Collateral Damage

*The Legacy of the secret war in Laos**

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Abstract: As part of its Cold War counterinsurgency operations in Southeast Asia, the US government conducted a "Secret War" in Laos from 1964-1973. This war constituted one of the most intense bombing campaigns in human history. As a result, Laos is now severely contaminated with UXO (Unexploded Ordnance) and remains one of the poorest countries in the world. In this paper, we document the negative long-term impact of conflict on Laotian economic development using highly disaggregated and newly available grid-cell data on bombing campaigns, satellite imagery, and development outcomes. We find that bombings have a negative, significant and economically meaningful impact on nighttime lights, expenditures and poverty rates. Almost 50 years after the conflict officially ended, bombed regions are poorer and growing at slower rates than unbombed areas. A one standard deviation increase in the total pounds of bombs dropped is associated with a 9.15% decrease in nightlights. To tackle the potential endogeneity of bombing, we use as instruments the distance to the Vietnamese Ho Chi Minh Trail as well as to US military airbases outside Laos established before the conflict started. Using census data at the village and individual levels, and exploiting the timing of conflict, we show the deleterious impact of bombing on human capital accumulation and structural transformation. We further show how UXOs impacted health and how bombings affected settlement patterns in the long term.

Keywords: Conflict, Laos, Persistence, Cold War, UXO, Development, Growth, Health, Human Capital, Structural Transformation, Migration

JEL Codes: D74, N10, N15, O10, O53

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"When buffalos fight, it is the grass that suffers."
- Laotian proverb[1]

1 Introduction

As we have seen recently, 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. Several 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. 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 scrutinize 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% survive 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 not explode. As a result, Laos is one of the most contaminated countries in the world in terms of UXOs (Unexploded Ordnances).[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]

[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.

[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, Lebanon, Iran, Iraq, Myanmar and Vietnam. 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).

Theoretically, Rohner, Thoenig, and Zilibotti (2013) and Acemoglu and Wolitzky (2014) have formally demonstrated how societies can enter vicious cycles of conflict. 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 and 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 standard 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 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 561,000 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 actual timing of conflict. We also have access to administrative data of geo-located UXO accidents from the National Regulatory Authority for Mine Action in Laos (NRA) covering *daily* incidents from 1950 to 2011.[6]

We conduct the empirical analysis in the following manner. First, we partition the country into (2,216) grid cells of 10km x 10km, 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.[7] Similarly, when aggregating the data for different years, we include time fixed effects, to take into account for potential trends during the different 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

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

Demilitarized Zone), distance to the Vietnam border and distance to the nearest district capital, to get closer to a causal estimate of the bombing effect. OLS results reveal a negative and significant relationship between conflict incidence (number of bombs dropped) 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 a 36% decrease in (total) nightlights with respect to their mean, an effect that corresponds to a 10.05% fall in GDP per capita.[8]

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 among the higher parts of the distribution, suggesting the former case.[9] To tackle the potential endogeneity issue, we employ an Instrumental Variables (IV) identification strategy. Our first instrument is the distance to the Vietnamese Ho Chi Minh Trail—mostly constituted by underground tunnels. Intuitively, we exploit the asymmetric information that is inherent in violent confrontations. Additionally, we use 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 posterior Laotian conflict, as detailed in Sections 2 and 4.3.

Our IV estimates confirm the baseline OLS and FEs 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 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 (standardized) coefficient for bombs of -0.0915, which now has a more causal interpretation. We also test for potential spatial spillovers, but find little evidence for them (cf. Chiovelli, Michalopoulos, and Papaioannou (2018)).

The negative aftereffects of conflict appear to transcend the immediate effects of bombing, hampering key economic investments in the long term. Bombed areas have *lower* levels of human capital, in terms of literacy and health. We complement these aggregate findings with an analysis of the data at the *individual* level. To this end, we

[8]See Section 5.2, footnote 39, for details behind this estimate.

[9]Moreover, our baseline results are robust to controlling for pre-conflict population density in 1960 as in Table A-5.

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, received significantly *less* years of schooling (a fall of 5% with respect to the mean) with respect to those old enough to have been completed their school years. In modern times, now that these affected individuals have entered the labor 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.[10] Hence, war remnants appear to have negatively affected human capital accumulation and retarded the broader structural transformation of the Laotian economy. Lastly, we study the interaction with migration. We find that bombings decreased the rates of internal migration by around 10%. Taken together, these rural-urban migration patterns help explain the negative long-run development consequences of the Laotian war.

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 number of bombs received. We find that in the former people have lower expenditures, worse health, and higher poverty rates, while these areas are less densely populated, meaning that the nightlights results translate into relevant development outcomes. We also 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 with respect to other countries still grappling with the legacies of violence. In particular, we compare the case of Laos with its Cambodian and Vietnamese neighbors (Miguel & Roland, 2011; Dell & Querubin, 2018; Lin, 2020).[11] The findings for structural transformation are in line with those for Cambodian rural areas, as in 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 due 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,

[10] We observe no significant effect on manufacturing.

[11] 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.

as in Mozambique (Chiovelli et al., 2018).

We contribute threefold to the conflict literature summarized 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 consequences 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. Moreover, 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 during wars, 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 major 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, was *not* part of the analysis in Miguel and Roland (2011).[12] 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 on anti-American sentiment.[14] Lin (2020) looks at the problem of UXOs in Cambodia, which shares a border with Laos, finding that agricultural land has become less productive due to UXOs. We find empirical support for some of these findings and provide novel identification strategies and mechanisms of transmission.

We also build on the literature on historical conflict. Fontana, Nannicini, and Tabellini (2018) 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. 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 (2020) document the demographic impact of the Triple Alliance War (1864-1870) in South America. Fergusson, Ibáñez, and Riaño (2020) further 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 the Laotian case as well. Here, we add to the modern literature on the impact of bombing (Redding & Sturm, 2016; Dericks & Koster, 2018; Adena, Enikolopov, Petrova, & Voth, 2020; Harada, Ito, & Smith, 2020) with a major Cold War bombing campaign. More broadly, this article is also related to the large literature on long-term economic persistence, recently summarized by Nunn (2020). Here we focus on conflict as a source of economic persistence, leading to underdevelopment.

To recap, conceptually, the impact of conflict on long-term 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

[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)." We discuss other differences with respect to this article in Section 7.

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

[14]We do not have for Laos disaggregated data allowing us to test such institutional mechanisms.

psychological well-being brought by war. However, countries can recover economically fairly quickly, as has been noted in the mostly urban scenarios during postwar Britain, Japan and Germany (Vonyó, 2018). This recovery would be consistent with models of unconditional or conditional convergence, 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 hampers key human capital investments, even after the ceasefire. The presence of such artifacts can alter structural transformation, urbanization and migration patterns, even in the long run, generating a "Conflict Trap." Perhaps the most important paper on this concept shows a causal relationship between negative income shocks and increased conflict (Miguel et al., 2004). However, the opposite direction, from conflict to poverty, remains largely unexplored. 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 a lack of investments in demining and other productive activities, as we compare the Laotian case with that of neighboring Cambodia and Vietnam.

The rest of the paper is organized 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.

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)). It pitted the Communist Pathet Lao against the Royal Lao Government. The country was of key geostrategic interest, given the neighboring civil war in Cambodia (1967-1975) and the Vietnam War (1955-1975), in what is known as the Second Indochina War.[16] Laos was essentially seen through the lens of President

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

[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 Campuchea,

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. Accordingly, the US intervened in Laos, as part of its anti-Communist counterinsurgency operations in the region, 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 ever visit the Southeast Asian nation. In this historic visit, Obama first acknowledged that, "as the fighting raged next door in Vietnam, your neighbors and foreign powers, including the United 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 part of China. A feeble coalition of political forces ruled the country until the North Vietnamese invaded northern Laos in 1959. As infighting continued, so did foreign involvement in the country by American, Thai and Vietnamese troops. In 1964, the US conducted its first reconnaissance aerial missions and on June 9 President Lyndon B. Johnson authorized 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.[17]

A series of covert military operations by the CIA and the US Air Division were carried out in Laos and Vietnam, including Operation Steel Tiger, Operation Tiger

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).

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

Hound, and Operation Commando Hunt. These series of operations actually gave rise to the military CIA (Kurlantzick, 2017). Aside from the northern Plain of Jars, the US heavily bombed southeast Laos, given its strategic proximity to the Vietnamese Ho Chi Minh Trail (see, Figure 3), which we use as an instrument. 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, about a third of which did not explode. More than 87,000 km^2 of land is contaminated with UXO 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 problem 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 13.3 million dollars were spent in bombing during the war every day.

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. Table A-1 presents the summary statistics for the key dependent and independent variables.

[18] There is even a black market for explosives, which exacerbate the problem. We thank QA Do for noting this.

[19] For more details see, https://reliefweb.int/sites/reliefweb.int/files/resources/blindgaenger-problem-volksrepublik-laos_EN.pdf

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 10km-by-10km. In Figure A-1, we present the synthetic grid and the principal administrative divisions of the country, consisting of 18 provinces and 141 districts. 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, described next.

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. 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, respectively. To make the interpretation of our coefficients easier, we focus on stable lights only,[20] and use a conventional logarithmic transformation of one plus the sum of light intensity divided by the area of the grid cell in square kilometers. We refer to this measure as lights or luminosity interchangeably, following recent convention (Chiovelli et al. (2018)).

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. 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 type 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 kilometer at the grid cell level.

[20] As opposed to total lights, the measure of stable lights excludes ephemeral events, such as fires and water reflections.

Geographic and Location Controls To account for potential geographic confounders, we use geophysical, and weather information from DIVA-GIS and WorldClim spatial data. We aggregate information on average altitude, temperature, and precipitation within each grid cell. We also use the standard deviation of elevation as a measure of ruggedness. To control for spatial confounders of conflict and additional spatial determinants of economic activity, we use the latitude and longitude of each grid cell as supplementary controls. Moreover, we include the Euclidean distance to the closest portion of the Vietnam border as well as the distance from the cell to the nearest district capital. Finally, we also include the distance to the 17^{th} parallel (the Vietnamese Demilitarized 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. These are the two most recent censuses digitized and available, giving us a more granular picture of the whole country. All of the information comes from the Lao DECIDE info platform, an initiative of the Laotian Government to improve access to official data.[21] Panel A of Figure A-2 presents the geographical distribution of the 10,522 villages reported in 2005. This represents an even more disaggregated level than the grid cells described before. We employ information on UXO contamination, human capital levels, development outcomes, urbanization, 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.[22] To bypass this constraint, we constructed a synthetic set of village boundaries based on Thiessen / Voronoi polygons.[23] Panels B and C of Figure A-2 shows 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

[21] 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.

[22] 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."

[23] We use this method based on the coordinates reported in each census (and control for area). This method allocates space to the nearest point feature in a set of points. It 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. For a recent application in the literature see Depetris-Chauvin and Özak (2020).

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 for Laos.

Health, Human Capital and Urbanization 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 disabled people 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 kilometers.

Development Outcomes We complement our analysis of nightlight 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 Finally, 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 used two datasets to perform the analysis. The first is the 10% sample of the microlevel data of the 2005 Census. This sample includes around 561,000 individual observations and comes from the IPUMS project for Laos. 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 our empirical 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. This map also includes the type of aircraft deployed from each of these bases by the

Pacific Air Forces (PACAF) in 1965.[24] This information helps us to recover the effective fly paths taken during the bombing campaigns and the type of aircraft most likely to be used in each campaign. Additionally, we digitized a map of the "hidden" parts of the Ho Chi Minh Trail, consisting of a complex set of underground paths, nowadays exhibited in the Highway 9 War Museum in Laos.[25] We present the original maps in Appendix Figure A-3 and a 1970 transportation network one in A-4.

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, estimate equations of the form,

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

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 1964-1973$_{g,d}$ is the total weight in pounds jettisoned within grid cell g in district d from 1965 to 1973 per square kilometer, while Luminosity$_{g,d,t=\tau}$ represents the log of one plus the total number of stable lights per square kilometer within the same grid cell g.[26] 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 the grid cell level, as described in Section 3.1, which include average altitude, temperature, precipitation, ruggedness, latitude, longitude, distance to the closest portion of the Vietnam border, distance to the nearest district capital, and the distance to the 17th parallel (the Vietnamese Demilitarized Zone).[27] The parameter of interest in this model is γ_τ

[24] 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, González, Martínez, Munoz, and Prem (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.

[25] Officially "The Lao-Vietnam Legacy of Joined Victory Battle on the Road 9 Area Museum." The Ho Chi Minh Trail is known as the Truong Son Route by the Vietnamese. We thank Q.A. Do for this remark.

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

[27] 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.

and represents the conditional long-term correlation between historical conflict and economic activity at year τ. In this formulation, econometric identification just 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 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 allows us to exploit the within-district or within-province variation in the intensity of conflict. Relative to the OLS specification, this specification allows us to control for potentially omitted characteristics at the province or district level for which we did not have information before. Additionally, to account for the spatial correlation of these groups of observations we cluster our standard errors at the same level of the fixed effects.[28]

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

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

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 that are common to all grid cell units in a given year. This specification accounts not only for specific differences across the timing of the three cross sections (such as the use of different satellites or nation-wide economic policies), but also helps increase the statistical precision of our estimates of γ.

Our results are robust to different methods of inference accounting for alternative geographical interdependence of the error term. In Appendix Table A-3, we present the results for different distance thresholds as suggested by Conley (1999) and in Table A-4 we explicitly estimate potential spatial spillovers in the unobserved component of our regressions following L.-F. Lee and Yu (2010). This is a standard reference for spatial auto-regressive models in panel data and allows us to model this type of error structure directly. In both cases, our quantitative results are unchanged.

[28] Either 18 provinces or 144 districts.

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 hand, 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. 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,

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

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, as in Dieterle and Snell (2016), though we also report linear specifications. We propose two instruments described next: 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 combine both instruments in the IV 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 neighboring Vietnamese conflict. For instance, part of the trail corresponded to ancient Vietnamese footpaths. The idea here is that Laotian bombings due to the proximity of the HCMT constitute a collateral damage from the broader Indochinese confrontation. Importantly, we control for distance to Vietnam and its Demilitarized 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 more exogenous, and less related to other types of visible infrastructure, assuaging potential exclusion restriction concerns.[29] The intuition is to exploit the asymmetric information, inherent in conflict, in particular the part that was unknown to US soldiers at the time. We present an example of the original maps used in Appendix Figure A-3 and our digitization 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. Most of the bombing operations were carried out from these military and naval bases.[30] 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.[31] 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 et al. (2018)). Figure 3 is a stylized 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 dynamic. Namely, we employ individual-level data from the 2005 Census described in detail in Section 3.3. We exploit the differential impact of bombing intensity across provinces (of birth) for different cohorts. This allows us to bypass some of the potential remaining problems, even with

[29]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, materialized. 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 what known, but that the more specific location of the actual trail sometimes was not.

[30]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.

[31]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.

the IV estimates. In particular, we estimate the following econometric specification,

$$y_{ipk} = \delta_k + \lambda_p + \sum_k \gamma_k \left(\log(1 + \text{Bombs 1964-1973})_p \times d_{ipk}\right) + \mathbf{X_i'}\beta_i + \epsilon_{ipk} \qquad (4)$$

where, y_{ipk} represents educational attainment or labour market outcomes of individual i, who was born at province p and belongs to cohort k in 1964. Here we look at educational outcomes around the outset of the war, and labor 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 kilometer. 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 those 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.[32] We see this as an important and complementary way of identifying the effect of conflict.

5 Baseline Results

5.1 OLS Results

Before presenting any regression table, 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.[33] 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

[32]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) or too young to be affected, which is not the case. In the Appendix, we further calculate the triple interaction effect of the timing of conflict and migration, decomposing the human capital and labor effects between migrants and non-migrants. In particular we run:

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

where M_i is an indicator variable equal to one if individual i is a long-term migrant in 2005 and zero otherwise.

