also the Thai army. The majority of these minefields are found in the western regions of Cambodia, notably in "K-5 mine belt" along the border with Thailand. Meanwhile, eastern and northeastern parts of Cambodia are contaminated with unexploded ordnance (UXO) primarily from U.S. air and artillery attacks during the Vietnam War and conflicts along the Vietnam border (Roberts 2011, Martin et al. 2019).

bodia is recognized as one of the most heavily UXO-affected countries with thousands of individuals being incapacitated and losing their lives (Moyes et al. 2002, Martin et al. 2019). Typical injuries from UXO accidents consist of extensive limb amputations, cuts from fragments, eardrums, and blindness caused by fragments or the blast (Moyes et al. 2002). Since 1979, Cambodia has witnessed over 64,700 casualties due to UXO, leading to more than 19,700 fatalities (Martin et al. 2019). Cambodia bears the world's highest per capita amputee rate, with 25,000 UXO-related amputees. UXO also causes hindrances to infrastructure, makes land unusable, and leads to interruptions in both water supplies and irrigation systems (Hamlin et al. 2018, Martin et al. 2019).

UXO from aerial bombs is commonly discovered in soft ground. Dense vegetation, akin to soft ground, makes ordnance less likely to explode, resulting in a higher proportion remaining undetonated. In other words, areas with high soil fertility that were bombed during conflicts are more likely to contain UXO (Moyes et al. 2002, Lin 2022). Ethnographic field work indicates that due to the presence of UXO, farmers today change their agriculture practices, for example through using hand held tools in an effort to not dig too deep. The effect is to render fertile land unproductive due to the high risks associated with farming (Lin 2022).

When investigating the impacts of local area exposure to bombing on health, we also take into account the occurrence of UXO due to bombing at present. It is unlikely that areas with a higher risk of UXO today would experience positive effects on health, as the relevant mechanisms we examine in the later part of the study measure today's living environment. We first show that pre-bombing soil fertility is independent of bombing locations in our empirical strategy and then show that it is a strong predictor for local areas to experience casualties from explosive remnants of war today. Given that UXO failure is more likely in softer ground, we will examine the heterogeneous impacts on areas that pre-bombing are classified with fertile soil – likely frequent UXO occurrences – versus areas classified with pre-bombing infertile soil – likely less frequent UXO occurrences. We anticipate that the impacts of residing in areas exposed to bombing in the past on health today will vary depending on the current risk of encountering UXO.

3 Data

In this section, we outline the data utilized in our study. To comprehensively examine the long-term impacts of local area exposure to bombing and their underlying mechanisms, we integrate diverse data sources, including individual-level health data from the Demographic and Health Survey (DHS), spatial data on US airstrike missions, and other historical and contemporary data on demographic, economic and healthcare characteristics.

3.1 Bombing and the identification of bombing areas

The bombing data used in this study, compiled by Yale University (Cambodian Genocide Program), provides information on 115,273 bombing sites targeted in Cambodia between October 1965 and May 1975. This dataset includes details such as the date of the bombing, precise locations, the number and type of aircraft involved in the sorties, bombing loads, and ordnance types.

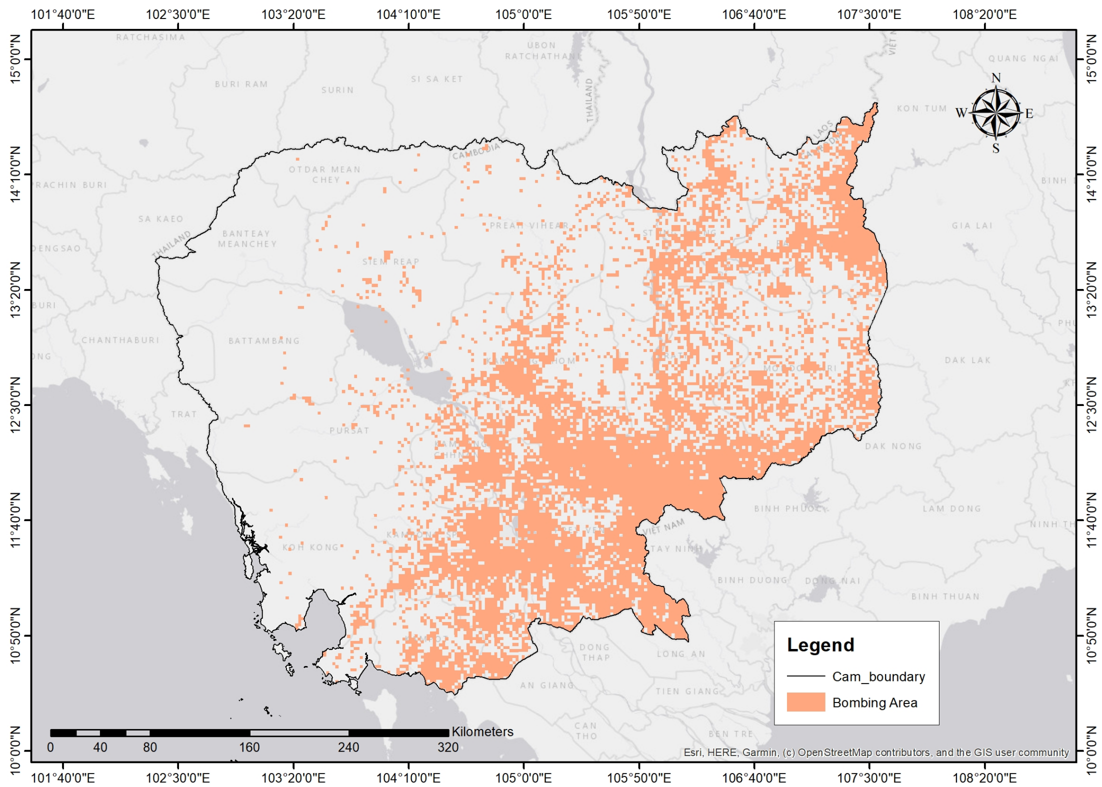
We use the dataset to pinpoint regions heavily affected by bombing in the past, referred to as bombing areas. These designated areas must accurately capture the clustered patterns of bombing incidents, as areas beyond these boundaries are minimally impacted. Clustering analysis, which is utilized widely across various scientific disciplines, including geography, public health, and ecology (Aldstadt 2009, Grubesic et al. 2014), stands as a fundamental tool in this exploration.

Spatial cluster detection integrates location attributes and events to detect meaningful patterns in geographical activities. In the fields of epidemiology and health-related sciences, clustering techniques help understand how location specific features impact health outcomes (Rushton & Elliott 2003, Elliott & Wartenberg 2004, Beale et al. 2008, Auchincloss et al. 2012). A common approach for identifying point clustering in the data space is by utilizing grid cell densities (Ankerst et al. 1999), sometimes mentioned as quadrat analysis in the literature. This method creates a geographic histogram partitioning the data space into distinct, non-overlapping regions or cells. Cells with a significant number of objects signify cluster centers. Using this approach has several benefits (Boots & Getls 1988). First, most of the points in the data space are used for the analysis. Second, this approach enables the identification of high-density regions in the data with square quadrats (or grid cells) easily combined and merged into larger regions (Boots & Getls 1988). However, the effectiveness of this method relies on the user-defined size of the cells because small cells can lead to a noisy density estimate, while large cells may excessively smooth the density estimate (Ankerst et al. 1999, Cheng et al. 2018).

Within our specific context, it is crucial for the designated bombing areas to accurately capture the spatial patterns and distribution of the bombing incidents. These areas must depict the geographical regions affected by the bombing, ensuring a precise representation of the impact zones. Based on this grid-based clustering technique, we divide the country map into geographic grid cells. We use an approach commonly employed by ecologists to identify the size of the grid cells. As outlined by Boots & Getls (1988), a suitable quadrat or grid size can be estimated as double the area per point, in particular: $I = \sqrt{2 \times A/n}$, where I denotes the calculated length of the side of a grid cell, A denotes the area of the focused region, and n denotes the number of features – airstrikes in our case – in the study area.

Our cell size equals 5.856 km^2 (2.42 km on each side) given Cambodia's overall area

Figure 2: Areas of bombing in Cambodia(1965-1975)



Notes: The map depicts areas that suffer from bombing during 1965-1975 period. Map overlaid on World Light Gray Base map (Canvas Map) on ArcGIS.

being 337,561 km^2 and the number of airstrikes being 115,273.[8] In total, the country is divided into 31799 grid cells. After identifying the bombing loads in each cell, only cells that have bombing loads greater than 0 are selected, and then spatially combined into bombing areas. Figure 2 illustrates the spatial distribution of identified bombing areas. These specified areas depict the clustered spatial occurrences of bombing, and we consider areas outside these boundaries as the areas not exposed to bombing. It is evident that the bombing areas are not evenly dispersed throughout the country, but rather predominantly concentrated in the eastern and southern regions of Cambodia along the borders with Vietnam.

3.2 Cambodia Demographic and Health Survey

Our empirical analysis builds upon four waves of the Cambodia Demographic and Health Survey (DHS 2000, 2005, 2010, and 2014).[9] We rely solely on the DHS individual women's

[8]This is similar to the cell size selected by Kohama et al. (2020) who examines how the economic characteristics of conflict zones influence the choice of military strategies.

[9]Demographic and Health Surveys (DHS) Program has conducted six surveys in Cambodia, including CDHS 1998, 2000, 2005, 2010, 2014, and 2021-2022. Data on the exact locations of clusters or GPS data is not available in Cambodia DHS 1998. Meanwhile, DHS 2021-2022 does not provide information on anemia level – one of the outcomes analysed in this study.

data, as it offers extensive health information that is not available for the male sample. DHS surveys provide the geo-location of a cluster which is a group of 25-30 households participating in the surveys. Therefore, a household cluster in DHS can be considered an enumeration area, or a village in rural or urban areas. To keep respondents' confidentiality, GPS locations of clusters are displaced geospatially. Specifically, urban points are randomly displaced by a maximum distance of 2 kilometers, while rural points are randomly displaced by up to 10 kilometers. The randomness of this displacement ensures classical measurement error with unbiased estimates. Since clusters are not displaced across their large administrative border (province-level), and because province-fixed effects are controlled in our specification, our estimates are not affected by this displacement procedure.

We use three outcomes as measures of health status. Our first outcome is Height-for-age Z-score (HAZ), which is an established proxy for health (e.g., Islam et al. 2017, Rosales-Rueda 2018). Height-for-age Z-score represents the number of standard deviations of an individual's actual height from the median height of the population, calculated based on the sample. A below-median HAZ is an indication of stunting or malnutrition (Leroy & Frongillo 2019). Our second outcome is being underweight, which is constructed based on women's Body Mass Index (BMI) and has been used in Kountchou et al. (2019) and Conti et al. (2024) as an indicator of health status. Women are considered underweight when their BMI is under 18.5 kg/m^2 (Weir & Jan 2019). BMI is commonly used to identify associated health risks and a low BMI reflects poor nutritional status, which may be due to insufficient food availability or economic deprivation in the population (WHO 1995). Our last outcome of interest is anemia, an indicator of inadequate nutrition and overall poor health, often associated with iron deficiency (WHO 2008), that has been used as a health outcome in prior research (Aguilar & Vicarelli 2011, Rosales-Rueda 2018). The classification of anemia status is determined by measuring hemoglobin levels, which are obtained through blood tests conducted by the DHS Program. Based on the available DHS data, individuals are categorized into two groups: those experiencing moderate or severe anemia, and those with mild anemia or no anemia.

We also use data on households elevation/altitude provided by Cambodia DHS in our balance checks as we expect households' elevation/altitude would not change due to bombing. This data is collected from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model for the specified coordinate locations of DHS clusters.

In addition, we exploit data on women's education, specifically, secondary education completion, and household possessions of durable goods to assess demographic and economic developments at household locations in the post-bombing period. In particular, we construct a variable called "family wealth" based on households' accessibility to electricity and ownership of durable goods.[10]

[10] Durable goods include radio television, telephone, refrigerator, wardrobe, sewing machine, means of transport like bicycle, animal-drawn cart, motorcycle/scooter, car/truck, boat with or without a motor.

3.3 Pre-bombing data

We exploit several datasets before the bombing or thereabouts to assess the balance across bombing boundaries in the pre-bombing period.

Soil types in 1962. We use the data on the distribution of soil types in Cambodia provided by Crocker (1962) to identify pre-bombing soil fertility.[11] Based on soil classifications by the Cambodian government (Kohama et al. 2020), we create a dummy variable, Soil fertility in 1962, which equals 1 if a DHS cluster is located in areas that are considered fertile and equals 0 otherwise.[12]

1970 Indochina Atlas. We digitize three maps from the Indochina Atlas for location specific measures of transportation links, agriculture, and population.[13] The Indochina Transportation map depicts the major roads and railways of the country in 1970 (Appendix, Figure G.2). We geo-reference the map and measure the distance from DHS households to 1970 roads and railways. The Indochina Agriculture map outlines regions where agricultural activities took place (Appendix, Figure G.3). We then match this information with household locations to determine whether there were any agricultural activities at DHS households during the pre-bombing period. Finally, the Indochina Population map displays population density (persons per square kilometers) in Indochina (Appendix, Figure G.4), enabling us to identify the population density at DHS clusters in 1970.

Global Agro-Ecological Zones (GAEZ). To assess the climate and potential crop productivity at DHS clusters, we use the agro-ecological zones (AEZ) classification developed by The Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA). This AEZ classification offers a comprehensive assessment of bio-physical resources essential for agricultural production.[14] Based on the Dominant AEZ classification dataset which is part of the GAEZ v4 Theme 1 Land and Water Resources, we match household clusters in the DHS with their corresponding

[11] The data were provided to Open Development Cambodia in ESRI Shapefile format by Save Cambodia's Wildlife's 2013 Atlas Working Group. For more details, see https://opendevelopmentcambodia.net.

[12] Specifically, among sixteen different soil types given in Crocker (1962), the following six types of soils are classified as fertile: Latosols, Alluvial soils, Brown alluvial soils, Lacustrine alluvial soils, Regurs, and Brown hydromorphics (Kohama et al. 2020).

[13] These maps were released in October 1970 by the Directorate of Intelligence, Office of Basic and Geographic Intelligence, U.S. Central Intelligence Agency and are available at https://maps.lib.utexas.edu.

[14] The AEZ map incorporates thermal and moisture regimes, soil/terrain qualities, the presence of irrigated soils, and the identification of areas with significant bio-physical limitations such as extreme cold, arid deserts, steep terrains, and poor soil conditions. Geographical regions classified within the same AEZ category share similar climatic attributes, including rainfall and temperature patterns, which consequently contribute to comparable agricultural potentials. Several studies use GAEZ data to control for geographic characteristics or local agricultural suitability (e.g., Whatley & Gillezeau 2011, Cagé & Rueda 2016). Data can be accessed via https://gaez.fao.org.

AEZ zone (Appendix, Figure G.1). Subsequently, we create a binary variable indicating whether a household is located in a grid cell characterized as tropics and lowland.

3.4 Post-bombing economic and healthcare development data

We utilize the following datasets to evaluate post-bombing economic growth and health-care infrastructure development.

Cambodia Socio-Economic Survey 2014. To capture households' economic development at present, we use the Cambodia Socio-Economic Survey (CSES) 2014, a nationally representative survey of 12,096 households in 1,008 villages. The survey contains information about households' economic activities, agricultural and non-agricultural incomes, vulnerability to food shortages, and field productivity. Although CSES 2014 does not provide geo-locations of households, we are able to geo-locate households using village coordinates provided by Cambodia 2008 Population Census.

Night-time light intensity. We use night-time light emissions data collected by U.S. Air Force Defense Meteorological Satellite Program (DMSP) as a proxy for economic development. Satellite night light data is considered a valuable proxy for economic activities where traditional data are lacking or unreliable (Henderson et al. 2012). A growing number of economics studies, particularly in development economics, have utilized DMSP data to explore various topics (Gibson et al. 2020). In this paper, we use the average visible, cloud-free light detections multiplied by the percent frequency of light detection.[15] Data are detailed at 30 arc-second grid cells (1km at the Equator), enabling us to identify night-time light intensity at a certain DHS household village in its survey year. The value of this proxy ranges between 0 and 63 and is used as an outcome for the economic activity of a household village (a DHS household cluster).

Market Density. We investigate market density using the Commune Database produced by Cambodia National Committee for Subnational Democratic Development.[16] The data was constructed based on the number of markets per 5 km^2 and is reported as a density ranging from 0 to 1. We standardise this variable and use it as another indicator for economic development.

[15] We draw this from the Version 4 DMSP Operational Linescan System Nighttime Lights Time Series which provides annual data from 1992 to 2013. This data is available at https://ncei.noaa.gov.

[16] This data was provided to Open Development Cambodia directly by Save Cambodia's Wildlife's 2013 Atlas Working Group. See https://opendevelopmentcambodia.net for more details.

UN-Adjusted Population Density. To analyze population density at DHS clusters, we use UN-Adjusted Population Density.[17] The data demonstrates the number of people per square kilometer, adjusted to match the corresponding official United Nations population estimates in each country.[18] In particular, we use population data for 2000, 2005, 2010, and 2014 to identify the population density of each DHS location in each survey year.

Health facilities in Cambodia (2010). We use distance to health facilities as proxies for health infrastructure development and healthcare accessibility. Distances to hospitals, district-level health centres, and health facilities, in general, are calculated using data on health facilities in Cambodia (2010).[19] This dataset provides comprehensive information on healthcare facilities in Cambodia, including national hospitals, referral hospitals, health centers, and health posts.

Based on the classification of health facilities in Cambodia's Health Strategic Plan 2016–2020 (Ministry of Health (MOH) 2016), we divide health facilities into different groups: (1) hospitals, including national and referral hospitals (2) district-level health centres including health centres and health posts and (3) all health facilities include all hospitals and health facilities in Cambodia. Then, we calculate the distances from a household to the nearest hospital, the nearest district-level health center, and the nearest health facility.

3.5 Descriptive statistics

Table 1 reports the summary statistics of variables used in this study. In general, health outcomes are comparable on average between the two groups residing inside and outside bombing areas, while there are noticeable variations in some demographic and economic characteristics.

For geographic and pre-bombing characteristics, the locations inside bombing areas have higher average elevation/altitude and are more likely to be classified as tropics and lowland. These locations also had higher soil fertility in 1962. Additionally, the mean distance to Vietnam's borders is significantly lower for those inside the bombing areas, aligning with the historical narrative. However, there were no significant differences with respect to population density and agricultural activities in 1970. In addition, for the whole

[17] The data is collected by the WorldPop research program, based in the School of Geography and Environmental Sciences at the University of Southampton. This program provides different types of gridded population count datasets, which are available at a resolution of 30 arc-seconds (approximately 1km at the equator). The data can be accessed via https://hub.worldpop.org.

[18] The units are the number of people per square kilometer, calculated using each country's total population, and adjusted to align with the official United Nations population estimates - Revision of World Population Prospects 2019 (United Nations, Department of Economic and Social Affairs Population Division 2019).

[19] Cambodia's Ministry of Health (MoH) originally compiled the data, which was subsequently contributed to the Humanitarian Data Exchange (HDX) by the Office for the Coordination of Humanitarian Affairs (OCHA). Open Development Cambodia's team gathered data from Google Maps and utilized references from Cambodia's Ministry of Health. See https://opendevelopmentcambodia.net for more details.

