

The aerial bombing of Cambodia and the recovery of communities*

Otto Lenhart[†] Jonathan Norris[†] Thi Tham Ta[†]

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Abstract

Post-conflict communities diverge: some recover within a generation, others stagnate for decades. We show that whether ordnance detonated or remained buried influences which path a community takes. Using geo-coded data on all US airstrikes in Cambodia (1965–1975) and a spatial regression discontinuity around bombing boundaries, we exploit pre-bombing soil conditions that are orthogonal to bombing locations. Soft soil reduces the likelihood of detonation, creating exogenous variation in UXO risk. Grounding our analysis in a vintage-capital framework, we separate a *reset* channel, where destruction clears outdated capital and allows rebuilding at higher productivity, from a *risk* channel, where persistent UXO constrains economic activity long after fighting ends. More than three decades after the last bomb fell, communities with a higher risk of unexploded bombs face more UXO incidents, worse health, lower economic development, reduced household income, and constrained agricultural productivity. Communities where ordnance detonated show stronger health, higher development, and greater household welfare. We trace these effects from community infrastructure through household conditions down to the productivity of individual agricultural fields. Recovery depends on whether conflict leaves room to reset and grow, or a legacy of risk that constrains activity for decades.

Keywords: Cambodia, bombing, conflict, unexploded ordnance, health, economic development

JEL-Codes: D74, I15, O11, O13

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1 Introduction

Post-conflict communities diverge. Some recover within a generation; others stagnate for decades (Rohner & Thoenig 2021). The economics literature offers competing explanations. Destruction of physical capital can *reset* vintage constraints, clearing the way for new infrastructure and investment, as documented after the Boston Fire by Hornbeck & Keniston (2017) and in Japanese cities by Davis & Weinstein (2002). Yet conflict can also leave behind persistent hazards in the form of unexploded ordnance (UXO) that constrains economic activity long after fighting ends (Guo 2020, Nguyen et al. 2024, Riano & Valencia Caicedo 2024). What determines which path a community takes?

We propose that a single conflict can produce both forces simultaneously, generating what we call the *reset* and *risk* channels. Where ordnance detonated, there is destruction but no lingering hazard. Communities can rebuild over what was lost with vintage constraints and coordination costs relaxed, ultimately shaping community welfare in the long run. Where ordnance failed to detonate, the remnants of war persist in the ground, taxing productivity by constraining land use, deterring investment, and exposing populations to ongoing danger. We develop this conceptual framework in Section 3. Whether a community experiences a *reset* or faces persistent *risk* depends on a factor orthogonal to the conflict itself: the likelihood that dropped bombs actually exploded.

Isolating these channels is difficult. Militaries do not bomb at random; they select targets based on strategic value, so bombed and unbombed areas differ in ways that also shape long-run development. Comparing them directly confounds destruction with pre-existing differences. Nor is UXO risk random: it correlates with bombing intensity and location characteristics related to target selection that may also correlate with long-run outcomes. The empirical challenge is to find variation in the detonation rate that is independent of both bombing intensity and local economic potential, so that we can compare outcomes across communities where the same conflict left different legacies.

We address this challenge in Cambodia, one of the most heavily bombed countries

in history. Between 1965 and 1975, the US dropped over 2.7 million tons of munitions across 115,273 airstrike missions. We use geo-coded data on the universe of these strikes from the Yale University Cambodian Genocide Program to identify bombing areas and construct bombing boundaries.¹ To distinguish locations with high versus low UXO risk, we draw on Lin (2022), who demonstrates with extensive ethnographic fieldwork that bombs were less likely to detonate on soft soil, because soft ground absorbs impact energy rather than transferring it to the fuse mechanism. We match pre-bombing soil conditions from Crocker (1962) to locations, creating a soft/hard soil measure that captures exogenous variation in detonation failure rates and, therefore, in current UXO risk.

Crucially, we show that pre-bombing soil type is orthogonal to bombing locations and to a range of measures of bombing intensity, including total bombing loads, cluster munitions, and B-52 strikes (Section 5). This allows us to employ a spatial regression discontinuity design (RDD), similar to Bühler (2023), Dell (2010), and Dell et al. (2018), and to estimate it separately within soft-soil areas and within hard-soil areas. Within each soil type, we compare outcomes on either side of bombing boundaries, holding local geographic and pre-bombing economic conditions constant. In soft-soil areas, the bombed side carries higher UXO risk, which we call the *risk* channel. In hard-soil areas, the bombed side experienced destruction but faces minimal UXO risk, which we call the *reset* channel. For this comparison to be valid, outcomes must change gradually over space in the absence of bombing, and people must not have sorted around bombing boundaries. We provide extensive evidence supporting both assumptions.

To test these channels, we construct a dataset spanning more than 30 years post-bombing. We extract individual health outcomes from four waves of the Cambodian Demographic and Health Survey (DHS, 2000–2014) with household geo-coordinates. We match UXO incident data and local development measures to the universe of village locations from the 2008 Cambodia Population Census. We also draw on household-level data from the Cambodia Socio-Economic Survey (CSES) and Agricultural Census on

¹We use a grid-based clustering method from epidemiology that preserves the spatial distribution of strikes. See Section 4 for details.

income, agricultural productivity, and risk-taking behavior.²

We begin by confirming that UXO incidents are concentrated where our framework predicts. Bombing raises the probability of a UXO incident by 5.1 percentage points more in soft-soil than in hard-soil communities, and the number of incidents is more than 50% higher than the mean. Bombed hard-soil communities show no such increase.

We then turn to health as our primary indicator of community welfare, a key outcome that economic conditions ultimately serve (Sen 1999, Deaton 2008, Fleurbaey 2009). Health is also the welfare measure in our data with the richest observed variation across individuals and communities. We construct an index from five physical health measures — height-for-age, weight-for-height, BMI, corpulence index, and anemia — following Anderson (2008). We find a stark divergence: in soft-soil areas, women in bombed communities have significantly worse health, with the index falling by 0.032 points (about 7% of a standard deviation); in hard-soil areas, women in bombed communities show stronger health outcomes, with the index rising by 0.027 points (6% of a standard deviation). The divergence is consistent across all five component measures and persists more than 30 years after the last bomb fell. These results are robust across alternative bandwidths, polynomial orders, grid-cell fixed effects, different bombing intensity thresholds, a uni-dimensional RDD, and placebo tests using shifted bombing boundaries.

To explain this divergence in well-being, we turn to community economic development and household conditions. We construct an economic development index from tangible measures of infrastructure and living standards, combining information on access to public services, physical infrastructure, and human capital at the village level. In soft-soil areas, bombed villages score significantly lower on this index; in hard-soil areas, bombed villages surpass their unbombed neighbours. Household data from the CSES reinforce this pattern: in hard-soil areas, households in bombed communities report higher income, more valuable durable goods, and greater food security; in soft-soil areas, the opposite holds.

²See Section 4 for further details.

If persistent UXO risk constrains daily economic activity, we should see its mark most clearly in agriculture, where people work the land directly and face the danger first-hand. Ethnographic evidence confirms this: Lin (2024) documents that, to reduce the chance of detonation, farmers in UXO-affected areas use hand tools rather than ploughs, move slowly, and avoid clearing new land. We test this prediction using field-level data from the CSES. Bombed soft-soil households cultivate less land, earn lower crop revenues, suffer higher post-harvest losses, and invest less in their plots. They are also less likely to take out agricultural loans and borrow smaller amounts when they do, consistent with constrained behaviour under persistent risk.

Data from the 2013 Agricultural Census then sharpens the picture on both sides of the divergence. In soft-soil areas, bombed households also hold smaller livestock stocks and pull back from forest land use, without compensating through off-farm work. These are the margins ethnography predicts when UXO risk binds. In hard-soil areas, bombed households reorient toward market-oriented production and non-farm labour, indicating that the reset channel operates not by restoring pre-war subsistence farming but by opening a path away from it.

Based on the growth model we develop in Section 3, we map these margins into a productivity tax. Using our estimates, we find that UXO risk acts like an approximately 47% tax on total factor productivity ($\tau \approx 0.47\text{--}0.51$), which translates into a 27% output gap in terms of agricultural activity. The tax rises ($\tau = 0.67$) on aggregate household income as the direct drag compounds through accumulation. By tracing these effects from community infrastructure through household welfare down to individual agricultural fields, we provide unusually granular evidence on how the remnants of conflict constrain long-run economic activity.

Our findings contribute to several literatures. First, we advance the literature on post-conflict recovery. Evidence is mixed: some economies return to balanced growth (Davis & Weinstein 2002, Miguel & Roland 2011), while others show persistent negative effects (Abadie & Gardeazabal 2003, Yamada & Yamada 2021, Kešeljević et al. 2025), and recent work highlights the long-run costs of UXO specifically (Guo 2020, Nguyen

et al. 2024, Riano & Valencia Caicedo 2024). We reconcile these findings by showing that the same conflict can produce both outcomes, depending on whether ordnance detonated or remained buried.

Second, we contribute to the literature on demining and clearance by focusing on aerial UXO rather than conventional landmine fields. In Cambodia, estimates of clearance benefits remain mixed (Cameron et al. 2010, Harris 2000), while Chiovelli et al. (2025) show that clearance in Mozambique can unlock connectivity and local economic activity. Our results suggest that evaluations of aerial bombing legacies may understate returns to clearance when they omit long-run effects on health and household welfare.

Third, we add to the literature on the long-term health consequences of conflict. Most studies focus on direct exposure *in utero* or in early childhood and on intergenerational transmission (Akbulut-Yuksel 2014, Akresh et al. 2012, 2023, Camacho 2008, Duque 2017, Islam et al. 2017, Mansour & Rees 2012, Moyano 2017). Few examine how conflict shapes health in the long run (Palmer et al. 2019, Yamashita & Trinh 2022).³ We show that health can diverge across communities exposed to the same conflict, depending on whether the remnants of war constrain or permit recovery.

Fourth, we speak to the literature on how historical shocks shape long-run development (Dell & Olken 2020, Dell et al. 2018, Dell 2010). Conflict destroys infrastructure, food systems, and human capital (Levy 2002, Frost et al. 2017, Ghobarah et al. 2003, Leon 2012), but post-war investment can gradually offset these losses (Strauss & Thomas 2008). We show that whether this offset occurs depends on the legacy conflict leaves behind: where the remnants of war no longer pose a threat, communities recover and even surpass their neighbours; where persistent risk remains, recovery stalls.

Fifth, our field-level evidence that farmers facing persistent hazard invest less, borrow less, and cultivate less land connects to a broader literature showing that risk is a binding constraint on agricultural productivity in developing countries (Rosenzweig & Binswanger 1993, Dercon & Christiaensen 2011, Karlan et al. 2014, Goldstein & Udry

³Palmer et al. (2019) find more disability in locations exposed to intense bombing in Vietnam; Yamashita & Trinh (2022) find that Agent Orange exposure in southern Vietnam is still associated with greater disability 30 years later.

2008). Our evidence extends this logic to persistent physical hazard from unexploded ordnance. The implication is that improving agricultural productivity may require first reducing the risks farmers face, whether from UXO or other adverse conditions.

We next present Cambodia's historical background (Section 2) and develop the conceptual framework (Section 3). We then describe the data (Section 4), lay out the empirical strategy and validity checks (Section 5), and report the results (Section 6). Section 7 concludes.

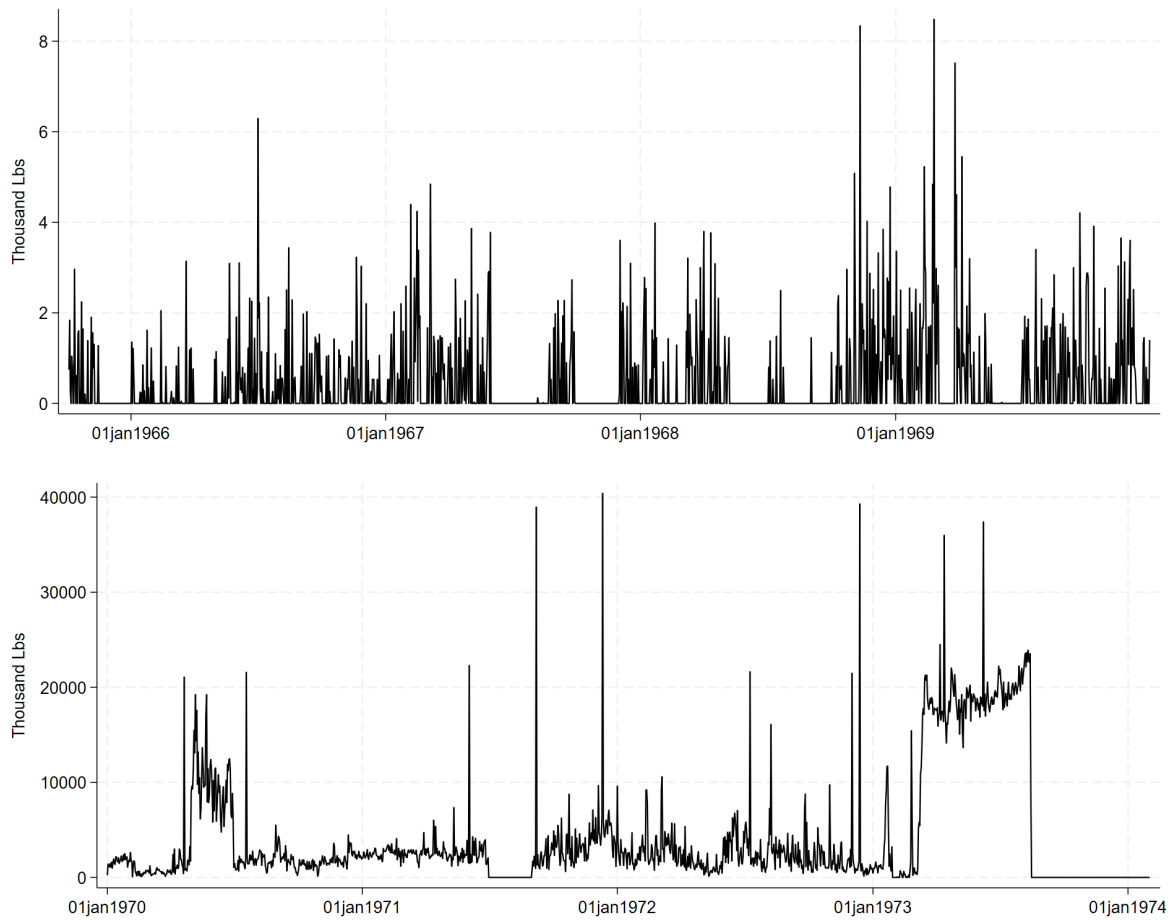
2 Historical background

Over the last century, Cambodia endured colonisation, civil wars, and genocide (Rany et al. 2012, Chandler 2018). After 90 years as a French protectorate (1863–1953), the country gained independence at the Geneva Conference on November 9th, 1953. A coup d'état on 18 March 1970 deposed Prince Sihanouk and installed the Lon Nol Government, setting off a civil war that lasted until 1975. In April 1975, the Khmer Rouge under Pol Pot seized power, beginning a period of genocide. The regime fell in 1979 when Vietnamese forces installed a new government, but political instability persisted until the 1991 Paris Peace Conference established a UN protectorate (Rany et al. 2012, Chandler 2018, Bühler & Madestam 2023).

Between 1965 and 1973, the Vietnam-American War spilled into Cambodia through extensive bombing campaigns, making it one of the most heavily bombed countries in history (Owen & Kiernan 2006). Beginning in 1965 under the Johnson administration, the US bombed Cambodia to disrupt supply lines and destroy Communist bases. The initial intense wave, known as the Menu campaign, targeted border areas and ended in May 1970 after the coup. From 1970 onward, the campaign expanded as the US sought both to eradicate Vietnamese Communist forces and to support Lon Nol's regime in the civil war. Congress halted funding in 1973 upon discovering Nixon's deception about the military campaign (Owen & Kiernan 2006).

Data from Yale University (Cambodian Genocide Program) record 2,757,107 tons of

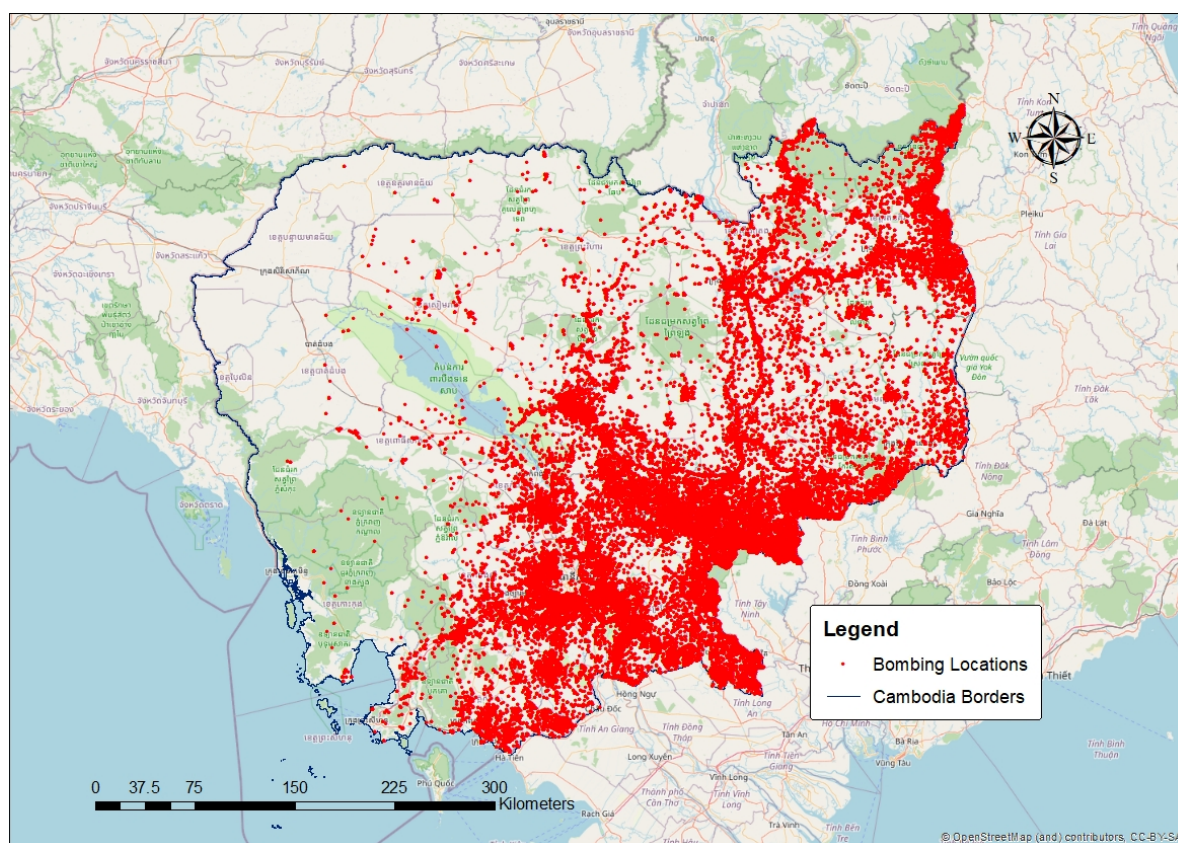
Figure 1: US ordnance dropped on Cambodia



Notes: Calculations by the authors from the Yale University Cambodia Genocide Project data on the universe of US airstrikes in Cambodia with detailed information on payload sizes for each strike.

munitions dropped on 115,273 bombing sites in Cambodia, far exceeding the worldwide total ordnance dropped by the Allies during World War II (Owen & Kiernan 2006). Figure 1 shows the escalation: from January 1970, daily bombing loads rose from less than one ton to hundreds or tens of thousands of tons per day. Figure 2 shows that while many strikes concentrated in eastern Cambodia near the Vietnamese border, the campaign spread across significant portions of the interior. Early estimates placed civilian casualties between 50,000 and 150,000, though Ear (1995) alleges the true toll reached 600,000, not counting starvation and displacement. The bombing also had immediate health consequences, reducing life expectancy and worsening nutritional outcomes (Moyano 2017).