[33]We report the relationships for individual years and different specifications in Figure A-5.

robustness of this finding, estimating OLS, Fixed Effects, 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 in bombs decreases lights by -0.026. All of these estimates use lights measured in 1993, which is the closest to the end of the conflict. Only ruggedness enters negatively and significantly consistently, in terms of geographic controls, and temperature emerges positively in the full specifications. With respect to the location variables, the distances to the Demilitarized Zone, Vietnam and the closest provincial capital, 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, just marginally larger. The same holds true for lights in 2013, in Columns 7 to 9, where the coefficients emerge larger in magnitude, and are now on the order of 5%, 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.

We test for potential spillovers in Table A-4 following the model of L.-F. Lee and Yu (2010), a standard reference. In terms of spatial correlation, there seems to be none in 1993 and some for the later years.[34] Despite this, the coefficient of interest remains negative and significant after we correct for this and, if anything, is larger throughout, in the odd columns. We find no spillover effects except in 2013, where they appear significant but *positive* (cf. Chiovelli et al. (2018)). For robustness, we introduce two important controls and run additional specifications. The first one, is population at the district level in 1960, to take into account for potential pre-trends for this demographic variable. As can be seen in Table A-5, results are unaffected by this addition. We do not employ this control going forward, as we use district fixed effects in Section 5.2, which takes care of this and other potentially relevant variables at the district level. Additionally, we control for roads (see Figure A-4 for the 1970 infrastructure map). This is most probably a "bad control" in the language of Angrist and Pischke (2008). Still, our results are unaffected by this addition and, if anything, increase slightly in magnitude, as can be seen in Table A-6.[35] We also re-estimate our model dropping outliers in terms of luminosity: without upper, lower or both tails (reported in Table A-7, Panel A). Lastly, we show in Table A-8 that the effect is concentrated on rural areas,

[34]Which supports our later clustering at the fixed effect level.

[35]To complete this empirical exercise, we show the impact of our independent variable of interest, bombs, on the bad control, roads, in Table A-18, following Pei, Pischke, and Schwandt (2019).

and important heterogeneity, which we explore later in the mechanisms section.[36]

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. Overall, 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 most specifications. Overall, it does not seem that bombed areas are experiencing a growth boom, as has occurred in other commonly studied postwar scenarios. Some fundamental variables such as human capital investments and labor outcomes might have recovered, as we show in the mechanisms section, but we still do not observe convergence in growth rates, perhaps due to more permanent changes in settlement patterns, as we explore in the mechanisms section.

5.2 Fixed Effects Results

The next set of empirical results introduce province and district fixed effects, to control for time invariant characteristics at these levels of disaggregation. 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—beyond population—that are not available at this level of granularity. The first two columns repeat the full specifications from Table 1, for reference. As we can see in Table 3, Column 3, more bombs are associated with less lights in 1993, 2003 and 2013, after introducing province fixed effects. The negative magnitudes are similar to those reported previously, though the levels of significance fall slightly in some cases. The negative relationship remains strong after adding location controls in Column 4. The negative and significant bombing coefficients remain so when we add district fixed effects instead, in Column 5, and when we further control for location characteristics, in Column 6. The significantly negative results are present for the three years: 1993, 2003, and 2013 in Panels A, B and C, respectively, increasing slightly over time suggesting compounding effects and path dependence. Relative to the OLS estimates, the magnitudes decrease slightly, but are in the same ballpark as before. The fixed effect results indicate that the negative impact of bombing is also present at more local (within province and district) levels.

Figure A-5 illustrates the results just described, plotting the relationship between lights and bombs non-parametrically. The first row presents the results with controls and province fixed effects for 1993, 2003 and 2013. The negative relationship is clear

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

across the board, perhaps suggesting a non-linear fit. The second row presents the plots for the specification with controls and district fixed effects. Again, the relationship is strongly negative, and now appears linear.

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 standardized coefficient is -0.025, similar to the more basic fixed effects results, and even the OLS estimates presented before. We proceed to interpret the economic significance of this baseline estimate. To 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 10.05% fall in GDP per capita.[37] This 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 (labor) mobility in the mechanisms section. Though we present our IV estimates next, 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 Instrumental Variables Results

Though robust, the results in the previous sections might still be biased. They could be underestimates, since bombing was costly and presumably targeted key infrastructure, hampering development in the future.[38] On the contrary, the results could be biased upwards, if bombings targeted mostly poor and isolated places. To get a sense of the potential biases, we run quantile regressions, reported in 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 is suggestive of the first scenario. To correct for such potential biases, regardless of

[37]To reach this estimate, we compute the relative size of our coefficient with respect to the sample mean as $\frac{-0.0248}{0.0683}$, then we use Henderson et al. (2012) estimated elasticity of GDP to lights of 0.277, and calculate the corresponding GDP fall as $\frac{-0.0248}{0.0683} \times 0.277 = -0.1005$.

[38]We find some evidence for this case in Table A-18 with respect to roads.

their direction, we employ an Instrumental Variables strategy, as described in Section 5.3. Recall that we have two instruments: 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. Figure 3 depicts both of these instruments in a map, with Laos depicted in grid cells.

5.3.1 First Stage Results

Before running any regression, we plot the unconditional relationship between bombing and the two instruments, along with a quadratic fit. As can be seen in 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 appears that this relationship is potentially non-linear. Many of the observations appear less than 100 kilometers from the trail, suggesting the more localized nature of this first instrument. Figure A-7 Panel B, plots the relationship between bombs and distance to the nearest US base outside Laos. There appears to be a hump-shaped relationship between these two variables, with a maximum between 100 and 200 kilometers. To capture these non-linearities, we estimate Equation (3) using a quadratic first stage, allowing for heterogeneous effects, as in Dieterle and Snell (2016).[39]

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, first negatively and then positively so, once fixed effects are added. In all cases, the F-statistic is well above 10 (Stock, Yogo, et al., 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.[40]

5.3.2 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

[39] Yet we also report linear estimates, as suggested by referees.

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

magnitude increases in the last specification.[41]

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 specification, in Column 3, the standardized coefficient is -0.0915 which is very similar to the last coefficient for distance to the Ho Chi Minh Trail in Table 5. The Sargan over identification tests suggest that instruments are not correlated with the error term and therefore we can not reject the null hypothesis under which both instruments are valid. Because of the potential correlation between the Ho Chi Minh Trail and roads, we further control for road access in Table A-12, which leaves the results unchanged. Lastly, we run the IV regressions for the the South and the North of the country separately, in Table A-13 finding very similar, and only slightly larger, coefficients in the former case.[42] This partition confirms that the deleterious impact of bombing was generalized to the whole country.

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 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.[43] 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. A distribution of the IV estimates is depicted in Figure A-8 where we run the IV analysis, dropping one district at a time. We see there that the distribution is centered around -0.092. Overall, the IV estimates, despite their potential limitations, confirm the large negative effects of conflict for long-term development, something we explore further in the next section, where we also exploit the *timing* of conflict.

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

[42] 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 theater of war.

[43] 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 our R-squared of the first stage are all above 50% and F-stats are confidently above 10 (Stock et al., 2005). These also satisfy in 4 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 (2020).

5.4 Difference-in-Differences Results

5.4.1 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 the 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.

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. We observe no pre-trends with respect to this human capital variable, which is to say no significant impact of our dummy for cohorts which were too old to be affected where the conflict started (17 years and older in 1964). We observe the first, negative, effects for the cohort 0-4 years of age in 1964. The coefficient becomes increasingly negative and significant for the subsequent cohorts: 5 to 9 and 10 to 14 years, reaching a trough for the 15 to 19 and 10 to 19 year old categories, a few years after the war. The most affected cohorts receive 0.2 less years of schooling, or 5% with an average of four.[44] 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. Results are consistent if we use quinquennial, instead of yearly variation (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.[45] 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 conclude the human capital analysis by looking at literacy using the same 2005 census. We find that in areas that were bombed, literacy levels are *lower* than in areas that were not bombed, which is consistent with the years of schooling results above. This is evident in the distributions, split by median number of bombs, as well as in the corresponding regressions (Figure A-11, Panel A and and Table 8, Panel A). The coefficient remains negative and significant throughout. Overall, our educational

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

[45] 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.

results are in line with those for Guatemala, Peru and Colombia (Chamarbagwala & Morán, 2011; Leon, 2012; Fergusson et al., 2020; Prem et al., 2021).[46]

5.4.2 Sectoral Employment and Structural Transformation

To complement the individual-level analysis, we examine structural transformation.[47] Most recently, Porzio, Rossi, Santangelo, et al. (2020) relate human capital accumulation and structural transformation in a panel of countries. We start by looking at the probability of being employed in modern times, in Figure 6.[48] 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 lowest coefficients, roughly correspond to those generations with lower educational attainment in the previous set of results, 40 years later.

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. Recall that we had already shown that the effects are concentrated on rural areas (Table A-8). It appears now that people that 10 to 49 years of age are *more* likely to be employed in agriculture, during the last 12 months. The positive and significant estimates peak at 0.02. We find the opposite, corresponding pattern when we look at services in Figure 7, Panel B. It appears now that those aged from 10 to 49 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).[49] Combined, our results highlight human capital accumulation and structural transformation working in tandem as mechanisms of transmission of the war legacies.

In sum, we find 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 the affected cohorts in the labor market today essentially correspond to those that received less years of schooling

[46] Bautista, González, Martinez, Muñoz, and Prem (2020) report a similar dip for *tertiary* education in Chile under Pinochet.

[47] We thank Eli Berman for suggesting this important angle.

[48] Similar results using quinquennia instead of years are reported in Figure A-13.

[49] The results by sector also hold when using quinquennial, as opposed to yearly variation, Figure A-14.

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 processes. Our findings on structural transformation for Laos are also in line with those for historical conflict in Cambodia (Lin, 2020), Colombia (Fergusson et al., 2020) and Austria (Eder, 2016).

6 Mechanisms of Persistence

In this section we look at transmission channels of the main effect. To this end we use Census data from 2005 and 2011, at the village level.[50] We further employ high-frequency data on UXO accidents starting in 1950. With this information, we expand on the pernicious direct (health) and indirect development effects of UXO contamination (following Unruh, Heynen, and Hossler (2003)) in the next subsection. We then expand on population density, settlement patterns and and migration, as broader spatial mechanisms of transmission of the main effects in Section 6.2. Section 7 discusses the results and contrasts the Laotian case with the rest of the Indochina.

6.1 UXO Contamination and Health

We start by examining UXO contamination as a mechanism of transmission of the economic impact of bombing. We find first a very high (almost linear) correlation between bombing campaigns and agricultural land that has been contaminated by UXOs (Figure A-9, Panel A). These results at the extensive margin are also present at the intensive margin, in Panel B. The relationship is again very tight and almost linear. Using a median sample split, in Figure A-10 Panel A, we find that areas that are above the median in terms of bombings also have higher levels of of UXO contamination in agricultural land. In terms of agricultural outcomes, we observe in Table A-16 that UXO contamination is correlated with areas more suitable for cultivation, as in (Lin, 2020). However, as in Cambodia, farmers have not been able to exploit this available land, and report smaller farm sizes, in Panel B.

To further explore the UXO channel, we use a geo-located panel with *daily* data on UXO accidents from 1950 to 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

[50] This data is even more disaggregated than the pixel level data employed before. See Figure A-2 for an illustration.

Trail, one of our instruments. To exploit the time variation available in this data, we use linear fits by decade. The results are summarized in Figure 4. First we observe no relationship between UXO accidents during the 1950s and the total number of bombs dropped. This is reasonable, as bombing campaigns started in 1964, suggesting no pre-trends or the presence of other types of mines. The relationship between bombs and UXO accidents becomes positive and highly significant for 1960. This relationship decreases slightly, but is still apparent for the 1970s decade. It falls further for the 1980s decade and again for the 1990s and 2000s. Still, even at these lower levels, the positive association is evident: UXO accidents are concentrated in areas that received more bombs historically.

In light of the previous exercise, we examine the relationship between bombing and health, using census data. We focus on disability status, which is closely related to the UXO accidents results just reported. In many cases, when bombs explode, they maim or gravely injury the victims. This tragic reality is evident in our analysis, in Figure A-11, Panel B. Fewer people report no disabilities in areas that received less bombs and the converse is true for more affected areas. The coefficient is positive and significant, except in the full specification (in Table 8, Panel B).[51] The results for the census confirm the findings from the UXO panel.

Given the very strong association between bombing and UXO accidents, we revisit our baseline findings to see whether this channel can completely explain away our main result, in a "bad controls" framework (Angrist & Pischke, 2008). First, we find a strongly positive relationship between total bombs and the total number of UXO accidents, aggregated from our panel data set (Table 7 Part I and Figure A-10 Panel B). Second, we control for the total number of UXO accidents in our regression of lights on bombs (in Table A-14). We see that the coefficient of UXO accidents and UXO accidents per capita is insignificant, but contributes in reducing the magnitude of the bombing coefficient. Interestingly, it does not fully reduce the magnitude or alter the overall significance of our main findings. We repeat the exercise at the village level, with UXO contamination in Table A-15, and find very similar results: a negative coefficient for UXO contamination, which becomes insignificant in the full specification. We take these results as suggestive that the bombing effect is potentially working through *other* potential mechanisms aside UXO contamination, which we explore next.

[51] Table A-17 presents the full interaction with UXO contamination, which emerges as a statistically significant predictor of disability.

6.2 Population Density and Rural-Urban Migration

We also study population density and rural-urban migration as mechanisms of transmission. First, we find that areas that were bombed are *less* densely populated than bombed areas (Figure A-11, Panel C). The estimated coefficient is negative, sizable and significant with and without controls and province fixed effects (Table 8, Panel C).[52] It does not appear that Laos experienced a population boom after the war, as in other postwar contexts, or at least these numbers have stabilized in the long run.

We analyze migration as a potential mechanism of poverty persistence, as in Dell (2010); Méndez-Chacón and Van Patten (2019). Conceptually, there could be opposing effects with respect to this variable. On the one hand, conflict might have had increased forced displacement (Ibáñez & Vélez, 2008). On the other, increased transportation costs might have induced people to stay in their territory. To empirically test this mechanism, we use the individual-level data from the 2005 Census, which crucially asks people about their province of birth. Using this information, first we find relatively low levels of 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; Phouxay & Tollefsen, 2011).

We proceed the analysis by looking directly at how the probability of migrating is affected by conflict, estimating a version of Equation (4). Recall that we had already controlled for this factor in the human capital accumulation regressions. We present the results for migration in Figure 8. We find that cohorts affected by conflict have a *lower* probability to migrate internally. The effect is statistically significant and on the order of -0.01, or 10% with respect to the sample mean. This result ties the results for structural transformation with those for rural to urban migration, two fundamental pillars underpinning modern economic development (see Porzio et al. (2020) and Lagakos (2020) for recent related contributions).

We further analyze the triple interaction with migration, in the Appendix, following the specification in footnote 32. Non-migrants appear to receive significantly *less* years of schooling during the conflict years, as seen in Figure A-15, Panel A. The effect for migrants is reversed, in Panel B. The results for labor outcomes parallel those for human capital accumulation. We find that the negative impact on the probability of working is concentrated among non-migrants, in Figure A-16. We can see, in Figure A-17, Panel A, that non-migrants are *more* likely to be working in agriculture, while this effect

[52] These results also speak to the spillover analysis presented previously, in Table A-4.

is not present for migrants, in Panel B. The effect of services appears concentrated on non-migrants again in Figure A-18 and we find no impact for manufacturing, by migrating status in Figure A-19. Overall, it appears that migration, or the lack thereof, is exacerbating the educational and structural transformation trends described before. Though there might be selection into migration, our findings are consistent with those in other contexts, such as WWII Poland (Becker, Grosfeld, Grosjean, Voigtlander, & Zhuravskaya, 2020).

