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. We leverage geo-coded individual data and a spatial regression discontinuity adapted to many boundaries. Our study is separate from those that focus on the impact of being exposed to bombings as a child; rather, we study how such disasters can map to health outcomes for future generations. We show that in fact, regions directly affected by bombings exhibit better health outcomes compared to those just beyond the bombing boundaries, indicated by higher Height-for-age Z-scores and a decreased likelihood of anemia. This result remains robust to a variety of potential threats to identification. We then leverage a wide range of data to show that improvements in soil fertility and access to health facilities are likely mechanisms explaining the observed enhancements in health outcomes. Our evidence suggests that in the post-conflict period, infrastructure development favored areas that experienced greater degradation in the past. Our results overall offer an important lesson that while disasters can have harmful impacts, how outcomes are transformed for future generations will depend. Put differently, disaster is not necessarily destiny.

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

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1 Introduction

There is substantial evidence that conflict can affect individual health outcomes in the short- and long-run. Exposure to conflict when in utero or during early-life can have detrimental effects on future outcomes, including 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). Later generations may be affected through intergenerational transmission by those harmed from direct exposure (Strauss & Thomas 2008) and from environmental and infrastructure degradation. The literature, however, is sparse on the link between local area development post-conflict and its very long-term consequences on individuals, although there is evidence for variation in post-conflict recovery paths. Some studies find that local development post-conflict is harmed in the long-term (Abadie & Gardeazabal 2003, Yamada & Yamada 2021). On the other hand, Davis & Weinstein (2002) found Japanese cities bombed during World War II were able to revert to pre-war growth trends. Also, Miguel & Roland (2011) found long-run positive effects for district-level outcomes from past US bombing in Vietnam. Thus, while there is variation in post-war local development, an open question in the literature is the extent that health outcomes are affected for individuals living in areas that experienced greater conflict and degradation in the past and whether this depends on the extent of later development.

We address these questions leveraging a wide range of data from Cambodia. Based on 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. We employ a spatial regression discontinuity (RD) design to compare individuals on two sides of bombing boundaries, thereby yielding precise estimates of the local treatment effect on the health outcomes of the population at the boundaries. Furthermore, we investigate the effects on all-age populations and heterogeneous effects on different generations. We also explore variations in the effects depending on the current risk of encountering unexploded ordnance from US bombing. Finally, we offer a new understanding of post-conflict and post-disaster recovery by analysing soil fertility and healthcare accessibility, and we show that these are plausible mechanisms driving our results.

Data sources and identification. We gather geo-coded information from diverse data sources, encompassing individual-level health data from the Cambodian Demographic and Health Survey (DHS), spatial information on US airstrike missions, UN-adjusted population density, and other relevant data on geographic and economic development characteristics. We examine the impact of living in areas exposed to bombing in the past on three health indicators: Height-for-age Z-scores, Body Mass Index and Anemia Level. We use a spatial RD to compare individuals who reside near what we define as bombing boundaries boundary, using the boundary as a cutoff point. Similar to Dell

(2010), Dell et al. (2018), we use a multidimensional RD design employing the latitude and longitude of household locations as running variables. We show that our design passes a range of checks around the core RD assumptions and we cross-verify our main results with a unidimensional RD using distance to bombing boundaries as a running variable. We then turn to potential mechanisms around environmental and health infrastructure development. We leverage soil datasets in 1962 and 2003 to identify how bombing affects soil fertility. We also utilize information from 2010 on health facilities in Cambodia, using distance to health facilities as a proxy for healthcare accessibility. Finally, we analyze individuals' perceptions of their overall health problems.

Effects on health outcomes. Our findings indicate that individuals residing in areas heavily bombed in the past do not experience a decline in their current health status. In fact, we observe consistent positive, long-term health effects across all specifications. Specifically, for women residing in bombing areas, their Health-for-age Z-scores show an increase of approximately 2.7% in comparison to those living outside these areas. The influence on height is more significant for later generations with women born after 1975 exhibiting a rise of around 4% in their Health-for-age Z-scores.[1] In terms of anemia, women on the bombing side have a 2.1 percentage point lower likelihood of severe anemia, marking a reduction of over 20% compared to the average rate. The impact on anemia is notably stronger among older generations, with 3% drop in the likelihood of suffering anemia. This translates to a significant 26% change relative to the average anemia rate within this age group population.[2] We do not find any impacts on body mass index. Moreover, when dividing the country into two distinct regions based on the likelihood of encountering unexploded ordnance, we found that positive health impacts were concentrated in pre-bombing areas with infertile soil where the ground was likely harder (Foth 1951, Fitzpatrick 1996) and thereby bomb detonation too, reducing the probability of unexplored ordinance at the present.[3]

Environment and development. We found that improved health outcomes observed in people residing in the bombing areas are consistent with improvements in soil fertility and health care access in these locations relative to our control locations. Although pre-bombing soil fertility levels were similar on both sides of the bombing boundaries, there was a notable improvement in soil fertility on the bombing side three decades after the bombing. This suggests that exposure to bombing had a long-term positive impact on

[1]In our study, younger (or later) generations are those born after the bombing period and therefore, they were not directly affected by the bombings. Our findings suggest that positive treatment effects on Height-for-age Z-scores are primarily pronounced in these younger individuals who didn't face severe consequences from the bombing and have gained benefits from post-war developments.

[2]These findings are consistent with the fact that anemia is more common among the elderly population (Timiras & Brownstein 1987, Anía et al. 1997, Gaskell et al. 2008).

[3]Unexploded ordnance (UXO) is frequently found in soft ground where soil is highly fertile (Moyes et al. 2002, Lin 2022). See Section 2 for further discussions on UXO problems in Cambodia.

the regeneration of land and enhanced soil conditions in the affected areas, which in Section 6.1 we discuss and draw on a broad background of literature to explain why this is not surprising. Additionally, regarding health accessibility, we found that distances to health facilities were significantly shorter for those on the bombing side, even in the region where health facilities are highly concentrated. We also find those living inside our bombing boundaries today report fewer overall health problems consistent with better access to care. Given the fact that the national healthcare system in Cambodia was totally destroyed due to US bombings and the Khmer Rouge Genocide, our findings indicate that areas previously affected by bombing exhibit better healthcare developments in the post-conflict period.

Related literature. Existing literature on war and human conflicts has presented a range of inconsistent findings regarding their effects on different aspects of human life, including health. Studies examining the effects of conflicts on health can be categorized into three groups: (1) the long-run impacts of early life health on subsequent health outcomes (2) the transmission of health effects to second generations, and (3) long-term multigenerational health effects.

A wide range of studies has looked at the impacts of conflicts on health outcomes by examining generations who are directly exposed to conflicts either *in utero* or in their early childhood. Most of these studies are grounded in the "Fetal Origins Hypothesis", which posits a connection between prenatal environment and the development of future diseases (Barker 1990). Economists have expanded this hypothesis by scrutinizing the effects of various shocks and living environments on future outcomes (Almond & Currie 2011). Numerous papers have found negative impacts of shocks on different health indicators, such as 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).

Another set of research investigates the effects on health outcomes of the next generations whose parents suffer from wars and conflicts. Strauss & Thomas (2008) highlights that the transformation of health inputs into health outputs, given technological and biological constraints, reveals various mechanisms underlying the correlations in health across generations. As concluded by Strauss & Thomas (2008), parents' health inputs, family background, and environmental factors are determinants of an individual's health, with evidence found in BritainEmanuel et al. (1992), Denmark (Eriksson et al. 2005), and Cambodia (Moyano 2017, Islam et al. 2017).

War and conflicts will 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).

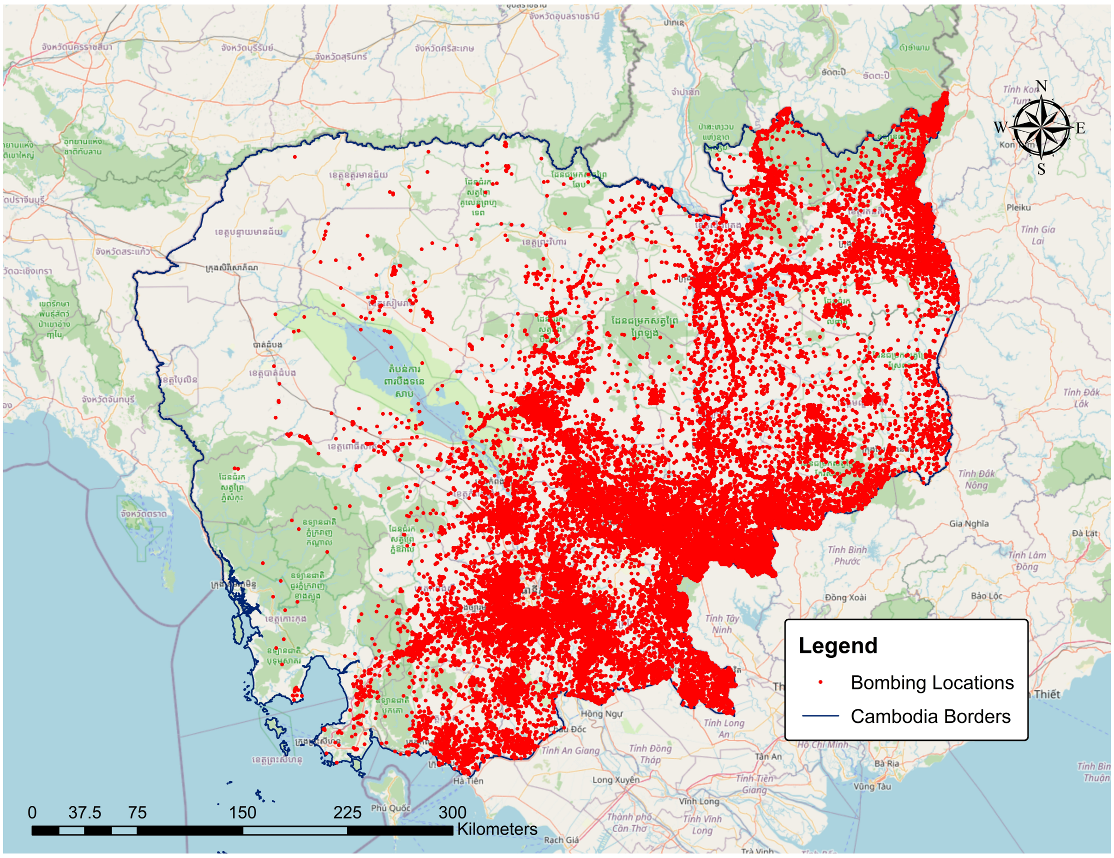
Literature on the long-term effects of conflicts on regions' status quo also shows mixed results. Several papers have found results consistent with conflict trap theory, indicating the long-run negative effect of external shocks relative to the ex-ante condition (Abadie & Gardeazabal 2003, Yamada & Yamada 2021, Harada 2022, Lin 2022). However, some studies observe contrasting results and provide empirical support for neoclassical growth theory, suggesting that economies have the potential to 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 an opportunity for greater economic development. This theory is exemplified in the work undertaken by Hornbeck & Keniston (2017) who investigate the Boston Fire of 1872 and demonstrate that the destruction of outdated buildings following the fire created opportunities for substantial development afterwards.

With regard to health issues, 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 though the war already ended about forty years ago.

Contribution. This paper, therefore, will contribute to the limited literature on the long-term impacts of human conflicts. Differing from previous studies that primarily focused on individuals directly exposed to conflicts or their subsequent offspring, our study concentrates on the health outcomes of the present population, providing novel insights into the potential long-term impacts of local area exposure to bombing on health. Additionally, this paper also offers a valuable understanding of post-conflict and post-disaster recovery, which holds important implications for policymakers in the post-conflict period. Moreover, empirically speaking, by using a spatial regression discontinuity design, this paper adds to the body of research on spatial data analysis, a rapidly growing field thanks to the better accessibility of micro-level geocoded data.

In the following section, we provide a historical overview of the US bombing campaign in Cambodia. Section 3 discusses all datasets used in this paper. Section 4 describes the empirical strategy and assumptions behind this framework. Section 5 presents the findings. Section 6 examines different mechanisms that potentially lead to our results. Finally, Section 7 concludes the paper.

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.

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 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 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 Cambodian population's health 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 U.S. bombings, 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).[4] Cambodia 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. 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

[4]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).

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). Due to the presence of UXO, farmers would change their agriculture practices, unexpectedly rendering fertile land unproductive due to the high risks associated with farming (Lin 2022).

When investigating the impacts of bombing on the health outcomes of the current population, we also take into account the occurrence of UXO due to bombing at the present time. We would not expect that areas with a higher likelihood of UXO today would experience positive effects on health outcomes, as our the mechanisms we test later are around living today in better environments. Thus, due to the higher likelihood of UXO failure in softer ground, we will examine the heterogeneous impacts of bombing 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 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 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, population density, and other relevant data on geographic and economic 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 about 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 utilized.

Using the provided dataset, our task is 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 enhance understanding of how location specific features impact health outcomes (Rushton & Elliott 2003, Elliott & Wartenberg 2004, Beale et al. 2008, Auchincloss et al. 2012). One 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. The method involves the creation of a histogram by partitioning the data space into distinct, non-overlapping regions or cells. Cells with a significant number of objects signify cluster centres. One advantage of this approach is that it utilizes most of the points in the pattern during analysis. Additionally, square quadrats can easily combined and merged together 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 bombings, 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 adjust 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 in the study area.

Our cell size equals 5.856 km^2 (2.42 km on each side) given Cambodia's overall area being 337,561 km^2 and the number of airstrikes being 115,273.[5] 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.

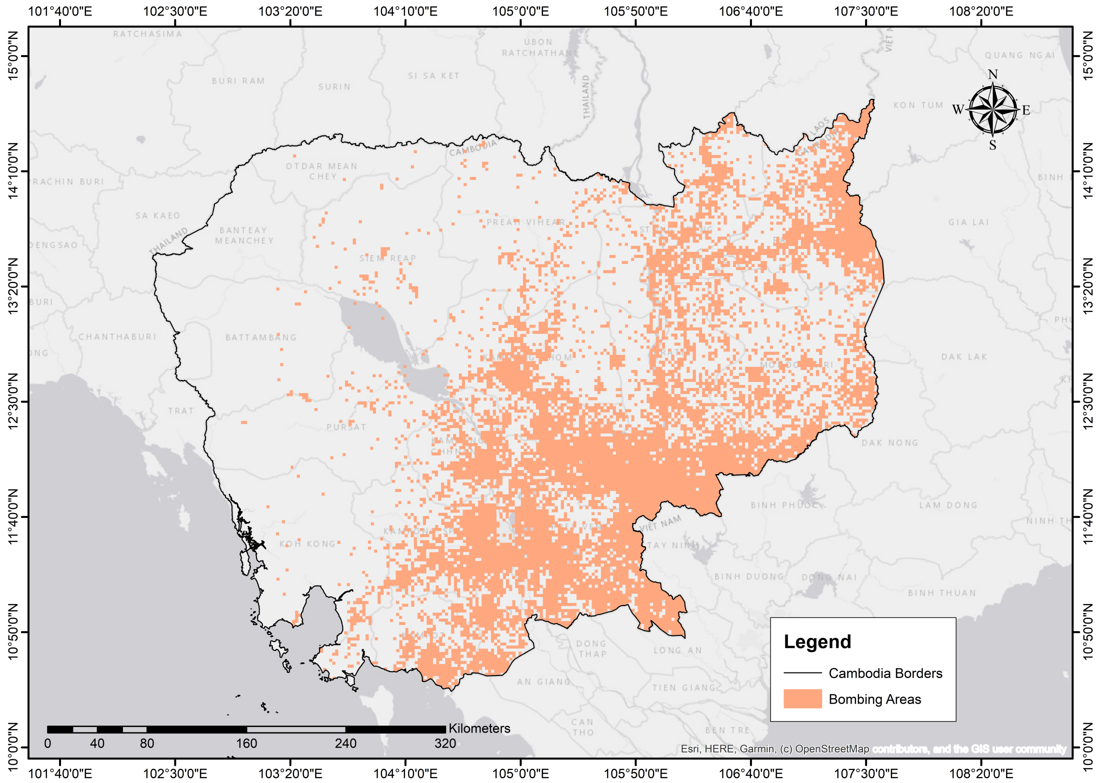
3.2 Cambodia Demographic and Health Survey

Our empirical analysis builds upon four waves of the Cambodia Demographic and Health Survey (DHS 2000, 2005, 2010, and 2014).[6] We rely solely on the DHS individual women's data, as it offers extensive health information that is not available for the male sample.

[5]These are similar to the cell sizes selected by Kohama et al. (2020) who look at a link between bombing and mining.

[6]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.

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.

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. For the purpose of keeping 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. The 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). The second outcome is Body Mass Index (BMI), which has been used in Akbulut-Yuksel (2017), Vuong et al. (2021) as an indicator of health status. BMI reflects an individual's weight status, commonly used to identify weight abnormality (underweight or overweight/obesity) and associated health risks (WHO 1995). The final outcome of interest is the level of anemia, a demonstration of inadequate nutrition and overall poor health, often associated with iron deficiency (WHO 2008), that has be utilized 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.

To conduct balance checks, we also exploit the data on geographical and demographic characteristics provided by Cambodia DHS. Geographical data is elevation/altitude in meters from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model for the specified coordinate locations of DHS clusters. Meanwhile, demographic characteristics encompass details regarding population age and educational attainment of the survey respondents.

Since socioeconomic disparities can impact healthcare utilization and outcomes, our study also utilizes data on women's difficulty in seeking medical assistance as an indicator of healthcare access at the DHS cluster. Specifically, we examine the challenges faced by women in seeking medical care, including the following issues: (1) not knowing where to go (2) getting permission to go (3) getting money for treatment (4) distance to health facilities (5) having to take transport (6) reluctance to seek care alone (7) concerns about the availability of female health providers, (8) concerns about the availability of any healthcare provider, and (9) concerns about the availability of essential medications. Based on this data, we create a dummy variable which is coded 1 if they face at least one of the aforementioned obstacles.