Figure 2: 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.

3 Conceptual framework: destruction, risk, and recovery

This section develops a simple growth framework to explain how a bombing campaign can produce divergent long-run outcomes across communities. The core mechanism is the interaction between destructive shocks and the vintage structure of community capital. Whether destruction leaves behind a persistent hazard determines which path a community takes. Historical and ethnographic evidence from Cambodia is anecdotally supportive of each element of the framework, and we draw on it throughout.

Vintage capital. Community infrastructure — roads, irrigation, schools, and agricultural systems — embodies the technology available when it was built (Solow 1960). Old infrastructure still functions, so communities continue to use it even when better

alternatives exist. But the gap between old and new technology matters: it compounds over time through savings and reinvestment, shaping the living conditions that residents depend on.

Consider output $y = Ak^\alpha$, where A captures the productivity of installed capital and k is the capital stock per capita. A constant fraction s of output is saved and invested, and capital depreciates at a rate δ . Let A_o denote the technology level embodied in old-vintage capital and $A_n > A_o$ denote the current frontier. A community operating with old-vintage technology sits at a steady-state capital stock $k_o^* = (sA_o/\delta)^{1/(1-\alpha)}$. The frontier steady state, $k_n^* = (sA_n/\delta)^{1/(1-\alpha)}$, is strictly higher. Yet poor, credit-constrained communities do not make the switch: replacing working infrastructure means forgoing the output it currently produces, and when much of that infrastructure is collective, no single household can justify the cost alone. The result is persistent lock-in at the lower steady state.

Now, suppose bombing destroys the existing capital stock. When communities rebuild, all new investment embodies the frontier technology A_n . Whether this amounts to a fresh start depends on what bombing leaves behind. If all ordnance detonates, the community simply rebuilds with better technology. However, unexploded ordnance left in the ground can impose a persistent drag on productive activity. We capture this as a productivity tax $\tau \in [0, 1)$ on effective output. Capital then accumulates according to $\dot{k} = s(1 - \tau)A_n k^\alpha - \delta k$, with steady state $k^* = (s(1 - \tau)A_n/\delta)^{1/(1-\alpha)}$. This single expression nests two channels, depending on τ .

The reset channel ($\tau = 0$). When all ordnance detonates, destruction leaves no lasting hazard. The opportunity cost of upgrading vanishes, as there is no old capital producing output that must be forgone, and rebuilding necessarily uses frontier technology. The community converges to the higher steady state $k_n^* > k_o^*$. In the standard Solow model, where technology is disembodied, destruction merely triggers faster convergence back to the *same* steady state (Davis & Weinstein 2002, Miguel & Roland 2011, Blattman & Miguel 2010). With vintage capital, the prediction is stronger: destruction triggers

convergence to a *higher* steady state. Gilchrist & Williams (2004) formalise this mechanism to explain the postwar catch-up of Germany and Japan, showing that destruction of old-vintage capital followed by frontier-technology rebuilding generates persistently higher productivity growth. The coordination failure that sustained the old equilibrium also dissolves: when all community infrastructure is destroyed simultaneously, there is no status quo to coordinate away from. This is the logic behind findings of renewed growth after the Boston Fire (Hornbeck & Keniston 2017) and what we call the *reset* channel.

Cambodia's historical record is anecdotally consistent with this mechanism. The US bombing displaced rural populations, and after the conflicts, communities returned and resettled into devastated landscapes, prioritising reconstruction in areas perceived as usable and secure (Chandler 2018, Locard 2004). Ethnographic work documents that local agrarian systems and infrastructure were often rebuilt from scratch, with institutions re-developed rather than restored (Locard 2004, Vickery 1999, Guillou 2012). This pattern of ground-up reconstruction in bombed areas is precisely what the reset channel predicts.

The risk channel ($\tau > 0$). The prediction changes when destruction leaves behind a persistent hazard. Not all bombs detonated. Failures left unexploded ordnance (UXO) buried in the ground, and Cambodia's contamination runs deep: the US aerial bombing, the Vietnamese invasion of 1979, and civil wars through the 1980s each added to the problem (Martin et al. 2019).⁴ Cambodia is one of the most heavily UXO-affected countries in the world (Moyes et al. 2002, Martin et al. 2019). Since 1979, UXO has caused over 64,700 casualties and more than 19,700 deaths (Martin et al. 2019). Beyond the human toll, UXO renders land unusable, disrupts water supplies and irrigation, and blocks infrastructure development (Hamlin et al. 2018, Martin et al. 2019).

⁴It 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 the Thai army. The majority of these minefields are found in western Cambodia, notably in the "K-5 mine belt" along the Thai border. Eastern and northeastern Cambodia, by contrast, is contaminated primarily with UXO from U.S. aerial bombing (Roberts 2011, Martin et al. 2019).

With $\tau > 0$, the steady state falls to $k_\tau^* = (s(1 - \tau)A_n/\delta)^{1/(1-\alpha)}$. This lies below the pre-shock steady state k_o^* whenever $(1 - \tau)A_n < A_o$. In other words, when the productivity drag from UXO exceeds the vintage gain. Because savings and investment depend on output, the direct productivity loss τ is amplified through the capital accumulation channel. For example, a 10% reduction in effective output translates to a roughly 15% reduction in steady-state capital and output (with $\alpha = 1/3$).⁵ Persistent risk can therefore push a community *below* its pre-shock steady state even when new capital embodies better technology.

The ethnographic evidence is consistent with this compounding logic. Lin (2022) documents that farmers in UXO-contaminated areas cultivate less land, use hand tools rather than ploughs, move slowly, avoid deep tilling, and in general are less productive to reduce risk. These behavioural adaptations reduce output, which constrains savings, which limits investment, which further depresses productivity.

Divergent recovery. UXO from aerial bombs concentrates in soft ground, because soft soil absorbs impact energy rather than transferring it to the fuse mechanism, reducing the likelihood of detonation (Moyes et al. 2002, Lin 2022). Because fertile soils in Cambodia tend to be soft, bombed fertile areas are the most likely to contain UXO. This creates a natural separation between the two channels. In hard-soil areas, where bombs were more likely to detonate, destruction clears the slate and the community converges toward $k_n^* > k_o^*$, the *reset* channel. In soft-soil areas, where bombs were less likely to detonate, UXO imposes a persistent tax on activity and the community converges toward $k_\tau^* < k_o^*$, the *risk* channel. The predicted ordering is:

$$k_{\text{risk}}^* < k_{\text{no-shock}}^* < k_{\text{reset}}^* \tag{1}$$

⁵We follow Gollin (2002) in the calibration of $\alpha = 1/3$. Correcting for self-employment income, which is prevalent in low-income economies, Gollin (2002) shows that factor shares are broadly stable across countries, supporting this choice. If anything, $\alpha = 1/3$ is conservative: a higher capital share would amplify the accumulation channel and produce larger implied values of τ .

Bombed hard-soil communities should eventually surpass their unbombed neighbours, while bombed soft-soil communities should fall behind. The divergence in k^* matters because community capital, including infrastructure, services, and economic conditions, shapes the welfare of the people who depend on it. Health, our measure of welfare, reflects this directly: the infrastructure, services, and economic conditions of a community determine residents' physical well-being (Sen 1999, Deaton 2008, Fleurbaey 2009). We therefore expect the divergence to register clearly in health outcomes. Economic development and agricultural productivity trace the underlying channels through which community conditions translate into well-being. The empirical analysis that follows tests each of these predictions. We also return to this framework in Section 6.5, where we combine our econometric estimates with the steady-state mapping above to recover a value for the productivity tax τ .

4 Data

We assemble data from multiple sources spanning more than 30 years after the bombing. Health outcomes are measured at the individual level from DHS surveys; UXO incidents and economic development are measured at the census village level. Household economic conditions, field productivity, and risk-taking behavior come from the CSES. Village coordinates from the 2008 Cambodia Population Census define the universe of locations to which we merge all other datasets. Detailed variable definitions and data sources are in Appendix A.

Bombing and the identification of bombing areas. We use geo-coded data on 115,273 US bombing sites in Cambodia (October 1965 – May 1975) from the Yale University Cambodian Genocide Program. The data record bombing dates, precise locations, aircraft, bombing loads, and ordnance types. To identify bombing areas, we apply a grid-based clustering technique that captures the spatial concentration of strikes, a method widely used in geography, public health, and ecology (Aldstadt 2009, Grubestic

et al. 2014).⁶

We divide the country into small geographic grid cells. Cell size matters: too small produces noise, too large over-smooths (Ankerst et al. 1999, Cheng et al. 2018). Following Boots & Getis (1988), we set cell size as $I = \sqrt{2 \times A/n}$, where A is Cambodia’s area (337,561 km²) and n is the number of strikes (115,273). This yields cells of 5.856 km² (2.42 km per side), dividing the country into 31,799 grid cells after excluding cells outside national boundaries or over permanent water bodies.⁷ Cells with any bombing loads are classified as bombing areas. Because strikes cluster spatially, bombed and unbombed cells each form contiguous zones. A bombing boundary is a cell edge where a bombed zone meets an adjacent unbombed zone (Figure A.1); edges internal to a single zone are not boundaries.

Figure 3 shows the resulting bombing areas, which preserve the spatial distribution of strike locations. Bombing areas concentrate in eastern and southern Cambodia along the Vietnamese border but extend into the interior. Our treatment variable equals 1 for locations within bombing areas and 0 otherwise.⁸

4.1 Outcome variables

Health. Our primary measure of individual well-being is a *Health Index* constructed from four waves of the Cambodia Demographic and Health Surveys (2000, 2005, 2010, and 2014). Although the DHS covers a subset of villages rather than the full universe, it provides the richest source of individual-level health measures, surveying a large sample of women across multiple waves. DHS surveys provide geolocations for household clusters of 25–30 households, which we refer to as *DHS villages* to distinguish them from *census villages* in the 2008 Population Census.⁹ Following Anderson (2008), we combine five standardized health outcomes into a weighted summary index: Height-for-age Z-

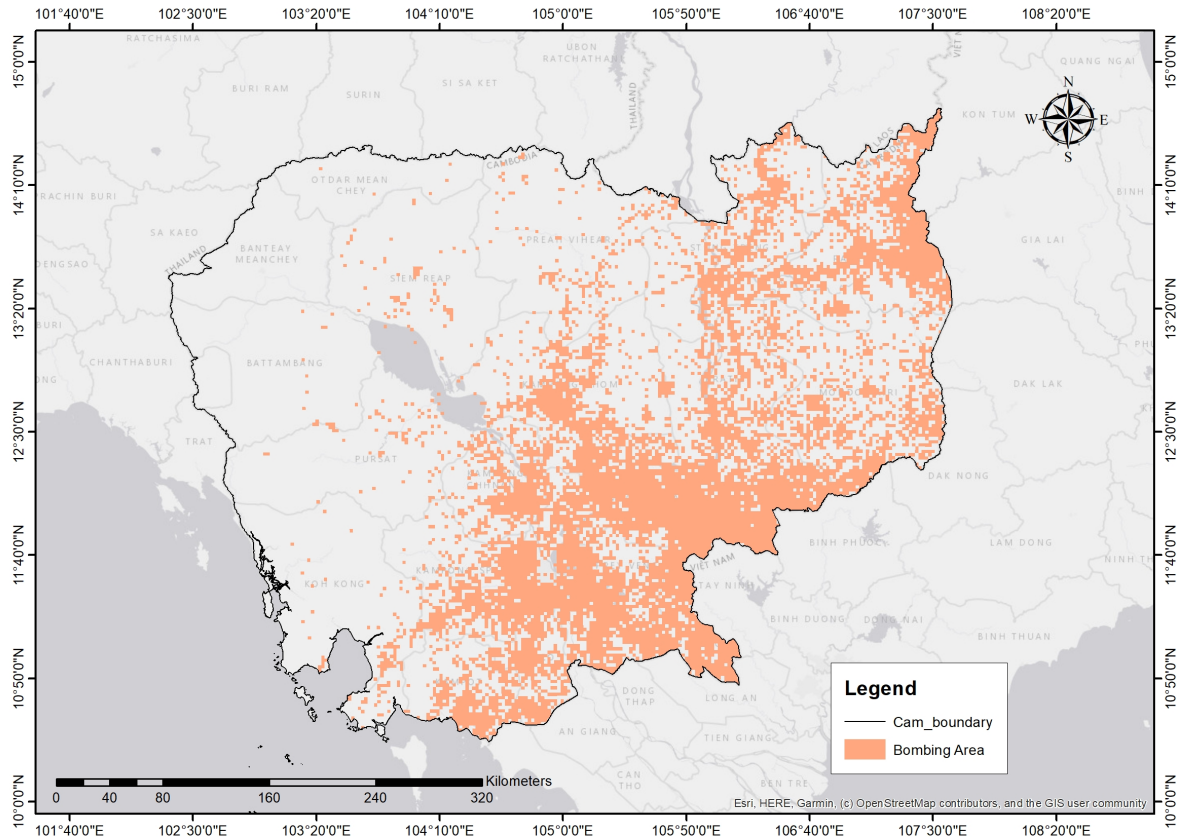
⁶See Appendix A Section A.1 for further details.

⁷This is similar to the cell size selected by Kohama et al. (2020), who examine how the economic characteristics of conflict zones influence the choice of military strategies.

⁸In robustness checks (Appendix B), we re-define treatment using intensity thresholds, where locations are treated only if bombing load exceeds the 2nd, 5th, or 10th percentile of the positive bombing distribution.

⁹See Appendix A Section A.2.1 for further details on variable construction.

Figure 3: 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.

scores, Weight-for-height Z-scores, a healthy Body Mass Index, a healthy Corpulence Index, and an indicator for non-anemia.

Economic development. To capture village-level infrastructure and living standards, we construct an *Economic Development Index* (or *Economic Index*) following Anderson (2008). We merge the universe of village locations from the 2008 Population Census with data on distance to schools (2012), distance to hospitals (2010), and coverage by major radio networks (2012). We add census indicators on the share of households with access to improved water, electricity, and sanitation; home ownership; adult literacy; school attendance; and employment. Together, these form a composite index of tangible village-level development.¹⁰

¹⁰See Appendix A Section A.2.2 for further details.

Household economic conditions and field productivity. We use Cambodia Socio-Economic Surveys (CSES) from 2009 and 2014 to measure household income, expenditure, durable goods, food security, field-level agricultural productivity (cultivated area, crop revenue, post-harvest losses, investment), and risk-taking behavior (loan-taking for agricultural activities). The CSES does not report household geolocations but provides village names, which we match to village coordinates from the 2008 Census.

Agricultural household structure. We complement the CSES with the 2013 Cambodia National Agricultural Census, a full enumeration of agricultural households that we geolocate via the 2008 Population Census village identifiers. The Agricultural Census is structural rather than transactional, thus it does not record harvest yields, sale prices, or crop revenue, which we observe in the CSES. We use the Agricultural Census to construct household-level indicators of crop orientation (share of parcels in commercial crops, whether the main purpose of production is sale), livestock scale (log Tropical Livestock Units and an above-median indicator), forest land use, and the share of household labor time allocated to crop cultivation, livestock, and non-farm activities.

Unexploded ordnance. To measure UXO prevalence, we use data on Mine/ERW casualties (2005–2013), which record the location of landmine and explosive remnants of war incidents.¹¹ We restrict to ERW incidents plausibly associated with aerial bombing — Cluster Bomb Unit (CBU) submunitions, fuses, ammunition, and unidentified ordnance — and exclude landmines and other ground-based weapons. For each census village, we count incidents within a 3-km radius and construct a binary indicator equal to 1 if any incidents occurred.

¹¹See Section 6.1.

4.2 Pre-bombing data and controls

Soil type. We use the distribution of soil types in Cambodia from Crocker (1962) to classify pre-bombing soil conditions.¹² Following the classification in White et al. (1997) and Kohama et al. (2020), we create a binary variable equal to 1 if a village is located on fertile (soft) soil and 0 otherwise.¹³ This is the key variable that distinguishes high from low UXO risk areas. See Appendix C for further discussion of soil classification.

Pre-bombing geographic and economic controls. We digitize three maps from the 1970 Indochina Atlas for transportation links, agriculture, and population density. Although bombing began in the mid-1960s, daily bombing loads escalated over a thousandfold from 1970 onward (Owen & Kiernan 2006), so the vast majority of strikes postdate these maps (see Figure 1). We also use the Global Agro-Ecological Zones (GAEZ) classification from the FAO and IIASA to capture climate and potential crop productivity.¹⁴ Descriptive statistics for all variables are in Table A.1 and Table A.2 (Appendix A).

5 Empirical strategy and validity

To test heterogeneous development patterns, we develop a spatial regression discontinuity (RD) design that compares outcomes on either side of bombing boundaries. We estimate the design separately within soft-soil and hard-soil areas, exploiting pre-bombing soil type to distinguish the *reset* and *risk* channels. We show that soil type is orthogonal to bombing locations (Table 1), so the soil split isolates variation in detonation risk rather than bombing intensity.

¹²The data were provided to Open Development Cambodia in ESRI Shapefile format by Save Cambodia's Wildlife's 2013 Atlas Working Group. For more details, see <https://opendevelopmentcambodia.net>.

¹³Among sixteen soil types in Crocker (1962), six are classified as fertile (soft): Latosols, Alluvial soils, Brown alluvial soils, Lacustrine alluvial soils, Regurs, and Brown hydromorphics (Kohama et al. 2020).

¹⁴We create a binary variable indicating whether a village is located in a grid cell classified as tropics and lowland. See Appendix A Section A.3 for further details.

5.1 A spatial approach

Following Bühler (2023) and Dell & Olken (2020), our regressions take the form:

$$Y_{icgpt} = \alpha + \beta_1 \text{Bombing}_c + \beta_2 \text{Bombing}_c \times \text{SoftSoil}_c + \beta_3 \text{SoftSoil}_c \quad (2) \\ + f(\text{Geo}_c) + \lambda \mathbf{X}_c + \theta_g + \delta_p + \mu_t + \epsilon_{icgpt}.$$

The outcome Y_{icgpt} varies by individual i in community c . Our primary outcome is the *Health Index* from the DHS, which provides detailed health measures for a large sample of women across four survey waves. We also examine UXO incidents and economic development using the universe of census villages. We further draw household outcomes from the CSES, and using households' village names, match CSES villages to census villages to obtain geo-locations.

A location is bombed ($\text{Bombing}_c = 1$) if it falls within an identified bombing area (Figure 3). To distinguish the *reset* and *risk* channels, we interact Bombing_c with an indicator for soft soil. If the *reset* channel operates in hard-soil areas, we expect $\hat{\beta}_1 > 0$. If bombed soft-soil areas face persistent *risk* through UXO, we expect $\hat{\beta}_2 < 0$ and $\hat{\beta}_1 + \hat{\beta}_2 < 0$ consistent with stagnation. We also present specifications that estimate β_1 separately within soft-soil and hard-soil sub-samples, allowing all coefficients to vary across soil types.

