Collateral Damage
The Legacy of the Secret War in Laos*,†‡

Juan Felipe Riaño[1,§] Felipe Valencia Caicedo[2,¶]

Abstract: We investigate the long-term impact of conflict on economic development, focusing on the US "Secret War" in Laos (1964-1973). We show that regions heavily bombed during the conflict experienced lower economic development, even 50 years after it officially ended. Our research employs multiple empirical strategies and data on bombing campaigns, satellite imagery, and development indicators. A one standard deviation increase in bombing intensity decreases GPD per capita by 7.1%. We demonstrate the persistent effects of bombing campaigns on human capital accumulation, structural transformation, and migration patterns, stressing the role of Unexploded Ordnance (UXO) contamination as the primary mechanism of transmission.

Keywords: Conflict, Laos, Persistence, UXO, Development, Structural Transformation

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*Correspondence address: *juan.felipe.riano@georgetown.edu, felipe.valencia@ubc.ca*

†**Mailing address:** Department of Economics, Georgetown University, 37th St NW & O St NW, Washington, DC, 20057

‡**Mailing address:** Vancouver School of Economics, University of British Columbia, 6000 Iona Drive, Vancouver, BC, V6T 2E8

§E-mail: *juan.felipe.riano@georgetown.edu*

¶E-mail: *felipe.valencia@ubc.ca*

"When buffalos fight, it is the grass that suffers."

– Laotian proverb[1]

1 Introduction

As we have recently seen, the destructive nature of conflict is hard to overstate. Armed confrontations bring havoc not only to combatants, but also to innocent bystanders and local businesses. While the short-term effects of war have been extensively documented in the literature,[2] there is no consensus about the long-term impact of conflict on economic development. Important papers have found no long-lasting effects after bombings in Japan, Germany and Vietnam (Davis & Weinstein, 2002; Brakman, Garretsen, & Schramm, 2004; Miguel & Roland, 2011).[3] This emphasis on postwar recovery appears at odds with the "Conflict Trap" hypothesis, according to which countries remain poor due partly to conflict. Here we expand our understanding of the multifaceted impact of conflict by looking at a setting in which explosive remnants of war abound and where investments in demining and public good provision have been lacking.

To scrutinise the long-term legacies of conflict, we focus on the Lao People's Democratic Republic (Laos), a country of more than 7 million people in the Indochinese Peninsula. Today Laos is one of the poorest countries in the world. Almost a quarter of the population lives under extreme poverty; 80% survives on less than $2.50 dollars per day (PPP 2005) and 70% lives in rural areas. Due to the US military intervention during the Laotian Civil War (1959-1975), Laos is also the most heavily bombed country in human history. It is estimated that during nine years, from 1964 to 1973, the country received approximately one bomb every eight minutes, a third of which did

[1] Quoted in Conboy (1995).

[2] Surveyed in Ray and Esteban (2017); Blattman and Miguel (2010); Bauer et al. (2016).

[3] Dincecco and Onorato (2018); Voigtländer and Voth (2013); Gennaioli and Voth (2015); Becker, Ferrara, Melander, and Pascali (2019) even find *positive* effects in the longer run.

not explode. As a result, Laos is one of the most contaminated countries in the world in terms of UXOs (Unexploded Ordnances), presenting a major threat to civilians.[4] In this paper we ask whether this legacy of war can be one of the fundamental drivers of Laos' chronic underdevelopment.

In essence, we conduct an empirical test of the "Conflict Trap" hypothesis (Collier, 1999; Collier et al., 2003; Collier, 2007). The idea behind the conflict trap is similar to that of poverty traps, relying on the shape of the aggregate production function.[5] Theoretically, Rohner, Thoenig, and Zilibotti (2013) and Acemoglu and Wolitzky (2014) have formally demonstrated how societies can enter vicious cycles of conflict. Such cycles can distort long-term growth convergence dynamics. Empirically, Miguel, Satyanath, and Sergenti (2004) have already shown that poverty increases the incidence of conflict, but the opposite direction—from conflict to poverty—is less well understood. We revisit this relationship in the Laotian context, finding a negative and significant effect of the intensity of bombing on economic development. In particular, we stress the role of UXOs in generating these persistent effects, and how bombings have affected health, human capital accumulation, structural transformation, and migration patterns.

To test this hypothesis and its transmission mechanisms, we combine novel grid-cell level data on the incidence of conflict with fine-grained economic indicators. We employ information on more than 1.6 million bombing missions that have been recently declassified by the US Department of Defense, and 30 arc second nighttime light data from the US Air Force Defense Meteorological Satellite Program. In particular, we look

[4]This does *not* mean that the UXO problem is limited to Laos. A recent survey by Frost et al. (2017) found that UXOs are present in more than 60 countries, and pose both physical and psychological risks to the population. Affected countries include Afghanistan, Cambodia, Colombia, Lebanon, Iran, Iraq, Myanmar Vietnam, and now Ukraine. The survey noted the small number of studies looking at socioeconomic impacts. Here we focus on UXOs from dropped bombs, instead of planted landmines.

[5]See Dasgupta and Ray (1986); Azariadis and Drazen (1990), the survey by Kraay and McKenzie (2014) and most recently Balboni, Bandiera, Burgess, Ghatak, and Heil (2020).

at the Historical Records of US Combat Activities from 1965 to 1975, and data from the 1993, 2003, and 2013 satellite missions—to track the evolution of the luminosity variable over time. We complement this income proxy using actual development outcomes from the Lao Population and Agricultural Censuses of 2005 and 2011. This comprehensive data is available for 10,522 villages and 560,480 individuals, allowing us to explore both the spatial and temporal dimensions of conflict. To this end, we estimate OLS, fixed effects and IV models at high degree of spatial disaggregation, as well as Differences-in-Differences (DiD) models that take into account the timing of conflict. We also make use of administrative data on geo-located UXO accidents from the National Regulatory Authority for Mine Action in Laos (NRA) covering *daily* incidents from 1950 to 2011, which we incorporate in a Structural Equation Model (SEM) to test this main mechanism of transmission.[6]

We conduct the empirical analysis in the following manner. First, we partition the country into 2,216 artificial grid cells of 0.1° x 0.1°,[7] which allows us to control—using fixed effects—for time invariant characteristics at the province (Laos has 18 provinces) and district (and 141 districts) levels.[8] Similarly, when aggregating the data for different years, we include time fixed effects, to control for potential trends during various cross sections. We also take into account in our estimates the potential effect of a large set of geographic and location characteristics at the grid-cell level, including altitude, ruggedness, temperature, precipitation, latitude and longitude—which are standard in the literature of conflict. Additionally, we control for other characteristics relevant for this particular context, such as distance to the 17^{th} parallel (the Vietnamese Demilitarised Zone), distance to the Vietnam border and distance

[6] An accident is defined as being involved in an incident with a UXO and either having died as a result or survived with injuries, see Boddington and Chanthavongsa (2008) for an overview of these data.

[7] In the Cartesian plane, this is equivalent to 11.1km x 11.1 km grid cells at the equator.

[8] This grid-cell analysis also helps us to bypass potential endogenous border formation concerns.

to the nearest population centre, to get closer to a causal estimate of the bombing effect. OLS results reveal a negative and significant relationship between conflict incidence (intensity of bombing) and income (nightlights). A summary of this negative relationship can be seen in Figure 1. In terms of magnitudes, we find that a one standard deviation increase in bombs leads to approximately a 7.1% fall in GDP per capita.[9]

Still, OLS and fixed effects estimates might be biased, as bombing was probably not random. More productive places could have been targeted—since bombing was a costly activity—or some already poor and isolated areas might have been attacked more intensely. Using quantile regressions, we show that the effect is concentrated at the upper tail of the nightlight distribution, suggesting the former case.[10] To tackle this potential endogeneity issue, we employ an Instrumental Variables (IV) strategy. Intuitively, we exploit the asymmetric information that is inherent in violent confrontations. Our first instrument is the distance to the Vietnamese Ho Chi Minh Trail—mostly constituted by underground tunnels and obeying the dynamics of the broader Indochinese confrontation. Additionally, we use the distance to the nearest US air base *outside* Laos established *before* the beginning of the conflict started in the 1960s. This sensitive information comes from declassified CIA documents. We believe that the location of these bases in South Vietnam and Thailand, can be viewed as largely exogenous to the eventual Laotian conflict, as detailed in Sections 2 and 4.3.

Our IV estimates confirm the baseline OLS and fixed effects findings. First, we find a negative and strong relationship between bombing intensity and both distance to the Ho Chi Minh Trail and the nearest US air base. We also estimate a quadratic

[9]See Section 5.2, footnote 38, for details behind this estimate.

[10]Moreover, our baseline results are robust to controlling for pre-conflict population density in 1960 as well as to dropping lower and upper tail observations from the nightlight distribution. See section 5.3 for these and additional exercises.

relationship in the first stage, to allow for heterogeneous effects, as in Dieterle and Snell (2016). Using these instruments, we find again a negative and highly significant relationship between the number of bombs dropped and lights in 1993, 2003, and 2013. In our preferred specification, we obtain a (standardised) coefficient for bombs of -0.109 (i.e., a 10% fall), which now has a more causal interpretation. We also test for spatial spillovers but find little evidence for them.

The negative aftereffects of conflict appear to transcend the immediate effects of bombing, hampering long-lasting economic investments. Bombed areas have *lower* levels of human capital, in terms of literacy and health. We expand on these aggregate results with an analysis of the data at the *individual* level. To this end, we use a difference-in-differences specification, where we identify off the level of exposure to conflict for individuals from different cohorts, born in different provinces. This allows us to look more closely at the *timing* of conflict. We find that those who were still young in 1964, when the bombing campaigns started, and those who were born just after it received significantly *less* years of schooling — a fall of 5% with respect to the mean — as opposed to those old enough to have completed their school years. In modern times, now that these affected individuals have entered the labour market, they have a lower probability of being employed as a whole. Furthermore, when employed, they are *more* likely to be working in agriculture, and less in services.[11] Hence, war remnants appear to have negatively affected human capital accumulation and retarded the broader structural transformation of the Laotian economy (as in Fergusson, Ibáñez, and Riaño (2020)). Lastly, we study the relation with migration. We find that bombings decreased the rates of internal migration by around 10%. Taken together, these structural transformation and rural-urban migration patterns help explain the negative long-run development consequences of the Laotian war.

[11] We observe no significant effect on manufacturing.

To further test the validity of our findings—as well as to explore potential mechanisms of transmission, we use data from censuses at the village level. We find that bombs are tightly related to UXO contamination of agricultural land at the extensive and intensive margins. We confirm these findings using a high-frequency panel of UXO accidents starting in 1950, where we find a higher incidence of accidents in more heavily bombed areas from the 1960s to today. We also divide the sample between villages that are above and below the median in terms of the total amount of bombs received. We find that in the former people have lower expenditures, worse health, and higher poverty rates. These areas are also less densely populated, meaning that the nightlights results translate into relevant development outcomes. Using a Structural Equation Model, we estimate that about 24% of the documented negative effect of bombing on economic development is mediated by UXO contamination. We further show that affected villages appear to have worse public goods provision, in terms of electricity, water supplies, and educational infrastructure.

Before concluding, we discuss the case of Laos relative to other countries still grappling with the legacies of violence. In particular, we compare Laos with its Cambodian and Vietnamese neighbours (Miguel & Roland, 2011; Dell & Querubin, 2018; Lin, 2020). The findings for structural transformation are in line with those for Cambodian rural areas (Lin, 2020). With respect to Vietnam, it seems that differences in outcomes emerge, not due to the level of disaggregation of the data, or the specific development outcomes employed, but rather to public good investments, especially in UXO clearance. Indeed, very little has been invested in demining, which could have very large returns, especially when conducted close to infrastructure hubs, as in Mozambique (Chiovelli, Michalopoulos, & Papaioannou, 2018).

We contribute threefold to the conflict literature summarised in the next section.

First, we stress the special role of UXOs in generating the lingering aftereffects of conflict, affecting not only health directly, but also broader human capital investments. We also examine the Laotian case using highly-disaggregated and newly available data—along with modern econometric techniques—to provide more credible empirical estimates of the negative and sizable *economic* costs of war in the long run. Lastly, we study structural transformation and rural-urban migration as plausible transmission channels of the negative effects of bombing and UXO contamination on long-term development.

1.1 Literature and Conceptual Framework

Social scientists have spent considerable effort studying the causes and consequences of conflicts, especially in the short run. In their seminal piece Fearon and Laitin (2003) found that civil war is often preceded by prior conflict and poverty. In a defining survey Blattman and Miguel (2010) stressed economic factors leading to war and advocated in particular for more research about the socioeconomic consequences of conflict. Bauer et al. (2016) pointed out the *positive* social repercussions of war, via increased cooperation.

Despite abundant evidence on the short-term impacts of conflict, its longer-term consequences remain less understood. The negligible and even *beneficial* effects of war have been identified in the literature. Economists have documented the swift urban and economic recovery of Japan and Germany during the postwar era (Davis & Weinstein, 2002; Brakman et al., 2004). Closer to the area of study, Miguel and Roland (2011) find virtually no economic effects after the bombing of Vietnam, one of the most intense military campaigns in history. Furthermore, at the cross-country level, war has been found to increase fiscal capacity (Gennaioli & Voth, 2015; Dincecco & Onorato, 2018), a finding that Becker et al. (2019) confirm sub-nationally for Germany. These results for Europe, echo the famous quip by historian Charles Tilly that "war makes states and states make war." Researchers have even stressed a Malthusian mechanism, whereby lower population density can increase wages and spur subsequent economic growth (Voigtländer & Voth, 2013). We contribute to this historical conflict literature by documenting the *negative* and sizable long-term economic effects of a major bombing campaign.

The main surveys on conflict in economics stress the impact of violence on developing countries (Ray & Esteban, 2017; Blattman & Miguel, 2010; Bauer et al., 2016). Here we focus on the role of UXOs, which notably were not part of the analysis in Miguel and Roland (2011).[12] We discuss other differences with respect to this article in Section 7, where we focus on differential investments in demining. Other closely related papers to the present work study conflict in Mozambique, Vietnam, and Cambodia. Chiovelli et al. (2018), stress the large economic benefits of *clearing* the landmines left after the Mozambican Civil War (1977-1992).[13] Closer to the area of interest, Dell and Querubin (2018) find causal effects of the Vietnam bombing campaign on anti-American sentiment. Lin (2020) looks at the problem of UXOs in Cambodia, which shares a border with Laos, finding that fertile agricultural land has become *less* productive due to UXOs. We find empirical support for some of these findings and provide novel identification strategies, along with mechanisms of transmission. In particular, we find that UXOs are keeping Laos more rural and restricting Laotian's mobility.

We also build on the historical conflict literature. On the political front, Fontana,

[12]Quoting from their article, "In terms of other possible factors, we do not have complete information on unexploded ordnance (UXO), landmines or Agent Orange use, and unfortunately cannot focus on these in the main empirical analysis (however, there is obviously a strong correlation between bombing and later UXO density) (p. 2)." For the revisited role of UXOs in Vietnam see the recent work by Nguyen, Tran, and Vu (2021).

[13]Prem, Purroy, and Vargas (2021) provide an important counterexample, by pointing out that demining campaigns are more useful when the conflict has already stopped.

Nannicini, and Tabellini (2023) show that the Italian Civil War led to decades of political extremism, while Gagliarducci, Onorato, Sobbrio, and Tabellini (2019) look at how media helped coordinate the Italian resistance during WWII. Tur-Prats and Valencia Caicedo (2020) examine the cultural and political consequences of the Spanish Civil War.[14] In terms of mechanisms, Fergusson et al. (2020) show that conflict hampered structural transformation during the *La Violencia* (1948-1958) period in Colombia. Though in a different context, we show that this channel plays an important role in Laos as well. In the more distant past, Feigenbaum, Lee, and Mezzanotti (2018) show that Sherman's march during the American Civil War brought widespread capital destruction and Alix-Garcia, Schechter, Valencia Caicedo, and Zhu (2022) document the demographic impact of the Triple Alliance War (1864-1870) in South America. Here, we add to the modern literature on the impact of bombing (Redding & Sturm, 2016; Dericks & Koster, 2021; Adena, Enikolopov, Petrova, & Voth, 2020; Harada, Ito, & Smith, 2020) with a major Cold War operation. More broadly, this article is also related to the large literature on long-term economic persistence, recently summarised by Nunn (2020). Here we focus on conflict as a source of long-term underdevelopment.

Conceptually, the impact of conflict on development can be multifaceted and time-varying. In the short run, the costs of war can be staggering. The World Bank estimates that after a typical civil war, a country's GDP is 15% lower and its citizens face increased poverty rates of up to 30% (Collier et al., 2003). These purely economic calculations do not incorporate the invaluable loss of life, social cohesion, and psychological well-being brought by war. However, countries can recover economically fairly quickly, as has been noted in the urban scenarios of postwar Britain, Japan, and Germany (Vonyó, 2018). This recovery would be consistent with models of unconditional convergence,

[14]It is worth nothing that Laos is one of the four existing Communist countries in the world along with China, Cuba and Vietnam, which precludes any meaningful electoral analysis.

which could extend to rural areas.

However, these convergence dynamics can be hampered, even in the long run, if the damages extend from physical to human capital (Waldinger, 2016), which was the case in Laos. In the current context, we document how, beyond bombing, UXO contamination hampered key human capital investments, even after the ceasefire. The presence of such dangerous artifacts can alter structural transformation, urbanisation, and migration patterns, generating a "Conflict Trap." Such a trap would be consistent with the more general development poverty traps (Barrett & Carter, 2013). Perhaps the most important paper on this concept shows a causal relationship between negative income shocks and increased conflict (Miguel et al., 2004). Still, we know less about the converse relationship. A notable exception is the work of Abadie and Gardeazabal (2003) examining the negative impact of the ETA terrorist group on the Basque economy. Still, this synthetic control approach is essentially a contemporaneous exercise. We provide here an empirical test of the other direction of the conflict trap hypothesis in the long-run, in a country where war literally fell from the sky.[15] These harmful dynamics can be exacerbated by lower investments in demining and other productive activities, as we compare the Laotian case with that of neighbouring Cambodia and Vietnam.

The rest of the paper is organised as follows. Section 2 covers the relevant historical background. We then present the data and empirical strategy in Sections 3 and 4, followed by the main empirical results in Section 5—divided into OLS, FEs, IV and DiD estimates. Section 6 contains the mechanisms of transmission and 7 discusses our findings more broadly. We conclude in Section 8 with the main lessons of the study along with their potential policy relevance.

[15] Diminishing the role of the state capacity angle, which we also test empirically.

2 Background

The "Secret War" in Laos The Laotian Civil War (1959-1975) was a proxy conflict during the broader Cold War confrontation between the US and the USSR (see Malis, Querubin, and Satyanath (2021) for a survey). It pitted the Communist Pathet Lao against the Royal Lao Government. The country was of key geostrategic interest, given the neighbouring civil war in Cambodia (1967-1975) and the Vietnam War (1955-1975), in what is generally known as the Second Indochina War.[16] Laos was essentially seen through the lens of President Eisenhower's "Domino Theory" of the Cold War, according to which if one country fell to Communism in the region, it could precipitate the downfall of others. In his words, "If Laos were lost, the whole of Southeast Asia would follow." Accordingly, the US intervened in Laos, as part of its anti-Communist counterinsurgency operations, though the conflict remained "secret" in the US at the time, as was later acknowledged. Many of the bombing campaigns in Laos obeyed the broader Indochinese confrontation, and the eventualities of the Vietnamese conflict, which informs the title of our study.

Perhaps the best summary of the situation was provided by President Barack Obama in his 2016 visit to Laos. Obama was the first US president to visit the Southeast Asian nation. In his historic visit, Obama first acknowledged that, "as the fighting raged next door in Vietnam, your neighbours and foreign powers, including the United

[16]The Cambodian Civil War (1967-1975) pitted the Khmer Rouge, supported by North Vietnam and the Viet Cong, against the Kingdom of Cambodia and the Khmer Republic, supported by the US and South Vietnam. It was won by the Khmer Rouge, and led to the establishment of Democratic Kampuchea, under Pol Pot (see Iwanowsky and Madestam (2019); Lin (2020)). The Vietnam War was fought between North and South Vietnam from 1955 to 1975. The North Vietnamese were supported by the Soviet Union and China, while the southern Vietnamese by a coalition of countries led by the United States, including South Korea and Thailand, see (Miguel & Roland, 2011; Dell & Querubin, 2018). We refer the interested reader to the historical accounts by Stuart-Fox (1997); Chandler (2018); Taylor (2013).

States, intervened here. It was a secret war, and for years, the American people did not know. Even now, many Americans are not fully aware of this chapter in our history, and it's important that we remember today." He then noted that as a result of the Secret War, "Over nine years—from 1964 to 1973—the United States dropped more than two million tons of bombs here in Laos—more than we dropped on Germany and Japan combined during all of World War II. It made Laos, per person, the most heavily bombed country in history." Adding that locals recall that "bombs fell like rain."

The immediate political context for the war was the transfer of power from France to the Royal Lao government under the Geneva accords of 1954. Laos had been a French protectorate since 1893 and formed part of French Indochina—which also included Vietnam, Cambodia and parts of China. A feeble coalition of political forces ruled the country until the North Vietnamese invaded northern Laos in 1959. As infighting continued, foreign involvement in the country by American, Thai and Vietnamese troops increased. In 1964, the US conducted its first reconnaissance aerial missions and on June 9 President Lyndon B. Johnson authorised the bombing of Communist forces in the Plain of Jars in northern Laos, under Operation Barrel Roll, formally starting the Secret War. We employ the term "Collateral Damage" since even though there was an underlying internal conflict in Laos, the massive bombing campaign was carried out by external military forces, in classic Cold War fashion.[17]

A series of covert military operations by the CIA and the US Air Division were conducted in Laos and Vietnam, including Operation Steel Tiger, Operation Tiger Hound, and Operation Commando Hunt. These operations helped to give rise to the military CIA (Kurlantzick, 2017). Aside from the Plain of Jars, the US heavily bombed southeast Laos, given its strategic proximity to the Vietnamese Ho Chi Minh Trail,

[17] Echoing the local proverb we quote in the epigraph.

where the Viet Cong enemy troops were stationed (see, Figure 3). This area was of key geo-strategic interest, as is connected South and North Vietnam. From 1964 to 1973 the US conducted 580,000 bombing missions in Laos, in what amounted to a scorched earth tactic. Despite the heavy bombing, the Pathet Lao resisted and the Royal Lao Army was weakened. As part of the Paris peace agreements signed on January 27, 1973 to end the Vietnam War, the US effectively pulled out of Laos. The Pathet Lao finally captured Vientiane in 1975, forcing King Savang Vatthana's abdication, putting an end to the conflict, and proclaiming the Lao People's Democratic Republic, a regime that is still in power today.

The aftermath of the conflict As a result of the war 200,000 people, one tenth of the Laotian population, were killed. It is estimated that twice as many were wounded and up to 300,000 people were forcibly displaced. Officially, 728 Americans, mostly CIA contractors died in Laos (Kurlantzick (2017)). In total, over 270 million cluster bombs or 'bombies' were dropped in the country, a third of which did not explode. More than 87,000 km^2 of land is currently contaminated with UXOs making the use of land impossible or very dangerous. Approximately 50,000 Laotians, most of them civilians—especially children—have been killed or injured by such artifacts.[18] For decades, the issue was hardly addressed until the foundation in 2006 of the National Regulatory Authority (NRA) on UXO / Mine Action Sector.[19] Despite its recent efforts to solve this problem, less than 1% of the total UXO contamination has been cleared, making this the number one development issue in the country (Boddington & Chanthavongsa, 2008). Very little is currently invested in clearance: around 4.9 million dollars a year, while in comparison 13.3 million dollars were spent in bombing during the war every *day*.

[18] There is even a black market for such explosives in the region, which exacerbates the problem. We thank Q.A. Do for noting this.

[19] For more details see the detailed report at https://reliefweb.int.

3 Data

In this section we describe the different sources and levels of aggregation of the main variables used in the empirical analysis. We employ information at the synthetic grid-cell, village and individual levels.[20]

3.1 Synthetic Grid-cell Level Data

In our baseline analysis we examine the relationship between historical conflict and economic activity at the grid-cell level. To this end, we divide the country into 2,216 cells of $0.1°$ by $0.1°$.[21] This level of granularity allows us to net out fixed effects at the province and even the district levels. We collate information on economic activity and historical bombing, geographic and location controls at this level of disaggregation.

Economic Activity We use nighttime light satellite data as a proxy of economic activity following Henderson, Storeygard, and Weil (2012). Our data comes from the fourth version of the DMSP-OLS Nighttime Lights time series, collected by the National Oceanic and Atmospheric Administration (NOAA) since 1992 (National Centers for Environmental Information, 2013). We aggregate up these lights at the grid-cell level. Figure 2, Panel A depicts nightlights in 2013. We use the information on lights at 30 arc seconds for 1993, 2003, and 2013, accounting for the impact of conflict after approximately 20, 30, and 40 years. To reduce the measurement error and make the interpretation of our coefficients easier, we employ stable lights, and use a conventional logarithmic transformation of one plus the sum of light intensity divided by the area of

[20] Appendix Table A-1 presents the summary statistics for the key variables.

[21] In Appendix Figure A-1, we present the synthetic grid and the principal administrative divisions of the country, consisting of 18 provinces and 141 districts.

the grid cell in square kilometres.[22] We refer to this measure as lights or luminosity interchangeably.

Historical Bombing To measure historical conflict, we rely on the U.S. combat activity records from the U.S. National Archives and Records Administration (NARA). We use data compiled by the U.S. Department of Defense on the recorded bombing missions for the whole Indochinese Peninsula from 1965 to 1973, depicted in Figure 2 Panel B (US Department of Defense, 2005). This previously classified data constitutes the universe of bombing operations for these years and consists of a daily panel of individual operations with the exact coordinates of each deployment. It includes 1,635,759 aerial missions and around 13,000,000 bombs. For each air mission, it specifies the type and the number of aircraft involved, the kind and quantity of the ammunition expended, and, when available, the target of the mission with the bomb damage assessment. Similar to our measure of economic activity, and as a primary independent variable, we compute the logarithm of one plus the total weight in pounds of ordnance jettisoned from 1965 to 1973 per square kilometre at the grid-cell level.

Geographic and Location Controls To account for potential geographic confounders, we use geophysical, and weather information from DIVA-GIS (Hijmans, Cruz, Rojas, & Guarino, 2017) and WorldClim spatial data (Fick & Hijmans, 2017). We aggregate information on average altitude, temperature, and precipitation within each grid cell. We also use terrain ruggedness from Nunn and Puga (2012). To control for spatial confounders of conflict and additional geographic determinants of economic activity, we use the latitude and longitude of each grid cell as supplementary controls. Furthermore, we include the Euclidean distance to the closest portion of the Vietnam border as well as the distance from the cell to the nearest populated centre from

[22] As opposed to total lights, the measure of stable lights excludes ephemeral events, such as fires and water reflections. We use other functional forms for robustness.