3.3 Population density

In order to analyze population density at DHS clusters, we use UN-Adjusted Population Density 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 demonstrates the number of people per square kilometer, adjusted to match the corresponding official United Nations population estimates in each country, prepared by the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (Revision of World Population Prospects 2019). 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.

3.4 Global Agro-Ecological Zones (GAEZ)

To assess the climate 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. 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. 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 AEZ zone (Appendix, Figure F.1). Subsequently, we create a binary variable indicating whether a village is located in a grid cell characterized as tropics and lowland.

3.5 Other data for economic development characteristics

3.5.1 Soil fertility

Soil fertility is an indicator used to measure agricultural productivity at DHS clusters. Using soil information before and after the bombing period from two different data sources, our study investigates the impact of the bombings on soil fertility in Cambodia.

The first soil dataset employed is the data on the distribution of soil types in Cambodia provided by Crocker (1962). We define soil fertility according to soil classifications by the Cambodian government (Kohama et al. 2020). We then 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.[7]

The second soil dataset is the soil fertility map (2003) indicating soil fertility levels across various regions in Cambodia. The Cambodia Tree Seed Project (CTSP), supported by Danida in partnership with the Forestry Administration and the German Development Service (DED), collected extensive geographic and ecological data (Jalonen et al. 2009, Brun 2013).[8] CTSP gathered information on soil fertility and categorized soils into three fertility levels: high, medium, and low. In particular, the collected data includes details on soil textures (such as sand, loamy sand, sandy loam, silty clay, or clay) and other soil information in specific areas (Moestrup et al. 2006). Due to the distinct texture characteristics associated with each soil type, the soil fertility measurements in the CTSP

[7]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).

[8]The data is available in ESRI Shapefile format at Open Development Cambodia.

project align with the soil fertility data derived from the 1962 soil type dataset.

This dataset has three levels of soil fertility: high, medium, and low. In order to get consistent measures of soil fertility before and after the bombing period, we create a dummy variable, Soil fertility in 2003. We code this as 1 if fertility is either high or medium and as a 0 if fertility is low.

3.5.2 Distance to health facilities

We use distance to health facilities as proxies for economic development and healthcare accessibility. Distances to hospitals, district-level health centers, and health facilities, in general, are calculated using data on health facilities in Cambodia (2010) collected and developed by Open Development Cambodia.[9] Open Development Cambodia's team gathered data from Google Maps and utilized references from the Cambodia's Ministry of Health. 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 centers include health centers 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.

3.6 Descriptive statistics

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

In particular, Height-for-age Z-scores are not significantly different between outside and inside groups. However, individuals living outside the bombing areas show marginally higher average BMIs compared to those within the bombing areas. Additionally, no noticeable difference is observed between the inside-bombing and outside-bombing groups regarding the mean value of anemia level.

We observe the mean distance to Vietnam's borders is significantly lower for those inside the bombing areas, aligning with the historical narrative. Concerning demographic characteristics, while age and education levels show no significant differences between the two groups, areas within bombing zones exhibit considerably lower unconditional mean population density compared to regions outside. Additionally, these bombed areas are

[9] 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).

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)
Body Mass Index (BMI)	21.40	21.47	21.31	21.21	21.23	21.18	21.25	21.28	21.21
	(3.31)	(3.32)	(3.29)	(3.21)	(3.24)	(3.18)	(3.24)	(3.24)	(3.24)
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)
Demographic 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)
Age of respondents	29.90	29.60	30.28	30.09	29.98	30.20	29.99	29.69	30.29
	(10.08)	(10.05)	(10.10)	(10.14)	(10.11)	(10.16)	(10.07)	(10.01)	(10.12)
Primary education	0.83	0.81	0.84	0.83	0.84	0.83	0.84	0.84	0.84
	(0.38)	(0.39)	(0.36)	(0.37)	(0.37)	(0.37)	(0.36)	(0.36)	(0.37)
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)
Urban areas	0.29	0.34	0.23	0.23	0.29	0.17	0.27	0.36	0.17
	(0.46)	(0.47)	(0.42)	(0.42)	(0.45)	(0.38)	(0.44)	(0.48)	(0.38)
Geographic characteristics									
Elevation/Altitude (meters)	37.56	34.06	41.99	34.58	32.10	36.98	34.34	29.81	38.98
	(68.62)	(51.82)	(85.04)	(71.03)	(59.34)	(80.69)	(71.12)	(52.08)	(86.13)
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)
Economic development characteristics									
Soil fertility in 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)
Soil fertility in 2003	0.71	0.65	0.78	0.69	0.63	0.74	0.71	0.66	0.77
	(0.46)	(0.48)	(0.41)	(0.46)	(0.48)	(0.44)	(0.45)	(0.47)	(0.42)
Medical help difficulty	0.80	0.81	0.77	0.79	0.79	0.79	0.79	0.79	0.79
	(0.40)	(0.39)	(0.42)	(0.40)	(0.40)	(0.41)	(0.41)	(0.41)	(0.41)
Distance (km) to									
Hospital (2010)	12.33	13.09	11.36	13.43	13.69	13.17	12.45	12.45	12.45
	(12.50)	(13.77)	(10.61)	(13.25)	(14.52)	(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	139.17	193.87	70.02	88.89	98.73	79.36	95.13	116.45	73.29
	(117.44)	(124.11)	(56.52)	(73.47)	(78.87)	(66.45)	(77.45)	(85.81)	(60.47)
Capital	132.49	160.54	97.02	93.91	96.13	91.77	96.30	99.19	93.33
	(99.14)	(102.93)	(81.29)	(78.75)	(78.18)	(79.25)	(80.03)	(81.14)	(78.77)
Distance to 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)
Observations	31016	17317	13699	12042	5925	6117	18378	9298	9080

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.

less likely to be urban at present. Meanwhile, in terms of economic characteristics, areas that experienced the bombing tended to have higher soil fertility both in 1962 (before the bombing) and in 2003 (after the bombing) in their unconditional mean difference. Furthermore, individuals residing inside the bombing areas generally have shorter distances to hospitals and health facilities. To make clear comparisons, we turn now to a 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), Dell & Olken (2020), our regressions take the form:

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

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, controlling for distance to the capital of Cambodia - the largest urban city and distance to Vietnam borders. $\mathbf{X}_i$ contains demographic characteristics of the woman, including age and education. The δ_p is province-fixed effects, playing a role as spatial fixed effects and ensuring that the specification is comparing 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. Based on Gelman & Imbens (2019), a local linear RD polynomial is selected for the baseline specification, in particular, $f(Geo_c) = latitude + longitude$. These geographic running variables allow us to capture geographic variability in the outcome and isolate any discontinuous effects around bombing boundaries. Higher orders of RD polynomials (quadratic and cubic polynomials) are used in robustness checks[10]. In all regressions, a triangular kernel is employed, where the weight assigned to each observation diminishes as the distance from the threshold increases.

Literature on spatial RD analysis has emphasized the crucial role of incorporating segment-fixed effects within the framework of RD design. Boundary-segment fixed effects, which are used in the papers of Dell (2010), Dell et al. (2018), Dell & Olken (2020), 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, our main specification includes province-fixed

[10] 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 $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat^3 + lon^3 + lat \times lon + lat^2 \times lon + lat \times lon^2$.

effects, so we make comparisons between individuals in the same province.

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.[11] Particularly, we replace province-fixed effects with 50x50km grid-cell fixed effects, ensuring a comparison between individuals situated within a highly confined area.[12] 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 C, we test the RD design with a unidimensional RD polynomial. Specifically, distance to bombing boundaries is used 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). We do not choose these unidimensional RD models as our main specification because they possess limited degrees of freedom to capture smooth variations near the boundary with our multi-dimensional geographic running variables (Dell 2010). However, since a more flexible approach may not guarantee a more reliable estimate, these unidimensional designs 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.

4.2.1 Assumption 1: Smooth variance of covariates at bombing boundaries

The 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 *dist* denotes distance to bombing boundaries, then $E[c_1|dist]$ and $E[c_0|dist]$ must be continuous at the discontinuity. 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 evaluate the plausibility of this assumption, we use regression (1) to examine a wide range of geographic and demographic characteristics on two sides of bombing boundaries. Table 2 evaluates the validity of this design by assessing different baseline characteristics including geographic characteristics (elevation, tropics/lowland

[11]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.

[12]In this approach, we divide the country into 79 grid cells of 50x50km. See Figure F.3.

Table 2: Balance check

	Dependent variable is:					
	Geography			Demography		
	(1) Elevation	(2) Tropics/lowland	(3) Soil Fertility	(4) Age	(5) Primary Edu.	(6) Secondary Edu.
Bombing	7.642	0.028	-0.000	-0.059	0.003	0.023
	(5.217)	(0.040)	(0.039)	(0.201)	(0.013)	(0.018)
Mean	34.58	0.585	0.334	30.09	0.835	0.318
Observations	12042	12042	12042	12042	12042	12042
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/humid 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 soil was fertile in 1962 (before the bombing). Primary Edu. and Secondary Edu. are binary variables indicating whether a respondent has graduated from primary and secondary education. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

and soil fertility in 1962) and demographic ones (population age and education level). All of these characteristics are measured at the DHS survey cluster level and used as outcome variables for regression (1). We find no evidence that there are any discontinuities of geographic and demographic features at the bombing boundaries.

4.2.2 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 the bombing induced individuals to move outside bombing areas into non-bombing areas at the current time. Historically speaking, internal migration was significant during the 1970-1990 period in Cambodia due to wars and conflicts (Islam et al. 2017, Diepart & Ngin 2020, Chann 2021). People were displaced from their hometowns because of the bombing and sought refuge often migrating to cities to make a living (Chann 2021). Later on, during the Khmer Rouge Period (1975–1979), citizens in urban areas were forced to move to the countryside and most urban cities were empty (Diepart & Ngin 2020, Chann 2021). The Khmer Rouge regime collapsed in 1979, followed by a massive internal migration of citizens who afterwards mostly returned to their hometowns. Nevertheless, conflicts and political instability in the later period still induced migration within the country. Also, since peace was established in the country in 1998, the pattern of migration from rural to urban areas is significant due to the process of urbanization and industrialization (Diepart & Ngin 2020).

We check whether local area exposure to bombing in the past affects the migration status of individuals far into the future at our period of analysis. The results are shown in Table 3. First, we examine the population density on two sides of the bombing boundaries, using the UN-Adjusted Population Density collected by the WorldPop research program.

Table 3: Checking the second identifying assumption

	Dependent variable is:		
	(1) Population density	(2) Never moving	(3) Urban areas
Bombing	-0.294	0.031	-0.030
	(0.368)	(0.027)	(0.032)
Mean	1.654	0.637	0.226
Observations	12042	4617	12042
Clusters	865	418	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. Standard errors reported in parenthesis are at the DHS survey cluster level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Running regression (1) with the dependent variable being the number of people per square kilometre, we do not observe any statistically significant difference in population density between the two sides of bombing boundaries.

Secondly, we consider migration status ("never moving") as a dependent variable in regression (1) and check whether bombing induces current migration.[13] We observe small and insignificant coefficient in Table 3, suggesting that around our boundaries local area exposure to bombing in the past does not have long-term effects on current migration or, in other words, there is no correlation between the current population's migration status and local area past bombing exposure.

Finally, Cambodia's history indicates a migration pattern primarily from rural to urban areas during bombing periods and, conversely, from urban to rural areas during the Khmer Rouge period. To check the movements of individuals across boundaries, we test whether bombing affects individuals' decision of living in rural/urban areas using our main specification. The small magnitude and insignificance of the estimate demonstrate no clear discontinuity in terms of urban or rural patterns on two sides of the bombing boundaries.

5 Results

5.1 The long-term impacts on women's health

Table 4 (Panel A) reports the results of the main RD design that estimates the long-term impacts of local area exposure to bombing on different health outcomes of the current population nearly five decades after the bombing occurred. Interestingly, the results suggest that residing in areas heavily bombed in the past does not deteriorate the

[13]Data on migration status is only available in Cambodian DHS 2000 and 2004.

health capital of individuals who are currently living in these locations. On the contrary, across all specifications, we can observe evidence of positive long-term health effects. Specifically, for women currently living in bombing areas, their Health-for-age Z-scores increase by 0.05 (about 2.7%) compared to those living outside bombing areas. We see no effects on BMI, but for anemia, we find better health outcomes among those living in bombing areas. Women living inside bombing areas are about 2.1 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. Meanwhile, for BMI, we do not observe any discontinuity at the cut-off boundaries.

Table 4: The long-term effects of bombing on health

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.050*	0.047*	0.021	0.027	-0.021***	-0.021***
	(0.029)	(0.026)	(0.090)	(0.083)	(0.008)	(0.007)
Mean	-1.816	-1.809	21.16	21.21	0.0977	0.0953
Observations	9133	12042	9133	12042	9133	12042
Clusters	659	865	659	865	659	865
Panel B: Individuals born by 1975						
Bombing	0.019	0.021	0.102	0.116	-0.030**	-0.030**
	(0.037)	(0.033)	(0.149)	(0.137)	(0.013)	(0.012)
Mean	-1.857	-1.853	21.74	21.81	0.117	0.116
Observations	3603	4770	3603	4770	3603	4770
Clusters	654	859	654	859	654	859
Panel C: Individuals born after 1975						
Bombing	0.070**	0.064**	-0.032	-0.025	-0.012	-0.013
	(0.035)	(0.031)	(0.096)	(0.089)	(0.009)	(0.008)
Mean	-1.788	-1.780	20.78	20.81	0.0854	0.0821
Observations	5530	7272	5530	7272	5530	7272
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, and distance to Vietnam borders 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.

We also split these effects by those born during or after the bombing periods. This division is crucial as we anticipate that the impact of bombing on health might vary depending on whether an individual is from a 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. Panel B and C in Table 4 present the heterogeneous effects of bombing 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 people who were born before 1975. In particular, women born after 1975 and who currently residing in bombing areas witness an increase of 0.070 (or 0.064) in their Health-for-age Z-scores, equivalent to approximately 4%, 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.

Because BMI decreases with increasing height, it is reasonable that the coefficient of BMI for women born after 1975 is negative, while it is positive for women born by 1975. However, these estimates are both insignificant, meaning there is no discontinuity at the bombing boundaries in terms of BMI 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.[14] 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. A possible explanation is improved medical care and support in reducing anemia risk, which we investigate in Section 6.

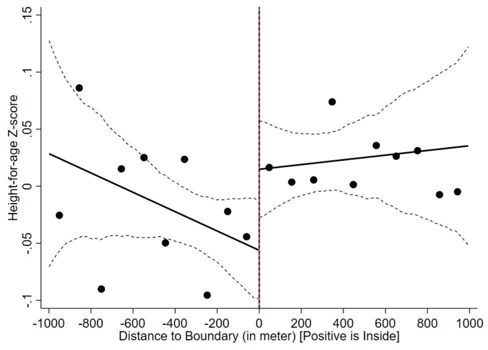
Briefly, our findings suggest that residing in regions of Cambodia that experienced substantial destruction in the past does not adversely affect individuals' health outcomes; in fact, we observe positive impacts.[15] These findings are consistent with a hypothesis based on post-war development, indicating that environmental and infrastructure improvements

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

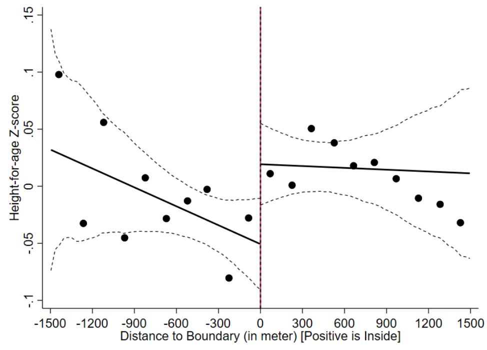
[15] The unidimensional RD design produces comparable results to our primary analysis. See section C.2.

Figure 3: The impacts of bombing on health: RD plots

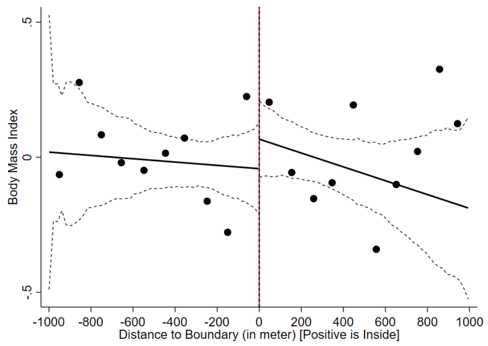
Panel A: Within 1km bandwidth **Panel B: Within 1.5km bandwidth**



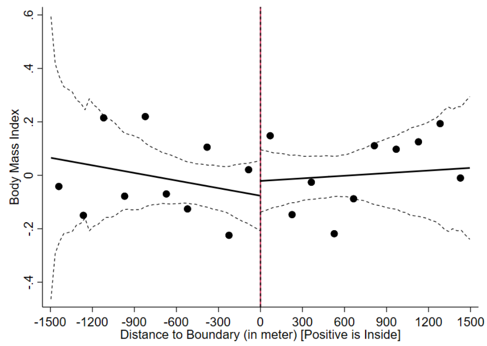
(a) Height-for-age Z-score



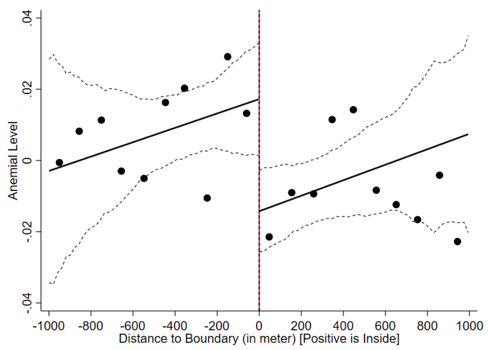
(b) Height-for-age Z-score



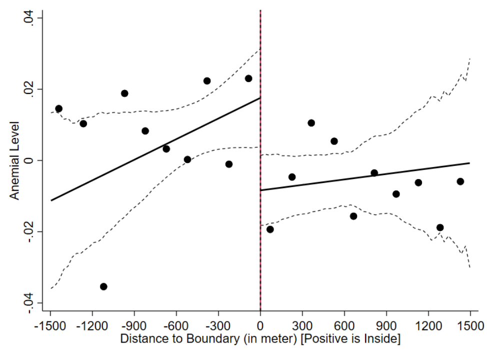
(c) Body Mass Index



(d) Body Mass Index



(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.

can diminish local area negative shocks and potentially yield long-term benefits. We examine this further in Section 6, where we shed light on potential mechanisms behind our results.