A bombing boundary is the outline of a bombed zone, i.e., the line where bombed and unbombed grids meet (Figure A.1). Grid edges interior to either zone are not boundaries, so villages sitting more than the chosen bandwidth from any such outline, including those deep inside a contiguous bombed or unbombed region, are excluded from the sample.

We select the bandwidth using the data-driven procedure of Calonico et al. (2020); applied to our main outcome, the *Health Index*, the optimal bandwidth is 2km. All regressions use a triangular kernel, giving more weight to observations closer to the boundary. Unless specified otherwise, all analyses use this bandwidth, while we provide

extensive robustness checks to alternative bandwidth choices.¹⁵

Leveraging boundaries. Standard spatial RD designs exploit pre-existing administrative or geographic borders (Dell 2010, Dell et al. 2018). No such boundary exists for bombing exposure. Our approach adapts the spatial RD framework by constructing boundaries from the data: because bombing strikes cluster spatially, bombed grid cells form contiguous zones of different sizes and unbombed cells likewise form contiguous zones, and the boundaries emerge where these zones meet (see Figure A.1 for an example). This produces borders that reflect the actual spatial dispersion of strikes rather than any pre-determined feature.

Why should these constructed boundaries be useful for identifying discontinuities? In practice, any set of bombing boundaries approximates a latent truth, so ours are inevitably measured with error. Two features work in our favor. First, our grid-based method (Section 4) draws borders that are both consistent with the spatial dispersion of strikes (Figure A.1) and random relative to local features, as our balance tests in Section 5.2 confirm. Second, because this measurement error is random, it attenuates our estimates toward zero, working against us finding effects. We provide evidence consistent with this intuition later through placebo tests that shift the boundaries.

Fixed effects. Because bombing boundaries run through different parts of the country, conditions can vary widely between distant boundaries. To ensure we compare locations that face similar geographic and economic environments, θ_g includes 50×50 km grid-cell fixed effects (79 grid cells; see Figure D.5) and δ_p includes province fixed effects (Dell 2010, Dell et al. 2018, Dell & Olken 2020, Lehner 2021).¹⁶ One concern is that within a 50 km grid, treated and control locations may differ. We address this by progressively replacing 50×50 km grid fixed effects with smaller grids and province fixed effects with district fixed effects, tightening comparisons to increasingly narrow areas (Appendix B). Results remain robust throughout.

¹⁵The *Economic Development Index* also has an optimal bandwidth of approximately 2km. We show that our results are robust to alternative bandwidths in Appendix B.

¹⁶There are 25 provinces in Cambodia. The smallest province is Kep, covering an area of 336 km², while Mondulkiri is the largest at 14,288 km².

Narrowing comparisons. As a more demanding test, we construct nearest-incident border-segment fixed effects. Each edge along such a boundary — one side of a 2.42 km grid cell — is a border segment. Each village is assigned to its nearest segment, and the fixed effect forces comparisons among villages that share the same local stretch of boundary. The large number of segments means there are too many fixed effects to estimate the model separately within each soil type, so we use border-segment fixed effects only in the interacted specification (Equation 2) as a robustness check. Results, reported in Appendix D, Table D.6, confirm our main findings.

Running variables. The function $f(Geo_c)$ controls for smooth spatial variation using demeaned x- and y-coordinates as running variables. Following Gelman & Imbens (2019), our baseline uses a local linear polynomial ($f(Geo_c) = x + y$), while we examine higher-order polynomials in robustness checks. The key assumption is that outcomes would have changed gradually over space in the absence of bombing, so any sharp change at the boundary reflects the bombing itself.

Controls. The vector X_c includes a set of pre-bombing characteristics. These are elevation, tropics/lowland classification, 1970 population density, agricultural activities, and distance to main roads and railways from the 1970 Indochina Atlas, plus distance to the capital and to the Vietnamese border to capture conflict intensity. Also, when using DHS health data, we include survey-year fixed effects (μ_t).

Inference. For DHS health analyses, where multiple individuals are surveyed in the same village, we cluster standard errors at the DHS village level. For census-village-level analyses — UXO incidents and economic development — each village is a single observation, so village-level clustering is not feasible. We instead cluster at the commune level, the next administrative unit, which groups villages in close proximity and accounts for spatial correlation among neighbouring communities. For CSES household and field-level outcomes, we cluster at the village level. As a complementary approach to spatial correlation, we report Conley (1999) standard errors for our key results (Appendix, Table D.5), which allow the error covariance to decay smoothly with distance rather than imposing discrete cluster boundaries.

Our design rests on three assumptions. First, in the absence of bombing, outcomes would not jump at the boundary but instead change gradually over space. Second, people could not precisely sort around bombing boundaries independent of the bombing itself. Third, bombing locations and pre-bombing soil type are independent of one another. We investigate each in turn.

5.2 Validity

Independence of Bombing and 1962 Soil Types. Table 1 shows that 1962 soil types are strongly independent of bombing in our design. In particular, they are uncorrelated with the treatment indicator (column 1) and with a range of bombing measures known to produce unexploded ordnance (Lin 2022), including bombing loads (column 2), cluster munitions (column 3), and bombs delivered by B-52 aircraft (column 4). We conduct the analysis on two core samples for our analysis. The DHS sample covers the villages where we measure our main outcome, the individual-level *Health Index*. The census sample covers the universe of villages, giving us greater statistical power for village-level outcomes. In both samples, the evidence supports our strategy of using 1962 soil types to separate the *reset* and *risk* channels.

No jumps in pre-bombing characteristics at boundaries. If bombing boundaries coincided with pre-existing differences in geography or economic conditions, those differences, rather than bombing, could drive our results. We test this by checking whether pre-bombing characteristics are balanced across bombing boundaries (Dell 2010). Table 2 reports results for DHS villages; Table D.1 (Appendix D) repeats the exercise for the full universe of census villages. We find no evidence of discontinuities in the pooled sample (Panel A). To support our use of 1962 soil type to disaggregate the analysis, we re-run these balance checks separately within soft-soil and hard-soil areas (Panels B and C). No estimate is statistically significant at conventional levels and magnitudes are small. In the larger census sample (Appendix Table D.1), a handful of covariates reach statistical significance in the sub-sample panels, but all are small

Table 1: Independence of Bombing and 1962 Soil Types

	Dependent variable is:			
	(1) Bombing	(2) Ln(Bombing Load)	(3) Cluster Bombs	(4) B52
<i>Panel A: Population Census Villages</i>				
Soil 1962	-0.010 (0.022)	-0.259 (0.319)	-0.009 (0.014)	-0.004 (0.008)
Mean	0.559	8.008	0.139	0.043
$ \beta /\text{Mean}$	0.017	0.032	0.062	0.082
Observations	7013	7013	7013	7013
Clusters	1104	1104	1104	1104
<i>Panel B: DHS Villages</i>				
Soil 1962	-0.006 (0.049)	-0.101 (0.707)	-0.002 (0.028)	0.013 (0.016)
Mean	0.502	7.326	0.120	0.056
$ \beta /\text{Mean}$	0.013	0.014	0.019	0.232
Observations	1043	1043	1043	1043
Clusters	602	602	602	602

Note: The sample is restricted to villages within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight. We control for 50x50km grid fixed effects and province fixed effects in all regressions. *Soil 1962* is a dummy variable demonstrating whether the soil was fertile(soft) in 1962 (before the bombing). *Bombing* is our treatment variable indicating locations inside our defined bombing areas. *Ln(Bombing Load)* is the natural log transform of Bombing Load. *Cluster Bombs* is a dummy variable indicating whether the bombing grid contains cluster bombs. *B52* is a dummy variable equal to 1 if the grid was bombed by B-52 aircraft and 0 otherwise. B-52 bombers have a high payload capacity, allowing them to deliver large volumes of ordnance over a target area. Standard errors reported in parentheses are clustered at the commune level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

in magnitude relative to their means. The most notable is tropics/lowland in soft-soil census villages, a time-invariant characteristic directly tied to soil classification that we control for. Overall, the continuity assumption holds in both soil types.

No sorting around bombing boundaries. Our design requires that people could not precisely choose which side of a bombing boundary they lived on. This concerns sorting independent of the bombing itself and not migration caused by bombing. Since bombing was determined by military strategy and our boundaries are constructed post-hoc from strike data, civilians could not have anticipated or manipulated their position relative to these cutoffs. Our grid-based method draws boundaries that are independent of features that might drive sorting. Consistent with this, 1970 population density is balanced

Table 2: Balance check - DHS villages

	Dependent variable is:						
	(1) Elevation	(2) Tropics/lowland	(3) Agri. Activities	(4) Pop. Density	(5) Dist. to roads	(6) Dist. VN	(7) Dist. to capital
Panel A: All observations							
Bombing	-3.046 (2.208)	0.031 (0.039)	0.003 (0.018)	-0.010 (0.015)	0.083 (0.442)	-0.152 (0.489)	-0.342 (0.965)
Bombing \times Soft Soil	12.073** (5.250)	0.049 (0.065)	-0.002 (0.033)	0.007 (0.028)	-0.081 (0.776)	0.222 (0.825)	-0.466 (1.533)
Mean	39.510	0.599	0.943	0.812	6.467	88.342	101.714
$ \beta /\text{Mean}$	0.077	0.052	0.003	0.012	0.013	0.002	0.003
Observations	1051	1053	1053	1053	1053	1053	1053
Clusters	611	611	611	611	611	611	611
Panel B: Soft soil (1962)							
Bombing	9.951 (6.120)	0.080 (0.051)	0.002 (0.026)	-0.024 (0.023)	-0.167 (0.638)	-0.140 (0.683)	-0.160 (1.143)
Mean	46.150	0.559	0.924	0.814	6.020	74.872	88.164
$ \beta /\text{Mean}$	0.216	0.144	0.002	0.029	0.028	0.002	0.002
Observations	381	381	381	381	381	381	381
Clusters	252	252	252	252	252	252	252
Panel C: Hard soil (1962)							
Bombing	-2.277 (2.030)	0.025 (0.039)	0.006 (0.017)	-0.009 (0.015)	0.089 (0.444)	-0.092 (0.460)	-0.131 (0.982)
Mean	35.752	0.622	0.954	0.810	6.719	95.946	109.362
$ \beta /\text{Mean}$	0.064	0.040	0.006	0.011	0.013	0.001	0.001
Observations	670	672	672	672	672	672	672
Clusters	418	418	418	418	418	418	418

Note: The unit of analysis is DHS villages. The sample is restricted to villages within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight. We control for 50x50km grid fixed effects and province fixed effects in all regressions. *Tropics/lowland* is a dummy variable indicating whether this location falls within areas classified as "tropics, humid" in the agro-ecological zones classification. Columns (3) (4) (5) use data from the Indochina Atlas, published in October 1970. *Agri. Activities* indicate whether there were any agricultural activities in these areas in 1970. *Pop. Density* is a binary variable reflecting if the population density in 1970 was at least 10 inhabitants per square kilometre. *Dist. to roads* refers to distance (in km) to 1970 main roads/railways. *Dist. VN* indicates distance to Vietnam border. *Dist. to capital* refers to distance to the capital of Cambodia. Standard errors reported in parentheses are clustered at the commune level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

across bombing boundaries in both samples (column 4 in Table 2 and Table D.1).

No spillovers across boundaries (SUTVA). Our estimates assume that outcomes on one side of the boundary are not affected by conditions on the other side (Keele & Titiunik 2015). Two types of spillovers could violate this. First, people in bombed soft-soil areas (high UXO risk) might relocate to nearby unbombed areas. If they do, they likely lack resources and would depress outcomes in our control locations, making it harder to detect the harmful effects of UXO. Second, bombs may have missed their targets and struck both treated and control locations. This would push outcomes in the same direction on both sides of the boundary, again shrinking the measured difference. Both spillovers bias our estimates toward zero, working against us finding effects. A donut exercise (Appendix B) that excludes observations closest to bombing boundaries confirms that our results hold and, if anything, grow stronger.

6 The Long-Run Effects of Bombing on Communities

The conceptual framework (Section 3) predicts that bombing can either *reset* vintage constraints, shifting communities toward a higher steady state, or leave persistent *risk* through unexploded ordnance, pushing communities below their pre-shock level. To test this, we estimate the effects of bombing separately across soft-soil areas (high UXO risk) and hard-soil areas (low UXO risk). We begin with a first-stage analysis of UXO incidents, then turn to health as our primary measure of well-being, and finally assess community-level economic development, household income, and field productivity.

6.1 First-stage: UXO Incidents in Communities

If soft soil causes more detonation failures, bombed soft-soil communities should have more UXO incidents today. Table 3 tests this using our empirical design and two outcomes: whether any UXO incident occurred near a village (Panel A) and the total number of incidents (Panel B).¹⁷

The results confirm this prediction. Bombing raises the probability of a UXO incident by 5.1 percentage points more in soft-soil than in hard-soil communities (Panel A, column 1), and the number of incidents is also significantly higher (Panel B, column 1). Both estimates are robust to Conley standard errors that account for spatial correlation (Appendix, Table D.5). These findings also hold under the most demanding specification with a high-dimensional set of nearest-incident border-segment fixed effects reported in the Appendix Table D.6.

Landmines additionally contaminate Cambodia, particularly the K5 minebelt in the northwest, where mines were laid during the conflict between Vietnamese forces and the Khmer Rouge. Unlike aerial UXO, mine placement does not depend on soil conditions, and this region also received fewer US airstrikes. Dropping villages in the K5 belt does not change our results (column 2).

We then split the sample by soil type and estimate the model within each sub-sample.

¹⁷We count the number of incidents within a 3km radius around each village.

Table 3: Regression Discontinuity - UXO incidents

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: UXO likelihood						
Bombing	-0.016 (0.010)	-0.016 (0.010)	0.040** (0.019)	0.035* (0.019)	-0.018* (0.010)	-0.017* (0.010)
Bombing × Soft Soil	0.051** (0.021)	0.048** (0.022)				
Mean	0.065	0.059	0.076	0.062	0.059	0.057
Observations	7012	6613	2521	2396	4489	4215
Clusters	1104	1013	559	522	827	752
Exclude K5 Belt	No	Yes	No	Yes	No	Yes
Panel B. Number of UXO Incidents						
Bombing	-0.018 (0.012)	-0.021* (0.011)	0.048** (0.022)	0.034* (0.019)	-0.022* (0.012)	-0.021* (0.012)
Bombing × Soft Soil	0.054** (0.025)	0.049** (0.023)				
Mean	0.076	0.063	0.090	0.065	0.068	0.063
Observations	7012	6613	2521	2396	4489	4215
Clusters	1104	1013	559	522	827	752
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is census villages (2008 Population Census). The sample is restricted to villages whose centroids are within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight. In all models, we control for households' spatial locations (x- and y- coordinates), distance to Vietnam borders, distance to the capital, 50x50km grid fixed effects, province fixed effects and other pre-bombing characteristics. We count the number of UXO incidents within 3km of villages and construct the binary outcome equal to 1 if there are any UXO incidents in a 3-km buffer. Standard errors reported in parentheses are clustered at the commune level. In the Appendix, Table D.5, we also report spatial adjusted Conley standard errors for UXO likelihood. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Bombed soft-soil communities have both a higher likelihood and a higher number of UXO incidents (columns 3–4). In hard-soil areas, the estimates are small and, if anything, slightly negative (columns 5–6). This is consistent with our framework: on hard ground, aerial bombs were more likely to detonate on impact, leaving little residual UXO. The ERW incident data also capture ordnance from the civil war with the Khmer Rouge and the Vietnamese invasion, which explains why unbombed areas are not entirely free of incidents. The key pattern is the stark contrast: bombing sharply raises UXO risk on soft soil but not on hard soil.

This first-stage evidence maps directly onto the *reset* and *risk* channels. Where bombs landed on soft ground, many failed to detonate, and UXO now constrains what communities can do with their land. Where bombs landed on hard ground, they detonated, leaving destruction but no lingering hazard — conditions under which communities could rebuild. We now turn to whether this distinction explains long-run differences in well-being and economic development.

6.2 Health

We begin with health, where the divergence in community conditions registers most directly in people’s lives. Differences in community capital matter because they shape the well-being of residents, which is captured by health (Sen 1999, Deaton 2008, Fleurbaey 2009). The DHS also provides an empirical advantage: multiple individuals are surveyed within each village, giving our spatial design rich within-village variation and substantial power to detect effects at bombing boundaries.

Table 4 reports spatial RD estimates for the *Health Index*. If the *risk* channel operates through UXO constraining activity and harming well-being, we should see worse health in bombed soft-soil areas. If the *reset* channel operates through rebuilt environments, we should see stronger health in bombed hard-soil areas.

We start with the interacted model. The interaction of bombing with soft soil is large and significant ($\hat{\beta}_2 = -0.054$, $p < 0.01$, column 1), indicating that bombed soft-soil communities have substantially worse health than bombed hard-soil communities.¹⁸ This gap of over 12% of a standard deviation (SD=0.43) is robust to Conley standard errors that adjust for spatial correlation (Appendix, Table D.5).

The sub-sample regressions sharpen this picture. In soft-soil areas, the *Health Index* falls by 0.032 points in bombed communities ($\hat{\beta}_1 = -0.032$, $p < 0.05$), about 7% of a standard deviation (column 3). In hard-soil areas, the index rises by 0.027 points ($\hat{\beta}_1 = 0.027$, $p < 0.01$), roughly 6% of a standard deviation (column 5). The total divergence between bombed soft-soil and bombed hard-soil communities is thus 0.060

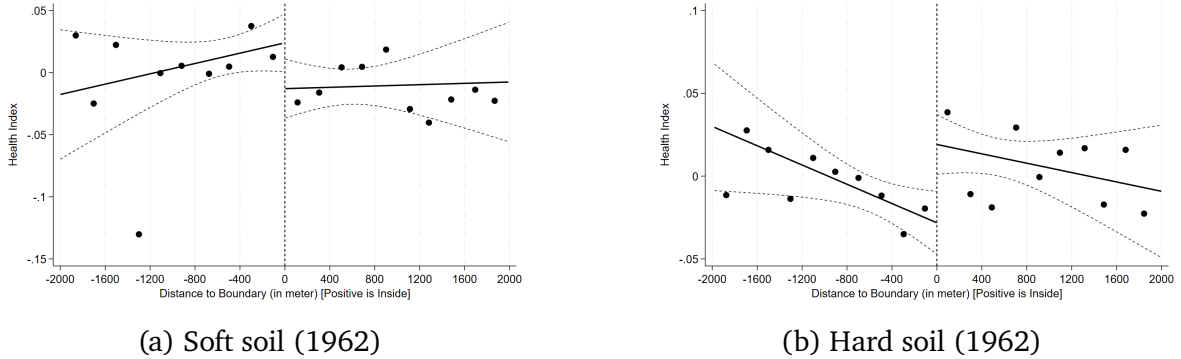
¹⁸See Appendix Table A.1 for summary statistics of *Health Index*.