Natural Earth (2009).[23] Finally, we also include the distance to the 17^{th} parallel (the Vietnamese Demilitarised Zone), a potentially powerful predictor of bombing intensity during the Vietnam War, used as an instrument by Miguel and Roland (2011).

3.2 Village Level Data

Information at the village level consists of two geo-located censuses: the population census of 2005 and the agricultural census of 2011 (Government of Lao PDR, 2020b, 2020a). These are the two most recent censuses digitised and available for Laos, giving us an even more granular picture of the whole country encompassing about 10,522 villages.[24] All of the information comes from the Lao DECIDE info platform, an initiative of the Laotian Government to improve access to official data.[25] We employ information on UXO contamination, human capital levels, development outcomes, urbanisation, and public good provision at the village level, detailed next. An important limitation of this data is that there is no official demarcation of village boundaries in Laos. To bypass this constraint, we constructed a synthetic set of village boundaries based on Thiessen / Voronoi polygons and the coordinates of administrative centres.[26]

[23]The distance to the closest population centre in this database includes all the first and second level administrative capitals, major cities and towns, plus a sampling of smaller towns in sparsely inhabited regions. This source favours the regional significance of population centres over administrative divisions in determining the selection of places.

[24]Panel A of Appendix Figure A-2 presents the geographical distribution of the 10,522 villages reported in 2005. This constitutes an even more disaggregated level than the grid cells described before. We repeat the nightlight results at this level of disaggregation in Table A-14.

[25]This project is supported by the Swiss Agency for Development and Cooperation (SDC) and the Centre for Development and Environment (CDE) of the University of Bern.

[26]According to the Census, data is "captured at the administrative centres of villages but did not explicitly include village boundaries in part because these have yet to be defined for most villages." We use this method based on the coordinates reported in each census. It allocates space to the nearest point feature in a set of points. This method defines a polygon, such that every coordinate within this area is closer to the selected location than to any other site in the sample of points. Panels B and C of Appendix Figure A-2 show the construction of the Thiessen polygons around the administrative centres according to the 2005 Census. We use the same procedure for the 2011 Census.

UXO Contamination Using information from the agricultural census of 2011, we can explore the intensive and extensive margins of UXO contamination. We use two variables, a dummy variable that equals to one if there is any agricultural land contaminated by UXOs at the village level, as well as the official estimate of the total area in hectares affected by it. For the latter, we use the log transformation of one plus the total number of hectares contaminated. The mere inclusion of these variables in the census highlights the importance of this phenomenon in Laos (National Regulatory Authority for UXO/Mine Action in Lao PDR, 2015).

Health, Human Capital and Urbanisation We study the role of conflict on additional outcomes at the village level. In particular, we look at the influence of historical conflict on 1) the fraction of households with people with disabilities and 2) the fraction of literate households and 3) population density, measured as the log of the total population at the village level divided by its area in square kilometres.

Development Outcomes We complement our analysis of nightlights data using more tangible measures of development. In particular, we use the information on the log of estimated average per capita expenditure (in kips per month) and the percent of the population living below the poverty line within each village in 2005.

Public Goods Provision and Infrastructure We explore the role of conflict on the provision of public goods. We focus our analysis on three specific indicator variables of such investments, namely the presence of primary schools, the availability of electricity and water supply.

3.3 Individual-level Data

We employ individual-level information to estimate the long-term impact of conflict with regards to human capital accumulation, structural transformation, and migration. We use two datasets to perform the analysis. The first is the 10% sample of the micro-level data of the 2005 Census. This sample includes around 561,000 individual observations and comes from the IPUMS project for Laos (Minnesota Population Center, 2020). We use the data for years of schooling, long-term migration, and labour market outcomes such as employment status and sector of employment. Second, we rely on a daily panel of UXO accidents from 1950 to 2001, recording the number of people disabled or dying due to such artifacts. This data comes from the National Regulatory Authority for UXO / Mine Action Sector in Lao PDR and includes 48,180 geo-located incidents (Boddington & Chanthavongsa, 2008). Both of these datasets allow us to explore the timing of conflict.

3.4 Historical Maps

For the identification strategy, we rely on two sets of historical maps. The first is a recently declassified map on U.S military bases active during the Secret War (USAF Historical Division Liaison Office, 1966). This map also includes the type of aircraft deployed from each of these bases by the Pacific Air Forces in 1965. This information helps us to recover the flight paths taken during the bombing campaigns and the type of aircraft used in each campaign. Additionally, we digitised a map of the "hidden" parts of the Ho Chi Minh Trail (Museum of Lao-Vietnam Legacy of Joined Victory Battle on the Road 9 Area, 2013).[27]

[27] This consisted of a complex set of underground paths. We present the original maps in Appendix Figure A-3 and a 1970 transportation network one in Appendix Figure A-4. The Ho Chi Minh Trail is known as the Truong Son Route by the Vietnamese. We thank Q.A. Do for this remark.

4 Empirical Strategy

4.1 OLS Models: Cross-sectional Variation

We begin our empirical analysis by exploring the cross-sectional relationship between historical bombing campaigns and the current levels of economic activity, proxied by luminosity at the grid-cell level. In particular, we estimate equations of the form,

$$\text{Luminosity}_{g,d,t=\tau} = \gamma_\tau \cdot \log(1 + \text{Bombs 1964-1973})_{g,d} + \boldsymbol{X_g'}\boldsymbol{\Gamma} + \xi_{g,t=\tau}, \tag{1}$$

where g indexes grid cells, d districts (or provinces) and t years. We estimate this equation for each cross section $\tau \in \{1993, 2003, 2013\}$. In Equation (1), Bombs $1964\text{-}1973_{g,d}$ is the total weight in pounds jettisoned within grid cell g in district d from 1965 to 1973 per square kilometre, while $\text{Luminosity}_{g,d,t=\tau}$ represents the log of one plus the total number of stable lights per square kilometre within the same grid cell g.[28] We include a comprehensive set of geographical and location controls at the grid-cell level X_g that account for exogenous but potentially confounding factors at this level of disaggregation, as described in Section 3.1. These include average altitude, temperature, precipitation, ruggedness, latitude, longitude, distance to the closest portion of the Vietnam border, distance to the nearest population centre, and the distance to the 17th parallel (the Vietnamese Demilitarised Zone).[29] The parameter of interest in this model is γ_τ and represents the conditional long-term correlation between historical

[28]We explore alternative transformations of the dependent variable since the presence of zeros could distort the estimation of our parameter of interest. In Appendix Table A-2 we present these results for $\log(0.0001 + Lights/Km^2)$ and $\log\left(Lights/Km2 + \sqrt{(Lights/Km2)^2 + 1}\right)$. We show that our transformation is the most conservative of all and gives us the smallest coefficient of the transformations commonly used in the literature.

[29]Notice that distance to other borders, for example Thailand, are implicitly taken into account since we include the distance to the Vietnam border, the distance to the the DMZ and more importantly, longitude and latitude, which span these other distances.

conflict and economic activity at year τ. In this formulation, econometric identification comes from the fact that bombs are lagged in time with respect to lights, but there could still be other omitted variables to interpret the estimates causally. To improve upon these potential challenges, we turn next to fixed effects models.

4.2 Fixed-effects Models: Within Province, District and Year Variation

The high degree of disaggregation of our data allows us to control for time invariant characteristics at the province and district levels, which may be correlated with contemporaneous economic activity or the historical prevalence of conflict. To this end, we include a full set of province or district fixed effects in Equation (1), which permits us to exploit the within-district or within-province variation in the intensity of conflict. Relative to the OLS specification, this estimation allows us to control for potentially omitted characteristics for which we did not have information before.

We also estimate the following pooled regression model, using all years:

$$\text{Luminosity}_{g,d,t} = \alpha_d + \delta_t + \gamma \cdot \log(1 + \text{Bombs 1964-1973})_{g,d} + \boldsymbol{X_g'\Gamma} + \xi_{g,t}, \qquad (2)$$

where, α_d represents the full set of district (or province) fixed effects, and δ_t a group of year fixed effects that control for time specific characteristics and are common to all grid-cell units in a given cross-section. This specification accounts not only for specific differences across the timing of the three years (such as the use of different satellites or nation-wide economic policies), but also helps to increase the statistical precision of our estimates of γ.

We present multiple methods of inference accounting for alternative serial and geographic interdependence of the error term $\xi_{g,t}$. For example, we document our results for different levels of clustering (grid, district, and province) and distance thresholds (100km, 200km, 300km, 500km, 1000km, and 1500km), as in Conley (1999). In addition, we explicitly estimate potential spatial spillovers in the unobserved component of our regressions following L.-F. Lee and Yu (2010).[30]

4.3 IV Models: Addressing the Endogeneity of Bombing

An important limitation of the previous econometric models is the strategic nature of bombing. On the one hand, bombing was costly, so more productive places may have been targeted during the war, as we show empirically later. On the other, bombing campaigns may have targeted already poor and isolated places, leading to overestimates of the main effect, which does not seem to be the case.[31] To tackle the potential endogeneity of conflict, we employ an Instrumental Variables estimation strategy. We run similar (second stage) equations as before, but accounting in the first stage for the non-random nature of bombing. The idea here is to use a variable $Z_{g,d}$ that would be predictive of historical bombing but that is not directly correlated with economic activity today. We employ two such variables. Specifically, we run first-stage equations of the form,

$$\log(1 + \text{Bombs 1964-1973})_{g,d} = \rho_d + \beta \cdot f\left(Z_{g,d}\right) + \boldsymbol{X_g'}\mathbf{\Pi} + \varepsilon_{g,d}, \tag{3}$$

where the index notation and controls are analogous to Equation (1), and ρ_d are province or district fixed effects. We include a second-degree polynomial $f\left(Z_{g,d}\right)$ for the instrument to account for the potential non-linearities on the intensity of bombing,

[30]This is a standard reference for spatial auto-regressive models in panel data and allows us to model this type of error structure directly. See the notes in Appendix Table A-4 for more details about this error structure.

[31]See Section 5.4 for empirical evidence on this.

as in Dieterle and Snell (2016), though we also report linear specifications. We propose two instruments based on the informational asymmetries of conflict: the distance to the hidden part of the Vietnamese Ho Chi Minh Trail, and the proximity to US air bases outside Laos, built before the conflict started. We also combine both instruments in the analysis.

Distance to the Ho Chi Minh Trail We use the Euclidean distance from the grid cell's centroid to the closest part of the Trail. The "trail," which actually consisted of a series of paths, roads and tunnels, constituted the main supply route to and from North Vietnam, and a key reason for why this country was able to withhold the American invasion. We view the trail as an important strategic bombing target for the US, but also one more related to the internal dynamics of the neighbouring Vietnamese conflict. The idea here is that Laotian bombings due to the proximity of the HCMT constitutes a collateral damage from the broader Indochinese confrontation. Importantly, we control for distance to Vietnam and its Demilitarised Zone, as well as for road access in our IV estimates. Furthermore, we focus here on the part of the trail that was not visible from the air, mostly consisting on tunnels and hidden paths, which we see as plausibly exogenous, and less related to other types of visible infrastructure, assuaging potential exclusion restriction concerns.[32] For instance, we examine the relationship with roads empirically in Table A-17. The general intuition is to exploit the asymmetric information, inherent in conflict, in particular the part that was unknown to US soldiers at the time.

[32]Quoting a US pilot who fought in Vietnam: "We wanted to blow it all up, the trucks and supplies and infrastructure, but what we could see was the road itself.[...] More a maze than a road, the trail disappeared, returned to view, dissolved, emerged, contracted, expanded, split, reunited, vanished, materialised. We blasted a big chunk of Laos, the 600-year-old monarchy, the Land of a Million Elephants, to bony, lunar dust. Yet somehow the Ho Chi Minh Trail, itself the enemy, was always there. Killing it was like trying to put socks on an octopus." (McPeak, 2017). In terms of our instrument, we interpret that the general area to be bombed was known, but that the more specific location of the actual trail sometimes was not. We present an example of the original maps used in Appendix Figure A-3 and our digitisation of them in Figure 3.

Distance to US Air Bases Outside Laos For the second instrument, we use distance to the closest American base *outside* Laos, in South Vietnam, Thailand and Japan. We also consider bases built *before* the onset of the conflict, in 1960. Given the location and the timing, we view the bases as exogenous to the Laotian Civil War, but of strategic importance once the US started intervening in the country against the Communist forces. Most of the bombing operations were carried out from these military and naval bases.[33] We take the distance to the nearest base (16 of them in total), but results are robust to using other measures (such as average distances) and less bases (the nearest 5 or 10). Information on the exact location of these military bases comes from recently declassified CIA documents.[34] Again, the instrument exploits the inherent informational asymmetries of war, in this case unknown by Laotians. With some important differences, we follow the literature in the usage of military bases as instruments (Dube and Naidu (2015); Bautista, González, Martínez, Munoz, and Prem (2018)).[35] Figure 3 is a stylised map of the Indochina Peninsula with the location of the HCMT and the military bases.

4.4 Difference-in-differences: The Timing of Conflict

As an alternative identification strategy, we exploit cohort and yearly variation in the degree of exposure to conflict. This strategy allows us to move beyond the purely spatial identification of the main effect, to look at its temporal dynamics. Namely, we employ individual-level data from the 2005 Census detailed in Section 3.3. We exploit the

[33] An important exception is the base of Long Tieng, in Northern Laos, also known as *Lima Site*. We do not include this base in our calculations for the instrument.

[34] Data come from p. 81 of the report "USAF Plans and Operations in Southeast Asia 1965" by the USAF Historical Division Liaison Office in 1966. Declassified document since 05/16/2006.

[35] We are not the first ones employing this type of information for identification. For instance, Dube and Naidu (2015) exploit the location of U.S. bases to evaluate the effect of US military aid on conflict in Colombia and Bautista et al. (2018) to study the impact of political repression in Chile. Different from both of these settings, we look in this case at military bases *outside* of the country, built before the Civil War started.

differential impact of bombing intensity across provinces (of birth) for different cohorts. This allows us to bypass some of the potential concerns even of the IV estimates. In particular, we estimate the following econometric specification,

$$y_{i,p,k} = \delta_k + \lambda_p + \sum_k \gamma_k \left(\log(1 + \text{Bombs 1964-1973})_p \times d_{i,p,k}\right) + \boldsymbol{X_i'\Gamma} + \epsilon_{i,p,k}, \quad (4)$$

where, y_{ipk} represents educational attainment or labour market outcomes of individual i, born at province p belonging to cohort k in 1964. Here we look at educational outcomes around the outset of the war, and labour outcomes approximately 40 years later. As before, Bombs 1964-1973$_p$ corresponds to the total weight in pounds jettisoned in province p from 1965 to 1973 per square kilometre. Similarly, d_{ipk}, is a set of dummy variables that equals 1 if individual i was born in province p and belongs to cohort k, and 0 otherwise. We include a full set of province λ_p and cohort δ_k fixed effects and individual controls X_i, such as sex and long-term migration status. The coefficients of interest are the difference-in-differences estimates γ_k of the average impact of bombing on birth cohort k. For cohorts k in their schooling years and younger, γ_k is an unbiased measure of the impact of bombing if there are no omitted time-varying and province-specific characteristics correlated with conflict incidence.[36] We see this as an important and complementary way of identifying the effect of conflict.

[36] We verify the plausibility of this assumption by checking whether bombing helps to explain the change in years of schooling for cohorts that were too old (i.e., those older than 17 years old in 1964) to be affected, which is not the case.

5 Baseline Results

5.1 OLS Results

Before presenting any regressions, Figure 1 captures the essence of the empirical results. We combine nightlights (for 2013), in the left panel, with the total number of bombs (dropped from 1965 to 1973) in the middle panel. We then present the bin-scatter on the right, where we pool all of our nightlight observations.

There we can already see a negative and significant (linear) association between these two variables (net of location controls, province and year fixed effects). In what follows we test the robustness of this finding, estimating OLS, FEs, IV and DiD models.

We begin our econometric analysis reporting the OLS results from estimating Equation (1). As can be seen in Table 1, areas that were bombed appear less lit, in Column 1. The negative coefficient is significant at the 1% level. This holds true after controlling for basic geographic controls, in Column 2, and a larger set of location covariates in Column 3. A one standard deviation increase in bombs is associated with a decrease in lights of 3.8%. All of these estimates use lights measured in 1993, which is the closest to the end of the conflict. Ruggedness and temperature enter negatively and significantly across specifications. With respect to the location variables, the distances to the Demilitarised Zone, Vietnam and the closest population centres, appear all negative and broadly significant. Still, they do not alter the bombing coefficient. We repeat the exercise using instead lights in 2003, in Columns 4 to 6, which leaves the result almost unchanged, appearing just marginally larger. The same holds true for lights in 2013, in Columns 7 to 9, where the coefficients also emerge larger in magnitude, and are now on the order of 6%, suggesting cumulative effects. Overall, it seems that areas that were bombed during the war are poorer (less lit) in modern times, all the way up to 2013.

Table 2 looks at the effect on growth rates, instead of levels. We use the same controls set as before and look now at *changes* in nightlights. It does *not* seem that bombed areas are growing significantly more, but quite the opposite. This is true when considering growth rates from 1993 to 2003 in Columns 1 to 3, from 2003 to 2013 in Columns 4 to 6 and from 1993 to 2013 (the longer difference) in Columns 7 to 8. The coefficients are always negative, and significant at the standard levels in some specifications. Overall, it does not seem that bombed areas are experiencing a growth boom in Laos, as has occurred in other commonly studied postwar scenarios. The results are more consistent instead with a conflict trap dynamic. Some fundamental variables such as human capital investments and labour outcomes might have recovered, as we show later, but we still do not observe convergence in growth rates, perhaps due to more permanent changes in human capital acquisition and settlement patterns, as we examine in the mechanisms section.

5.2 Fixed Effects Results

The next set of empirical results control for time invariant characteristics at the province and district levels. These may include additional geographic, weather or location characteristics that are not part of our control set, as well as other historical, social and political variables that are not available at this level of granularity. The first two columns in Table 3 repeat the full specifications from Table 1, for reference. As we can see in Column 3, more bombs are associated with less lights in 1993, 2003 and 2013, after introducing province fixed effects. The negative relationship remains strong after adding location controls in Column 4 and remains so when adding district fixed effects, in Column 5, and when controlling for location characteristics, in Column 6. Importantly, the coefficients are similar to those reported previously and significant for the three years: 1993, 2003, and 2013, increasing slightly over time suggesting compounding effects and potential path dependence. Again, we do not find evidence in favour of convergence. Relative to the OLS estimates, the magnitudes decrease slightly, but are in the same ballpark as before. The fixed effects results indicate that the negative impact of bombing is also present at more local (within province and district) levels.[37]

Finally, we pool all observations to estimate the specification in Equation (2), where we include year fixed effects to take into account potential time differences. The results in the most basic specifications, without and with geographic controls are presented in the first two columns of Table 4. The coefficient for bombs on lights is again negative and strongly significant. We progressively add province and district fixed effects in Columns 3 and 4, as well as location controls in the last three columns. The coefficient is always negative and its significance varies from the 5% to the 1% levels. In the most stringent specification, with both sets of controls, year and district fixed effects, the standardised coefficient is -0.020, similar to the more basic fixed effects results, and the OLS estimates presented before. We proceed to interpret the economic significance of this baseline estimate. To this end, we turn to the seminal article by Henderson et al. (2012). We use our preferred specification in Table 4, Column 7, and their baseline specification in Table 2, Column 1. A one standard deviation increase in the total pounds of bombs dropped is associated with a 7.1% fall in GDP per capita.[38] This

[37]Appendix Figure A-5 illustrates the results just described, plotting the relationship between lights and bombs non-parametrically using bin-scatters. The first row presents the results partialling-out province fixed effects and controls for 1993, 2003 and 2013. The negative relationship is clear across the board. The second row presents the plots for the specification with controls and district fixed effects leading to similar negative correlations. For reference, in Appendix Figure A-22, we also present the within-variation in bombing intensity we observe at different geographical levels.

[38]To reach this estimate, we compute the relative size of our coefficient with respect to the sample

sizable decrease gives some empirical support to the Conflict Trap hypothesis in the aggregate, suggesting an S-shaped factor accumulation function and the presence of multiple equilibria. We look more closely at factor (labour) mobility in the mechanisms section. Though we present our preferred IV estimates in Section 5.4, the fixed effects results imply that to invalidate our estimates, there would have to be omitted variables working at the within province, district and year levels.

5.3 Robustness of the OLS and FEs Specifications

We introduce two important controls and run some additional specifications for robustness. The first one, controls directly for population in 1960 at the district level to take into account potential pre-trends in this demographic variable (Halpern, 1961). As can be seen in Appendix Table A-5, our results are unaffected by this addition. We do not employ this control going forward, as we use district fixed effects which take care of this and other potentially relevant variables at the district level. Additionally, we control for road access in 1970 which is most probably a "bad control" in the language of Angrist and Pischke (2008).[39] Still, our results are unaffected by this addition and, if anything, increase slightly in magnitude, as can be seen in Appendix Table A-6.[40] We also re-estimate our model dropping outliers in terms of luminosity: without upper, lower or both tails as reported in Table A-7, Panel A. Next, we show in Appendix Table A-8 that the effect is concentrated on rural areas, an important heterogeneity, which we explore later in the mechanisms section.[41] Finally, we test for potential spillovers in Appendix Table A-4. Following L.-F. Lee and Yu (2010) —who propose a correct

mean of luminosity across years as $\frac{-0.020}{0.078}$, then we use Henderson et al. (2012) estimated elasticity of GDP to lights of 0.277, and calculate the corresponding GDP fall as $\frac{-0.020}{0.078} \times 0.277 = -0.071$.

[39]See Appendix Figure A-4 for the 1970 infrastructure map based on which the control was created.

[40]This test is also related to the validity of the first instrument, as mentioned before. To complete this empirical exercise, we show the impact of our independent variable of interest, bombs, on the bad control, roads, in Appendix Table A-17, following Pei, Pischke, and Schwandt (2019).

[41]We thank Sascha Becker for suggesting these tests and Raquel Fernandez for the rural angle.

estimation of a spatial auto-regressive panel data model with fixed effects— we do not find evidence of systematic spillover effects. For 1993 and 2003, for example, the effect of neighbouring grids was not statistically significant, and only until 2013 did there seem to be evidence of potentially positive spillovers. These could be the result of unlocked mobility restrictions or increases in market access due to UXO clearance (Chiovelli et al. (2018)). Despite this, our coefficient of interest remains negative and significant after we correct for this influence and, if anything, it is larger throughout. These results are confirmed using Conley standard errors at different thresholds in Table A-3.

5.4 Instrumental Variables Results

Though robust, the results in the previous sections might still be biased. They could be underestimates of the real effect, since bombing was costly and presumably targeted key infrastructure, hampering development in the future.[42] On the contrary, the results could be biased upwards, if bombings targeted mostly poor and isolated places, such as jungle areas. To get a sense of the potential biases, we run quantile regressions, reported in Appendix Figure A-6. We see that the OLS effect is working at around the 70th percentile of the distribution of nightlights. This holds true for 1993, and if anything is even higher for the later years, which provides suggestive evidence against the upward bias. To correct for such potential biases, regardless of their direction, we employ the Instrumental Variables strategy described in Section 4.3.

[42] We find some evidence for this case in Appendix Table A-17 with respect to roads.

5.4.1 First Stage Results

Before running any regression, we plot the unconditional relationship between bombing and the two instruments, along with a quadratic fit. Recall that we have two instrumental variables: the distance from the hidden part of the Vietnamese Ho Chi Minh Trail and to the nearest US air bases outside Laos, built before the war started. As can be seen in Appendix Figure A-7 Panel A, the total number of bombs dropped is a negative function of distance to the Ho Chi Mihn Trail. It also shows that this relationship is potentially non-linear. Many of the observations appear less than 100 kilometres from the trail, suggesting the more localised nature of this first instrument. Panel B, plots the relationship between bombs and distance to the nearest US base outside Laos. There is a hump-shaped relationship between these two variables, with a maximum between 100 and 200 kilometres. To capture these non-linearities, we estimate Equation (3) using a quadratic first stage, allowing for potential heterogeneous effects, as in Dieterle and Snell (2016).[43]

Table 5 Panel B reports the first stages of our instruments, for distance to Ho Chi Minh in Table 5A and distance to the closest US air base in Table 5B. In the first case, the linear coefficient is negative and significant a the 1% level throughout. The quadratic term is also highly significant and positive. In all cases, the F-statistic is well above 10 (Stock & Yogo, 2005). The case for the air bases instrument is similar. Strongly positive and significant throughout linearly, and negative and now significant throughout quadratically. Again, the F-statistic is larger than 10 in all cases.[44]

[43]We also report linear estimates, as suggested by referees, which leaves our qualitative results unchanged.

[44]For completeness, Appendix Table A-9 reports the first stage tables for the two instruments with the full set of controls, province and district fixed effects.

5.4.2 Second Stage Results

Table 5 Panel A presents our baseline second stage results. We see in Table 5A that the instrumented effect of bombs is negative and significant throughout. The estimates are stable, and slightly decrease in size when district fixed effects are added. These results corroborate that this instrument captures more local variation. A similar negative and significant relationship appears for the second instrument, in Table 5B. In this case, the magnitude increases in the last specification.[45]

Table 6 presents results *combining* both instruments, which allows us to obtain more precise estimates and run over-identification tests. The linear form of this combination shows a negative and significant coefficient at the 1% level, in Panel A. Something similar occurs in Panel B, when we use both the linear and quadratic terms. The coefficients are largely stable throughout. In the last and preferred specification in Panel B, the standardised coefficient is -0.109, quantitatively similar to the ones in Table 5. The Sargan-Hansen over-identification test of our most demanding specification suggest that instruments are not correlated with the error term and therefore we cannot reject the null hypothesis under which both instruments are valid.[46]

In general, the IV magnitudes appear larger than the corresponding OLS specifications, which is consistent with our preliminary interpretation of the former as underestimates. Namely, more productive areas were probably targeted during the

[45]Reduced form estimates are presented in Table A-10. Table A-11 contains the second stage results for our two instruments, by year.

[46]Because of the potential correlation between the Ho Chi Minh Trail and roads, we further control for road access in Appendix Table A-12, which leaves the qualitative results unchanged. Lastly, we run the IV regressions for the the South and the North of the country separately, in Appendix Table A-13 finding very similar, and only slightly larger, coefficients in the former case. Looking at the North of the country allows us to estimate the IV model for an area where the Ho Chi Minh Trail is practically absent, but still covers the Plain of Jars theatre of war. This partition confirms that the deleterious impact of bombing was generalised to the whole country.

aerial bombing campaigns. The difference between the OLS and IV results can be driven by the fact that the latter estimate local average treatment effects (LATEs), whereas the the former is a potentially biased estimate of the average treatment effect (ATE), see (Imbens & Angrist, 1994; Becker, 2016) for a more in-depth discussion.[47] In this set-up, though Laos was heavily bombed, some areas suffered disproportionately more from the war. Since we estimate the model with province and district fixed effects, were are also capturing a more local variation of the treatment.[48] Still, there could be additional dynamic effects from the proposed instruments. Overall, the IV estimates, despite their potential limitations, confirm the large negative effects of conflict for long-term development, along the lines of a conflict trap, something we explore further in the next section, where we also exploit the *timing* of conflict.