Table 1: Descriptive statistics

	All observations			Within 1.5 km distance			Within 3 km distance		
	All	Outside	Inside	All	Outside	Inside	All	Outside	Inside
Health outcomes									
Height-for-age Z-score	-1.79	-1.78	-1.80	-1.81	-1.81	-1.81	-1.80	-1.78	-1.81
	(0.87)	(0.87)	(0.88)	(0.88)	(0.88)	(0.88)	(0.87)	(0.87)	(0.88)
Being underweight	0.17	0.16	0.18	0.18	0.19	0.18	0.18	0.18	0.18
	(0.38)	(0.37)	(0.38)	(0.39)	(0.39)	(0.39)	(0.39)	(0.38)	(0.39)
Anemia	0.09	0.09	0.09	0.10	0.10	0.09	0.09	0.09	0.09
	(0.29)	(0.29)	(0.28)	(0.29)	(0.30)	(0.29)	(0.29)	(0.29)	(0.29)
Geographic characteristics									
Elevation/Altitude (meters)	37.56	34.06	41.99	34.58	32.10	36.99	34.34	29.81	38.99
	(68.62)	(51.82)	(85.03)	(71.02)	(59.33)	(80.67)	(71.11)	(52.07)	(86.12)
Tropics, lowland	0.55	0.49	0.61	0.59	0.55	0.62	0.57	0.50	0.63
	(0.50)	(0.50)	(0.49)	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)	(0.48)
Pre-bombing characteristics									
Soil fertility (1962)	0.37	0.36	0.38	0.33	0.31	0.36	0.36	0.34	0.37
	(0.48)	(0.48)	(0.49)	(0.47)	(0.46)	(0.48)	(0.48)	(0.47)	(0.48)
Agricultural activities (1970)	0.56	0.55	0.58	0.62	0.63	0.61	0.62	0.65	0.60
	(0.50)	(0.50)	(0.49)	(0.49)	(0.48)	(0.49)	(0.48)	(0.48)	(0.49)
Population density (1970)	0.39	0.35	0.43	0.46	0.46	0.46	0.46	0.48	0.45
	(0.49)	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Distance (km) to roads/railways (1970)	6.42	7.32	5.28	6.47	6.13	6.81	5.94	5.74	6.14
	(8.52)	(9.91)	(6.15)	(7.04)	(6.97)	(7.09)	(6.90)	(7.08)	(6.70)
Post-bombing characteristics									
Population density	1.67	2.34	0.82	1.70	2.22	1.19	2.19	3.42	0.94
	(5.41)	(6.79)	(2.59)	(4.95)	(5.90)	(3.73)	(6.78)	(8.85)	(3.13)
Market density	-0.00	0.13	-0.16	0.02	0.15	-0.10	0.11	0.35	-0.14
	(1.00)	(1.24)	(0.51)	(1.02)	(1.23)	(0.74)	(1.20)	(1.53)	(0.62)
Family Wealth	0.33	0.33	0.33	0.32	0.32	0.31	0.33	0.34	0.32
	(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.18)
Secondary education	0.33	0.33	0.33	0.32	0.33	0.31	0.34	0.36	0.32
	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)	(0.46)	(0.47)	(0.48)	(0.47)
Distance (km) to									
Hospital (2010)	12.33	13.09	11.36	13.42	13.69	13.17	12.45	12.44	12.45
	(12.50)	(13.77)	(10.60)	(13.25)	(14.51)	(11.90)	(12.84)	(14.18)	(11.30)
District health center (2010)	3.21	3.47	2.87	3.23	3.41	3.07	3.07	3.09	3.06
	(3.10)	(3.70)	(2.05)	(2.86)	(3.38)	(2.22)	(2.74)	(3.17)	(2.20)
Health facility (2010)	3.16	3.40	2.85	3.20	3.34	3.06	3.03	3.01	3.04
	(3.08)	(3.67)	(2.05)	(2.87)	(3.40)	(2.23)	(2.75)	(3.20)	(2.20)
Other characteristics									
Distance (km) to									
Vietnam borders	139.16	193.86	70.02	88.89	98.75	79.35	95.13	116.46	73.28
	(117.44)	(124.11)	(56.51)	(73.47)	(78.88)	(66.44)	(77.44)	(85.81)	(60.47)
Capital	132.48	160.53	97.02	93.91	96.13	91.76	96.29	99.19	93.32
	(99.14)	(102.93)	(81.29)	(78.74)	(78.17)	(79.24)	(80.03)	(81.14)	(78.76)
Nearest strike	6.58	11.25	0.68	1.35	1.80	0.92	1.55	2.27	0.81
	(13.94)	(17.28)	(0.49)	(0.79)	(0.77)	(0.54)	(1.12)	(1.09)	(0.52)
Thai borders	169.70	129.57	220.43	202.81	194.17	211.18	199.76	182.25	217.69
	(84.07)	(80.88)	(55.89)	(61.52)	(60.62)	(61.23)	(62.65)	(60.23)	(59.96)
Observations	31021	17319	13702	12046	5926	6120	18383	9300	9083

Note: The table provides the mean/standard deviation of the corresponding variables. "All" means the whole sample, "Outside" means the sample includes observations located outside bombing areas, and "Inside" means the sample includes observations located inside bombing areas. "Within 1.5 km distance" means the sample is restricted to observations located within 1.5 km of bombing boundaries. "Within 3 km distance" the sample is restricted to observations within 3 km of bombing boundaries.

sample, we observe significantly shorter distances to 1970 main roads or railways for those living inside bombing areas.

Finally, for post-bombing characteristics, education level (completion of secondary education) and family wealth are similar between the two groups, whereas areas within bombing zones exhibit considerably lower unconditional mean population density and market density compared to regions outside. Furthermore, individuals residing inside the bombing areas generally have shorter distances to hospitals and health facilities. To make clear comparisons, we now turn to an identification strategy based on spatial discontinuities.

4 Empirical strategy and specification checks

4.1 Empirical framework

This research employs a spatial regression discontinuity (RD) design to discover the long-term impacts of local area exposure to bombing on health outcomes. The spatial RD design exploits discontinuous transformations at bombing boundaries, comparing individuals living in areas heavily bombed 40 years ago to those living in adjacent locations that did not suffer from bombing with the idea that bombing boundaries act as cut-offs. Similar to designs in Dell (2010), Dell et al. (2018), and Dell & Olken (2020), our regressions take the form:

$$Y_{icpt} = \alpha + \beta \times Bombing_c + f(Geo_c) + Strike_c + \gamma \mathbf{D}_c + \theta Age_i + \delta_p + \tau_t + \epsilon_{ict} \quad (1)$$

where Y_{ict} is the outcome variable of interest for a woman i in cluster c, province p in survey year t, and $Bombing_c$ is an indicator equal to 1 if an individual is currently living in areas that were bombed in the past and equal to zero otherwise. $Strike_c$ controls for 1-km distance-to-nearest-strike fixed effects so that we remove potential indirect spillover effects from distance to strike locations. $\mathbf{D}_c$ is a vector of geographic covariates, including distance to the capital of Cambodia - the largest urban city, distance to Vietnam borders, and all other pre-bombing characteristics.[20] Age_i is a non-linear control of the woman's age, including age and age^2, and δ_p is a vector of province-fixed effects, playing a role as spatial fixed effects to ensure comparisons of individuals within a province. Finally, τ_t is survey-year fixed effects. Standard errors are clustered at the DHS survey cluster level.

The function $f(Geo_c)$ is the multidimensional RD polynomial controlling for smooth functions of geographic locations of cluster c, with demeaned latitude and longitude as running variables. This subsumes the distance to the bombing boundaries but accounts for the two-dimensional nature of geographic space. Since we aim to compare individuals living at similar geographic positions on opposite sides of the boundaries, this multidimensional polynomial precisely captures the gradual variation of unobservable factors in two geographical dimensions. If living inside bombing areas causes any differences from living outside, we accurately identify the discontinuity at the boundaries with our treatment $Bombing_c$. Following Gelman & Imbens (2019), a local linear RD polynomial is selected for the baseline specification $f(Geo_c) = latitude + longitude$. We examine specifications with higher orders of RD polynomials (quadratic and cubic polynomials) in robustness checks.[21] In all regressions, a triangular kernel is employed, where the weight assigned to each observation diminishes as the distance from the bombing boundaries

[20] Pre-bombing characteristics include geographic characteristics (elevation, tropics/lowland, soil fertility in 1962), demographic characteristics (population density in 1970) and other economic characteristics (agricultural activities and distance to main roads/railways in 1970). In Section 4.2, we provide evidence that these characteristics are balanced across bombing boundaries.

[21] Quadratic polynomial will take the form as $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat \times lon$. Cubic polynomial will take the form as $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat^3 + lon^3 + lat \times lon + lat^2 \times lon + lat \times lon^2$.

increases.

Literature on spatial RD analysis has emphasized the crucial role of incorporating segment-fixed effects within the framework of RD design (Dell 2010, Dell et al. 2018, Dell & Olken 2020). Boundary-segment fixed effects ensure that the analysis compares observations in a close geographic vicinity. In our context, bombing boundaries are numerous and spread throughout the country. In order to control for geographic treatment effect heterogeneity and to ensure that we compare individuals located very close to each other in the same province, we include province-fixed effects in our main specification.

A concern, however, is that any within-province sorting would bias our effects. We address this through refinements of province-fixed effects in our robustness checks.[22] Particularly, we replace province-fixed effects with 50x50km grid-cell fixed effects, ensuring a comparison between individuals situated within a highly confined area.[23] We will show later that our results from this approach remain strongly robust.

In terms of bandwidth selection, the estimation sample is restricted to individuals falling within the bandwidth of 1km and 1.5km around bombing boundaries. Samples with other bandwidth restrictions are analysed in robustness checks.

In appendix D, we use a more parsimonious RD design with a uni-dimensional RD polynomial. Specifically, we use distance to bombing boundaries as a running variable. The local linear unidimensional polynomial has a function as $f(Geo_c) = \eta dist_c$ with the forcing variable $dist_c$ denoting the Euclidean distance between a household location and the closest point on bombing boundaries. Higher-order polynomials will take the following form: $f(Geo_c) = \sum_{k=1}^{a} \eta_k dist_c^k$. For unidimensional RD specifications, optimal bandwidths are selected following Calonico et al. (2014).

Although the uni-dimensional RD polynomial plays a similar role in capturing the smooth changes at the bombing boundaries, we do not choose uni-dimensional models as our main specification because they lack a clear economic interpretation in the case of geographic space with two-dimensional changes. Compared to the same-order multidimensional polynomial, the uni-dimensional one possesses fewer degrees of freedom to smoothly capture the variation near the boundary (Dell 2010). However, because a more flexible approach may not guarantee a more reliable estimate (Dell 2010), the uni-dimensional specifications offer valuable crosschecks for our multidimensional RD analysis.

4.2 Validity of RD Assumptions

The spatial RD design requires two identifying assumptions: a smooth variance of covariates at bombing boundaries and no sorting around cutoffs.

[22] There are 25 provinces in Cambodia. The smallest province is Kep, covering an area of 336 square kilometers, while Mondulkiri is the largest with an area equal to 14,288 square kilometers.

[23] In this approach, we divide the country into 79 grid cells of 50x50km. See Figure G.6.

Table 2: Balance check

	Dependent variable is:					
	(1) Elevation	(2) Tropics/lowland	(3) Soil Fertility	(4) Agri. Activities	(5) Pop. Density	(6) Dist. to roads
Bombing	7.663	0.028	0.000	-0.004	-0.013	0.820
	(5.217)	(0.040)	(0.039)	(0.035)	(0.025)	(0.554)
Mean	34.58	0.585	0.335	0.621	0.458	6.472
Observations	12046	12046	12046	12046	12046	12046
Clusters	865	865	865	865	865	865

Note: The unit of analysis is survey respondents. The sample restricted to those living within 1.5km bandwidth from bombing boundaries. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. "Tropics/lowland" is a dummy variable reflecting whether this location belongs to areas classified as "tropics, humid" based on agro-ecological zones classification. "Soil Fertility" is also a dummy variable demonstrating whether the soil was fertile in 1962 (before the bombing). The last three columns use data from the Indochina Atlas, published in October 1970. Agri. activities indicate whether there were any agricultural activities in these areas in 1970. Pop. density is a binary variable reflecting if the population density in 1970 was at least fifty inhabitants per square kilometre. Dist. to roads refers to distance (in km) to 1970 main roads/railways. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Assumption 1: Smooth variance of covariates at bombing boundaries. A key assumption of the RD design is the smooth variance of all relevant factors and covariates besides the treatment. In particular, if c_1 and c_0 denote potential outcomes under treatment and control, and *lat, lon* denote latitude and longitude of household locations, then $E[c_1|lat, lon]$ and $E[c_0|lat, lon]$ must be continuous at the discontinuity, as described in Dell (2010). This assumption allows for individuals on the non-bombing side to serve as a valid counterfactual for individuals on the bombing side. In order to assess the plausibility of this assumption, we use equation 1 to examine a wide range of geographic, demographic and economic characteristics on two sides of bombing boundaries in the pre-bombing period or thereabouts. Results are reported in Table 2. We assess geographic characteristics (elevation, tropics/lowland, soil fertility), demographic characteristics (population density) and other pre-bombing economic characteristics (agricultural activities and distance to main roads/railways). All of these characteristics are measured at the DHS survey cluster level and used as outcome variables in equation 1. We find no evidence that there were discontinuities of geographic, demographic or economic features at the bombing boundaries. Particularly, the estimates for elevation, tropic/lowland are both insignificant, indicating a smooth variation of geographic features (columns 1-2). In terms of soil fertility and agriculture activities, the coefficients are noticeably small in magnitude and inefficient (columns 3-4). In addition, we do not observe any statistically significant difference in 1970 population density between the two sides of bombing boundaries (column 5). Finally, for distance to 1970 main roads and railways (column 6) the estimate is insignificant and small in comparison to the mean of 6.472km.

Assumption 2: No sorting around bombing boundaries. Another important assumption for the validity of our design is that individuals cannot sort themselves around the cut-off boundaries. This assumption would be violated if individuals at the time of bombings were able to sort themselves around locations more likely to be bombed. Consistent with assumption 2 we find that population density from 1970 was balanced across bombing boundaries with no statistically significant differences (column 5 in Table 2). We provide more evidence consistent with this assumption in the Appendix, Table G.2, showing that DHS respondents in our design around the bombing borders are not different in their reported migration status.[24]

5 Results

5.1 Bombing and UXO risk at the present time

In Section 2, we provide a detailed discussion on UXO problems in Cambodia and highlighted reasons why UXO may be more prevalent in areas where soil was softer and more fertile at the time of bombing. Now, we test whether UXO is more prevalent in regions with pre-bombing softer soil (Moyes et al. 2002, Lin 2022) by using data on ERW casualties from 2005 to 2013 across Cambodia.[25] This is crucial for our subsequent analyses of primary treatment effects, split by pre-bombing soil fertility.

Table 3 presents the result. We find that if areas were fertile in 1962, they are 1% more likely to have ERW casualties at the present time, which is nearly half the baseline predicted probability. This evidence is consistent with our expectations following the discussion in Section 2 and motivates our use of 1962 soil fertility to split the main health effects. Additionally, the local exposure to bombing increases the likelihood of having ERW casualties in that area by 0.8%.[26] As expected, we see more ERW causalities where bombing occurred, but importantly, our RD assumption checks in Table 2, indicate that bombing and 1962 soil fertility are independent. Furthermore, when we include the interaction between bombing and 1962 soil fertility (column 2), we observe a small and insignificant coefficient on ERW causalities. This further supports that within our design bombing locations are random to 1962 soil fertility and do not differentially predict ERW casualties today.

Turning back to our balance tests, in section 4.2, we showed that soil fertility in 1962 was indifferent on two sides of the bombing boundaries. To further support our use of soil fertility to split our coming analysis, we split the country by 1962 soil fertility and re-run these checks, finding that all pre-bombing characteristics vary smoothly at the bombing boundaries, except the tropics/lowland in fertile areas (Table G.1). Thus, our evidence for the continuity assumption holds in both fertile and infertile areas. In the following analyses, we use pre-bombing soil fertility information to divide the country into two

[24] Data on migration (moving) status is only available in Cambodian DHS 2000 and 2004.

[25] The original data provides detailed locations of casualties resulting from explosive remnants of war (ERW) and mines in Cambodia between 2005 and 2013. The data was compiled by The Cambodia Mine/ERW Victim Information System (CMVIS) of the Cambodian Mine Action and Victim Assistance Authority (CMAA) and shared via the Office for the Coordination of Humanitarian Affairs (OCHA) on the Humanitarian Data Exchange (HDX) platform. In this analysis, we only use information on casualties due to ERW.

[26] We note that ERW casualties can include those from separate causes than the US aerial bombing campaign (Roberts 2011, Martin et al. 2019)

Table 3: The likelihood of having ERW casualties (data from 2005-2013)

	(1) ERW Casualties		(2) ERW Casualties	
	β / SE	Mfx	β / SE	Mfx
Bombing	0.386***	0.008***	0.372**	0.008**
	(0.132)		(0.147)	
Soil fertility in 1962	0.464***	0.010***	0.442***	0.010***
	(0.100)		(0.138)	
Bombing × Soil fertility in 1962			0.042	
			(0.183)	
Observations	31777		31777	
LR chi2	597.147		597.199	
Prob > chi2	0.000		0.000	
Baseline predicted probability	0.022		0.022	

Note: The unit of analysis is 2.42km grid cells (the size of bombing grid cells). We count the number of casualties in each grid cell and construct the binary outcome equal to 1 if there are any casualties due to ERW in this grid-cell area. The first model is: $logit(P(ERWOccurance = 1|Bombing, soil1962, province, distance-to-Vietnam)) = \beta_0 + \beta_1 Bombing + \beta_2 Soil1962 + \beta_3 Province + \beta_4 Dist\_VN$. The second model includes the interaction term of bombing and soil fertility in 1962 ($\beta_5 Bombing \times Soil1962$). β/SE denotes coefficient and standard error. Mfx denotes marginal effect. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

distinctive regions: (1) fertile areas with high occurrences of UXO and (2) infertile areas with a lower likelihood of encountering UXO.

5.2 Baseline results

The results of the main RD design are reported in Table 4 (Panel A). We estimate the long-term impacts of local area exposure to bombing on different health outcomes of the current population from three to five decades after the bombing occurred. Across all specifications, and maybe surprisingly, we observe positive long-term health effects. Specifically, for women currently living in bombing areas, their Health-for-age Z-scores increase by 0.06 (about 3%) compared to those living outside bombing areas. Also, while we see no effects on the likelihood of being underweight, we see a lower likelihood of being anemic among those living in bombing areas. Women living inside bombing areas are about 2.2 to 2.3 percentage points less likely to suffer from serious anemia, a decrease of more than 20% compared to the mean. Whether observations are restricted within 1 km or 1.5km bandwidth, this effect remains statistically significant and quantitatively important. Figure 3 illustrates the main results graphically. There is a clear jump in Health-for-age Z-scores and a significant drop in anemia for women residing within bombing areas.

These results may seem unexpected, but they become clearer when we split the effects between locations with high and low UXO exposure. Panels B and C in Table 4 illustrate

Table 4: The long-term effects of local area exposure to bombing on health

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km
Panel A: All population						
Bombing	0.060**	0.056**	-0.006	-0.009	-0.023***	-0.022***
	(0.029)	(0.026)	(0.010)	(0.009)	(0.008)	(0.007)
Mean	-1.815	-1.809	0.187	0.185	0.0977	0.0954
Observations	9136	12046	9136	12046	9136	12046
Clusters	659	865	659	865	659	865
Panel B: Fertile areas (1962)						
Bombing	-0.035	-0.032	0.038**	0.021	0.009	0.003
	(0.051)	(0.044)	(0.016)	(0.014)	(0.012)	(0.011)
Mean	-1.785	-1.793	0.182	0.177	0.0792	0.0799
Observations	3094	4030	3094	4030	3094	4030
Clusters	230	301	230	301	230	301
Panel C: Infertile areas (1962)						
Bombing	0.082**	0.074**	-0.027**	-0.025**	-0.034***	-0.030***
	(0.035)	(0.033)	(0.012)	(0.011)	(0.011)	(0.010)
Mean	-1.831	-1.817	0.190	0.189	0.107	0.103
Observations	6042	8016	6042	8016	6042	8016
Clusters	429	564	429	564	429	564

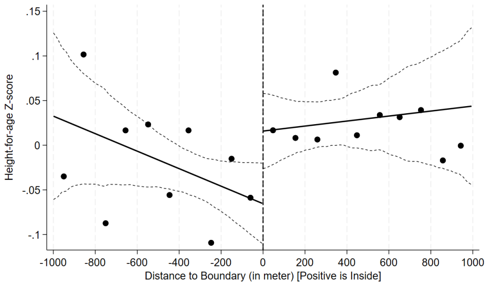
Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

the heterogeneous effects of local area exposure to bombing in the past on two distinct regions. In high fertility areas where UXO is more likely to appear, we observe null effects on health across all specifications, except being underweight (Panel A). Women living in pre-bombing fertile areas are more likely to be underweight, although this is not a significant effect. Our evidence in fertile areas, suggest either null or harmful effects. Evidence from ethnographic work suggests that while people over time adapt to their new living conditions, such as through alternative agricultural practices to reduce risk exposure, their locations do not gain through re-development (Lin 2022, 2024).

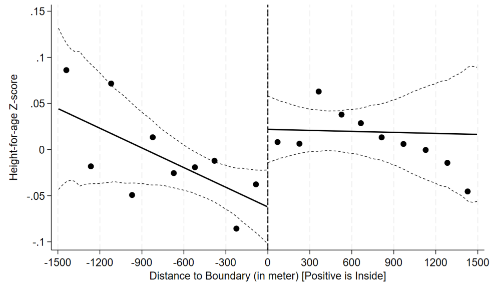
Meanwhile, in infertile areas with a lower UXO likelihood (Panel B), we see significant positive effects on health outcomes. Specifically, women residing in infertile areas and on the bombing side have their Height-for-age Z-scores increased by around 0.08 or 4.5%. The probability for them to be underweight decreases by around 2.5 percentage

Figure 3: The impacts of local area exposure to bombing on health: RD plots

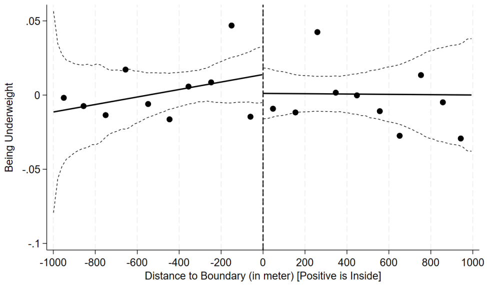
Panel A: Within 1km bandwidth **Panel B: Within 1.5km bandwidth**



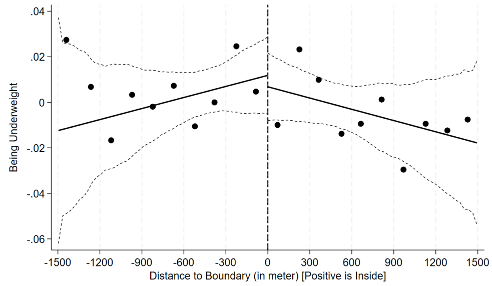
(a) Height-for-age Z-score



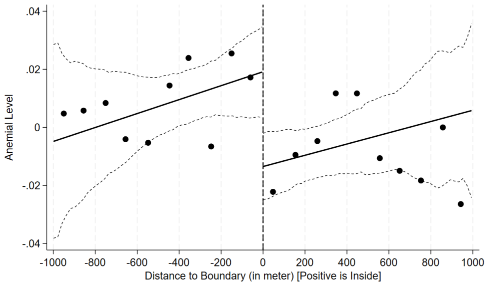
(b) Height-for-age Z-score



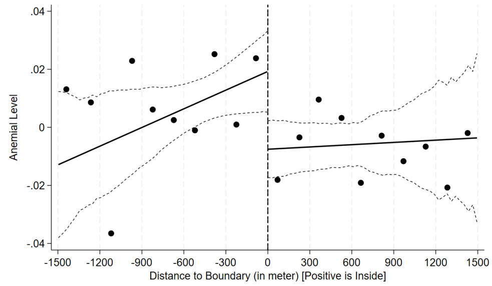
(c) Being underweight



(d) Being underweight



(e) Anemia Level



(f) Anemial level

Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in latitude and longitude and other control variables. Solid lines depict a local linear regression, separately estimated on each side of the threshold, while dashed lines represent 95% confidence intervals. "Negative" values of distance indicate locations outside the bombing areas.

points, representing a 13% reduction relative to the mean. This effect is not only large in magnitude but also statistically significant. Additionally, they are also less prone to anemia, with a reduction of 3.4 percentage points (or 3 percentage points in 1.5km bandwidth analysis), equivalent to a drop of more than 30% compared to the mean likelihood of anemia.