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

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bombing	0.025** (0.010)	0.028*** (0.010)	-0.032** (0.014)	-0.030** (0.015)	0.027*** (0.010)	0.030*** (0.011)
Bombing × Soft Soil	-0.054*** (0.017)	-0.058*** (0.018)				
Mean	-0.013	-0.013	-0.010	-0.015	-0.015	-0.011
Observations	17268	15647	6242	5801	11026	9846
Clusters	1051	954	381	355	670	599
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is DHS survey respondents. The sample is restricted to those living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the DHS village level. *Health Index* is the standardized weighted summary index variable created from multiple health outcomes, including Height-for-age Z-scores, Weight-for-height Z-scores, a healthy Body Mass Index, a healthy Corpulence Index, and an indicator for non-anemia (See Table D.2 for results on individual health outcomes). ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure 4: The impacts of local area exposure to bombing on health: RD plots



Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in spatial coordinates and other control variables. Solid lines depict local linear regressions, 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.

index points, or 14% of a standard deviation. Figure 4 illustrates these effects: a clear drop at the bombing boundary in soft-soil areas and a clear jump in hard-soil areas.

Table D.2 (Appendix D) reports effects on the individual components of the *Health Index*: height-for-age, weight-for-height, healthy BMI, healthy corpulence index, and non-anemia. The pattern is consistent across all five measures, with negative estimates

in soft-soil areas and positive estimates in hard-soil areas, though not all individual components reach significance on their own.

The divergence extends beyond women’s own health to their children’s survival. Child mortality differs by 3.9 percentage points ($p < 0.01$) between bombed soft-soil and hard-soil areas (Appendix Table D.3), driven primarily by significantly lower child mortality in hard-soil areas ($\hat{\beta}_1 = -0.021$, $p < 0.01$), where the *reset* channel appears to produce tangible gains in child survival.

As with UXO incidents, we verify that landmines in the K-5 mine belt are not driving our results by dropping provinces along the belt (columns 2, 4, and 6). The estimates are virtually unchanged, and in some specifications slightly larger. The interacted model also holds under the more demanding, high-dimensional border-segment fixed effects (Appendix Table D.6), confirming that the divergence between soft-soil and hard-soil communities survives highly local comparisons.

Appendix B subjects these results to a wide range of sensitivity checks. The estimates remain stable across alternative bandwidths, polynomial orders, grid-cell fixed effect specifications, different bombing intensity thresholds, and a uni-dimensional RDD.¹⁹ Placebo tests using shifted boundaries show no evidence of spurious discontinuities.

A natural concern is that the divergence between soil types reflects differential consequences of destruction on high versus low agricultural-potential land rather than UXO risk. Soft soils in Cambodia tend to be more fertile, so bombing could have different effects there for reasons unrelated to detonation failure. Our primary estimates address this directly: the sub-sample regressions compare bombed versus unbombed communities *within* the same soil type, holding agricultural potential constant on both sides of the boundary.

The concern has more bite when comparing effects *across* soil types, the comparison captured by the interaction term. Three features of our evidence push against the agricultural-potential interpretation. First, Table 1 shows that soil type is orthogonal to bombing treatment and intensity in our design, so any divergence in effects reflects

¹⁹In a uni-dimensional RDD, we use distance to bombing boundaries as a running variable.

what happens *after* bombs land, not how many land. Second, the first-stage results show that the interaction maps onto actual UXO incidents: bombed soft-soil communities have significantly more UXO, while bombed hard-soil communities do not. Third, if the divergence reflected agricultural potential, we would expect the *reset* channel to be *stronger* on soft soil, not weaker, as higher-potential land would have more to gain from a vintage upgrade. We observe the opposite: bombed soft-soil communities fare worse, not better, contradicting an agricultural-potential interpretation. We add further tests on alternative channels alongside our next results on economic development.

The health results point to the divergence predicted by the conceptual framework: $k_{\text{risk}}^* < k_{\text{no-shock}}^* < k_{\text{reset}}^*$. In bombed communities where UXO persists, well-being is lower more than 30 years after the last bomb fell. In bombed communities where ordnance detonated, well-being is higher.

To understand what drives this divergence in well-being, we turn next to community economic development and household conditions.

6.3 Communities' economic development

Our framework's risk tax τ operates partly through community infrastructure: constrained land use and deterred investment should produce weaker infrastructure and living standards in bombed soft-soil areas. In hard-soil areas, where destruction cleared vintage constraints without leaving persistent hazard, we expect stronger development. Table 5 tests these predictions using the *Economic Development Index* measured across the universe of census villages.

The interacted model confirms the pattern. Bombed soft-soil villages score significantly lower on the index than bombed hard-soil villages ($\hat{\beta}_2 = -0.045$, $p < 0.05$, column 1), a gap of about 14% of a standard deviation (SD=0.32).²⁰ The sub-samples reveal where this gap comes from. In soft-soil areas, the index drops by 0.040 points in bombed villages ($\hat{\beta}_1 = -0.040$, $p < 0.05$), roughly 12% of a standard deviation (column 3). In hard-soil areas, bombed villages show stronger development by 0.016

²⁰See Appendix Table A.2 for summary statistics of *Economic Development Index*.

points ($\hat{\beta}_1 = 0.016$, $p < 0.1$), about 5% of a standard deviation (column 5). Figure 5 illustrates the effects with a drop in soft-soil areas and a jump in hard-soil areas at bombing boundaries.

These findings are slightly larger when we drop provinces along the K-5 mine belt. The interaction strengthens to $\hat{\beta}_2 = -0.052$ ($p < 0.05$, column 2), with sub-sample estimates of $\hat{\beta}_1 = -0.044$ ($p < 0.05$, column 4) in soft-soil areas and $\hat{\beta}_1 = 0.020$ ($p < 0.05$, column 6) in hard-soil areas. The interaction estimate is also robust to Conley standard errors that account for spatial correlation (Appendix, Table D.5). Moreover, under the more demanding high-dimensional border-segment fixed effects, the interacted estimate points in the same direction but loses precision (Appendix Table D.6).

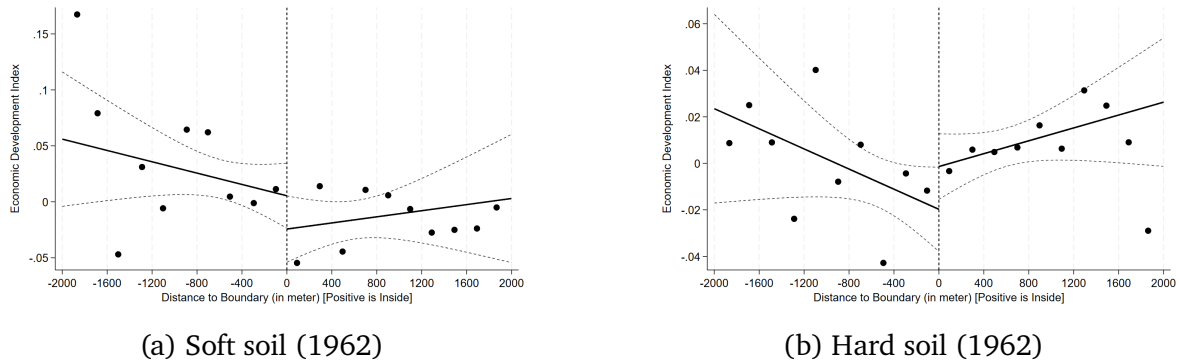
Table 5: Economic Development Index (*Unit: Census Villages*)

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bombing	0.013 (0.010)	0.017* (0.010)	-0.040** (0.017)	-0.044** (0.017)	0.016* (0.009)	0.020** (0.010)
Bombing \times Soft Soil	-0.045** (0.021)	-0.052** (0.022)				
Mean	0.023	0.029	0.027	0.032	0.020	0.028
Observations	7012	6613	2521	2396	4489	4215
Clusters	1104	1013	559	522	827	752
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is 2008 Population Census villages. The sample is restricted to villages within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the commune level. *Economic Development Index* is the standardized weighted summary index variable created from multiple outcomes including distance to schools, hospitals, locations within big radio network and other indicators of development such as the share of households with access to water, electricity, toilets, own dwellings, literacy, school attendance and employment rate (See Table D.4 for results on individual economic outcomes). ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.4 (Appendix D) reports effects on the individual components of the index. In soft-soil areas, bombed villages are significantly farther from health facilities, with other infrastructure measures (access to water, electricity, sanitation, dwellings) pointing in the same negative direction though not individually significant. In hard-soil areas,

Figure 5: Economic Development Index (Census Villages): RD plots



Note: The points represent binned residuals derived from a main regression of the outcome variable on a linear polynomial in spatial coordinates and other control variables. Solid lines depict local linear regressions, 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.

bombed villages show significantly higher employment, school attendance, and literacy rates. These component patterns are consistent with UXO risk suppressing infrastructure on soft soil and the *reset* channel broadening economic opportunity on hard soil.

Two alternative explanations could account for the divergence in economic development. First, if bombed hard-soil areas attract more post-conflict aid or NGO projects because they are safer to operate in, the economic gains we observe could reflect aid inflows rather than organic recovery. We test this using village-level data on NGO projects from the CSES (Appendix Table D.8). The results push against this interpretation: bombed hard-soil villages actually receive significantly *fewer* NGO projects ($\hat{\beta}_1 = -0.113$, $p < 0.05$, Panel B, column 5), not more. The stronger development in these areas therefore does not appear to be driven by external support.

Second, if bombing causes differential migration, the composition of who lives in bombed versus unbombed areas could shift, and the divergence might reflect selection rather than the *reset* and *risk* channels operating on communities in place. We examine migration status in both the DHS and CSES samples (Appendix Table D.7). In the DHS, the interaction of bombing with soft soil is small and insignificant (Panel A), indicating no differential migration between bombed soft-soil and hard-soil areas. In the CSES, the interaction is significant, with bombed soft-soil households less likely to have mi-

grated (Panel B). This is the opposite of what a selection story would predict: if people were fleeing UXO risk, we would expect more out-migration from soft-soil areas, not less. Contemporary population (Appendix Table D.9) shows no significant difference across bombing boundaries in soft-soil areas, further suggesting that the population composition has not shifted differentially. Thus, population characteristics such as literacy rates could diverge over time, but through the *reset* and *risk* channels acting on communities in place rather than through migration. Together, these tests support the interpretation that the divergence in economic development reflects the *reset* and *risk* channels operating on communities rather than differential aid or migration selection.

The economic results reinforce the health findings. Bombed communities where UXO persists have weaker infrastructure, worse access to services, and lower living standards. Bombed communities where ordnance detonated have rebuilt and, in some dimensions, surpassed their unbombed neighbours. We next ask whether this pattern extends to household-level economic conditions and agricultural productivity.

6.4 Households' income and productivity

If the *reset* and *risk* channels shape community-level development, they should also reach individual households. The conceptual framework implies that the productivity tax τ depresses output and savings at every level, from community infrastructure down to household income. In soft-soil areas, we therefore expect lower household income, fewer assets, and greater food vulnerability. In hard-soil areas, where vintage upgrading can operate without persistent hazard, households should share in the broader recovery. Ethnographic work by Lin (2022, 2024) grounds these predictions concretely: where UXO risk is high, farmers reduce the area they cultivate, avoid investing in their land, and work with constant caution. Communities do not develop, and productivity suffers. We test these predictions using the Cambodian Socio-Economic Survey (CSES), which provides household-level data on income, expenditure, assets, food security, agricultural productivity, and borrowing behaviour.

Table 6 reports effects on household economic conditions and quality of life. In soft-

Table 6: Post-bombing Development at household level (CSES)

	Dependent variable is:			
	<i>Unit of Analysis: Households</i>			
	Ln(Income)	Ln(Expenditure)	Ln(Durable)	Food Secure
	(1)	(2)	(3)	(4)
Panel A: All observations				
Bombing	0.295*** (0.107)	0.020 (0.034)	0.130* (0.071)	0.041* (0.022)
Bombing × Soft Soil	-0.544*** (0.160)	-0.055 (0.049)	-0.341*** (0.115)	-0.107*** (0.035)
Mean	14.048	16.412	14.104	0.862
Observations	11136	11136	11135	11136
Clusters	746	746	746	746
Panel B: Soft soil (1962)				
Bombing	-0.272** (0.124)	-0.050 (0.038)	-0.253*** (0.096)	-0.079*** (0.028)
Mean	13.939	16.547	14.398	0.875
Observations	4675	4675	4674	4675
Clusters	323	323	323	323
Panel C: Hard soil (1962)				
Bombing	0.275** (0.111)	0.019 (0.033)	0.119* (0.070)	0.043** (0.022)
Mean	14.126	16.315	13.892	0.852
Observations	6461	6461	6461	6461
Clusters	423	423	423	423

Note: All regressions include households living within 2km of a treated-control interface (a bombing boundary). *Income* demonstrates households' income from agricultural and non-agricultural activities. *Expenditure* indicates households' total expenditure, including food, non-food, and housing expenses. *Durable* represents the total value of durable goods (TV, bicycle, radio, phone, etc.). All of these variables are transformed $\ln(\text{Cambodian riel} + 10000)$. *Food Secure* is a dummy variable equal to 1 if households report that they do not go hungry. All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders, and other pre-bombing characteristics. Standard errors reported in parentheses are clustered at the village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

soil areas, bombing is associated with significantly lower income ($\hat{\beta} = -0.272$, $p < 0.05$, approximately 24% lower), lower value of durable assets ($\hat{\beta} = -0.253$, $p < 0.01$), and reduced food security ($\hat{\beta} = -0.079$, $p < 0.01$; Panel B).²¹ In hard-soil areas, the pattern reverses: households in bombed areas earn significantly more ($\hat{\beta} = 0.275$, $p < 0.05$, approximately 32% higher), own more durable goods ($\hat{\beta} = 0.119$, $p < 0.10$),

²¹Food security is a binary indicator for whether households report not going hungry. The coefficient implies that bombed soft-soil households are 7.9 percentage points more likely to experience food shortages, relative to a mean of 88%.

and report greater food security ($\hat{\beta} = 0.043, p < 0.05$; Panel C). The divergence in household conditions mirrors the community-level results, confirming that the *reset* and *risk* channels reach individual families.

Table 7: Field Productivity and Risk Taking Behaviour

	Dependent variable is:					
	Field Productivity <i>Unit: Agricultural Fields</i>				Risk Taking <i>Unit: Households</i>	
	Ln(Area) (1)	Ln(Revenue) (2)	Loss Rate (3)	Investment (4)	Loan Taken (5)	Ln(Loan Amount) (6)
Panel A: All observations						
Bombing	-0.062 (0.074)	-0.136 (0.089)	0.003 (0.003)	-0.019 (0.023)	0.029 (0.031)	0.094 (0.168)
Bombing × Soft Soil	-0.215* (0.119)	-0.110 (0.153)	0.009 (0.006)	-0.072 (0.044)	-0.072 (0.047)	-0.355 (0.260)
Mean	8.271	13.331	0.020	0.120	0.262	10.521
Observations	13852	13839	13183	13856	3707	3707
Clusters	604	604	602	604	648	648
Panel B: Soft soil (1962)						
Bombing	-0.358*** (0.096)	-0.314** (0.122)	0.012** (0.006)	-0.052 (0.038)	-0.072* (0.038)	-0.434* (0.221)
Mean	8.387	13.584	0.023	0.132	0.298	10.775
Observations	4865	4857	4641	4868	1530	1530
Clusters	236	236	236	236	266	266
Panel C: Hard soil (1962)						
Bombing	-0.085 (0.072)	-0.119 (0.084)	0.002 (0.002)	-0.010 (0.022)	0.043 (0.030)	0.147 (0.159)
Mean	8.208	13.194	0.018	0.114	0.237	10.343
Observations	8987	8982	8542	8988	2175	2175
Clusters	368	368	366	368	380	380

Note: All regressions include observations living within 2km of a treated-control interface (a bombing boundary). The unit of analysis for the first 4 columns is fields (agricultural land). *Area Cultivated* represents the size of the cultivated area (m²). *Area Cultivated* is transformed $\ln(\text{Area Cultivated} + 1)$. *Crop Revenue* indicates total revenue from the field: $\text{Revenue} = (\text{QuantityHarvested} - \text{PostHarvestLoss}) \times \text{SalesPrice}$. *Crop Revenue* is also log transformed $\ln(\text{Cambodian riel} + 10000)$. *Loss Rate* is the post-harvest loss rate, defined as the ratio of quantity lost to total quantity. *Investment* refers to the number of investments on parcel. The unit of analysis for the last 2 columns is CSES households. *Loan Taken* is a dummy variable indicating whether a household takes a loan for agricultural activities. *Agri Loan* denotes the amount of loan taken for agricultural activities. All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders, and other pre-bombing characteristics. Standard errors reported in parentheses are clustered at the village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table 7 turns to agricultural productivity and risk-taking behaviour, where the *risk* channel should bite hardest. The unit of analysis for the first four columns is individual agricultural fields, constructed from household reports on all fields they cultivate. In

soft-soil areas, bombed fields are substantially smaller ($\hat{\beta} = -0.358, p < 0.01$) and generate less revenue ($\hat{\beta} = -0.314, p < 0.05$; Panel B), corresponding to reductions of approximately 30% in cultivated area and 27% in crop revenue. Two additional outcomes sharpen the picture. Post-harvest loss rates are significantly higher in bombed soft-soil areas ($\hat{\beta} = 0.012, p < 0.05$), an increase of more than half relative to the sample mean of 2.3%. Field-level investment points in the same direction ($\hat{\beta} = -0.052$), though the estimate does not reach conventional significance. Together, these results describe constrained agricultural activity in which farmers cultivate less land, lose more of what they harvest, invest less in their fields, and earn less from them. This is precisely what the *risk* channel predicts, and it echoes the ethnographic evidence in Lin (2022), where communities living under the threat of UXO adopt cautious, low-productivity farming as a way of life.

Turning to borrowing behaviour, households in bombed soft-soil areas are less likely to take agricultural loans ($\hat{\beta} = -0.072, p < 0.10$) and borrow smaller amounts when they do ($\hat{\beta} = -0.434, p < 0.10$; Panel B). While these estimates are only marginally significant, they point in a consistent direction: households facing persistent UXO risk have less capacity and less willingness to take on debt, further limiting their ability to invest and grow. In hard-soil areas, none of the CSES field-level outcomes are significant (Panel C), suggesting that the stronger household incomes in Table 6 are driven by non-agricultural activities, consistent with communities that have rebuilt and diversified beyond farming.

The 2013 Agricultural Census (Appendix Table D.10) adds a structural view to the CSES evidence in Tables 6 and 7. The Census lacks yields and revenue but we can extract information on what households grow, what they hold, and how they allocate land and labor. The *risk* channel predicts contraction on the margins where UXO avoidance binds; the *reset* channel predicts reorganization toward markets and off-farm work.

In soft-soil areas, bombed households hold smaller livestock stocks: Tropical Livestock Units are roughly 3.9% lower ($\hat{\beta} = -0.039, p < 0.01$), and the probability of holding an above-median sized herd drops by 3.2 percentage points ($\hat{\beta} = -0.032$,

$p < 0.01$). Because cattle and buffalo supply the draught power households use to plow, the livestock contraction is the inventory counterpart to the smaller fields and reduced cultivated area in Table 7. Maintaining livestock is itself land-intensive. Rural Cambodian cattle and buffalo are tethered near the home during the growing season and fed through a labour-intensive ‘cut-and-carry’ system in which household members gather native grasses from roadsides, paddy bunds, and other non-cultivated land, with communal grazing on post-harvest paddies in the dry season (Mong et al. 2013). Forest-land use shows the same contraction ($\hat{\beta} = -0.024$, $p < 0.01$), a 43% reduction against the 5.6% Panel B baseline.²² Avoiding foraging, fuelwood collection, and small-scale forest use is the same cautious calculation the ethnographic evidence cited above captures: stay on cleared ground, even at the cost of foregone income and smaller herd sizes. The time freed by pulling back does not move to off-farm work. Livestock labor falls ($\hat{\beta} = -0.029$, $p < 0.01$), but non-farm labor shows a sharp null ($\hat{\beta} = 0.009$, $p > 0.10$). Households under persistent UXO risk shrink on-the-land capital without any compensating shift into non-farm activity.