5.5 Difference-in-Differences Results

5.5.1 Human Capital: Years of Schooling and Literacy

In the following sections we zoom into the role of human capital accumulation and the process of structural transformation, exploiting the timing of conflict. To this end, we employ individual-level data from the 2005 Census and the empirical specifications detailed in Section 4.4. Having this information allows us to bypass some of the limitations of the spatial, cross-sectional analyses presented so far, and expand on the dynamics of the bombing shock.

[47]Another potential explanation for this difference is the presence of weak instruments. This possibility, however, seems unlikely once we look at the IV statistics we report in Table 5, where our R-squared of the first stage are all above 50% and F-stats are confidently above 10 (Stock & Yogo, 2005). These also satisfy in 2 of our 6 specifications the most stringent and new threshold of 104.7 suggested by the recent work of D. S. Lee, McCrary, Moreira, and Porter (2022). A distribution of the IV estimates is depicted in Appendix Figure A-8 where we run the IV analysis, dropping one district at a time. We see there that the distribution is centred around -0.109.

[48]Which is also consistent with the spillovers results.

Our main results for years of schooling are presented in Figure 5. Here we plot the coefficients for years of schooling for cohorts of different ages at the time the bombing started, in 1964, following Equation 4. We observe no pre-trends with respect to this human capital variable, which is to say no significant impact of our dummy for cohorts that were too old to be affected when the conflict started (17 years and older in 1964). We observe the first, negative, effects for the cohorts 0 to 10 years of age in 1964. The coefficient becomes increasingly negative and significant for the subsequent cohorts even a few years after the war. The most affected cohorts receive 0.2 less years of schooling or 5% less with respect to an average of about four.[49] The effect is still negative and significant, but starts decreasing in magnitude for the 25 to 29 year old cohorts, until it becomes statistically insignificant for the 35 to 39 year olds. The educational outcomes take decades to recover, hampering long-term convergence. Results are consistent if we use quinquennial, instead of yearly variation (see Appendix Figure A-12). We also look at the provision of schools in Table 9, which is lower in UXO-contaminated areas. Still, this is not enough to rule out potential demand-side effects.[50] Overall, we find the patterns sensible, with no pre-trends and a dip in human capital attainment affecting the most children in their prime educational years. We find that those who were born just after conflict (i.e., those with negative ages in 1964) are the most affected, consistent with a potential effect of the remnants of war.

We conclude the human capital analysis by looking at literacy rates using the same 2005 census, in the aggregate. We find that in areas that were heavily bombed, literacy levels are *lower* than in areas that were less bombed, which is consistent with the individual-level years of schooling results above. This is evident in the

[49] See Appendix Table A-1 for the descriptive statistics.

[50] For instance, in their paper, Feigenbaum et al. (2018) find no persistence in the manufacturing sector after the US Civil War, in a general context of high growth. In our case, low demand for services may come from a negative income effect from the war. We see these forces as complementing each other.

distributions, split by the median number of bombs in Figure A-11, Panel A, as well as in the corresponding regressions in Table 8, Panel A. The coefficient remains negative and significant throughout. Overall, our educational results are in line with those for Guatemala, Peru and Colombia (Chamarbagwala & Morán, 2011; Leon, 2012; Fergusson et al., 2020; Prem et al., 2021).

5.5.2 Sectoral Employment and Structural Transformation

To complement the individual-level analysis, we examine structural transformation.[51] We start by looking at the probability of being employed in modern times, in Figure 6. We follow the same structure as before, but now we look at cohorts using 2005 as a baseline year. We find no effect for cohorts that are at the two extremes of the distribution: 10 to 14 and more than 55 years of age. However, we find a negative and significant dip for those between 25 to 49 years of age. The largest coefficients correspond to those generations with lower educational attainment in the previous set of results 40 years before (i.e., those younger than 17 years old in 1964 or younger than 58 years old in 2005).

We move next from the probability of employment to an intensive margin analysis of occupational structure in terms of agriculture, industry, and services. We find, using the same 2005 cutoff, a hump-shaped relationship for agricultural employment, in Figure 7, Panel A. It appears now that people from 10 to 41 years of age in 2005 (i.e., born after 1964) are *more* likely to be employed in agriculture during the last 12 months. The positive and significant estimates peak at 0.01 to 0.02.[52] We find the

[51] We thank Eli Berman for suggesting this important angle. Most recently, Porzio, Rossi, and Santangelo (2022) relate human capital accumulation and structural transformation in a panel of countries as well.

[52] Recall that we had already shown that the effects are concentrated on rural areas, see Appendix Table A-8. The results also hold when using quinquennial, as opposed to yearly variation. See Appendix Figure A-14.

opposite when we look at services in Figure 7, Panel B. It appears now that those aged from 10 to 41 years are significantly *less* likely to be employed in the service sector, by around 10% of the sample mean. We find no significant impact on the probability of being employed in the manufacturing sector in Figure 7, Panel C.

In sum, we show that conflict retarded structural transformation in Laos, by tying people to the agricultural sector and slowing the transition into manufacturing and, especially, services. Affected cohorts also exhibit a lower overall probability of being employed. Coupled with the education results, we find that affected cohorts of the labour market in modern times essentially correspond to those that received less years of schooling in the past. Altogether, these results suggest that human capital accumulation and structural transformation are important channels of transmission of the deleterious impact of conflict in the long-run. Though the effects are not permanent, they took decades to return to normal, affecting regional growth convergence processes. Our findings for Laos are also in line with those for historical conflict in Cambodia (Lin, 2020), Colombia (Fergusson et al., 2020) and Austria (Eder, 2022).

6 Mechanisms of Persistence

In this section we look at transmission channels of the main effect in more depth. We stress the role of UXO contamination and population mobility. To this end we use Census data from 2005 and 2011, at the *village* level[53]—which is even more disaggregated than the grid-cell data used before—and employ high-frequency data on UXO accidents starting in 1950.

[53]See Figure A-2 for an illustration.

6.1 UXO Contamination

We start by examining UXO contamination as a mechanism of transmission of the economic impact of bombing.

First, we document in Table 7 Part I, a high and positive correlation between bombing campaigns and agricultural land contaminated with UXOs, both at the extensive and intensive margins.[54] We then show how this contamination correlates with agricultural outcomes. We find that similar to Lin (2020), the higher the intensity of contamination (i.e., the higher intensity of bombing) the larger the areas that are considered *suitable* for cultivation. However, as in Cambodia, farmers have not been able to exploit this available land productively, and report smaller farm sizes on average.[55]

To further explore the UXO channel, we use a geo-located panel with *daily* data on UXO accidents from 1950 to 2011 (National Regulatory Authority for UXO/Mine Action in Lao PDR, 2011). Figure 2, Panel C depicts this data geographically by number of accidents. We see a high prevalence of counts at the grid-cell level in the Plain of Jars (in the central northern part of the country) and near the Ho Chi Minh Trail. We then show that bombing intensity is also highly correlated with the number of UXO accidents. To exploit the time variation available in this data and rule out the potential persistence of UXO from previous conflicts, we summarise the evolution of such correlation by using quadratic fits by decade in Figure 4.[56] There are two main takeaways. First, we observe no relationship between UXO accidents during the 1950s

[54]See Appendix Figure A-9 as well as Appendix Figure A-10 Panel A for complementary evidence supporting this claim. There, we find that areas that are above the median in terms of bombings also have higher levels of UXO contamination of agricultural land.

[55]For these results, see Appendix Table A-15.

[56]Results also hold using non-parametric estimations instead.

and the total number of bombs dropped. As bombing campaigns started in 1964, these results suggest no pre-trends in the presence of other types of mines related to previous conflicts. Second, the relationship between bombs and UXO accidents becomes large and positive for the 1960s and the 1970s, and then starts falling progressively until the 2000s. Still, even at these lower levels, the positive association is evident and persistent: UXO accidents are concentrated in areas that have received more bombs historically.[57] This grim reality shows the continued burden of conflict on civilian victims, who are often children.

In light of the previous exercise, we examine the relationship between bombing and health outcomes. We focus on disability status, which is closely related to the UXO accidents results just reported. In many cases, when landmines and UXO explode, they maim or gravely injury the victims. This tragic reality is evident in Table 8. Households report more disabilities in areas that received more bombs. The coefficient of UXO contamination on disability is positive and significant, except in the full specification.[58] The point estimates are also economically meaningful. A one standard deviation increase in the intensity of bombing is associated with about 1.2% to 10% increase (with respect to a sample mean) in the fraction of households with disabilities. These results confirm and complement the findings from the UXO accidents presented before showing that the bombing and the remnants of war are most likely generating persistent disabilities in the civilian population. In the next sub-section we conduct a more formal mediation analysis of the impact of UXOs on economic development.

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[57] See Panel B of Appendix Figure A-10 documenting the overall correlation.

[58] Notice however that in Appendix Table A-16 when we present the complete analysis with Bombing intensity and UXO contamination, the latter emerges as a statistically significant predictor of disability. Moreover, Appendix Figure A-11, Panel B shows that the whole distribution of disability is skewed to the right for heavily bombed places.

6.1.1 Mediation analysis: Structural Equation Model

Given the previous associations, we now ask how much of our baseline findings could be ultimately mediated by UXO contamination. Our analysis needs to account for the fact that aggregate UXO contamination and economic development are in practice latent variables, and therefore require further assumptions to assess the chain of causality between them.[59] To address this issue and drawing from the previous results, we construct and estimate a Structural Equation Model that incorporates this feature.[60] Figure 8 summarises the model structure using path diagram notation. We are interested in estimating the direct effect of bombing on economic development (γ_1), the direct effect of bombing on UXO contamination (β_1), the direct effect of UXO contamination on economic development (γ_2), the indirect —or the mediated— effect of bombing intensity on economic development via UXO contamination ($\gamma_2 \cdot \beta_1$), as well as the total effect of bombing ($\gamma_1 + \gamma_2 \cdot \beta_1$). If the mediation is complete, the estimates of β_1 and γ_2 must be statistically different from zero and the one for γ_1 statistically indistinguishable from zero. However, if the mediation is partial, the estimates of β_1, γ_1, and γ_2 must be all statistically different from zero.

In adopting this structural approach, we are able to evaluate the relevance of the underlying causal channels and test the empirical validity of our overarching theory using a unified methodological approach. However, this process requires additional assumptions that we deem reasonable based on the documented evidence thus far.

[59] This means that they are unobservable and can only be inferred indirectly through measurable proxies and additional structure. For example, relying on the existing literature, throughout we have implicitly assumed that nightlights are an adequate proxy of economic development and that UXO accidents are a selected fraction of total UXO contamination.

[60] We refer the reader to Bollen (1989) and Mehmetoglu (2018) for a detail treatment of this specific type of models. Notice that recent mediation analysis such as Imai, Keele, Tingley, and Yamamoti (2011) and Acharya, Blackwell, and Sen (2016) are not appropriate in this context because both require observing the mediating variables (Mehmetoglu, 2018). We refer the reader to the Online Appendix A for identification details on the model.

For instance, we build on the assumption of the plausibly exogenous nature of the instruments and explicitly model the importance of geographical and location factors based on the results presented in previous sections.

The Direct and Indirect Effects of Bombing Table A-18 presents the results of the maximum likelihood estimation of the model described before. Although the magnitude of the (MLE) coefficients in this table cannot be directly compared to the ones reported in previous sections, we can still analyse the coherence of the relationships estimated within the model and draw connections with previous results. Two things are worth noting. First, latent variables seem to capture correctly the nature of the measurement problem according to our previous results. For example, overall UXO contamination is positively associated with the number of UXO accidents, the percentage of households with disabilities, and the intensive margin of UXO contamination of agricultural land. Similarly, aggregate economic development is positively associated with levels of luminosity and expenditures per capita, and negatively related to the percentage of households in poverty within the village. Second, the relationship between the variables of interest are also consistent with our previous results. More specifically, a higher intensity of bombing implies higher levels of UXO contamination and lower levels of economic development. Likewise, more UXO contamination emerges as a significant deterrent of economic activity.

Since $\hat{\beta}_1, \hat{\gamma}_1$, and $\hat{\gamma}_2$ are all statistically different from zero, we determine that we are in a partial mediation scenario. To understand how big this mediation is, we compute the Indirect to Total Effect Ratio as $\frac{|\hat{\gamma}_2 \cdot \hat{\beta}_1|}{|\hat{\gamma}_1 + \hat{\gamma}_2 \cdot \hat{\beta}_1|} = \frac{0.017}{0.071} = 0.237$. This lets us conclude that about 24% of the total effect of bombing intensity on economic development is partially mediated by UXO contamination. Similarly, we notice that the Indirect to Direct Effect Ratio $= \frac{|\hat{\gamma}_2 \cdot \hat{\beta}_1|}{|\hat{\gamma}_1|} = \frac{0.017}{0.054} = 0.309$, which means that the mediated effect is about 0.3 times as large as the direct effect of bombing estimated with our model, a non-negligible fraction. Overall, we conclude that UXO contamination is one of the key mechanisms of transmission of the economic impact of bombing, accounting for almost a quarter of the total effect. However, as it is clear from our analysis, there are still *other* potential mechanisms of transmission not necessarily related to UXOs and that we cannot—given a lack of additional exclusion restrictions—separately identify with our current model. We explore some of those next.

6.2 Population Density and Rural-Urban Migration

We argue that changes in population density and variation in rural-urban migration are other two additional mechanisms of transmission. To back up this claim, we proceed in several steps. First, we show that areas that were heavily bombed in the past are *less* densely populated today.[61] The estimated coefficient in Table 8 Panel C is negative and significant with and without controls and province fixed effects. These results are also economically meaningful: a one standard deviation increase in the intensity of bombing is associated with a decrease of about 12% in population density at the village level. Therefore, as opposed to other postwar contexts, it does not appear that Laos experienced a population boom after the war.

Second, we analyse migration as a potential mechanism of poverty persistence, as in Dell (2010). Conceptually, there could be two opposing effects with respect to this variable. On the one hand, conflict might have increased forced displacement fostering internal and external migration (Ibáñez & Vélez, 2008). On the other, increased transportation costs and changes in risk aversion might have induced people to stay in their territory. To empirically test this mechanism, we use the individual-level data

[61]See Appendix Figure A-11, Panel C for an illustration o this finding.

from the 2005 Census, which crucially asks people about their province of birth and current place of residence. Using this information, we find relatively low levels of long-term migration, in the order of 11% for the whole sample. Moreover, almost 40% of internal migrants report moving from other provinces to the capital of Vientiane. This rough estimate of rural to urban migration is consistent with the predominance of this type of population movement in Laos (Phouxay, 2010). It is important to note that with respect to international migration, Phouxay and Tollefsen (2011) find that only 5.2% of respondents have moved abroad. Of these international migrants 59.4% are female and 82% had moved to Thailand.

Third, we look directly at how the probability of migrating is affected by conflict at the individual level estimating a version of Equation 4. We present the results for this exercise in Figure 9. We find that cohorts heavily affected by conflict have a *lower* probability to migrate internally. The effect of increasing bombing intensity in one standard deviation is statistically significant and on the order of -0.01, or 10% with respect to the sample mean. Hence Laos has stayed significantly more rural because of the war, consistent with the employment results. Finally, we analyse our main results on human capital accumulation and structural transformation decomposing the effects between migrants and non-migrants.[62] We find that the negative impacts on years of schooling, probability of working, and sector of employment are concentrated only in non-migrants, and if anything reversed for the long-term migrants. We do not conduct

[62] In particular we run a modified Equation 4 using the triple interaction with migration as follows,

$$\begin{aligned} y_{i,p,k} = \delta_k + \lambda_p + \sum_k \left(B_p \times d_{i,p,k} \times M_i\right) \eta_k + \sum_k \left(B_p \times d_{i,p,k}\right) \gamma_k \\ + \sum_k (d_{i,p,k} \times M_i) \rho_k + \psi(B_p \times M_i) + \phi M_i + \epsilon_{i,p,k} \end{aligned} \tag{5}$$

where M_i is an indicator variable equal to one if individual i is a long-term migrant in 2005 and zero otherwise and $B_p \equiv \log(1 + \text{Bombs 1964-1973})_p$. We present the results of these estimations in Appendix Figures A-15 to A-19.

a fuller analysis of migration, where we could study, for instance, the potential role of selection into this process.

Overall these results tie the findings on structural transformation with those on rural to urban migration, two fundamental pillars underpinning modern economic development according to the literature (see, for example, Porzio et al. (2022) and Lagakos (2020)). It appears that migration, or the lack thereof, is exacerbating the educational and structural transformation trends shown before. Though there might be selection into long-term migration, our findings are consistent with those in other contexts, such as Poland and Colombia (Becker, Grosfeld, Grosjean, Voigtlander, & Zhuravskaya, 2020; Fergusson et al., 2020).

7 Discussion

A natural follow-up question is whether the results for Laos extend to other contexts. In particular, our findings appear to be at odds with those of Miguel and Roland (2011) for Vietnam, where the authors find little to no economic effect after the massive bombing campaigns in that country.[63] We hypothesise that the apparent differences could emerge due to several reasons. First, there could be disparities because of the degree of disaggregation of the data used in the analysis. In our baseline regression we employ 6,648 observations and use data from 10,522 villages and more than half a million individuals, whereas in the earlier study $N = 584$. The importance of disaggregated data for the empirical analysis of conflict has been pointed out by Montalvo and Reynal-Querol (2017) and Harari and Ferrara (2018). Recall that our baseline results hold within provinces and districts, which we believe is a step forward in the literature.

[63]These results are confirmed by Dell and Querubin (2018), though they focus on political attitudes. We do not have for Laos disaggregated data allowing us to test such institutional mechanisms.

Still, to make the results more comparable, we aggregate up our results to the district level (i.e., focusing only on the between variation). As can be seen in the Appendix,[64] our results remain robustly negative to this refinement (across all years).

There could also be some differences in the particular development outcomes employed. We used nightlights in our baseline specification for Laos, whereas Miguel and Roland (2011) studied consumption, expenditures and poverty rates in 1999 for Vietnam. To make the analyses more comparable, and motivated by our mediation analysis, we use as alternative outcomes the total expenditures per capita and the fraction of households in poverty in 2005 at the village level. We find that in areas that were heavily bombed, people report lower expenditures and higher poverty rates as well.[65] Table 7, Part II reports the corresponding negative and positive estimates. Overall, the baseline effects for nightlights translate into worse development outcomes for Laos.

Lastly, we look at potential differences in public good provision. We hypothesise that providing these services to the population could be costlier and more difficult in the presence of unexploded bombs.[66] Recall that there appear to be less schools in UXO contaminated areas, in Table 9. We also find in the middle panel that villages that were bombed more historically have significantly less access to electricity now (cf. Miguel and Roland (2011)). We find a similar pattern when looking at water supply. Villages that were bombed or that suffer from UXO contamination have significantly

[64] See Panel B of Appendix Table A-7 as well as Appendix Figure A-20.

[65] Appendix Figure A-21, Panel A, shows the distributions for areas above (shifted to the left) and below (shifted to the right) the median of bombing. Consistent with this, these places also have higher poverty rates, as can be seen in Panel B of this same figure.

[66] This has been suggested too by Kakar, Bassani, Romer, and Gunn (1996) and the Swiss Agency of Development and Cooperation after years of working with the Laotian government. They argue that, "The demand for land suitable for agriculture, industry and infrastructure - such as roads, schools, hospitals, and water supply systems - is quickly rising. However, much of the land in Lao PDR is not safe to use." due to UXOs. See, `https://reliefweb.int/sites/reliefweb.int/files/resources/blindgaenger-problem-volksrepublik-laos_EN.pdf`

less access to this vital supply. These findings suggest that (the lack of) state capacity might be playing an important role in perpetuating the legacies of war in Laos.[67] The fact that war was largely external to the country, might have also precluded any developmental gains, such as improved fiscal capacity.

Specific outcomes aside, there could be national institutional, cultural and educational level differences between the countries analysed. Miguel and Roland (2011) stress the role of investments, which have been minimal in Laos, as seen in the public good provision results above. In contrast, the national and international investments in Vietnam have been very large. A recent article by Nguyen et al. (2021) shows that UXO prevalence in Vietnam (which had not been analysed in the previous study) also decreased investment. There could still be other factors at play, such as economic isolation and regional trade patterns.[68] Though UXOs are still an issue in Vietnam, the magnitude of the problem is much larger in Laos, where only 1% of the mines have been cleared, despite recent efforts (Martin, Dolven, Feickert, & Lum, 2019). At the current pace, it would take more than a century to declare Laos mine free.[69] The demining agenda should take centre stage both nationally and internationally with foreign aid and technical assistance, with organisation such as HALO Trust. Even a 100 USD million commitment to UXO removal, as the one proposed in 2010 by the US, would total less than what this last country spent during one week of bombing Laos. Also in the Indochinese peninsula, Lin (2020) documents the deleterious impact of UXOs, especially on agricultural land, in line with our rural and structural transformation findings. Demining efforts in that country have also been small and UXO contamination

[67] We thank Jared Rubin for suggesting this angle.

[68] Using access to roads in 1970 (Perry Castaneda Library Map Collection, 2019) and distance to population centres to proxy for the potential costs of market access, we did not find any significant heterogeneous effects of bombing on economic activity mediated by this cost.

[69] Since 1999, UXO Laos has cleared 116 cluster bombs, 12,868 bombies, 43 landmines and 26,036 other UXOs (McGoff, 2019).

remains an important issue. Outside Southeast Asia, our results also differ from those of Germany and Japan, where urban structures had been consolidated for centuries or millennia, providing important complementary evidence for more rural settings. Globally, UXO contamination remains a significant and growing threat to public health (Frost et al., 2017), suggesting more settings to study this important issue, beyond a few successful cases of recovery and growth.

8 Conclusions

We use newly available and highly disaggregated data to document the *negative* long-term economic impact of conflict. We find that places which were more heavily bombed from 1964 to 1973—in the context of the Laotian Civil War—are poorer today. Results are robust to controlling for covariates, fixed effects and IV estimations, using distance to the Vietnamese Ho Chi Mihn Trail and proximity to US air bases outside of Laos, suggesting a causal effect. We use rich individual-level census data, and exploit time variation, to show how bombing has led to decreased human capital accumulation, hindered structural transformation and dampened rural-urban migration in the long run. We employ census data at the village level to show how our results for nightlights extend to relevant development outcomes such as literacy, health, expenditures, urbanisation, and poverty rates. We use this data along with a panel of UXO accidents to show how war has affected the health of the local population.

We contribute to the literature on the aftermath of conflict, by showing the negative and sizable *economic* impact of a war that formally ended decades ago. We thus provide a relevant counterpoint to the existing historical literature showing nil effects, as well as empirical support to the Conflict Trap hypothesis, whereby conflict perpetuates poverty. We also single out UXO contamination as a key element in the negative impact of bombing, decades after a conflict formally ends. Even after the official ceasefire, civilians have been affected directly through UXO accidents as well as *indirectly* through lower educational investments and less labour mobility into modern sectors and urban centres. These mechanisms can help explain the lack of postwar convergence, observed in other settings. This pernicious combination of factors helps explain why Laos remains one of the poorest countries in the world today. Though the level of UXO contamination in Laos is extreme, Explosive Remnants of War (ERW) remain a global development issue (Borrie, 2003).

We believe that our findings could better inform policies in both affected and attacking countries. First, the demining agenda should take centre stage in affected areas, as has already happened in Mozambique (Chiovelli et al., 2018) and is currently ongoing in places such as Colombia (Prem et al., 2021). The problem of UXO is not contained to Laos and extends to neighbouring Cambodia (Lin, 2020) and Vietnam (Nguyen et al., 2021), in the Indochinese Peninsula. Though unexploded bombs and mines are a thing of the past in most European countries that fought WWII, they are still a pressing issue in the Balkan region, Syria, Afghanistan, Iraq and now Ukraine (Munroe et al., 2023). Political leaders and advisors can learn from the specific channels of transmission of the effects of UXOs, including decreased industrialisation and human mobility. They can, for instance, improve the targeting of their existing policies or implement new programmes geared towards alleviating the pernicious lingering economic consequences of historical warfare, especially in the context of cluster bombs. Ideally, policymakers in attacking countries might want to think twice about the long-term humanitarian and socioeconomic legacy of their military actions, weighing the large and permanent economic damages to the civilian population against their more immediate political and strategic objectives.