Overall, the positive effects we have observed are sensible in that they are entirely driven by pre-bombing infertile areas with a lower likelihood of UXO.[27] The presence of

[27]We observe the same impact heterogeneity with the unidimensional RD design. See Table D.1.

UXO may create long-term harmful effects, which is consistent with existing literature on how bombings and UXO shape the local population's outcomes (Lin 2022, 2024, Riano & Valencia Caicedo 2024). However, in areas where UXO are less likely, adverse health effects can diminish over multiple generations as local areas are re-constituted and can grow (Devakumar et al. 2014). Post-conflict investments can gradually offset negative impacts and even lead to better outcomes (Strauss & Thomas 2008).[28]

One concern is that the areas contaminated with UXO from aerial bombs may overlap with minefields laid by the Khmer Rouge and other forces in the later period. The likelihood of encountering landmines would not necessarily follow the soil fertility dimension as does aerial dropped bombs. This could obfuscate our heterogeneity analysis split by soil fertility because some areas that were infertile in 1962 are still dangerous today due to leftover mines. We, therefore, conduct additional analysis to show that our results are consistent and that pre-bombing soil quality plays an important role in determining the impact of local area exposure to bombing. First, since landmines are primarily concentrated in western Cambodia, particularly in the "K-5 mine belt" along the Thai border (Martin et al. 2019), we exclude provinces sharing borders with Thailand[29] and repeat our analysis split by soil fertility (Table C.1). Second, as the Khmer Rouge fled to the west after being overthrown in 1979 (Power 2017, Dayley 2018), they might have laid mines along their path. These mines were likely placed along existing transportation routes towards the Thai border, some of which may have overlapped with the areas targeted by bombings. We perform our analysis again, controlling for distance to the Thai border (Table C.2). Across all of these refinements, our results remain unchanged. Positive effects are only observed in areas that were infertile in the past, reinforcing our interpretation and emphasizing the importance of UXO risks in shaping the impacts of bombing today.

5.3 Robustness

We conduct multiple robustness checks to test the sensitivity of the results and address potential concerns associated with our spatial RD design. We show that our results are robust to subsample analysis, alternative bandwidths, different orders of polynomials, a wide range of specifications, placebo tests and using 50x50km grid-cell fixed effects instead of province fixed effects in the main regression. These robustness results are presented in Appendix A - Robustness checks.

Grid-cell fixed effects. Spatial RD designs often include border-segment fixed effects to guarantee a comparison of observations in very close geographic proximity. Within our context, because there are numerous bombing borders widespread across the country, we employ province-fixed effects to ensure that we compare individuals within a specific

[28]We'll discuss more in Section 6.

[29]There are seven provinces that share borders with Thailand, including Banteay Meanchey, Battambang, Oddar Meanchey, Pailin, Preah Vihear, Pursat and Koh Kong.

province. However, we are also concerned that provinces may be too broad to account for between-area heterogeneity. Therefore, instead of using province-fixed effects to control for spatial variation, we divide the country into highly confined areas of 50x50km grid cells and control for grid-cell fixed effects in our main regression. Overall, the country is divided into 79 grid cells (Figure G.6). Table A.1 demonstrates that when grid-cell fixed effects are employed, the results remain similar: living in bombing areas is associated with better health outcomes and these effects are concentrated in infertile areas with a lower probability of UXO. In our grid-cell fixed effect models, the coefficients for Height-for-age Z-scores and being underweight remain consistent, and the reduction in anemia levels also remains similar if comparatively somewhat smaller in magnitude than in province-fixed effect models.

Choice of polynomial orders. Figures A.1, A.3, and A.5 plot the main coefficients for different orders of RD polynomial in latitude and longitude with two different options of bandwidth. The results are consistent when higher orders of polynomials are used in the main regression with significantly positive effects on HAZ and a considerable drop in anemia level for people living in bombing areas. We also continue to find that the positive impacts are especially substantial for those residing in pre-bombing infertile areas, whereas there are null or even negative effects in fertile areas.

Bandwidth sensitivity. We conduct sensitivity checks to different choices of bandwidth ranging from 0.5 to 2.5 km with 0.1km intervals. Figures A.2, A.4 and A.6 show that our results are robust to any choice of bandwidths. Especially, for all bandwidths, we observe the consistent heterogeneous effects on two groups of population, based on whether they reside in pre-bombing fertile or infertile areas.

Alternative specifications. In Tables A.2, A.3 and A.4 we investigate robustness to various specifications. The first four columns show the results when higher polynomials in latitude and longitudes are employed in the main regression. [30] The following two columns present outcomes without the inclusion of a triangular kernel weight.[31] Columns (7) (8) (9) (10) exclude the distance to the capital and the distance to Vietnam's borders in the main regressions. The last two columns run a *donut* exercise by removing all observations close to bombing boundaries (within 0.25km) and keeping the remaining data to fit the current spatial RD model. The objective of the *donut* exercise is to address the potential issue of systematic disparities between border populations and populations further away from bombing boundaries. In general, the enduring impacts on health outcomes remain consistent across different specifications. For HAZ, Table A.2 shows estimates of

[30] Quadratic polynomial will take the form as $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat \times lon$. Cubic polynomial will take the form as $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat^3 + lon^3 + lat \times lon + lat^2 \times lon + lat \times lon^2$.

[31] A triangular kernel involves decreasing the weight assigned to each observation as the distance from the boundaries increases

the bombing effect remain significant and stable across specifications, underscoring the reliability of our findings. Even in the more restrictive *donut* model the effects remain strong and significant. Similarly, we observe consistent results on the likelihood of being underweight A.3. Although there are no observable effects for the entire population, we see null or even negative effects for those living in fertile areas. Conversely, women in infertile areas are less likely to be underweight, indicating a positive impact on weight. Finally, Table A.4 also suggests a solid result on anemia. Our estimates are robust in terms of magnitude and significance level across different specification choices.

Placebo tests. We conduct placebo tests to confirm that the treatment effect does not come from other factors such as random variation or bias. Placebo boundaries are created by shifting bombing areas by 3km in all directions (north/ east/ west/ south). Then, we re-assign treatment and estimate the treatment effects in placebo situations both for the aggregate effects and again split by soil fertility. As illustrated in Table A.5, there are no placebo-boundary effects on Height-for-age Z-score, except in the case of a westward border shift, where the estimate goes in the opposite direction of our main result. For the likelihood of being underweight, we generally observe no effects (Table A.6). In fertile areas, we can see some negative impacts when the border shifts eastward, yet in other cases, the estimates are indifferent from zero. Meanwhile, the effects in infertile areas are all indifferent from zero, opposite our main findings which show the impacts on weight predominantly driven by individuals residing in infertile areas. In terms of anemia level (Table A.7), coefficients are statistically insignificant for all directional shifts, except when borders are shifted southward. Although we observe significant coefficients for the southward shift, these coefficients are positive, meaning worse health for individuals living in bombing areas, again contrary to our main findings. Throughout all of these many placebos the majority of estimates are null, and for those that are significant, we do not find them concerning. They do not indicate any clear pattern. It is not surprising to have a significant effect with an ample number of placebos, and most importantly, all of these particular estimates are opposite to our actual estimates.

5.4 Heterogeneous effects on different generations

We also split these effects by those born during or after the bombing periods, anticipating that the impacts on health might vary based on whether an individual is from an older or younger cohort. Any positive mechanisms from later local area development to boost areas with greater degradation in the past may impact younger cohorts differently than older cohorts. For example, anemia may be most relevant among older cohorts and depend on their relative access to health care. Table 5 presents the heterogeneous effects on two groups of the population: people born before and after 1975.

We find statistically significant long-run positive effects of living in bombing areas on the height of populations born after 1975, while these effects are indifferent from zero for

Table 5: Heterogeneous effects on different generations

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km
Panel A: Individuals born by 1975						
Bombing	0.015	0.018	-0.015	-0.017	-0.032**	-0.030**
	(0.037)	(0.033)	(0.015)	(0.014)	(0.013)	(0.012)
Mean	-1.857	-1.853	0.168	0.163	0.117	0.115
Observations	3603	4771	3603	4771	3603	4771
Clusters	654	859	654	859	654	859
Panel B: Individuals born after 1975						
Bombing	0.090***	0.081***	-0.000	-0.004	-0.015	-0.015*
	(0.035)	(0.031)	(0.013)	(0.011)	(0.009)	(0.008)
Mean	-1.788	-1.780	0.199	0.199	0.0855	0.0822
Observations	5533	7275	5533	7275	5533	7275
Clusters	647	850	647	850	647	850

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

people who were born before 1975. In particular, women born after 1975 and currently residing in bombing areas witness an increase of 0.090 (or 0.081) in their Health-for-age Z-scores, equivalent to approximately 5%, compared to those living outside. The observed findings confirm that positive treatment effects on Height-for-age Z-scores are likely to be concentrated among subsequent generations who did not experience severe negative consequences of the bombing and have benefited from post-war investments. In terms of being underweight, we do not see any discontinuities at the bombing boundaries for both groups.

Anemia is a health issue that affects people of all ages, with a higher prevalence among older individuals (Timiras & Brownstein 1987, Anía et al. 1997, Gaskell et al. 2008). Age plays a significant role in determining both hemoglobin levels and anemia, with older adults generally having lower hemoglobin levels than their younger counterparts (Salive et al. 1992, Gaskell et al. 2008). Our summary statistics reveal that 11.7% of older generations typically suffer from anemia, whereas this rate decreases to only 8.5% in the younger group. When examining the impact of residing in past bombing locations on anemia levels, it becomes apparent that the effect on anemia would notably show up in older generations.[32] Older people residing in areas heavily affected by the bombing exhibit a significantly lower risk of anemia, approximately 3.0 percentage points lower than their counterparts on the other side. This effect is substantial and statistically significant. It represents 26% shift relative to the mean of anemia in this age group population.

In appendix B, we present the results with generation splits in combination with pre-bombing soil fertility categories. Within fertile areas marked by a prevalence of UXO, we find null effects or somewhat negative impacts across different generations. On the contrary, in less fertile areas with a reduced chance of UXO, we observe effect heterogeneity on two different generations, which are consistent with our results in this section. In particular, positive effects on height notably show up in younger generations while beneficial impacts on weight and anemia are more pronounced in older generations.

In summary, our analysis indicates that after more than three decades since the bombing incidents, individuals residing in local areas exposed to the past bombing demonstrate better health outcomes. These positive impacts on health are sensible because they are entirely driven by areas which were infertile before the bombing. These areas are precisely those expected to have a lower probability of UXOs at the present time. Where UXOs are less prevalent, positive post-bombing developments are more likely to be useful and improvements in infrastructure achievable. Our results are consistent with this narrative and lead us to our following investigation of mechanisms.

6 Mechanisms

In this section, we examine channels that may shed light on the positive health impacts observed among people living in bombing areas with a low likelihood of UXO contamination. We test whether better health outcomes observed in people residing on the bombing side are driven by economic developments and healthcare accessibility focused on these areas. Post-war investments can progressively diminish and counteract the negative shocks of war (Strauss & Thomas 2008), potentially leading to the reversal of adverse health effects and even improvement over multiple generations. We provide evidence suggesting that previously bombed areas with a lower current probability of UXO exhibit more favorable economic and healthcare characteristics. Meanwhile, bombing-affected areas with a high risk of UXO experience either null or worse outcomes relative to non-bombed locations.

6.1 Economic development in the post-bombing period

Table 6 shows the effects of local exposure to bombing on several contemporary economic development indicators. Although the aggregate effects are not significant (Panel A), we observe contrasting effects in pre-bombing fertile and infertile areas: there are beneficial impacts on economic development in infertile areas, whereas fertile areas show null or negative impacts.

[32]Our main specification already controls for nonlinearity in age (*age* and age^2)

Table 6: Economic Development Indicators

	Dependent variable is:									
	Population Density		Light Intensity		Market Density		Family Wealth		Secondary Edu.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations										
Bombing	-0.146	-0.262	-0.854	-1.050	-0.041	-0.061	0.015*	0.015*	0.031*	0.027
	(0.380)	(0.356)	(0.700)	(0.657)	(0.069)	(0.064)	(0.008)	(0.007)	(0.018)	(0.017)
Mean	1.599	1.697	4.187	4.628	-0.00397	0.0235	0.315	0.319	0.314	0.318
Observations	9136	12046	200992	265012	9136	12046	9041	11919	9136	12046
Clusters	659	865	659	865	659	865	659	865	659	865
Panel B: Fertile areas (1962)										
Bombing	-0.749	-0.833	-2.995**	-2.799**	-0.198	-0.196*	-0.014	-0.009	-0.034	-0.028
	(0.811)	(0.720)	(1.333)	(1.193)	(0.124)	(0.111)	(0.013)	(0.012)	(0.035)	(0.032)
Mean	3.353	3.407	7.491	7.501	0.292	0.306	0.360	0.356	0.393	0.378
Observations	3094	4030	68068	88660	3094	4030	3053	3981	3094	4030
Clusters	230	301	230	301	230	301	230	301	230	301
Panel C: Infertile areas (1962)										
Bombing	0.379**	0.243	0.573	0.161	0.105*	0.072	0.025**	0.021**	0.050**	0.044**
	(0.160)	(0.152)	(0.564)	(0.555)	(0.053)	(0.050)	(0.010)	(0.009)	(0.021)	(0.019)
Mean	0.701	0.838	2.495	3.184	-0.155	-0.119	0.292	0.301	0.273	0.288
Observations	6042	8016	132924	176352	6042	8016	5988	7938	6042	8016
Clusters	429	564	429	564	429	564	429	564	429	564

Note: The unit of analysis is survey respondents (individuals). All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) (7) (9) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) (8) (10) include individuals living within 1.5 km of bombing boundaries. Population Density indicates households' current population density (the number of people per square kilometer).Light Intensity is night-time light emissions at DHS household villages. Market Density is a standardized variable showing the density of market at DHS household clusters. Family Wealth is a dummy variable constructed based on households' accessibility to electricity and ownership of durable goods. Secondary Edu. is a binary variable indicating whether a respondent has graduated from secondary education. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

In fertile areas, local exposure to bombing leads to null or even negative effects on economic development (Panel B). Even though population density is insignificantly different between inside and outside bombing areas (columns 1-2), we observe a statistically significant decrease on night-time light intensity, with a drop of 2.995 or 2.799, representing an almost 40% decline compared to the mean (columns 3-4). We find a similar negative effect on market density, suggesting fewer markets within bombing-affected areas (columns 5-6).[33] These findings are consistent with the literature on how conflicts and UXO affect economic growth. Bombing and the ongoing threat from UXO stifle economic growth, trapping populations in cycles of poverty (Yamada & Yamada 2021, Lin 2022, Riano & Valencia Caicedo 2024).

In contrast, infertile areas experience beneficial impacts of local exposure to bombing on economic development (Panel C). First, the modern population density is higher for locations inside the bombing areas (columns 1-2). Second, while night-time light intensity is indifferent, current market density appears to be higher on the bombing side (columns 3-4). Third, households residing inside the bombing areas are wealthier with better access to electricity and more possession of durable goods (columns 7-8). Finally, the likelihood of women residing within the bombing areas completing secondary education is significantly

[33] We observe no significant differences in family wealth (columns 7-8) and education level (columns 9-10) between two sides of the bombing boundaries.

higher, with an increase of 5.0 or 4.4 percentage points, more than 15% compared to the mean (columns 9-10). This evidence suggests that regions with lower UXO likelihood have experienced a more successful post-conflict recovery, with improved economic conditions and better human capital accumulation. These areas have been developed more effectively due to the reduced risks from UXO, allowing restoration and growth, and overall healthier local economies.

Table 7: CSES Data: Economic Development

	Dependent variable is:							
	Household				Field Productivity			
	Income		Food Shortage		Areas Cultivated		Crop Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations								
Bombing	0.321	0.348	0.002	-0.003	0.016	0.013	0.141	0.201
	(0.284)	(0.252)	(0.027)	(0.025)	(0.013)	(0.012)	(0.210)	(0.208)
Mean	13.34	13.38	0.130	0.130	0.955	0.958	13.17	13.26
Observations	3649	4507	3803	4715	4195	5072	4193	5069
Clusters	314	390	314	390	253	316	253	316
Panel B: Fertile areas (1962)								
Bombing	-0.346	-0.294	0.063*	0.059*	0.019	0.014	-0.641***	-0.535**
	(0.369)	(0.343)	(0.035)	(0.031)	(0.019)	(0.019)	(0.219)	(0.246)
Mean	12.89	12.91	0.125	0.127	0.963	0.963	13.29	13.34
Observations	1616	1962	1680	2052	1535	1851	1534	1850
Clusters	137	168	137	168	98	121	98	121
Panel C: Infertile areas (1962)								
Bombing	1.070**	0.986***	-0.044	-0.050	0.013	0.011	0.697***	0.674***
	(0.425)	(0.374)	(0.038)	(0.035)	(0.016)	(0.014)	(0.250)	(0.250)
Mean	13.70	13.74	0.135	0.132	0.951	0.954	13.11	13.22
Observations	2033	2545	2123	2663	2660	3221	2659	3219
Clusters	177	222	177	222	155	195	155	195

Note: The unit of analysis for the first 4 columns is households. Regressions (1) (3) include households living within 1km from bombing boundaries. Regressions (2) (4) include households living within 1.5 km of bombing boundaries. *Income* demonstrates households' agricultural and non-agricultural income. *Income* is transformed ln(Cambodian riel +1). *Food Shortage* is a dummy variable indicating whether households suffer from food shortage during the last 30 days. The unit of analysis for the last 4 columns is fields (agricultural land). Regressions (5) (7) include fields located within 1km from bombing boundaries. Regressions (8) (10) include fields located within 1.5 km of bombing boundaries. *Areas Cultivated* shows the percentage of field cultivated compared to total field. *Crop Revenue* indicates total revenue from the field: $Revenue = (QuantityHarvested - PostHarvestLoss) \times SalesPrice$. *Crop Revenue* is also transformed ln(Cambodian riel +1). All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders, and other pre-bombing characteristics are present in all regressions. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

To further validate this mechanism, we exploit CSES data to investigate the impacts of local exposure to bombing on household income, household vulnerability and agricultural productivity. We again find significant beneficial effects in infertile areas and adverse effects in fertile areas (Table 7). Specifically, in fertile areas (Panel B), although households' income is indifferent across bombing boundaries (columns 1-2), households residing on the bombing side are more likely to suffer from food shortage (columns 3-4). In terms of field productivity, while there is no clear discontinuity in the proportion of cultivated land to the size of the field (columns 5-6), revenues are lower for fields located inside the bombing areas (columns 7-8). Our findings are aligned with narrative and empirical evidence in Lin (2022, 2024) that historical bombing of high-fertility land, where bombs were likely to fail, have persistent negative impacts on household production and welfare, as farmers change cultivation practices and cut investments in agricultural capital, reducing profit margins and increasing poverty levels.

Meanwhile, we observe some positive effects in infertile areas. Households living inside bombing areas have income about 7% higher than those living outside (columns 1-2). However, the likelihood of food shortage is indifferent across bombing boundaries (columns 3-4). Regarding field productivity, we do not observe any effects on the percentage of cultivated land (columns 5-6), but crop revenue is significantly higher for fields on the bombing side (columns 7-8), suggesting more efficient farming in these areas. In infertile areas with lower UXO risks, households have a greater potential for recovery and growth post-conflict. In our case, households have not only recovered but have also achieved significant improvements in their economic conditions with higher income and crop revenue.

Overall, our evidence suggests that improved economic development in bombing-affected regions is a possible mechanism behind better health outcomes. These positive effects are strong in areas which are infertile in the pre-bombing period and currently have a lower likelihood of UXO, while we see null or harmful effects in areas where UXO are more likely. In the next section, we explore healthcare accessibility in Cambodia as another likely mechanism for our results.

6.2 Healthcare accessibility

6.2.1 Health system in Cambodia

During the 1970s, the dual impacts of US bombings and the Khmer Rouge regime resulted in the physical devastation of society and completely dismantled the national healthcare system (Annear 1998). Half of the hospitals had already shut down as early as 1971 and the availability of medicines became scarce due to the civil war and bombings. The remaining healthcare infrastructure was further destroyed during the Khmer Rouge regime from 1975 to 1979 (WHO 2015).

Developing the whole healthcare system from scratch, Cambodia focused on rebuilding a functional hospital system, providing training for fresh healthcare staff, and reconstructing health facilities. However, it was not until 1995 that a comprehensive reform in health was implemented (Annear 1998). In the 1980s, re-established public health facilities were mainly concentrated in the capital areas. Subsequently, in 1995, Cambodia embarked on a health reform initiative known as Health Coverage Plan aimed at building health facilities in rural regions, including health centers and district hospitals (Grundy et al. 2009). At present, Cambodia's health facilities encompass various types, including health posts, health centers, district referral hospitals, provincial referral hospitals, and national hospitals.