In hard-soil areas, the Census describes the complementary rearrangement (Appendix Table D.10). Bombed households are more likely to report sale as the main purpose of production ($\hat{\beta} = 0.017$, $p < 0.10$). They also allocate a larger share of labor to non-farm activities ($\hat{\beta} = 0.027$, $p < 0.05$), a 12% rise over the 22.6% baseline. Tropical Livestock Units fall modestly, by roughly 1.6% ($\hat{\beta} = -0.016$, $p < 0.10$), but the livestock labor share is unchanged, so the reallocation runs into off-farm work rather than across farm activities. These patterns give structural content to the income and food-security gains in Table 6. Once the UXO hazard has been defused by detonation at impact, the *reset* is not a return to pre-war subsistence farming but an opening toward markets and off-farm livelihoods, an opening that soft-soil households, pinned to cleared cultivated plots, do not have.

²²Cambodia’s forests were heavily bombed during the war, and post-conflict clearance has concentrated on cultivated plots rather than forest interiors, leaving forest land among the most UXO-contaminated environments in the country.

6.5 Quantifying the productivity tax

The household and field-level results complete the empirical picture and give concrete content to the productivity tax τ in the conceptual framework. Less land cultivated, lower revenues, higher losses, less investment, and reduced borrowing are the specific margins through which persistent risk suppresses accumulation. The *risk* channel not only suppresses community-level development indices; it reaches into the daily economic lives of families, constraining what they farm, what they earn, and how much they invest. The *reset* channel allows households in hard-soil areas to recover in income and food security, though this recovery operates through non-agricultural rather than agricultural pathways. Tracing the consequences of UXO persistence from community infrastructure, through household welfare, down to the productivity of individual fields provides unusually granular evidence on how the remnants of conflict constrain long-run economic activity (Yamada & Yamada 2021, Lin 2022, Riano & Valencia Caicedo 2024).

Our framework and estimates let us put a number on τ . Comparing a bombed soft-soil community to a bombed hard-soil community holds the post-destruction technology level A_n fixed, so the steady-state ratio reduces to $y_{\text{risk}}^*/y_{\text{reset}}^* = (1 - \tau)^{\alpha/(1-\alpha)}$. With $\alpha = 1/3$, the exponent is $1/2$, so $\tau = 1 - \exp(2(\hat{\beta}_1^{\text{soft}} - \hat{\beta}_1^{\text{hard}}))$ for each log-scale outcome. Applied to the household and field estimates in Tables 6 and 7, we recover $\tau \approx 0.47$ from field-level crop revenue, 0.51 from cultivated area, 0.53 from the value of durable goods, and 0.67 from total household income.²³

Three points follow that neither the framework nor the treatment effects deliver alone. First, the spread across outcomes tells us τ is not a uniform tax on all activity. Agricultural production surfaces (crop revenue, cultivated area) carry a tax of roughly

²³For field-level outcomes where the hard-soil coefficient is indistinguishable from zero, we take $\hat{\beta}_1^{\text{hard}} = 0$. Two biases point in opposite directions. Because income, durables, and revenue are transformed as $\ln(y + 10,000)$, the coefficients attenuate toward zero relative to raw log-output, biasing our τ estimates downward. In the other direction, the formula assumes equal pre-shock output across soft- and hard-soil no-shock counterfactuals; if unbombed soft-soil communities are more productive at baseline — plausible given higher fertility — the $\hat{\beta}_1^{\text{soft}} - \hat{\beta}_1^{\text{hard}}$ gap embeds part of that differential, biasing τ upward. The two biases partially offset.

0.47–0.51, while aggregate household measures run higher (0.53–0.67), consistent with the accumulation channel of the framework compounding a direct productivity drag through depressed savings and investment. The framework predicts this compounding, while the data quantify it. Second, τ binds hardest on margins that require contact with the land, a structural feature the simple framework does not impose, but the data reveal and which matches the behavioural adaptations documented ethnographically by Lin (2022). Third, mapping these magnitudes back to Equation 1 shows that the risk-channel loss exceeds the vintage-capital gain by a wide margin. A τ of 0.47 on agricultural productivity swamps any plausible upgrade from old-vintage to frontier technology in Cambodian smallholder agriculture, which explains why bombed soft-soil communities fall *below* their no-shock neighbours rather than merely short of the reset benchmark. The framework, paired with the estimates, shows why the divergence is so stark.

7 Conclusion

Why do communities exposed to the same aerial bombing campaign experience diverging long-run outcomes? We study this question in the context of US bombing in Cambodia, exploiting the interaction between bombing boundaries and pre-bombing soil conditions that determine whether dropped ordnance detonated or remained buried. A simple vintage-capital framework predicts that destruction without lingering hazard can shift communities to a higher steady state, while persistent risk pushes them below their pre-shock level.

The data confirm this divergence. In hard-soil areas, where bombs were more likely to detonate, bombed communities show stronger health, higher economic development, and greater household welfare relative to their unbombed neighbours, consistent with the *reset* channel. In soft-soil areas, where bombs were less likely to detonate, bombed communities face more UXO incidents, worse health, lower economic development, reduced household income, and constrained agricultural productivity, consistent with the

risk channel. We trace these effects from community infrastructure through household welfare down to the productivity of individual agricultural fields.

These findings carry three implications. First, the long-run costs of UXO extend far beyond casualties. Persistent ordnance constrains land use, depresses investment, and undermines health decades after conflict ends, and these costs compound through the capital accumulation channel. Evaluations that focus on casualty reduction alone understate the true burden. At the same time, communities where ordnance no longer poses a threat have rebuilt and surpassed their unbombed neighbours, suggesting that clearance can unlock sustained economic recovery, not just safety (Frost et al. 2017, Chiovelli et al. 2025).

Second, our field-level evidence that farmers facing persistent hazard invest less, borrow less, and cultivate less land speaks to a challenge that extends beyond UXO. Wherever risk constrains productive activity, whether from unexploded ordnance, uninsured weather shocks, or insecure property rights, improving agricultural productivity may require first reducing the risks farmers face. These margins echo findings in settings far from post-conflict Cambodia (Rosenzweig & Binswanger 1993, Karlan et al. 2014, Goldstein & Udry 2008).

Third, the distinction between destruction that can be rebuilt over and hazards that constrain ongoing activity may help explain divergent post-conflict trajectories beyond Cambodia. Many conflicts leave behind a mix of both: destruction in some places, but in others, minefields, contaminated land, or damaged institutions that impose ongoing costs. Our results suggest that the balance between these two legacies, one that permits a vintage upgrade and one that taxes future productivity, can be a powerful determinant of whether recovery leapfrogs or stalls. Disentangling these channels in other post-conflict settings is a promising direction for both research and policy design.

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Appendix

- A Detailed description of the datasets
- B Robustness
- C Soil classification in Cambodia
- D Additional Tables and Figures

A Detailed description of the datasets

In this section, we provide detailed descriptions of the datasets used in this paper, including their sources, construction, and key variables.

A.1 Bombing and the identification of bombing areas

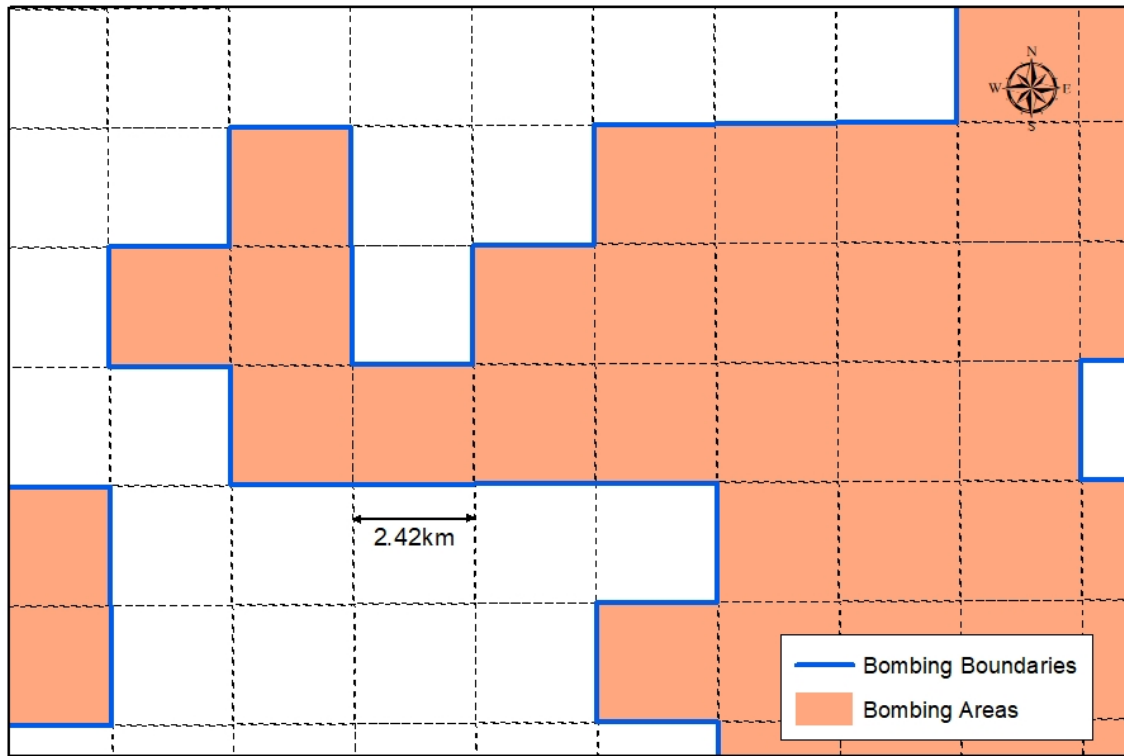
The bombing data used in this study was compiled by the Yale University Cambodian Genocide Program and provides information on 115,273 bombing sites targeted in Cambodia between October 1965 and May 1975. This dataset includes details such as the date of the bombing, precise locations, the number and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

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

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

In our specific context, it is crucial that the designated bombing areas accurately capture the spatial patterns and distribution of bombing incidents. These areas must depict the geographical regions affected by the bombing, ensuring a precise representation of the impact zones. Based on this grid-based clustering technique, we divide the country map into geographic grid cells. We use an approach commonly employed by ecologists to identify the size of the grid cells. As outlined by Boots & Getis (1988), a

Figure A.1: Bombing boundaries and bombing areas



Notes: We exploit the spatial discontinuity around the bombing boundaries which separate areas exposed to past bombing from those that weren't. A boundary is only the outline where bombed and unbombed cells meet; grid edges interior to either zone are not boundaries. Map was drawn on ArcGIS.

suitable quadrat or grid size can be estimated as double the area per point, in particular: $I = \sqrt{2 \times A/n}$, where I denotes the calculated length of the side of a grid cell, A denotes the area of the focused region, and n denotes the number of features – airstrikes in our case – in the study area.

Our cell size equals 5.856 km^2 (2.42 km on each side), given Cambodia's overall area being $337,561 \text{ km}^2$ and the number of airstrikes being 115,273.¹ In total, the country is divided into 31,799 grid cells.² After identifying the bombing loads in each cell, only cells that have bombing loads greater than 0 are selected and defined as bombing areas. Figure A.1 demonstrates the way we construct bombing areas, zooming in on an actual portion of our data, and later how we construct bombing boundaries from the grid cells. Figure 3 in Section 4 then shows the spatial distribution of identified bombing areas in

¹This is similar to the cell size selected by Kohama et al. (2020) who examines how the economic characteristics of conflict zones influence the choice of military strategies.

²While this approach would produce about 57,600 cells based on the total national area, not all cells were suitable for analysis. Cells that fell outside the national boundary and overlapped permanent water bodies were removed. After applying these exclusions, 31,799 grid cells remained and were used in the analysis.

Cambodia, which captures the clustering of strike locations, with areas outside these areas classified as unexposed.

A.2 Data on recovery

A.2.1 Health Index: Cambodia Demographic and Health Surveys

Our analysis builds upon four waves of the Cambodia Demographic and Health Surveys (DHS 2000, 2005, 2010, and 2014).³ We rely on the DHS individual women's data, as it offers extensive health information that is not available for the male sample. DHS surveys provide the geo-location of a cluster, which is a group of 25-30 households participating in the surveys. A household cluster in DHS can be considered an enumeration area, or a village in rural or urban areas. To keep respondents' confidentiality, GPS locations of clusters are displaced geospatially. Specifically, urban points are randomly displaced by up to 2 kilometers, while rural points are displaced by up to 10 kilometers. The randomness of this displacement ensures classical measurement error and thus unbiased estimates.

We follow Anderson (2008) to generate a standardized weighted summary *health index* of women comprising the following components:

1. *Height-for-age Z-scores (HAZ)*. HAZ is calculated by DHS using the WHO Growth Reference, reporting the difference between an individual's actual height and the median height of a reference population of the same age and sex.⁴ A below-median HAZ is an indication of stunting or malnutrition (Leroy & Frongillo 2019).
2. *Weight-for-height Z-scores (WHZ)*. WHZ is also calculated by DHS using the WHO Growth Reference, measuring the number of standard deviations below or above the median normative weight for women of her age and weight. Very low weight-for-height z-scores indicate malnutrition, reflecting body weight substantially below the healthy reference level for a given height.
3. *Healthy Body Mass Index*. This variable is constructed based on women's Body Mass Index (BMI). BMI has been widely used in literature as an indicator of health status (Kountchou et al. 2019, Conti et al. 2024). Women are considered to have a healthy BMI if their BMI is between 18.5 and 25 kg/m² (Weir & Jan 2019).

³Demographic 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.

⁴Height-for-age Z-score is calculated based on WHO Growth Reference tools, factoring in sex, age, and height data, with computations performed via WHO Anthro-based software. See https://dhsprogram.com/data/Guide-to-DHS-Statistics/Nutritional_Status.htm for more details.

4. *Health Corpulence Index.* Corpulence Index (CI), also known as Ponderal Index (PI) or Rohrer's Index, is a measure of body corpulence calculated as weight divided by height cubed, unlike BMI which normalizes by height squared. This adjustment makes the index more appropriate for very short or very tall individuals (Roth 2018). We check the correlation between BMI and CI within our sample and find a moderate positive association ($r = 0.367$), indicating that while the two measures are related, they capture distinct aspects of body composition, which motivates us to use both indices. We then construct a variable called *Healthy CI*, which is defined as a CI between 11 and 15 (Mohajan 2023).
5. *No Anemia.* Anemia is an indicator of inadequate nutrition and overall poor health, often associated with iron deficiency (WHO 2008), that has been used as a health outcome in prior research (Aguilar & Vicarelli 2011, Rosales-Rueda 2018). Anemia status is classified by measuring hemoglobin levels, which are obtained through blood tests conducted by the DHS Program. Based on available DHS data, individuals are categorized into two groups: those with moderate or severe anemia and those with mild or no anemia.

By pooling information across multiple outcomes that capture the same latent dimension, a summary index reduces measurement error by averaging out idiosyncratic noise in individual outcome measures. We first recode each variable so that higher values indicate better health. We then standardize each variable and compute a weighted average. The weights are based on the inverse of the covariance matrix of the standardized variables, maximizing the information captured by the index (Anderson 2008).

A.2.2 Post-bombing economic development data

We utilize the following datasets to evaluate post-bombing economic growth and infrastructure development. We begin by using data from the 2008 Population Census and additional infrastructure datasets to construct an Economic Development Index that captures development at the census village level. We then draw on the Cambodia Socio-Economic Surveys from 2009 and 2014 to evaluate households' current levels of economic development.

Economic Development Index. Similar to the variable *Health Index*, we also use Anderson (2008)'s approach to construct a standardized weighted index of economic development based on the following components:

1. *School Locations in Cambodia (2012).* We use this dataset to calculate the distance to the nearest school, which serves as a proxy for infrastructure development at the census village level. This dataset contains the geographic locations of schools

as well as detailed information on preschools, primary schools, high schools, and colleges.⁵ We compute the distance from each census village to the nearest school. To ensure that higher values indicate better economic conditions, we reverse the sign of the distance variable so that larger values correspond to shorter distances to schools and, therefore, better economic development.

2. *Health facilities in Cambodia (2010)*. We use distance to hospitals as a proxy for health infrastructure development and healthcare accessibility. The dataset on health facilities provides comprehensive information on healthcare facilities in Cambodia, including national hospitals, referral hospitals, health centers, and health posts.⁶ We then calculate the distances from each census village to the nearest hospital. We reverse the sign of the distance measure so that higher values correspond to shorter distances and thus better economic development.
3. *Radio Station in Cambodia (2012)*. This dataset provides information on radio stations across each province of Cambodia.⁷ Based on this dataset, we construct a dummy variable equal to 1 if census villages are located within a big radio network.
4. *Data from 2008 Population Census*. Using data from the 2008 Population Census data, we construct several indicators to measure development at the village level: (1) the percentage of households having access to improved water sources (including piped water, tube/pipe well, protected dug well and rain water); (2) the percentage of households having electricity as main source of light (including city power, generators, and both); (3) the percentage of households having toilet facility within premises; (4) dwelling tenure status (the proportion of households living in their own dwellings); (5) adult literacy rate (the percentage of literate individuals aged 15 and above among the total population aged 15 and above); (6) school attendance rate (the percentage of individuals (aged 6 and over) who are attending school); and (7) employment rate. Higher values of these indicators reflect higher levels of economic development.

⁵It was originally compiled by the Ministry of Education, Youth and Sports and later shared by the Office for the Coordination of Humanitarian Affairs (OCHA) through the Humanitarian Data Exchange (HDX). Open Development Cambodia (ODC) downloaded the data from HDX <https://data.humdata.org> in ESRI Shapefile format and converted it into other file formats. See <https://opendevelopmentcambodia.net> for more details.

⁶Cambodia's Ministry of Health (MoH) originally compiled the data, which was subsequently contributed to the Humanitarian Data Exchange (HDX) by the Office for the Coordination of Humanitarian Affairs (OCHA). Open Development Cambodia's team gathered data from Google Maps and utilized references from Cambodia's Ministry of Health. See <https://opendevelopmentcambodia.net> for more details.

⁷The data were collected from the fmscan.org website by Open Development Cambodia's mappers and were originally available in image format. See <https://opendevelopmentcambodia.net> for more details.

Cambodia Socio-Economic Survey 2009 and 2014. To capture households' economic development at present, we use the Cambodia Socio-Economic Survey (CSES) 2009 and 2014, which are nationally representative surveys covering 12,000 households across 720 villages in 2009 and 12,096 households across 1,008 villages in 2014. The surveys contain information about households' economic activities, agricultural and non-agricultural incomes, expenditures, vulnerability to food shortages, field productivity, and risk-taking behaviors. Although CSES 2009 & 2014 do not provide geo-locations of households, we are able to geo-locate households using village coordinates provided by the 2008 Population Census. We selected the 2009 and 2014 waves because they use a roughly equal sampling scheme and size, and they come after the 2008 census.