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Affiliations

[1] Department of Economics, Georgetown University, Washington, DC, USA, 20057

[2] Vancouver School of Economics, University of British Columbia, IZA, Kiel and CEPR, Vancouver, BC, Canada. V6T 1L4

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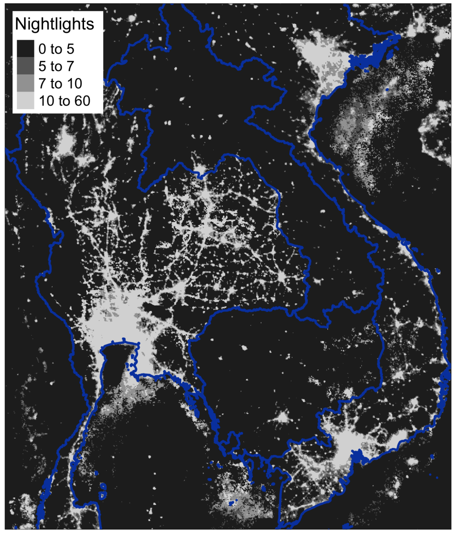
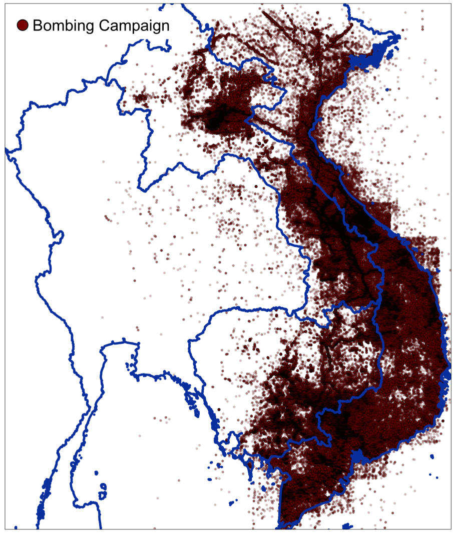
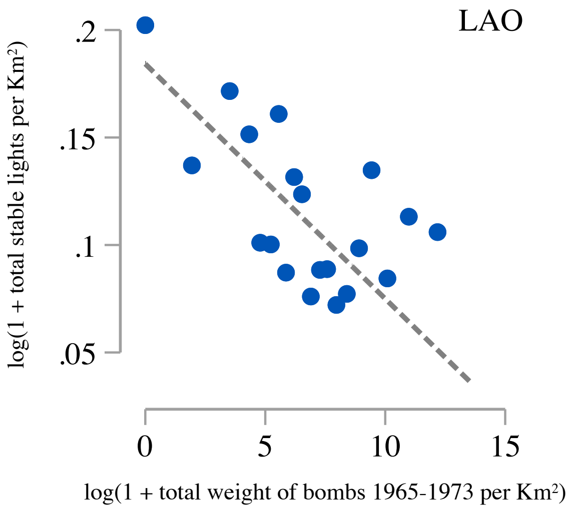
Figure 1: *Indochina: Stable Lights and US Bombing Events from 1965 and 1973*



Panel A: This figure displays the Indochina peninsula and the 2013 stable nightlights in grayscale. Country borders are displayed in blue

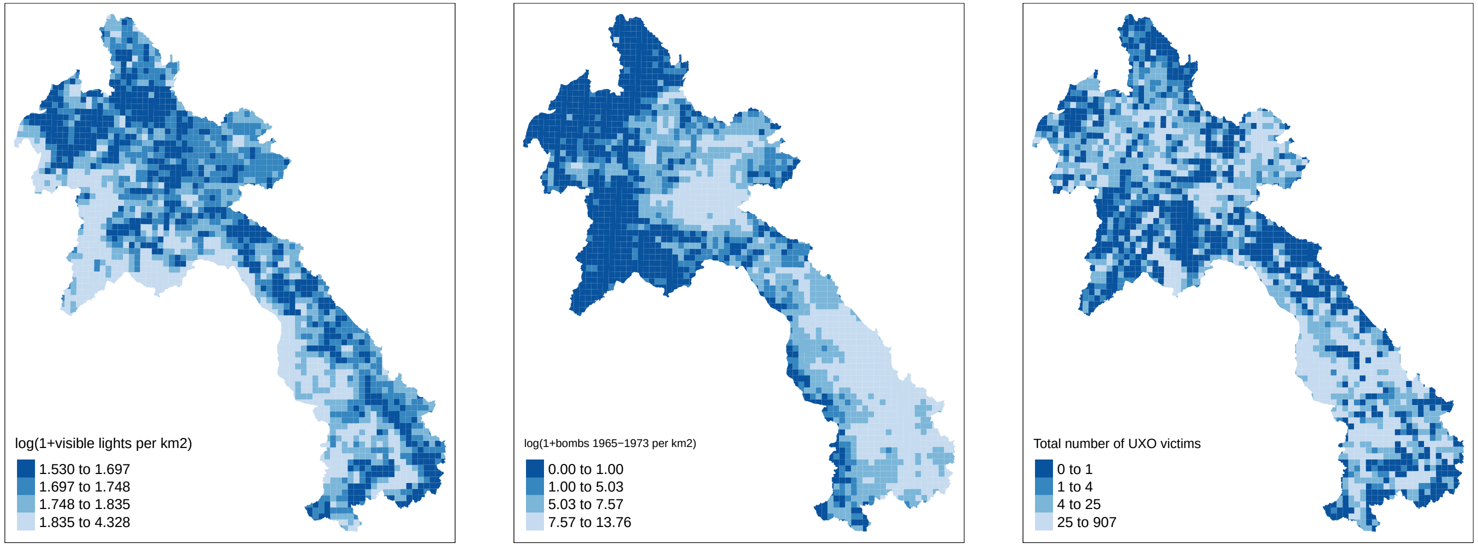


Panel B: This figure displays the Indochina peninsula and the US Bombing Campaigns in the region from 1965 to 1973, in red. Each dot represents a single campaign. Country borders are displayed in blue



Panel C: This figure presents a Bin-scatter for Laos between Luminosity and Bombing intensity controlling for province fixed effects, year fixed effects, and geographical and location covariates.

Figure 2: *Luminosity, Bombs and UXO*

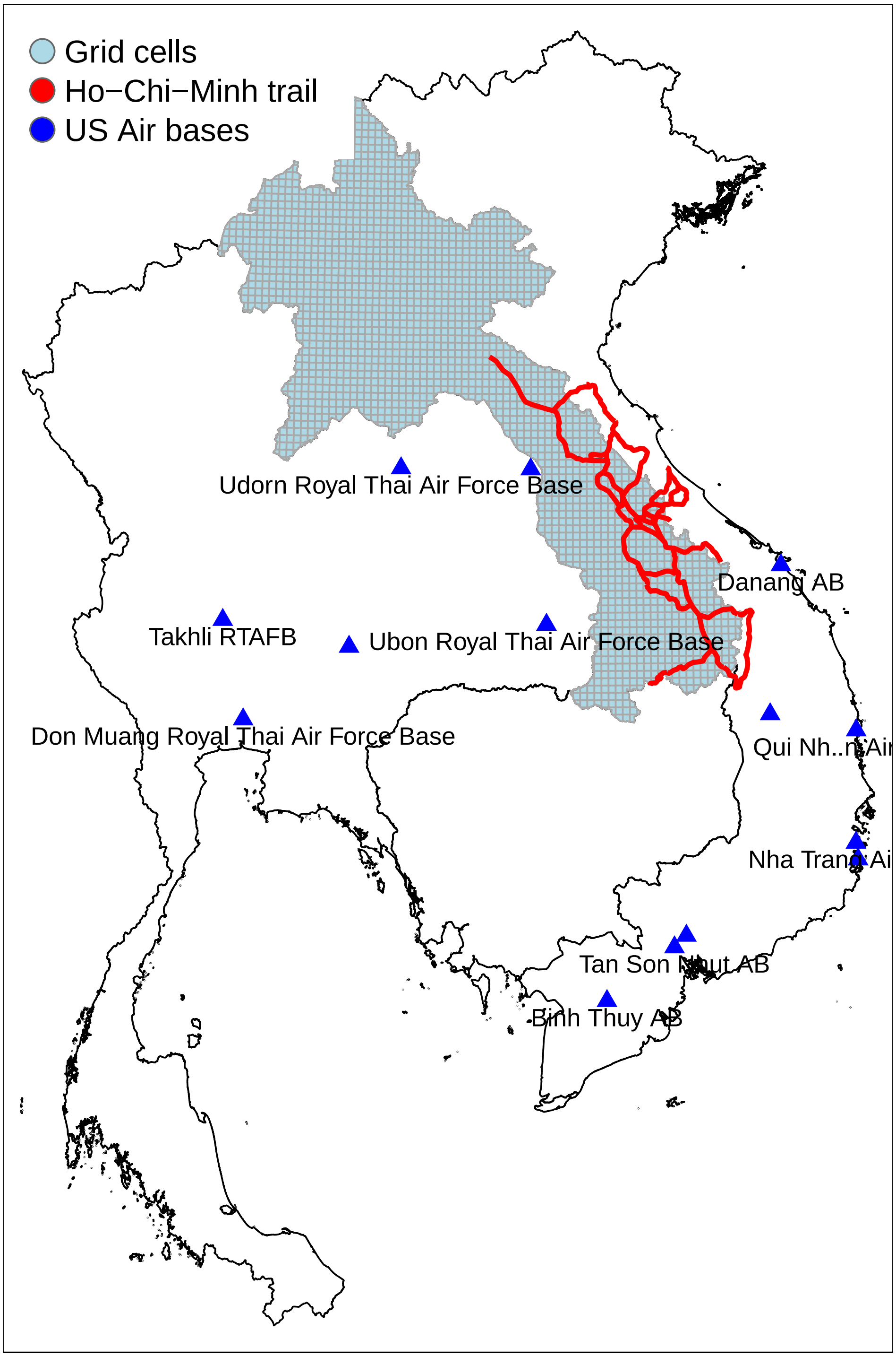


Panel A: Luminosity measured as the total sum of visible lights in 2013 per Km2 at the grid-cell level (in logs).

Panel B: Bombing measured as total pounds jettisoned from 1965- to 1973 per km2 (in logs).

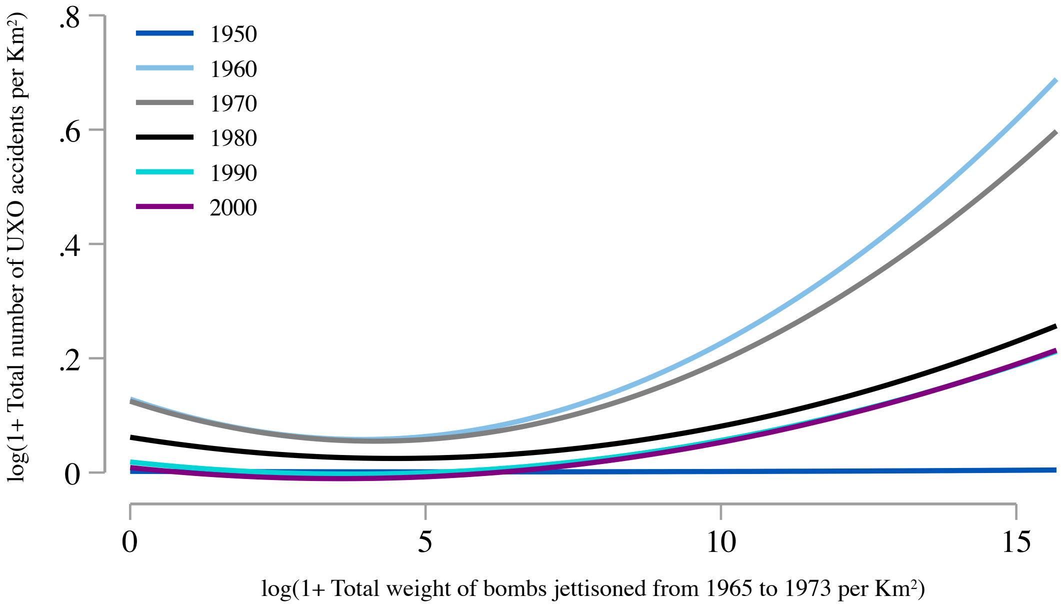
Panel C: UXO victims from 1950 to 2011.

Figure 3: *US Air Bases Outside Laos and the Ho Chi Minh Trail*



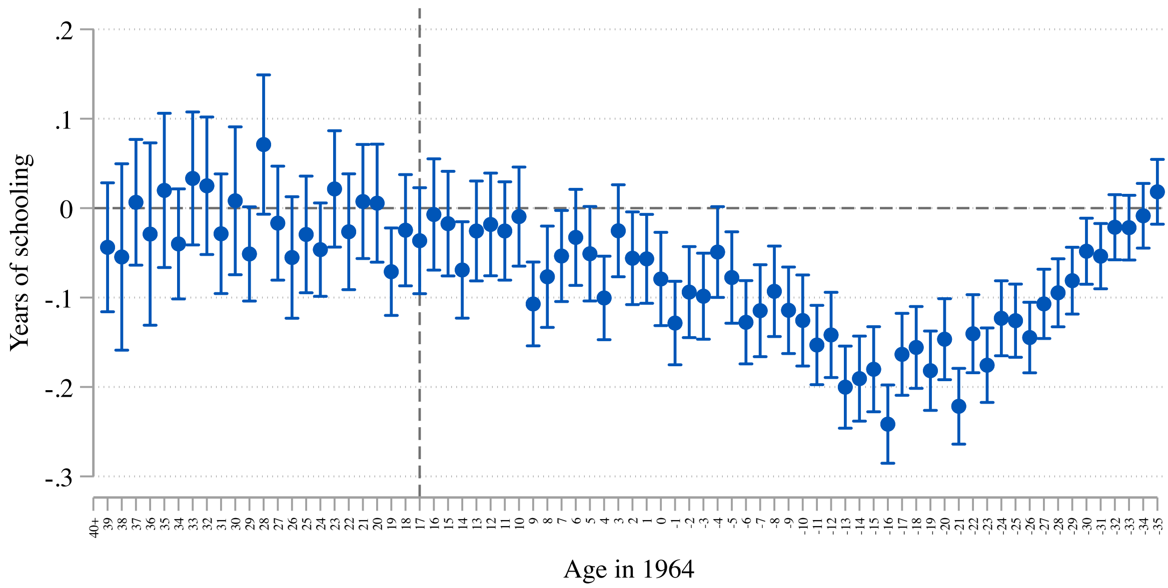
Notes: This figure presents the map of Thailand, Cambodia, Vietnam, and Laos and the grid cell partition used in the empirical analysis. In dark blue, it depicts the location of US airbases outside Laos and the georeferencing of the Vietnamese Ho Chi Minh trail. Information was digitised based on historical maps presented in Appendix Figure A-3.

Figure 4: *Panel of UXO Victims and Bombing Intensity with Quadratic Fits by Decade of Occurrence*



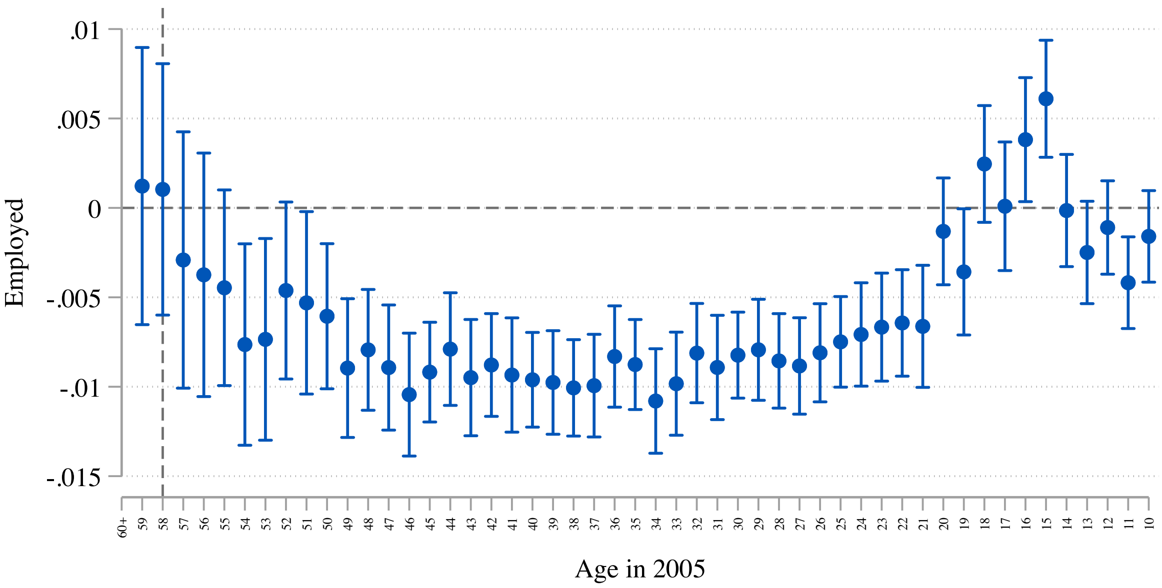
Notes: This figure presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance) and bombing intensity from 1964 to 1973. It uses panel data on UXO accidents and data on the bombing at the village level. The figure shows simple quadratic fits of the raw data by decade.

Figure 5: *Impact of Bombing on Years of Schooling, using Micro-level Data from the Population Census of 2005*



Notes: The estimation sample includes individuals from 10 to 98 years old in 2005. Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is years of schooling. The excluded cohort is composed by individuals with 40 years or more in 1964. The 17-year-old cohort is marked with a vertical dashed line as a reference point. It corresponds to the age upon which Laotians should have finished high school.

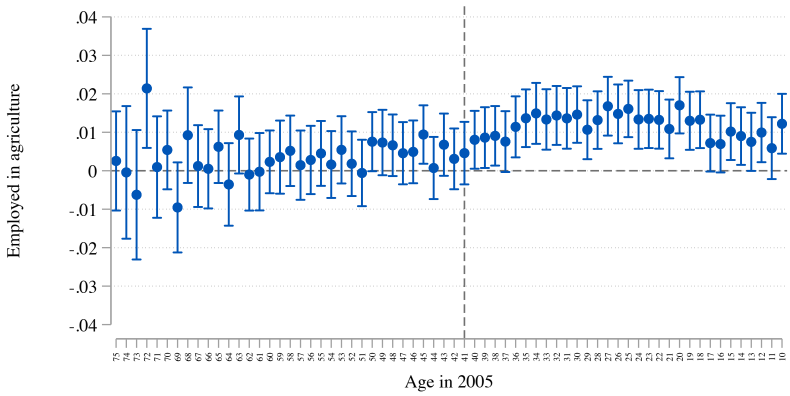
Figure 6: *Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005*



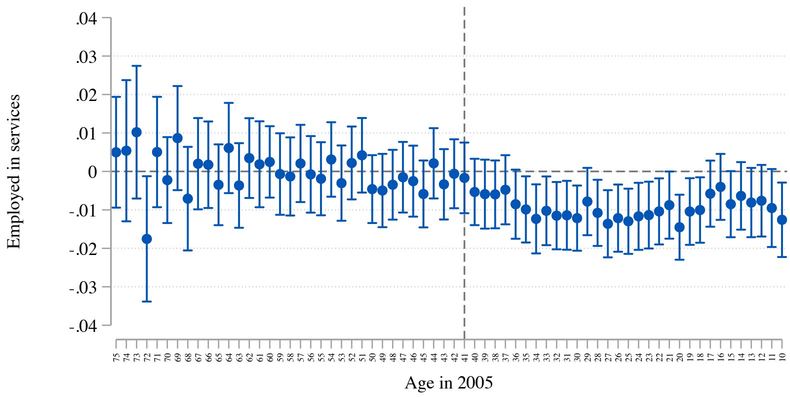
Notes: The estimation sample includes individuals from 10 to 98 years old in 2005. Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome is an indicator of employment. The excluded cohort in Panel B is people older that 60 (official age of retirement) in 2005, i.e., older than 20 in 1964. The 58 years old cohort marked with a vertical line as reference point as the cohort that was 17 in 1964.

Figure 7: *Impact of Bombing on the Probability of Working in Agriculture, using Micro-level Data from the Population Census of 2005 (yearly)*

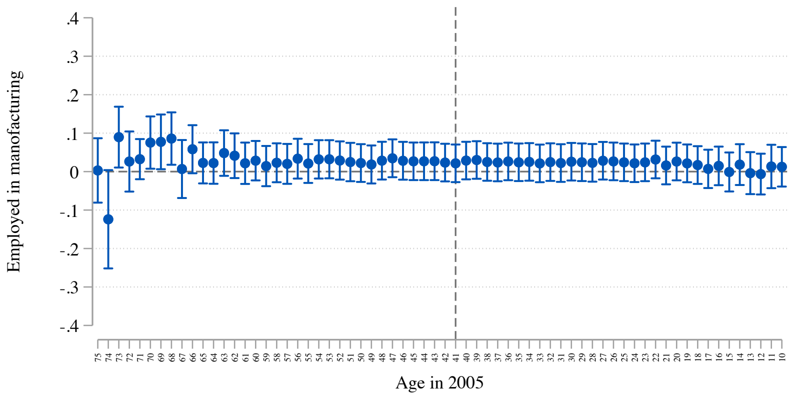
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services

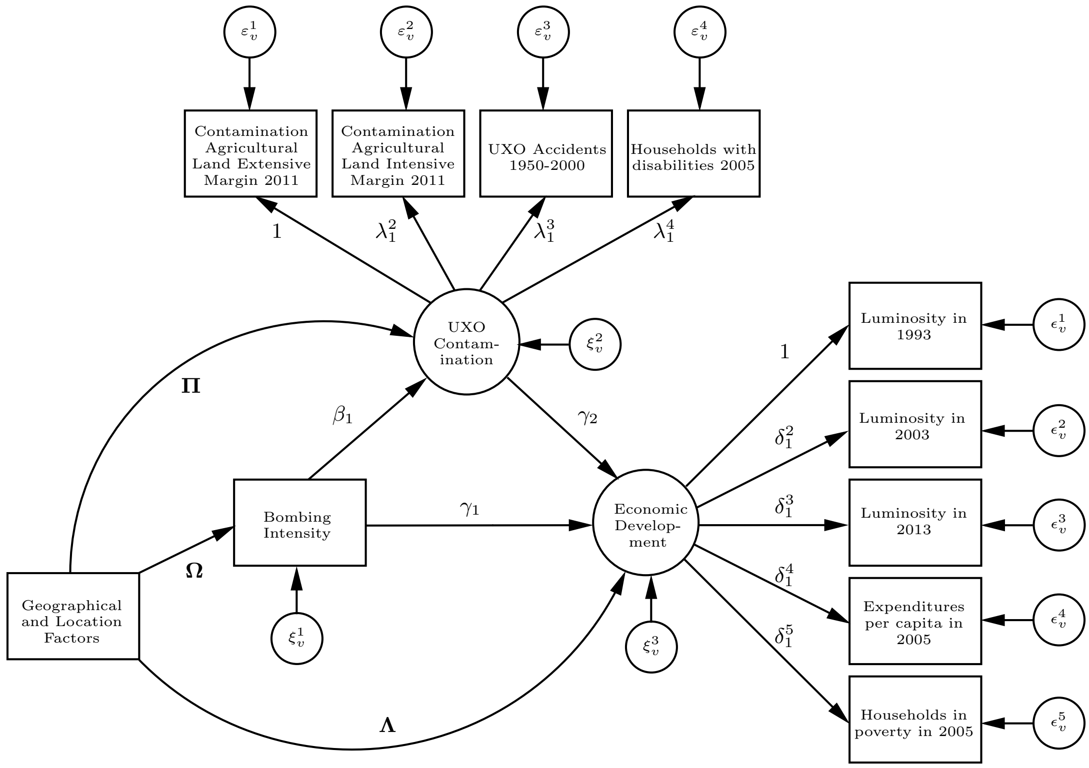


Panel C: Probability of Working in Manufacturing



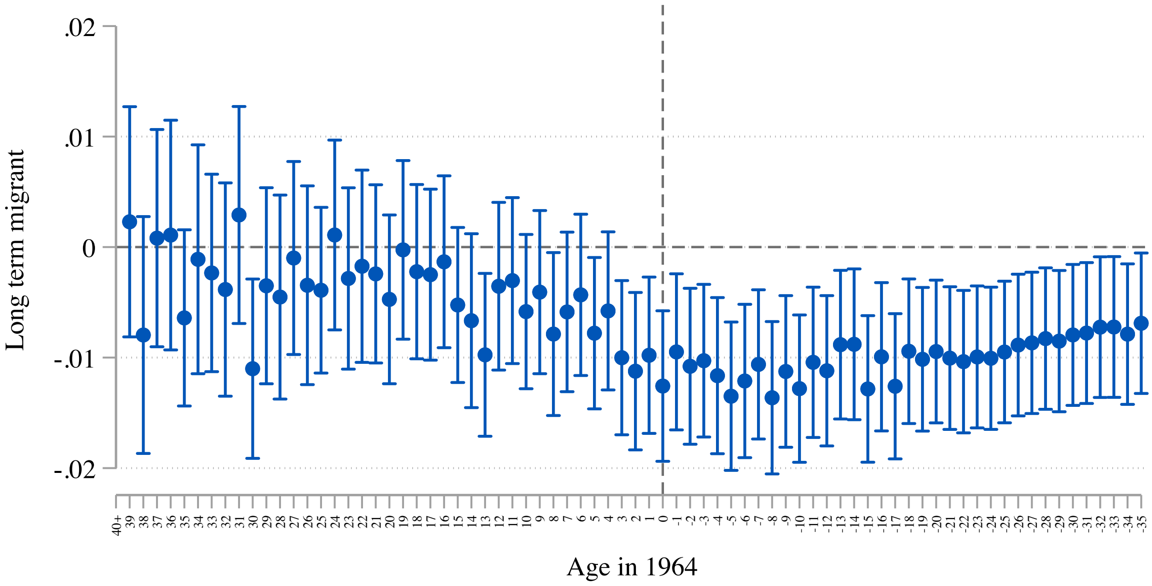
Notes: Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is an indicator variable of working in each one of the sectors defined by each panel. The excluded cohort is composed by individuals with 76 years or more in 2005. The 41 years old cohort marked with a vertical line as reference point since those are the individuals who were born in 1964.

Figure 8: *Path Diagram for the Structural Equation Model Studying UXO Contamination as Mechanism of Transmission*



Notes: This figure presents the structure of the model used to evaluate UXO contamination as a mechanism of transmission in path diagram notation. Observed variables are represented in boxes, while latent/unobserved variables are represented in circles. Arrows connecting boxes and circles mean linear relationships between variables in the specified direction. The symbols over the arrows represent the coefficients to be estimated. Bold symbols represent vectors of coefficients. Details on the assumptions and identification are reported in the Online Appendix A.

Figure 9: *Impact of Bombing on the Probability of Migration, using Micro-level Data from the Population Census of 2005 (yearly)*



Notes: Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is an indicator of being long-term migrant. We define long-term migration as living in a different province than that of birth. The excluded cohort is composed of individuals who were 40 years or older in 1964. The 0-year-old cohort is marked with a vertical dashed line as a reference point.