The construction of these healthcare facilities is based on population coverage and geographical access, and they are organized by operational districts (ODs) - the smallest administrative level in Cambodia's healthcare management system (WHO 2015). Each OD has one district referral hospital and is in charge of a number of health centers, although some ODs may have two district hospitals. The population coverage of a referral hospital is from 100,000 to 200,000, whereas a health center caters to a population of 10,000 to 20,000 people. In remote areas with smaller populations, health posts are available, offering similar services to health centers but on a smaller scale. A typical health post serves a population of approximately 2000 to 3000 people (WHO 2015). Figure G.5 visually presents the locations and distributions of health facilities in Cambodia in 2010. The map shows that health facilities are highly concentrated around the capital city and in the central flatlands of the country. Especially, among 9 national hospitals in Cambodia, 8 are located in the capital - Phnom Penh.

In the following section, we provide evidence suggesting that improved health outcomes observed in people living in bombing areas are attributed to better health accessibility in those areas. We use distance to health facilities as an indicator of healthcare access. To ensure a comprehensive evaluation of health accessibility, we conduct analyses for both the entire country and a restricted region around the capital, where health facilities are noticeably clustered. The defined restricted region (Figure E.1) includes the capital city and adjacent provinces.[34]

6.2.2 Distances to health facilities

With our empirical design, we look at distances to different health facilities as indicators of healthcare accessibility. We find statistically significant evidence that people living in areas which suffered degradation in the past from bombing have better healthcare access. Additionally, these effects are entirely driven by pre-bombing infertile regions with a lower likelihood of UXO.

Table 8 displays the results.[35] For the whole country analysis (Panel A), the distance to the nearest hospital is shorter for people living on the bombing side (-1.630 km and -1.513 km). The drop in the distance to district-level health centres is over 0.5 km, which is also statistically significant. The results are consistent when we examine the distance to any available health facilities. There is a considerable decline in distance to the nearest

[34] See Appendix E for a detailed RD analysis with observations in restricted region.

[35] We categorized health facilities into three groups: (1) hospitals, including national and referral hospitals, (2) district-level health centers, including health centers and health posts, and (3) any health facilities, including all hospitals and health facilities in Cambodia. Subsequently, we computed the distances from each household to the nearest hospital, the nearest district-level health centre, and the nearest health facility. See section 3.4

Table 8: Distance to health facilities

	Dependent variable is Distance (km) to					
	Hospital		District health center		Any health facility	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km
Panel A: The whole country						
Bombing	-1.630*	-1.513*	-0.563***	-0.537***	-0.474**	-0.459**
	(0.922)	(0.852)	(0.211)	(0.204)	(0.206)	(0.200)
Mean	13.72	13.42	3.261	3.234	3.220	3.195
Observations	9136	12046	9136	12046	9136	12046
Clusters	659	865	659	865	659	865
Panel B: Fertile areas (1962)						
Bombing	0.551	0.448	0.352	0.329	0.544**	0.498**
	(1.303)	(1.278)	(0.269)	(0.247)	(0.250)	(0.231)
Mean	9.967	10.20	2.653	2.692	2.577	2.621
Observations	3094	4030	3094	4030	3094	4030
Clusters	230	301	230	301	230	301
Panel C: Infertile areas(1962)						
Bombing	-1.671	-1.269	-0.889***	-0.818***	-0.857***	-0.788***
	(1.041)	(0.976)	(0.265)	(0.260)	(0.266)	(0.261)
Mean	15.64	15.05	3.572	3.507	3.548	3.484
Observations	6042	8016	6042	8016	6042	8016
Clusters	429	564	429	564	429	564

Note: Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

health facility for people within the bombing areas (-0.474 km and -0.459 km).

When we split the effects by pre-bombing soil fertility, we observe null or somewhat negative effects in fertile areas, whereas the beneficial effects are strong and statistically significant in infertile areas. Particularly, in fertile areas with a high occurrence of UXO (Panel B), although distances to the nearest hospital and district health center are almost the same across the boundaries, the distance to any nearest health facility for those on the bombing side is significantly longer. This distance increases by 0.544km or 0.498km, equivalent to about 20% of the average distance. Meanwhile, in infertile areas, across all specifications, we observe negative estimates, indicating shorter distances to health facilities for those living inside the bombing areas (Panel C). There is a considerable and statistically significant decrease in the distance to the nearest district health center (-0.896 km and -0.813 km). We also observe a similar result for the distance to any health facility, with a drop of approximately 0.8 km, more than 20% compared to the mean. Our analysis overall supports the story that in low-fertility regions, post-war investments in healthcare infrastructure can gradually offset the negative impacts of bombing and even lead to better outcomes (Strauss & Thomas 2008). In contrast, fertile regions with high UXO threats tend to receive lower investment in healthcare infrastructure. The persistent risk of UXO in these regions may deter investment and development efforts, and as a result, hinder them from recovering fully from past conflicts.

A similar analysis for the region around the capital where health facilities are concentrated also yielded robust statistical evidence that individuals residing in bombing areas exhibit improved accessibility to healthcare services and these improvements are observed in infertile areas with a lower likelihood of UXO (Table E.2, Appendix E).

In summary, our evidence suggests that better health outcomes observed in bombed areas can be attributed to improved economic conditions and enhanced healthcare accessibility in these areas. Most importantly, these beneficial effects are completely driven by pre-bombing infertile areas with a lower likelihood of UXO at the present time. Meanwhile, in fertile areas where UXO becomes more prevalent, we observe null or even negative effects on economic development and healthcare accessibility.

7 Conclusion

This study employs a spatial regression discontinuity approach to explore the long-term effects of local area exposure to US bombing in Cambodia on health. Unlike studies concentrating on those directly exposed to bombings, our research investigates how these events can shape health outcomes for future generations. We show that after more than three decades since the bombing incidents, individuals residing in regions previously affected by bombings demonstrate better health outcomes. While at first suprising, we show that these positive effects are sensible because they are concentrated in pre-bombing infertile regions with a lower UXO prevalence at the present. Meanwhile, in areas where remnants of war are more likely, we find null or even negative impacts on health. We provide evidence that our main results can be attributed to economic growth and improved healthcare accessibility in the post-conflict era. In areas with a lower UXO probability, bombing-affected areas experience enhanced economic conditions and better access to healthcare. On the contrary, in areas with a higher UXO probability, local exposure to bombing appears to have null or even detrimental effects on both economic development and healthcare access.

Our findings carry significant implications for all countries that have experienced with past conflicts, underscoring the power of post-war recovery efforts and post-conflict strategic investments. These initiatives play an important role in mitigating the adversities caused by war and conflicts and paving the way for healing and development. In the case of Cambodia, in regions free from the lingering hazards of conflicts, substantial investments in economic infrastructure and public healthcare have reduced the negative impacts of bombing and even led to improved health outcomes. However, in regions where UXO remained a threat, development was hindered, and the negative impacts continued to persist. This highlights the critical role of UXO clearance in facilitating long-term recovery, because without such efforts, regions with remnants of war are more likely to be left behind and unable to develop. The consequences then play out not only on economic outcomes but on health and well being. Future studies should broaden the current scope of existing research on health and conflicts, to consider how post-conflict investments and developments can shape population health. Understanding post-conflict recovery is vital for assessing community resilience and offers valuable guidance for policymakers.

References

Abadie, A. & Gardeazabal, J. (2003), 'The economic costs of conflict: A case study of the basque country', *American economic review* **93**(1), 113–132.

Aghion, P. & Howitt, P. (1990), 'A model of growth through creative destruction'.

Aguilar, A. & Vicarelli, M. (2011), 'El nino and mexican children: medium-term effects of early-life weather shocks on cognitive and health outcomes', *Cambridge, United States: Harvard University, Department of Economics. Manuscript* .

Akbulut-Yuksel, M. (2014), 'Children of war the long-run effects of large-scale physical destruction and warfare on children', *Journal of Human resources* **49**(3), 634–662.

Akbulut-Yuksel, M. (2017), 'War during childhood: The long run effects of warfare on health', *Journal of Health Economics* **53**, 117–130.

Akresh, R., Bhalotra, S., Leone, M. & Osili, U. (2023), 'First-and second-generation impacts of the biafran war', *Journal of Human Resources* **58**(2), 488–531.

Akresh, R., Bhalotra, S., Leone, M. & Osili, U. O. (2012), 'War and stature: Growing up during the nigerian civil war', *American Economic Review* **102**(3), 273–277.

Aldstadt, J. (2009), Spatial clustering, *in* 'Handbook of applied spatial analysis: Software tools, methods and applications', Springer, pp. 279–300.

Anía, B. J., Suman, V. J., Fairbanks, V. F., Rademacher, D. M. & III, L. J. M. (1997), 'Incidence of anemia in older people: an epidemiologic study in a well defined population', *Journal of the American Geriatrics Society* **45**(7), 825–831.

Ankerst, M., Breunig, M. M., Kriegel, H.-P. & Sander, J. (1999), 'Optics: Ordering points to identify the clustering structure', *ACM Sigmod record* **28**(2), 49–60.

Annear, P. (1998), 'Health and development in cambodia', *Asian Studies Review* **22**(2), 193–221.

Auchincloss, A. H., Gebreab, S. Y., Mair, C. & Diez Roux, A. V. (2012), 'A review of spatial methods in epidemiology, 2000–2010', *Annual review of public health* **33**, 107–122.

Barker, D. J. (1990), 'The fetal and infant origins of adult disease.', *BMJ: British Medical Journal* **301**(6761), 1111.

Beale, L., Abellan, J. J., Hodgson, S. & Jarup, L. (2008), 'Methodologic issues and approaches to spatial epidemiology', *Environmental health perspectives* **116**(8), 1105–1110.

Boots, B. N. & Getls, A. (1988), 'Point pattern analysis'.

Cagé, J. & Rueda, V. (2016), 'The long-term effects of the printing press in sub-saharan africa', *American Economic Journal: Applied Economics* **8**(3), 69–99.

Calonico, S., Cattaneo, M. D. & Titiunik, R. (2014), 'Robust nonparametric confidence intervals for regression-discontinuity designs', *Econometrica* **82**(6), 2295–2326.

Camacho, A. (2008), 'Stress and birth weight: evidence from terrorist attacks', *American Economic Review* **98**(2), 511–515.

Chandler, D. (2018), *A history of Cambodia*, Routledge.

Cheng, W., Wang, W. & Batista, S. (2018), Grid-based clustering, *in* 'Data clustering', Chapman and Hall/CRC, pp. 128–148.

Clodfelter, M. (1995), 'Vietnam in military statistics: A history of the indochina wars, 1772-1991. london: Mcfarland & company', *Inc., Publishers* .

Conti, G., Poupakis, S., Ekamper, P., Bijwaard, G. E. & Lumey, L. H. (2024), 'Severe prenatal shocks and adolescent health: Evidence from the dutch hunger winter', *Economics & Human Biology* **53**, 101372.

Crocker, C. D. (1962), 'The general soil map of the kingdom of cambodia and the exploratory survey of the soils of cambodia', *Phnom Penh, Cambodia: Royal Cambodian Government Soil Commission/United States Agency for International Development* .

Davis, D. R. & Weinstein, D. E. (2002), 'Bones, bombs, and break points: the geography of economic activity', *American economic review* **92**(5), 1269–1289.

Dayley, R. (2018), *Southeast Asia in the new international era*, Routledge.

Dell, M. (2010), 'The persistent effects of peru's mining mita', *Econometrica* **78**(6), 1863–1903.

Dell, M., Lane, N. & Querubin, P. (2018), 'The historical state, local collective action, and economic development in vietnam', *Econometrica* **86**(6), 2083–2121.

Dell, M. & Olken, B. A. (2020), 'The development effects of the extractive colonial economy: The dutch cultivation system in java', *The Review of Economic Studies* **87**(1), 164–203.

Devakumar, D., Birch, M., Osrin, D., Sondorp, E. & Wells, J. C. (2014), 'The intergenerational effects of war on the health of children', *BMC medicine* **12**(1), 1–15.

Duque, V. (2017), 'Early-life conditions and child development: Evidence from a violent conflict', *SSM-population health* **3**, 121–131.

Ear, S. (1995), 'Cambodia's economic development in historical perspective (1953-1970)', *The Berkeley McNair Journal* **3**, 25–37.

Elliott, P. & Wartenberg, D. (2004), 'Spatial epidemiology: current approaches and future challenges', *Environmental health perspectives* **112**(9), 998–1006.

Emanuel, I., Filakti, H., Alberman, E. & Evans, S. J. (1992), 'Intergenerational studies of human birthweight from the 1958 birth cohort. 1. evidence for a multigenerational effect', *BJOG: An International Journal of Obstetrics & Gynaecology* **99**(1), 67–74.

Eriksson, T., Bratsberg, B., Raaum, O. et al. (2005), Earnings persistence across generations: Transmission through health?, *in* 'Unpublished paper presented at the EALE/SOLE meeting'.

Gaskell, H., Derry, S., Andrew Moore, R. & McQuay, H. J. (2008), 'Prevalence of anaemia in older persons: systematic review', *BMC geriatrics* **8**(1), 1–8.

Gelman, A. & Imbens, G. (2019), 'Why high-order polynomials should not be used in regression discontinuity designs', *Journal of Business & Economic Statistics* **37**(3), 447–456.

Ghobarah, H. A., Huth, P. & Russett, B. (2003), 'Civil wars kill and maim people—long after the shooting stops', *American Political Science Review* **97**(2), 189–202.

Gibson, J., Olivia, S. & Boe-Gibson, G. (2020), 'Night lights in economics: Sources and uses 1', *Journal of Economic Surveys* **34**(5), 955–980.

Grubesic, T. H., Wei, R. & Murray, A. T. (2014), 'Spatial clustering overview and comparison: Accuracy, sensitivity, and computational expense', *Annals of the Association of American Geographers* **104**(6), 1134–1156.

Grundy, J., Khut, Q. Y., Oum, S., Annear, P. & Ky, V. (2009), 'Health system strengthening in cambodia—a case study of health policy response to social transition', *Health policy* **92**(2-3), 107–115.

Guo, S. (2020), 'The legacy effect of unexploded bombs on educational attainment in laos', *Journal of Development Economics* **147**, 102527.

Hamlin, J., Jaupi, L. & States, T. H. T. W. U. (2018), 'Minefield sketch maps in humanitarian mine action', *The Journal of Conventional Weapons Destruction* **22**(1), 5.

Harada, M. (2022), 'War violence decreases long-term human well-being: The evidence from the strategic bombing to japan during wwii', *International Journal of Community Well-Being* pp. 1–26.

Henderson, J. V., Storeygard, A. & Weil, D. N. (2012), 'Measuring economic growth from outer space', *American economic review* **102**(2), 994–1028.

Hornbeck, R. & Keniston, D. (2017), 'Creative destruction: Barriers to urban growth and the great boston fire of 1872', *American Economic Review* **107**(6), 1365–1398.

Islam, A., Ouch, C., Smyth, R. & Wang, L. C. (2016), 'The long-term effects of civil conflicts on education, earnings, and fertility: Evidence from cambodia', *Journal of Comparative Economics* **44**(3), 800–820.

Islam, A., Ouch, C., Smyth, R. & Wang, L. C. (2017), 'The intergenerational effect of cambodia's genocide on children's education and health', *Population and Development Review* **43**(2), 331–353.

Kohama, S., Ohtsuki, K. & Tominaga, Y. (2020), 'Bombing and mining in war: Evidence from cambodia', *Journal of Global Security Studies* **5**(2), 319–338.

Kountchou, A., Sonne, S., Gadom, G. et al. (2019), The local impact of armed conflict on children's nutrition and health outcomes: evidence from chad, *in* 'CSAE Conference, University of Oxford'.

Leroy, J. L. & Frongillo, E. A. (2019), 'Perspective: what does stunting really mean? a critical review of the evidence', *Advances in Nutrition* **10**(2), 196–204.

Levy, B. S. (2002), 'Health and peace', *Croatian medical journal* **43**(2), 114–116.

Lin, E. (2022), 'How war changes land: Soil fertility, unexploded bombs, and the underdevelopment of cambodia', *American journal of political science* **66**(1), 222–237.

Lin, E. (2024), *When the Bombs Stopped: The Legacy of War in Rural Cambodia*, Princeton: Princeton University Press.

Mansour, H. & Rees, D. I. (2012), 'Armed conflict and birth weight: Evidence from the al-aqsa intifada', *Journal of development Economics* **99**(1), 190–199.

Maric, N. P., Dunjic, B., Stojiljkovic, D. J., Britvic, D. & Jasovic-Gasic, M. (2010), 'Prenatal stress during the 1999 bombing associated with lower birth weight—a study of 3,815 births from belgrade', *Archives of women's mental health* **13**, 83–89.

Martin, M. F., Dolven, B., Feickert, A. & Lum, T. (2019), 'War legacy issues in southeast asia: Unexploded ordnance (uxo)', *Current Politics and Economics of South, Southeastern, and Central Asia* **28**(2/3), 199–230.

Miguel, E. & Roland, G. (2011), 'The long-run impact of bombing vietnam', *Journal of development Economics* **96**(1), 1–15.

Ministry of Health (MOH) (2016), *Health Strategic Plan 2016–2020*, Phnom Penh: MOH.

Moyano, P. (2017), 'The intergenerational health effects of the us bombing campaign in cambodia'.

Moyes, R., Lloyd, R. & McGrath, R. (2002), *Explosive remnants of war: Unexploded ordnance and post-conflict communities*, Landmine Action.

Owen, T. & Kiernan, B. (2006), ‘Bombs over cambodia. the walrus’.

Palmer, M., Nguyen, C., Mitra, S., Mont, D., Groce, N. et al. (2016), ‘The long-term impact of war on health’, *HiCN WP (216)* .

Palmer, M., Nguyen, C. V., Mitra, S., Mont, D. & Groce, N. E. (2019), ‘Long-lasting consequences of war on disability’, *Journal of Peace Research* **56**(6), 860–875.

Power, J. (2017), The killing fields–cambodia, pol pot and the khmer rouge, *in* ‘Ending War Crimes, Chasing the War Criminals’, Brill Nijhoff, pp. 95–103.

Rany, S., Zain, A. N. M., Jamil, H. et al. (2012), ‘Cambodia’s higher education development in historical perspectives (1863-2012)’, *International Journal of Learning and Development* **2**(2), 224–241.

Riano, J. F. & Valencia Caicedo, F. (2024), ‘Collateral damage: The legacy of the secret war in laos’, *The Economic Journal* .

Roberts, W. C. (2011), *Landmines in Cambodia*, Cambria Press.

Rosales-Rueda, M. (2018), ‘The impact of early life shocks on human capital formation: evidence from el niño floods in ecuador’, *Journal of health economics* **62**, 13–44.

Rushton, L. & Elliott, P. (2003), ‘Evaluating evidence on environmental health risks’, *British Medical Bulletin* **68**(1), 113–128.

Salive, M. E., Cornoni-Huntley, J., Guralnik, J. M., Phillips, C. L., Wallace, R. B., Ostfeld, A. M. & Cohen, H. J. (1992), ‘Anemia and hemoglobin levels in older persons: relationship with age, gender, and health status’, *Journal of the American Geriatrics Society* **40**(5), 489–496.

Sonne, S. E. W. & Nillesen, E. (n.d.), ‘Long-term effects of violent conflict on second-generation health outcomes: evidence from liberia’.

Strauss, J. & Thomas, D. (2008), ‘“health over the life course.” in p. schultz and j. strauss’.

Timiras, M.-L. & Brownstein, H. (1987), ‘Prevalence of anemia and correlation of hemoglobin with age in a geriatric screening clinic population’, *Journal of the American Geriatrics Society* **35**(7), 639–643.

United Nations, Department of Economic and Social Affairs Population Division (2019), *World Population Prospects 2019*.
URL: *https://population.un.org/wpp/*

Weir, C. B. & Jan, A. (2019), ‘Bmi classification percentile and cut off points’.

Whatley, W. & Gillezeau, R. (2011), ‘The impact of the transatlantic slave trade on ethnic stratification in africa’, *American Economic Review* **101**(3), 571–576.

WHO (1995), *Physical status: The use of and interpretation of anthropometry, Report of a WHO Expert Committee*, World Health Organization.

WHO (2008), 'Worldwide prevalence of anaemia 1993-2005: Who global database on anaemia.'.

WHO (2015), *The Kingdom of Cambodia health system review*, World Health Organization Regional Office for the Western Pacific.

Yamada, T. & Yamada, H. (2021), 'The long-term causal effect of us bombing missions on economic development: Evidence from the ho chi minh trail and xieng khouang province in lao pdr', *Journal of Development Economics* **150**, 102611.