5.2 Robustness

We conduct several 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.

Non-mover sample. To address concerns about the potential movements of people around the cut-off boundaries, we conducted a similar analysis with a subsample of individuals who never move [16]. The results are consistent with our main findings (Table A.1). HAZs are higher for those living inside bombing areas by approximately 0.1 for a 1-km bandwidth sample and 0.079 for a 1.5-km bandwidth sample. These magnitudes are somewhat larger but qualitatively similar to the estimates we found when running regressions with all observations (0.05 and 0.047). However, we do not observe heterogeneous effects for two groups of populations, potentially due to limited sample sizes when segmenting the population into smaller subgroups. With respect to BMI, there is no sizeable discontinuity at the bombing boundaries although the results suggest that women inside bombing areas have lower Body Mass Index. For anemia, people on the bombing side continue to be less likely to suffer from anemia. The drop remains significant and is larger in magnitude (more than 4.5% for all population and more than 6% for those born by 1975).

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 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, particularly, 50x50km grid cells, and control for grid-cell fixed effects in our main regression. Overall, the country is divided into 79 grid cells (Figure F.3). Table A.2 demonstrates that when grid-cell fixed effects are employed, the results remain similar: living in bombing areas is associated with better health outcomes. In our grid-cell fixed effect models, the coefficients for Height-for-age Z-scores remain consistent, and the reduction in anemia levels also remains similar if comparatively somewhat smaller in magnitude than in province-fixed effect models.

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

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 of bombing on the Height-for-age Z-score and a considerable drop in anemia level for people living in bombing areas. We also continue to find that the impacts on Height-for-age Z-score are especially substantial for those born after the bombings, whereas effects on anemia are notably observable among the older cohorts.

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 of bombing on two groups of population: those born before and after the bombing period.

Specification variety. In Tables A.3, A.4 and A.5 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 [17]. The following two columns present outcomes without the inclusion of a triangular kernel weight.[18] 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 of bombing on health outcomes remain generally consistent across different specifications. Displaying the effects of bombing on HAZ, Table A.3 shows that our coefficients remain significant and stable in magnitude across various specifications. While slight differences exist, the estimates closely align, underscoring the reliability of our findings. Interestingly, the effects are even more significant and larger in magnitude in the *donut* model. Table A.5 also suggests a solid result on anemia. Our estimates are robust in terms of magnitude and significance level across different specification choices. In the *donut* exercise, while there are no significant differences in effects for the two population groups, point estimates indicate that the impact on older generations is still more substantial compared to the younger group.

[17] 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 $f(Geo_c) = lat + lon + lat^2 + lon^2 + lat^3 + lon^3 + lat \times lon + lat^2 \times lon + lat \times lon^2$.

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

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. As illustrated in Table A.6, there are no placebo-boundary effects on Height-for-age Z-score, except in the case of a westward border shift. Yet, all of these estimates are negative, indicating that individuals on the bombing side have lower heights compared to those on the other side, which contradicts our main results. The effects of bombing on BMI in placebo situations are also indifferent from zero (Table A.7). In terms of anemia level (Table A.8), coefficients are not different from zero 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. Most estimate are nulls, and for these significant estimates, we do not find them concerning. It is not surprising to have a significant effect with an ample number of placebos, and most importantly, all of these effects are opposite to our actual estimates.

5.3 Analysis based on UXO risk

In Section 2, we provide a detailed discussion on UXO problems in Cambodia and that UXO may be more prevalent 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. [19] We found that if areas were fertile in 1962, they were 1% more likely to have ERW casualties at the present time, which is nearly half the baseline predicted probability. The evidence here is consistent with our expectations following our discussion in Section 2 and motivates our use of 1962 soil fertility to split our main health effects.

Additionally, the local exposure to bombing increases the likelihood of having ERW casualties in that area by 0.8% (Table 5). This outcome aligns with our expectation, and we note that ERW casualties can include those from separate causes than the US aerial bombing campaign (Roberts 2011, Martin et al. 2019). Thus, as expected, we see more ERW causalities where bombing occured, but importantly, our RD assumption check in Table 2, indicates that bombing and 1962 soil feritlity are independent. Furthermore, when we include the interaction between bombing and 1962 soil fertility (column 2), we observe a small and insignificant coefficient. This strengthens our confidence that bombing was random to 1962 soil fertility and does not differentially predict ERW casualties today. This is crucial as next we proceed to analyze our primary treatment effects, categorized

[19]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.

by 1962 soil fertility.

Table 5: 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.

We use pre-bombing soil fertility information to divide the country into two distinctive regions: (1) fertile areas with high occurrences of UXO and (2) infertile areas with a lower likelihood of encountering UXO. In section 4.2.1, we showed that soil fertility in 1962 was indifferent on two sides of the bombing boundaries. Our treatment is independent of pre-bombing soil fertility; therefore, we use this heterogeneity analysis to further validate that the positive effects we have observed are sensible in that they are not likely to occur in higher probability UXO areas.

Table 6 illustrates the heterogeneous effects of local area exposure to bombing in the past on these regions. In high fertility areas where UXO is more likely to appear, we observe null effects on health across all specifications (Panel A). Meanwhile, in infertile areas which are less likely to have UXO (Panel B), we see significant positive effects on health outcomes.[20] 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%. Additionally, they are also less prone to anemia, with a reduction of 3.5 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.

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 across different generations. On the contrary, in less fertile areas with

[20]We observe the same impact heterogeneity with the unidimensional RD design. See Table C.2.

a reduced chance of UXO, we observe effect heterogeneity on two different generations, which are consistent with our main results in Section 5.1.

Table 6: Heterogeneous effects on different regions

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km	(5) <1km	(6) <1.5km
Panel A: Fertile areas (1962)						
Bombing	-0.036	-0.025	-0.189	-0.154	0.002	-0.000
	(0.048)	(0.042)	(0.163)	(0.139)	(0.011)	(0.011)
Mean	-1.786	-1.793	21.31	21.36	0.0789	0.0797
Observations	3091	4027	3091	4027	3091	4027
Clusters	230	301	230	301	230	301
Panel B: Infertile areas (1962)						
Bombing	0.083**	0.073**	0.117	0.102	-0.035***	-0.030***
	(0.035)	(0.032)	(0.106)	(0.099)	(0.011)	(0.010)
Mean	-1.831	-1.817	21.08	21.13	0.107	0.103
Observations	6042	8015	6042	8015	6042	8015
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, and distance to Vietnam borders 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.

In summary, our analysis indicates that the positive effects on health of residing in local areas exposed to past bombing 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 in the environment are more likely to be useful and improvements in infrastructure achievable. Our results here are consistent with this and lead us to our following investigation of mechanisms.

6 Mechanisms

In this section, we examine the channels that could potentially shed light on the positive health impacts of bombing on people living in bombing areas. We test whether better health outcomes observed in people residing on the bombing side are driven by economic developments 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 over multiple generations and restoring the region to its pre-war conditions. By examining soil fertility and healthcare accessibility, we provide evidence suggesting that areas previously affected by bombing exhibit more favourable economic and healthcare characteristics.

6.1 Bombing and Soil fertility

We conducted an analysis of soil fertility in 1962, which was before the bombing occurred, and in 2003, after a span of three decades of bombing, using our main regression.[21] Table 7 presents the findings. There was no significant difference in soil fertility between the two sides of the bombing boundaries in 1962. However, we observed a discontinuity at bombing boundaries in 2003. In particular, soil fertility in 2003 increased by almost 10% on the bombing side. The coefficients are not only large in magnitude but also statistically significant, which indicates that the period of bombing has played a role in restoring and enhancing soil conditions in the affected areas. We found similar results when analysing soil fertility using a unidimensional RD design (Table C.3).

Table 7: Soil Fertility

	Dependent variable is:			
	Soil fertility in 1962		Soil fertility in 2003	
	(1) <1km	(2) <1.5km	(3) <1km	(4) <1.5km
Bombing	-0.009	-0.000	0.099***	0.094***
	(0.042)	(0.039)	(0.036)	(0.033)
Mean	0.339	0.335	0.695	0.690
Observations	9109	12018	9109	12018
Clusters	657	863	657	863

Note: The unit of analysis is survey respondents. Province fixed effects, distance to the capital, and distance to Vietnam borders are present in all regressions. Regressions (1) (3) include individuals living within 1km from bombing boundaries. Regressions (2) (4) 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.

While wars and conflicts are generally associated with destruction and negative consequences, warfare can still benefit soil in several ways (Certini et al. 2013). The first positive impact is the unexpected fertilization of soil. Nitrogen and phosphorus, which are vital components in fertilizers, are also utilized to produce explosives and bombs (Paull et al. 2009, Certini et al. 2013). After the end of World War II, a substantial amount of ammonium nitrate, the primary component used in the production of explosives, was left

[21]Our study employs two separate soil datasets: data on soil types in Cambodia provided by Crocker (1962) and soil fertility map (2003) from Save Cambodia's Wildlife's 2006 Atlas Working Group. See section 3.5.1 for more details. When running soil fertility in 2003 on soil fertility in 1962 and other control variables using OLS and logit/probit models, we found a significant correlation between soil fertility in 1962 and 2003, indicating that the fertility level in 1962 strongly predicts the fertility level in 2003.

behind (Pollan 2006). During the post-war period, the US government repurposed military infrastructure for civilian purposes. This lead to a significant breakthrough in 1947 when major ammunition factories in Alabama transitioned from producing detonators to manufacturing chemical fertilizers, contributing to the industrialization of the food system in the USA (Pollan 2006). It is plausible that the enrichment of soil in the post-war era is partly attributed to the residues of explosive ingredients.

Second, wartime can contribute to the natural regeneration of land. The establishment of abandoned and unoccupied areas during conflicts alleviates pressures on specific habitats and allows natural ecological progression (McNeely 2003, Certini et al. 2013). Development delay due to the decline in economic activities during wartime creates opportunities for the restoration of certain overexploited resources including soil. Additionally, the instability of living in vulnerable areas can impede human expansion (Hanson et al. 2009). For instance, the border between Thailand and Peninsular Malaysia was a focal point of insurgency in the past. As a result, this expansive region remained unaffected by contemporary logging activities, making it a haven for abundant wildlife resources (McNeely 2003). Similarly, Korea's Demilitarized Zone is also exemplary of a well-preserved ecological region thanks to the strict prohibition of civilian access (Kim 1997, Shin et al. 2012). Despite the severe ecological impacts of destructive bombings in the Second Vietnam War, areas along the Ho Chi Minh trail have unveiled numerous unknown species, highlighting natural resilience, while post-war development poses an even greater threat to nature (McNeely 2003).

These stories suggest that there was a delay in the development and use of land in bombed areas of Cambodia, providing an opportunity for the restoration of natural resources, including soil.[22] Since the history of Cambodia shows that people were uprooted from their hometowns due to conflicts and bombing in the 1970s (Diepart & Ngin 2020), the observed positive impacts of bombing on soil in 2003 suggest that bombing restrained agricultural activities in these regions, and has indirectly facilitated land regeneration.

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).

[22]Different from the study of Kohama et al. (2020) which examines the entire bombing region and suggests that US airstrikes were more likely to target areas characterized by fertile soil and agricultural suitability, our study focuses on small areas just around the bombing boundaries and found that soil fertility was indifferent across the boundaries in 1962.

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 F.2 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 sections, we provide evidence suggesting that improved health outcomes observed in people living in bombing areas are attributed to better health accessibility in those areas. First, 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 D.1) includes the capital city and adjacent provinces. [23] Second, by analysing perceived challenges in accessing medical assistance, we demonstrate that individuals residing in the areas subjected to bombing are less likely to face obstacles when seeking healthcare.

6.2.2 Distances to health facilities

Considering distances to different health facilities as indicators of healthcare accessibility and using the main regression, we found statistically significant evidence that people living in areas that suffered degradation from bombing have better healthcare access.

[23] See Appendix D for a detailed RD analysis with observations in restricted region

Table 8: 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: The whole country						
Bombing	-1.709*	-1.479	-0.492**	-0.460**	-0.405*	-0.384*
	(1.013)	(0.936)	(0.217)	(0.207)	(0.211)	(0.203)
Mean	13.72	13.43	3.261	3.234	3.220	3.196
Observations	9133	12042	9133	12042	9133	12042
Clusters	659	865	659	865	659	865
Panel B: Restricted region						
Bombing	0.671	0.868	-0.503**	-0.413**	-0.378*	-0.303
	(0.661)	(0.600)	(0.221)	(0.207)	(0.212)	(0.200)
Mean	9.439	9.341	2.705	2.725	2.646	2.669
Observations	6247	8145	6247	8145	6247	8145
Clusters	455	587	455	587	455	587

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

Table C.4 displays the results.[24] For the whole country analysis (Panel A), the distance to the nearest hospital is shorter for people living on the bombing side (-1.709km and -1.479km). The magnitude of the drop in the distance to district-level health centres is almost 0.5 km, which is statistically significant at 5% significance level. The results are consistent if we consider the distance to any available health facilities as a dependent variable. There is a considerable decline in distance to the nearest health facility for people within the bombing areas (about -0.4 km). These empirical results suggest that there are significant disparities in access to health services between populations living inside or outside the destructive areas. A similar analysis for the region around the capital also yielded robust statistical evidence that individuals residing in bombing areas exhibit improved accessibility to healthcare services (Panel B). Although there is no significant difference in terms of distance to hospitals, individuals residing on the bombing side experience a notable reduction in proximity to healthcare facilities with the distance to the nearest health centre being approximately 0.5 or 0.4 km shorter. We found similar results with the unidimensional RD design (Table C.4).

[24]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 3.5.2

Table 9: Difficulty in seeking medical help

	Dependent variable is: Difficulty in seeking medical help					
	All population		Born by 1975		Born after 1975	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: At least 1 problem						
Bombing	-0.024	-0.018	0.007	0.010	-0.044**	-0.036**
	(0.015)	(0.014)	(0.017)	(0.016)	(0.018)	(0.017)
Mean	0.795	0.794	0.832	0.831	0.770	0.769
Observations	9133	12042	3603	4770	5530	7272
Clusters	659	865	654	859	647	850
Panel B: At least 2 problems						
Bombing	-0.025	-0.018	0.011	0.009	-0.048**	-0.036*
	(0.019)	(0.018)	(0.024)	(0.022)	(0.021)	(0.020)
Mean	0.614	0.609	0.655	0.651	0.587	0.582
Observations	9133	12042	3603	4770	5530	7272
Clusters	659	865	654	859	647	850

Note: 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.

6.2.3 Perceived problems in seeking medical help

In addition to distance to health facilities, there are several other factors that can impede women from obtaining medical advice or treatment for their own well-being. DHS surveys have asked participants about problems that have hindered them from seeking medical help. These problems include (1) lack of knowledge about where to seek help (2) getting permission to go (3) lack of financial resources (4) distance to health facilities (5) transport issues (6) not wanting to go alone (7) availability of female health providers (8) concerns about no provider (9) concerns about drug availability. Based on this information, we create a dummy variable equal to 1 if they encounter at least one or two of the specified problems. Using the main strategy to analyze problems in seeking medical help, we found that women born after 1975 and living in bombing areas were less likely to have problems accessing healthcare.

Our findings are presented in Table 9. Women on the bombing side are around 2% less likely to have difficulties when seeking medical assistance. Especially for those born after 1975, the estimate is not only statistically significant but also larger in magnitude (approximately 4%). We observe consistent results with health difficulty indicating that women face at least two problems. Women are around 2% less likely to have problems when seeking medical assistance, although this effect is not significant due to large standard errors. However, estimates for cohorts born after 1975 are still statistically significant and indicate larger effects: they are around 4% less likely to have difficulty in healthcare access. The unidimensional RD design also yields similar results (Table C.5).

Overall, our analysis reveals that women residing in areas affected by the bombing, especially those among the cohorts born after 1975 in the past, have a lower probability of facing obstacles when accessing healthcare services.

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 showed that after more than three decades since the bombing incidents, individuals residing in regions previously affected by bombings demonstrated better health outcomes. Specifically, women residing in these regions witness a height improvement of about 2.7% and a reduced likelihood of anemia by over 20%. The estimated effects vary between the two population groups: positive impacts on height are particularly significant for individuals born after 1975 who were not directly affected by the bombing while beneficial impacts on anemia are notably evident in the elderly population. When considering the likelihood of UXO, we found that positive effects were concentrated in fertile regions with lower UXO prevalence, while areas with higher UXO probability showed null effects. Our results could be attributed to enhancements in soil fertility and improved healthcare accessibility in these areas. Bombing appears to have had a lasting positive effect on land regeneration and enhanced soil quality in the impacted regions. Additionally, these areas have witnessed superior healthcare advancements in the post-conflict era.

Existing literature on health and conflicts mainly focuses on the impact of conflicts on those directly exposed to the conflict, and only a limited number of studies explore the enduring impacts of war on future generations. The study most closely related to our research is the work of Palmer et al. (2016), which investigates the influence of bombing intensity on district-level disability in Vietnam. Their findings reveal persistent negative effects, even four decades after the war had concluded. Nevertheless, this research only considers the aggregated district-level metrics, whereas our study looks at the individual-level health outcomes by comparing people inhabiting regions profoundly affected by historical bombing incidents with those living in nearby areas.