Table 1: *OLS Estimates: Luminosity and Bombs*

Dependent Variable	Luminosity 1993			Luminosity 2003			Luminosity 2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bombs	−0.024***	−0.027***	−0.038***	−0.030***	−0.035***	−0.049***	−0.057***	−0.070***	−0.064***
	(0.005)	(0.005)	(0.009)	(0.006)	(0.006)	(0.010)	(0.012)	(0.012)	(0.017)
Altitude		−0.066***	−0.158**		−0.095***	−0.212***		−0.199***	−0.539***
		(0.015)	(0.061)		(0.020)	(0.072)		(0.037)	(0.106)
Ruggedness		−0.031***	−0.028***		−0.050***	−0.047***		−0.099***	−0.096***
		(0.006)	(0.005)		(0.008)	(0.007)		(0.015)	(0.014)
Temperature		−0.051***	−0.174**		−0.073***	−0.229***		−0.125***	−0.544***
		(0.014)	(0.073)		(0.020)	(0.085)		(0.038)	(0.125)
Precipitation		−0.003	−0.009		−0.002	−0.006		0.006	0.027*
		(0.003)	(0.006)		(0.005)	(0.008)		(0.011)	(0.016)
Longitude			−0.151**			−0.222***			−0.506***
			(0.060)			(0.070)			(0.105)
Latitude			−0.125**			−0.170**			−0.356***
			(0.057)			(0.066)			(0.100)
Distance to DMZ			−0.047***			−0.071***			−0.128***
			(0.010)			(0.011)			(0.018)
Distance to Vietnam border			−0.075***			−0.113***			−0.209***
			(0.023)			(0.027)			(0.047)
Distance to Population centre			−0.049***			−0.072***			−0.161***
			(0.009)			(0.011)			(0.017)
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R−squared	0.013	0.057	0.120	0.012	0.075	0.156	0.012	0.110	0.218

Notes: Observations are at the grid-cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. All variables are standardised. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: *OLS Estimates: Luminosity Growth and Bombs*

Dependent Variable	Luminosity Growth 1993-2003			Luminosity Growth 2003-2013			Luminosity Growth 1993-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bombs	−0.001	−0.004	−0.005	−0.010	−0.018**	0.006	−0.015*	−0.026***	−0.007
	(0.003)	(0.003)	(0.004)	(0.007)	(0.007)	(0.010)	(0.009)	(0.010)	(0.012)
Altitude		−0.019**	−0.033		−0.057***	−0.235***		−0.093***	−0.302***
		(0.008)	(0.025)		(0.022)	(0.054)		(0.027)	(0.067)
Ruggedness		−0.014***	−0.015***		−0.024**	−0.028***		−0.049***	−0.054***
		(0.003)	(0.003)		(0.009)	(0.009)		(0.012)	(0.012)
Temperature		−0.014*	−0.031		−0.016	−0.216***		−0.043	−0.284***
		(0.008)	(0.030)		(0.022)	(0.062)		(0.028)	(0.079)
Precipitation		0.002	0.004		0.009	0.036***		0.012	0.041***
		(0.003)	(0.004)		(0.006)	(0.009)		(0.008)	(0.012)
Longitude			−0.051**			−0.187***			−0.279***
			(0.024)			(0.057)			(0.070)
Latitude			−0.028			−0.112**			−0.168**
			(0.022)			(0.055)			(0.067)
Distance to DMZ			−0.018***			−0.025**			−0.058***
			(0.004)			(0.011)			(0.012)
Distance to Vietnam border			−0.028***			−0.047			−0.097***
			(0.010)			(0.031)			(0.035)
Distance to Population centre			−0.016***			−0.059***			−0.088***
			(0.003)			(0.009)			(0.011)
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R−squared	0.092	0.114	0.136	0.203	0.235	0.274	0.135	0.186	0.242

Notes: Observations are at the grid-cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. All variables are standardised. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: *Fixed Effects Estimates: Luminosity and Bombs*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable: Luminosity 1993						
Bombs	−0.027***	−0.038***	−0.029***	−0.033***	−0.016***	−0.013**
	(0.005)	(0.009)	(0.008)	(0.008)	(0.006)	(0.006)
R−squared	0.057	0.120	0.171	0.196	0.534	0.539
Panel B: Dependent Variable: Luminosity 2003						
Bombs	−0.035***	−0.049***	−0.034***	−0.041***	−0.018**	−0.015*
	(0.006)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
R−squared	0.075	0.156	0.208	0.243	0.502	0.508
Panel C: Dependent Variable: Luminosity 2013						
Bombs	−0.070***	−0.064***	−0.051***	−0.058***	−0.037**	−0.031*
	(0.012)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
R−squared	0.110	0.218	0.248	0.303	0.469	0.485
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	No	Yes	No	Yes	No	Yes
Province Fixed Effects	No	No	Yes	Yes	No	No
District Fixed Effects	No	No	No	No	Yes	Yes
Number of Provinces			18	18		
Number of Districts					141	141
Observations	2,216	2,216	2,216	2,216	2,216	2,216

Notes: Observations are at the grid-cell level. Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within the each grid cell, while Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. All variables including in the regression are standardised. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: *Fixed Effects Estimates: Pooled OLS of Luminosity on Bombs*

Dependent Variable	Luminosity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bombs	−0.037***	−0.044***	−0.038***	−0.024**	−0.050***	−0.044***	−0.020**
	(0.007)	(0.007)	(0.011)	(0.009)	(0.011)	(0.011)	(0.009)
Geographical Controls		Yes	Yes	Yes	Yes	Yes	Yes
Location Controls					Yes	Yes	Yes
Province Fixed Effects			Yes			Yes	
Districts Fixed Effects				Yes			Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Provinces			18			18	
Number of Districts				141			141
Observations	6,648	6,648	6,648	6,648	6,648	6,648	6,648
R−squared	0.034	0.097	0.206	0.409	0.172	0.241	0.417

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. All variables including in the regression are standardised. Errors clustered at the grid-cell level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: *Instrumental Variables Estimates: Pooled IV of Luminosity on Bombs*

Table 5A - Instrument I: Distance to the Ho Chi Minh Trail

	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	−0.165***	−0.132***	−0.105***
	(0.040)	(0.038)	(0.027)
Panel B: Dependent variable is Bombs, model:	FS	FS	FS
Distance to Ho Chi Minh trail	−0.008***	−0.014***	−0.022***
	(0.001)	(0.001)	(0.002)
Distance to Ho Chi Minh trail^2	0.009***	0.022***	0.026***
	(0.001)	(0.002)	(0.003)
R−squared	0.551	0.629	0.772
F−stat	363.8	43.69	30.38
Controls that apply for all panels			
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Table 5B - Instrument II: Distance to the Closest US Air Base

	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	−0.145***	−0.127***	−0.521**
	(0.031)	(0.029)	(0.210)
Panel B: Dependent variable is Bombs, model:	FS	FS	FS
Distance to US air base	0.014***	0.014***	0.004***
	(0.001)	(0.001)	(0.002)
Distance to US air base^2	−0.020***	−0.013***	−0.009***
	(0.001)	(0.002)	(0.003)
R−squared	0.601	0.648	0.750
F−stat	531.7	59.40	13.82
Controls that apply for all panels			
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within the grid cell from 1965 to 1973 per square kilometre. All variables included in the regressions are standardised. Distance to the Ho Chi Minh Trail refers to Euclidean distance but uses the parts of the trails that were not entirely known by the US authorities. Distance to the closest US airbase refers to Euclidean distance but is computed using US airbases founded before 1960 and located outside Laos. Robust standard errors in parentheses cluster at the grid-cell level. ***p<0.01, **p<0.05, *p<0.1

Table 6: *Instrumental Variables Estimates: Pooled IV of Luminosity on Bombs, Combining both Instruments*

Dependent variable: Luminosity	(1)	(2)	(3)
Panel A: Instruments are distance to the Ho Chi Minh Trail and distance to the closest air base, ***linear form***			
Model:	2SLS	2SLS	2SLS
Bombs	−0.163***	−0.124***	−0.149***
	(0.030)	(0.024)	(0.033)
Hansen J statistic (over-identification test of all instruments)			2.060
Chi-sq(1) p-value			0.151
Panel B: Instruments are distance to the Ho Chi Minh Trail and distance to the closest air base, ***linear plus quadratic terms***			
Model:	2SLS	2SLS	2SLS
Bombs	−0.160***	−0.138***	−0.109***
	(0.031)	(0.027)	(0.028)
Controls that apply for all panels			
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Distance to the Ho Chi Minh Trail refers to such Euclidian distance but using the parts of the trails that were not entirely known by the US authorities. Distance to the closest US airbase refers to such Euclidean distance but is computed using US airbases founded before 1960 and located outside Laos. All variables included in the regressions are standardised. Robust standard errors in parentheses cluster at the grid-cell level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: *OLS Estimates at the Village Level: Mechanisms of Transmission and Development Outcomes*

	(1)	(2)	(3)
Part I: Unexploded Ordnance			
Panel A: Dependent variable is 1(*Land is contaminated by UXO*)			
Bombs	0.196***	0.163***	0.135***
	(0.004)	(0.005)	(0.005)
R−squared	0.294	0.309	0.341
Panel B: Dependent variable is log(1+ agricultural area contaminated by UXO/Village area)			
Bombs	0.234***	0.224***	0.172***
	(0.010)	(0.012)	(0.010)
R−squared	0.147	0.165	0.209
Observations	8,643	8,643	8,643
Part II: Additional Development Outcomes			
Panel C: Dependent variable is the log(1+total expenditures/population)			
Bombs	−0.105***	−0.041***	−0.025***
	(0.003)	(0.004)	(0.004)
R−squared	0.088	0.305	0.370
Panel D: Dependent variable is the fraction of households in poverty			
Bombs	0.070***	0.024***	0.016***
	(0.002)	(0.002)	(0.002)
R−squared	0.130	0.353	0.459
Observations	10,522	10,522	10,522
Controls that apply to all panels			
Province fixed effects			Yes
Geographical Controls		Yes	Yes
Location Controls		Yes	Yes

Notes: Observations are at the village level. Variable Bombs represents the total weight in pounds jettisoned from 1965 to 1973 per square kilometre. Variable Bombs is standardised. Panels C and D use data from the Population Census of 2005. Panels A and B use data from the Agricultural census of 2011. Robust standard errors in parentheses.

Table 8: *OLS Estimates at the Village Level: Mechanisms of Transmission*

	(1)	(2)	(3)
Panel A: Dependent variable is fraction of literate households			
Bombs	−0.057***	−0.027***	−0.024***
	(0.003)	(0.003)	(0.003)
R−squared	0.050	0.258	0.451
Panel B: Dependent variable is fraction of households with disabled people			
Bombs	0.011***	0.008***	0.001
	(0.001)	(0.001)	(0.001)
R−squared	0.024	0.086	0.129
Panel C: Dependent variable is log(Inhabitants/Km2)			
Bombs	−0.292***	−0.107***	−0.127***
	(0.016)	(0.018)	(0.020)
R−squared	0.029	0.322	0.366
Controls that apply for all panels			
Province fixed effects			Yes
Geographical Controls		Yes	Yes
Location Controls		Yes	Yes
Observations	10,522	10,522	10,522

Notes: Observations are at the village level. Variable Bombs represents the total weight in pounds jettisoned from 1965 to 1973 per square kilometre. Variable Bombs is standardised. Robust standard errors in parentheses.

Table 9: *Public Goods: Services and Educational Infrastructure*

Dependent variable:	Village has a primary school		
	(1)	(2)	(3)
Bombs	0.007		0.011*
	(0.006)		(0.006)
log(1+ agricultural area contaminated by UXO/Village area)		−0.012**	−0.014**
		(0.005)	(0.005)
R−squared	0.039	0.040	0.040
Dependent variable:	**Village has electricity**		
	(1)	(2)	(3)
Bombs	−0.040***		−0.039***
	(0.007)		(0.007)
log(1+ agricultural area contaminated by UXO/Village area)		−0.010**	−0.004
		(0.005)	(0.005)
R−squared	0.402	0.399	0.402
Dependent variable:	**Village has water supply**		
	(1)	(2)	(3)
Bombs	−0.016***		−0.015***
	(0.003)		(0.004)
log(1+ agricultural area contaminated by UXO/Village area)		−0.005***	−0.003
		(0.002)	(0.002)
R−squared	0.191	0.189	0.191
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	8,203	8,203	8,203

Notes: Observations are at the village level. Independent variables are standardised. Bombs is the log of one plus the total weight in pounds jettisoned within the village from 1965 to 1973 normalised by the village area. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Online Appendix

This version: December 19, 2023

A Structural Equation Model with Latent Variables

Let UXO_v and Development_v be the current unobserved levels of UXO contamination and aggregate economic development in village v. And define $\boldsymbol{C_v}$ as a vector of variables proxying for UXO contamination including the extensive and the intensive margin of agricultural land affected by UXOs, the number of UXO accidents, and the percentage of households with disabilities in village v. Similarly, let $\boldsymbol{D_v}$ be a vector of variables proxying for economic development at the village level including, luminosity in 1993, 2003, and 2013, expenditure per capita, and the percentage of households in poverty in village v in 2005. Based on these, we estimate the following system of twelve interdependent equations,

Structural

$$\log(1 + \text{Bombs 1964-1973})_v = \alpha_0 + \boldsymbol{X_v'\Omega} + \xi_v^1 \quad (6)$$

$$\text{UXO}_v = \beta_0 + \beta_1 \cdot \log(1 + \text{Bombs 1964-1973})_v + \boldsymbol{X_v'\Pi} + \xi_v^2 \quad (7)$$

$$\text{Development}_v = \gamma_0 + \gamma_1 \cdot \log(1 + \text{Bombs 1964-1973})_v + \gamma_2 \cdot \text{UXO}_v + \boldsymbol{X_v'\Lambda} + \xi_v^3 \quad (8)$$

Measurement

$$C_v^i = \lambda_0^i + \lambda_1^i \cdot \text{UXO}_v + \varepsilon_v^i \quad \forall\, C_v^i \in \boldsymbol{C_v} \quad (9)$$

$$D_v^j = \delta_0^j + \delta_1^j \cdot \text{Development}_v + \epsilon_v^j \quad \forall\, D_v^j \in \boldsymbol{D_v} \quad (10)$$

where $\boldsymbol{X_v}$ is the vector of exogenous geographical and location controls defined in Section 4. Exogenous and endogenous variables are assumed to follow a multivariate normal distribution with mean $\boldsymbol{\mu}$ and variance matrix $\boldsymbol{\Sigma}$.

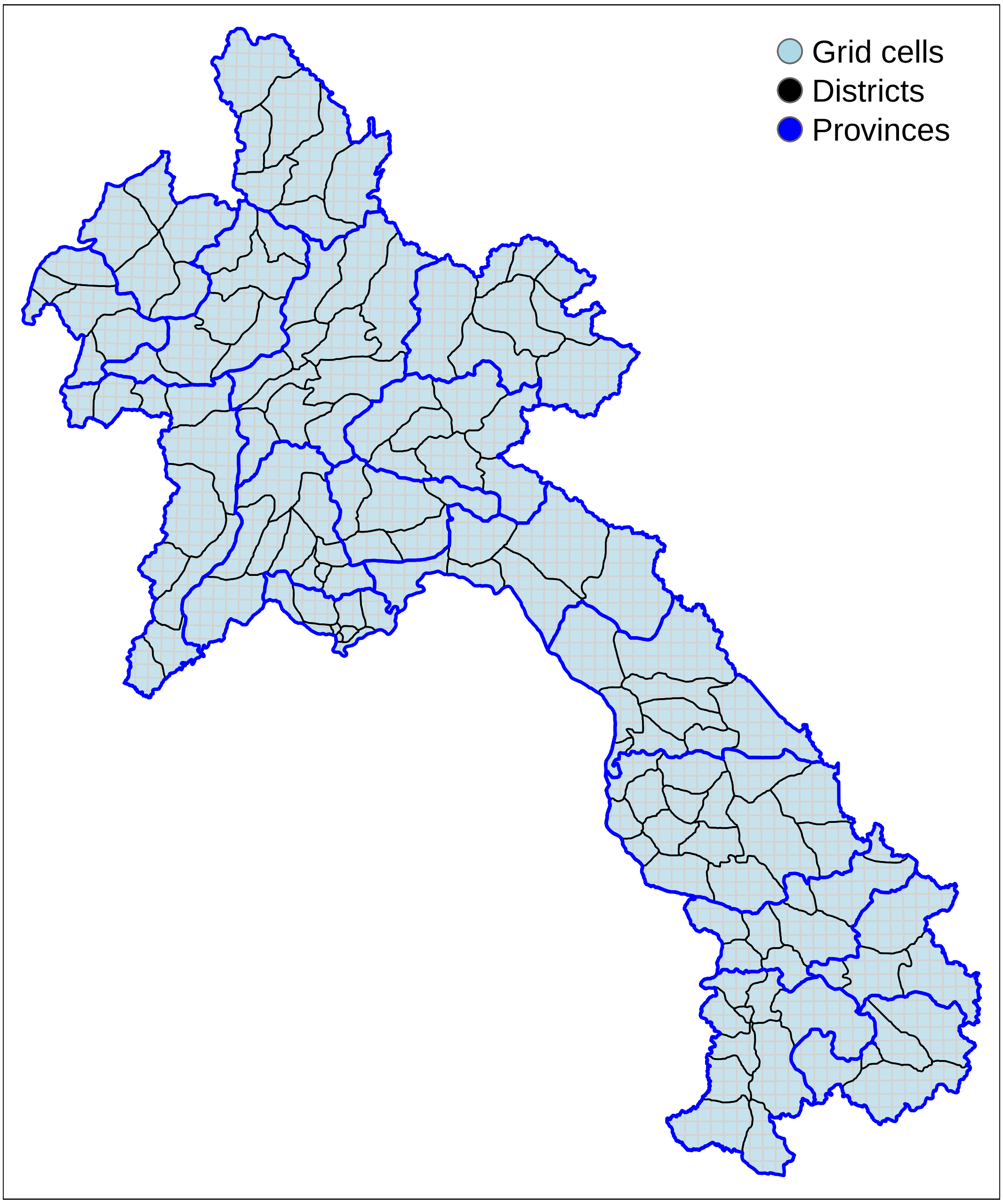
We assume all errors have mean zero and the covariance of exogenous variables and those errors is zero. Importantly, for identification, we scale the model such that $\lambda_0^1 = 1$, $\delta_0^1 = 1$, $\beta_0 = 0$, and $\gamma_0 = 0$ (i.e., the coefficients of the measurement equations are scaled based on the first proxy variable, and latent variables means are equal to zero). Finally, we allow for any potential correlation between exogenous variables to be estimated.

The structure of the model is summarised in Figure 8 using path diagram notation.

Online Appendix: Figures

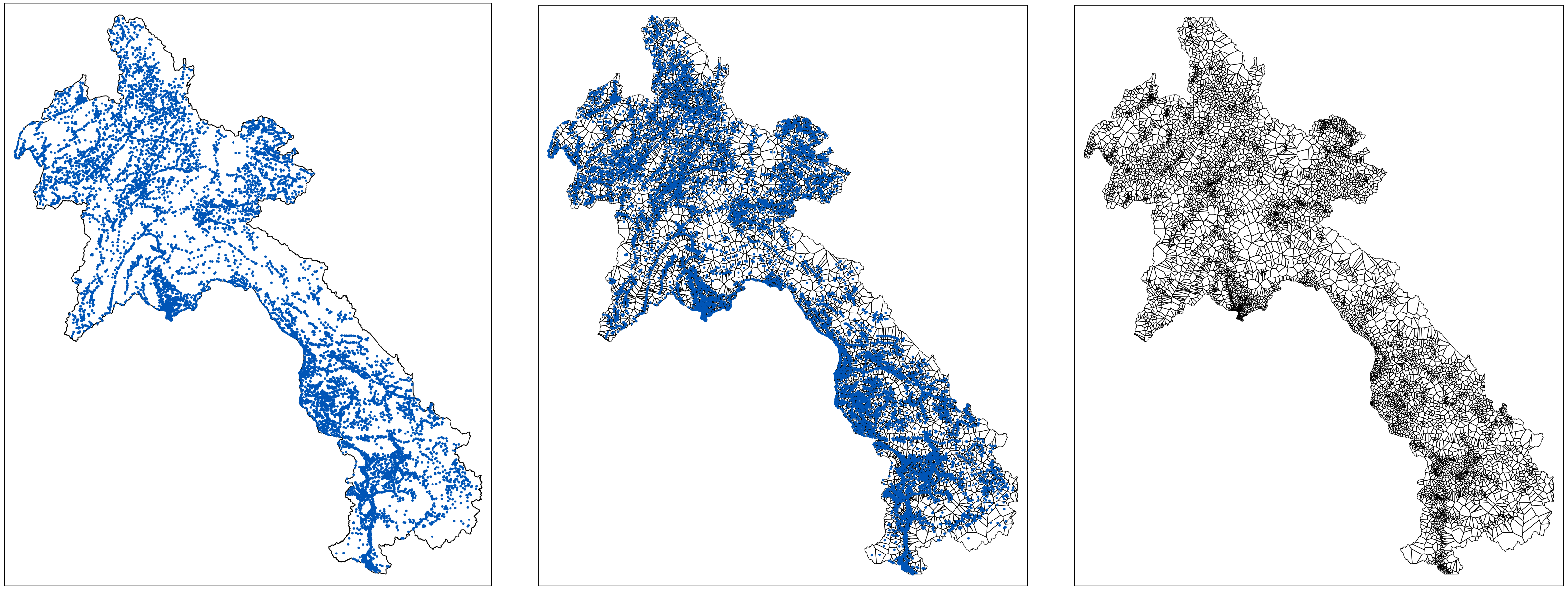
Online Appendix: Tables

Figure A-1: *Grid cell Level Analysis: Grid cells of 0.1°×0.1° for Laos*



Notes: This figure depicts the first two administrative divisions in Laos and the 2,216 synthetic grid cells used in the empirical analysis. Dark blue and black polygons represent provinces and districts, respectively. Grid cells are represented in light blue.

Figure A-2: *Village Level Boundary Construction*

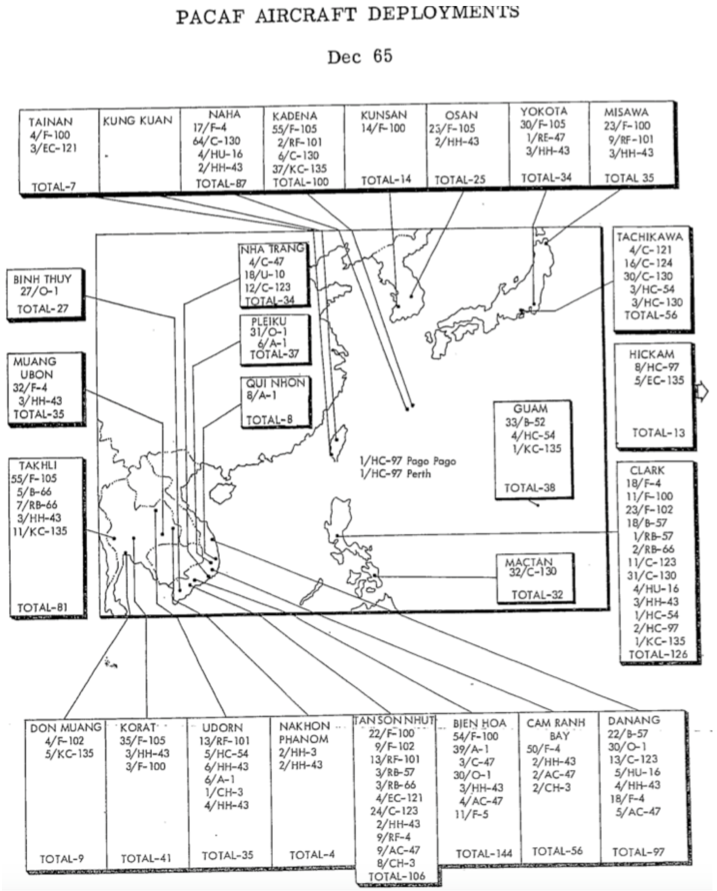


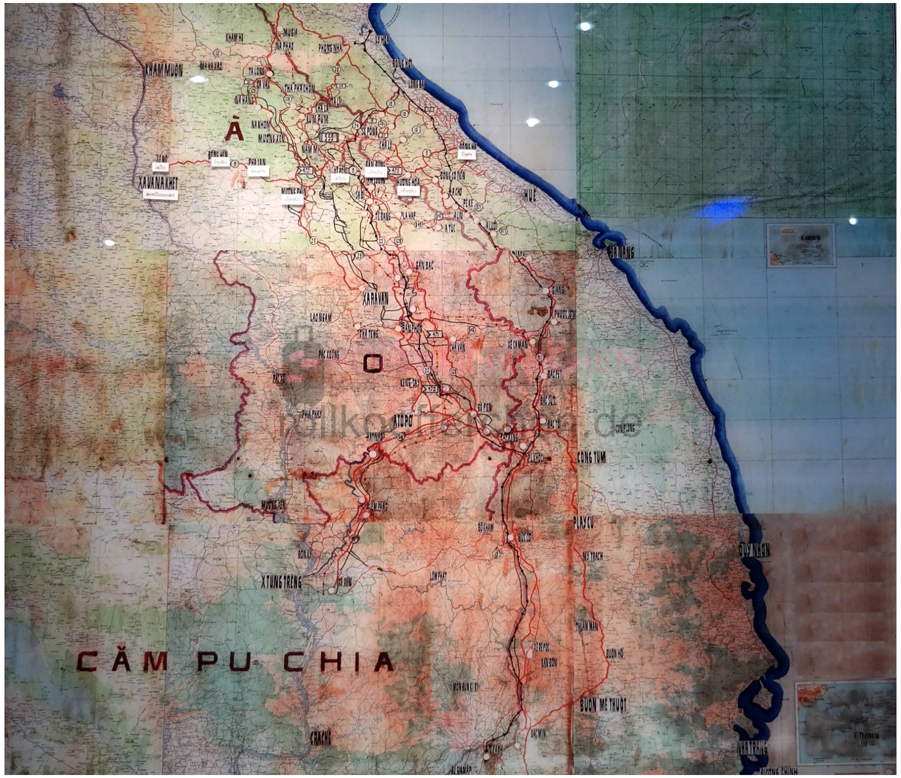
Panel A: Spatial location of villages in the census.

Panel B: Thiessen polygons.

Panel C: Implied village's boundaries.

Figure A-3: *Air Bases from the Pacific Air Forces in 1965 and The Ho Chi Minh Trail*





Panel A: Declassified document from the US Side

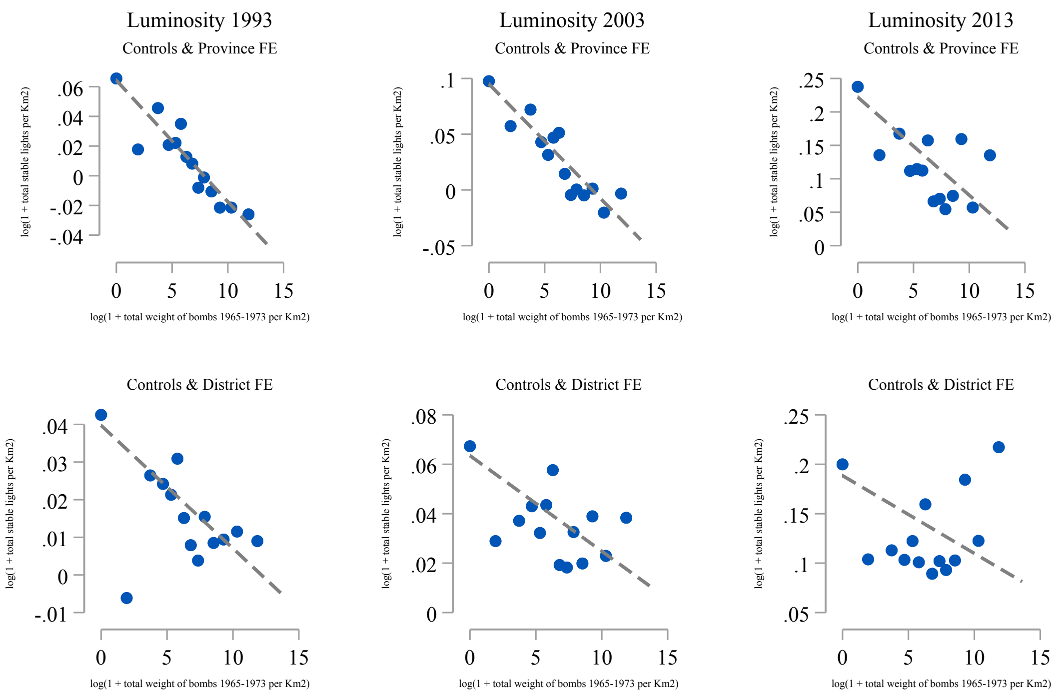
Panel B: Example of the map of supply routes from the Laotian side

Sources: Panel A comes from p. 81 of the report "USAF Plans and Operations in Southeast Asia 1965" by the USAF Historical Division Liaison Office in 1966. Declassified document since the 05/16/2006. Panel B comes from a map of the Ho Chi Minh Trail in the "Museum of Lao-Vietnam Legacy of Joined Victory Battle on the Road 9 Area."