7 Discussion and Additional Mechanisms

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 of that country.[53] We hypothesize that the apparent differences could emerge due to several reasons. First, the disparities could emerge 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. Still, to make the results more comparable, we aggregate up our results to the district level. As can be seen in Panel B of Table A-7 as well as Figure A-20, our results remain robustly negative (for all years) at this new level of aggregation.

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 rate in 1999 for Vietnam. To make the analyses more comparable, we use as alternative outcomes total expenditures and the fraction of houses in poverty in 2005. We find that in areas that were bombed, people report lower expenditures. Figure A-21, Panel A, shows the distributions for areas above (shifted to the left) and below (shifted to the right) the median for bombing. Consistent with this, these places also have higher poverty rates, as can be seen in Panel B of this same figure. Table 7, Part II reports the corresponding negative and positive estimates. Overall, the baseline effects for nightlights also translate into worse development outcomes for Laos.

Lastly, we look at potential differences in public good provision. We hypothesize

[53] These results are confirmed by Dell and Querubin (2018), though they focus on political attitudes.

that providing these services to the population could be costlier and more difficult in the presence of unexploded bombs.[54] Recall that there appear to be less schools in UXO contaminated areas, in Table 9. We also find 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 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.[55]

Specific outcomes aside, there could be national institutional, cultural and educational level differences between the countries analyzed. Miguel and Roland (2011) stress the role of investments, which have been minimal in Laos, as seen in the public good provision results above. The national and international investments in Vietnam have been very large. A recent article by (Nguyen, Tran, & Vu, 2021) shows that UXO prevalence in Vietnam decreases investment. There could still be other factors at play, such as economic isolation and regional trade patterns. 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.[56] Clearly, this demining agenda should take center stage both nationally and internationally with foreign aid. Even a 100 USD million commitment to UXO removal, as the one proposed in 2010 by the US, would total less than what this 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 remains an important issue. Outside Southeast Asia, our results also differ from those of Davis and Weinstein (2002) for Japan, where urban structures had been consolidated for millennia, stressing the importance of the rural angle in our setting. Globally, UXO contamination remains a 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.

[54]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`

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

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

8 Conclusions

We use newly available and highly disaggregated data to document the *negative* long-term economic impact of conflict. We find that places that were more heavily bombed from 1964 to 1973—in the context of the Laotian Civil War—are poorer today. Results are robust to IV estimation, 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 use census data at the village level to show how our results for nightlights extend to relevant development outcomes such as literacy, health, expenditures, urbanization, 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, 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 ceasefire, people have been affected directly through UXO accidents as well as *indirectly* through lower educational investments and less labor mobility into modern sectors and urban centers. This pernicious combination of factors—among others, such as migration—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 for both affected and attacking countries. First, the demining agenda should take center 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 neighboring Cambodia (Lin, 2020) and Vietnam, in the Indochinese Peninsula. Though unexploded 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. Local political leaders and advisors can learn from the specific channels of transmission of the effects of UXOs. They can, for instance, improve the targeting of their existing policies or implement new programs geared towards alleviating the pernicious lingering economic consequences of historical warfare. Ideally, policymakers in attacking countries might want to think twice about the long-term socioeconomic legacy of their military actions, weighing the large and permanent economic damages to the civilian population against their more immediate political goals and strategic objectives.

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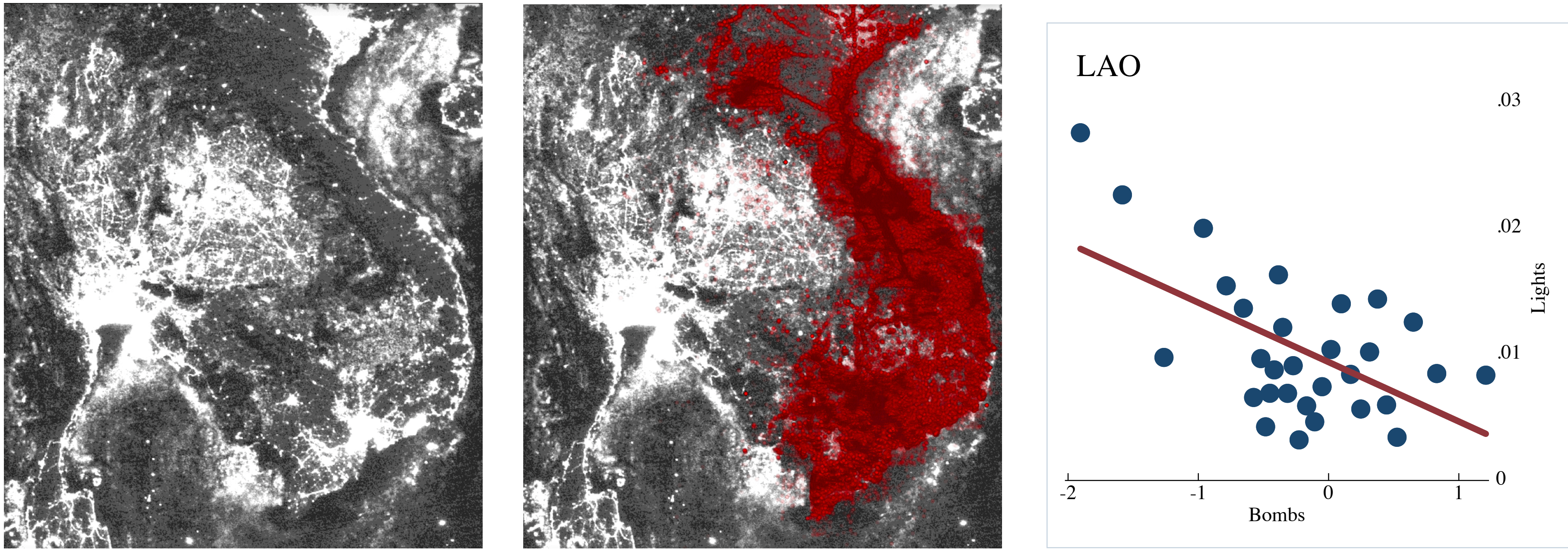
Figure 1: Indochina: Stable Lights in 2013 and US Bombing Events from 1965 and 1973

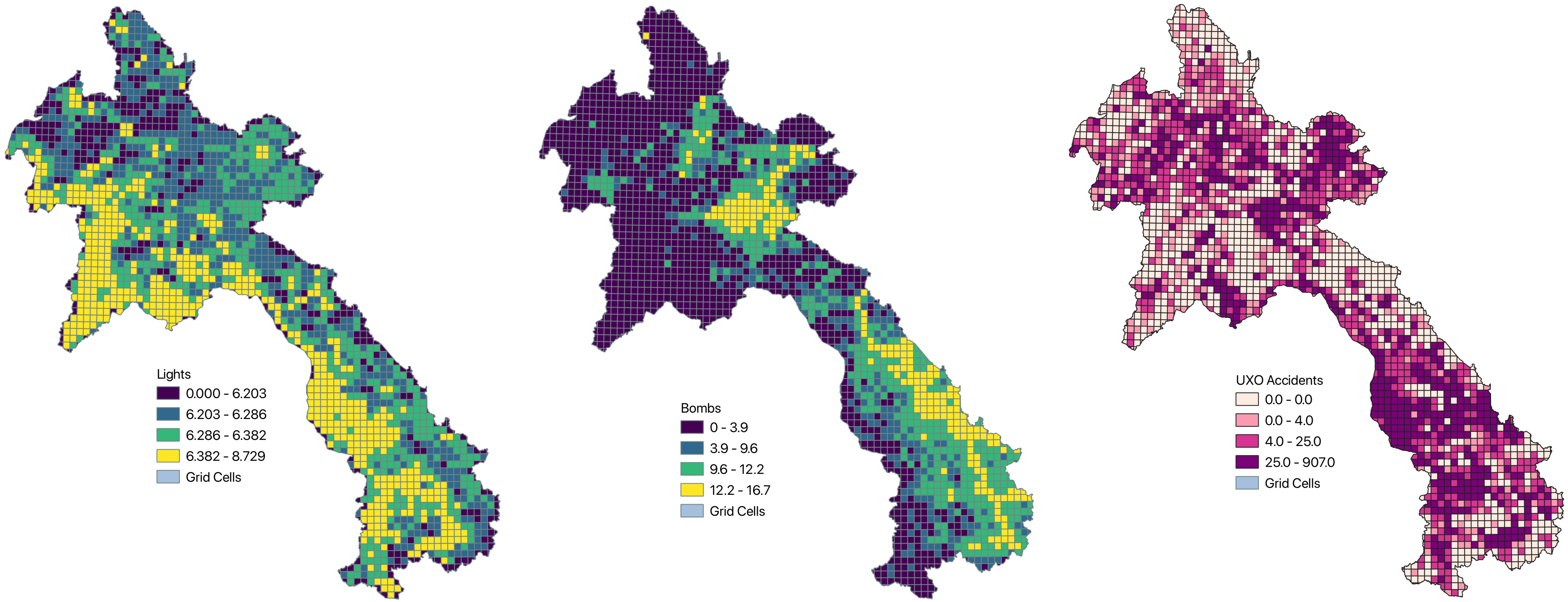


Panel A: Stable lights in 2013.

Panel B: US Bombing Events from 1965 to 1973.

Panel C: Bin-scatter controlling for province fixed effects year fixed effects and location controls.

Figure 2: Luminosity, Bombs and UXO

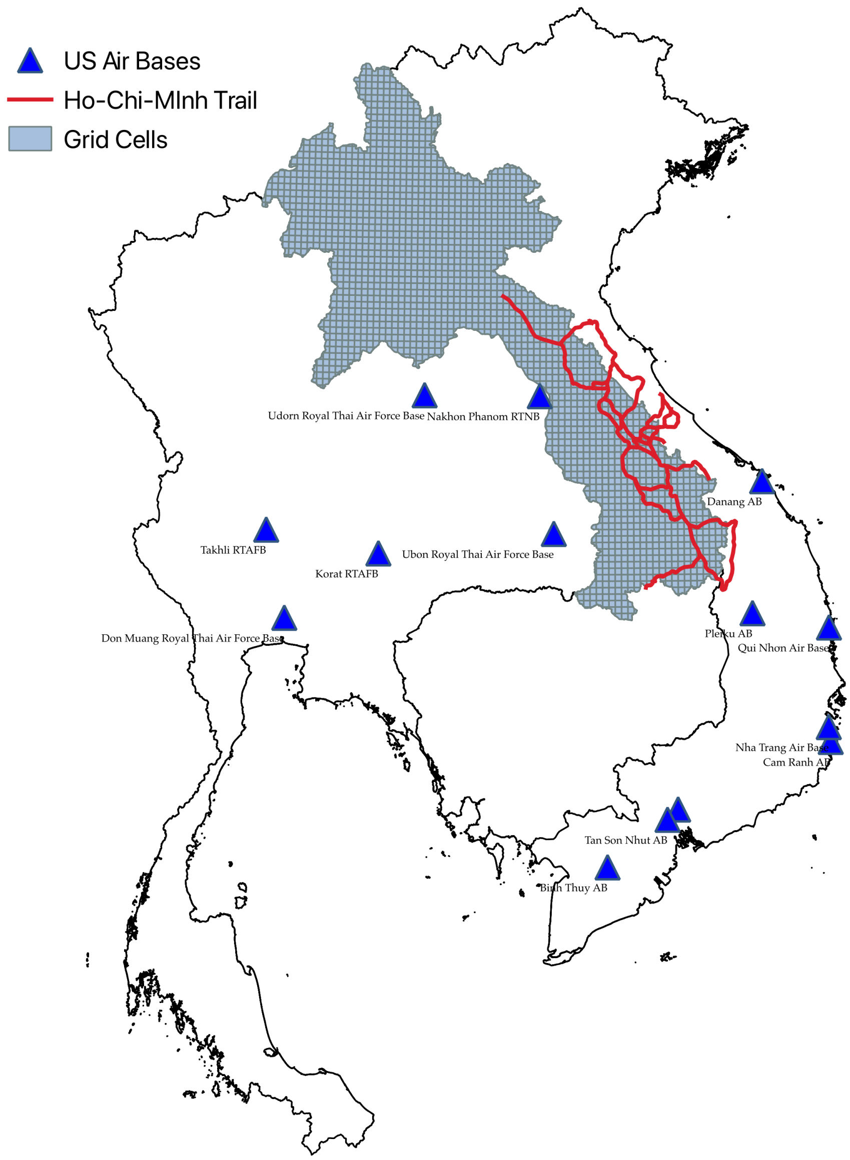


Panel A: Luminosity measured as the total sum of lights (stable and unstable) in 2013 at the grid cell level (in logs).

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

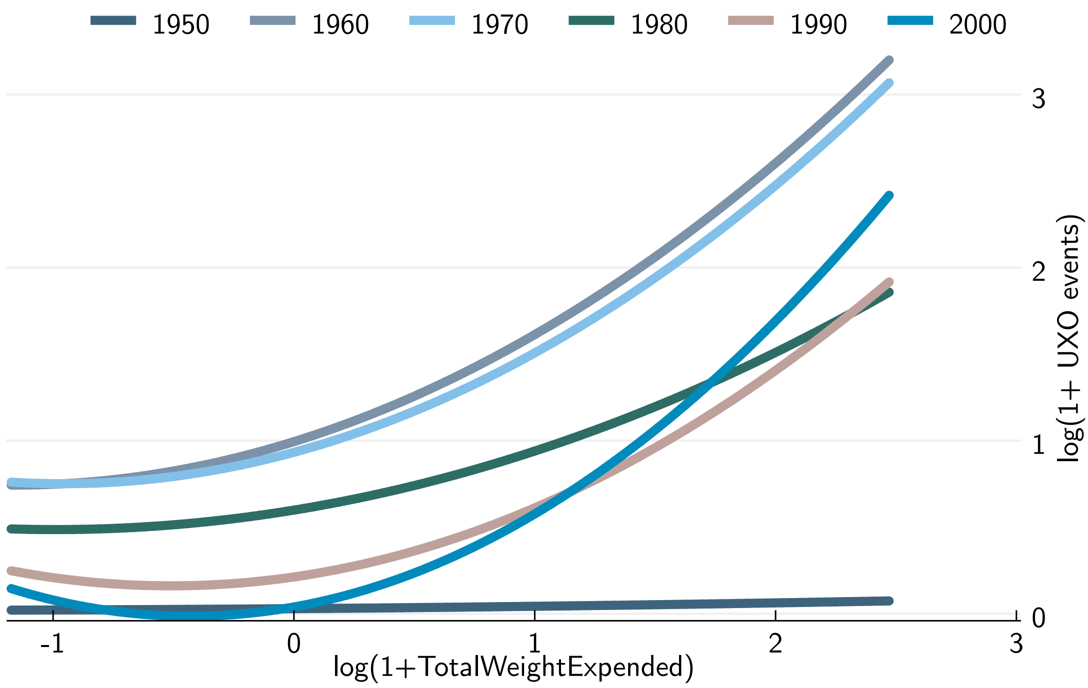
Panel C: UXO victims from 1950 to 2011.