Our findings carry significant implications for all countries that have struggled 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, the restoration of the natural environment and substantial investments in public healthcare have reduced the negative impacts of bombing and even led to improved health outcomes. Future studies should broaden the current scope of existing research on health and conflicts, which primarily concentrates on direct exposure to war 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.

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Appendix

A Robustness

Table A.1: Sample with non-mover only

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.100**	0.079*	-0.173	-0.135	-0.045***	-0.042***
	(0.045)	(0.043)	(0.139)	(0.128)	(0.017)	(0.016)
Mean	-1.871	-1.870	20.28	20.35	0.152	0.145
Observations	2282	2956	2282	2956	2282	2956
Clusters	303	398	303	398	303	398
Panel B: Individuals born by 1975						
Bombing	0.095	0.077	-0.046	0.008	-0.066**	-0.061**
	(0.064)	(0.058)	(0.206)	(0.192)	(0.028)	(0.026)
Mean	-1.888	-1.891	20.64	20.70	0.183	0.170
Observations	1106	1445	1106	1445	1106	1445
Clusters	268	352	268	352	268	352
Panel C: Individuals born after 1975						
Bombing	0.099	0.079	-0.197	-0.166	-0.020	-0.021
	(0.065)	(0.061)	(0.183)	(0.165)	(0.019)	(0.017)
Mean	-1.855	-1.851	19.95	20.01	0.122	0.121
Observations	1176	1511	1176	1511	1176	1511
Clusters	286	375	286	375	286	375

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, and distance to Vietnam borders 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.

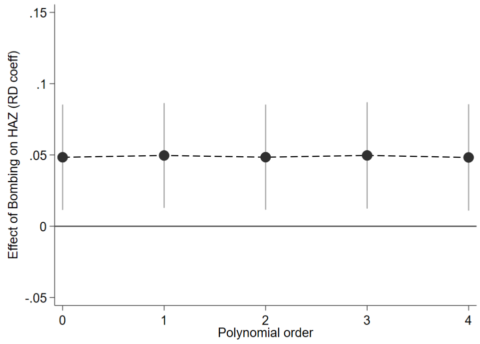
Table A.2: Control for 50x50km grid fixed effects

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.059**	0.047*	0.011	-0.011	-0.015*	-0.014**
	(0.029)	(0.026)	(0.095)	(0.086)	(0.008)	(0.007)
Mean	-1.816	-1.809	21.16	21.21	0.0977	0.0953
Observations	9133	12042	9133	12042	9133	12042
Clusters	659	865	659	865	659	865
Panel B: Individuals born by 1975						
Bombing	0.040	0.031	0.061	0.047	-0.024*	-0.021*
	(0.038)	(0.034)	(0.152)	(0.137)	(0.013)	(0.012)
Mean	-1.857	-1.853	21.74	21.81	0.117	0.116
Observations	3603	4770	3603	4770	3603	4770
Clusters	654	859	654	859	654	859
Panel C: Individuals born after 1975						
Bombing	0.082**	0.066**	-0.043	-0.056	-0.007	-0.008
	(0.036)	(0.032)	(0.101)	(0.091)	(0.009)	(0.008)
Mean	-1.788	-1.780	20.78	20.81	0.0854	0.0821
Observations	5530	7272	5530	7272	5530	7272
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, 50x50km grid fixed effects, distance to the capital, and distance to Vietnam borders 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.

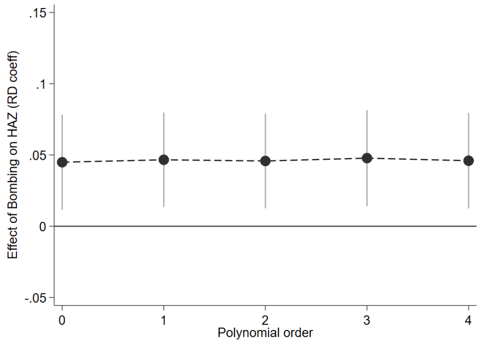
Figure A.1: Height-for-age Z-score: Sensitivity of Results to Different Orders of Polynomial

Panel A: Within 1km bandwidth

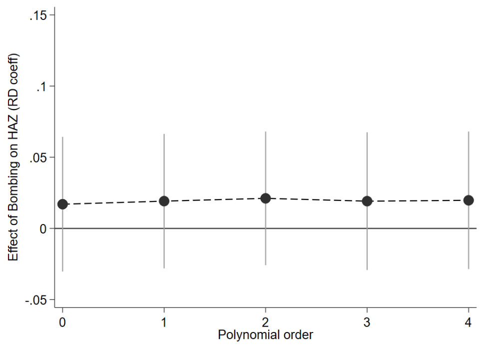


(a) All sample

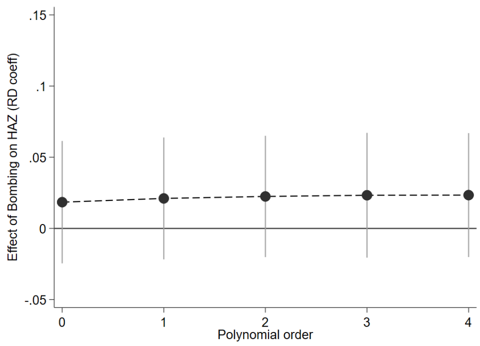
Panel B: Within 1.5km bandwidth



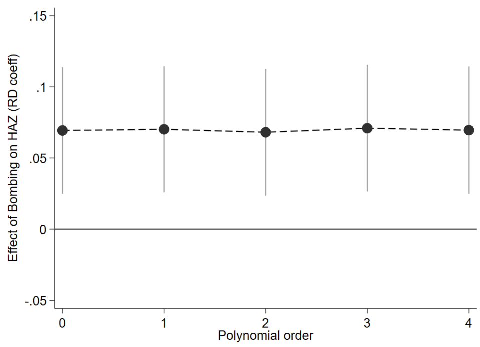
(b) All sample



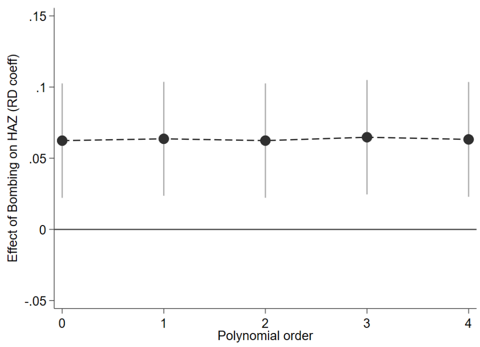
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975

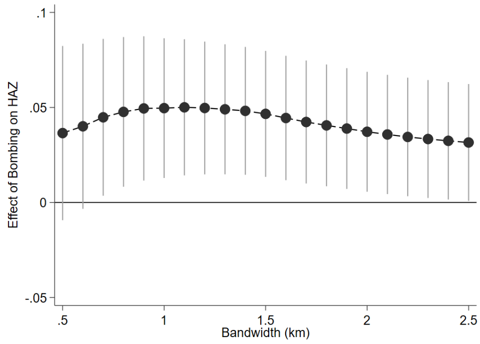


(f) Individuals born after 1975

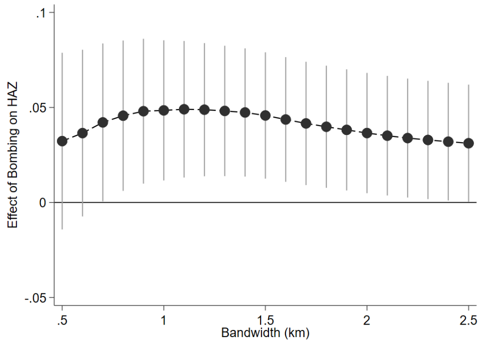
Note: Dependent variable is Height-for-age Z-score (HAZ). Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

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

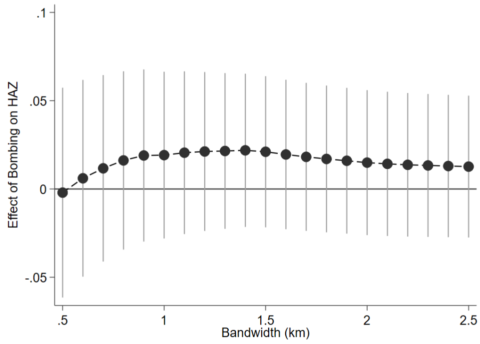
Panel A: Linear polynomial **Panel B: Quadratic polynomial**



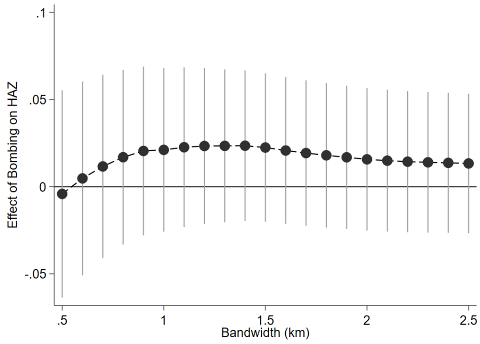
(a) All sample



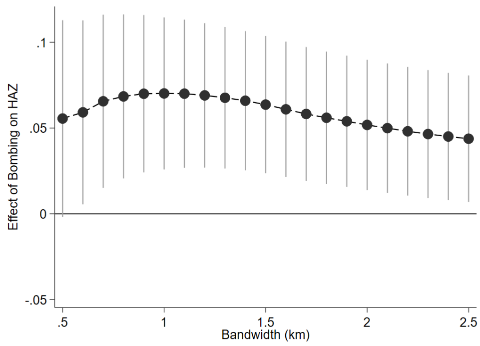
(b) All sample



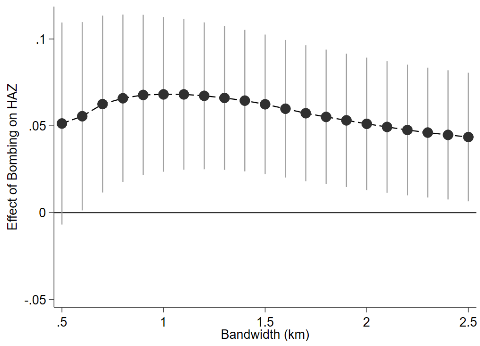
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975



(f) Individuals born after 1975

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

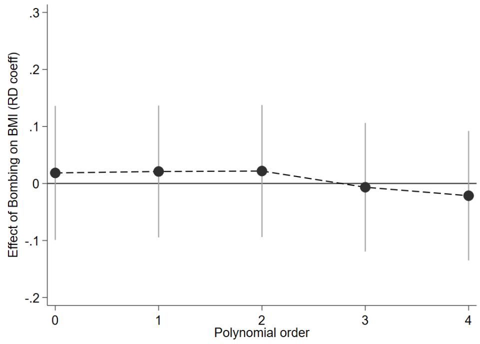
	Dependent variable is Heigh-for-age Z-score (HAZ)											
	Quadratic		Cubic		No weight		No dist_capital		No dist_vietnam		Donut 0.25km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All observations												
Bombing	0.048*	0.046*	0.050*	0.048*	0.050*	0.031	0.050*	0.047*	0.048*	0.045*	0.074**	0.061*
	(0.029)	(0.026)	(0.029)	(0.026)	(0.026)	(0.025)	(0.029)	(0.026)	(0.029)	(0.026)	(0.037)	(0.032)
Mean	-1.816	-1.809	-1.816	-1.809	-1.816	-1.809	-1.816	-1.809	-1.816	-1.809	-1.813	-1.805
Observations	9133	12042	9133	12042	9133	12042	9133	12042	9133	12042	6534	9443
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Panel B: Individuals born by 1975												
Bombing	0.021	0.022	0.019	0.023	0.023	0.009	0.020	0.022	0.016	0.018	0.057	0.047
	(0.037)	(0.033)	(0.038)	(0.034)	(0.034)	(0.033)	(0.037)	(0.033)	(0.037)	(0.033)	(0.049)	(0.043)
Mean	-1.857	-1.853	-1.857	-1.853	-1.857	-1.853	-1.857	-1.853	-1.857	-1.853	-1.860	-1.854
Observations	3603	4770	3603	4770	3603	4770	3603	4770	3603	4770	2574	3741
Clusters	654	859	654	859	654	859	654	859	654	859	466	671
Panel C: Individuals born after 1975												
Bombing	0.068*	0.062**	0.071**	0.065**	0.068**	0.044	0.070**	0.064**	0.069**	0.062**	0.094**	0.073*
	(0.035)	(0.031)	(0.035)	(0.031)	(0.031)	(0.029)	(0.035)	(0.031)	(0.035)	(0.031)	(0.044)	(0.039)
Mean	-1.788	-1.780	-1.788	-1.780	-1.788	-1.780	-1.788	-1.780	-1.788	-1.780	-1.782	-1.773
Observations	5530	7272	5530	7272	5530	7272	5530	7272	5530	7272	3960	5702
Clusters	647	850	647	850	647	850	647	850	647	850	464	667

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.

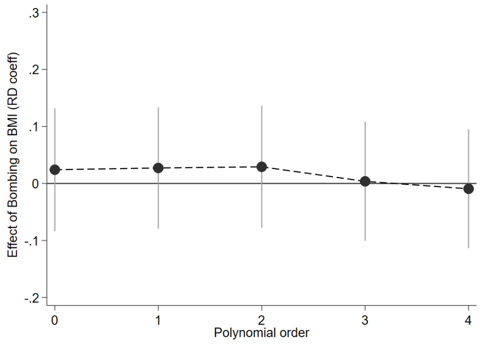
Figure A.3: Body Mass Index: Sensitivity of Results to Different Orders of Polynomial

Panel A: Within 1km bandwidth

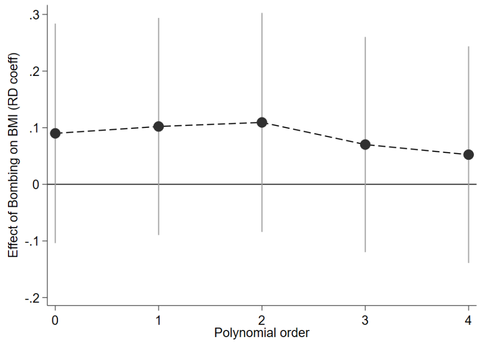
Panel B: Within 1.5km bandwidth



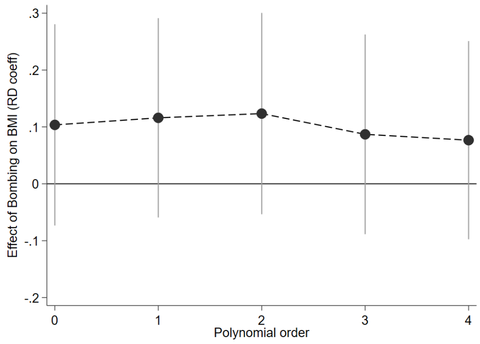
(a) All sample



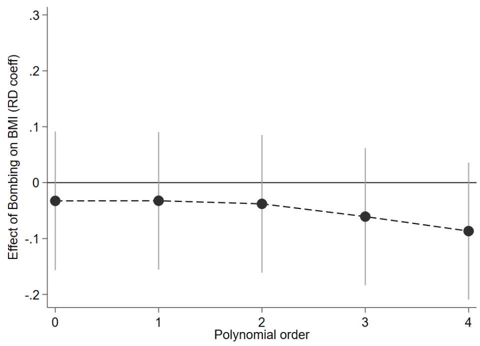
(b) All sample



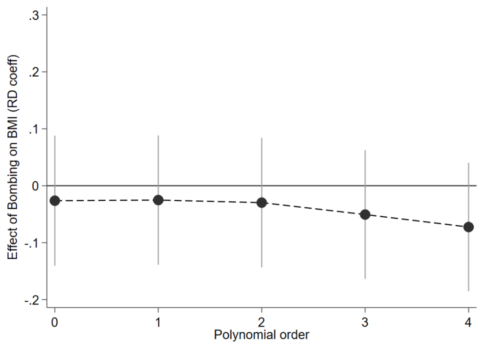
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975

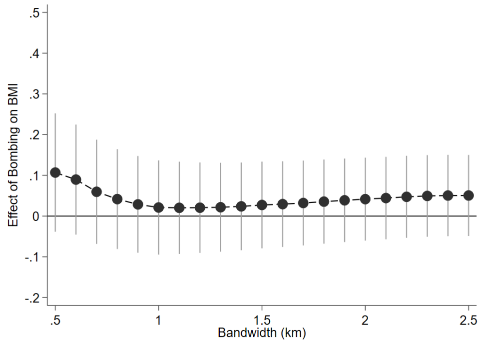


(f) Individuals born after 1975

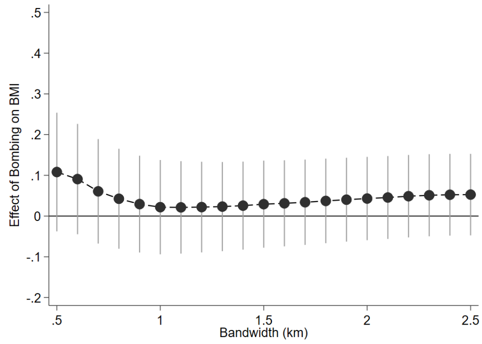
Note: Dependent variable is Body Mass Index (BMI). Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

Figure A.4: Body Mass Index: Sensitivity of Results to Bandwidth Choice

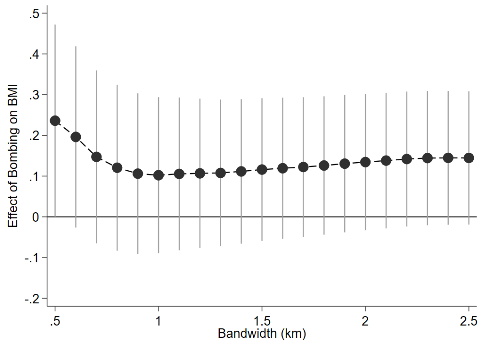
Panel A: Linear polynomial | **Panel B: Quadratic polynomial**



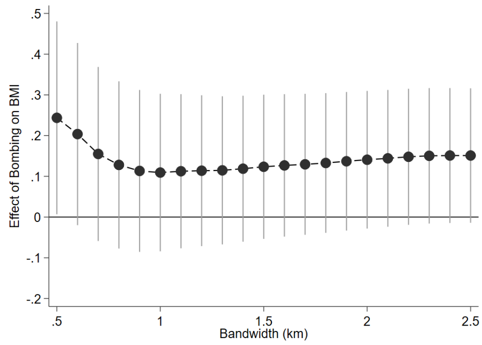
(a) All sample



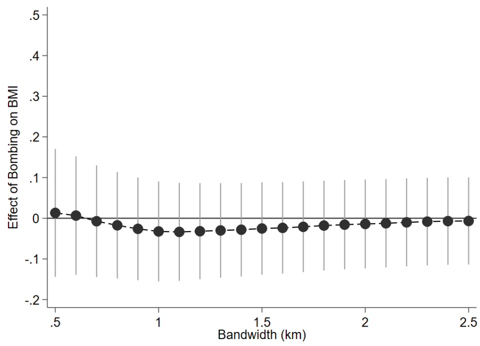
(b) All sample



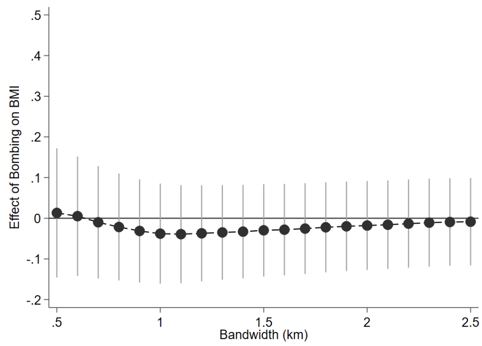
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975



(f) Individuals born after 1975

Note: Dependent variable is Body Mass Index (BMI). 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 regressions 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.