Figure A-4: *Transportation Network circa 1970*

Notes: This figure depicts the administrative divisions in Laos and the transportation network circa 1970. It includes roads, railroads and trails. Source: Perry Castaneda Library Map Collection, University of Texas, Austin. Available at: `https://legacy.lib.utexas.edu/maps/indochina_atlas/`

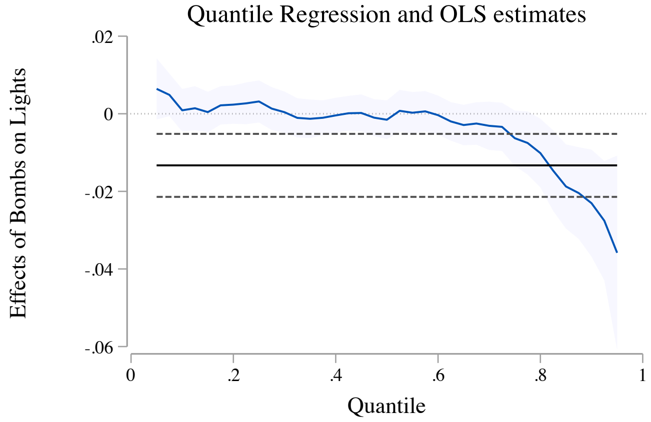
Figure A-5: *Bin-scatters of Lights on Bombs at the Grid Cell Level by Year*



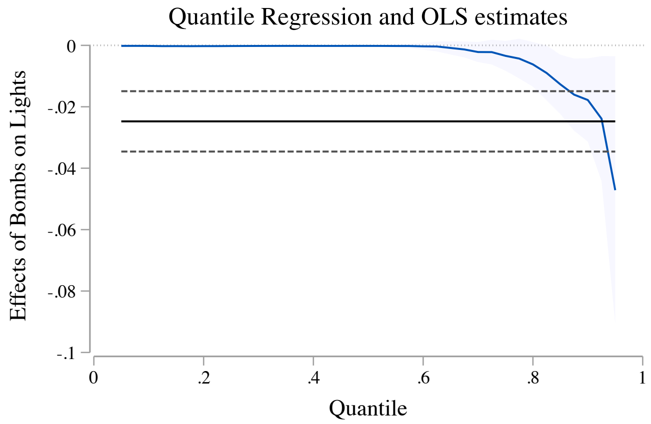
Notes: This figure depicts the relationship between Bombs and Luminosity using satellite data for each year separately. All panels are bin-scatters with overlapping quadratic fits of the underlying data. All figures control for location and geographical covariates. The first row includes province fixed effects, while the second row employs district fixed effects.

Figure A-6: *OLS and Quantile Regression Coefficients by Year*

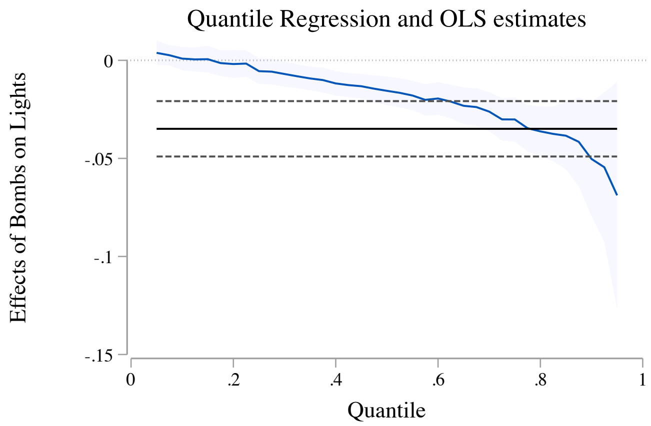
Panel A: Lights in 1993



Panel B: Lights in 2003



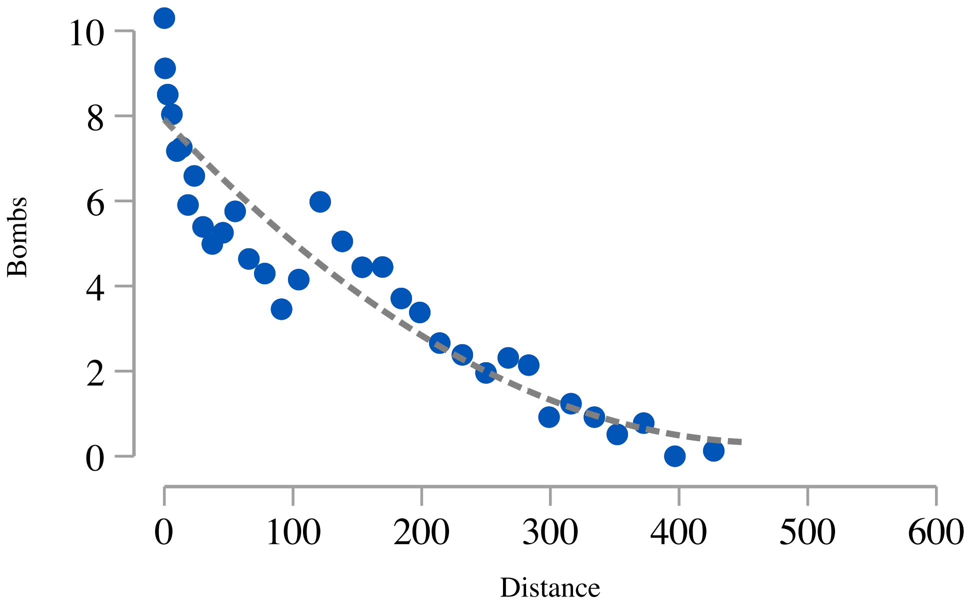
Panel C: Lights in 2013



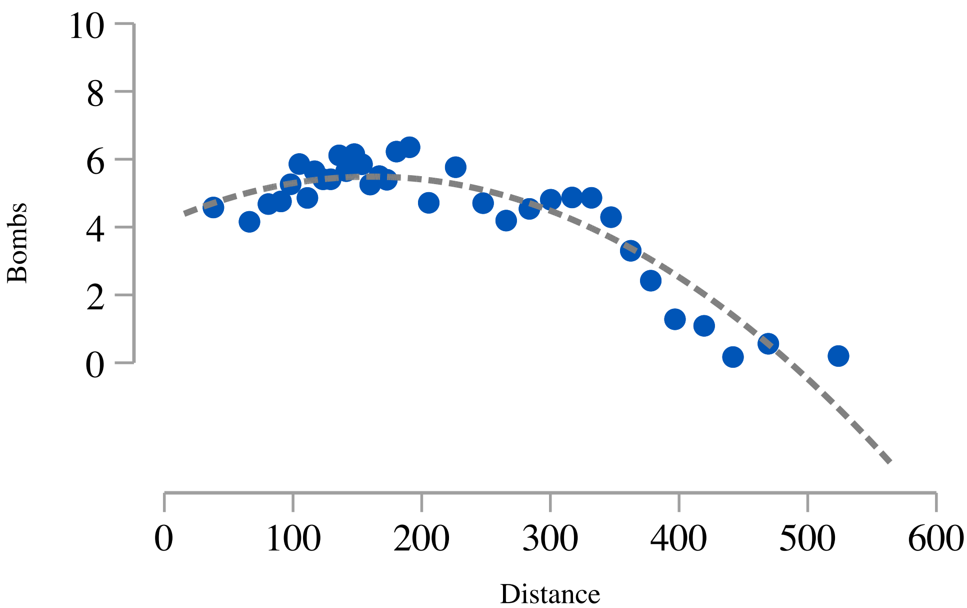
Notes: Quantile regression coefficients for the visible luminosity quantiles specified in the x-axis are reported in blue with 95% confidence intervals based on robust standard errors. OLS coefficients of the baseline specification in Equation (1) are reported as dashed black lines with dashed 95% confidence intervals.

Figure A-7: *Bin-scatters for the First Stages*

Panel A Distance to Ho Chi Minh Trail

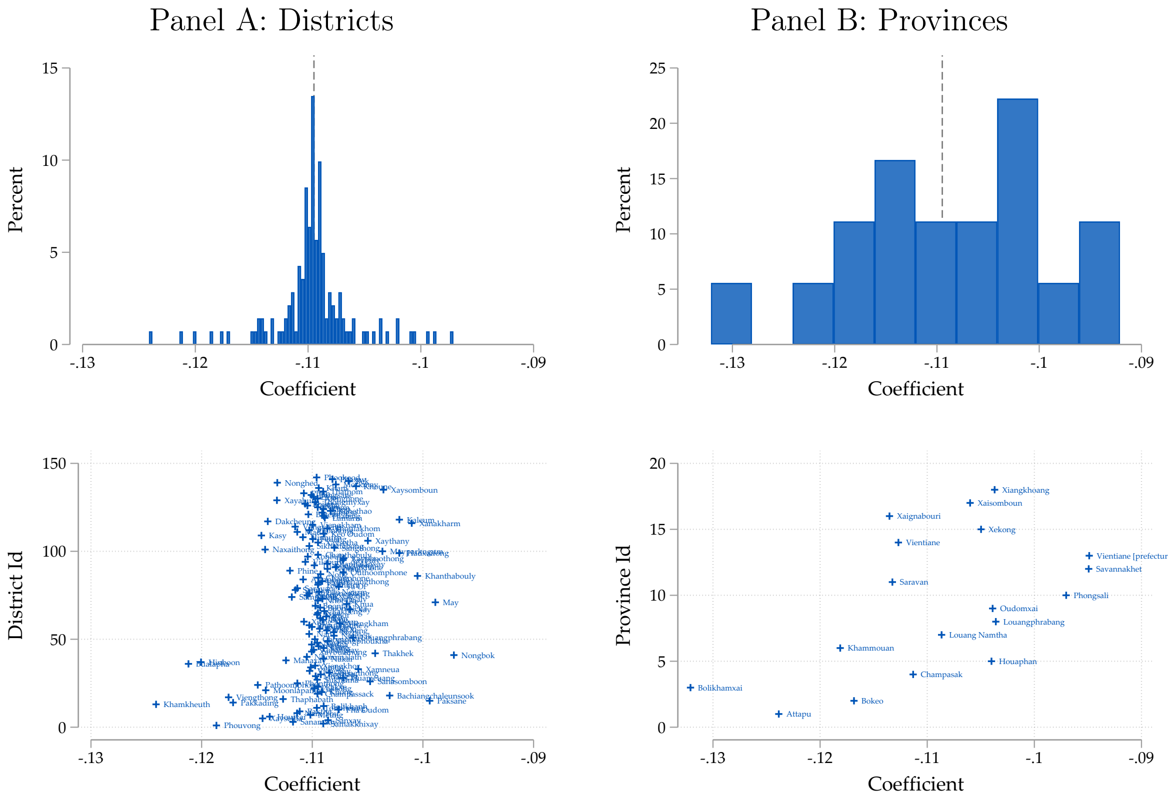


Panel B Distance to Closest US Air Base



Notes: This figure depicts the relationship between Bombs and the euclidean distance specified in each panel. Both panels are bin-scatters with overlapping quadratic fits of the underlying data.

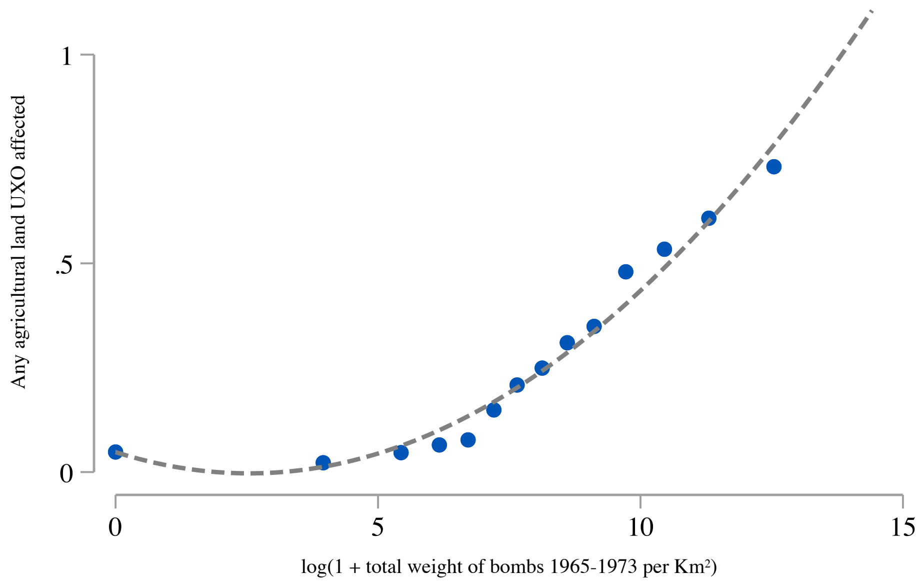
Figure A-8: *Distribution of Coefficients Dropping Districts and Provinces one at a time*



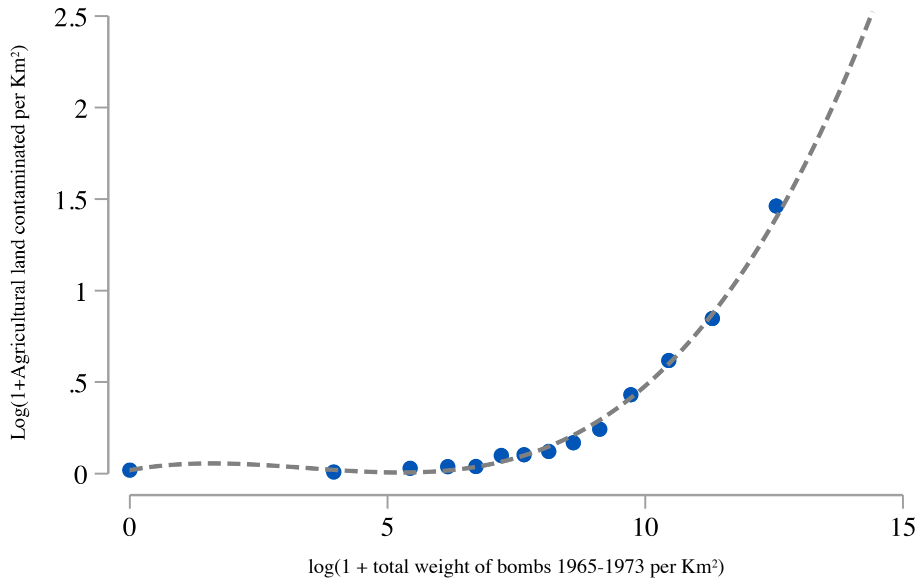
Notes: Distribution of the effect of Bombs on Luminosity when dropping one of the 141 districts (Panel A) and one of the 18 provinces (Panel B) at a time. The dashed line represents the IV estimate of the pooled sample.

Figure A-9: *Agricultural Census 2011: Intensive and Extensive Margin of UXO Contamination*

Panel A: Bin-scatter and linear fit Bombs and presence of UXO contamination



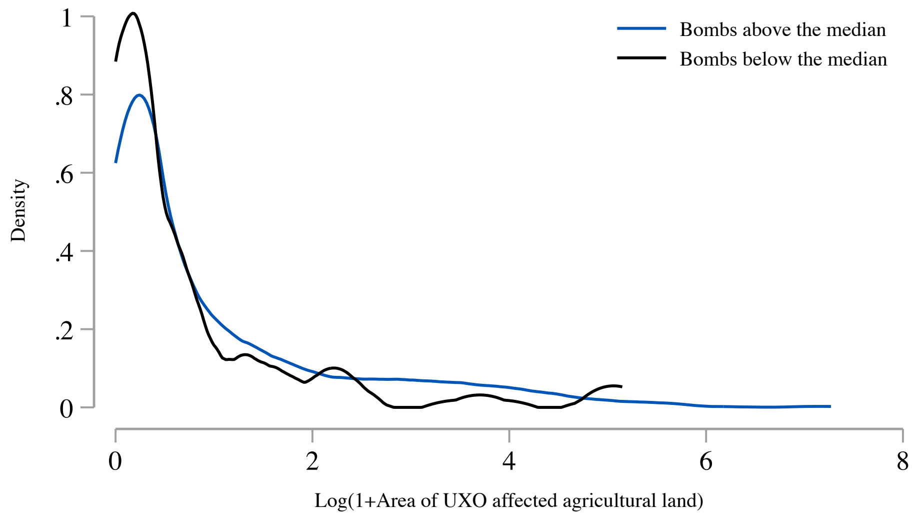
Panel B: Bin-scatter and linear fit Bombs and intensity of UXO contamination



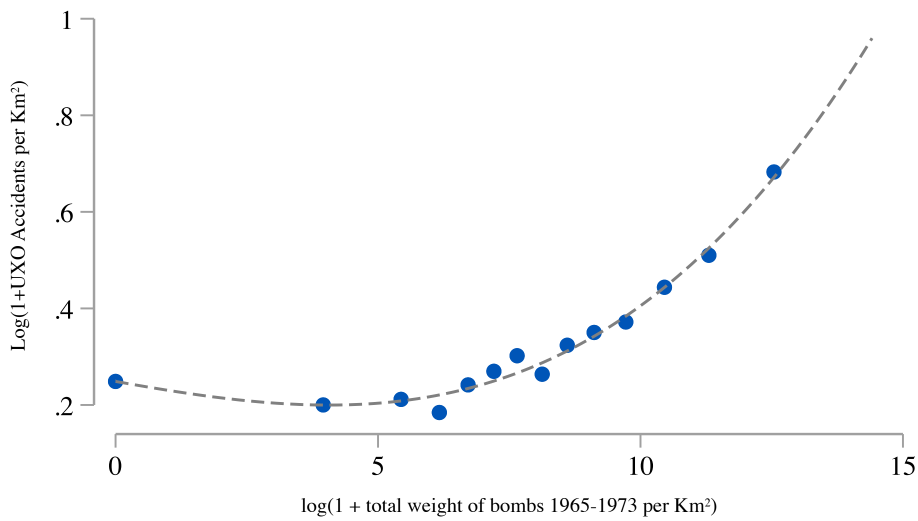
Notes: This figure presents the relationship between the intensive and the extensive margin of UXO contamination and the intensity of bombing. Both panels show bin-scatters with polynomial fits at the village level.

Figure A-10: *Contamination of Agricultural Land UXO Victims, and Bombing Intensity*

Panel A: Contamination of Agricultural Land



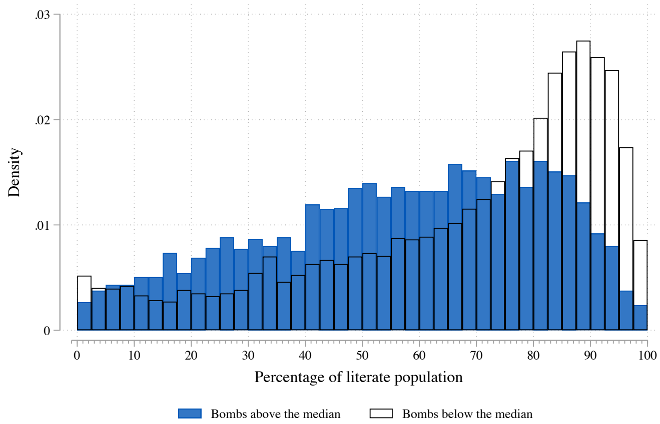
Panel B: UXO accidents and Bombing Intensity



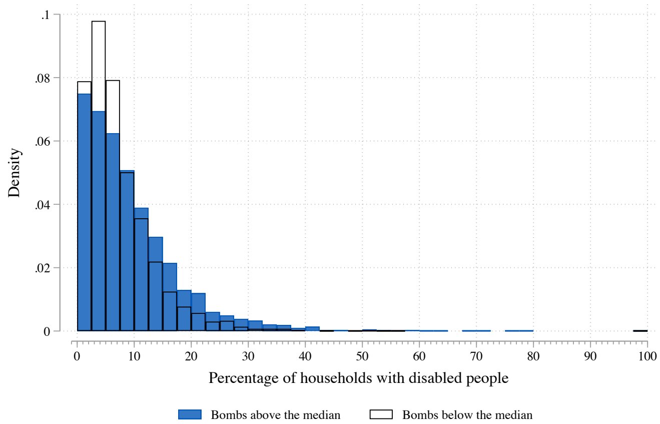
Notes: Panel A presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance from 1950 to 2010) and bombing intensity from 1964 to 1973. It uses panel data on UXO accidents and data on the bombing at the village level. Panel B presents the distribution of the agricultural land in the villages contaminated by UXOs above and below the median of bombing intensity.

Figure A-11: *Mechanisms of Transmission: Distributional Comparisons*

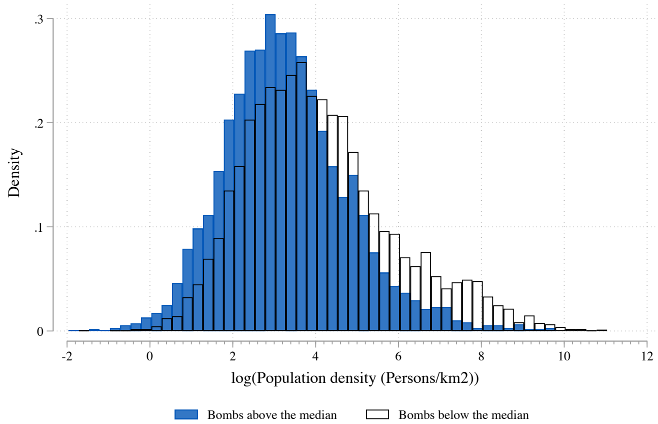
Panel A: Literacy



Panel B: Disability

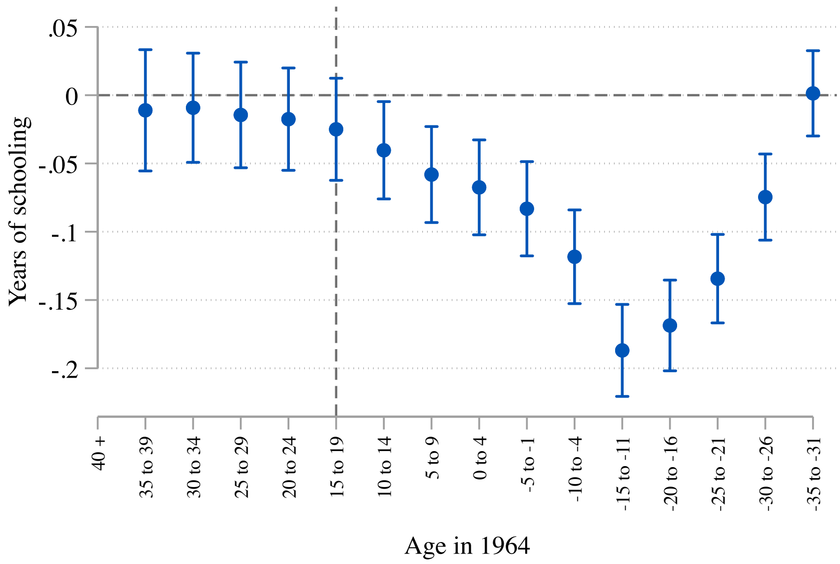


Panel C: Population Density



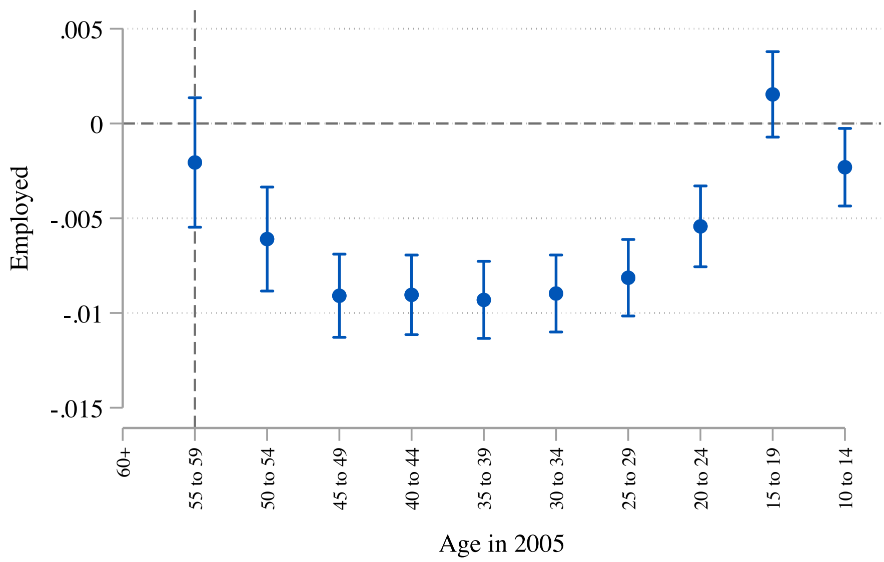
Notes: This figure presents the empirical distribution of the variables specified in each panel by the level of bombing intensity (above or below the median of bombs).

Figure A-12: *Impact of Bombing on Years of Schooling, using Micro-level Data from the Population Census of 2005 (Quinquennial)*



Notes: Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is years of schooling. The excluded cohort is composed by individuals with 40 years or more in 1964. The 15 to 19 years old cohort is marked with a vertical dashed line as reference point.

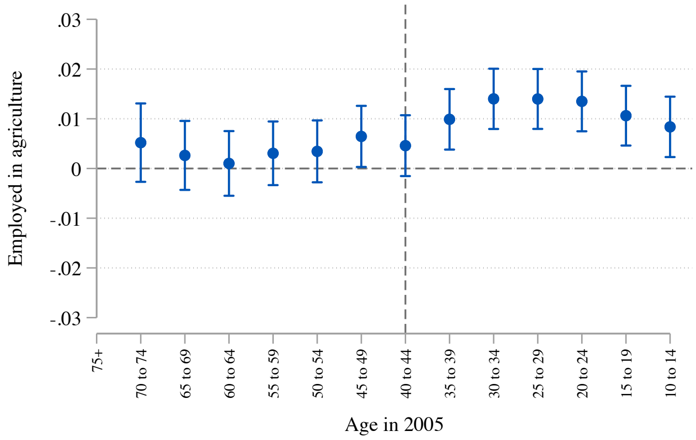
Figure A-13: *Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005 (Quinquennial)*



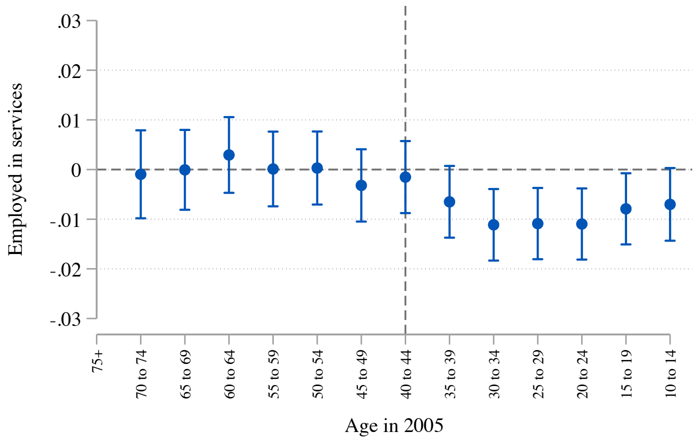
Notes: Figure reports point estimates and 95% confidence intervals of γ_k, from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors specified in the panels. The excluded cohort is composed by individuals older than 60 in 2005.