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



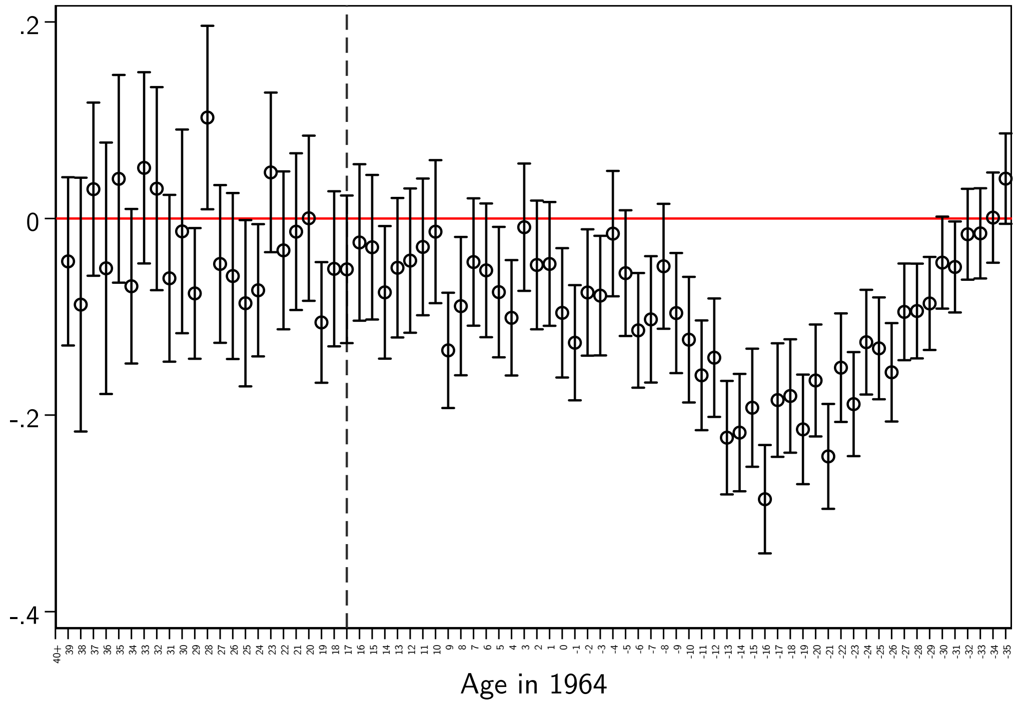
Notes: This figure presents the map of Thailand, Cambodia, Vietnam, and Laos and the grid cell partition used in the empirical analysis. In dark blue, it depicts the location of US airbases outside Laos and the georeferencing of the Vietnamese Ho Chi Minh trail. Information was digitized based on historical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

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



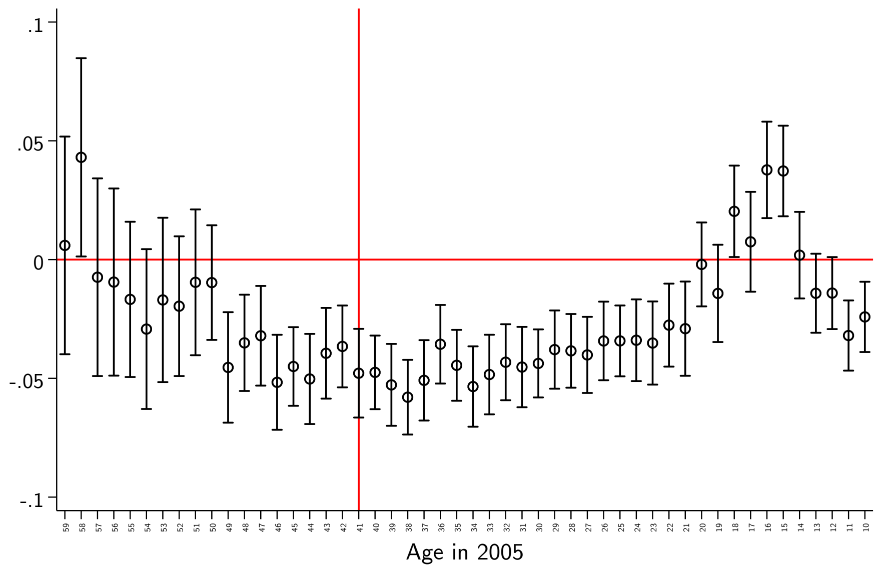
Notes: This figure presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance) and bombing intensity from 1964 to 1973. It uses panel data on UXO accidents and data on the bombing at the village level.

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 years old cohort marked with a vertical dashed line as reference point.

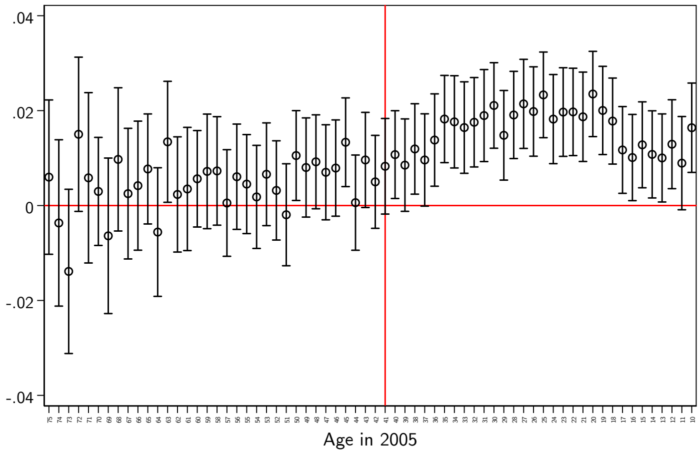
Figure 6: Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005



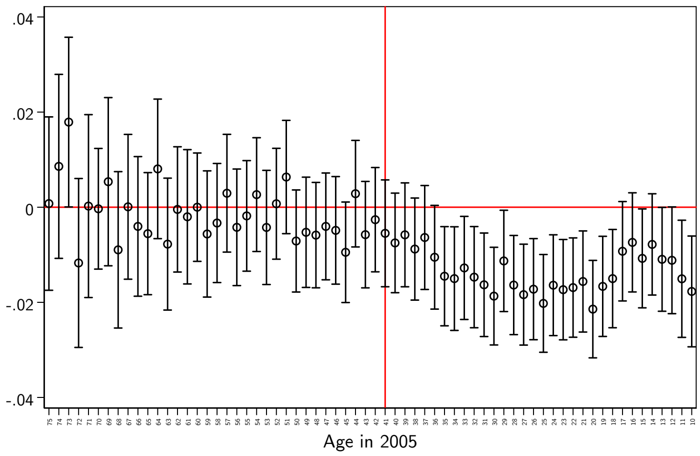
Notes: The estimation sample includes individuals from 10 to 98 years old in 2005. Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome is an indicator of employment. The excluded cohort in Panel B is people older that 60 (official age of retirement) in 2005, i.e., older than 20 in 1964. The 41 years old cohort marked with a vertical red line as reference point as the cohort that was born 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)

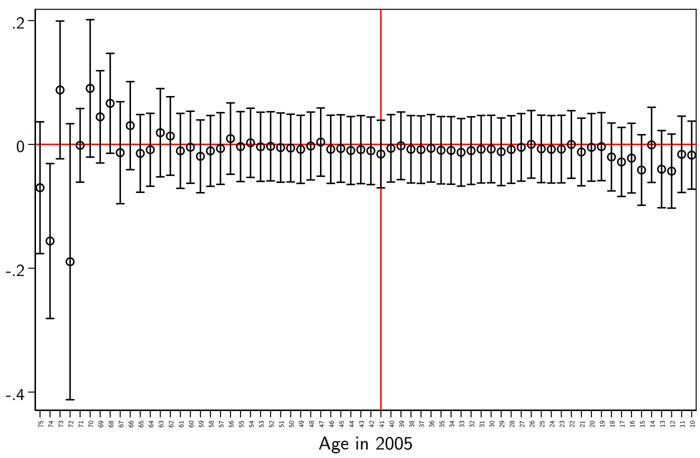
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services

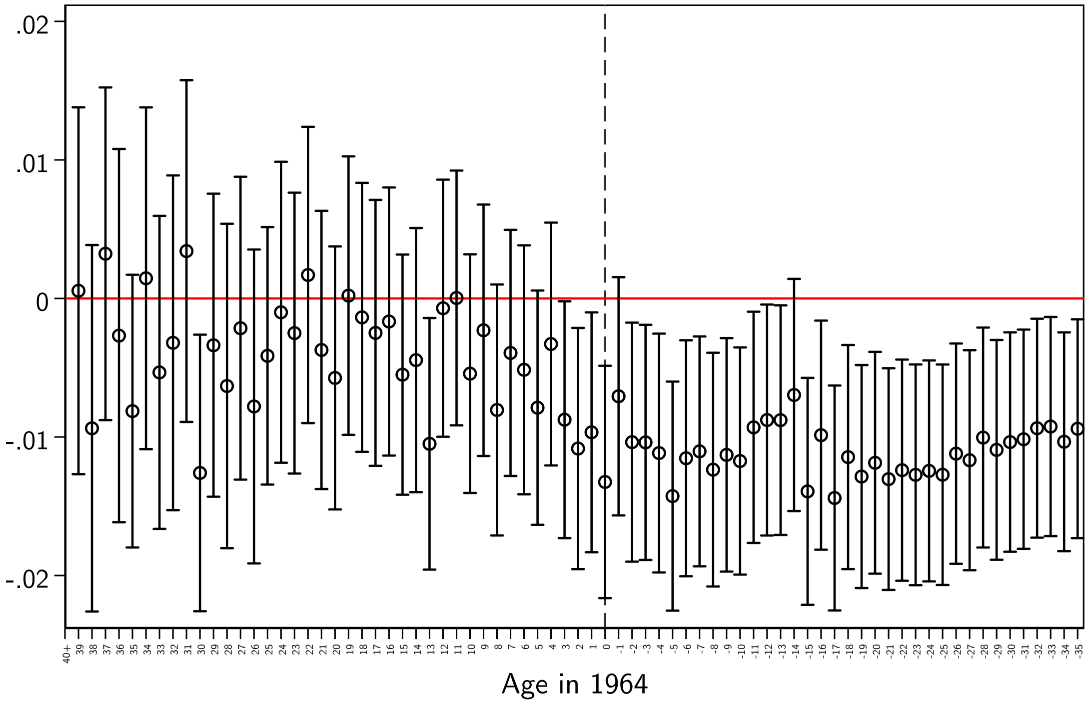


Panel C: Probability of Working in Manufacturing



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: 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 to that of birth. The excluded cohort is composed by individuals with 40 years or more in 1964.The 0 years old cohort marked with a vertical dashed line as 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	-0.0150***	-0.0144***	-0.0260***	-0.0198***	-0.0200***	-0.0338***	-0.0398***	-0.0412***	-0.0492***
	(0.0041)	(0.0037)	(0.0086)	(0.0049)	(0.0047)	(0.0097)	(0.0075)	(0.0074)	(0.0121)
Altitude		-0.0000**	0.0001**		-0.0000**	0.0001**		-0.0001***	0.0001
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0001)
Ruggedness		-0.0826***	-0.1010***		-0.1184***	-0.1515***		-0.1951***	-0.2710***
		(0.0222)	(0.0257)		(0.0256)	(0.0309)		(0.0476)	(0.0561)
Temperature		-0.0004	0.0120**		-0.0012	0.0182***		0.0003	0.0267***
		(0.0020)	(0.0054)		(0.0028)	(0.0064)		(0.0055)	(0.0091)
Precipitation		-0.0001	-0.0002*		-0.0000	-0.0002		-0.0000	0.0001
		(0.0001)	(0.0001)		(0.0001)	(0.0002)		(0.0001)	(0.0002)
Latitude			0.0037			0.0078			0.0039
			(0.0089)			(0.0106)			(0.0183)
Longitude			0.0041			0.0057			-0.0106
			(0.0102)			(0.0119)			(0.0197)
Distance to DMZ			-0.0155**			-0.0211***			-0.0308***
			(0.0061)			(0.0069)			(0.0087)
Distance to Vietnam Border			-0.0002*			-0.0003**			-0.0005**
			(0.0001)			(0.0001)			(0.0002)
Distance to Closest Capital			-0.0001***			-0.0002***			-0.0004***
			(0.0000)			(0.0001)			(0.0001)
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R-squared	0.0081	0.0257	0.0443	0.0098	0.0356	0.0611	0.0159	0.0612	0.0952

Notes: Observations are at the grid cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. 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	-0.0028**	-0.0036**	-0.0044	-0.0136***	-0.0152***	-0.0055	-0.0178***	-0.0203***	-0.0120**
	(0.0014)	(0.0015)	(0.0028)	(0.0039)	(0.0039)	(0.0046)	(0.0044)	(0.0047)	(0.0048)
Altitude		-0.0000**	0.0000*		-0.0000**	-0.0000		-0.0001***	-0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Ruggedness		-0.0249***	-0.0375***		-0.0409	-0.0754**		-0.0758**	-0.1267***
		(0.0058)	(0.0084)		(0.0329)	(0.0370)		(0.0351)	(0.0409)
Temperature		-0.0008	0.0046**		0.0018	0.0032		0.0008	0.0095*
		(0.0009)	(0.0021)		(0.0026)	(0.0049)		(0.0034)	(0.0054)
Precipitation		0.0000	0.0001		0.0001	0.0003**		0.0001	0.0004**
		(0.0000)	(0.0001)		(0.0001)	(0.0001)		(0.0001)	(0.0002)
Latitude			0.0036			-0.0061			-0.0014
			(0.0035)			(0.0110)			(0.0127)
Longitude			0.0011			-0.0178			-0.0164
			(0.0036)			(0.0118)			(0.0132)
Distance to DMZ			-0.0036*			-0.0036			-0.0087**
			(0.0021)			(0.0032)			(0.0037)
Distance to Vietnam Border			-0.0000			-0.0002			-0.0002
			(0.0000)			(0.0002)			(0.0002)
Distance to Closest Capital			-0.0000***			-0.0002***			-0.0002***
			(0.0000)			(0.0000)			(0.0001)
Controlling for initial luminosity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R-squared	0.1097	0.1213	0.1323	0.1386	0.1586	0.1758	0.1478	0.1763	0.1993

Notes: Observations are at the grid cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. 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	-0.0144***	-0.0260***	-0.0230*	-0.0229*	-0.0157**	-0.0155**
	(0.0037)	(0.0086)	(0.0113)	(0.0117)	(0.0075)	(0.0074)
R-squared	0.0257	0.0443	0.0212	0.0278	0.0058	0.0078
Panel B: Dependent Variable: Luminosity 2003						
Bombs	-0.0200***	-0.0338***	-0.0299**	-0.0295*	-0.0221**	-0.0220**
	(0.0047)	(0.0097)	(0.0141)	(0.0140)	(0.0102)	(0.0099)
R-squared	0.0356	0.0611	0.0259	0.0353	0.0090	0.0116
Panel C: Dependent Variable: Luminosity 2013						
Bombs	-0.0412***	-0.0492***	-0.0428**	-0.0433**	-0.0355***	-0.0369***
	(0.0074)	(0.0121)	(0.0180)	(0.0177)	(0.0129)	(0.0130)
R-squared	0.0612	0.0952	0.0372	0.0475	0.0139	0.0201
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 kilometer within the each grid cell, while Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. Robust standard errors in parentheses. If fixed effects are present standard errors clustered at the level of the fixed effect. *** 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	-0.0248***	-0.0252***	-0.0319**	-0.0244**	-0.0363***	-0.0319**	-0.0248**
	(0.0033)	(0.0032)	(0.0141)	(0.0098)	(0.0059)	(0.0141)	(0.0096)
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	0.0169	0.0459	0.0324	0.0167	0.0701	0.0404	0.0199

Notes: Observations are at the grid cell $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. 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 5: Instrumental Variables Estimates: Pooled IV of Luminosity on Bombs