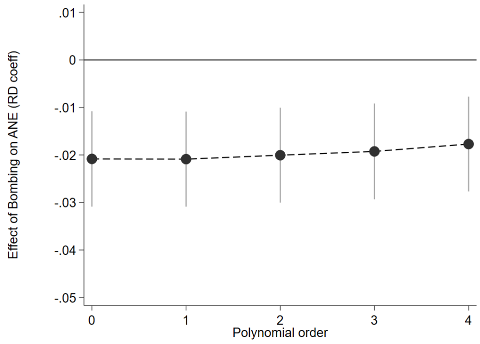
Table A.4: Body Mass Index - Robustness checks: different specifications with latitude-longitude as running variables

	Dependent variable is Body Mass Index											
	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
Pbmil A: All observations												
Bombing	0.022	0.029	-0.007	0.004	0.008	0.043	0.022	0.027	0.021	0.027	-0.117	-0.051
	(0.090)	(0.083)	(0.088)	(0.081)	(0.084)	(0.080)	(0.090)	(0.083)	(0.090)	(0.083)	(0.117)	(0.103)
Mean	21.16	21.21	21.16	21.21	21.16	21.21	21.16	21.21	21.16	21.21	21.14	21.20
Observations	9133	12042	9133	12042	9133	12042	9133	12042	9133	12042	6534	9443
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Pbmil B: Individuals born by 1975												
Bombing	0.109	0.123	0.070	0.087	0.126	0.158	0.102	0.116	0.101	0.116	-0.041	0.071
	(0.151)	(0.138)	(0.148)	(0.137)	(0.138)	(0.128)	(0.149)	(0.136)	(0.149)	(0.136)	(0.196)	(0.169)
Mean	21.74	21.81	21.74	21.81	21.74	21.81	21.74	21.81	21.74	21.81	21.71	21.81
Observations	3603	4770	3603	4770	3603	4770	3603	4770	3603	4770	2574	3741
Clusters	654	859	654	859	654	859	654	859	654	859	466	671
Pbmil C: Individuals born after 1975												
Bombing	-0.038	-0.030	-0.061	-0.051	-0.059	-0.022	-0.029	-0.024	-0.035	-0.029	-0.187	-0.129
	(0.096)	(0.089)	(0.096)	(0.088)	(0.090)	(0.086)	(0.096)	(0.089)	(0.095)	(0.088)	(0.125)	(0.111)
Mean	20.78	20.81	20.78	20.81	20.78	20.81	20.78	20.81	20.78	20.81	20.77	20.81
Observations	5530	7272	5530	7272	5530	7272	5530	7272	5530	7272	3960	5702
Clusters	647	850	647	850	647	850	647	850	647	850	464	667

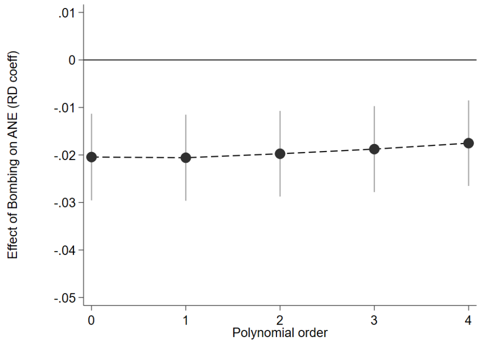
Note: The unit of analysis is survey respondents. Standard errors reported in parenthesis are at the DHS survey cluster level. Regression (9) (10) conduct a donut exercise that excludes observations within 0.25 km the bombing boundaries. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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

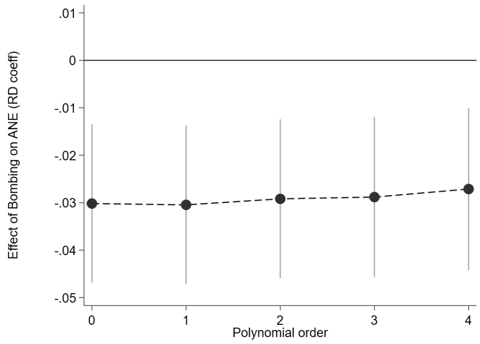
Panel A: Within 1km bandwidth **Panel B: Within 1.5km bandwidth**



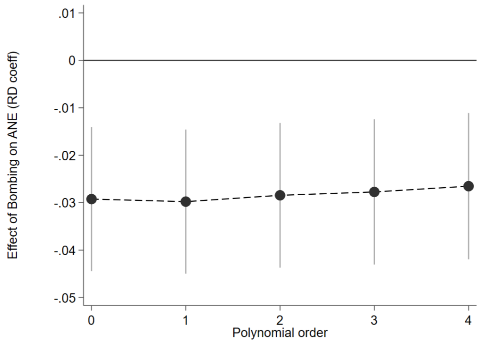
(a) All sample



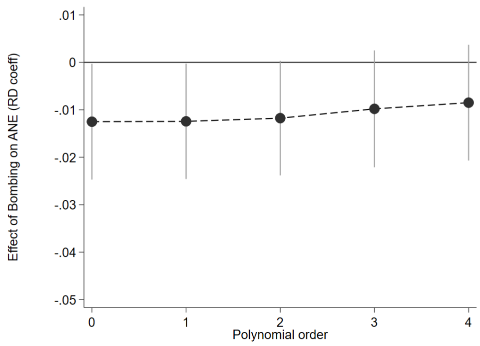
(b) All sample



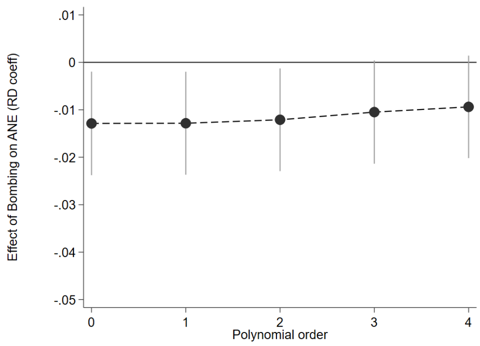
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975

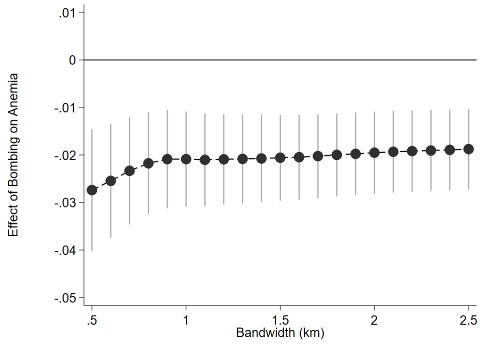


(f) Individuals born after 1975

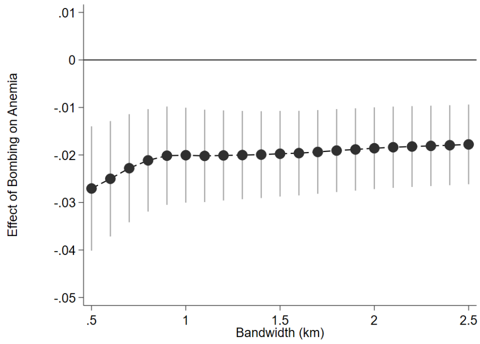
Note: Dependent variable is Anemia Level (ANE). Each dot represents the RD estimate using the specified order of RD polynomial in latitude and longitude. Range spikes represent 90% confidence intervals of the estimates.

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

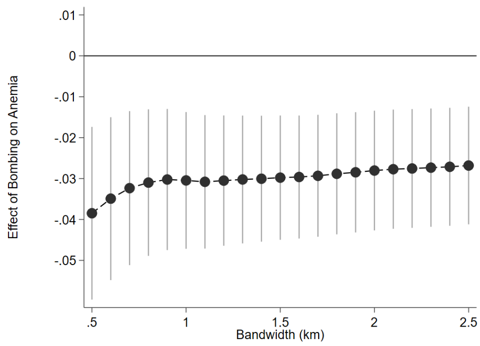
Panel A: Linear polynomial | **Panel B: Quadratic polynomial**



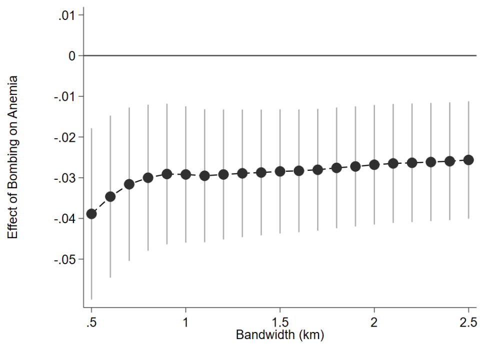
(a) All sample



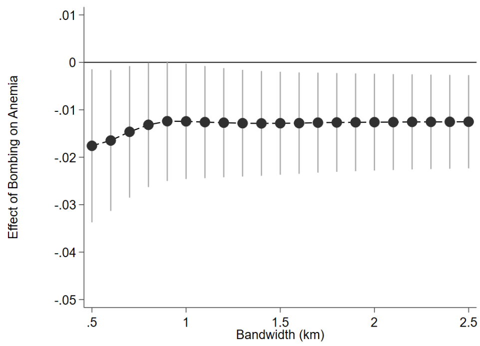
(b) All sample



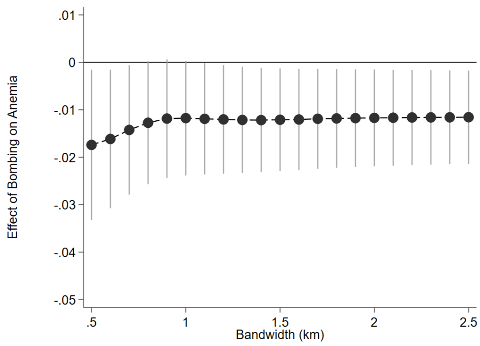
(c) Individuals born by 1975



(d) Individuals born by 1975



(e) Individuals born after 1975



(f) Individuals born after 1975

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.5: 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	-0.020**	-0.020***	-0.019**	-0.019***	-0.021***	-0.019***	-0.021***	-0.021***	-0.021***	-0.021***	-0.019*	-0.021**
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.011)	(0.009)
Mean	0.0977	0.0953	0.0977	0.0953	0.0977	0.0953	0.0977	0.0953	0.0977	0.0953	0.0978	0.0948
Observations	9133	12042	9133	12042	9133	12042	9133	12042	9133	12042	6534	9443
Clusters	659	865	659	865	659	865	659	865	659	865	471	677
Panel B: Individuals born by 1975												
Bombing	-0.029**	-0.028**	-0.029**	-0.028**	-0.031**	-0.026**	-0.030**	-0.030**	-0.030**	-0.029**	-0.023	-0.023
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.011)	(0.013)	(0.012)	(0.013)	(0.012)	(0.016)	(0.015)
Mean	0.117	0.116	0.117	0.116	0.117	0.116	0.117	0.116	0.117	0.116	0.118	0.116
Observations	3603	4770	3603	4770	3603	4770	3603	4770	3603	4770	2574	3741
Clusters	654	859	654	859	654	859	654	859	654	859	466	671
Panel C: Individuals born after 1975												
Bombing	-0.012	-0.012	-0.010	-0.010	-0.013	-0.013*	-0.012	-0.013	-0.013	-0.013	-0.014	-0.018*
	(0.009)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.012)	(0.010)
Mean	0.0854	0.0821	0.0854	0.0821	0.0854	0.0821	0.0854	0.0821	0.0854	0.0821	0.0846	0.0807
Observations	5530	7272	5530	7272	5530	7272	5530	7272	5530	7272	3960	5702
Clusters	647	850	647	850	647	850	647	850	647	850	464	667

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.6: 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
Phazl A: All observations								
Bombing	-0.006	0.003	-0.056*	-0.047*	0.002	0.001	0.001	-0.002
	(0.027)	(0.024)	(0.030)	(0.027)	(0.024)	(0.022)	(0.028)	(0.025)
Mean	0.623	0.769	0.560	0.711	0.633	0.757	0.614	0.781
Observations	9509	12658	8983	12422	10134	13211	9665	13404
Clusters	680	900	652	888	714	939	686	946
Phazl B: Individuals born by 1975								
Bombing	-0.036	-0.021	-0.018	-0.011	0.019	0.021	0.044	0.042
	(0.036)	(0.032)	(0.042)	(0.038)	(0.034)	(0.031)	(0.037)	(0.034)
Mean	0.637	0.775	0.573	0.708	0.633	0.762	0.626	0.778
Observations	3774	4963	3553	4781	3854	5068	3788	5197
Clusters	673	892	649	883	710	933	681	938
Phazl C: Individuals born after 1975								
Bombing	0.009	0.016	-0.080**	-0.070**	-0.007	-0.010	-0.024	-0.028
	(0.033)	(0.030)	(0.033)	(0.030)	(0.030)	(0.027)	(0.034)	(0.030)
Mean	0.614	0.765	0.552	0.713	0.633	0.754	0.606	0.783
Observations	5735	7695	5430	7641	6280	8143	5877	8207
Clusters	670	885	636	866	698	921	672	928

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: Body Mass Index - Robustness checks: Shifting borders

	Dependent variable is Body Mass Index							
	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
Pbmil A: All observations								
Bombing	0.035	0.071	0.068	0.042	0.045	0.008	0.047	0.045
	(0.098)	(0.087)	(0.096)	(0.086)	(0.091)	(0.082)	(0.099)	(0.089)
Mean	0.623	0.769	0.560	0.711	0.633	0.757	0.614	0.781
Observations	9509	12658	8983	12422	10134	13211	9665	13404
Clusters	680	900	652	888	714	939	686	946
Pbmil B: Individuals born by 1975								
Bombing	0.105	0.128	0.255*	0.216	0.114	0.080	-0.076	-0.073
	(0.163)	(0.146)	(0.154)	(0.140)	(0.143)	(0.129)	(0.155)	(0.141)
Mean	0.637	0.775	0.573	0.708	0.633	0.762	0.626	0.778
Observations	3774	4963	3553	4781	3854	5068	3788	5197
Clusters	673	892	649	883	710	933	681	938
Pbmil C: Individuals born after 1975								
Bombing	-0.066	-0.006	-0.025	-0.045	0.002	-0.042	0.122	0.122
	(0.098)	(0.088)	(0.103)	(0.092)	(0.096)	(0.088)	(0.105)	(0.093)
Mean	0.614	0.765	0.552	0.713	0.633	0.754	0.606	0.783
Observations	5735	7695	5430	7641	6280	8143	5877	8207
Clusters	670	885	636	866	698	921	672	928

Note: The table shows the results of placebo tests which shift bombing borders by 3 kilometres 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.8: Anemia - Robustness checks: Shifting borders

	Dependent variable is Anemia							
	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	0.003	0.001	0.005	0.003	0.001	0.003	0.015*	0.013*
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)
Mean	0.623	0.769	0.560	0.711	0.633	0.757	0.614	0.781
Observations	9509	12658	8983	12422	10134	13211	9665	13404
Clusters	680	900	652	888	714	939	686	946
Panel B: Individuals born by 1975								
Bombing	0.018	0.013	0.007	0.000	0.009	0.009	0.018	0.016
	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.013)	(0.012)
Mean	0.637	0.775	0.573	0.708	0.633	0.762	0.626	0.778
Observations	3774	4963	3553	4781	3854	5068	3788	5197
Clusters	673	892	649	883	710	933	681	938
Panel C: Individuals born after 1975								
Bombing	-0.006	-0.007	0.003	0.004	-0.005	-0.001	0.010	0.009
	(0.009)	(0.008)	(0.011)	(0.010)	(0.008)	(0.007)	(0.009)	(0.008)
Mean	0.614	0.765	0.552	0.713	0.633	0.754	0.606	0.783
Observations	5735	7695	5430	7641	6280	8143	5877	8207
Clusters	670	885	636	866	698	921	672	928

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 5.3, 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		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Individuals born by 1975						
Bombing	-0.100	-0.089	-0.233	-0.164	0.016	0.009
	(0.068)	(0.059)	(0.256)	(0.227)	(0.018)	(0.017)
Mean	-1.818	-1.812	21.99	22.05	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	0.014	0.026	-0.204	-0.168	-0.006	-0.007
	(0.052)	(0.047)	(0.173)	(0.150)	(0.017)	(0.014)
Mean	-1.765	-1.781	20.87	20.91	0.0738	0.0742
Observations	1869	2427	1869	2427	1869	2427
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, and distance to Vietnam borders 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. Across all specifications, we see null impacts across generations in fertile regions where the chance of encountering UXO is high. On the contrary, in infertile regions, the effects of bombing 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 0.90, equal to 5%, in their Health-for-age Z-scores. In terms of Body Mass Index, the older generation observes an improvement in their BMI if they are on the bombing side, whereas there is no significant difference in BMI among the younger generation. With regard to anemia, older people residing on the bombing

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

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: Individuals born by 1975						
Bombing	0.070	0.061	0.298*	0.282*	-0.060***	-0.051***
	(0.042)	(0.040)	(0.174)	(0.162)	(0.017)	(0.016)
Mean	-1.877	-1.874	21.61	21.69	0.132	0.129
Observations	2381	3170	2381	3170	2381	3170
Clusters	427	561	427	561	427	561
Panel B: Individuals born after 1975						
Bombing	0.090**	0.079*	0.026	0.012	-0.015	-0.014
	(0.045)	(0.041)	(0.115)	(0.109)	(0.012)	(0.011)
Mean	-1.801	-1.780	20.74	20.76	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, and distance to Vietnam borders 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.

side are less likely to suffer from anemia, with a drop of around 6 percentage points in anemia risk. This drop is equivalent to a 45% deviation from the mean value of anemia likelihood in this age group. Overall, this impact heterogeneity is consistent with our main results.