2013 Cambodia National Agricultural Census. We complement the CSES with the 2013 Cambodia National Agricultural Census, a full enumeration of agricultural households that we geolocate via the 2008 Population Census village identifiers. The Agricultural Census is structural rather than transactional, thus it does not record harvest yields, sale prices, or crop revenue, which we observe in the CSES. We use the Agricultural Census to construct household-level indicators of crop orientation (share of parcels in commercial crops, whether the main purpose of production is sale), livestock scale (log Tropical Livestock Units and an above-median indicator), forest land use, and the share of household labor time allocated to crop cultivation, livestock, and non-farm activities.

A.3 Pre-bombing data

We exploit several datasets from before the bombing or thereabouts for controls, heterogeneity dimensions, and balance testing.

Soil types in 1962. We use the data on the distribution of soil types in Cambodia provided by Crocker (1962) to identify pre-bombing soil fertility.⁸ Based on the discussion on soil type characteristics in White et al. (1997) and similar to the classification in Kohama et al. (2020), we create a dummy variable, Soil fertility in 1962, which equals 1 if a village is located in areas that are considered fertile (soft soil) and equals 0 otherwise.⁹ A detailed discussion on soil classification is provided in Appendix C.

⁸The data were provided to Open Development Cambodia in ESRI Shapefile format by Save Cambodia's Wildlife's 2013 Atlas Working Group. For more details, see <https://opendevelopmentcambodia.net>.

⁹Specifically, 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).

1970 Indochina Atlas. We digitize three maps from the Indochina Atlas for location-specific measures of transportation links, agriculture, and population.¹⁰ The Indochina Transportation map depicts the major roads and railways of the country in 1970 (Appendix, Figure D.2). We geo-reference the map and measure the distance from a village to 1970 roads and railways. The Indochina Agriculture map outlines regions where agricultural activities took place (Appendix, Figure D.3). We then match this information with village locations to determine whether there were any agricultural activities at a village during the pre-bombing period. Finally, the Indochina Population map displays population density (persons per square kilometer) across Indochina (Appendix, Figure D.4), enabling us to identify population density at the village level in 1970. We argue these are "pre-bombing" characteristics, because although bombing started in the mid 1960s, the bombs escalated over a thousand times since 1970 (Owen & Kiernan 2006), meaning that most of the strikes occurred after 1970 (see Figure 1).

Global Agro-Ecological Zones (GAEZ). To assess the climate and potential crop productivity at the village level, 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 provides a comprehensive assessment of biophysical resources essential to agricultural production.¹¹ 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 D.1). Subsequently, we create a binary variable indicating whether a village is located in a grid cell characterized as tropics and lowland.

A.4 Data on unexploded ordnance

Mine/ERW casualties (2005-2013). In addition to the above datasets, we use data on Mine/ERW casualties (2005-2013) to test whether UXO is more prevalent in regions with pre-bombing softer soil. This dataset provides detailed locations of landmine and remnants of war (ERW) incidents. The data also reports the number of victims and

¹⁰These maps were released in October 1970 by the Directorate of Intelligence, Office of Basic and Geographic Intelligence, U.S. Central Intelligence Agency and are available at <https://maps.lib.utexas.edu>.

¹¹The AEZ map incorporates thermal and moisture regimes, soil/terrain qualities, the presence of irrigated soils, and the identification of areas with significant bio-physical limitations such as extreme cold, arid deserts, steep terrains, and poor soil conditions. Geographical regions classified within the same AEZ category share similar climatic attributes, including rainfall and temperature patterns, which consequently contribute to comparable agricultural potentials. Several studies use GAEZ data to control for geographic characteristics or local agricultural suitability (e.g., Whatley & Gillezeau 2011, Cagé & Rueda 2016). Data can be accessed via <https://gaez.fao.org>.

casualties resulting from these incidents in Cambodia between 2005 and 2013.¹² In our analysis, we focus exclusively on incidents involving ERW likely originating from aerial bombing (CBU submunitions, fuses, and ammunition, other, and unknown) and exclude incidents related to landmines and other ground-delivered explosive weapons.¹³ We merge this dataset with 2008 Population Census data. We count the number of incidents within 3km of census village locations and construct a binary outcome equal to 1 if there are any incidents within this 3-km radius.

A.5 Descriptive Statistics

Table A.1 and A.2 report the summary statistics of variables used in this study. Table A.1 presents the variables measured at the DHS individual (DHS women) level. The results indicate that health outcomes are, on average, comparable between individuals residing inside and outside bombing areas, with those living inside bombing areas exhibiting a slightly higher health index. Table A.2 reports the variables constructed at the census village level. Similarly, there are no significant differences in UXO likelihood or in the Economic Development Index between villages located inside and outside the bombing areas. Additionally, both tables show that the mean distance to Vietnam's borders is significantly lower for those inside the bombing areas, aligning with the historical narrative.

¹²The 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. See <https://opendevelopmentcambodia.net> for more details.

¹³We note that UXO/ERW incidents can include those from separate causes than the US aerial bombing campaign (Roberts 2011, Martin et al. 2019).

Table A.1: Descriptive statistics (*Unit: DHS women*)

	All observations				Within 2km distance			
	All	Outside	Inside	Diff	All	Outside	Inside	Diff
Panel A: Health outcomes								
Health Index	0.00 (0.42)	0.01 (0.42)	-0.01 (0.42)	0.02*** (4.73)	-0.01 (0.43)	-0.01 (0.42)	-0.02 (0.43)	0.01* (2.23)
Height-for-age Z-score	-1.81 (0.89)	-1.79 (0.88)	-1.84 (0.89)	0.05*** (4.94)	-1.83 (0.89)	-1.82 (0.88)	-1.85 (0.90)	0.03* (2.05)
Weight-for-height Z-score	-0.96 (0.96)	-0.93 (0.96)	-1.01 (0.97)	0.08*** (6.80)	-1.03 (0.96)	-1.00 (0.96)	-1.06 (0.96)	0.06*** (3.39)
Healthy BMI ($18.5 \leq BMI < 25$)	0.71 (0.46)	0.71 (0.45)	0.70 (0.46)	0.01 (1.65)	0.71 (0.46)	0.71 (0.46)	0.70 (0.46)	0.00 (0.23)
Healthy Corpulence Index ($11 \leq CI < 15$)	0.69 (0.46)	0.69 (0.46)	0.70 (0.46)	-0.01 (-1.53)	0.71 (0.45)	0.71 (0.46)	0.71 (0.45)	-0.01 (-0.84)
No Anemia	0.91 (0.29)	0.90 (0.29)	0.91 (0.28)	-0.01* (-2.27)	0.91 (0.29)	0.90 (0.29)	0.91 (0.29)	-0.00 (-0.69)
Panel B: Pre-bombing characteristics								
Soil fertility (1962)	0.37 (0.48)	0.35 (0.48)	0.40 (0.49)	-0.05*** (-12.14)	0.36 (0.48)	0.33 (0.47)	0.39 (0.49)	-0.06*** (-12.10)
Elevation/Altitude (meters)	42.22 (76.74)	37.83 (59.67)	47.73 (93.53)	-9.90*** (-15.95)	40.76 (79.76)	36.61 (60.80)	44.98 (95.07)	-8.37*** (-9.42)
Tropics, lowland	0.55 (0.50)	0.49 (0.50)	0.62 (0.48)	-0.13*** (-33.75)	0.60 (0.49)	0.55 (0.50)	0.65 (0.48)	-0.10*** (-18.15)
Agricultural activities (1970)	0.93 (0.25)	0.92 (0.28)	0.96 (0.20)	-0.04*** (-23.56)	0.94 (0.23)	0.93 (0.25)	0.95 (0.22)	-0.02*** (-6.74)
Population density (1970)	0.75 (0.43)	0.68 (0.47)	0.83 (0.37)	-0.15*** (-46.80)	0.80 (0.40)	0.80 (0.40)	0.81 (0.40)	-0.01 (-1.15)
Distance (km) to roads/railways (1970)	6.51 (8.39)	7.42 (9.72)	5.36 (6.13)	2.05*** (33.56)	6.32 (6.90)	6.26 (7.04)	6.38 (6.76)	-0.12 (-1.55)
Panel C: Other characteristics								
Distance (km) to								
Vietnam borders	135.35 (116.53)	188.78 (124.39)	67.90 (55.09)	120.88*** (169.52)	89.97 (75.46)	105.33 (84.46)	74.25 (61.11)	31.08*** (38.07)
Capital	135.45 (101.41)	160.72 (103.31)	103.55 (89.28)	57.17*** (77.37)	102.69 (89.26)	104.84 (88.73)	100.48 (89.74)	4.37*** (4.41)
Thai borders	171.82 (83.50)	132.36 (81.45)	221.61 (54.34)	-89.25*** (-170.85)	201.36 (60.40)	189.13 (61.61)	213.87 (56.48)	-24.73*** (-37.74)
Observations	68506	38423	30083	68506	32495	16435	16060	32495

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 2 km distance" means the sample is restricted to observations located within 2 km of bombing boundaries. "Diff" shows the mean difference between treated (inside) and control (outside) groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Descriptive statistics (Unit: Census Villages)

	All observations				Within 2km distance			
	All	Outside	Inside	Diff	All	Outside	Inside	Diff
Panel A: Unexploded Ordnance (UXO)								
UXO Likelihood	0.09 (0.29)	0.11 (0.32)	0.07 (0.25)	0.05*** (9.25)	0.07 (0.25)	0.07 (0.25)	0.06 (0.24)	0.01 (0.89)
Number of incidents	0.11 (0.41)	0.15 (0.49)	0.08 (0.30)	0.08*** (10.88)	0.08 (0.31)	0.08 (0.32)	0.07 (0.30)	0.01 (1.19)
Panel B: Post-bombing economic outcomes								
Economic Development Index	0.00 (0.36)	-0.03 (0.37)	0.03 (0.35)	-0.06*** (-9.17)	0.02 (0.32)	0.02 (0.33)	0.02 (0.31)	-0.00 (-0.54)
Distance (km) to								
School (2012)	0.91 (0.99)	0.92 (1.19)	0.89 (0.75)	0.03* (1.97)	0.92 (0.87)	0.91 (0.92)	0.92 (0.83)	-0.01 (-0.62)
Hospital (2010)	14.14 (11.87)	15.73 (13.68)	12.66 (9.64)	3.07*** (15.31)	13.78 (11.80)	14.15 (12.92)	13.49 (10.83)	0.66* (2.27)
Radio Station (big network)	0.89 (0.32)	0.86 (0.35)	0.91 (0.28)	-0.06*** (-10.53)	0.92 (0.28)	0.91 (0.28)	0.92 (0.27)	-0.01 (-1.00)
Percentage of households having								
Improved Water	49.67 (38.14)	46.68 (38.46)	52.46 (37.62)	-5.78*** (-9.00)	52.63 (38.93)	52.68 (39.27)	52.59 (38.66)	0.09 (0.09)
Electricity	16.25 (29.22)	19.62 (32.83)	13.09 (24.97)	6.53*** (13.21)	14.07 (27.66)	17.94 (32.33)	11.03 (22.88)	6.91*** (10.07)
Toilet within premises	25.57 (28.42)	27.62 (31.42)	23.65 (25.13)	3.96*** (8.23)	23.86 (27.88)	26.06 (31.02)	22.12 (25.00)	3.94*** (5.74)
Own dwellings	94.87 (8.98)	94.02 (8.67)	95.67 (9.20)	-1.65*** (-10.92)	95.53 (7.88)	94.81 (8.76)	96.09 (7.07)	-1.28*** (-6.62)
Literacy Rate	73.86 (17.43)	72.56 (18.29)	75.08 (16.50)	-2.52*** (-8.58)	74.53 (17.15)	74.11 (17.86)	74.87 (16.57)	-0.76 (-1.82)
School Attendance Rate	28.98 (7.05)	28.62 (7.24)	29.33 (6.84)	-0.71*** (-5.94)	29.61 (7.02)	29.36 (7.22)	29.81 (6.86)	-0.45** (-2.64)
Employment Rate	98.79 (3.09)	98.49 (3.53)	99.07 (2.58)	-0.58*** (-11.14)	98.92 (2.87)	98.65 (3.38)	99.14 (2.38)	-0.49*** (-6.81)
Panel C: Pre-bombing characteristics								
Soil fertility (1962)	0.39 (0.49)	0.39 (0.49)	0.39 (0.49)	0.00 (0.10)	0.36 (0.48)	0.36 (0.48)	0.36 (0.48)	-0.00 (-0.39)
Elevation/Altitude (meters)	34.01 (55.35)	36.66 (55.82)	31.53 (54.80)	5.12*** (5.49)	31.18 (56.00)	30.37 (48.48)	31.83 (61.28)	-1.46 (-1.11)
Tropics, lowland	0.52 (0.50)	0.46 (0.50)	0.57 (0.50)	-0.11*** (-13.00)	0.53 (0.50)	0.49 (0.50)	0.55 (0.50)	-0.06*** (-4.63)
Agricultural activities (1970)	0.95 (0.21)	0.94 (0.24)	0.97 (0.17)	-0.03*** (-9.52)	0.95 (0.21)	0.95 (0.22)	0.96 (0.20)	-0.01* (-2.08)
Population density (1970)	0.79 (0.40)	0.69 (0.46)	0.89 (0.31)	-0.21*** (-31.04)	0.86 (0.35)	0.85 (0.36)	0.87 (0.34)	-0.02* (-2.43)
Distance (km) to roads/railways (1970)	7.76 (8.90)	9.29 (10.63)	6.33 (6.60)	2.96*** (19.69)	7.46 (7.37)	7.62 (7.68)	7.33 (7.12)	0.29 (1.65)
Panel D: Other characteristics								
Distance (km) to								
Vietnam borders	123.87 (114.78)	190.26 (127.67)	61.80 (47.75)	128.46*** (78.03)	80.57 (66.91)	95.65 (77.61)	68.68 (54.22)	26.97*** (16.42)
Capital	113.19 (95.44)	153.75 (104.87)	75.26 (66.07)	78.49*** (52.71)	81.74 (71.33)	85.94 (74.78)	78.43 (68.31)	7.50*** (4.33)
Thai borders	184.52 (81.82)	138.06 (83.73)	227.96 (49.96)	-89.90*** (-76.69)	210.42 (56.90)	198.19 (59.07)	220.06 (53.19)	-21.87*** (-16.08)
Observations	14073	6800	7273	14073	7014	3091	3923	7014

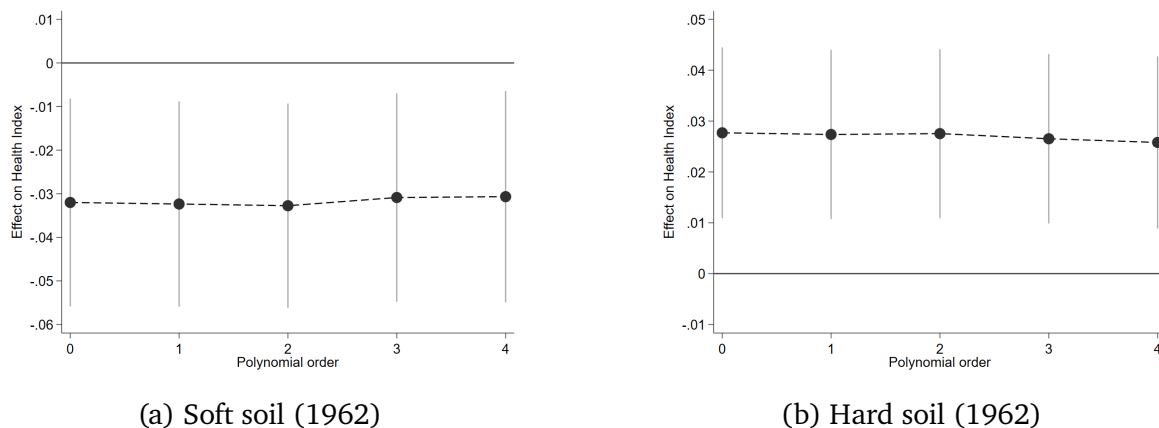
Note: The table provides the mean/standard deviation of the corresponding variables. "All" means the whole sample, "Outside" means the sample includes observations located outside bombing areas, and "Inside" means the sample includes observations located inside bombing areas. "Within 2 km distance" means the sample is restricted to observations located within 2 km of bombing boundaries. "Diff" shows the mean difference between treated (inside) and control (outside) groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Robustness

We conduct multiple robustness checks to assess the sensitivity of the results and address potential concerns associated with our spatial RD design. We show that our results on *Health Index* are robust to alternative bandwidths, different polynomial orders, different grid-cell fixed effects, a wide range of specifications including an uni-dimensional RDD, and placebo tests.

Choice of polynomial orders. Figure B.1 plots the main coefficients for different orders of RD polynomial in spatial coordinates. The results are consistent when higher orders of polynomials are used in the main regression with a substantial decline in the health index for soft-soil areas and consistently positive effects for hard-soil areas.

Figure B.1: Sensitivity of Results to Different Orders of Polynomial

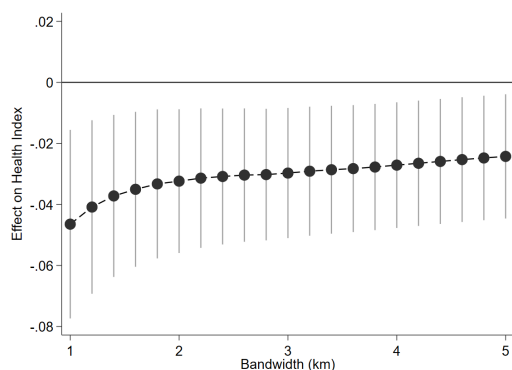


Note: Dependent variable is Health Index. Each dot represents the RD estimate using the specified order of RD polynomial in spatial coordinates. Range spikes represent 90% confidence intervals of the estimates.

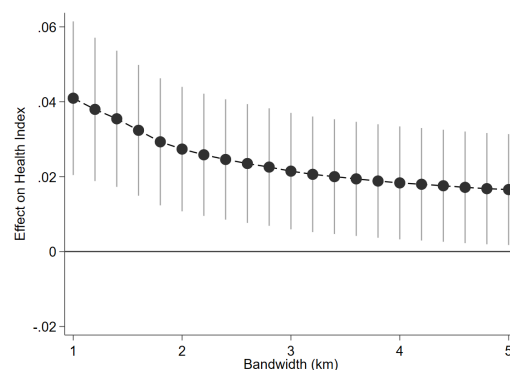
Bandwidth sensitivity. We conduct sensitivity checks to different choices of bandwidth ranging from 1 to 5 km with 0.2km intervals. Figure B.2 shows that our results are robust to any choice of bandwidths with negative health effects in soft soil regions and positive health effects in hard soil regions.

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 50x50km grid-fixed effects along with province fixed effects to ensure that we compare individuals within a confined area. However, we are also concerned that 50x50km grids may be too broad to account for between-area heterogeneity.