Table VIA - Instrument I: Distance to the Ho Chi Minh Trail	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	-0.1199***	-0.1235***	-0.0934***
	(0.0276)	(0.0331)	(0.0201)
Panel B: Dependent variable is Bombs, model:	FS	FS	FS
Distance to Ho Chi Minh Trail	-0.6614***	-1.0811***	-2.0007***
	(0.0420)	(0.0587)	(0.0918)
Distance to Ho Chi Minh Trail^2	-0.0548***	0.0520***	0.1459***
	(0.0089)	(0.0113)	(0.0209)
R-squared	0.5626	0.6352	0.7445
F-stat	656.5	163.1	77.81
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 VIB - Instrument II: Distance to the Closest US Air Base	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	-0.1448***	-0.1329***	-0.2651***
	(0.0336)	(0.0335)	(0.0779)
Panel B: Dependent variable is Bombs, model:	FS	FS	FS
Distance to closest US air base	1.2347***	1.2191***	0.4856***
	(0.0396)	(0.0504)	(0.0920)
Distance to closest US air base^2	-0.2322***	-0.1978***	-0.1487***
	(0.0071)	(0.0099)	(0.0184)
R-squared	0.5776	0.6375	0.7218
F-stat	697.9	167.2	30.79
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 $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. 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. 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	-0.1244***	-0.0968***	-0.1009***
	(0.0279)	(0.0230)	(0.0216)
Over identification test	0.0177	2.429	0.440
p-value	0.894	0.119	0.507
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	-0.1301***	-0.1107***	-0.0915***
	(0.0291)	(0.0258)	(0.0199)
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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. 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 standardized. 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	0.5699***	0.5455***	0.4130***
	(0.0166)	(0.0166)	(0.0901)
R-squared	0.2164	0.2220	0.1140
Panel B: Dependent variable is log(1+ area contaminated by UXO)			
Bombs	0.1886***	0.1820***	0.1383***
	(0.0041)	(0.0042)	(0.0254)
R-squared	0.2716	0.2746	0.1450
Observations	8,643	8,497	8,497
Part II: Additional Development Outcomes			
Panel A: Dependent variable is the log(1+total expenditures/population)			
Bombs	-0.1075***	-0.0395***	-0.0296**
	(0.0033)	(0.0039)	(0.0114)
R-squared	0.0921	0.2420	0.1585
Panel B: Dependent variable is the fraction of households in poverty)			
Bombs	0.0713***	0.0277***	0.0195*
	(0.0019)	(0.0021)	(0.0093)
R-squared	0.1340	0.3021	0.2586
Observations	10,522	10,280	10,280
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 kilometer. Variable Bombs is standardized. Panels A and B use data from the Population Census of 2005. Panels C and D use data from the Agricultural census of 2011. Robust standard errors in parentheses, if province fixed effects are present standard errors clustered at that level.

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

	(1)	(2)	(3)
Panel A: Dependent variable is fraction of literate households			
Bombs	-0.0574***	-0.0266***	-0.0276**
	(0.0026)	(0.0029)	(0.0130)
R-squared	0.0499	0.2164	0.2448
Panel B: Dependent variable is fraction of households with disabled people			
Bombs	0.0113***	0.0084***	0.0019
	(0.0008)	(0.0009)	(0.0018)
R-squared	0.0242	0.0825	0.0256
Panel C: Dependent variable is log(Inhabitants/Km2)			
Bombs	-0.3157***	-0.1418***	-0.1770***
	(0.0163)	(0.0178)	(0.0504)
R-squared	0.0335	0.2702	0.1918
Controls that apply for all panels			
Province fixed effects			Yes
Geographical Controls		Yes	Yes
Location Controls		Yes	Yes
Observations	10,522	10,280	10,280

Notes: Observations are at the village level. Variable Bombs represents the total weight in pounds jettisoned from 1965 to 1973 per square kilometer. Variable Bombs is standardized. Robust standard errors in parentheses, if province fixed effects are present standard errors clustered at that level. Data comes from the population census of 2005.

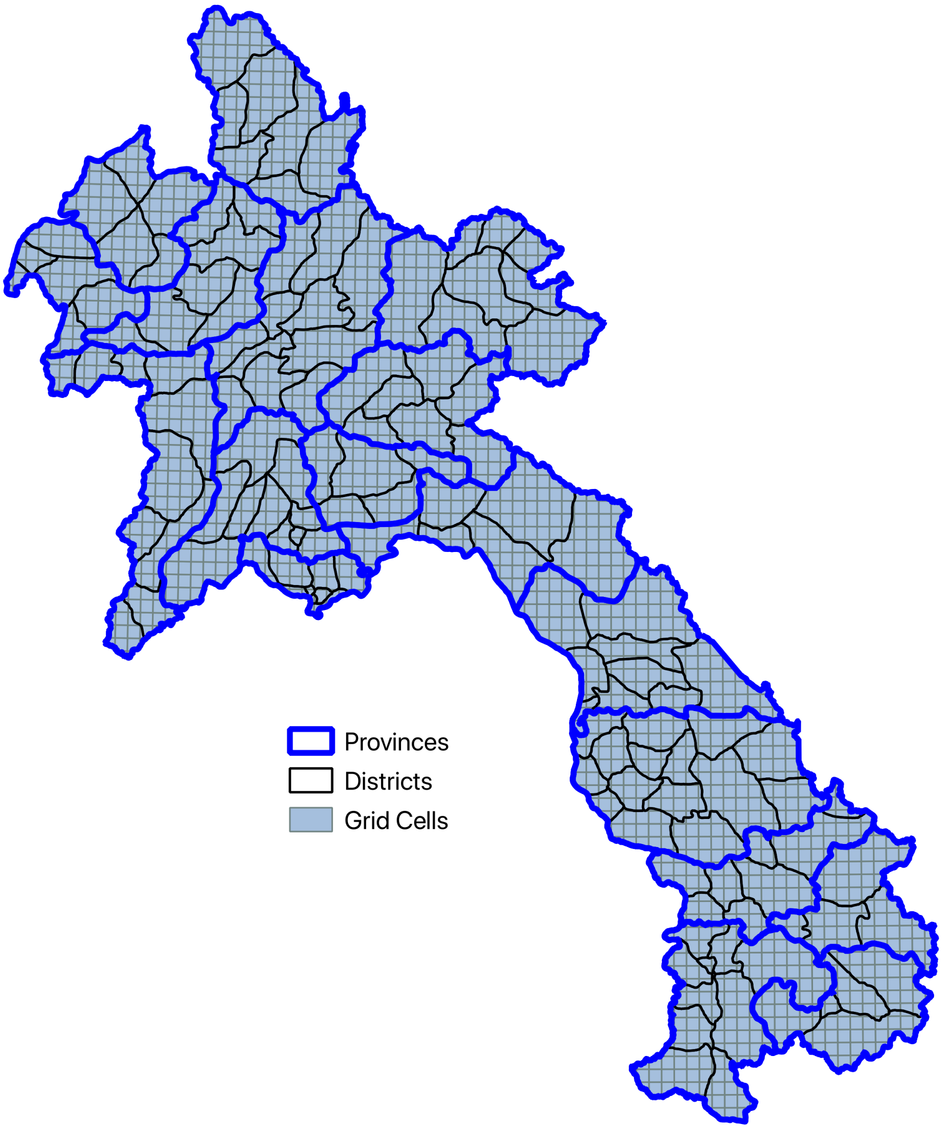
Table 9: Public Goods: Services and Educational Infrastructure

Dependent variable:	Village has a primary school		
	(1)	(2)	(3)
Bombs	0.0055		0.0098
	(0.0146)		(0.0145)
UXO Contamination		-0.0113	-0.0134**
		(0.0066)	(0.0062)
R-squared	0.0139	0.0145	0.0147
Dependent variable:	**Village has electricity**		
	(1)	(2)	(3)
Bombs	-0.0642***		-0.0621***
	(0.0154)		(0.0163)
UXO Contamination		-0.0192	-0.0063
		(0.0118)	(0.0127)
R-squared	0.1575	0.1476	0.1577
Dependent variable:	**Village has water supply**		
	(1)	(2)	(3)
Bombs	-0.0148***		-0.0137**
	(0.0044)		(0.0050)
UXO Contamination		-0.0064**	-0.0035
		(0.0028)	(0.0033)
R-squared	0.0333	0.0317	0.0335
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	10,382	10,382

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

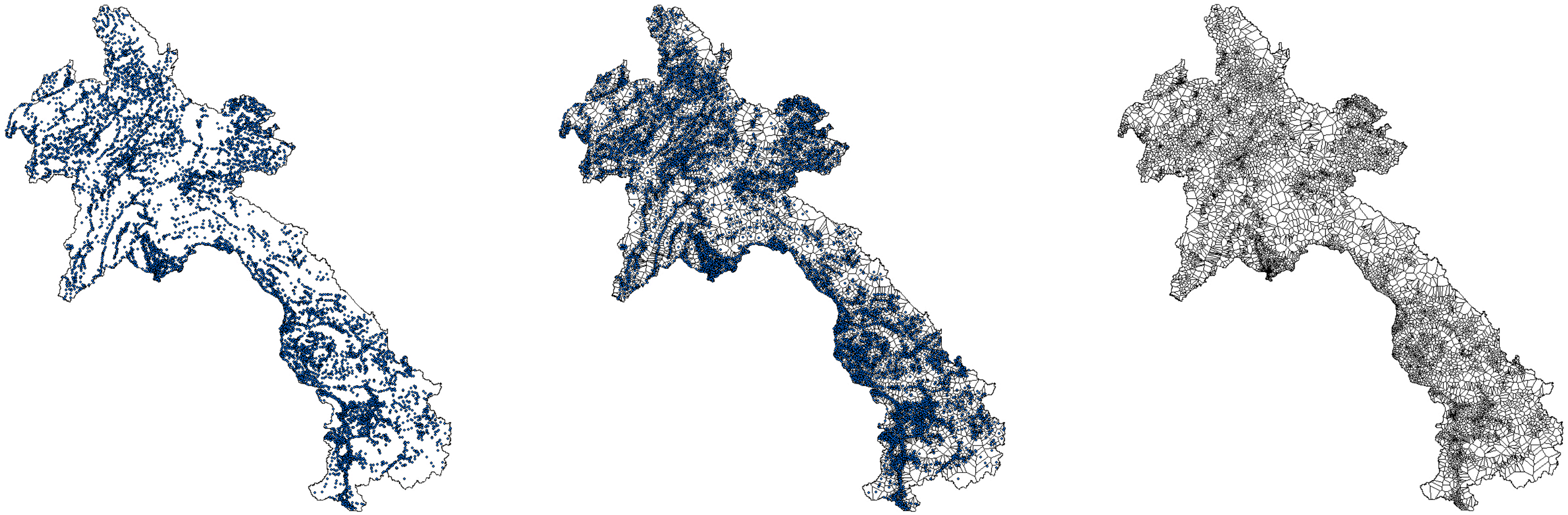
Online Appendix: Figures

Figure A-1: Grid cell Level Analysis: Grid cells of 10km $\times$ 10km 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. Provinces and Districts are represented by dark blue and black polygons respectively. Grid cells are represented in light blue.

Figure A-2: Village Level Boundary Construction

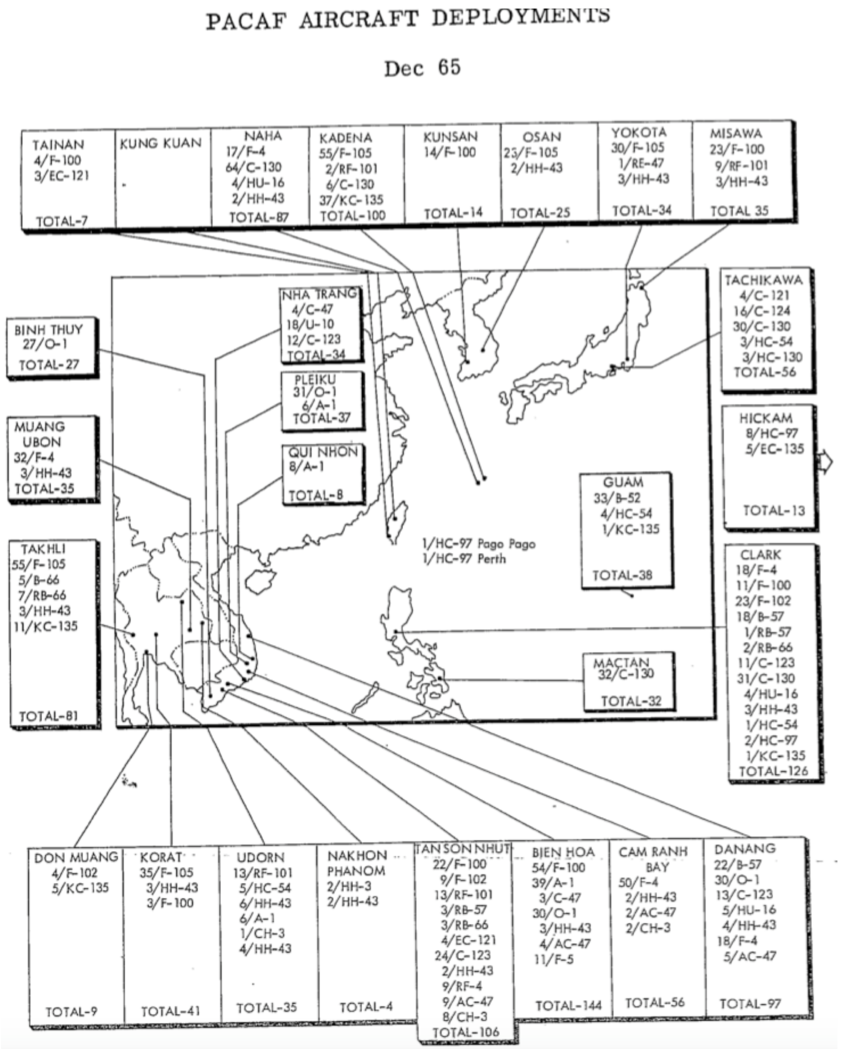


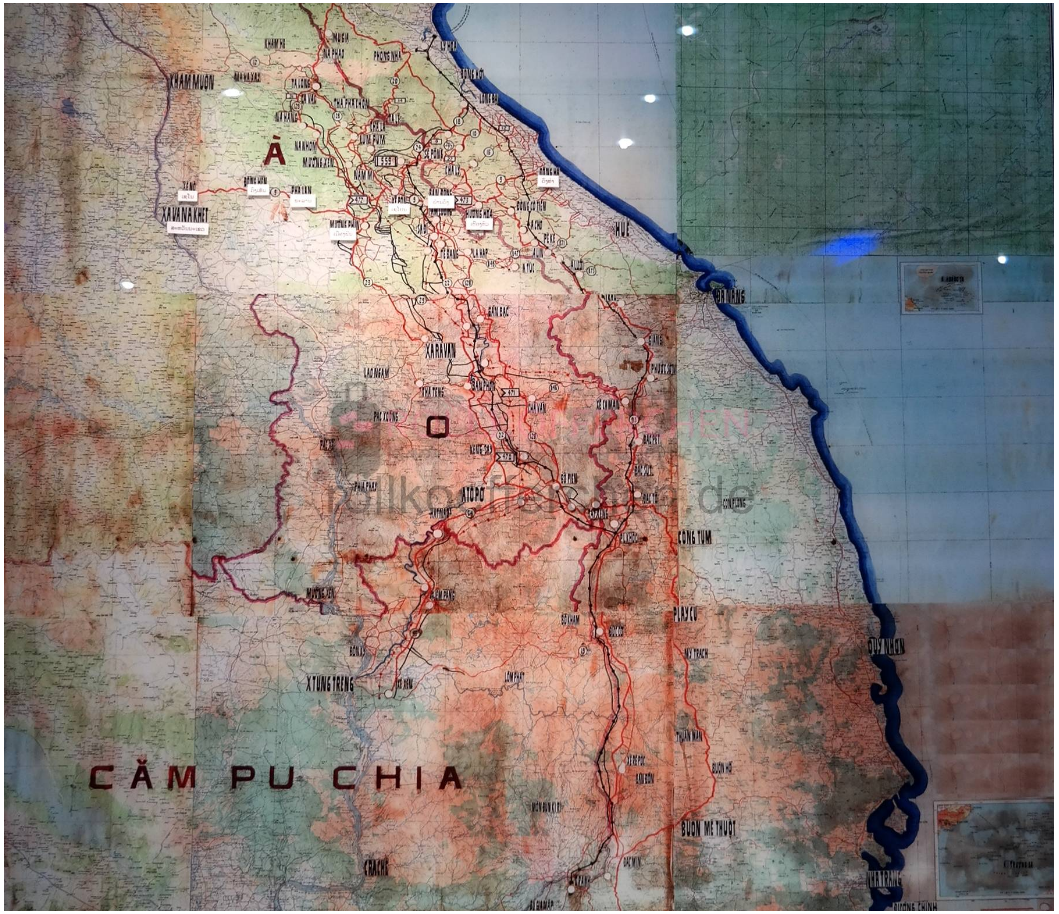
Panel A: Spatial location of villages in the census.