C Uni-dimensional RD design

C.1 Specification with unidimensional RD polynomial

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 running variables.

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: $f(Geo_c) = \sum_{k=1}^{a} \eta_k dist_c^k$. We also run regressions with the interaction term of the treatment variable with the distance to the bombing areas will be added to test the sensitivity of the results. This interaction term allows for different slopes of the functions on two sides of bombing boundaries. Specifically, with interaction terms, the linear function of RD polynomial will be $f(Geo_c) = \eta dist_c + \theta Bombing_c \times dis_c$ and higher order of RD polynomial will take the form of $f(Geo_c) = \sum_{k=1}^{a} \eta_k dist_c^k + \theta_k Bombing_c \times dis_c^k$.

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).

C.2 Results

The unidimensional RD design yields similar results as our main design (Table C.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 0.083 (approximately 4.6%) in HAZ. This effect is notably substantial for individuals born after 1975, showing a height increase of 0.116 (around 6.5%). In terms of BMI, people living in bombing areas have higher BMI, although this estimate is indistinguishable from zero. In terms of anemia, those on the bombing side face a 2.4% lower risk. Although the estimates are not statistically significant, the findings align consistently with the latitude-longitude RD results: the impact on anemia is more pronounced for individuals born before 1975 with a 2.3% increase in anemia likelihood, whereas it is only 2.1% for those born after 1975.

Figure C.1 visually illustrates the heterogeneous effects of bombing. Panel A shows the results with the sample including individuals born by 1975, while Panel B focuses on individuals born after the bombing. Across all graphs, we can observe some clear discontinuities at bombing boundaries. Specifically, in Panel B, we can observe a significant jump in HAZ for those located on the bombing side. BMI shows a continuity in both panels. Additionally, both panels show a noticeable decrease in anemia prevalence, particularly in Panel B, which examines those born after 1975.

Table C.1: Results with unidimensional RD design

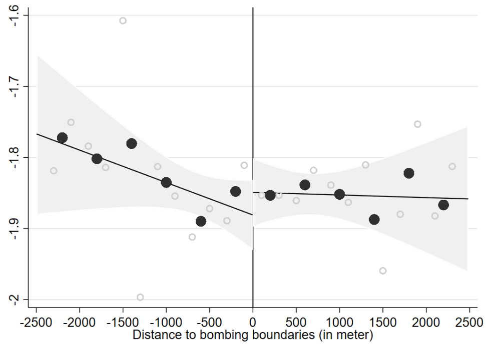
	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1) Linear	(2) Quad.	(3) Linear	(4) Quad.	(5) Linear	(6) Quad.
Panel A: All population						
Bombing	0.083**	0.084**	0.018	0.020	-0.024**	-0.025**
	(0.037)	(0.036)	(0.104)	(0.104)	(0.010)	(0.010)
Mean	-1.80	-1.80	21.2	21.2	0.091	0.091
Observations	14896	14896	18445	18445	15312	15312
Bandwidth (km)	2.05	2.05	3.04	3.04	2.10	2.10
Clusters	1054	1054	1300	1300	1082	1082
Panel B: Individuals born by 1975						
Bombing	0.023	0.026	0.107	0.115	-0.023	-0.024
	(0.040)	(0.040)	(0.169)	(0.171)	(0.015)	(0.015)
Mean	-1.84	-1.84	21.9	21.9	0.11	0.11
Observations	7510	7510	7022	7022	6752	6752
Bandwidth (km)	3.49	3.49	3.03	3.03	2.74	2.74
Clusters	1380	1380	1288	1288	1236	1236
Panel C: Individuals born after 1975						
Bombing	0.116***	0.118***	-0.054	-0.054	-0.021*	-0.021*
	(0.043)	(0.043)	(0.118)	(0.118)	(0.012)	(0.012)
Mean	-1.77	-1.77	20.8	20.8	0.077	0.077
Observations	9014	9014	10314	10314	9594	9594
Bandwidth (km)	2.01	2.01	2.47	2.47	2.18	2.18
Clusters	1021	1021	1160	1160	1085	1085

Note: The unit of analysis is survey respondents. Province fixed effects, distance to the capital, and distance to Vietnam borders 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.

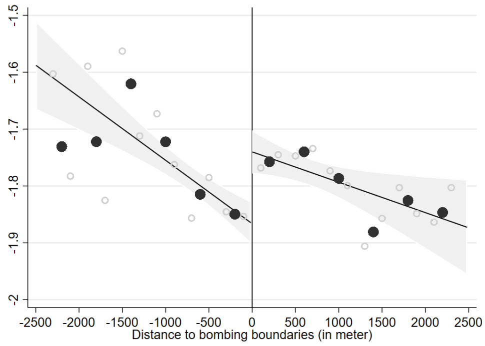
Figure C.1: Unidimensional RD design: Heterogeneous effects for two groups of population

Panel A: Born by 1975

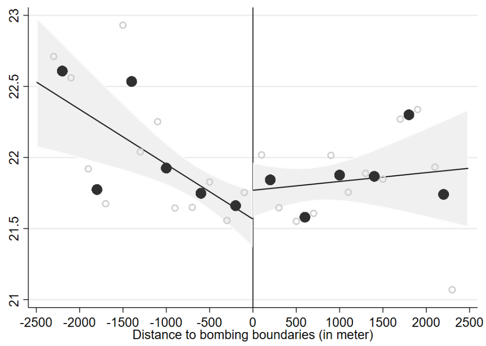
Panel B: Born after 1975



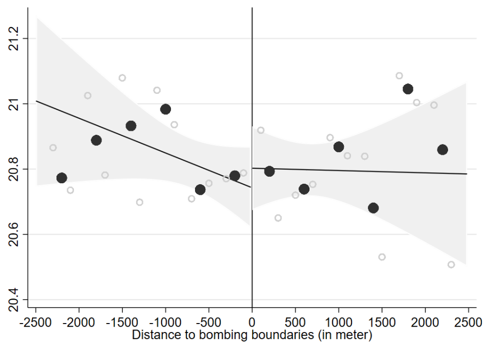
(a) Height-for-age Z-score



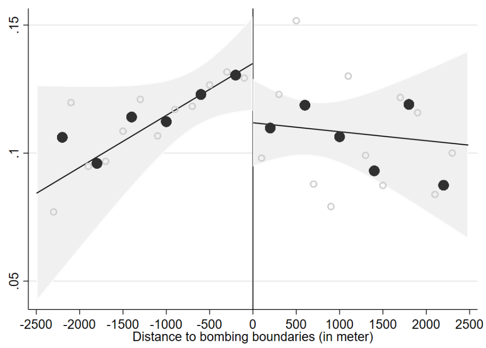
(b) Height-for-age Z-score



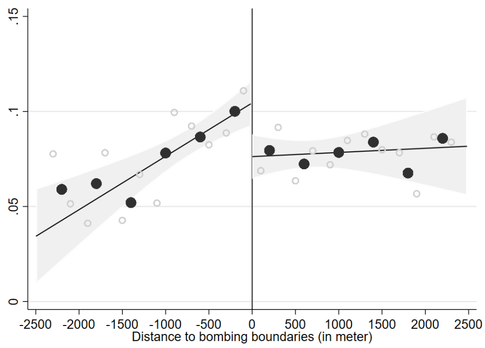
(c) Body Mass Index



(d) Body Mass Index



(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.

C.3 Additional tables and figures

Table C.2: Unidimensional RD design: Impact heterogeneity on different regions

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1) Linear	(2) Quad.	(3) Linear	(4) Quad.	(5) Linear	(6) Quad.
Panel A: Fertile areas (1962)						
Bombing	-0.009	-0.008	-0.218	-0.215	0.000	0.000
	(0.050)	(0.050)	(0.179)	(0.180)	(0.013)	(0.013)
Mean	-1.77	-1.77	21.5	21.5	0.075	0.075
Observations	6348	6348	6678	6678	6175	6175
Bandwidth (km)	2.81	2.81	3.08	3.08	2.69	2.69
Clusters	456	456	477	477	444	444
Panel B: Infertile areas (1962)						
Bombing	0.132***	0.135***	0.104	0.108	-0.043***	-0.044***
	(0.046)	(0.046)	(0.121)	(0.121)	(0.015)	(0.015)
Mean	-1.82	-1.82	21.2	21.2	0.10	0.10
Observations	9181	9181	12583	12583	8669	8669
Bandwidth (km)	1.92	1.92	3.46	3.46	1.72	1.72
Clusters	642	642	880	880	609	609

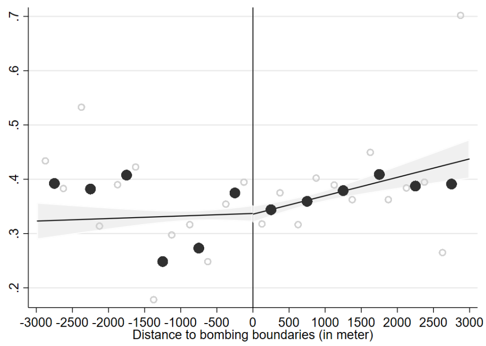
Note: The unit of analysis is survey respondents. Province fixed effects, distance to the capital, and distance to Vietnam borders are present in all regressions. Regressions (1) (3) (5) control for a linear polynomial in distance to the bombing boundaries. Regressions (2) (4) (6) control for quadratic 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.

Table C.3: Unidimensional RD design: Soil Fertility

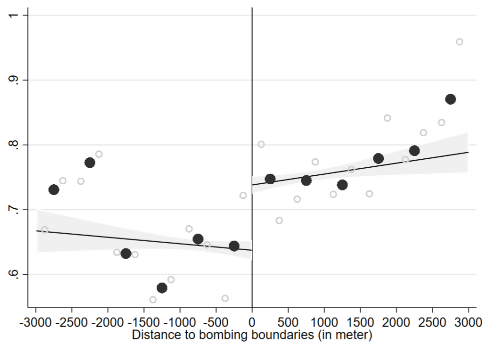
	Dependent variable is:			
	Soil fertility in 1962		Soil fertility in 2003	
	(1) Linear	(2) Quad.	(3) Linear	(4) Quad.
Bombing	0.028	0.033	0.127***	0.132***
	(0.048)	(0.048)	(0.040)	(0.040)
Mean	0.35	0.35	0.71	0.71
Observations	17698	17698	18377	18377
Bandwidth (km)	2.78	2.78	3.03	3.03
Clusters	1250	1250	1296	1296

Note: The unit of analysis is survey respondents. Regressions (1) (3) control for a linear polynomial in distance to the bombing boundaries. Regressions (2) (4) 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.

Figure C.2: Unidimensional RD design: Bombing and soil fertility



(a) *Soil fertility in 1962*



(b) *Soil fertility in 2003*

Note: "Distance to bombing boundaries" refers to the distance to the closest point in bombing boundaries. "Negative" values of distance indicate locations outside the bombing areas. Black dots represent the average of outcomes for observations within 5000-meter distance bins, while hollow dots represent the average for observations within 2500-meter distance bins. The solid line trends give the predicted values from a regression of soil fertility on a quadratic polynomial in distance to the bombing boundaries.

Table C.4: Unidimensional RD design: Distance to health facilities

	Dependent variable is Distance (km) to					
	Hospital		District health center		Any health facility	
	(1)	(2)	(3)	(4)	(5)	(6)
	Linear	Quad.	Linear	Quad.	Linear	Quad.
Panel A: The whole country						
Bombing	-2.140	-2.264*	-0.664**	-0.686**	-0.594**	-0.618**
	(1.311)	(1.313)	(0.265)	(0.267)	(0.260)	(0.262)
Mean	12.6	12.6	3.11	3.11	3.06	3.06
Observations	16914	16914	17018	17018	17061	17061
Bandwidth (km)	2.51	2.51	2.54	2.54	2.58	2.58
Clusters	1194	1194	1201	1201	1207	1207
Panel B: Restricted region						
Bombing	-0.296	-0.359	-0.701**	-0.703**	-0.566**	-0.556**
	(0.887)	(0.889)	(0.304)	(0.308)	(0.279)	(0.281)
Mean	9.09	9.09	2.74	2.74	2.67	2.67
Observations	9795	9795	8506	8506	9165	9165
Bandwidth (km)	2.06	2.06	1.61	1.61	1.85	1.85
Clusters	699	699	612	612	654	654

Note: The unit of analysis is survey respondents. Regressions (1) (3) (5) control for a linear polynomial in distance to the bombing boundaries. Regressions (2) (4) (6) control for a quadratic polynomial 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.

Table C.5: Unidimensional RD design: Difficulty in seeking medical help

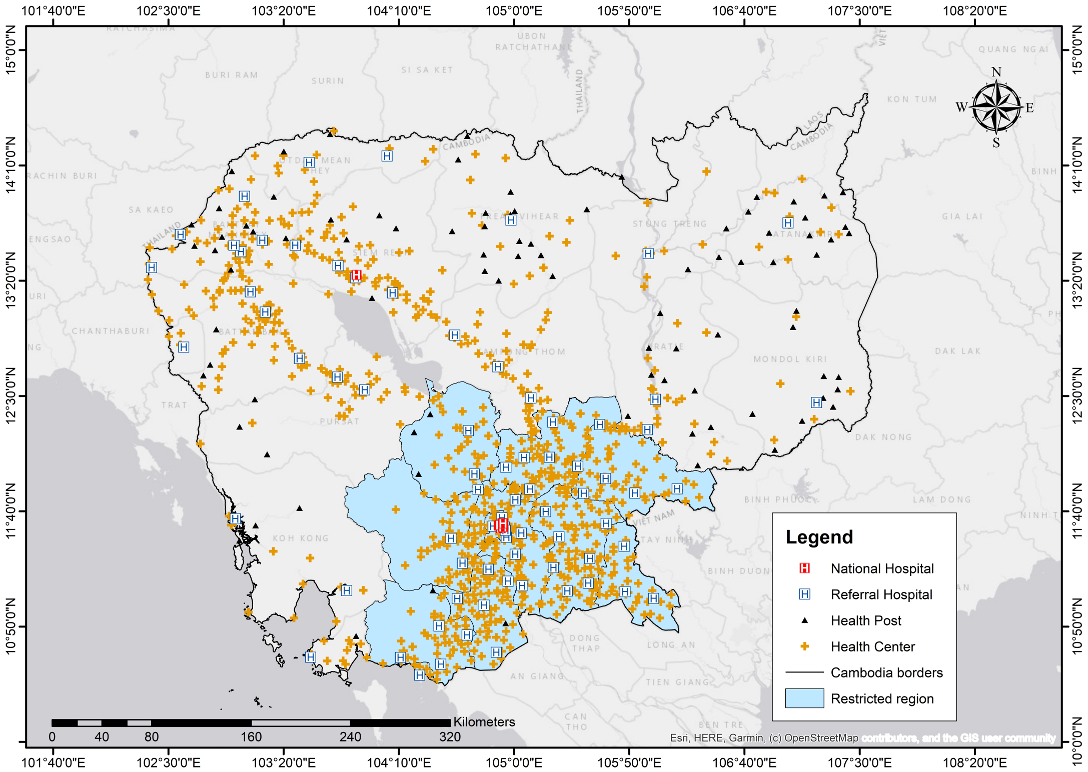
	Dependent variable is: Difficulty in seeking medical help					
	All population		Born by 1975		Born after 1975	
	(1) Linear	(2) Quad.	(3) Linear	(4) Quad.	(5) Linear	(6) Quad.
Panel A: At least 1 problem						
Bombing	-0.038**	-0.038**	-0.000	-0.002	-0.062***	-0.062***
	(0.018)	(0.018)	(0.020)	(0.020)	(0.022)	(0.022)
Mean	0.79	0.79	0.83	0.83	0.77	0.77
Observations	16550	16550	6833	6833	9682	9682
Bandwidth (km)	2.41	2.41	2.81	2.81	2.21	2.21
Clusters	1169	1169	1249	1249	1094	1094
Panel B: At least 2 problems						
Bombing	-0.040*	-0.041*	-0.002	-0.006	-0.069**	-0.069***
	(0.024)	(0.024)	(0.029)	(0.029)	(0.027)	(0.027)
Mean	0.61	0.61	0.66	0.66	0.59	0.58
Observations	15312	15312	6507	6507	8864	8864
Bandwidth (km)	2.10	2.10	2.53	2.53	1.97	1.97
Clusters	1082	1082	1188	1188	1008	1008

Note: The unit of analysis is survey respondents. Regressions (1) (3) (5) control for a linear polynomial in distance to the bombing boundaries. Regressions (2) (4) (6) control for a quadratic polynomial 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.