Figure B.2: Sensitivity of Results to Bandwidth Choice



(a) Soft soil (1962)

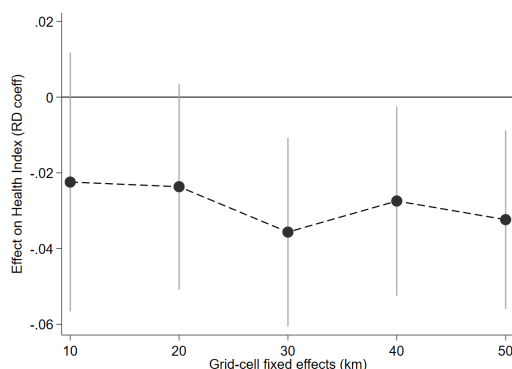


(b) Hard soil (1962)

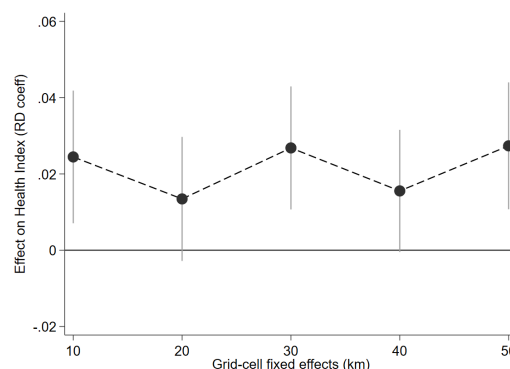
Note: Dependent variable is Health Index. Each sub-graph reports coefficient estimates and confidence intervals for different bandwidth levels ranging from 1 to 5 kilometers (horizontal axis) with 0.2km intervals. Each dot indicates the RD estimate using the specified bandwidth. Range spikes represent 90% confidence intervals of the estimates.

Therefore, instead of using 50x50km grids to control for spatial variation, we divide the country into smaller grid-cells, ranging from 10x10km, 20x20km up to 50x50km, and control for grid-cell fixed effects in our main regressions. Figure B.3 presents our results. When smaller-grid fixed effects are employed, the results remain similar: living in bombing areas is associated with better health in hard-soil areas and worse health in soft-soil areas.

Figure B.3: Sensitivity of Results to Different Grid Fixed Effects



(a) Soft soil (1962)



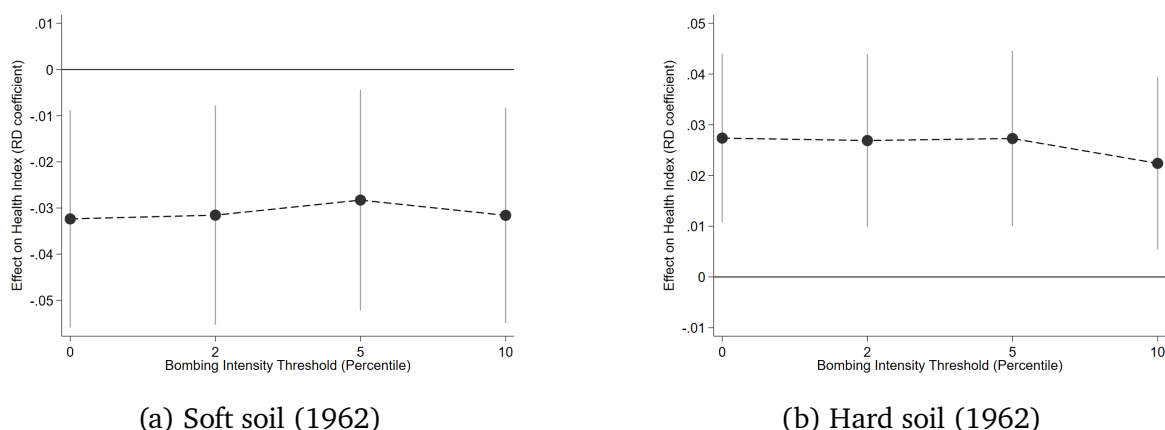
(b) Hard soil (1962)

Note: Dependent variable is Health Index. Each dot represents the RD estimate controlling for a specified grid-fixed-effects. Range spikes represent 90% confidence intervals of the estimates.

Alternative Bombing Intensity Thresholds To assess whether the results are sensitive to how bombing exposure is defined, we re-define treatment using thresholds

based on the distribution of positive bombing intensity rather than a binary indicator of any exposure (tonnage > 0). Specifically, I classify a grid as treated (bombed) only if its total bombing load exceeds cutoffs corresponding to the 2nd, 5th, and 10th percentiles of positive bombing distribution. This approach excludes areas with minimal exposure and focuses on locations substantially affected by bombing. Figure B.4 presents our results. The estimated effects remain stable across all thresholds, confirming that the results are not driven by marginally exposed locations and are robust to alternative, intensity-based definitions of treatment.

Figure B.4: Sensitivity of Results to Alternative Bombing Intensity Thresholds



Note: Dependent variable is Health Index. Each dot represents the RD estimate using a specified bombing intensity threshold (0, 2%, 5%, or 10%). Range spikes represent 90% confidence intervals of the estimates.

Uni-dimensional RD design We use the uni-dimensional RD design to cross-verify our results. The regressions take the same form as our main specification. However, in this setting, RD polynomial $f(Geo_c)$ uses a uni-dimensional measure, in particular, distance to bombing boundaries as a running variable. The local linear polynomial has a function as $f(Geo_c) = \eta dist_c + \theta Bombing_c \times dist_c$ 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: $f(Geo_c) = \sum_{k=1}^a \eta_k dist_c^k + \theta_k Bombing_c \times dist_c^k$. The interaction term of the treatment variable with the distance to the bombing areas is of great importance because it allows for different slopes of the functions on two sides of bombing boundaries. Table B.1 shows that a unidimensional RDD yields similar results, with coefficients even larger in magnitude.

Alternative specifications. In Table B.2, we investigate robustness to a wide range of specifications. The first column controls for 50x50km grid fixed effects and district

Table B.1: Uni-dimensional RDD

	All areas		Soft soil (1962)		Hard soil (1962)	
	Linear (1)	Quad. (2)	Linear (3)	Quad. (4)	Linear (5)	Quad. (6)
Bombing	0.057*** (0.017)	0.077*** (0.026)	-0.044* (0.024)	-0.071* (0.036)	0.060*** (0.018)	0.080*** (0.027)
Bombing \times Soft Soil	-0.091*** (0.030)	-0.145*** (0.045)				
Mean	-0.013	-0.013	-0.010	-0.010	-0.015	-0.015
Observations	17311	17311	6242	6242	11026	11026
Clusters	1053	1053	381	381	670	670

Note: The unit of analysis is DHS survey respondents. The sample is restricted to those living within 2km of a treated-control interface (a bombing boundary). All regressions control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. 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 parentheses are clustered at the DHS village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

fixed effects instead of province fixed effects.¹⁴ Column (2) shows the results when observations are clustered at bombing grids instead of DHS villages. Column (3) includes the distance to Thai border among the control variables. The following column presents outcomes without a triangular kernel weight.¹⁵ Columns (5) (6) exclude the distance to the capital and the distance to Vietnam's borders in the main regressions. The last column runs a *donut* exercise by removing all observations close to bombing boundaries (within 0.1km) 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. Table B.2 shows that our estimates are robust in terms of magnitude and significance level across different specification choices. Even in the more restrictive *donut* model, the effects remain strong and significant.

¹⁴In our dataset, households are located in 176 districts.

¹⁵A triangular kernel involves decreasing the weight assigned to each observation as the distance from the boundaries increases.

Table B.2: Robustness checks: different specifications with x- and y- coordinates as running variables

	Dependent variable is Health Index						
	Grid-&District-FE (1)	Cluster(Bombing Grid) (2)	With Dist. Thai (3)	No weight (4)	No Dist. Capital (5)	No Dist. Vietnam (6)	Donut 0.1km (7)
Panel A: All observations							
Bombing	0.028*** (0.010)	0.025** (0.010)	0.024** (0.010)	0.016* (0.010)	0.025** (0.010)	0.025** (0.010)	0.019* (0.011)
Bombing × Soft Soil	-0.049*** (0.018)	-0.054*** (0.018)	-0.053*** (0.017)	-0.045*** (0.015)	-0.054*** (0.017)	-0.054*** (0.017)	-0.053*** (0.017)
Mean	0.0945	0.0945	0.0945	0.0945	0.0945	0.0945	0.0948
Observations	17311	17268	17268	17268	17268	17268	16067
Clusters	1054	842	1051	1051	1051	1051	975
Panel B: Soft soil (1962)							
Bombing	-0.028* (0.015)	-0.032** (0.014)	-0.032** (0.014)	-0.030** (0.013)	-0.032** (0.014)	-0.032** (0.014)	-0.034** (0.015)
Mean	0.0802	0.0802	0.0802	0.0802	0.0802	0.0802	0.0801
Observations	6242	6242	6242	6242	6242	6242	5824
Clusters	381	290	381	381	381	381	357
Panel C: Hard soil (1962)							
Bombing	0.026** (0.010)	0.027*** (0.010)	0.025** (0.010)	0.017* (0.010)	0.027*** (0.010)	0.027*** (0.010)	0.020* (0.010)
Mean	0.102	0.102	0.102	0.102	0.102	0.102	0.103
Observations	11069	11026	11026	11026	11026	11026	10243
Clusters	673	567	670	670	670	670	618

Note: The unit of analysis is DHS survey respondents. Regressions (1) control for grid-fixed effects and district-fixed effects (instead of province fixed effects). Regressions (2) show the estimates when observations are clustered at bombing grids instead of DHS villages. Regressions (3) additionally control for distance to Thai borders. Regressions (4) exclude the triangular kernel weight. Regressions (5) (6) exclude the distance to the capital and the distance to Vietnam's borders, correspondingly. Regressions (7) conduct a donut exercise that excludes observations within 0.1 km of bombing boundaries. Standard errors reported in parentheses are clustered at the DHS village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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 5km in all directions (north/ east/ west/ south). Then, we re-assign treatment and estimate the treatment effects in placebo situations both for the aggregate effects and again split by 1962 soil conditions. As illustrated in Table B.3, there are no significant placebo-boundary effects on *health index* for both soft soil and hard soil areas.

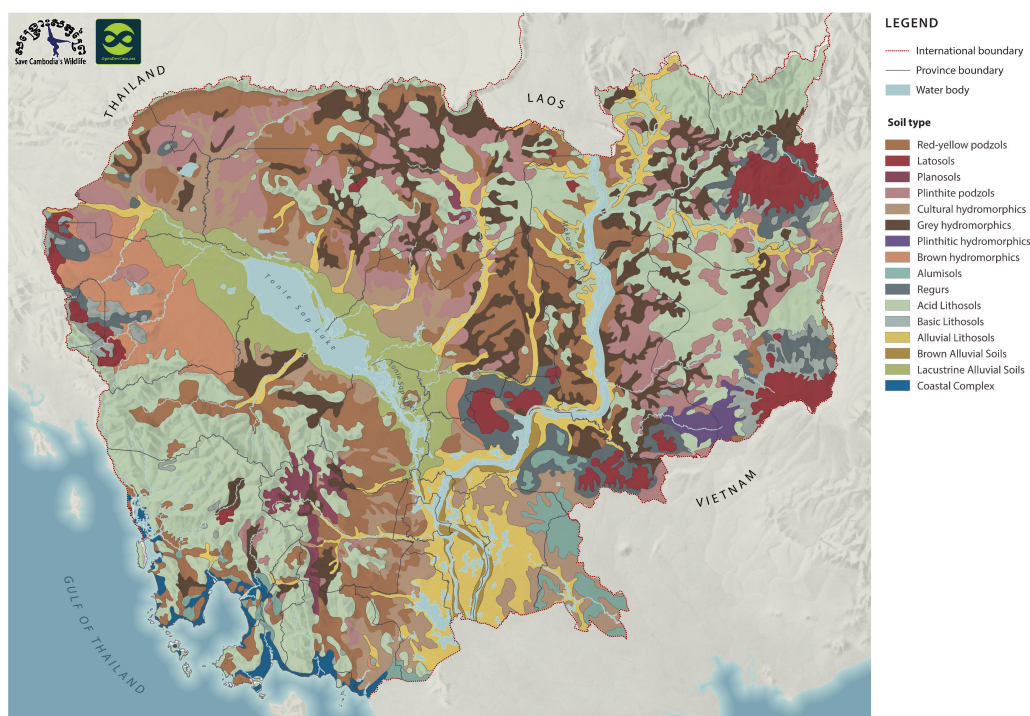
Table B.3: Robustness checks: Shifting borders

	Shift east (1)	Shift west (2)	Shift north (3)	Shift south (4)
Panel A: All observations				
Bombing	0.002 (0.010)	-0.010 (0.010)	-0.012 (0.010)	0.007 (0.010)
Bombing × Soft Soil (1962)	0.014 (0.017)	0.002 (0.016)	0.017 (0.016)	-0.012 (0.016)
Mean	0.402	0.390	0.407	0.399
Observations	18323	18327	18857	18339
Clusters	1113	1107	1144	1111
Panel B: Soft soil (1962)				
Bombing	0.011 (0.014)	-0.013 (0.015)	0.007 (0.013)	-0.004 (0.014)
Mean	0.440	0.410	0.416	0.382
Observations	7418	7004	7214	6548
Clusters	448	415	433	395
Panel C: Hard soil (1962)				
Bombing	-0.004 (0.010)	-0.011 (0.010)	-0.016 (0.010)	0.007 (0.010)
Mean	0.380	0.379	0.402	0.408
Observations	10905	11323	11643	11791
Clusters	665	692	711	716

Note: The table shows the results of placebo tests which shift bombing borders by 5 kilometers to four different directions: east-west-north-south. The unit of analysis is survey respondents. All regressions control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Standard errors reported in parentheses are clustered at the DHS village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

C Soil classification in Cambodia

Figure C.1: Soil types in Cambodia (Crocker, 1962)



Notes: The map displays the distribution of soil types in Cambodia, as documented by Crocker (1962). The data, in vector format, were provided to Open Development Cambodia by Save Cambodia's Wildlife's Atlas Working Group. See <https://opendevelopmentcambodia.net> for more details.

Crocker (1962) carried out an exploratory soil survey in Cambodia, followed by the publication of a general soil map at a 1:1,000,000 scale in 1963 (Kyuma & Kawaguchi 1966). The map classifies soil in Cambodia into 16 different soil types: red-yellow podzols, latosols, planosols, plinthite podzols, cultural hydromorphics, grey hydromorphics, plinthitic hydromorphics, brown hydromorphics, alumisols, regurs, acid lithosols, basic lithosols, alluvial lithosols, brown alluvial soils, lacustrine alluvial soils, and coastal complex (Figure C.1).

White et al. (1997) discuss the characteristics of each soil group in Cambodia and its potential for rice production. For example, Prey Khmer soils correspond to Red-Yellow Podzols and occasionally to Planosols, as identified by Crocker (1962). These soils have low water-holding capacity and limited potential for high rice yields. On the contrary, Kompong Siem Soils which are Regurs in Crocker (1962) are considered fertile and well-suited for rice cultivation, with top soil having good water holding capacity.

Based on the characteristics of each soil type described in White et al. (1997) and

similar to the classification in Kohama et al. (2020), we define these six soil types in Crocker (1962) as fertile (soft) soils: Latosols, Alluvial soils, Brown alluvial soils, Lacustrine alluvial soils, Regurs, and Brown hydromorphics. These soils often have good water-holding capacity and are suitable for rice production. Most importantly, since areas with soft or fertile soil are more likely to contain UXO (Moyes et al. 2002, Lin 2022),¹⁶ we use this classification of pre-bombing soil fertility in our analysis to disentangle the long-term effects of local area exposure to bombing in areas with fertile (soft) soil - a high likelihood of UXO versus areas with infertile (hard) soil - lower UXO occurrences.

¹⁶See Section 2.

D Additional Tables and Figures

Table D.1: Balance check - Population Census Villages

	Dependent variable is:						
	(1) Elevation	(2) Tropics/lowland	(3) Agri. Activities	(4) Pop. Density	(5) Dist. to roads	(6) Dist. VN	(7) Dist. to capital
Panel A: All observations							
Bombing	-0.924 (0.642)	-0.020 (0.016)	0.001 (0.009)	0.004 (0.008)	-0.006 (0.215)	0.231 (0.191)	-0.616 (0.419)
Bombing × Soft Soil	2.200* (1.130)	0.074*** (0.029)	-0.006 (0.015)	-0.023* (0.012)	-0.390 (0.364)	-0.241 (0.340)	1.254* (0.691)
Mean	31.183	0.525	0.953	0.861	7.456	80.567	81.738
$ \beta /\text{Mean}$	0.030	0.038	0.001	0.005	0.001	0.003	0.008
Observations	7013	7014	7014	7014	7014	7014	7014
Clusters	1105	1105	1105	1105	1105	1105	1105
Panel B: Soft soil (1962)							
Bombing	0.023 (0.785)	0.056** (0.025)	-0.007 (0.010)	-0.017** (0.007)	-0.316 (0.286)	-0.159 (0.247)	0.601 (0.498)
Mean	31.023	0.440	0.935	0.859	7.393	76.766	76.621
$ \beta /\text{Mean}$	0.001	0.127	0.007	0.020	0.043	0.002	0.008
Observations	2523	2523	2523	2523	2523	2523	2523
Clusters	560	560	560	560	560	560	560
Panel C: Hard soil (1962)							
Bombing	-0.253 (0.608)	-0.010 (0.016)	0.010 (0.008)	0.007 (0.008)	-0.029 (0.202)	0.031 (0.177)	-0.679* (0.405)
Mean	31.273	0.573	0.964	0.863	7.492	82.703	84.612
$ \beta /\text{Mean}$	0.008	0.017	0.011	0.009	0.004	0.000	0.008
Observations	4490	4491	4491	4491	4491	4491	4491
Clusters	828	828	828	828	828	828	828

Note: The unit of analysis is 2008 Population Census Villages. The sample is restricted to villages within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight. We control for 50x50km grid fixed effects and province fixed effects in all regressions. *Tropics/lowland* is a dummy variable indicating whether this location falls within areas classified as “tropics, humid” in the agro-ecological zones classification. Columns (3) (4) (5) use data from the Indochina Atlas, published in October 1970. *Agri. Activities* indicate whether there were any agricultural activities in these areas in 1970. *Pop. Density* is a binary variable reflecting if the population density in 1970 was at least 10 inhabitants per square kilometre. *Dist. to roads* refers to distance (in km) to 1970 main roads/railways. *Dist. VN* indicates distance to Vietnam border. *Dist. to capital* refers to distance to the capital of Cambodia. Standard errors reported in parentheses are clustered at the commune level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.2: Effects on health: Component Outcomes

	Dependent variable is:				
	(1) Height-for-Age	(2) Weight-for-Height	(3) Healthy BMI	(4) Healthy CI	(5) No Anemia
Panel A: All areas					
Bombing	0.084*** (0.025)	-0.007 (0.029)	0.012 (0.010)	0.004 (0.011)	0.017** (0.008)
Bombing × Soft Soil	-0.118*** (0.042)	-0.078 (0.049)	-0.014 (0.017)	-0.001 (0.019)	-0.020* (0.012)
Mean	-1.833	-1.027	0.705	0.708	0.905
$ \beta /\text{Mean}$	0.046	0.006	0.018	0.005	0.018
Observations	17238	13514	17237	17237	15179
Clusters	1051	941	1051	1051	1051
Panel B: Soft soil (1962)					
Bombing	-0.045 (0.034)	-0.081* (0.042)	0.003 (0.013)	-0.000 (0.016)	-0.008 (0.008)
Mean	-1.830	-1.001	0.697	0.691	0.920
$ \beta /\text{Mean}$	0.025	0.081	0.004	0.000	0.008
Observations	6231	4882	6231	6231	5458
Clusters	381	344	381	381	381
Panel C: Hard soil (1962)					
Bombing	0.076*** (0.026)	-0.009 (0.030)	0.015 (0.011)	0.007 (0.011)	0.017** (0.008)
Mean	-1.834	-1.042	0.710	0.718	0.898
$ \beta /\text{Mean}$	0.041	0.008	0.021	0.010	0.019
Observations	11007	8632	11006	11006	9721
Clusters	670	597	670	670	670