Figure A-14: *Impact of Bombing on the Probability of Working in Different Sectors, using Micro-level Data from the Population Census of 2005 (Quinquennial)*

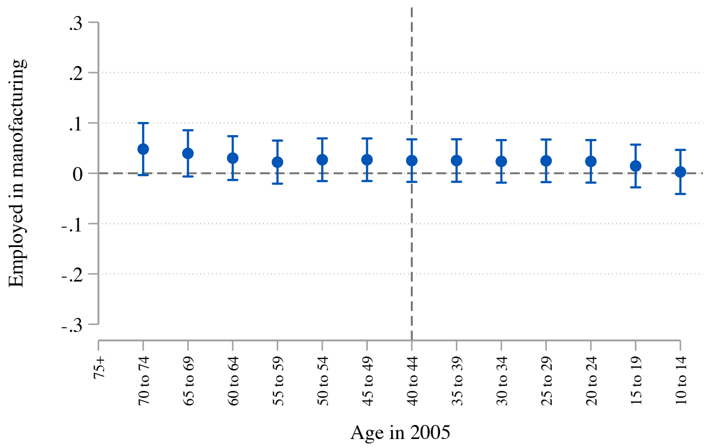
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services

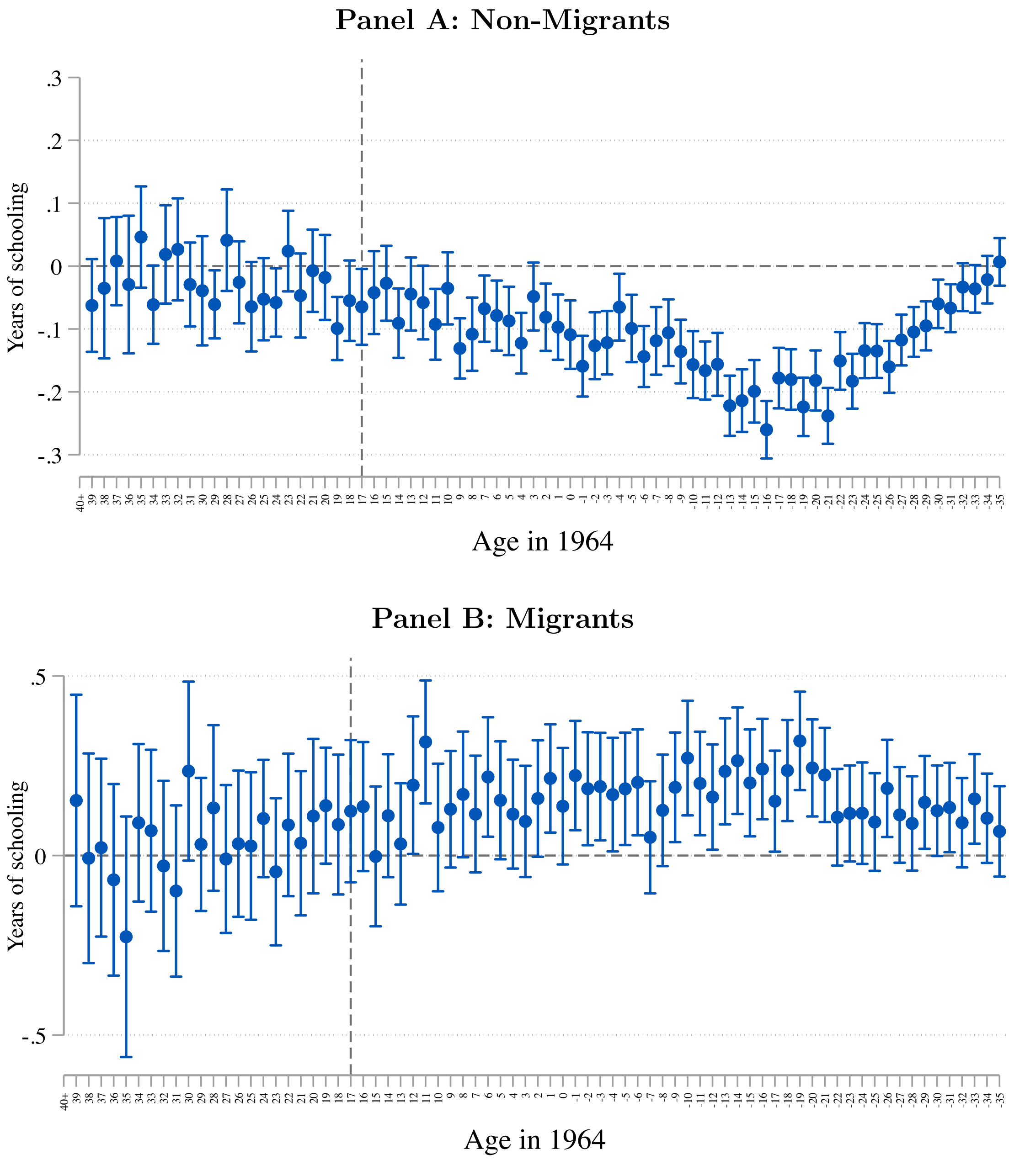


Panel C: Probability of Working in Manufacturing



Notes: Panel A, B, and C report point estimates and 95% confidence intervals γ_k from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors listed in the panels. The excluded cohort is composed of individuals with 75 years or more in 2005.

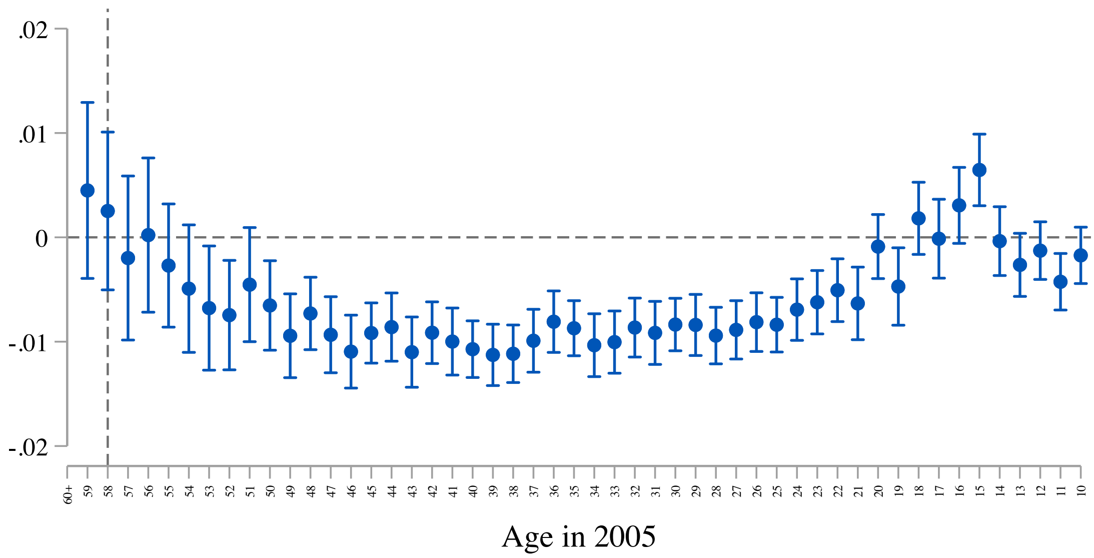
Figure A-15: *Impact of Bombing on Years of Schooling by Migration Status*



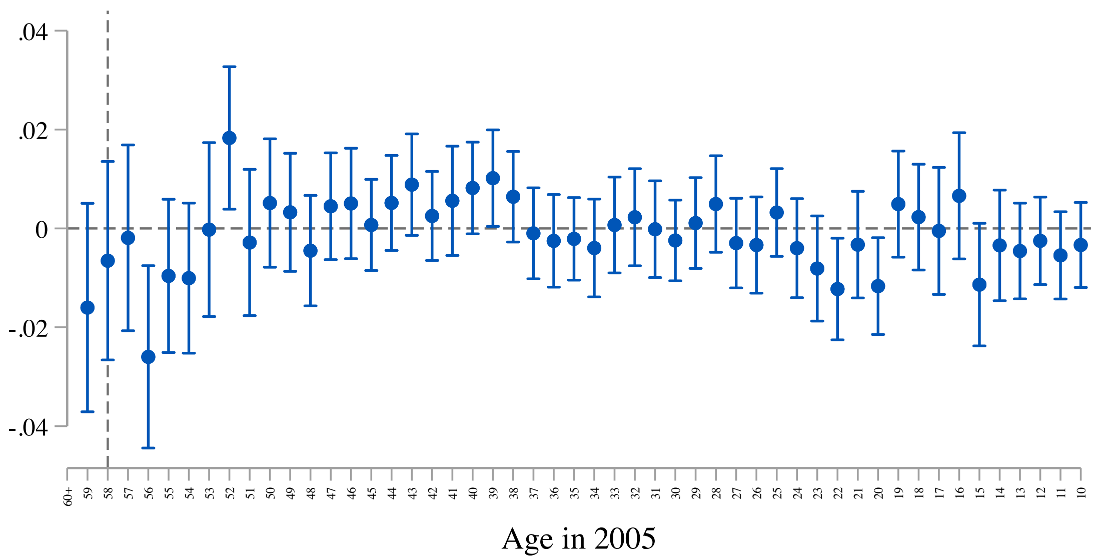
Notes: Panel A and B report the coefficients η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is years of schooling. The excluded cohort is composed by individuals with 40 years or more in 1964. The 17 years old cohort is marked with a vertical line as a reference point.

Figure A-16: *Impact of Bombing on the Probability of Being Employed by Migration Status*

Panel A: Non-Migrants

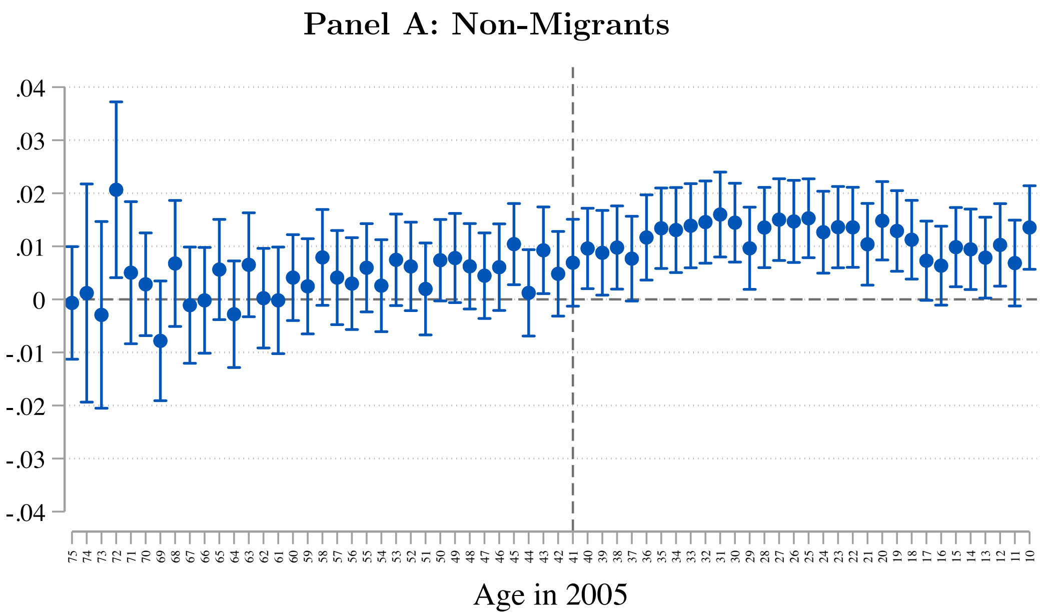


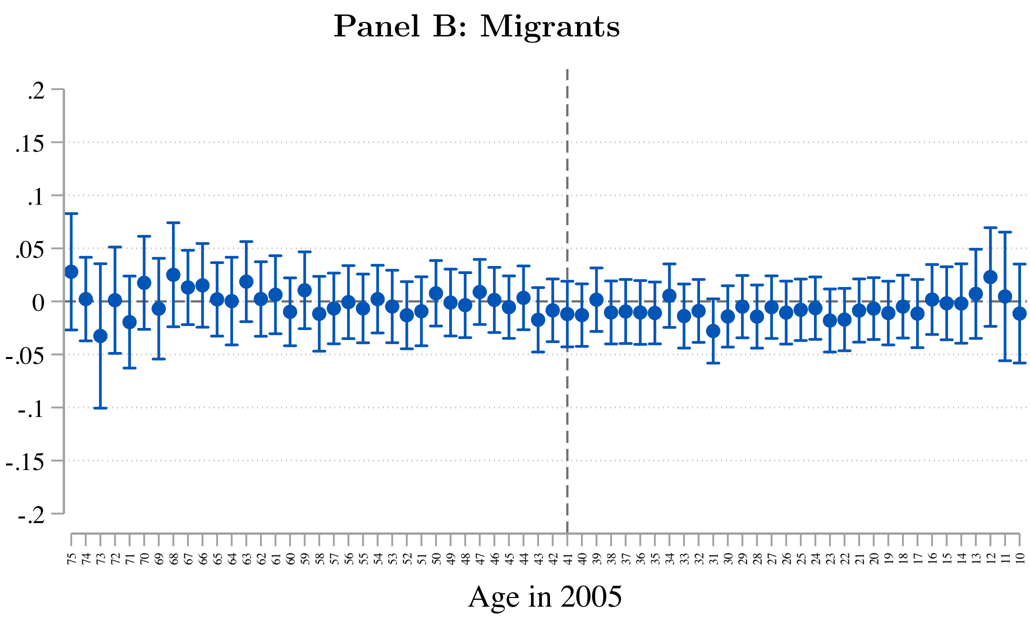
Panel B: Migrants



Notes: Panel A and Panel B report point estimates and 95% confidence intervals corresponding to η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed. The excluded cohort is composed by individuals with 60 years or more in 2005. The 41 years old cohort is marked with a vertical line as a reference point since those are the individuals who were born in 1964.

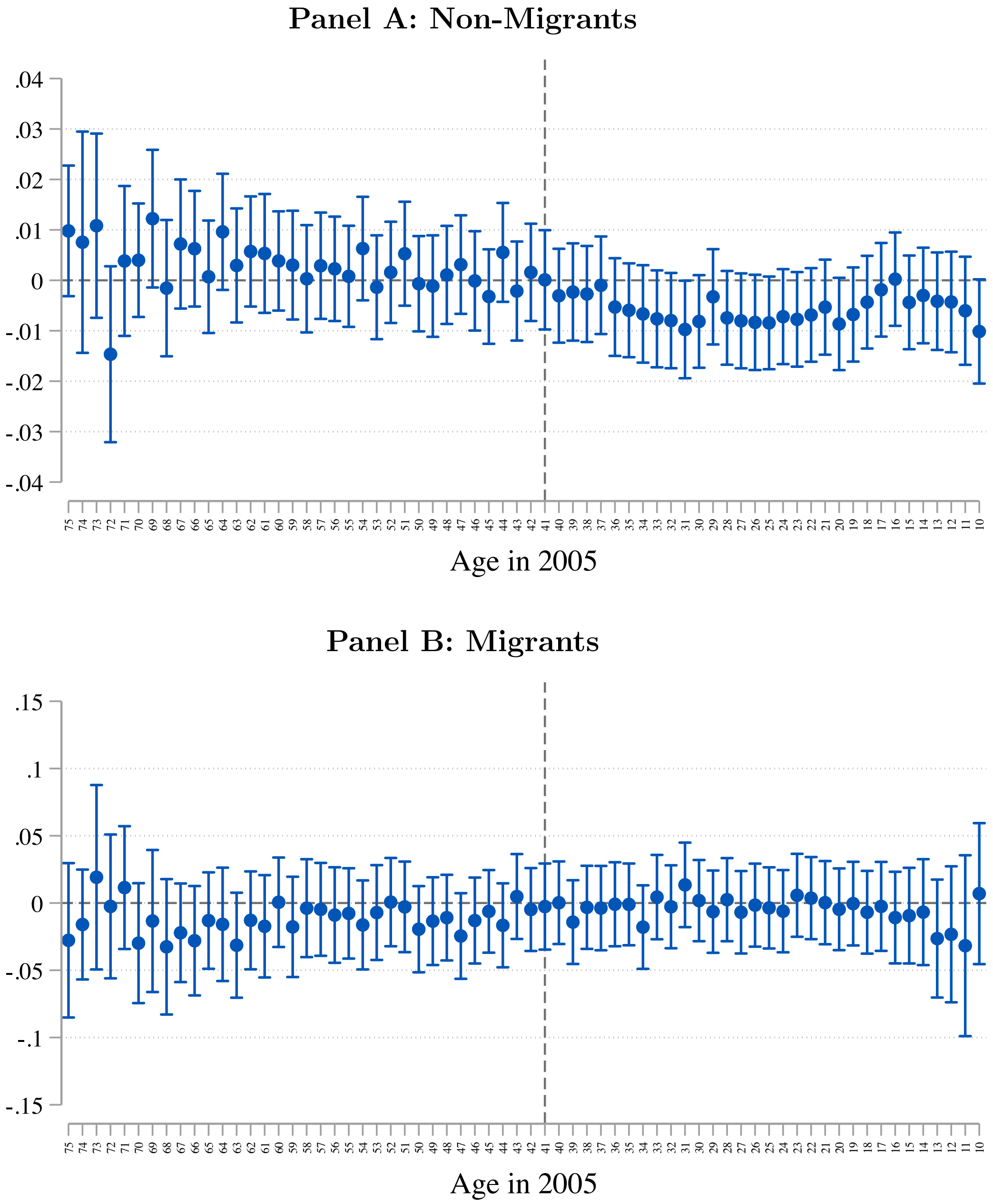
Figure A-17: *Impact of Bombing on the Probability of Working in Agriculture by Migration Status (yearly)*





Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in agriculture in 2005. The excluded cohort is composed by individuals with 76 years or more in 2005. The 41 years old cohort marked with a vertical line as reference point since those are the individuals who were born in 1964.

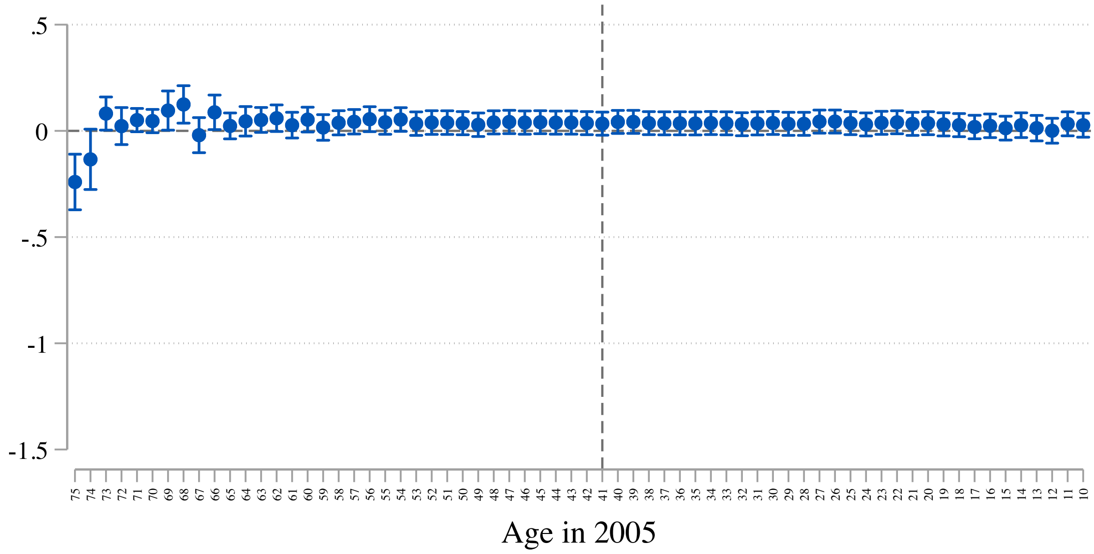
Figure A-18: *Impact of Bombing on the Probability of Working in Services by Migration Status*



Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in services in 2005. The excluded cohort is composed by individuals with 76 years or more in 2005. The 41 years old cohort is marked with a vertical line as a reference point since those are the individuals who were born in 1964.

Figure A-19: *Impact of Bombing on the Probability of Working in Manufacturing by Migration Status*

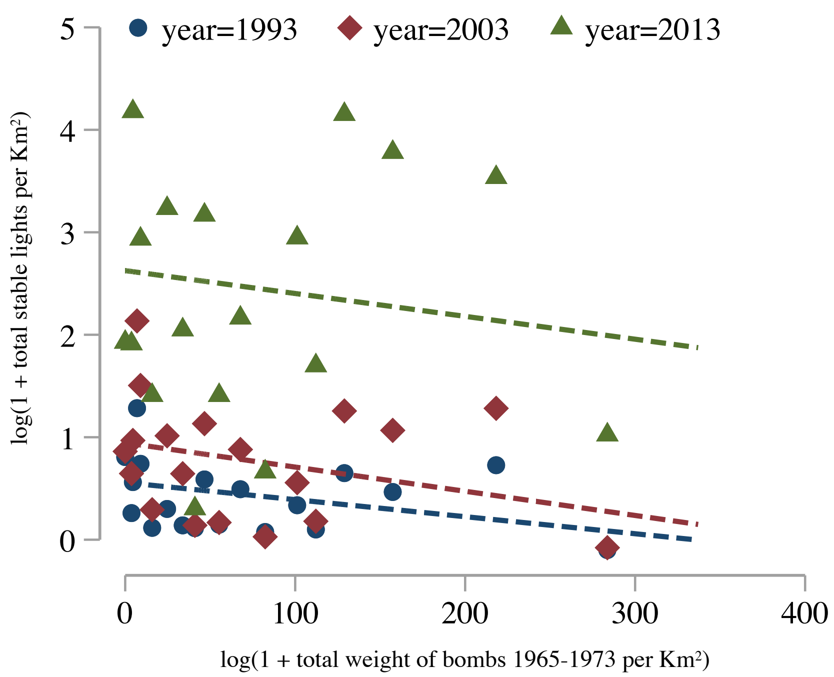
Panel A: Non-Migrants



Panel B: Migrants

Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in manufacturing in 2005. The excluded cohort is composed by individuals with 76 years or more in 2005. The 41 years old cohort marked with a vertical line as reference point since those are the individuals who were born in 1964.

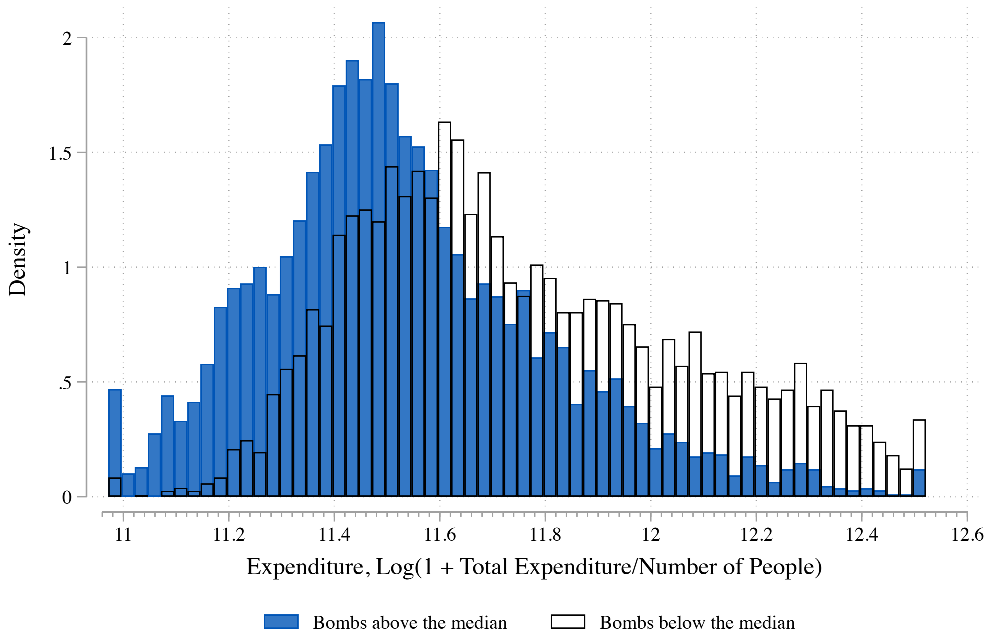
Figure A-20: *Luminosity & Bombs: Bin-scatters at the District Level by Year*



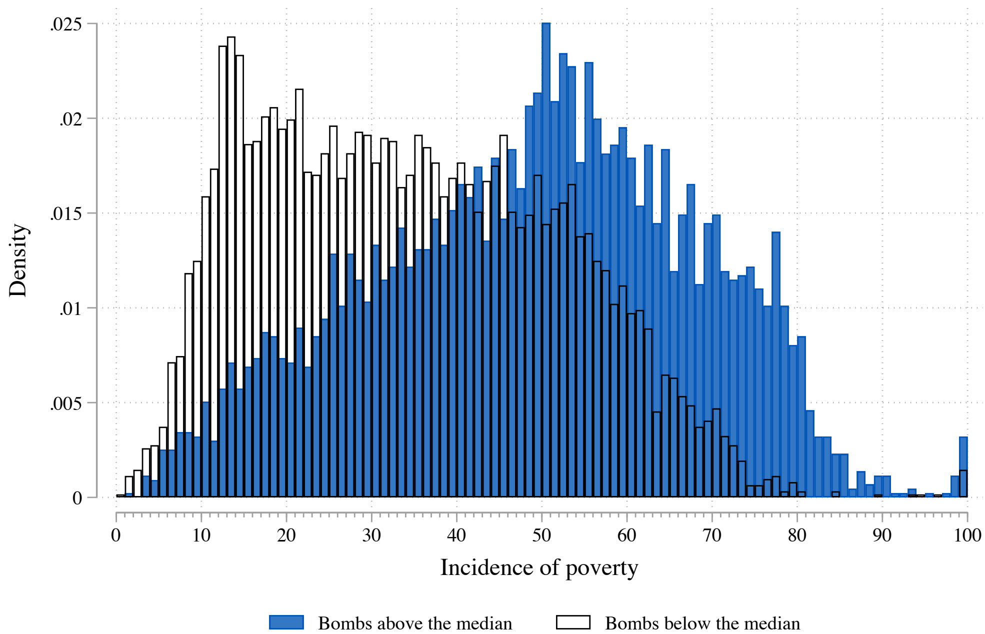
Notes: Figure presents the linear relationship between luminosity and bombing intensity. Observations are at the district level. To approximate the main specification in Miguel and Roland (2011) all bin-scatters control for district area, province fixed effects, average rainfall, average temperature, latitude of the district centroid and absolute distance to the Demilitarised Zone (DMZ or 17th parallel)

Figure A-21: *Comparing Distributions for Development Outcomes*

Panel A: Expenditure per capita



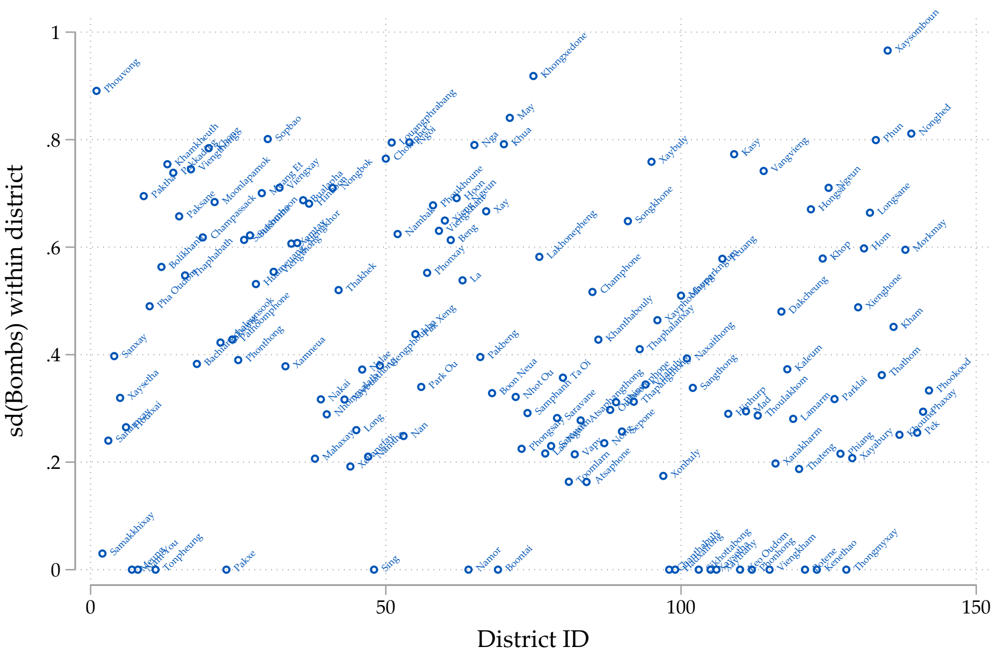
Panel B: Poverty Incidence



Notes: This figure presents the empirical distribution of the variables specified in each panel by the level of bombing intensity (above or below the median of bombs and UXO accidents at the village level).