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

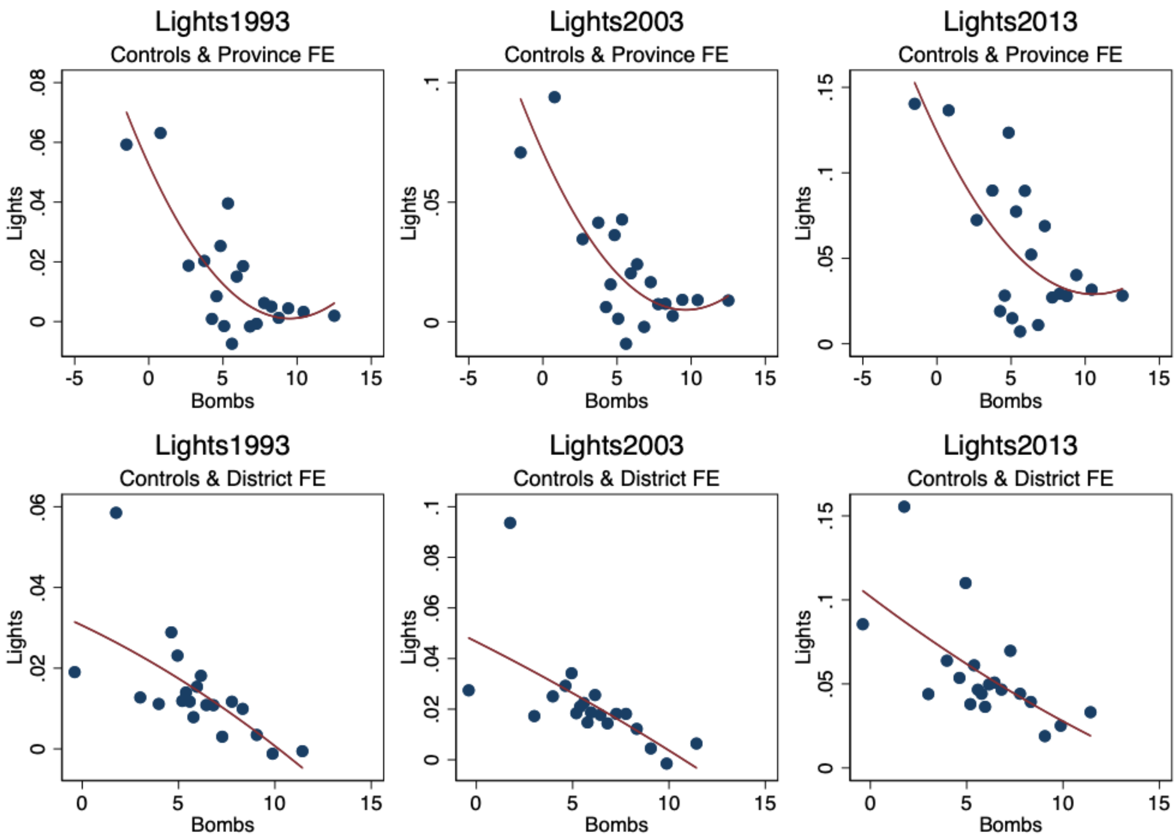
Panel B: Example of the map of supply routes from the Laotian side

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/

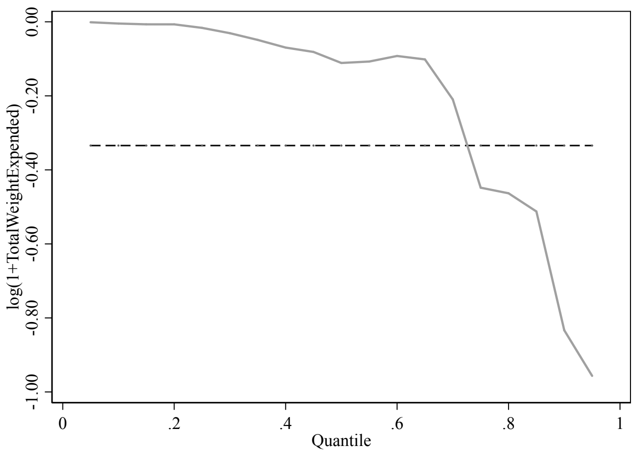
Figure A-5: Bin-scatters of Lights on Bombs at the Grid Cell Level by Year



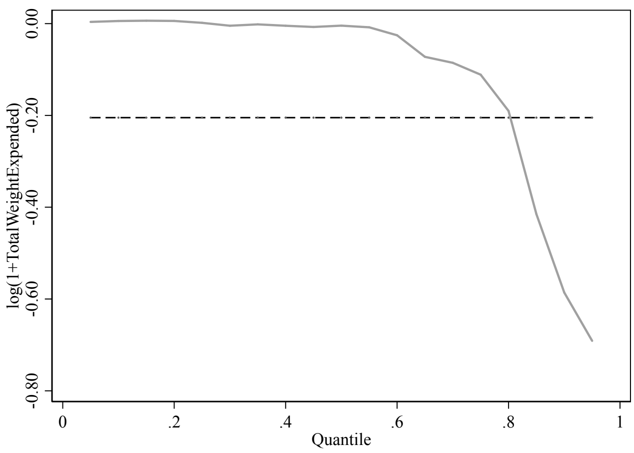
Notes: This figure depicts the relationship between Bombs and Luminosity using satellite data for each year separately. All panels are bin-scatters with overlapping quadratic fits of the underlying data. All figures control for location and geographical covariates. The first row includes province fixed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

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

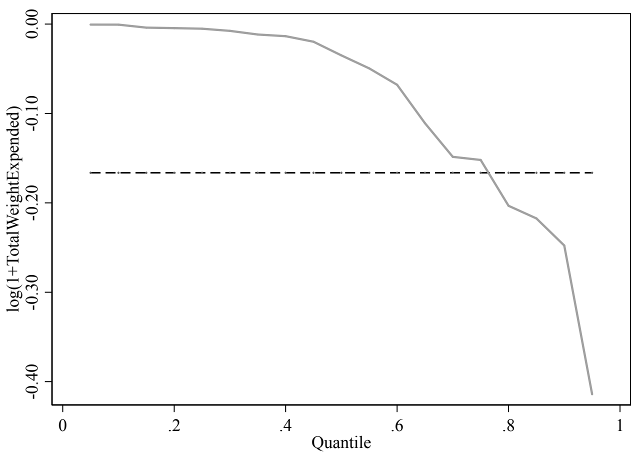
Panel A: Lights in 1993



Panel B: Lights in 2003



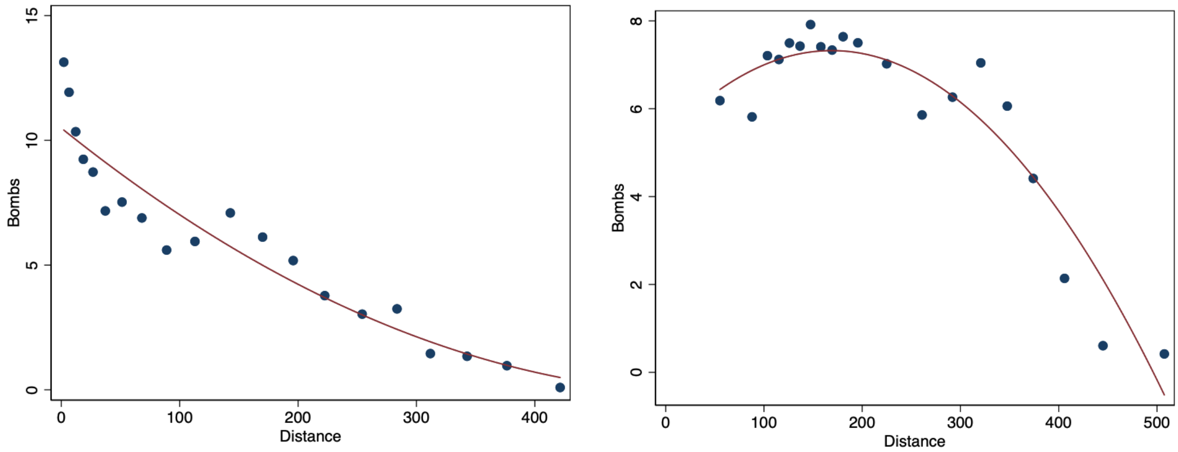
Panel C: Lights in 2013



Notes: OLS coefficients of the baseline specification in Equation (1) reported as dashed lines. Quantile regression coefficients for the quantiles specified in the x-axis are reported in gray.

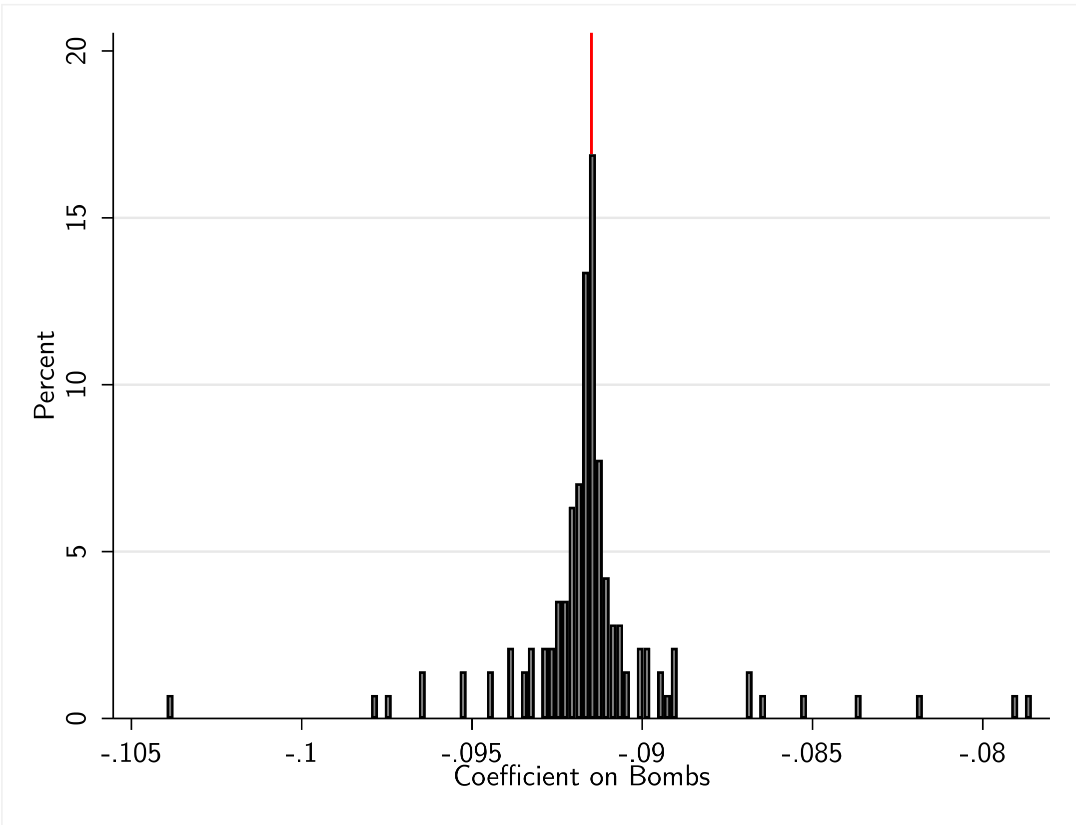
Figure A-7: Bin-scatters for the First Stages

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.

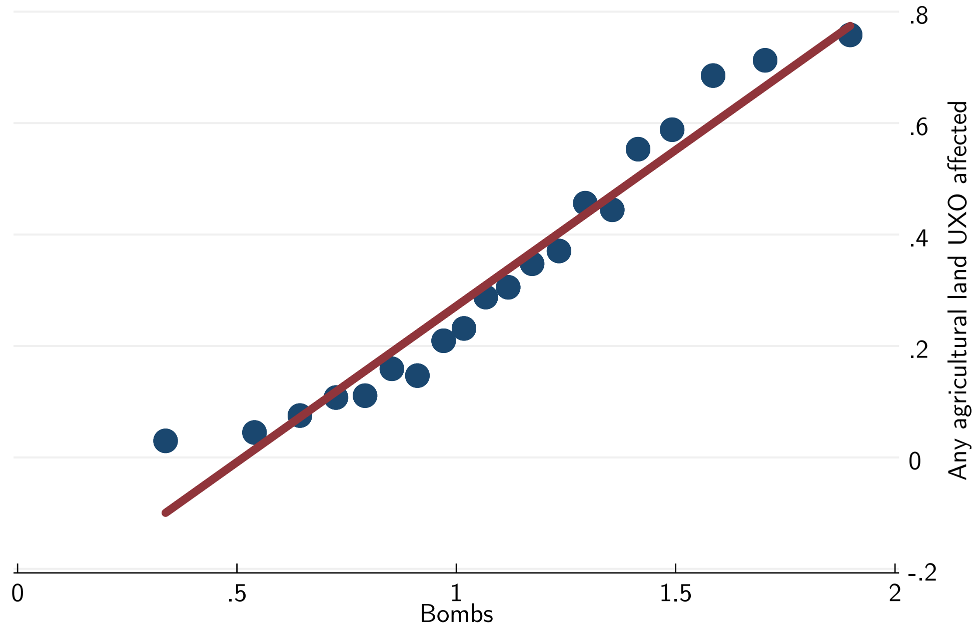
Figure A-8: Robustness IV: Distribution of Coefficients Dropping Individual Districts



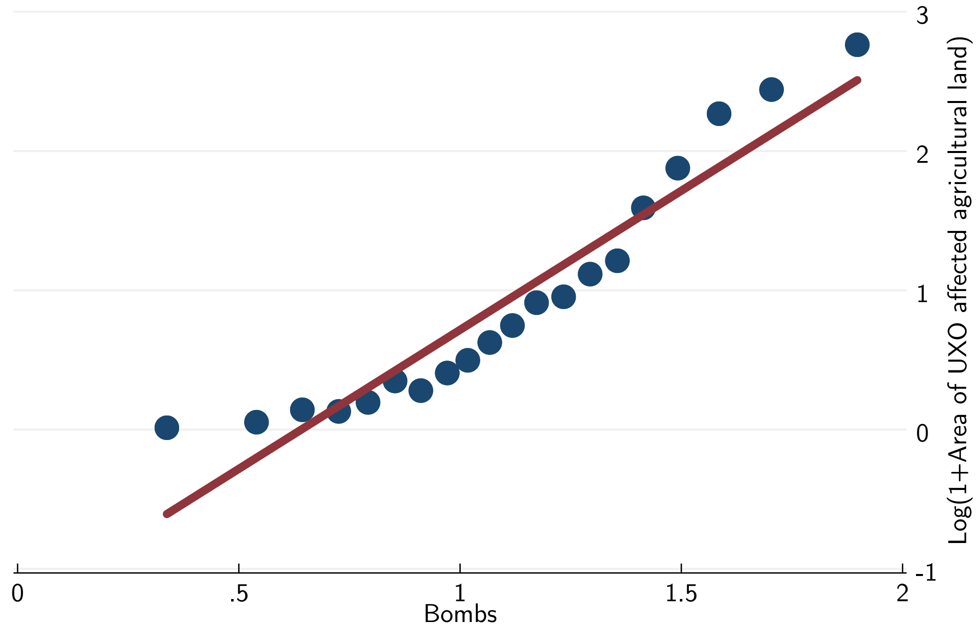
Notes: Distribution of the effect of Bombs on Lights when dropping one district at the time. The IV estimate of the pooled sample is represented by the red line.