D 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 D.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 D.2).

Figure D.1: Restricted region and health facilities

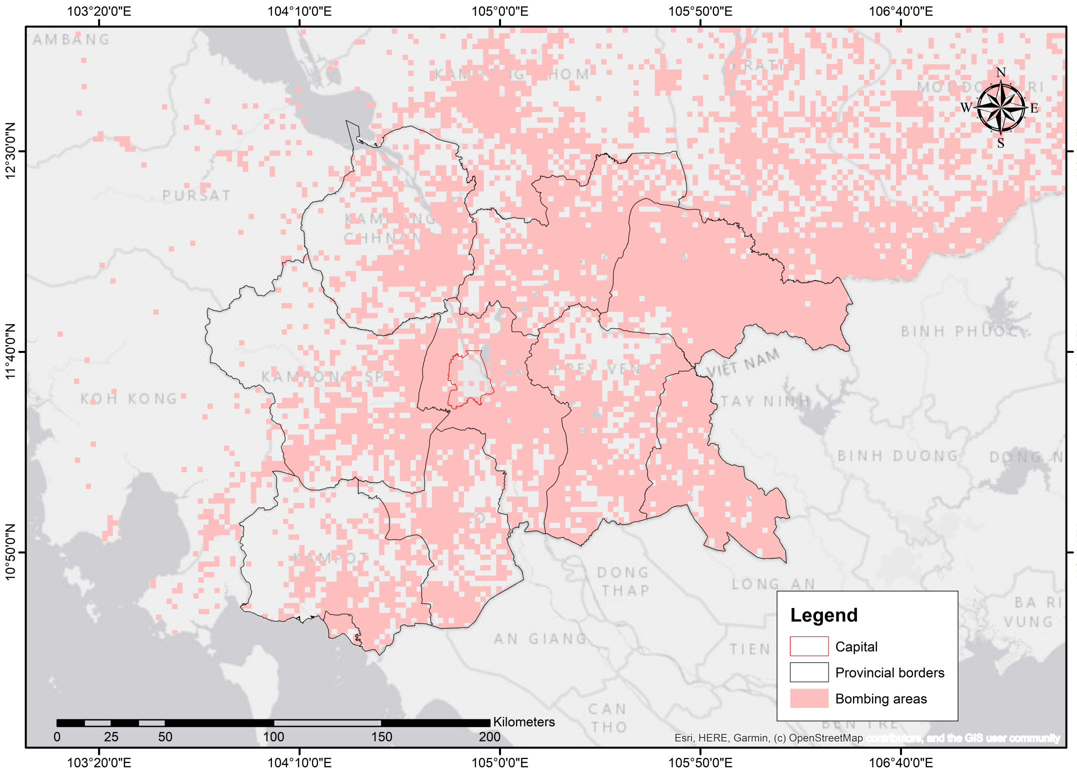


Notes: The map shows the restricted region for analysis. It also depicts locations of health facilities, including national hospital, referral hospitals, health centers, and health posts in Cambodia. Map overlaid on Open-StreetMap and drawn on ArcGIS.

The findings of our primary RD design, examining the lasting causal effects of bombing on various health outcomes in the restricted region, are presented in Table D.1. The results are also disaggregated for two distinct population groups. In terms of Height-for-age Z-scores, although coefficients are indistinguishable from zero, we observe consistent results with higher heights for people living on the bombing side. Especially, these positive effects are driven by the population born after 1975. In particular, analysis of the whole sample shows that within 1.5km bandwidth, HAZ is about 0.39 higher for people living in bombing areas. The magnitude is considerably bigger for those born after 1975 with approximately 0.6 higher in HAZ.

We found evidence that people on the bombing side have lower BMI. Specifically,

Figure D.2: Bombing in restricted region



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

on average, BMI declines by 0.190 or 0.157 if they are living in bombing areas. The drop is considerably significant and larger for people born after the bombing (0.221 or 0.192). However, this drop only represents a 1% change relative to the mean of BMI. Moreover, a lower BMI does not mean worse health because in some cases, a lower BMI may be desirable, especially for individuals who are naturally lean or have specific health conditions. Additionally, a person with a lower BMI is less likely to suffer from obesity. Since HAZ and BMI are two different measures used to assess different aspects of an individual's growth and development, our results do not show any contradictions.

Concerning anemia prevalence, individuals residing in areas subjected to bombing are less likely to experience anemia, particularly among the older generations. Regression findings for individuals born before 1975 indicate a significant decrease of approximately 3 percentage points in anemia prevalence, constituting nearly a 30% decrease relative to the average likelihood of anemia within this age group.

Table D.1: Regional analysis

	Dependent variable is:					
	Height-for-age Z-score		Body Mass Index		Anemia Level	
	(1)	(2)	(3)	(4)	(5)	(6)
	<1km	<1.5km	<1km	<1.5km	<1km	<1.5km
Panel A: All population						
Bombing	0.033	0.039	-0.190*	-0.157	-0.016*	-0.018**
	(0.035)	(0.031)	(0.114)	(0.104)	(0.009)	(0.008)
Mean	-1.779	-1.769	21.20	21.23	0.0869	0.0872
Observations	6247	8145	6247	8145	6247	8145
Clusters	455	587	455	587	455	587
Panel B: Individuals born by 1975						
Bombing	-0.005	0.004	-0.154	-0.104	-0.027	-0.031**
	(0.044)	(0.040)	(0.191)	(0.173)	(0.017)	(0.015)
Mean	-1.842	-1.833	21.88	21.91	0.107	0.107
Observations	2494	3274	2494	3274	2494	3274
Clusters	454	586	454	586	454	586
Panel C: Individuals born after 1975						
Bombing	0.059	0.062	-0.221*	-0.192*	-0.008	-0.009
	(0.042)	(0.038)	(0.125)	(0.114)	(0.010)	(0.009)
Mean	-1.737	-1.725	20.75	20.77	0.0735	0.0741
Observations	3753	4871	3753	4871	3753	4871
Clusters	447	576	447	576	447	576

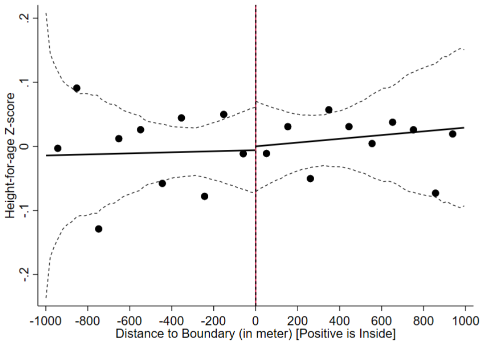
Note: The unit of analysis is survey respondents. All regressions use a local linear polynomial of latitude and longitude with a triangular kernel weight. Strike fixed effects, province fixed effects, distance to the capital, and distance to Vietnam borders are present in all regressions. Regressions (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.

E RD plots

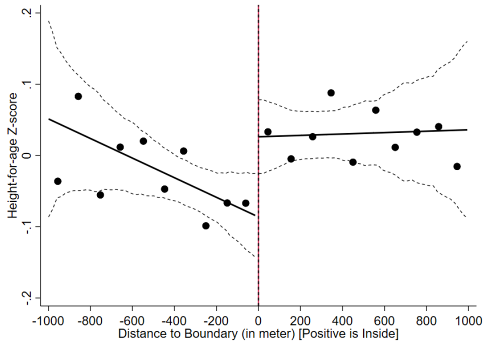
Figure E.1: Health outcomes: RD plots with 1km bandwidth

Panel A: Born by 1975

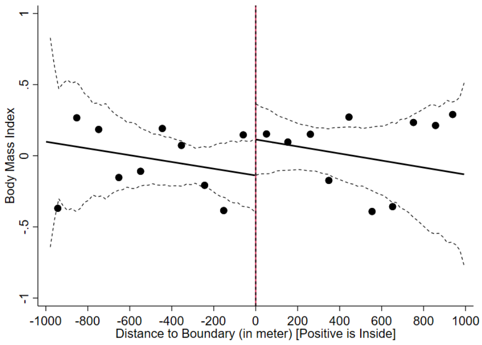
Panel B: Born after 1975



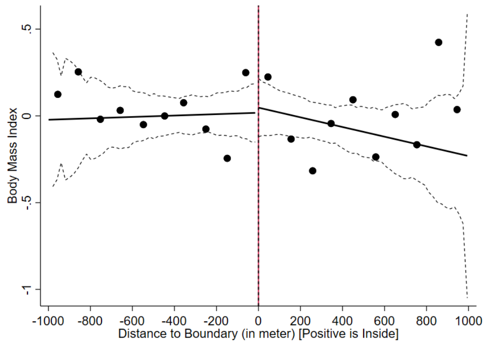
(a) Height-for-age Z-score



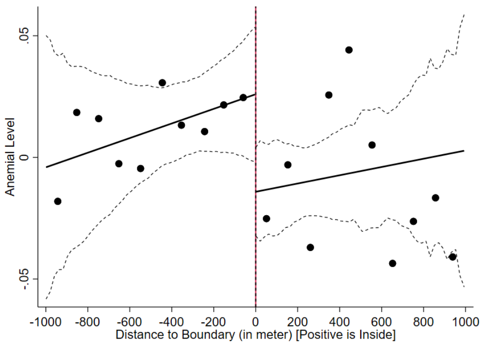
(b) Height-for-age Z-score



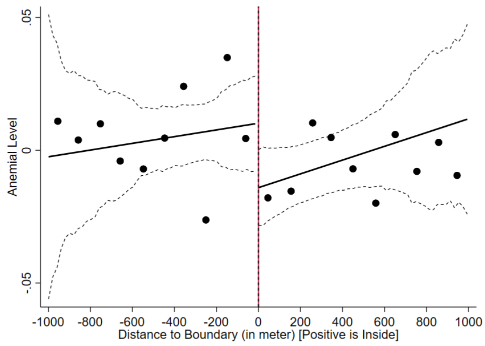
(c) Body Mass Index



(d) Body Mass Index



(e) Anemia Level



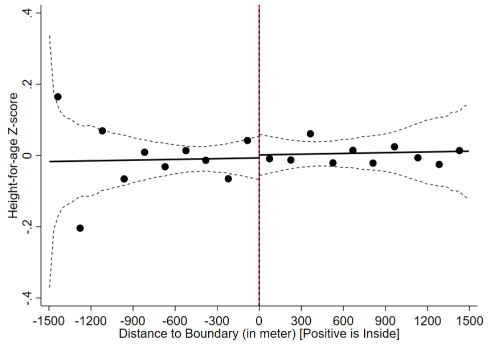
(f) Anemial level

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.

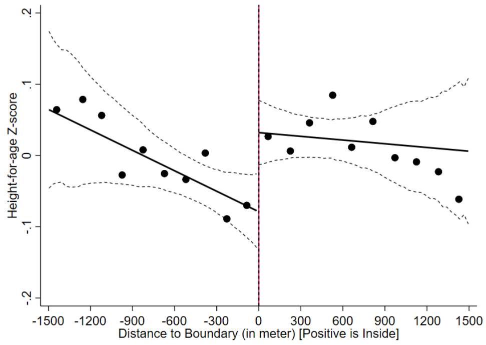
Figure E.2: Health outcomes: RD plots with 1.5km bandwidth

Panel A: Born by 1975

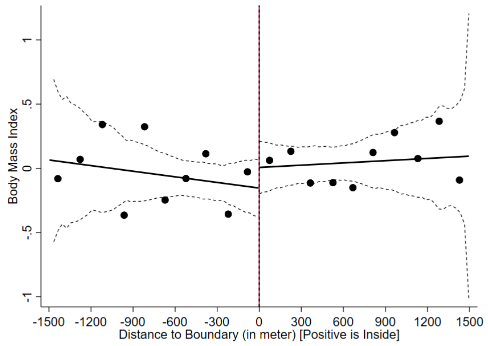
Panel B: Born after 1975



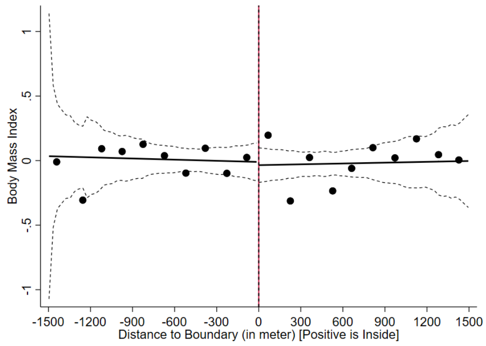
(a) Height-for-age Z-score



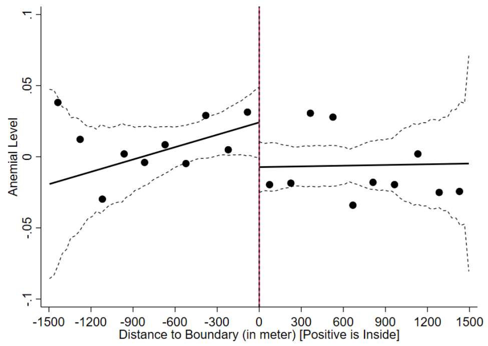
(b) Height-for-age Z-score



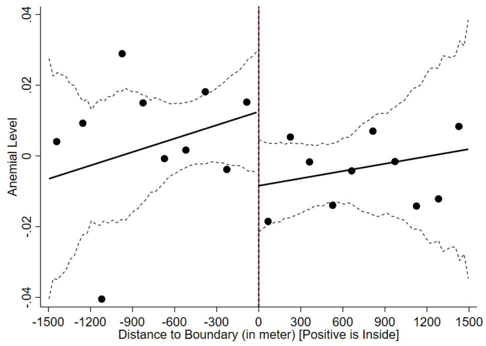
(c) Body Mass Index



(d) Body Mass Index



(e) Anemia Level



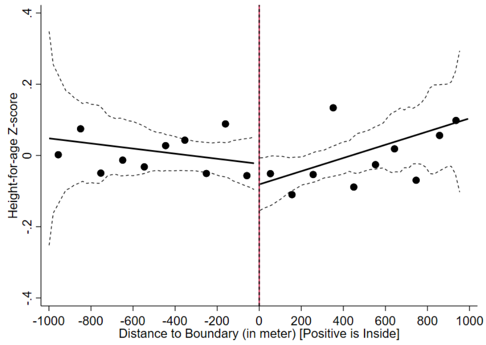
(f) Anemial level

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.

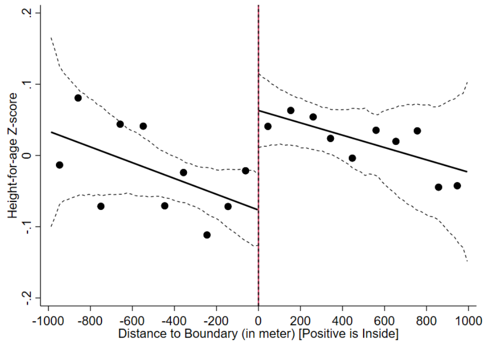
Figure E.3: Heterogeneity impacts splitting by pre-bombing soil fertility: RD plots with 1km bandwidth

Panel A: Fertile areas

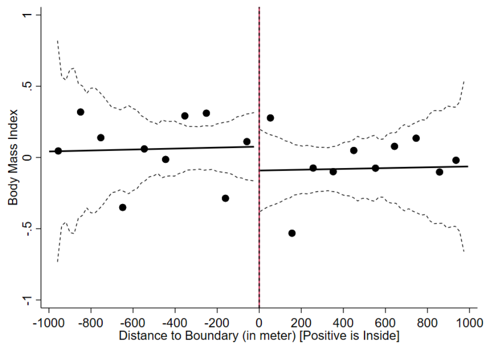
Panel B: Infertile areas



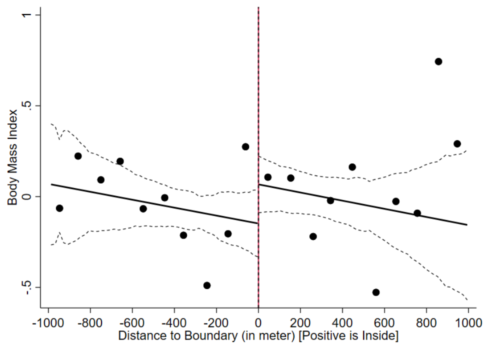
(a) Height-for-age Z-score



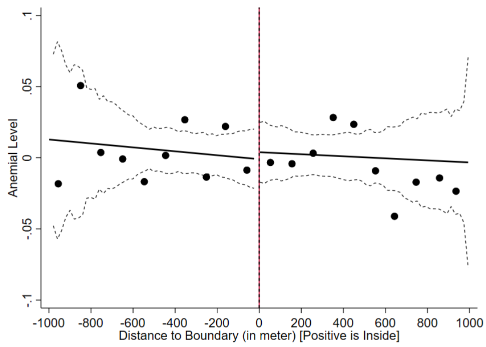
(b) Height-for-age Z-score



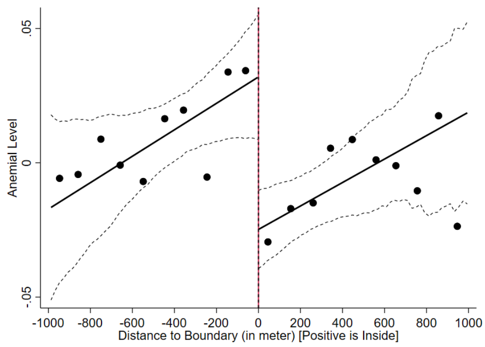
(c) Body Mass Index



(d) Body Mass Index



(e) Anemia Level

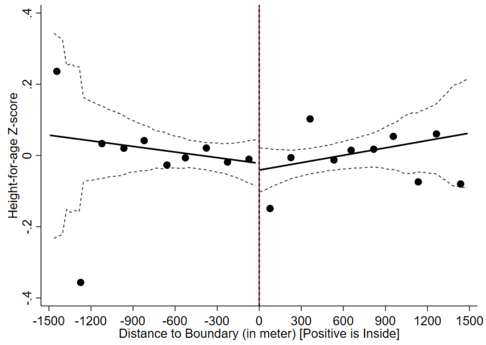


(f) Anemial level

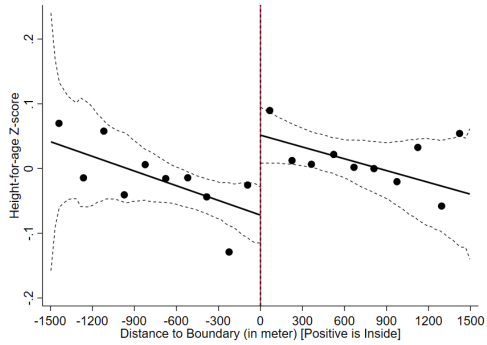
Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in latitude and longitude and other control variables. Solid lines depict a local linear regression, separately estimated on each side of the threshold, while dashed lines represent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