Appendix

A Robustness

Table A.1: Control for 50x50km grid fixed effects

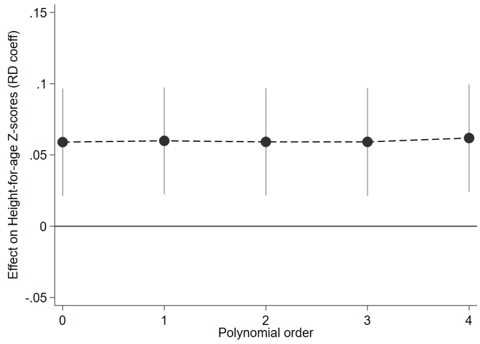
	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.070**	0.056**	-0.006	-0.007	-0.018**	-0.017**
	(0.029)	(0.027)	(0.010)	(0.009)	(0.008)	(0.007)
Mean	-1.815	-1.809	0.187	0.185	0.0977	0.0954
Observations	9136	12046	9136	12046	9136	12046
Clusters	659	865	659	865	659	865
Panel B: Fertile areas (1962)						
Bombing	-0.040	-0.034	0.023	0.008	0.018*	0.009
	(0.053)	(0.046)	(0.016)	(0.015)	(0.010)	(0.010)
Mean	-1.785	-1.793	0.182	0.177	0.0792	0.0799
Observations	3094	4030	3094	4030	3094	4030
Clusters	230	301	230	301	230	301
Panel C: Infertile areas (1962)						
Bombing	0.108***	0.087***	-0.025*	-0.020	-0.033***	-0.029***
	(0.036)	(0.033)	(0.013)	(0.012)	(0.011)	(0.010)
Mean	-1.831	-1.817	0.190	0.189	0.107	0.103
Observations	6042	8016	6042	8016	6042	8016
Clusters	429	564	429	564	429	564

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5km from bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

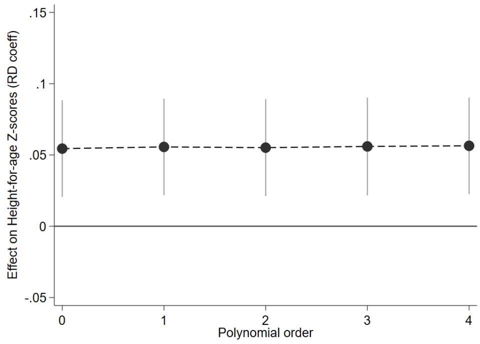
Figure A.1: Height-for-age Z-score: Sensitivity of Results to Different Orders of Polynomial

Panel A: Within 1km bandwidth

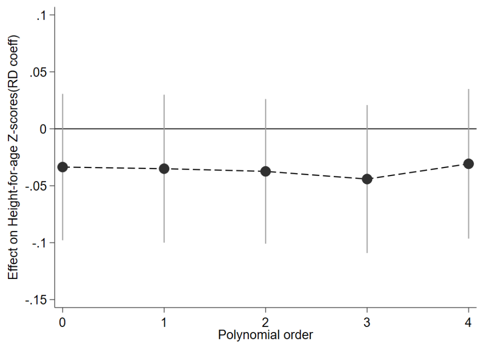
Panel B: Within 1.5km bandwidth



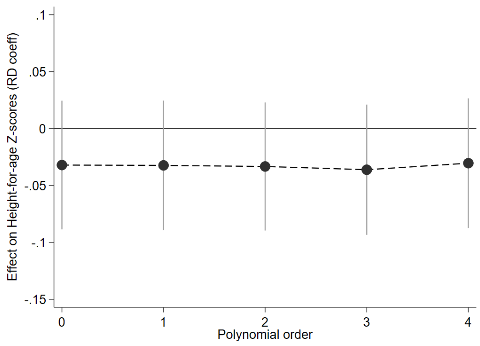
(a) All sample



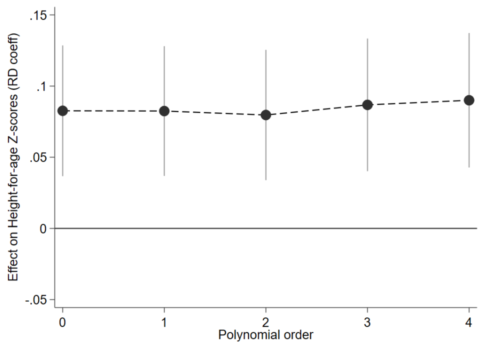
(b) All sample



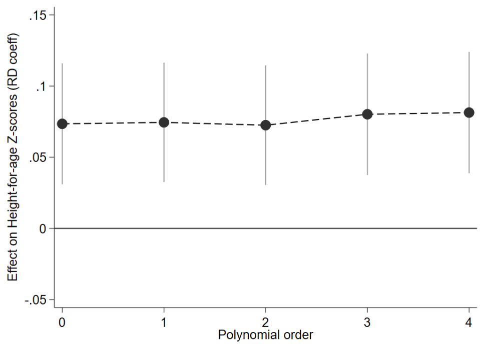
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)



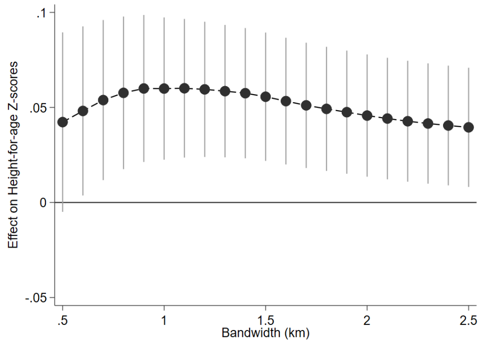
(f) Infertile areas (1962)

Note: Dependent variable is Height-for-age Z-score (HAZ). Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

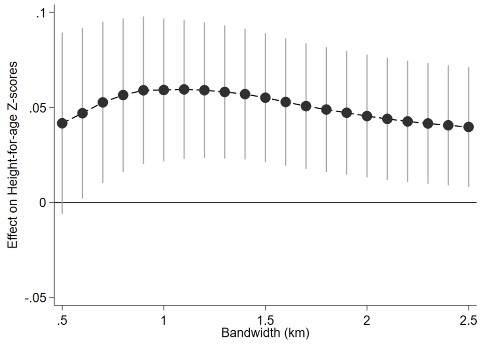
Figure A.2: Height-for-age Z-score: Sensitivity of Results to Bandwidth Choice

Panel A: Linear polynomial

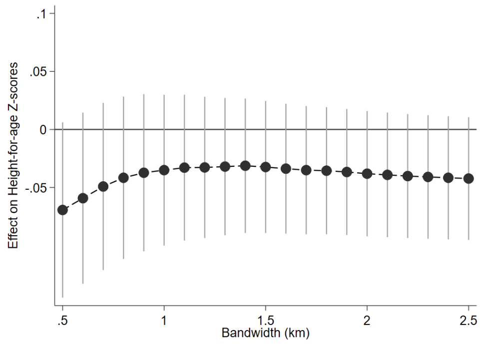
Panel B: Quadratic polynomial



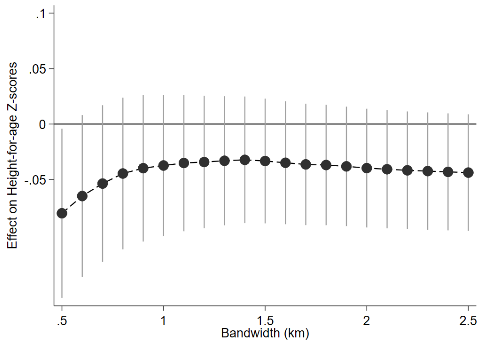
(a) All sample



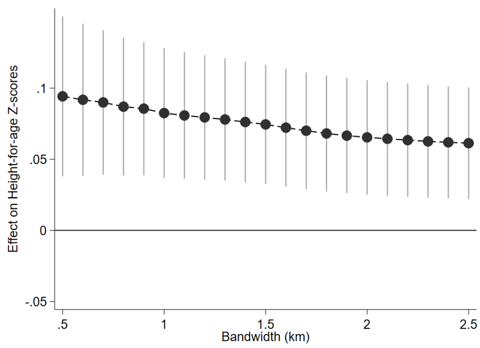
(b) All sample



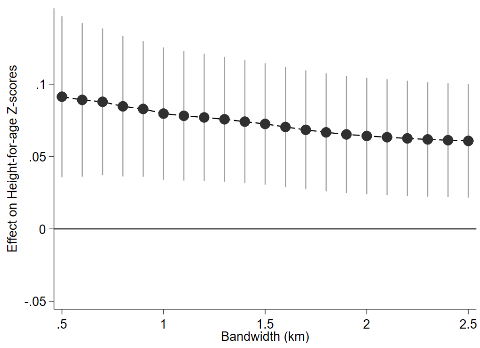
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)



(f) Infertile areas (1962)

Note: Dependent variable is Height-for-age Z-score (HAZ). Each sub-graph reports coefficient estimates and confidence intervals for different bandwidth levels ranging from 0.5 to 2.5 kilometers (horizontal axis) with 0.1km intervals. Each dot indicates the RD estimate using the specified bandwidth. Range spikes represent 90% confidence intervals of the estimates. Panel A displays the coefficients in regresions controlling for a linear polynomial in latitude and longitude. Panel B reports the coefficients in regressions controlling for a quadratic polynomial in latitude and longitude.

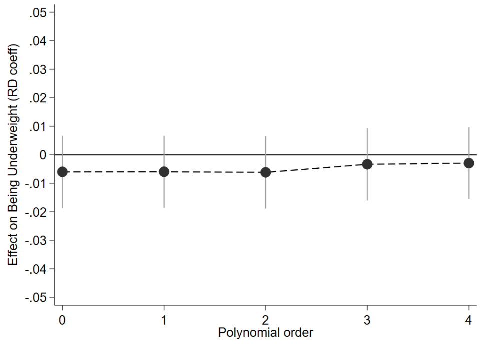
Table A.2: Heigh-for-age Z-score - Robustness checks: different specifications with latitude-longitude as running variables

	Dependent variable is Heigh-for-age Z-score (HAZ)											
	Quadratic		Cubic		No weight		No dist_capital		No dist_vietnam		Donut 0.25km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations												
Bombing	0.059**	0.055**	0.059**	0.056**	0.059**	0.038	0.060**	0.056**	0.058**	0.054**	0.090**	0.072**
	(0.029)	(0.026)	(0.030)	(0.027)	(0.027)	(0.025)	(0.029)	(0.026)	(0.029)	(0.026)	(0.038)	(0.033)
Mean	-1.815	-1.809	-1.815	-1.809	-1.815	-1.809	-1.815	-1.809	-1.815	-1.809	-1.812	-1.805
Observations	9136	12046	9136	12046	9136	12046	9136	12046	9136	12046	6537	9447
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Panel B: Fertile areas (1962)												
Bombing	-0.037	-0.033	-0.044	-0.036	-0.013	-0.044	-0.036	-0.032	-0.035	-0.032	0.059	0.022
	(0.049)	(0.044)	(0.051)	(0.045)	(0.044)	(0.041)	(0.051)	(0.044)	(0.050)	(0.044)	(0.074)	(0.054)
Mean	-1.785	-1.793	-1.785	-1.793	-1.785	-1.793	-1.785	-1.793	-1.785	-1.793	-1.762	-1.778
Observations	3094	4030	3094	4030	3094	4030	3094	4030	3094	4030	2173	3109
Clusters	230	301	230	301	230	301	230	301	230	301	164	235
Panel C: Infertile areas (1962)												
Bombing	0.080**	0.073**	0.087**	0.080**	0.070**	0.062**	0.082**	0.074**	0.081**	0.072**	0.094**	0.080*
	(0.036)	(0.033)	(0.036)	(0.033)	(0.033)	(0.031)	(0.035)	(0.033)	(0.035)	(0.033)	(0.045)	(0.041)
Mean	-1.831	-1.817	-1.831	-1.817	-1.831	-1.817	-1.831	-1.817	-1.831	-1.817	-1.838	-1.818
Observations	6042	8016	6042	8016	6042	8016	6042	8016	6042	8016	4364	6338
Clusters	429	564	429	564	429	564	429	564	429	564	307	442

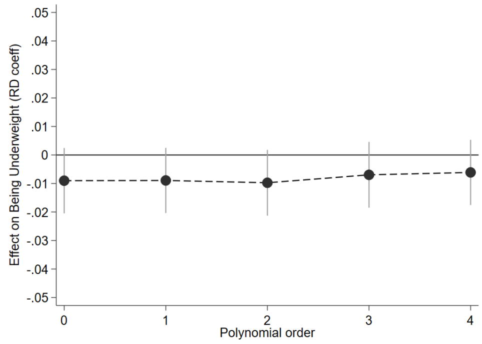
Note: The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. Regression (9) (10) conduct a donut exercise that excludes observations within 0.25 km the bombing boundaries. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure A.3: Being Underweight: Sensitivity of Results to Different Orders of Polynomial

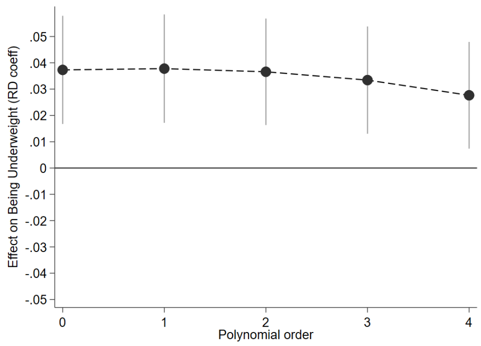
Panel A: Within 1km bandwidth | **Panel B: Within 1.5km bandwidth**



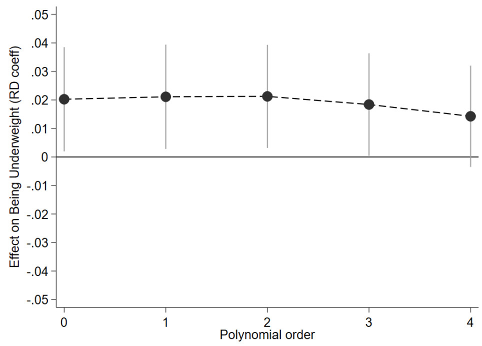
(a) All sample



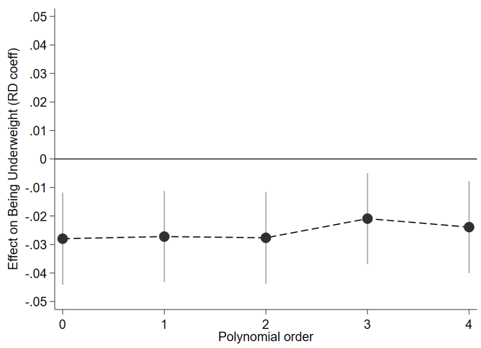
(b) All sample



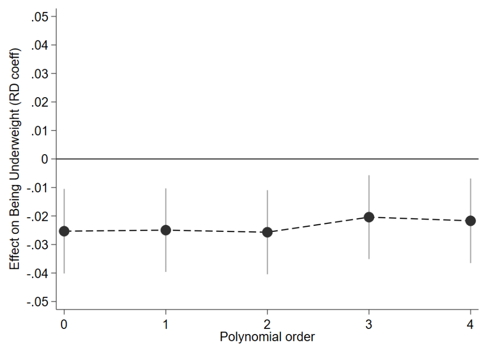
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)



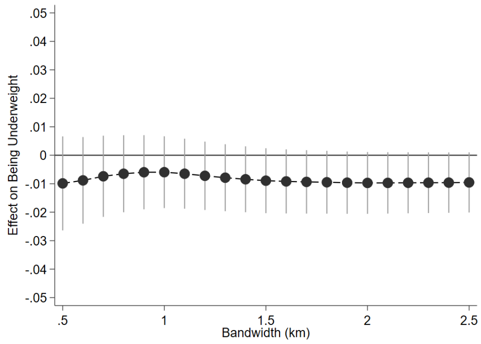
(f) Infertile areas (1962)

Note: Dependent variable is Being Underweight. Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

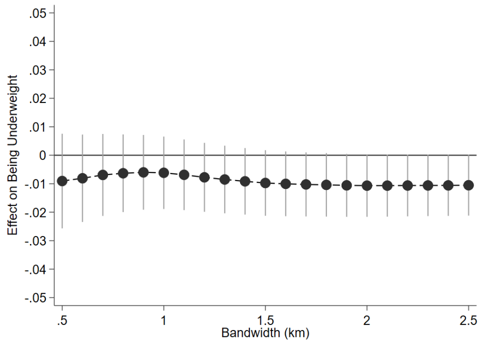
Figure A.4: Being Underweight: Sensitivity of Results to Bandwidth Choice

Panel A: Linear polynomial

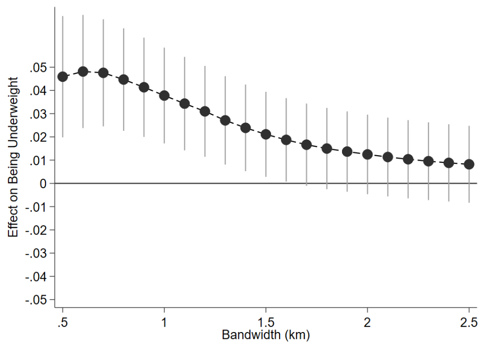
Panel B: Quadratic polynomial



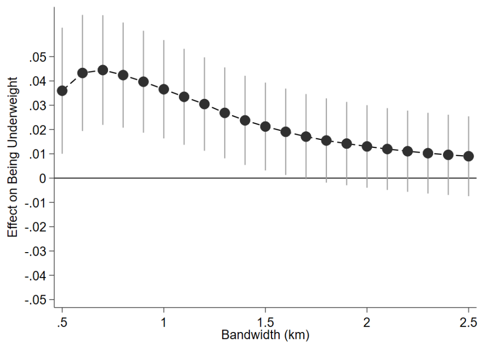
(a) All sample



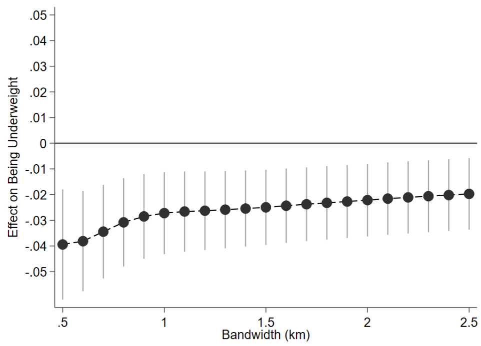
(b) All sample



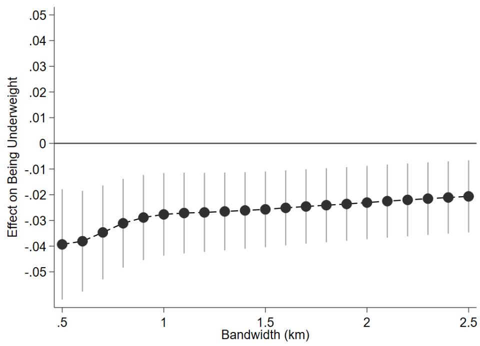
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)



(f) Infertile areas (1962)

Note: Dependent variable is Being Underweight. Each sub-graph reports coefficient estimates and confidence intervals for different bandwidth levels ranging from 0.5 to 2.5 kilometers (horizontal axis) with 0.1km intervals. Each dot indicates the RD estimate using the specified bandwidth. Range spikes represent 90% confidence intervals of the estimates. Panel A displays the coefficients in regresions controlling for a linear polynomial in latitude and longitude. Panel B reports the coefficients in regressions controlling for a quadratic polynomial in latitude and longitude.

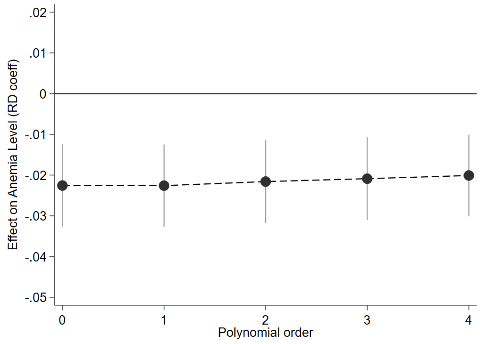
Table A.3: Being Underweight - Robustness checks: different specifications with latitude-longitude as running variables

	Dependent variable is being underweight											
	Quadratic		Cubic		No weight		No dist_capital		No dist_vietnam		Donut 0.25km	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km	(7) <1km	(8) <1.5km	(9) <1km	(10) <1.5km	(11) <1km	(12) <1.5km
Panel A: All observations												
Bombing	-0.006	-0.010	-0.003	-0.007	-0.007	-0.011	-0.006	-0.009	-0.006	-0.009	0.015	0.004
	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.008)	(0.010)	(0.009)	(0.010)	(0.009)	(0.012)	(0.011)
Mean	0.187	0.185	0.187	0.185	0.187	0.185	0.187	0.185	0.187	0.185	0.188	0.185
Observations	9136	12046	9136	12046	9136	12046	9136	12046	9136	12046	6537	9447
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Panel B: Fertile areas (1962)												
Bombing	0.037**	0.021	0.033**	0.018	0.020	0.001	0.038**	0.021	0.037**	0.019	0.038*	0.011
	(0.016)	(0.014)	(0.016)	(0.014)	(0.015)	(0.013)	(0.016)	(0.014)	(0.016)	(0.014)	(0.021)	(0.017)
Mean	0.182	0.177	0.182	0.177	0.182	0.177	0.182	0.177	0.182	0.177	0.179	0.173
Observations	3094	4030	3094	4030	3094	4030	3094	4030	3094	4030	2173	3109
Clusters	230	301	230	301	230	301	230	301	230	301	164	235
Panel C: Infertile areas (1962)												
Bombing	-0.028**	-0.026**	-0.021*	-0.020*	-0.021*	-0.019*	-0.027**	-0.025**	-0.027**	-0.025**	-0.000	-0.004
	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.015)	(0.014)
Mean	0.190	0.189	0.190	0.189	0.190	0.189	0.190	0.189	0.190	0.189	0.192	0.190
Observations	6042	8016	6042	8016	6042	8016	6042	8016	6042	8016	4364	6338
Clusters	429	564	429	564	429	564	429	564	429	564	307	442

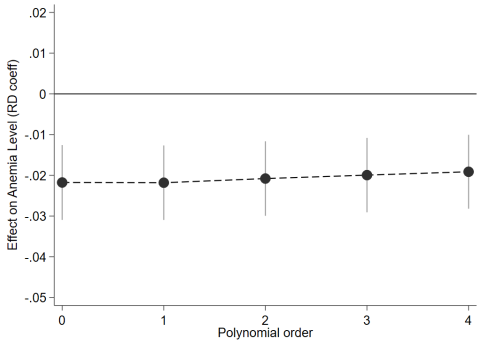
Note: The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. Regression (9) (10) conduct a donut exercise that excludes observations within 0.25 km the bombing boundaries. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure A.5: Anemia: Sensitivity of Results to Different Orders of Polynomial