Figure A-22: *Within-district and Within-province variation in bombing intensity*

Panel A: Within variation for each district



Panel B: Within variation for each province

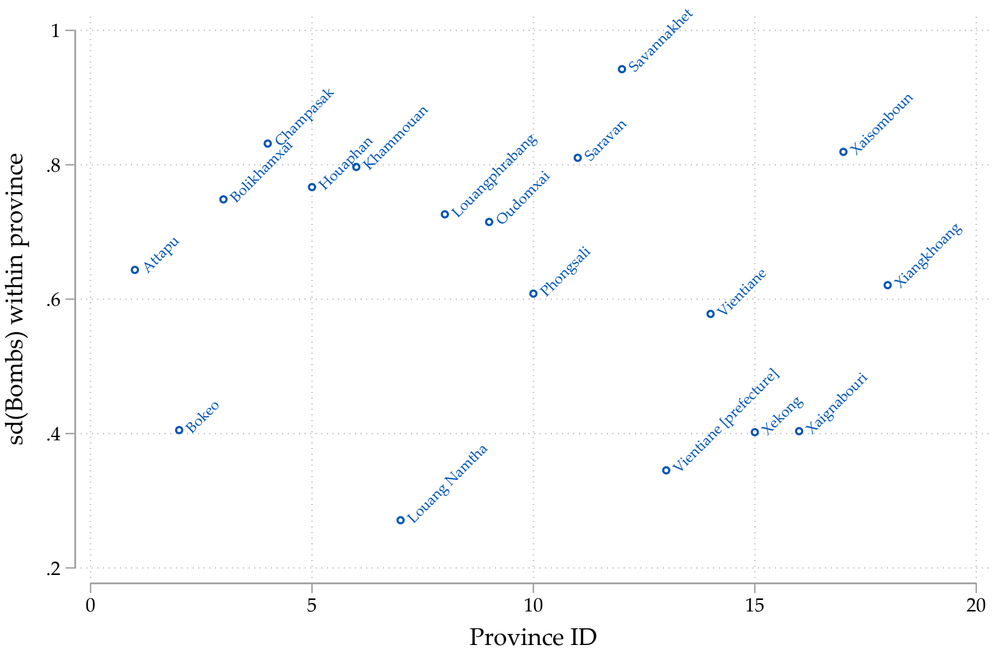


Table A-1: *Descriptive Statistics*

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: Grid cell level data				
Luminosity 1993 (log(1 + Total stable lights in 1993 per Km2))	0.0281	0.212	0	3.593
Luminosity 2003 (log(1 + Total stable lights in 2003 per Km2))	0.0497	0.275	0	3.881
Luminosity 2013 (log(1 + Total stable lights in 2013 per Km2))	0.157	0.523	0	4.328
Luminosity Growth 1993-2003	0.0216	0.122	-0.421	1.551
Luminosity Growth 2003-2013	0.108	0.338	-0.860	2.979
Luminosity Growth 1993-2013	0.129	0.407	-0.421	3.445
Visible Luminosity 1993 (log(1 + Total visible lights in 1993 per Km2))	1.491	0.122	1.228	3.593
Visible Luminosity 2003 (log(1 + Total visible lights in 2003 per Km2))	1.272	0.135	1.199	3.881
Visible Luminosity 2013 (log(1 + Total visible lights in 2013 per Km2))	1.803	0.227	1.530	4.328
Bombs (log(1 + Total pounds of bombs jettisoned from 1965 to 1973 per Km2))	4.426	3.976	0	13.76
Number of UXO accidents	21.74	47.66	0	907
Panel B: Micro level data				
Migrant	0.114	0.318	0	1
Years of Schooling	4.319	3.927	0	13
Employed	0.663	0.473	0	1
Sector of employment reported	0.645	0.479	0	1
- Agriculture	0.815	0.388	0	1
- Manufacturing	0.0563	0.230	0	1
- Services	0.128	0.335	0	1
Panel C: Village level data				
Log(1+Area of UXO affected agricultural land)	0.152	0.612	0	7.269
Land is contaminated by UXO	0.156	0.363	0	1
Log(1+total expenditures/population)	11.66	0.354	8.500	20.86
Fraction of households in poverty	0.406	0.195	0.00770	1
Fraction of literate households	0.631	0.257	0	1
Fraction of households with disabled people	0.0792	0.0730	0	1
Log(inhabitants/Km^2)	3.757	1.724	-1.966	10.88
Village has electricity access	0.353	0.478	0	1
Village has with water supply access	0.0641	0.245	0	1
Village has a primary school	0.802	0.399	0	1

Notes: Grid cell level data refers to a synthetic grid cell of $0.1° \times 0.1°$ covering Laos.

Table A-2: *OLS Results: Different Transformations of the Dependent Variable*

	(1)	(2)	(3)
Panel A: Dependent Variable		$\log(1 + Lights/Km2)$	
Bombs	-0.050***	-0.044***	-0.020**
	(0.011)	(0.011)	(0.009)
R-squared	0.172	0.241	0.417
Panel B: Dependent Variable		$\log\left(Lights/Km2 + \sqrt{(Lights/Km2)^2 + 1}\right)$	
Bombs	-0.065***	-0.058***	-0.026**
	(0.014)	(0.014)	(0.013)
R-squared	0.181	0.247	0.414
Panel C: Dependent Variable		$\log(0.0001 + Lights/Km2)$	
Bombs	-0.322***	-0.286***	-0.088
	(0.065)	(0.069)	(0.070)
R-squared	0.199	0.240	0.363
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
Districts Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Notes: Observations are at the grid cell × year level. Lights represent the total number of stable nightlights within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within the grid cell from 1965 to 1973 per square kilometre. Variable Bombs is standardised. Robust standard errors in parentheses clustered at the grid-cell level. *** p<0.01, ** p<0.05, * p<0.1

Table A-3: *Conley Standard Errors and Cluster Standard Errors: Pooled OLS of Luminosity on Bombs*

Dependent Variable	Luminosity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Cluster								
Threshold of influence	Grid Cell	District	Province	$\leq 100km$	$\leq 200km$	$\leq 300km$	$\leq 500km$	$\leq 1000km$	$\leq 1500km$
	−0.020**	−0.020*	−0.020**	−0.020*	−0.020**	−0.020**	−0.020***	−0.020***	−0.020***
	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.007)	(0.005)	(0.005)
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Districts Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Districts	141	141	141	141	141	141	141	141	141
Observations	6,648	6,648	6,648	6,648	6,648	6,648	6,648	6,648	6,648
R-squared	0.417	0.417	0.417	0.417	0.417	0.417	0.417	0.417	0.417

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Variable Bombs is standardised. Conley standard errors in parentheses for Columns 4 to 9 using the threshold reported in each column. Columns 1, 2 and 3 report cluster standard errors in parenthesis at the grid, district, and province level, respectively. *** p<0.01, ** p<0.05, * p<0.1

Table A-4: *Testing for Spillovers: A Spatial Auto-regressive Model*

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Luminosity 1993		Luminosity 2003		Luminosity 2013	
	Coeff β_0	Spillover λ_0	Coeff β_0	Spillover λ_0	Coeff β_0	Spillover λ_0
Panel A: Spatial autoregressive model						
Bombs	−0.044***	0.011	−0.057***	0.015	−0.113***	0.089***
	(0.009)	(0.012)	(0.011)	(0.015)	(0.021)	(0.028)
Geographical Controls		Yes		Yes		Yes
Location Controls		Yes		Yes		Yes
Observations		2,216		2,216		2,216
Moran's test p-value (H_0 : iid errors)		0.000		0.000		0.000
Panel B: Average Impacts						
Direct effect of Bombs		−0.0444		−0.0569		−0.113
		0.00754		0.0113		0.0207
Indirect effect of neighbours' Bombs		0.0102		0.0134		0.0820
		0.0110		0.00958		0.0175
Total effect of Bombs		−0.0342		−0.0435		−0.0309
		0.00893		0.0140		0.0256

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Variable Bombs is standardised. This table presents the estimates of a spatial auto-regressive model to understand potential spillover effects beyond first neighbours and in terms of unobserved shocks. To do so, we estimate the following model for the main equation and the error term:

$$y_i = \beta_0 \cdot Bombs_i + \lambda_0 \cdot \boldsymbol{W^n} Bombs_i + \boldsymbol{X'\beta} + \hat{U}_i$$
$$\hat{U}_i = \sigma_e \cdot \boldsymbol{W^n} U_i + V_i,\ V_i \sim N(0,1)$$

Where $\boldsymbol{W^n}$ is an adjacency $n \times n$ matrix between grid cells whose entries are equal to $1/distance_{i,j}$ and zeros in the diagonal. Here (i,j) represents all pairs of grid cells. In Panel A: *** p<0.01, ** p<0.05, * p<0.1. Due to output formatting limitations Panel B omits stars of statistical significance but coefficients can be interpreted as usual.

Table A-5: *Controlling for Population Density at the District Level in 1960*

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Luminosity					
Bombs	−0.032***	−0.045***	−0.052***	−0.027***	−0.017*
	(0.006)	(0.007)	(0.010)	(0.009)	(0.009)
Population Density in 1960	0.136***	0.124***	0.117***	0.117***	0.120***
	(0.016)	(0.018)	(0.017)	(0.017)	(0.013)
Geographical Controls		Yes		Yes	Yes
Location Controls			Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects					Yes
Observations	6,648	6,648	6,648	6,648	6,648
R-squared	0.171	0.196	0.216	0.250	0.319

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Variable Bombs and Population Density are standardised. Standard errors clustered at the grid-cell level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A-6: *Controlling for the Number of Roads in 1970*

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Luminosity					
Bombs	−0.051***	−0.054***	−0.088***	−0.064***	−0.058***
	(0.008)	(0.008)	(0.012)	(0.011)	(0.011)
Number of Roads circa 1970	0.065***	0.049***	0.061***	0.049***	0.049***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.009)
Geographical Controls		Yes		Yes	Yes
Location Controls			Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects					Yes
Number of Provinces			18		18
Observations	6,648	6,648	6,648	6,648	6,648
R-squared	0.064	0.113	0.157	0.187	0.256

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Variable Bombs and the Number of Roads are standardised. Standard errors clustered at the grid-cell level. *** p<0.01, ** p<0.05, * p<0.1

Table A-7: *Aggregating at the District Level and Excluding Observations in the Tails of the Distribution of Luminosity*

	(1)	(2)	(3)	(4)
	Luminosity	No Upper Tail Luminosity	No Lower Tail Luminosity	No Tails Luminosity
Panel A: Observations at the grid cell × year level				
Bombs	−0.049***	−0.024***	−0.194***	−0.112***
	(0.012)	(0.007)	(0.060)	(0.036)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	6,648	6,582	616	435
R-squared	0.182	0.097	0.236	0.111
Mean Dep Var	0.0783	0.0505	0.845	0.695
Panel B: Observations at the district × year level				
Bombs	−0.167***	−0.143***	−0.301***	−0.370**
	(0.050)	(0.045)	(0.093)	(0.141)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	423	418	198	110
R-squared	0.523	0.426	0.532	0.380
Mean Dep Var	0.230	0.189	0.492	0.660

Notes: Observations at the level indicated in each panel. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within the grid cell from 1965 to 1973 per square kilometre. Robust standard errors in parenthesis. Standard errors clustered at the grid-cell level in Panel A and at the district level in Panel B. Lower tail is defined by the lights below the 1st percentile. The lights above the 99th percentile determine the upper tail.

Table A-8: *Heterogeneous Results: Urban vs. Rural*

	(1)	(2)	(3)
Dependent variable: Luminosity			
	All	Urban	Rural
Bombs	−0.020**	0.008	−0.019***
	(0.009)	(0.055)	(0.007)
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	6,648	1,308	5,340
R-squared	0.417	0.568	0.272

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Variable Bombs is standardised. Standard Errors clustered at the grid-cell level. Rural grid cells are areas at 30km (or more) away from a population center.*** p<0.01, ** p<0.05, * p<0.1

Table A-9: *Instrumental Variables: First Stages*

Table A-9-A: *Instrument: Distance to the Ho Chi Minh Trail*

	(1)	(2)	(3)
Dependent Variable		Bombs	
Distance to Ho Chi Minh trail	-0.008***	-0.014***	-0.022***
	(0.001)	(0.004)	(0.003)
Distance to Ho Chi Minh trail^2	0.009***	0.022**	0.026***
	(0.001)	(0.009)	(0.007)
Altitude	1.571***	1.579***	1.709***
	(0.113)	(0.534)	(0.527)
Ruggedness	-0.027	-0.067	-0.037
	(0.021)	(0.052)	(0.030)
Temperature	1.698***	1.910***	2.096***
	(0.135)	(0.645)	(0.629)
Precipitation	-0.114***	0.057	-0.076
	(0.021)	(0.083)	(0.067)
Longitude	0.623***	0.637	0.189
	(0.118)	(0.607)	(0.905)
Latitude	0.803***	0.829	1.252*
	(0.117)	(0.492)	(0.732)
Distance to DMZ	-0.073**	-0.312**	-0.281
	(0.029)	(0.143)	(0.248)
Distance to Vietnam border	-0.158**	-0.308	-0.187
	(0.075)	(0.285)	(0.469)
Distance to Population centre	-0.060***	-0.022	-0.070
	(0.016)	(0.075)	(0.043)
Observations	2,216	2,216	2,216
R-squared	0.551	0.629	0.772
F	362.5	45.57	11.22
R-squared Adj	0.549	0.624	0.755
Number of Provinces		18	
Number of Districts			141

Table A-9-B: *Instrument: Distance to Closest Base*

	(1)	(2)	(3)
Dependent Variable		Bombs	
Distance to US air base	0.014***	0.014***	0.004
	(0.001)	(0.004)	(0.004)
Distance to US air base^2	-0.020***	-0.013**	-0.009
	(0.001)	(0.006)	(0.009)
Altitude	1.038***	1.546***	2.146***
	(0.112)	(0.523)	(0.590)
Ruggedness	-0.083***	-0.059	-0.048
	(0.021)	(0.052)	(0.037)
Temperature	1.179***	1.885***	2.679***
	(0.131)	(0.599)	(0.709)
Precipitation	0.079***	0.114	-0.027
	(0.023)	(0.069)	(0.086)
Longitude	0.080	0.420	0.139
	(0.117)	(0.699)	(0.764)
Latitude	-0.074	0.110	0.522
	(0.120)	(0.312)	(0.696)
Distance to DMZ	-0.538***	-0.831***	-0.560*
	(0.031)	(0.214)	(0.311)
Distance to Vietnam border	-0.780***	-0.591**	-0.845**
	(0.067)	(0.270)	(0.387)
Distance to Population centre	-0.110***	-0.032	-0.054
	(0.015)	(0.063)	(0.048)
Observations	2,216	2,216	2,216
R-squared	0.601	0.648	0.750
F	529.9	20.08	3.027
R-squared Adj	0.599	0.643	0.731
Number of Provinces		18	
Number of Districts			141

Notes: Observations at the grid-cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within the grid cell from 1965 to 1973 per square kilometre. Distance to the Ho Chi Minh Trail refers to euclidean distance but uses the parts of the trails that were not entirely known by the US authorities. Distance to the closest US airbase refers to euclidean distance but is computed using US airbases founded before 1960 and located outside Laos. Robust standard errors in parentheses, if Province or District Fixed Effects are present standard errors clustered at that level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-10: *Reduced Form Estimates: Pooled IV of Luminosity on Bombs*

Table A-10-A Distance to the Ho Chi Minh Trail	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	RF	RF	RF
Distance to Ho Chi Minh trail	0.002***	0.002***	0.002***
	(0.000)	(0.001)	(0.001)
Distance to Ho Chi Minh trail^2	−0.003***	−0.002**	−0.001
	(0.001)	(0.001)	(0.001)
Controls that apply for all panels			
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Table A-10-B Distance to the Closest US Air Base	(1)	(2)	(3)
Panel B: Dependent variable is luminosity, model:	RF	RF	RF
Distance to US air base	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.001)
Distance to US air base^2	0.002***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Controls that apply for all panels			
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within the grid cell from 1965 to 1973 per square kilometre. Distance to the Ho Chi Minh Trail refers to euclidian distance but uses the parts of the trails that were not entirely known by the US authorities. Distance to the closest US airbase refers to euclidean distance but is computed using US airbases founded before 1960 and located outside Laos. Robust standard errors in parentheses cluster at the grid-cell level. ***p<0.01, **p<0.05, *p<0.1

Table A-11: *Instrumental Variable Estimates (Yearly)*

Table A-11-A *Instrument: Distance to Ho Chi Minh Trail*

	(1)	(2)	(3)
Panel A: Dependent Variable Lights 1993			
Bombs	−0.128***	−0.092***	−0.056**
	(0.031)	(0.028)	(0.022)
Panel B: Dependent Variable Lights 2003			
Bombs	−0.169***	−0.134***	−0.081**
	(0.036)	(0.033)	(0.034)
Panel C: Dependent Variable Lights 2013			
Bombs	−0.199***	−0.171**	−0.179***
	(0.060)	(0.071)	(0.065)
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	2,216	2,216	2,216

Table A-11-B: *Instrument: Distance to Closest Base*

	(1)	(2)	(3)
Panel A: Dependent Variable Lights 1993			
Bombs	−0.114***	−0.096**	−0.227
	(0.025)	(0.041)	(0.221)
Panel B: Dependent Variable Lights 2003			
Bombs	−0.144***	−0.117**	−0.343
	(0.030)	(0.055)	(0.335)
Panel C: Dependent Variable Lights 2013			
Bombs	−0.178***	−0.169*	−0.994
	(0.046)	(0.092)	(0.889)
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	2,216	2,216	2,216

Notes: Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Robust standard errors in parentheses cluster at the grid-cell level, if Fixed Effects are present standard errors clustered at the level of the FE.

Table A-12: *Instrumental Variables Estimates: Pooled IV of Luminosity on Bombs, Combining both Instruments (Controlling for Road Access)*

Dependent variable: Luminosity			
	(1)	(2)	(3)
Panel A: Instruments are distance to the Ho Chi Minh Trail and distance to the closest air base, ***linear form***			
Model:	2SLS	2SLS	2SLS
Bombs	−0.185***	−0.152***	−0.173***
	(0.031)	(0.025)	(0.035)
Hansen J statistic (over-identification test of all instruments)			0.529
Chi-sq(1) p-value			0.467
Panel B: Instruments are distance to the Ho Chi Minh Trail and distance to the closest air base, ***linear plus quadratic terms***			
Model:	2SLS	2SLS	2SLS
Bombs	−0.189***	−0.166***	−0.128***
	(0.032)	(0.028)	(0.029)
Controls that apply for all panels			
Road Access in 1970	Yes	Yes	Yes
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects		Yes	
District Fixed Effects			Yes
Number of Provinces		18	
Number of Districts			141
Observations	6,648	6,648	6,648

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Distance to the Ho Chi Minh Trail refers to such euclidian distance but using the parts of the trails that were not entirely known by the US authorities. Distance to the closest US airbase refers to such euclidean distance but computed using US airbases founded before 1960 and located outside Laos. Variable Bombs is standardised. Robust standard errors in parentheses cluster at the grid-cell level. *** p<0.01, ** p<0.05, * p<0.1

Table A-13: *IV Heterogeneous Results: North vs. South*

	(1)	(2)
Dependent variable: Luminosity		
Sample of grids:	North	South
Panel A: Using both instruments		
Bombs	−0.085**	−0.114**
	(0.034)	(0.048)
Panel B: Distance to Ho Chi Minh Trail as Instrument		
Bombs	−0.084**	−0.172***
	(0.036)	(0.056)
Panel C: Distance to Closest Base as Instrument		
Bombs	−0.391**	−0.122
	(0.197)	(0.186)
Geographical Controls	Yes	Yes
Location Controls	Yes	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	4,812	1,836

Notes: Observations are at the grid cell × year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometre. Column 1 includes all the grids that are above the 17th parallel. Column 2 includes all the grids that are below the 17th parallel. Variable Bombs is standardised. Robust standard errors in parentheses clustered at the grid-cell level. *** p<0.01, ** p<0.05, * p<0.1

Table A-14: *Luminosity on Bombs and UXO Contamination (Village Level)*

Dependent variable:	Luminosity 1993		
	(1)	(2)	(3)
Bombs	-0.045***		-0.049***
	(0.004)		(0.005)
log(1+ agricultural area contaminated by UXO/Village area)		-0.013***	-0.001
		(0.003)	(0.003)
R-squared	0.380	0.398	0.401
Dependent variable:	**Luminosity 2003**		
	(1)	(2)	(3)
Bombs	-0.054***		-0.054***
	(0.006)		(0.007)
log(1+ agricultural area contaminated by UXO/Village area)		-0.006	0.007
		(0.008)	(0.008)
R-squared	0.392	0.414	0.416
Dependent variable:	**Luminosity 2013**		
	(1)	(2)	(3)
Bombs	-0.046***		-0.046***
	(0.010)		(0.012)
log(1+ agricultural area contaminated by UXO/Village area)		0.003	0.015
		(0.017)	(0.017)
R-squared	0.421	0.454	0.455
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,520	8,203	8,203

Notes: Observations are at the village level. Independent variables are standardised. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometre within each grid cell. Bombs is the log of one plus the total weight in pounds jettisoned within the village from 1965 to 1973 normalised by the village area. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A-15: *Agricultural Outcomes*

Panel A: Dependent variable:	Area potentially suitable for cultivation		
	(1)	(2)	(3)
Bombs	0.005		−0.052
	(0.035)		(0.036)
log(1+ agricultural area contaminated by UXO/Village area)		0.322***	0.335***
		(0.047)	(0.048)
R-squared	0.142	0.149	0.149
Panel B: Dependent variable:	Average farm size per household		
	(1)	(2)	(3)
Bombs	-0.196***		-0.220***
	(0.020)		(0.025)
log(1+ agricultural area contaminated by UXO/Village area)		-0.089***	-0.034
		(0.031)	(0.031)
R-squared	0.098	0.090	0.105
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,520	8,203	8,203

Notes: Observations are at the village level. Independent variables are standardised. Bombs is the log of one plus the total weight in pounds jettisoned within the village from 1965 to 1973 normalised by the village area. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A-16: *Disability*

Dependent variable:	Average number of people with disabilities		
	(1)	(2)	(3)
Bombs	1.878***		1.513***
	(0.466)		(0.554)
log(1+ agricultural area contaminated by UXO/Village area)		3.263***	2.886***
		(1.042)	(1.063)
R-squared	0.083	0.086	0.086
Dependent variable:	Fraction of households with disabled people		
	(1)	(2)	(3)
Bombs	0.002		0.001
	(0.001)		(0.001)
log(1+ agricultural area contaminated by UXO/Village area)		0.005***	0.005***
		(0.002)	(0.002)
R-squared	0.129	0.142	0.142
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,520	8,203	8,203

Notes: Observations are at the village level. Independent variables are standardised. Bombs is the log of one plus the total weight in pounds jettisoned within the village from 1965 to 1973 normalised by the village area. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A-17: *Roads*

Dependent variable:	Village has road access		
	(1)	(2)	(3)
Bombs	0.065***		0.060***
	(0.006)		(0.007)
log(1+ agricultural area contaminated by UXO/Village area)		0.023***	0.008
		(0.008)	(0.008)
R-squared	0.241	0.237	0.244
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	8,203	8,203

Notes: Observations are at the village level. Independent variables are standardised. Bombs is the log of one plus the total weight in pounds jettisoned within the village from 1965 to 1973 normalised by the village area. Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-18: *Structural Equation Model to Estimate the Direct and Indirect effects of Bombing on Economic Development*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Structural			Measurement of Latent Variables								
				Agricultural land UXO affected				Nightlights				
Dependent variable	Bombs	UXO Contamination	Economic Development	Extensive Margin	Intensive Margin	UXO Accidents	% with Disability	Luminosity in 1993	Luminosity in 2003	Luminosity in 2013	Expenditures per capita	% in Poverty
Bombs		0.164***	−0.054***									
		(0.005)	(0.007)									
UXO Contamination			−0.102***	1.000	1.289***	8.669***	0.044***					
			(0.019)	–	(0.054)	(1.246)	(0.004)					
Economic Development								1.000	1.293***	1.627***	0.303***	−0.119***
								–	(0.015)	(0.030)	(0.007)	(0.003)
Estimate coefficients for												
Geographical controls	Yes	Yes	Yes	–	–	–	–	–	–	–	–	–
Location controls	Yes	Yes	Yes	–	–	–	–	–	–	–	–	–
Intercept	0.022***	0	0	0.158***	0.154***	4.959***	0.080***	0.163***	0.241***	0.483***	11.675***	0.398***
	(0.008)	–	–	(0.003)	(0.006)	(0.143)	(0.001)	(0.006)	(0.007)	(0.010)	(0.004)	(0.002)

Notes: This Table presents the maximum likelihood estimation of a Structural Equation Model with latent variables. The latent variables in the model are UXO contamination and Economic Development. The model assumes all variables included follow a multivariate normal distribution with means and variances to be estimated. The model consists of twelve equations presented across columns, and it is summarised in Figure 8 and explained in Section 6.1.1. For details on identification, see Appendix A. Beyond the presented parameters, the model includes estimates for i) the mean of geographical and location controls, ii) the coefficients on geographical and location controls in columns 1,2 and 3, iii) The covariance matrix between controls, iv) The variances for the error terms. Observations are at the village level, including data for 8,203 villages. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.