Note: The unit of analysis is DHS survey respondents. The sample is restricted to those living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. *Healthy BMI* is defined as a BMI value between 18.5 and 25. *Healthy Corpulence Index (CI)* or Rohrer's Index is defined as a CI between 11 and 15. Standard errors reported in parentheses are clustered at the DHS village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.3: Child Mortality

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Child Mortality (Dummy)						
Bombing	-0.024*** (0.007)	-0.019*** (0.007)	0.010 (0.010)	0.015 (0.010)	-0.021*** (0.007)	-0.016** (0.007)
Bombing × Soft Soil	0.039*** (0.012)	0.038*** (0.012)				
Mean	0.179	0.177	0.174	0.176	0.182	0.177
Observations	32332	29373	11652	10889	20680	18484
Clusters	1051	954	381	355	670	599
Exclude K5 Belt	No	Yes	No	Yes	No	Yes
Panel B: Number of deaths						
Bombing	-0.043*** (0.013)	-0.032** (0.014)	0.008 (0.019)	0.012 (0.019)	-0.039*** (0.013)	-0.028** (0.014)
Bombing × Soft Soil	0.059** (0.024)	0.052** (0.024)				
Mean	0.288	0.284	0.287	0.292	0.289	0.279
Observations	32332	29373	11652	10889	20680	18484
Clusters	1051	954	381	355	670	599
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is DHS individuals (DHS women). The sample is restricted to those living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the DHS village level. Child mortality is a binary indicator equal to 1 if a woman has experienced the death of at least one child, and 0 otherwise. The number of deaths measures the total number of a woman's children who have died. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.4: Economic Index (2008 Population Census Villages): Individual Outcomes

	Dependent variable is:									
	Dist. School (1)	Dist. Hospital (2)	Radio Station (3)	Improved Water (4)	Electricity (5)	Toilet (6)	Own Dwellings (7)	Literacy (8)	School Attendance (9)	Employment (10)
Panel A: All observations										
Bombing	-0.009 (0.026)	-0.247 (0.225)	0.001 (0.005)	-0.944 (1.117)	-0.916 (0.753)	-0.243 (0.781)	0.308 (0.225)	0.888* (0.475)	0.491** (0.208)	0.192** (0.087)
Bombing × Soft Soil	0.026 (0.044)	0.708* (0.376)	-0.010 (0.007)	-1.282 (1.913)	-1.168 (1.594)	-0.444 (1.453)	-0.154 (0.536)	-0.171 (0.773)	-0.281 (0.384)	-0.370* (0.200)
Mean	0.915	13.780	0.916	52.628	14.074	23.857	95.530	74.531	29.613	98.924
Observations	7012	7012	7012	7012	7012	7012	7012	7012	7012	7012
Clusters	1104	1104	1104	1104	1104	1104	1104	1104	1104	1104
Panel B: Soft soil (1962)										
Bombing	0.010 (0.031)	0.707*** (0.269)	-0.007 (0.004)	-2.201 (1.555)	-1.975 (1.368)	-0.905 (1.197)	-0.209 (0.420)	0.778 (0.610)	0.183 (0.299)	-0.166 (0.173)
Mean	0.793	11.723	0.922	57.570	20.158	29.237	93.667	76.218	29.418	98.484
Observations	2521	2521	2521	2521	2521	2521	2521	2521	2521	2521
Clusters	559	559	559	559	559	559	559	559	559	559
Panel C: Hard soil (1962)										
Bombing	-0.009 (0.026)	-0.262 (0.224)	0.002 (0.005)	-0.496 (1.097)	-0.666 (0.733)	-0.101 (0.770)	0.289 (0.206)	0.841* (0.472)	0.457** (0.208)	0.192** (0.087)
Mean	0.984	14.936	0.912	49.852	10.656	20.835	96.576	73.583	29.723	99.171
Observations	4489	4489	4489	4489	4489	4489	4489	4489	4489	4489
Clusters	827	827	827	827	827	827	827	827	827	827

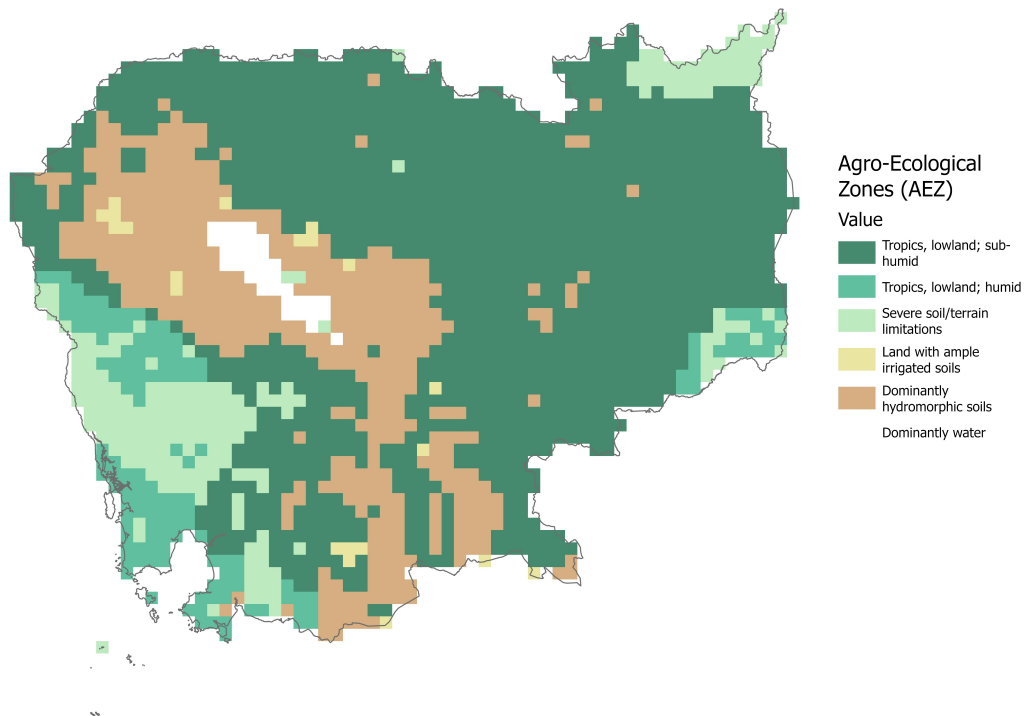
Note: The unit of analysis is census villages. All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. *Economic Development Index* is the standardized weighted summary index variable created from multiple outcomes in this table. *Dist. School* indicates the distance from each village to the nearest school (in km). *Dist. Hospital* indicates the distance from each village to the nearest hospital (in km). *Radio Station* indicates location within big radio networks. The subsequent columns report the percentage of households in the village having access to improved water (column 4), electricity (column 5), and toilets (column 6); the percentage living in owner-occupied dwellings (column 7); literacy rate (column 8); school attendance rate (column 9); and employment rate (column 10). Standard errors reported in parentheses are clustered at the commune level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.5: Conley Standard Errors

	Dependent variable is:		
	UXO Likelihood (1)	Health Index (2)	Economic Index (3)
Bombing	-0.016** (0.007)	0.025*** (0.004)	0.014* (0.008)
Bombing × Soft Soil	0.050** (0.025)	-0.054*** (0.019)	-0.045*** (0.017)
Mean	0.065	-0.013	0.023
Observations	7013	17268	7013

Note: All regressions use a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Standard errors are computed using Conley (1999)'s spatial correction. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure D.1: Agro-ecological Zones classes



Notes: The map overlays Cambodia to the agro-ecological zones (AEZs) as classified 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 D.2: Indochina Transportation in 1970



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

Figure D.3: Indochina Agriculture in 1970



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

Table D.6: Control for border segment fixed effects

	UXO Likelihood		Health Index		Economic Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Bombing	-0.004 (0.005)	-0.004 (0.006)	0.040** (0.017)	0.043** (0.017)	0.011 (0.012)	0.017 (0.012)
Bombing × Soft Soil	0.074*** (0.027)	0.074*** (0.028)	-0.051* (0.027)	-0.055** (0.028)	-0.025 (0.025)	-0.032 (0.025)
Mean	0.065	0.059	-0.013	-0.013	0.023	0.029
Observations	5656	5374	17311	15690	5656	5374
Clusters	965	900	1054	957	965	900
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

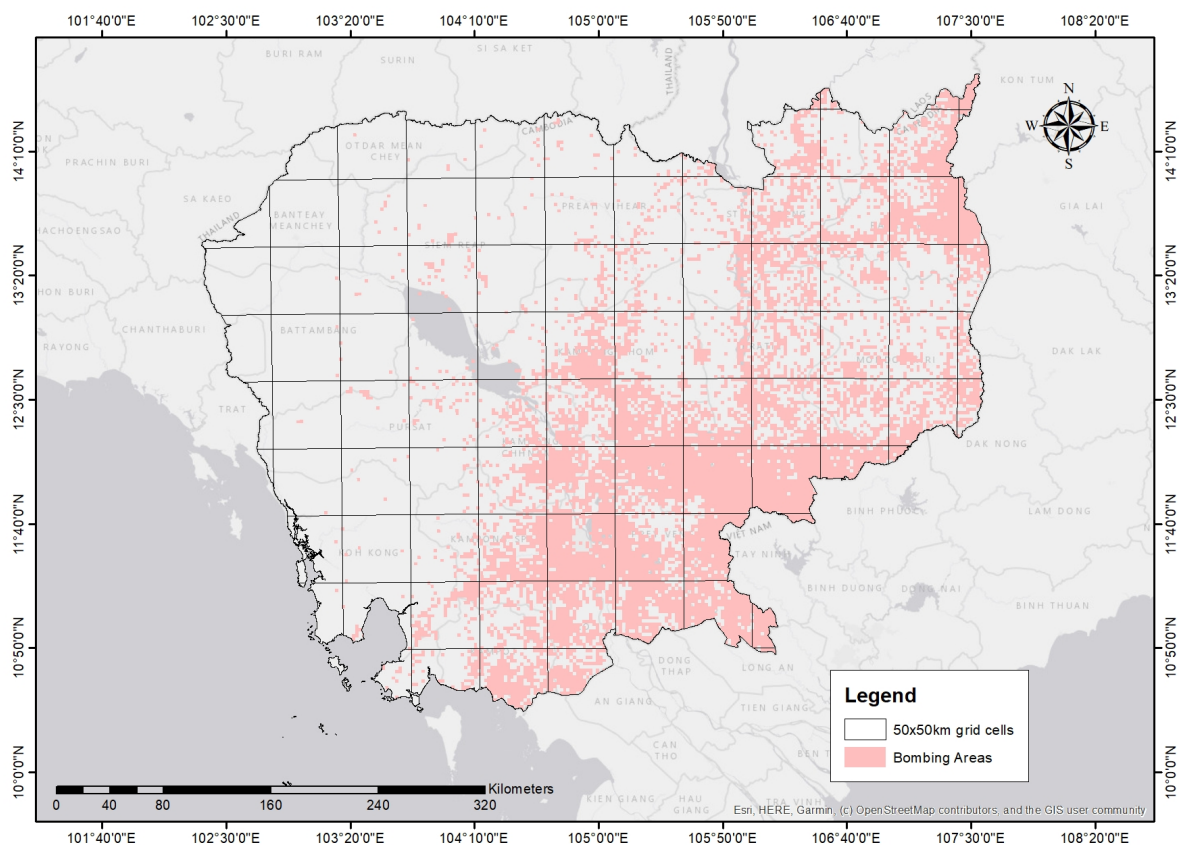
Note: The unit of analysis for columns (1) (2) (5) (6) is census villages. The unit of analysis for columns (3) (4) is DHS individuals. The sample is restricted to observations living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for distance to the capital, distance to Vietnam borders, border segment fixed effects and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the commune level for regressions (1) (2) (5) (6) and at the DHS village level for regressions (3) (4). *UXO Likelihood* is a dummy variable equal to 1 if any UXO incidents occur within a 3 km buffer, and 0 otherwise. *Health Index* is the standardized weighted summary index variable created from multiple health outcomes, including Height-for-age Z-scores, Weight-for-height Z-scores, a healthy Body Mass Index, a healthy Corpulence Index, and an indicator for non-anemia. *Economic Development Index* is the standardized weighted summary index variable created from multiple outcomes including distance to schools, hospitals, locations within big radio network and other indicators of development such as the share of households with access to water, electricity, toilets, own dwellings, literacy, school attendance and employment rate. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Figure D.4: Indochina Population in 1970



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

Figure D.5: 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.

Table D.7: Migration Status

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DHS Individuals						
Bombing	-0.036*	-0.021	-0.023	-0.022	-0.039*	-0.025
	(0.022)	(0.021)	(0.030)	(0.031)	(0.023)	(0.022)
Bombing × Soft Soil	0.002	-0.013				
	(0.034)	(0.033)				
Mean	0.340	0.331	0.343	0.338	0.339	0.326
Observations	15545	14184	5597	5336	9948	8848
Clusters	496	450	178	168	318	282
Exclude K5 Belt	No	No	No	Yes	No	Yes
Panel B: CSES Individuals						
Bombing	0.036	0.040	-0.060**	-0.048	0.027	0.028
	(0.023)	(0.025)	(0.029)	(0.032)	(0.023)	(0.024)
Bombing × Soft Soil	-0.096***	-0.094***				
	(0.034)	(0.035)				
Mean	0.354	0.357	0.401	0.407	0.325	0.326
Observations	23487	22354	9081	8620	14406	13734
Clusters	325	312	137	132	188	180
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is individuals. The sample is restricted to those living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the village level. The dependent variable, *Migration*, equals one if the individual has ever moved from their current village, and zero otherwise, constructed from self-reported residential history. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.8: NGO Project (CSES Village-level Data)

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: NGO Project (Dummy)						
Bombing	-0.019 (0.029)	-0.034 (0.030)	-0.002 (0.032)	-0.010 (0.032)	-0.023 (0.029)	-0.039 (0.030)
Bombing × Soft Soil	0.004 (0.042)	0.016 (0.043)				
Mean	0.268	0.263	0.268	0.263	0.268	0.263
Observations	2541	2433	1125	1100	1409	1329
Clusters	727	682	302	291	486	453
Exclude K5 Belt	No	Yes	No	Yes	No	Yes
Panel B: Number of NGO Projects						
Bombing	-0.101* (0.053)	-0.135** (0.053)	0.003 (0.051)	-0.012 (0.051)	-0.113** (0.052)	-0.150*** (0.052)
Bombing × Soft Soil	0.095 (0.074)	0.123* (0.074)				
Mean	0.425	0.412	0.425	0.412	0.425	0.412
Observations	2541	2433	1125	1100	1409	1329
Clusters	727	682	302	291	486	453
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is CSES villages. The sample is restricted to villages living within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the commune level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.9: Post-bombing Population

	All areas		Soft soil (1962)		Hard soil (1962)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bombing	-0.029 (0.022)	-0.040* (0.023)	-0.008 (0.035)	-0.019 (0.036)	-0.017 (0.022)	-0.028 (0.023)
Bombing \times Soft Soil	-0.002 (0.041)	-0.001 (0.043)				
Mean	6.570	6.575	6.694	6.702	6.501	6.503
Observations	7012	6613	2521	2396	4489	4215
Clusters	1104	1013	559	522	827	752
Exclude K5 Belt	No	Yes	No	Yes	No	Yes

Note: The unit of analysis is census villages. The sample is restricted to those within 2km of a treated-control interface (a bombing boundary). All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders, year- fixed effects and other pre-bombing characteristics. Regressions (2) (4) (6) exclude provinces along the K-5 mine belt. Standard errors reported in parentheses are clustered at the commune level. The dependent variable is $\ln(\text{Post-bombing Population})$. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table D.10: Agricultural Census (2013): crop orientation, livestock, forest, and labor allocation

	Dependent variable is:							
	Comm. Share (1)	Main Sale (2)	Ln Livestock (3)	Stock > Median (4)	Uses Forest (5)	Labor: Crop (6)	Labor: Livestock (7)	Labor: Non-farm (8)
Panel A: All observations								
Bombing	0.008*	0.015	-0.013	-0.007	-0.010	-0.000	0.007	0.024**
	(0.004)	(0.010)	(0.009)	(0.007)	(0.008)	(0.006)	(0.007)	(0.011)
Bombing × Soft Soil	-0.003	-0.008	-0.023	-0.021*	-0.020*	-0.008	-0.037***	-0.005
	(0.009)	(0.019)	(0.017)	(0.012)	(0.012)	(0.011)	(0.014)	(0.019)
Mean	0.085	0.211	0.783	0.564	0.085	0.664	0.569	0.228
Observations	937079	969674	969674	969674	966308	969674	969674	969674
Clusters	6569	6583	6583	6583	6583	6583	6583	6583
Panel B: Soft soil (1962)								
Bombing	-0.001	0.003	-0.039***	-0.032***	-0.024***	-0.009	-0.029***	0.009
	(0.008)	(0.016)	(0.014)	(0.010)	(0.008)	(0.009)	(0.011)	(0.014)
Mean	0.106	0.290	0.690	0.490	0.056	0.651	0.512	0.231
Observations	323929	339539	339539	339539	337999	339539	339539	339539
Clusters	2262	2266	2266	2266	2266	2266	2266	2266
Panel C: Hard soil (1962)								
Bombing	0.006	0.017*	-0.016*	-0.009	-0.010	0.000	0.006	0.027**
	(0.004)	(0.010)	(0.009)	(0.006)	(0.008)	(0.006)	(0.007)	(0.011)
Mean	0.074	0.168	0.834	0.604	0.100	0.671	0.600	0.226
Observations	613150	630135	630135	630135	628309	630135	630135	630135
Clusters	4307	4317	4317	4317	4317	4317	4317	4317

Note: The unit of analysis is agricultural households in the 2013 Cambodia National Agricultural Census. The sample is restricted to households in villages within 2km of a treated-control interface (a bombing boundary). *Comm. Share* is the share of a household's temporary-crop parcels planted with commercial (cash) crops. *Main Sale* is an indicator for whether the household's main purpose of production is sale rather than home consumption. *Ln Livestock* is $\ln(\text{TLU} + 1)$, where TLU is total livestock in Tropical Livestock Units (FAO weights). *Stock > Median* is an indicator equal to 1 if the household's TLU exceeds the sample median. *Uses Forest* is an indicator for whether the household uses forest land. *Labor: Crop*, *Labor: Livestock*, and *Labor: Non-farm* are the shares of enumerated household members whose primary activity is crop agriculture, livestock, or non-farm work (handicrafts, trade, other industry and services), respectively. All regressions use a local linear polynomial in spatial coordinates with a triangular kernel weight and control for 50x50km grid fixed effects, province fixed effects, distance to the capital, distance to Vietnam borders, and other pre-bombing characteristics. Standard errors reported in parentheses are clustered at the census village. ***(**)(*) indicates significance at the 1%(5%)(10%) level.