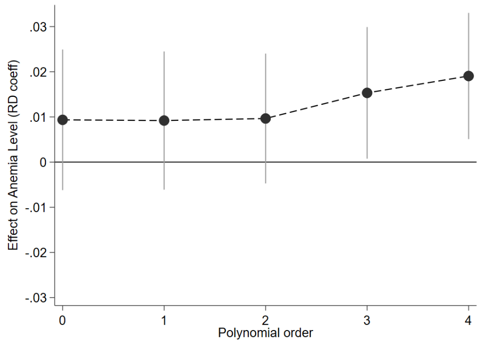
Panel A: Within 1km bandwidth **Panel B: Within 1.5km bandwidth**



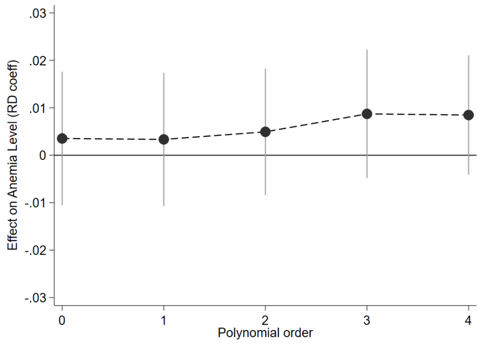
(a) All sample



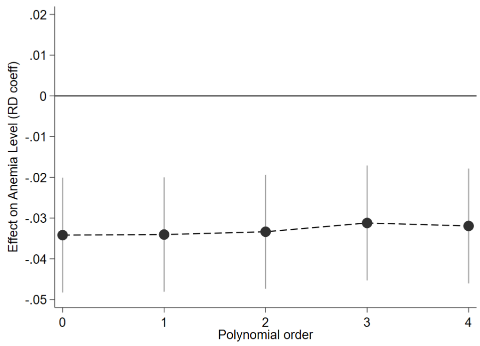
(b) All sample



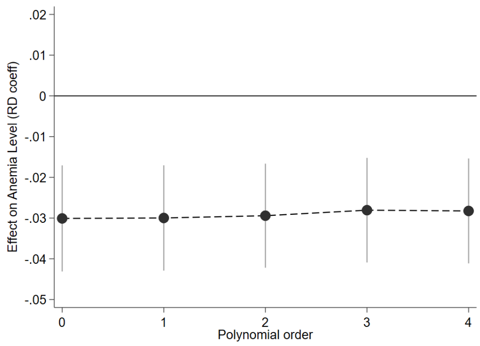
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)

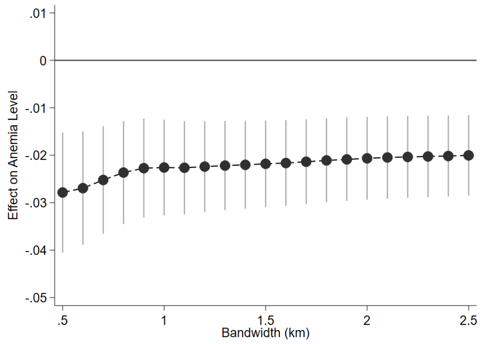


(f) Infertile areas (1962)

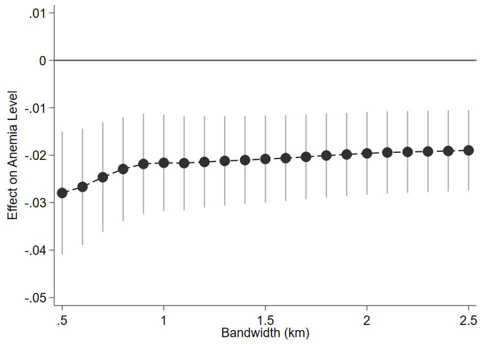
Note: Dependent variable is Anemia Level (ANE). Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

Figure A.6: Anemia level: Sensitivity of Results to Bandwidth Choice

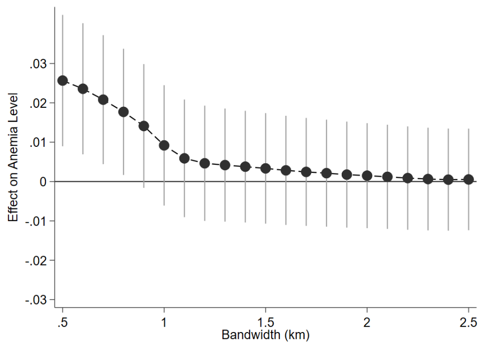
Panel A: Linear polynomial **Panel B: Quadratic polynomial**



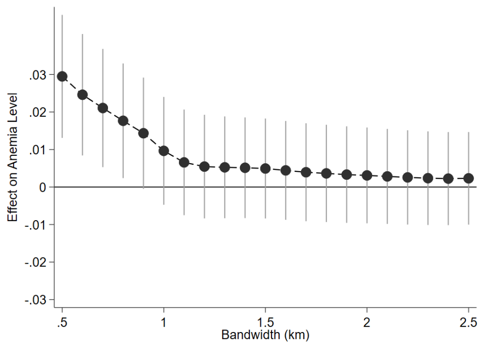
(a) All sample



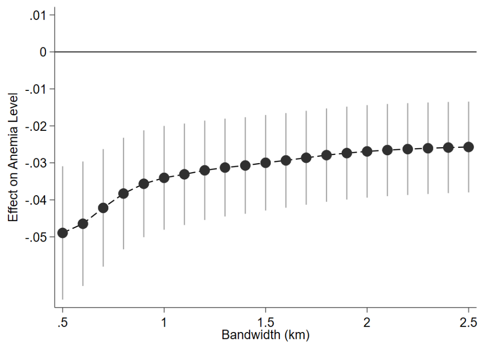
(b) All sample



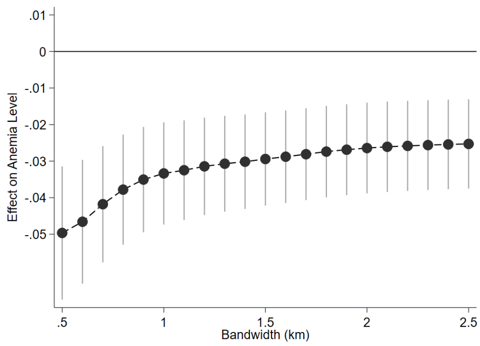
(c) Fertile areas (1962)



(d) Fertile areas (1962)



(e) Infertile areas (1962)



(f) Infertile areas (1962)

Note: Dependent variable is Anemia Level(ANE). Each sub-graph reports coefficient estimates and confidence intervals for different bandwidth levels ranging from 0.5 to 2.5 kilometers (horizontal axis) with 0.1km intervals. Each dot indicates the RD estimate using the specified bandwidth. Range spikes represent 90% confidence intervals of the estimates. Panel A displays the coefficients in regresions controlling for a linear polynomial in latitude and longitude. Panel B reports the coefficients in regressions controlling for a quadratic polynomial in latitude and longitude.

Table A.4: Anemia - Robustness checks: different specifications with latitude-longitude as running variables

	Dependent variable is Anemia Level											
	Quadratic		Cubic		No weight		No dist_capital		No dist_vietnam		Donut 0.25km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations												
Bombing	-0.022***	-0.021***	-0.021***	-0.020***	-0.022***	-0.020***	-0.022***	-0.022***	-0.023***	-0.022***	-0.019*	-0.022**
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)	(0.009)
Mean	0.0977	0.0954	0.0977	0.0954	0.0977	0.0954	0.0977	0.0954	0.0977	0.0954	0.0979	0.0948
Observations	9136	12046	9136	12046	9136	12046	9136	12046	9136	12046	6537	9447
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Panel B: Fertile areas (1962)												
Bombing	0.010	0.005	0.015	0.009	-0.006	-0.000	0.009	0.004	0.011	0.004	-0.003	-0.010
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)	(0.012)	(0.011)	(0.012)	(0.011)	(0.017)	(0.015)
Mean	0.0792	0.0799	0.0792	0.0799	0.0792	0.0799	0.0792	0.0799	0.0792	0.0799	0.0792	0.0801
Observations	3094	4030	3094	4030	3094	4030	3094	4030	3094	4030	2173	3109
Clusters	230	301	230	301	230	301	230	301	230	301	164	235
Panel C: Infertile areas (1962)												
Bombing	-0.033***	-0.029***	-0.031***	-0.028***	-0.027***	-0.024**	-0.034***	-0.030***	-0.034***	-0.030***	-0.021	-0.023*
	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.014)	(0.013)
Mean	0.107	0.103	0.107	0.103	0.107	0.103	0.107	0.103	0.107	0.103	0.107	0.102
Observations	6042	8016	6042	8016	6042	8016	6042	8016	6042	8016	4364	6338
Clusters	429	564	429	564	429	564	429	564	429	564	307	442

Note: The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. Regression (9) (10) conduct a donut exercise that excludes observations within 0.25 km the bombing boundaries. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.5: Height-for-age Z-score - Robustness checks: Shifting borders

	Dependent variable is Height-for-age Z-score							
	Shift east		Shift west		Shift north		Shift south	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations								
Bombing	-0.006	0.006	-0.055*	-0.044	0.006	0.004	0.004	0.000
	(0.027)	(0.025)	(0.030)	(0.027)	(0.024)	(0.022)	(0.029)	(0.026)
Mean	0.624	0.769	0.561	0.711	0.633	0.757	0.614	0.781
Observations	9513	12663	8987	12427	10138	13216	9666	13408
Clusters	680	900	652	888	714	939	686	946
Panel B: Fertile areas (1962)								
Bombing	-0.041	-0.027	-0.065	-0.063	-0.042	-0.050	0.011	0.009
	(0.044)	(0.038)	(0.050)	(0.046)	(0.035)	(0.034)	(0.049)	(0.042)
Mean	0.668	0.847	0.623	0.751	0.646	0.779	0.583	0.743
Observations	3415	4786	3305	4537	3805	4881	3412	4703
Clusters	254	350	247	332	269	349	248	339
Panel C: Infertile areas (1962)								
Bombing	0.001	0.015	-0.073**	-0.050	0.040	0.037	0.008	0.003
	(0.037)	(0.033)	(0.036)	(0.033)	(0.032)	(0.029)	(0.036)	(0.033)
Mean	0.601	0.730	0.529	0.691	0.627	0.746	0.629	0.800
Observations	6098	7877	5682	7890	6333	8335	6254	8705
Clusters	426	550	405	556	445	590	438	607

Note: The table shows the results of placebo tests which shift bombing borders by 3 kilometers to four different directions: east-west-north-south. The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.6: Being Underweight - Robustness checks: Shifting borders

	Dependent variable is Being Underweight							
	Shift east		Shift west		Shift north		Shift south	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations								
Bombing	0.005	-0.001	0.017	0.015	0.003	0.003	-0.009	-0.009
	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)
Mean	0.624	0.769	0.561	0.711	0.633	0.757	0.614	0.781
Observations	9513	12663	8987	12427	10138	13216	9666	13408
Clusters	680	900	652	888	714	939	686	946
Panel B: Fertile areas (1962)								
Bombing	0.046***	0.032***	0.029*	0.019	0.025*	0.018	0.000	-0.001
	(0.013)	(0.012)	(0.016)	(0.015)	(0.014)	(0.013)	(0.017)	(0.016)
Mean	0.668	0.847	0.623	0.751	0.646	0.779	0.583	0.743
Observations	3415	4786	3305	4537	3805	4881	3412	4703
Clusters	254	350	247	332	269	349	248	339
Panel C: Infertile areas (1962)								
Bombing	-0.013	-0.018	0.012	0.016	-0.004	-0.004	-0.006	-0.009
	(0.014)	(0.012)	(0.016)	(0.014)	(0.012)	(0.011)	(0.012)	(0.011)
Mean	0.601	0.730	0.529	0.691	0.627	0.746	0.629	0.800
Observations	6098	7877	5682	7890	6333	8335	6254	8705
Clusters	426	550	405	556	445	590	438	607

Note: The table shows the results of placebo tests which shift bombing borders by 3 kilometers to four different directions: east-west-north-south. The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.7: Anemia - Robustness checks: Shifting borders

	Dependent variable is Anemia Level							
	Shift east		Shift west		Shift north		Shift south	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations								
Bombing	0.001	-0.001	0.003	0.002	0.002	0.004	0.014*	0.013*
	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)
Mean	0.624	0.769	0.561	0.711	0.633	0.757	0.614	0.781
Observations	9513	12663	8987	12427	10138	13216	9666	13408
Clusters	680	900	652	888	714	939	686	946
Panel B: Fertile areas (1962)								
Bombing	0.018	0.013	0.011	0.011	0.004	0.009	0.029**	0.027**
	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.012)	(0.011)
Mean	0.668	0.847	0.623	0.751	0.646	0.779	0.583	0.743
Observations	3415	4786	3305	4537	3805	4881	3412	4703
Clusters	254	350	247	332	269	349	248	339
Panel C: Infertile areas (1962)								
Bombing	-0.007	-0.007	0.004	-0.001	0.000	0.001	0.004	0.003
	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)
Mean	0.601	0.730	0.529	0.691	0.627	0.746	0.629	0.800
Observations	6098	7877	5682	7890	6333	8335	6254	8705
Clusters	426	550	405	556	445	590	438	607

Note: The table shows the results of placebo tests which shift bombing borders by 3 kilometers to four different directions: east-west-north-south. The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

B Heterogenous effects in fertile and infertile areas

In section 5.1, we show that observed positive health impacts are driven by areas characterized by infertile soil and a lower probability of encountering unexploded ordnance. Meanwhile, we see no effects in areas where soil was fertile in 1962. We further deepen our understanding by investigating heterogeneous impacts on different generations in these regions.

Table B.1: Outcomes on different generations in fertile areas

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Individuals born by 1975						
Bombing	-0.128*	-0.117*	0.045*	0.025	0.015	0.009
	(0.070)	(0.060)	(0.024)	(0.020)	(0.019)	(0.017)
Mean	-1.818	-1.812	0.161	0.152	0.0867	0.0881
Observations	1222	1600	1222	1600	1222	1600
Clusters	227	298	227	298	227	298
Panel B: Individuals born after 1975						
Bombing	0.025	0.027	0.034*	0.018	0.005	-0.002
	(0.055)	(0.049)	(0.019)	(0.017)	(0.016)	(0.014)
Mean	-1.764	-1.780	0.196	0.193	0.0743	0.0745
Observations	1872	2430	1872	2430	1872	2430
Clusters	224	294	224	294	224	294

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table B.1 and B.2 display the results. In fertile regions where the chance of encountering UXO is high (Table B.1), we observe either null or slightly negative impacts across generations. On the contrary, in infertile regions (Table B.2), the effects on two generations are different. In particular, while the effects on height are indistinguishable from zero for people who were born before 1975, we observe statistically significant positive impacts for individuals born after the bombing with a jump of 0.097 (or 0.086) , equal to 5%, in their Health-for-age Z-scores. In terms of weight, the older generation is 3.9 percentage points more likely to be underweight if they are on the bombing side, whereas there is no significant difference in the likelihood of being underweight among the younger generation. With regard to anemia, older people residing on the bombing side are less

Table B.2: Outcomes on different generations in infertile areas

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Individuals born by 1975						
Bombing	0.055	0.051	-0.039**	-0.037**	-0.058***	-0.050***
	(0.042)	(0.040)	(0.019)	(0.018)	(0.017)	(0.016)
Mean	-1.877	-1.874	0.172	0.169	0.132	0.129
Observations	2381	3171	2381	3171	2381	3171
Clusters	427	561	427	561	427	561
Panel B: Individuals born after 1975						
Bombing	0.097**	0.086**	-0.022	-0.019	-0.017	-0.016
	(0.043)	(0.040)	(0.016)	(0.015)	(0.012)	(0.011)
Mean	-1.801	-1.780	0.201	0.202	0.0912	0.0861
Observations	3661	4845	3661	4845	3661	4845
Clusters	423	556	423	556	423	556

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

likely to suffer from anemia, with a drop of around 5.8 (or 5) percentage points in anemia risk. This drop is equivalent to around 40% deviation from the mean value of anemia likelihood in this age group. Overall, this impact heterogeneity is consistent with our results in Section 5.4.

C Aerial bombing and mining in later periods

Table C.1: Exclude provinces along K5 mine belt

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Fertile areas (1962)						
Bombing	-0.046	-0.042	0.043***	0.024*	0.016	0.010
	(0.053)	(0.047)	(0.016)	(0.014)	(0.012)	(0.011)
Mean	-1.784	-1.790	0.184	0.179	0.0796	0.0811
Observations	2865	3712	2865	3712	2865	3712
Clusters	216	280	216	280	216	280
Panel B: Infertile areas (1962)						
Bombing	0.082**	0.074**	-0.025*	-0.024*	-0.037***	-0.033***
	(0.036)	(0.034)	(0.014)	(0.012)	(0.012)	(0.011)
Mean	-1.815	-1.806	0.190	0.189	0.104	0.0992
Observations	5427	7237	5427	7237	5427	7237
Clusters	387	509	387	509	387	509

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table C.2: Controlling for distance to Thai borders

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Fertile areas (1962)						
Bombing	-0.035	-0.032	0.038**	0.021	0.009	0.003
	(0.051)	(0.044)	(0.016)	(0.014)	(0.012)	(0.011)
Mean	-1.785	-1.793	0.182	0.177	0.0792	0.0799
Observations	3094	4030	3094	4030	3094	4030
Clusters	230	301	230	301	230	301
Panel B: Infertile areas (1962)						
Bombing	0.082**	0.074**	-0.027**	-0.025**	-0.034***	-0.030***
	(0.035)	(0.033)	(0.012)	(0.011)	(0.011)	(0.010)
Mean	-1.831	-1.817	0.190	0.189	0.107	0.103
Observations	6042	8016	6042	8016	6042	8016
Clusters	429	564	429	564	429	564

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

D Uni-dimensional RD design

D.1 Specification with unidimensional RD polynomial

We use the uni-dimensional RD design to cross-verify our results. The regressions take the same form as our main specification. However, in this setting, RD polynomial $f(Geo_c)$ uses a mono-dimensional measure, in particular, distance to bombing boundaries as a running variable.

The local linear polynomial has a function as $f(Geo_c) = \eta dist_c$ with the forcing variable $dist_c$ denotes the Euclidean distance between a household location and the closest point on bombing boundaries. Higher-order polynomials will take the following form: $f(Geo_c) = \sum_{k=1}^{a} \eta_k dist_c^k$.

In terms of bandwidth selection, the estimation sample is restricted to individuals falling within a bandwidth around bombing boundaries chosen following Calonico et al. (2014).

D.2 Results

The unidimensional RD design yields similar results as our main design (Table D.1). In all analyses, individuals residing on the bombing side exhibit better health outcomes, specifically in height and reduced likelihood of anemia. About Height-for-age Z-scores, our estimates in unidimensional RD models are more significant and larger in magnitude: residents in bombing areas experience an average increase of 0.097 (approximately 5%) in Height-for-age Z-scores. In terms of the likelihood of being underweight, people living in bombing areas are less likely to be underweight, although this estimate is indistinguishable from zero. Regarding anemia, those on the bombing side face a 2.5% lower risk of anemia.

We also found consistent heterogeneous effects in two distinctive regions, with positive effects notably substantial for those living in pre-bombing infertile areas with a lower UXO occurrence. Particularly, in these infertile areas, those living on the bombing side experience an increase of 0.137 (or 0.141) in their Height-for-age Z-scores, equivalent to around 7.5% compared to the mean. They are also 3 percentage points less likely to be underweight and 4.3 percentage points less likely to suffer from severe anemia. Meanwhile, we do not observe positive health impacts in fertile areas with a high risk of UXO. The findings align consistently with the latitude-longitude RD results, with estimates not only larger in magnitude but also statistically significant.

Figure D.1 visually illustrates the heterogeneous effects of bombing. Panel A shows the results in fertile areas, while Panel B focuses on infertile areas. In Panel A, all outcomes are continuous, meaning women's health is indifferent across the bombing boundaries. However, in Panel B, across all graphs, we can observe some clear discontinuities at the bombing boundaries. There is a significant jump in Height-for-age Z-scores for those located on the bombing side. In terms of being underweight, we can see a small drop,

Table D.1: Results with unidimensional RD design

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1) Linear	(2) Quad.	(3) Linear	(4) Quad.	(5) Linear	(6) Quad.
Panel A: All population						
Bombing	0.097***	0.099***	-0.012	-0.012	-0.025**	-0.026**
	(0.038)	(0.037)	(0.011)	(0.011)	(0.010)	(0.010)
Mean	-1.80	-1.80	0.18	0.18	0.091	0.091
Observations	14887	14887	18406	18406	15385	15385
Bandwidth (km)	2.05	2.05	3.01	3.01	2.11	2.11
Clusters	1053	1053	1298	1298	1087	1087
Panel B: Fertile areas (1962)						
Bombing	-0.017	-0.017	0.016	0.016	0.005	0.005
	(0.053)	(0.053)	(0.018)	(0.018)	(0.013)	(0.013)
Mean	-1.77	-1.77	0.17	0.17	0.075	0.075
Observations	6330	6330	7019	7019	6179	6179
Bandwidth (km)	2.80	2.80	3.38	3.38	2.70	2.70
Clusters	454	454	499	499	444	444
Panel C: Infertile areas (1962)						
Bombing	0.137***	0.141***	-0.030**	-0.030**	-0.043***	-0.045***
	(0.047)	(0.047)	(0.015)	(0.015)	(0.015)	(0.015)
Mean	-1.82	-1.82	0.19	0.19	0.10	0.10
Observations	9182	9182	11070	11070	8670	8670
Bandwidth (km)	1.92	1.92	2.58	2.58	1.72	1.72
Clusters	642	642	776	776	609	609

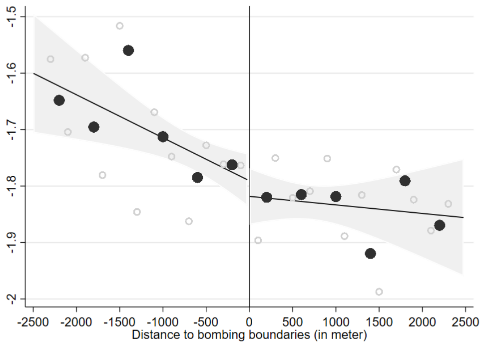
Note: The unit of analysis is survey respondents. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) control for a linear polynomial in distance to the bombing boundaries. Regressions (2) (4) (6) control for quadratic polynomials in distance to the bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

meaning that in infertile areas, women are less likely to be underweight. Additionally, there is a noticeable decrease in anemia prevalence for those living in infertile areas and on the bombing side.