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

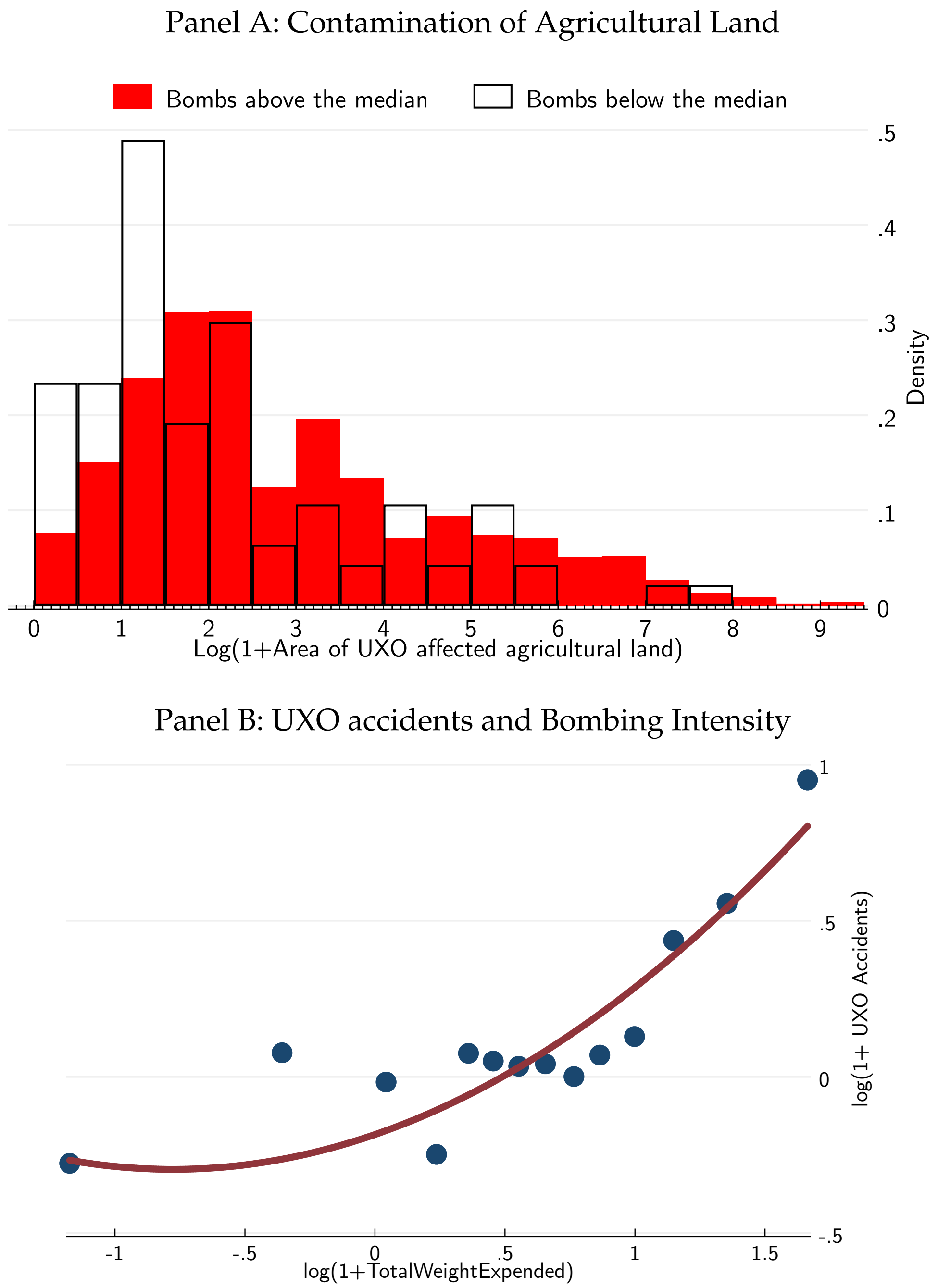


Panel B: Bin-scatter and linear fit Bombs and intensity of UXO contamination



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 linear fits at the village level.

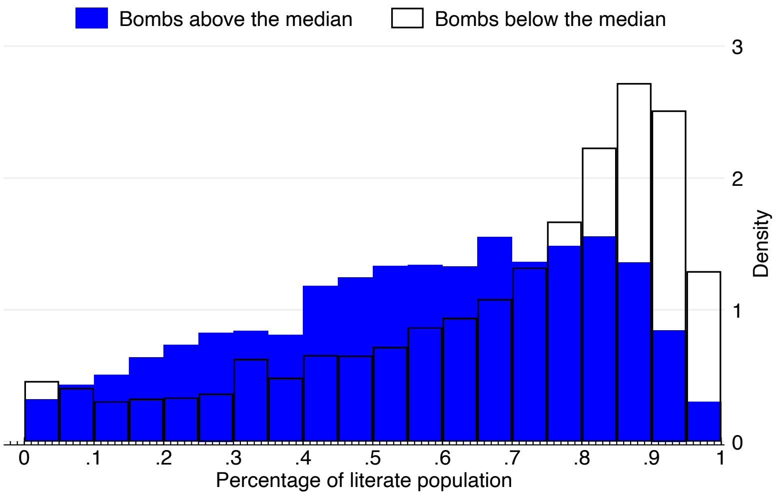
Figure A-10: Contamination of Agricultural Land UXO Victims, and Bombing Intensity



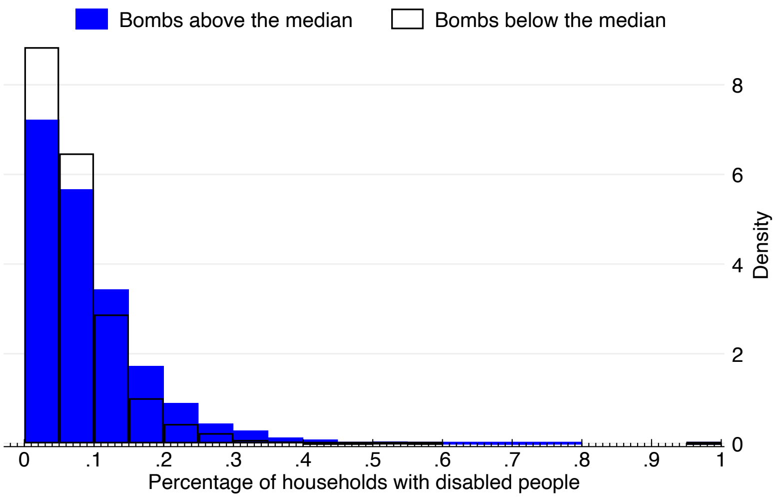
Notes: Panel A presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance from 1950 to 2010) and bombing intensity from 1964 to 1973. It uses panel data on UXO accidents and data on the bombing at the village level. Panel B presents the distribution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

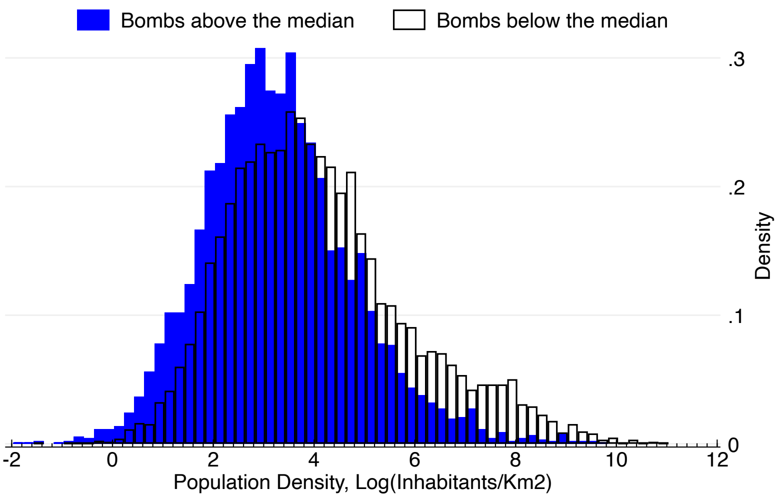
Panel A: Literacy



Panel B: Disability

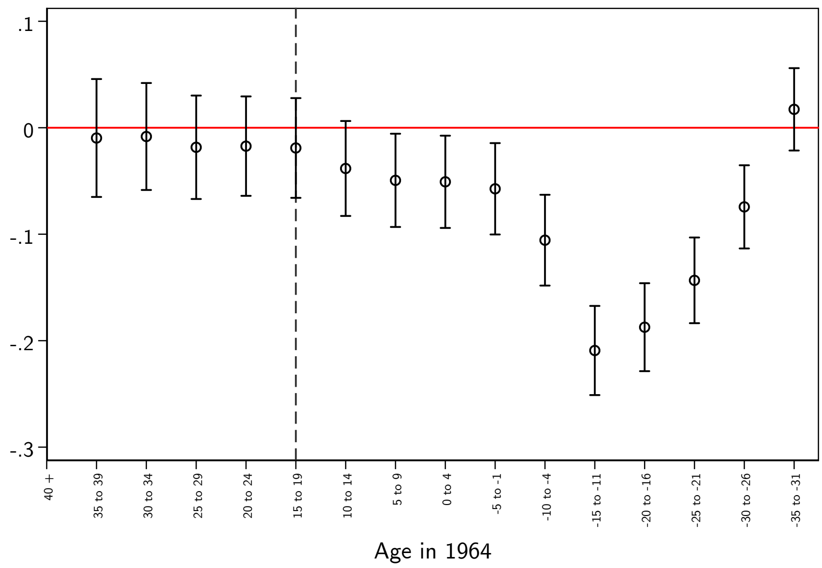


Panel C: Population Density



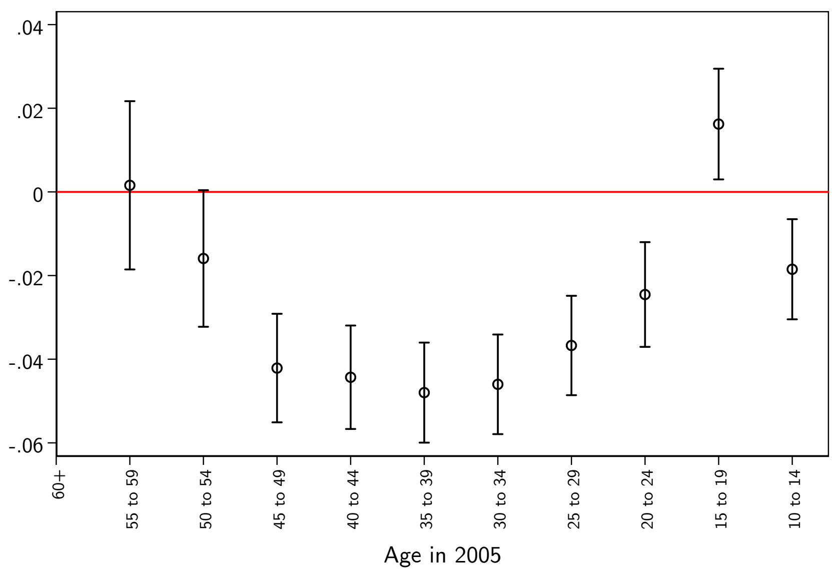
Notes: This figure presents the empirical distribution of the variables specified in each panel by the level of bombing intensity (above or below the median of bombs).

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 marked with a vertical dashed line as reference point.

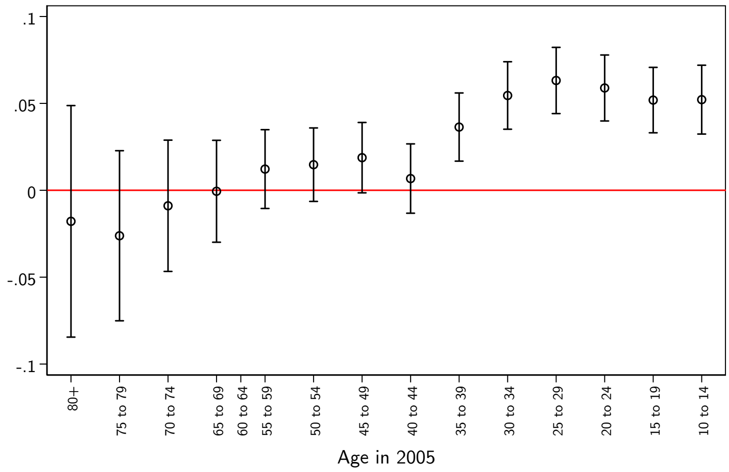
Figure A-13: Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005 (Quinquennial)



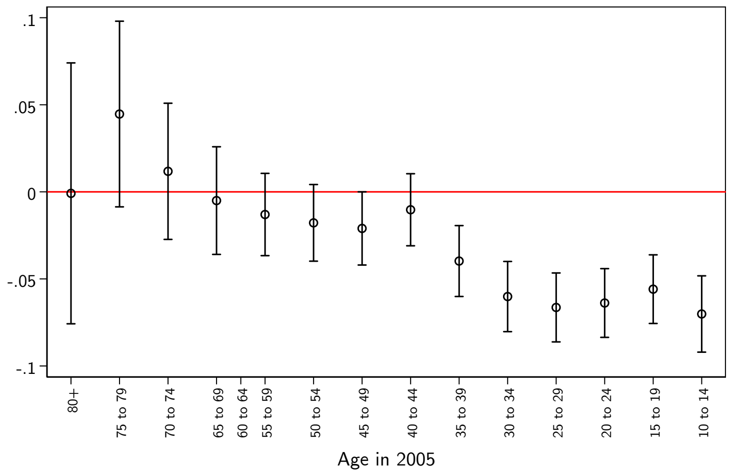
Notes: Figure reports point estimates and 95% confidence intervals of γ_k, from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors specified in the panels. The excluded cohort is composed by individuals older than 60 in 2005.