Figure E.4: Heterogeneity impacts splitting by pre-bombing soil fertility: RD plots with 1.5km bandwidth

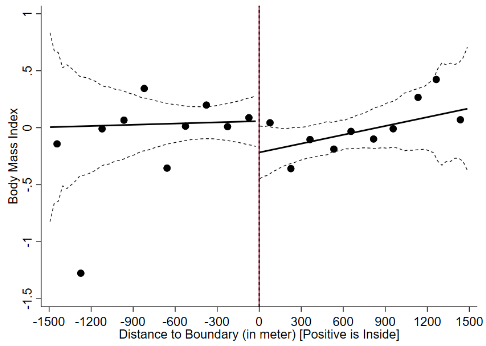
Panel A: Fertile areas | **Panel B: Infertile areas**



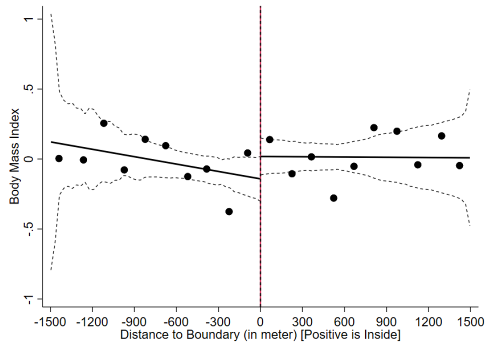
(a) Height-for-age Z-score



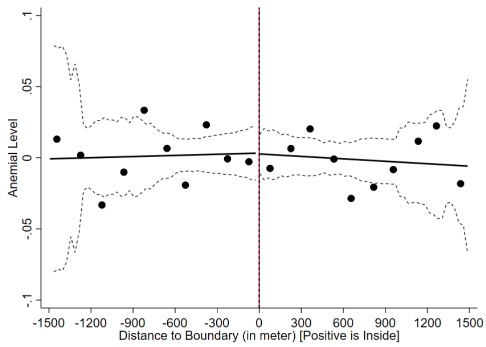
(b) Height-for-age Z-score



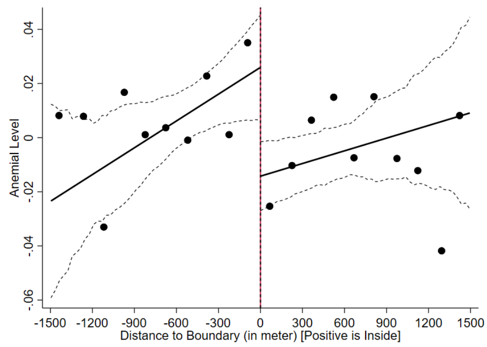
(c) Body Mass Index



(d) Body Mass Index



(e) Anemia Level



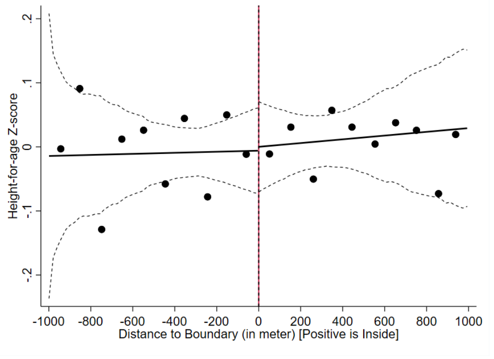
(f) Anemial level

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.

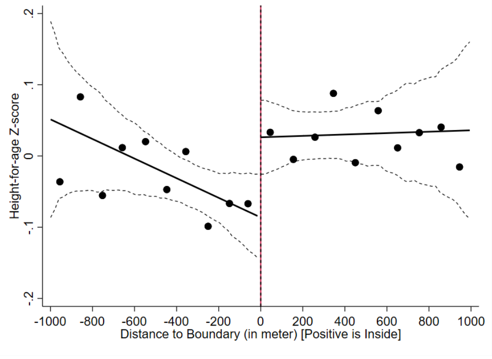
Figure E.5: Health outcomes: RD plots with 1km bandwidth

Panel A: Born by 1975

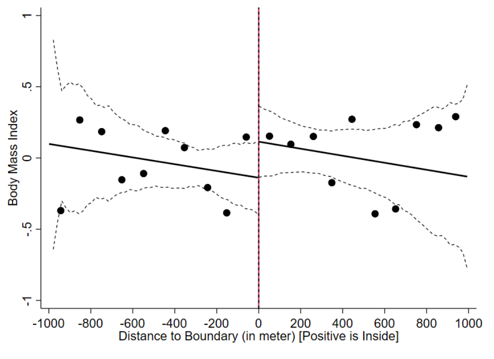
Panel B: Born after 1975



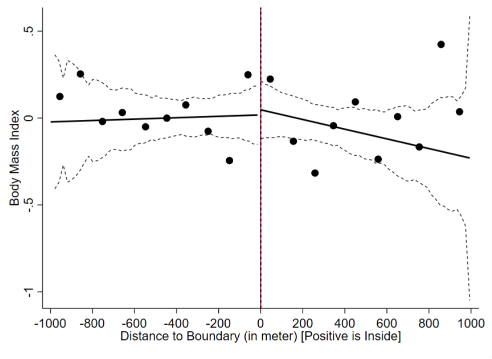
(a) Height-for-age Z-score



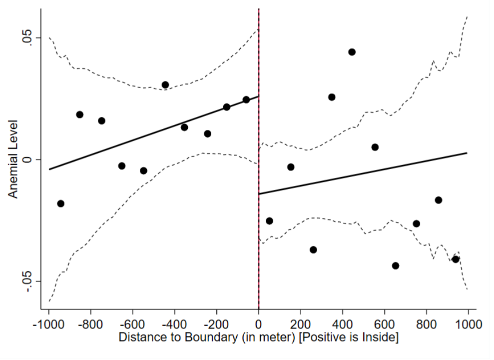
(b) Height-for-age Z-score



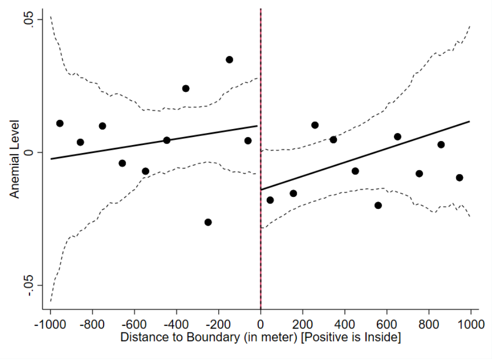
(c) Body Mass Index



(d) Body Mass Index



(e) Anemia Level

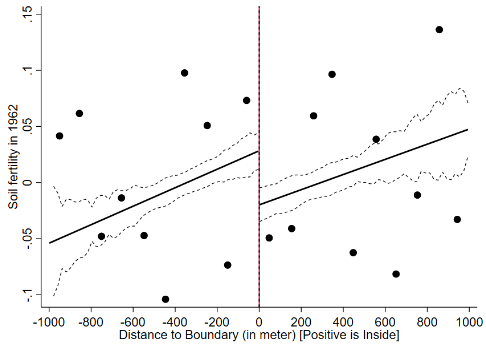


(f) Anemial level

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.

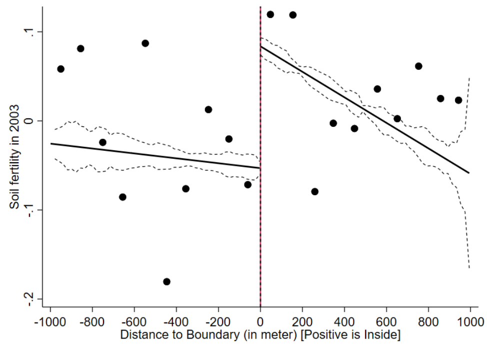
Figure E.6: Soil fertility in 1962 and 2003

Panel A: Soil fertility in 1962

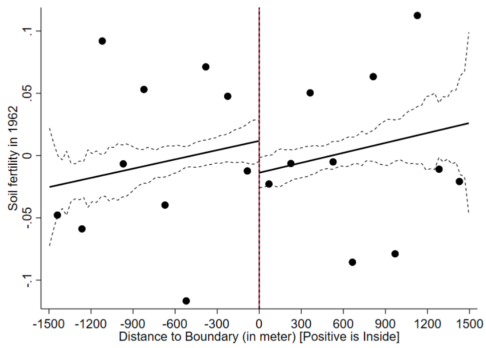


(a) 1km bandwidth

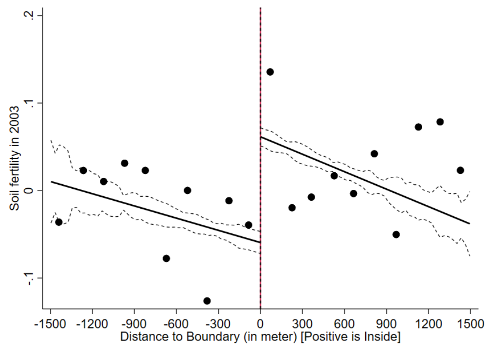
Panel B: Soil fertility in 2003



(b) 1km bandwidth



(c) 1.5km bandwidth

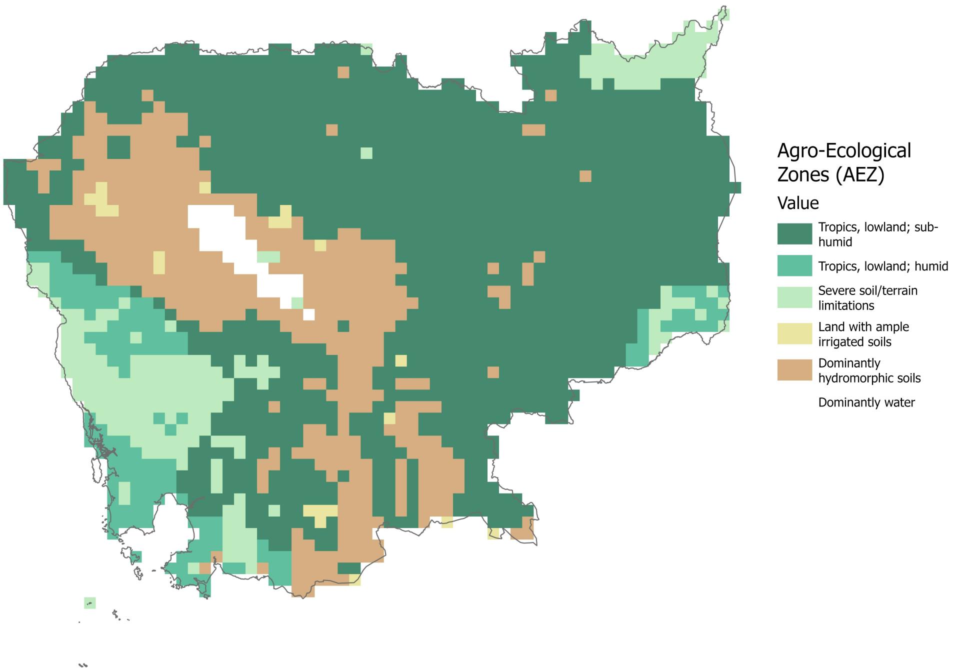


(d) 1.5km bandwidth

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.

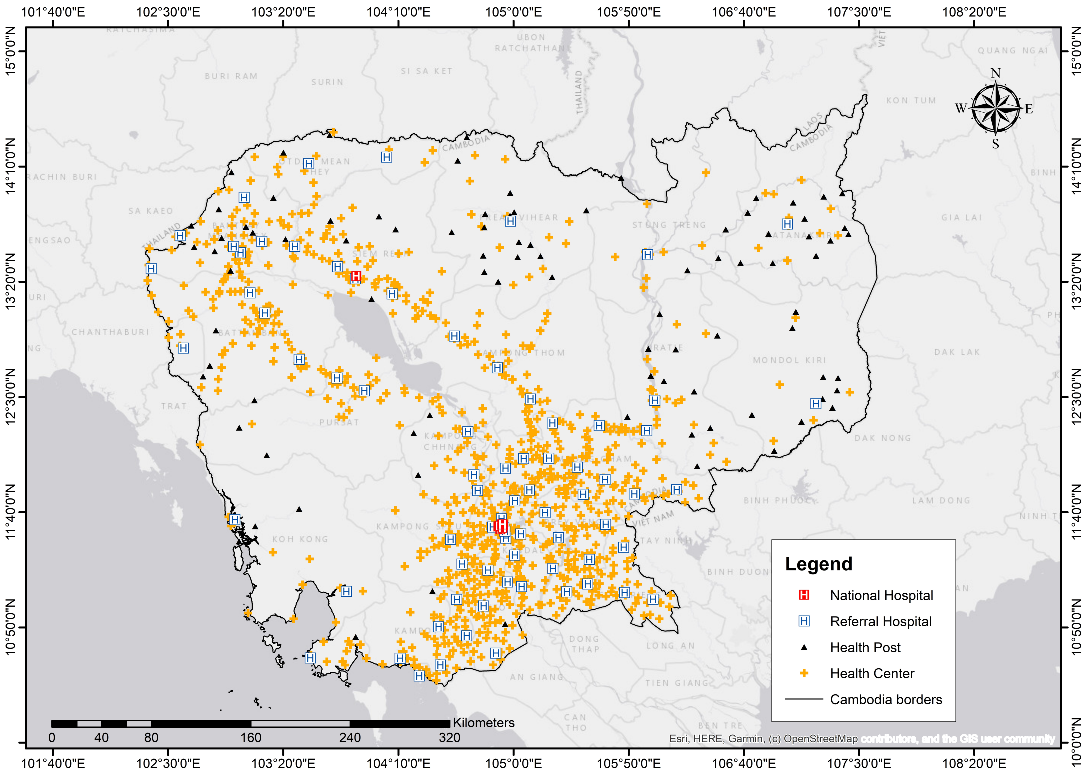
F Additional Tables and Figures

Figure F.1: Agro-ecological Zones classes



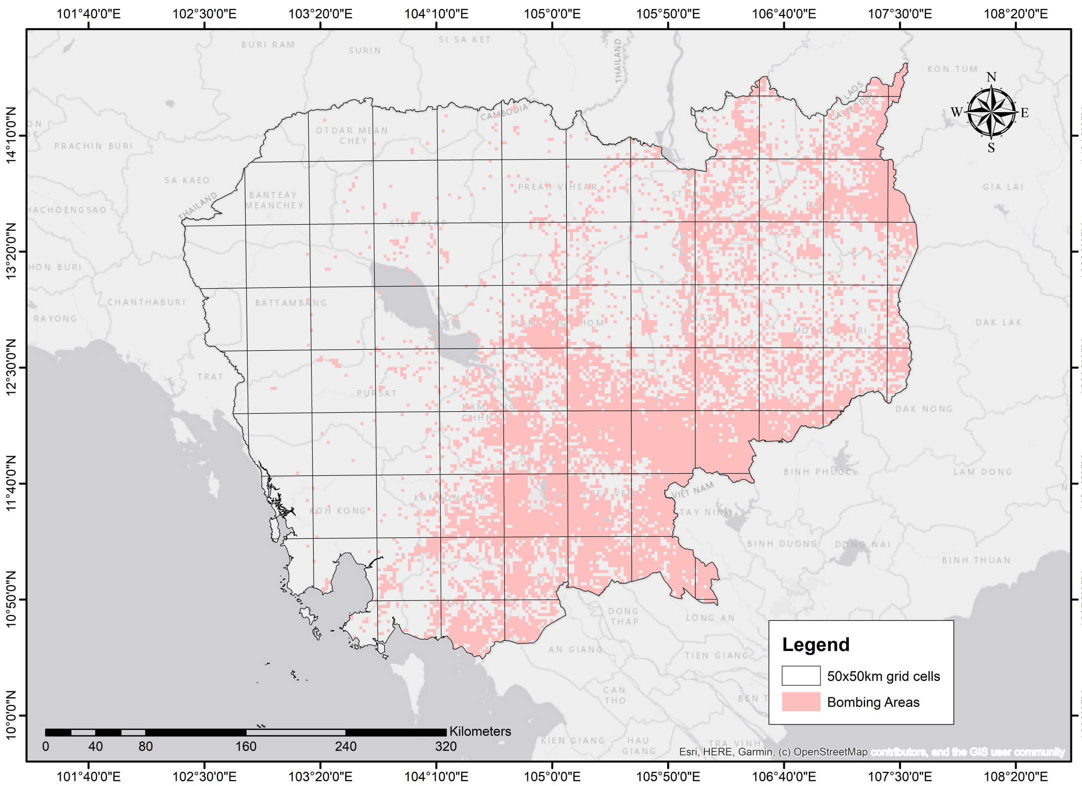
Notes: The map overlays Cambodia to the agro-ecological zones (AEZs) as classiffied by The Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA). Geographic areas belonging to the same AEZ category exhibit analogous climatic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

Figure F.2: 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 F.3: Generating 50x50km grid cells



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