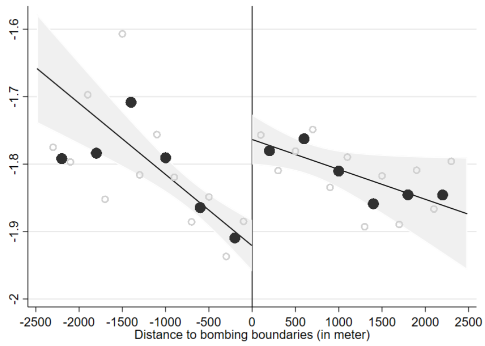
Figure D.1: Unidimensional RD design: Heterogeneous effects split by 1962 soil fertility

Panel A: Fertile areas (1962)

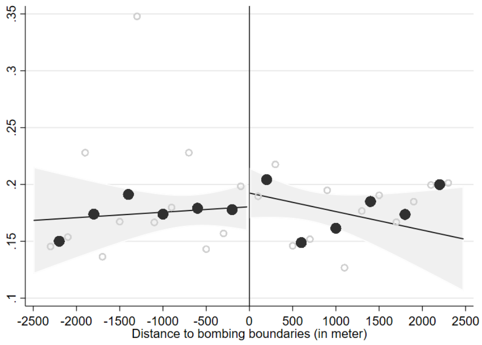
Panel B: Infertile areas (1962)



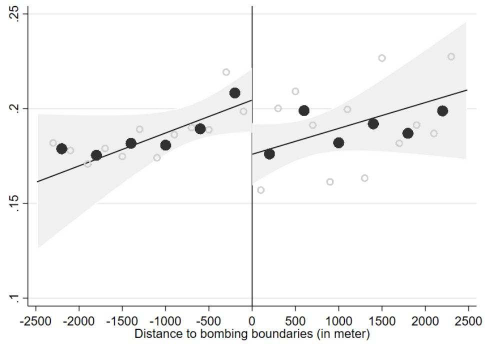
(a) Height-for-age Z-score



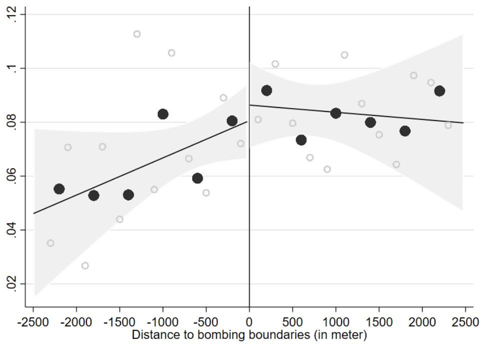
(b) Height-for-age Z-score



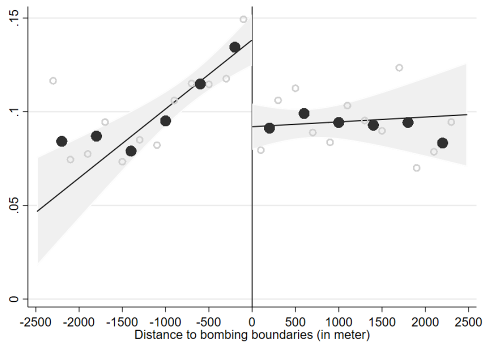
(c) Being Underweight



(d) Being Underweight



(e) Anemia Level



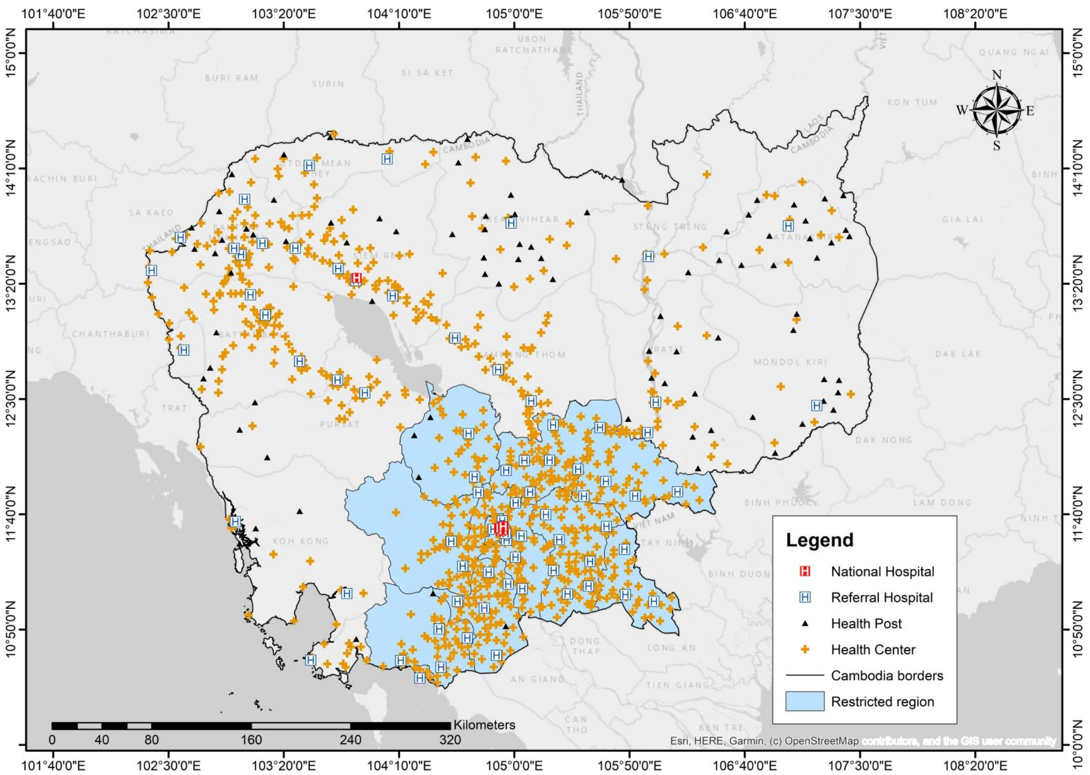
(f) Anemial level

Note: Solid dots present the average of outcomes for observations within 400-meter distane bins. Hollow dots present the average for observations within 200-meter distance bins. “Distance to bombing boundary” refers to the distance to the closest point in bombing boundaries. “Negative” values of distance indicate locations outside the bombing areas. The solid line trends give the predicted values from a regression of the outcome variable on a linear polynomial in distance to the bombing boundaries. Figures (a) (c) (e) illustrate results from the sample of population born by 1975 who experienced bombing, whereas figures (b) (d) (f) show results from a sample born after the bombing period.

E Restricted region analysis

To examine the consistency of our results, we restrict our analysis to the region around the capital. The defined restricted region (Figure E.1) encompasses the capital city and adjacent provinces, which display a noticeable clustering of health facilities. Interestingly, this particular region stands out for its concentrated level of bombing in the past compared to other regions in the country (Figure E.2).

Figure E.1: Restricted region and health facilities

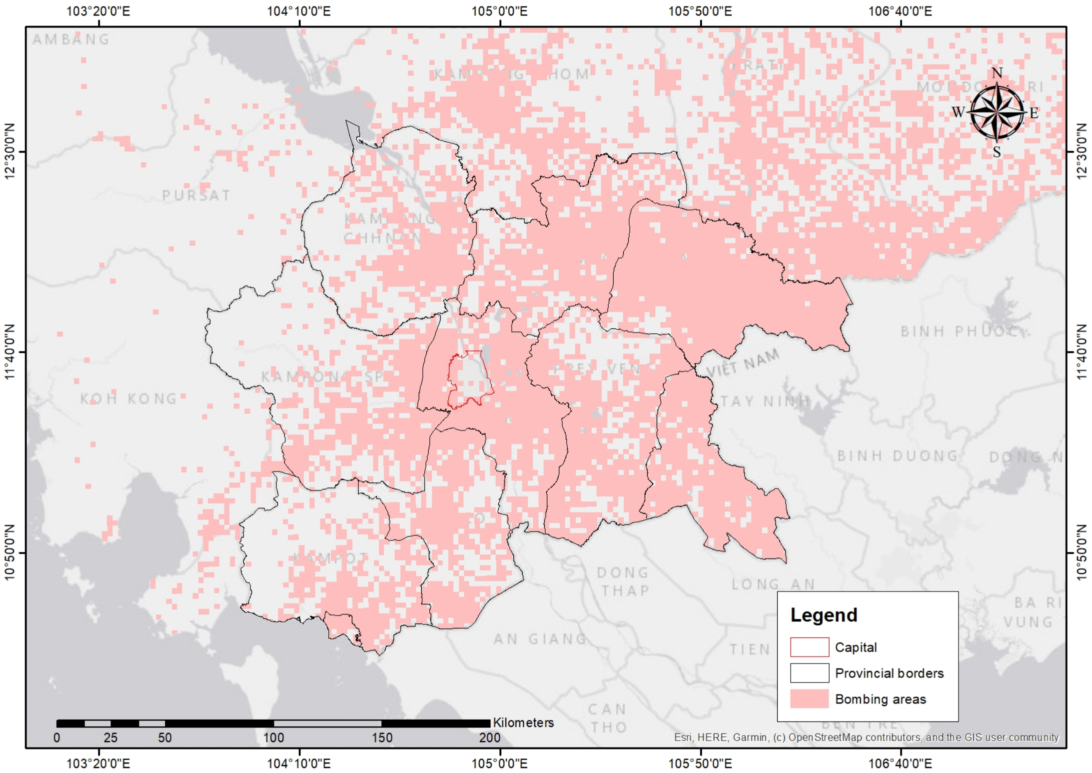


Notes: The map shows the restricted region for analysis. It also depicts locations of health facilities, including national hospital, referral hospitals, health centers, and health posts in Cambodia. Map overlaid on OpenStreetMap and drawn on ArcGIS.

The findings of our primary RD design, examining the lasting causal effects of living in bombing areas on various health outcomes in the restricted region, are presented in Table E.1. The results are also disaggregated for two distinct regions, with positive effects notably shown up in infertile areas. In terms of Height-for-age Z-scores, although coefficients for all population are indistinguishable from zero, we observe significant positive effects on height in infertile areas. In particular, those in infertile areas and on the bombing side have approximately 0.076 (or 0.079) higher Height-for-age Z-score, which is consistent with our main results.

Similarly, regarding the likelihood of being underweight, we found evidence of positive effects for those on the bombing side and living in infertile areas, with a reduction of about

Figure E.2: Bombing in restricted region



Notes: Map overlaid on OpenStreetMap base map and drawn on ArcGIS.

3 percentage points on the likelihood of being underweight. Meanwhile, in fertile areas, women are 5 percentage points (or 3 percentage points in 1.5km bandwidth analysis) more likely to be underweight.

Concerning anemia prevalence, individuals residing in areas subjected to bombing are less likely to experience anemia, particularly among those living in infertile areas. Regression findings for individuals in infertile areas indicate a significant decrease of 4.3 percentage points in anemia prevalence, constituting an approximately 45% decrease relative to the average likelihood of anemia within this group. On the contrary, in fertile areas, we can see somewhat negative impacts as women are more likely to suffer from serious anemia if they are on the bombing side.

Overall, we found that the positive effects were completely driven in infertile areas, which is consistent with our main analysis in Section 5.2. Additionally, in fertile areas with a higher likelihood of encountering UXO at present, we see null or even some significant negative impacts on health.

Table E.2 shows the effects on distance to health facilities in this restricted region. Even in the region where health facilities are concentrated, the distance to health facilities is significantly shorter for those on the bombing side. Most importantly, these positive effects are noticeable in pre-bombing infertile areas. The distance to the nearest district

Table E.1: Regional analysis

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.034	0.041	-0.002	-0.009	-0.018*	-0.020**
	(0.035)	(0.032)	(0.012)	(0.011)	(0.009)	(0.009)
Mean	-1.779	-1.769	0.191	0.189	0.0871	0.0873
Observations	6248	8147	6248	8147	6248	8147
Clusters	455	587	455	587	455	587
Panel B: Fertile areas (1962)						
Bombing	-0.076	-0.056	0.050***	0.031**	0.025**	0.013
	(0.057)	(0.050)	(0.017)	(0.015)	(0.012)	(0.011)
Mean	-1.771	-1.759	0.186	0.181	0.0738	0.0767
Observations	2248	2830	2248	2830	2248	2830
Clusters	168	213	168	213	168	213
Panel C: Infertile areas (1962)						
Bombing	0.076*	0.079**	-0.033*	-0.032**	-0.043***	-0.043***
	(0.043)	(0.040)	(0.017)	(0.016)	(0.013)	(0.013)
Mean	-1.783	-1.774	0.194	0.193	0.0945	0.0929
Observations	4000	5317	4000	5317	4000	5317
Clusters	287	374	287	374	287	374

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

health center drops by about 1km, roughly one-third of the average distance. Similarly, there is a significant decrease of 0.986 km (or 0.869km) in the distance to any health facility. Meanwhile, in fertile areas with a high probability of UXO, we observe negative impacts on healthcare accessibility, with the distance to the nearest hospital increasing by approximately 2.8km and the distance to any health facility increasing by around 0.4km for those living inside bombing areas.

Table E.2: Restricted region: Distance to health facilities

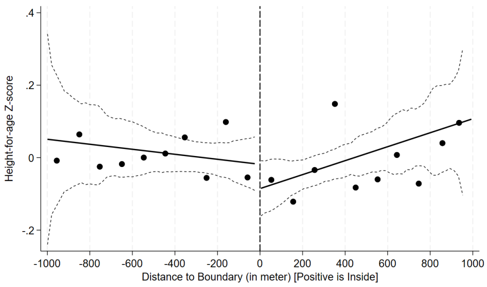
	Dependent variable is Distance (km) to					
	Hospital		District health center		Any health facility	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Restricted region						
Bombing	0.317	0.554	-0.632***	-0.524***	-0.507**	-0.415**
	(0.602)	(0.552)	(0.210)	(0.199)	(0.202)	(0.193)
Mean	9.439	9.340	2.705	2.725	2.645	2.670
Observations	6248	8147	6248	8147	6248	8147
Clusters	455	587	455	587	455	587
Panel B: Fertile areas (1962)						
Bombing	2.754***	2.843***	0.091	0.151	0.373*	0.401*
	(0.685)	(0.641)	(0.235)	(0.227)	(0.219)	(0.210)
Mean	7.562	7.368	2.243	2.283	2.139	2.183
Observations	2248	2830	2248	2830	2248	2830
Clusters	168	213	168	213	168	213
Panel C: Infertile areas(1962)						
Bombing	-1.313	-0.917	-1.029***	-0.908***	-0.986***	-0.869***
	(0.813)	(0.778)	(0.278)	(0.272)	(0.277)	(0.272)
Mean	10.49	10.39	2.964	2.961	2.930	2.929
Observations	4000	5317	4000	5317	4000	5317
Clusters	287	374	287	374	287	374

Note: Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

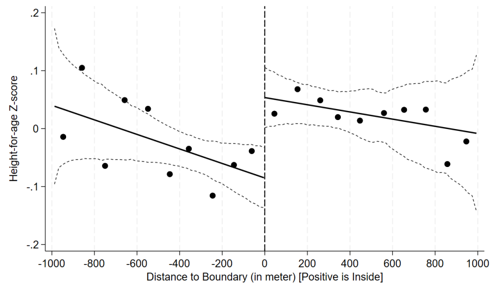
F RD plots

Figure F.1: Heterogeneity impacts splitting by pre-bombing soil fertility: RD plots with 1km bandwidth

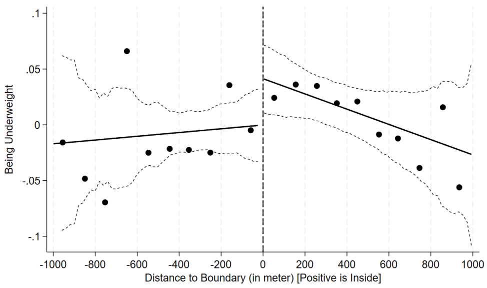
Panel A: Fertile areas **Panel B: Infertile areas**



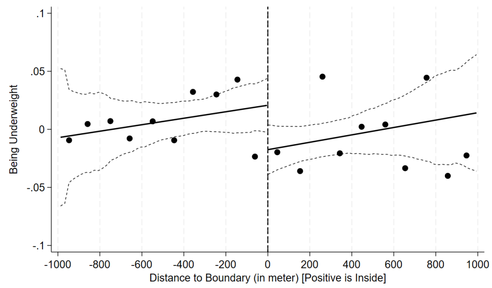
(a) Height-for-age Z-score



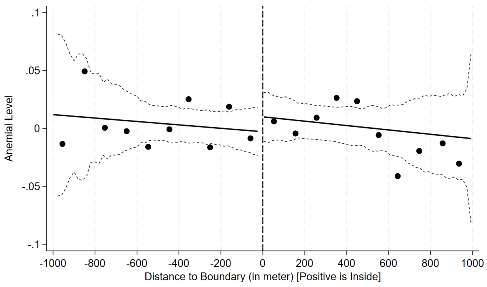
(b) Height-for-age Z-score



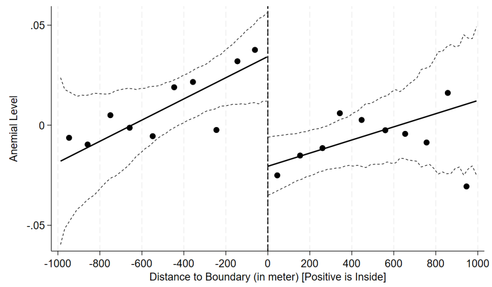
(c) Being underweight



(d) Being underweight



(e) Anemia Level

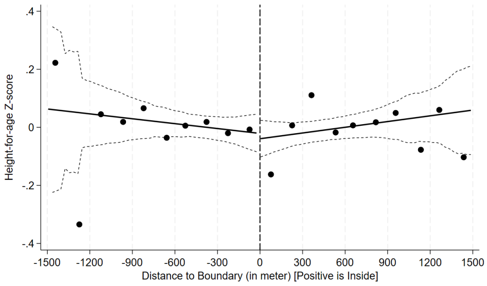


(f) Anemial level

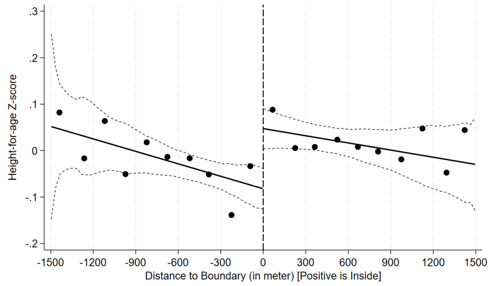
Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in latitude and longitude and other control variables. Solid lines depict a local linear regression, separately estimated on each side of the threshold, while dashed lines represent 95% confidence intervals. "Negative" values of distance indicate locations outside the bombing areas.

Figure F.2: Heterogeneity impacts splitting by pre-bombing soil fertility: RD plots with 1.5km bandwidth

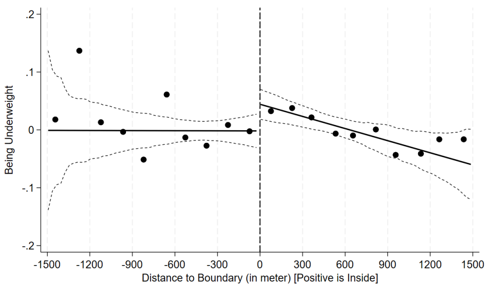
Panel A: Fertile areas | **Panel B: Infertile areas**



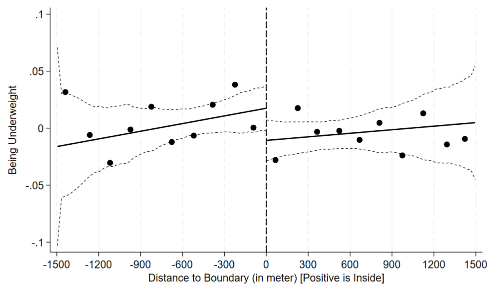
(a) Height-for-age Z-score



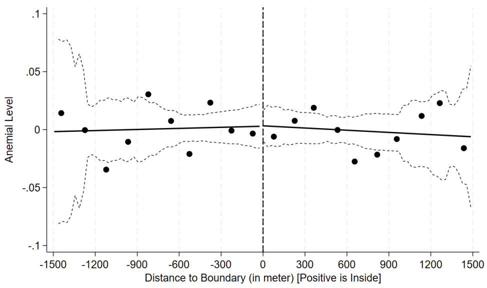
(b) Height-for-age Z-score



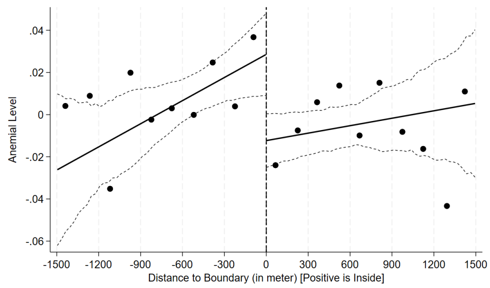
(c) Being underweight



(d) Being underweight



(e) Anemia Level



(f) Anemial level

Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in latitude and longitude and other control variables. Solid lines depict a local linear regression, separately estimated on each side of the threshold, while dashed lines represent 95% confidence intervals. "Negative" values of distance indicate locations outside the bombing areas.

G Additional Tables and Figures

Table G.1: Balance check split by 1962 soil fertility

	Dependent variable is:				
	(1)	(2)	(3)	(4)	(5)
	Elevation	Tropics/lowland	Agri. Activities	Pop. Density	Dist. to roads
Panel A: Fertile areas (1962)					
Bombing	8.917	0.116**	-0.050	0.043	0.765
	(8.201)	(0.058)	(0.048)	(0.033)	(0.756)
Mean	40.34	0.559	0.681	0.488	6.306
Observations	4030	4030	4030	4030	4030
Clusters	301	301	301	301	301
Panel B: Infertile areas (1962)					
Bombing	0.285	-0.033	0.059	-0.048	0.169
	(2.693)	(0.052)	(0.044)	(0.037)	(0.743)
Mean	31.69	0.598	0.591	0.442	6.556
Observations	8016	8016	8016	8016	8016
Clusters	564	564	564	564	564

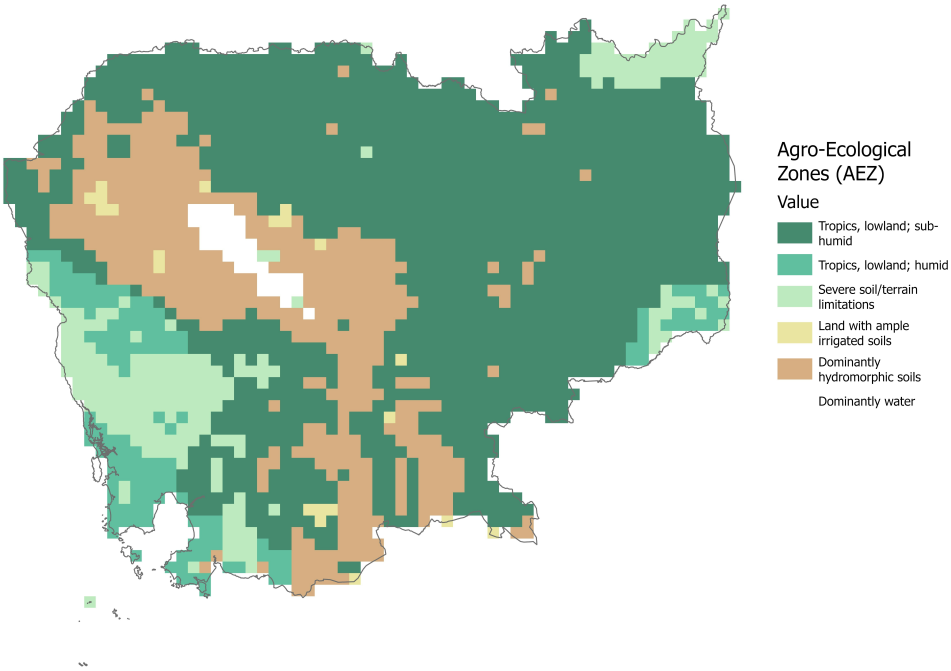
Note: The unit of analysis is survey respondents. The sample restricted to those living within 1.5km bandwidth from bombing boundaries. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. "Tropics/lowland" is a dummy variable reflecting whether this location belongs to areas classified as "tropics, humid" based on agro-ecological zones classification. The last three columns use data from the Indochina Atlas, published in October 1970. Agri. activities indicate whether there were any agricultural activities in these areas in 1970. Pop. density is a binary variable reflecting if the population density in 1970 was at least fifty inhabitants per square kilometre. Dist. to roads refers to distance to 1970 main roads/railways. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table G.2: Migration status

	Dependent variable is: Never moving		
	(1)	(2)	(3)
	All observations	Fertile areas	Infertile areas
Bombing	0.031	0.055	0.022
	(0.027)	(0.034)	(0.038)
Mean	0.637	0.626	0.643
Observations	4619	1533	3086
Clusters	418	143	275

Note: The unit of analysis is survey respondents. The sample restricted to those living within 1.5km bandwidth from bombing boundaries. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. "Never Moving" means individuals report having always live at their current locations. This information is only available in the DHS 2000 and 2004 surveys. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure G.1: Agro-ecological Zones classes

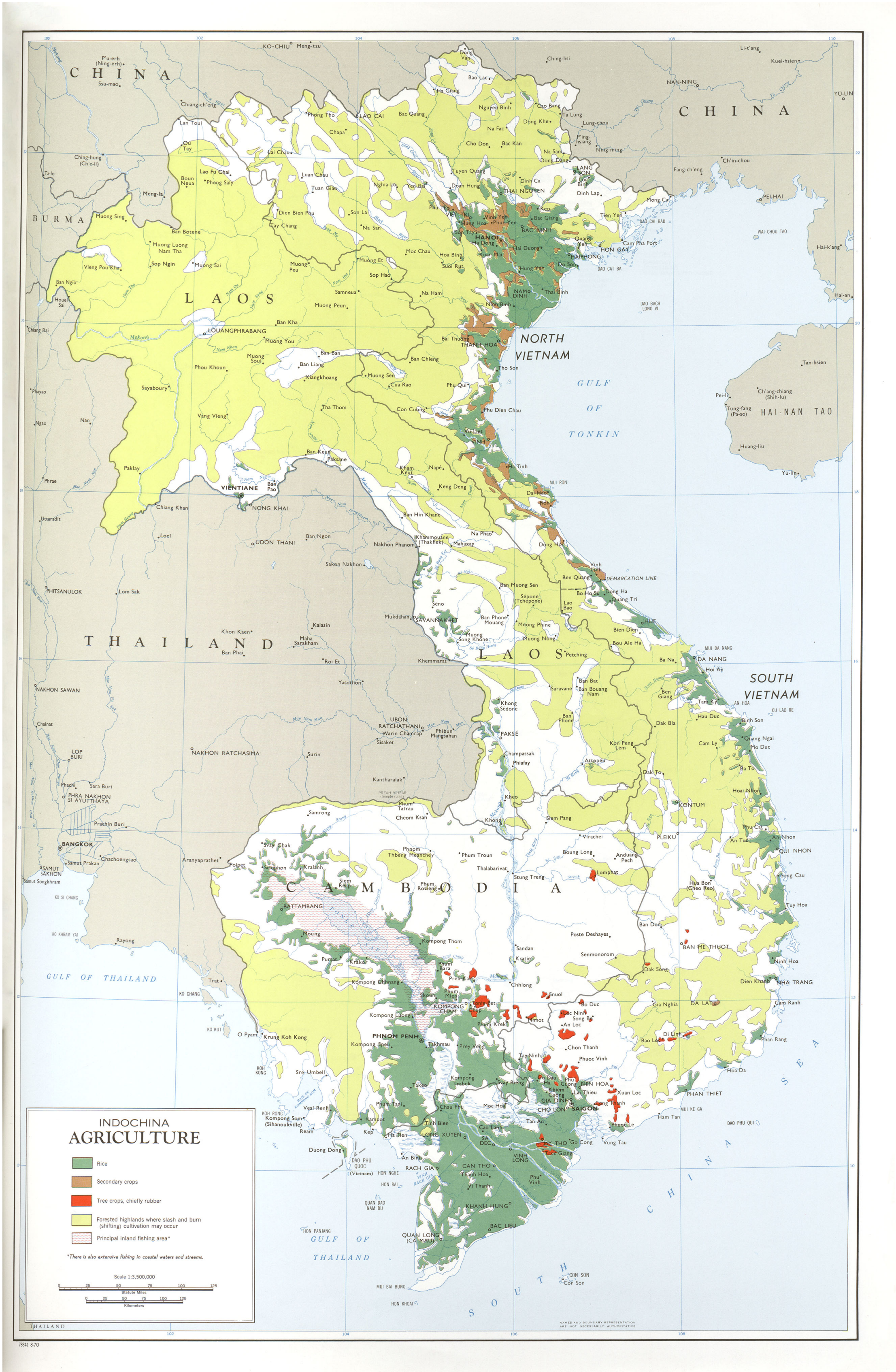


Notes: The map overlays Cambodia to the agro-ecological zones (AEZs) as classiffied by The Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA). Geographic areas belonging to the same AEZ category exhibit analogous climatic characteristics, encompassing rainfall and temperature patterns, and thus possess equivalent agricultural capabilities. Map is drawn on ArcGIS.

Figure G.2: Indochina Transportation in 1970

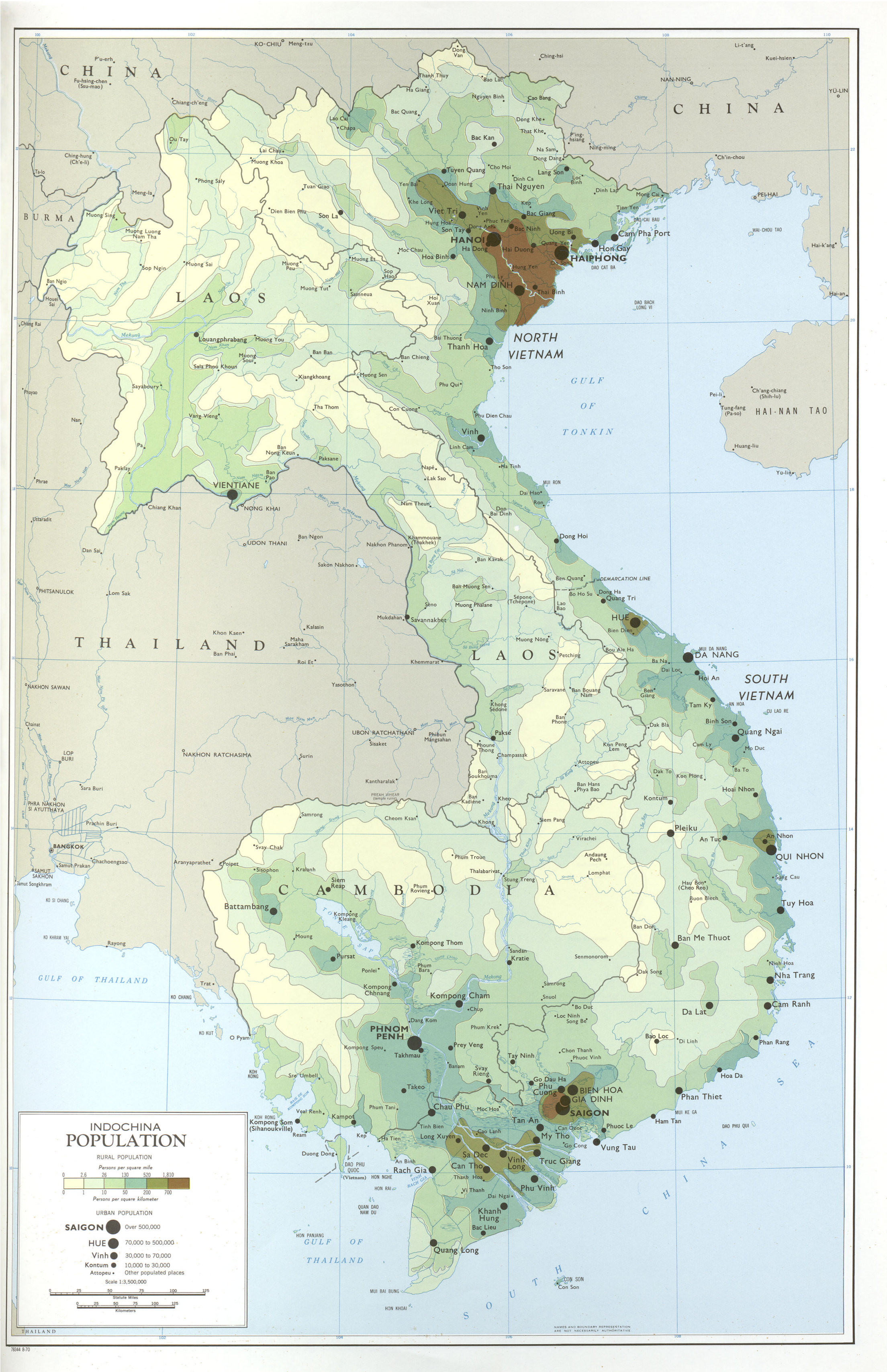
Notes: Indochina Transportation map, which was in "Indochina Atlas", published in October 1970 by the Directorate of Intelligence, Office of Basic and Geographic Intelligence, U.S. Central Intelligence Agency.

Figure G.3: Indochina Agriculture in 1970



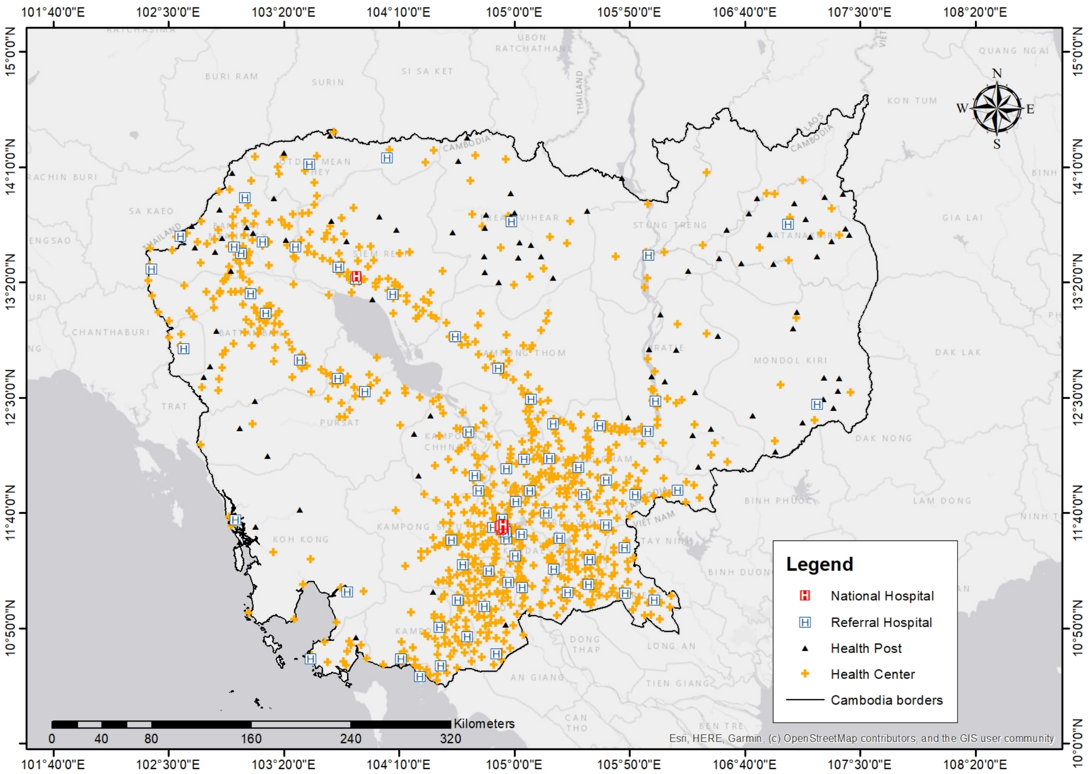
Notes: Indochina Agriculture map, which was in "Indochina Atlas", published in October 1970 by the Directorate of Intelligence, Office of Basic and Geographic Intelligence, U.S. Central Intelligence Agency.

Figure G.4: Indochina Population in 1970



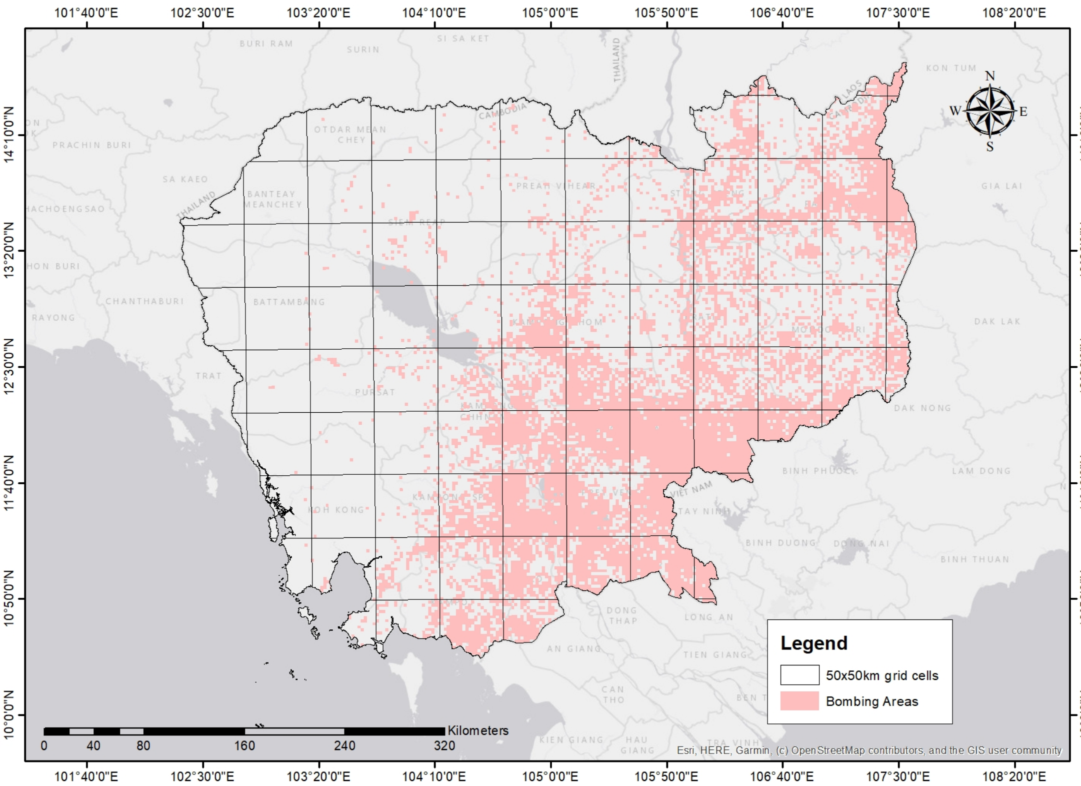
Notes: Indochina Population map, which was in "Indochina Atlas", published in October 1970 by the Directorate of Intelligence, Office of Basic and Geographic Intelligence, U.S. Central Intelligence Agency.

Figure G.5: Health facilities in Cambodia (2010)



Notes: The map depicts locations of health facilities, including national hospital, referral hospitals, health centers, and health posts in Cambodia. The Ministry of Health (MoH) of Cambosia originally compiled the data, which was then contributed by the Office for the Coordination of Humanitarian Affairs (OCHA) to the Humanitarian Data Exchange (HDX). Map overlaid on OpenStreetMap base map and drawn on ArcGIS.

Figure G.6: Generating 50x50km grid cells



Notes: The map illustrates how the country was divided into 50x50km grid-cells. Map overlaid on Open-StreetMap base map and drawn on ArcGIS.

Table G.3: The effects in areas with non-cluster bombs

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km
Panel A: All population						
Bombing	0.067**	0.060**	0.000	-0.004	-0.016*	-0.016**
	(0.032)	(0.028)	(0.010)	(0.009)	(0.008)	(0.008)
Mean	-1.815	-1.809	0.187	0.185	0.0977	0.0954
Observations	8310	10689	8310	10689	8310	10689
Clusters	601	770	601	770	601	770
Panel B: Fertile areas (1962)						
Bombing	-0.051	-0.044	0.047***	0.030*	0.012	0.007
	(0.053)	(0.047)	(0.017)	(0.016)	(0.012)	(0.011)
Mean	-1.785	-1.793	0.182	0.177	0.0792	0.0799
Observations	2790	3508	2790	3508	2790	3508
Clusters	207	261	207	261	207	261
Panel C: Infertile areas (1962)						
Bombing	0.096**	0.080**	-0.029**	-0.028**	-0.025**	-0.020*
	(0.040)	(0.036)	(0.013)	(0.012)	(0.012)	(0.011)
Mean	-1.831	-1.817	0.190	0.189	0.107	0.103
Observations	5520	7181	5520	7181	5520	7181
Clusters	394	509	394	509	394	509

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table G.4: The effects in areas with cluster bombs

	Dependent variable is:					
	Height-for-age Z-score		Being Underweight		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.029	0.040	-0.018	-0.018	-0.056***	-0.051***
	(0.041)	(0.039)	(0.018)	(0.015)	(0.015)	(0.012)
Mean	-1.835	-1.819	0.186	0.183	0.101	0.0963
Observations	5495	7283	5495	7283	5495	7283
Clusters	394	521	394	521	394	521
Panel B: Fertile areas (1962)						
Bombing	0.064	0.042	0.014	-0.009	-0.007	-0.017
	(0.083)	(0.069)	(0.024)	(0.021)	(0.020)	(0.018)
Mean	-1.766	-1.775	0.171	0.169	0.0747	0.0755
Observations	1833	2357	1833	2357	1833	2357
Clusters	132	174	132	174	132	174
Panel C: Infertile areas (1962)						
Bombing	0.009	0.036	-0.011	-0.011	-0.073***	-0.066***
	(0.051)	(0.049)	(0.023)	(0.021)	(0.017)	(0.015)
Mean	-1.870	-1.840	0.194	0.189	0.114	0.106
Observations	3662	4926	3662	4926	3662	4926
Clusters	262	347	262	347	262	347

Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics are present in all regressions. Regressions (1) (3) (5) include individuals living within 1km from bombing boundaries. Regressions (2) (4) (6) include individuals living within 1.5 km of bombing boundaries. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.