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)

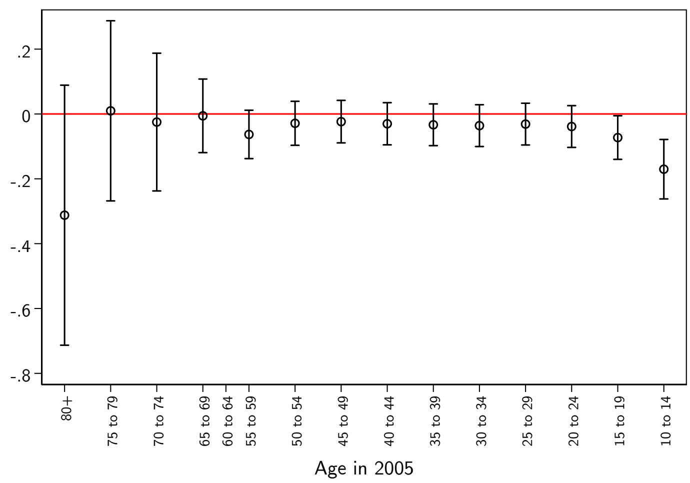
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services



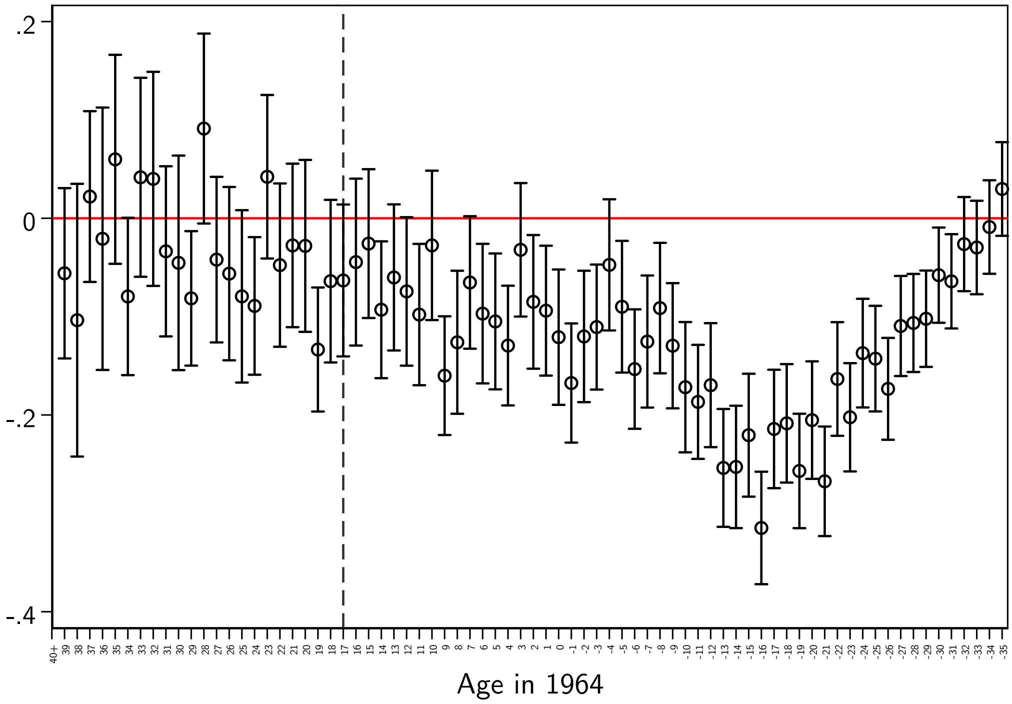
Panel C: Probability of Working in Manufacturing



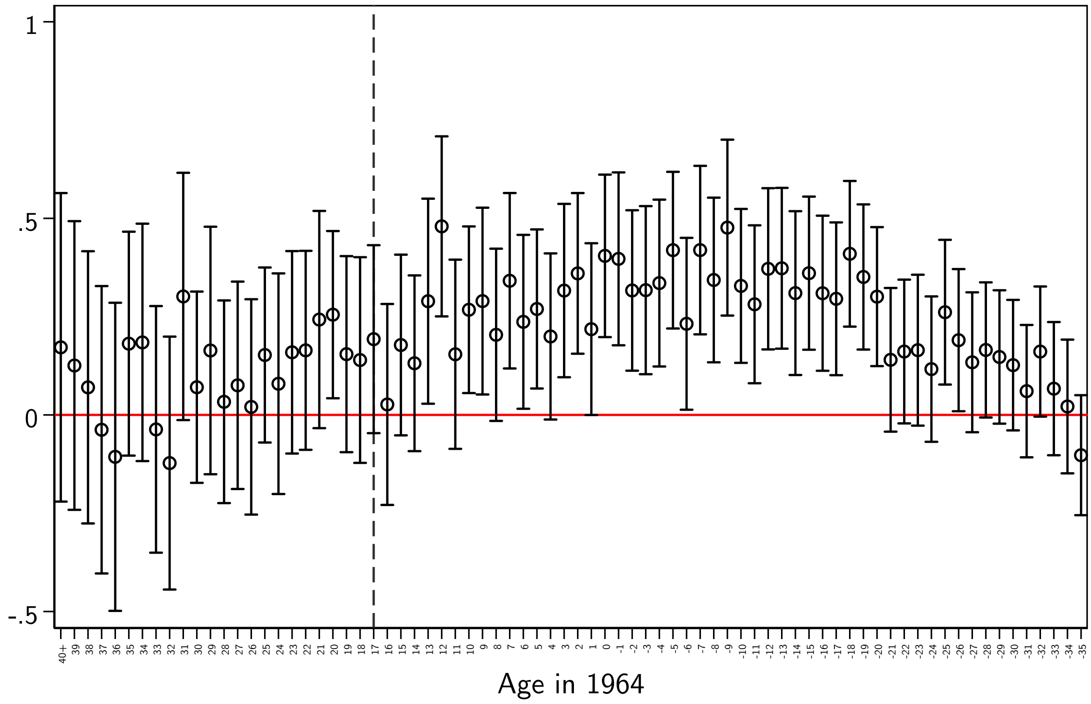
Notes: Panel A, B and C report point estimates and 95% confidence intervals γ_k from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors listed in the panels. The excluded cohort is composed by individuals with 60 to 64 years old in 2005.

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

Panel A: Non-Migrants



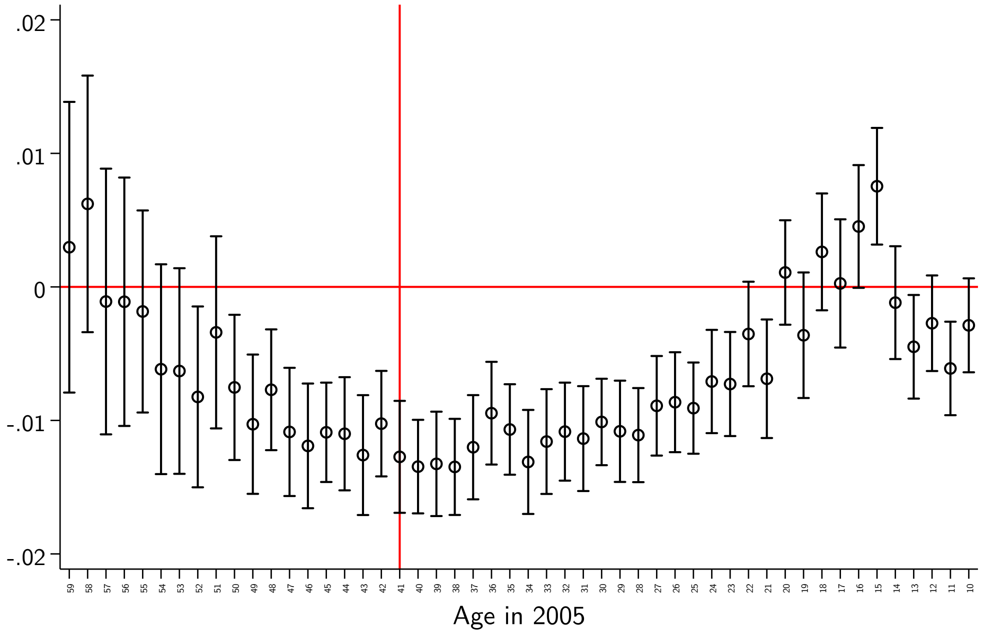
Panel B: Migrants



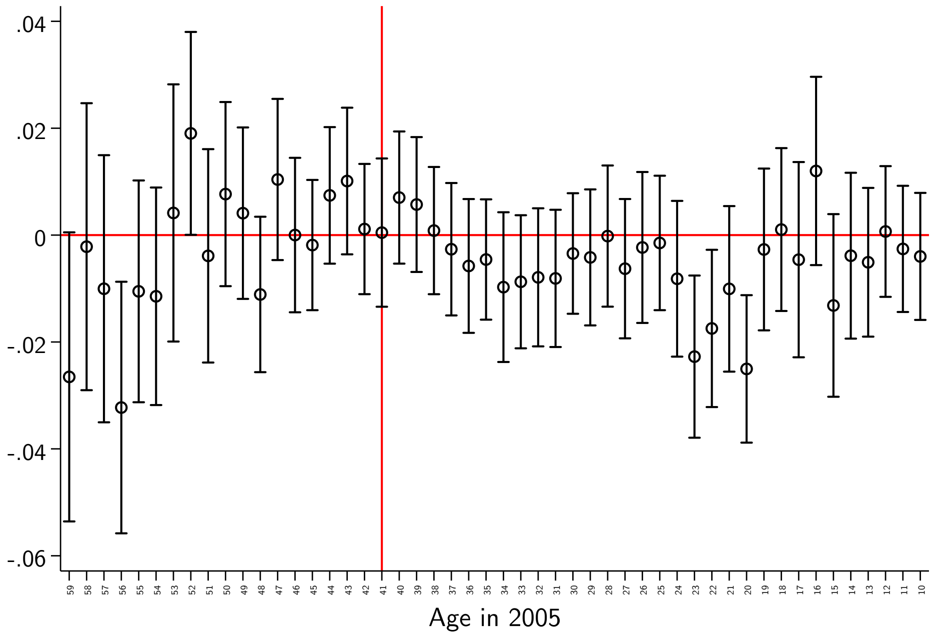
Notes: Panel A and B report the coefficients η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is years of schooling. The excluded cohort is composed by individuals with 40 years or more in 1964. The 17 years old cohort marked with a vertical line as reference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

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

Panel A: Non-Migrants



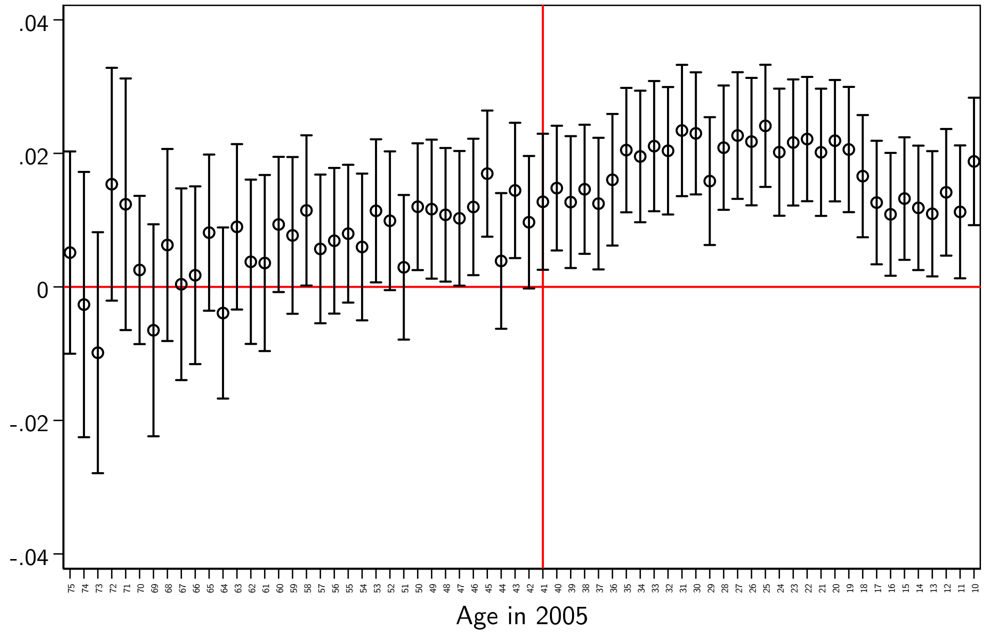
Panel B: Migrants



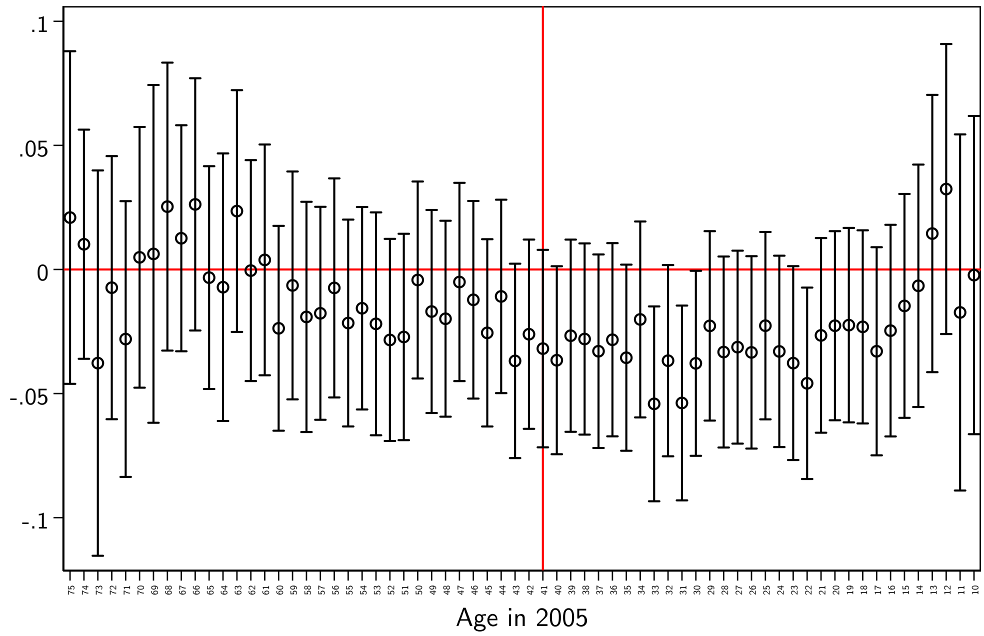
Notes: Panel A and Panel B report point estimates and 95% confidence intervals corresponding to η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed. The excluded cohort is composed by individuals with 60 years or more in 2005.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

Panel A: Non-Migrants



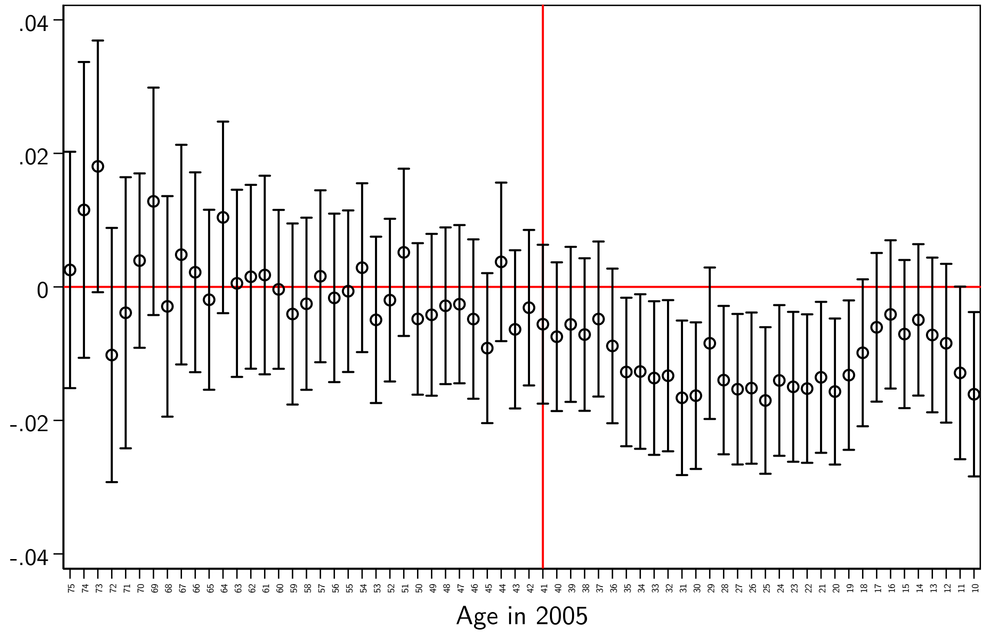
Panel B: Migrants



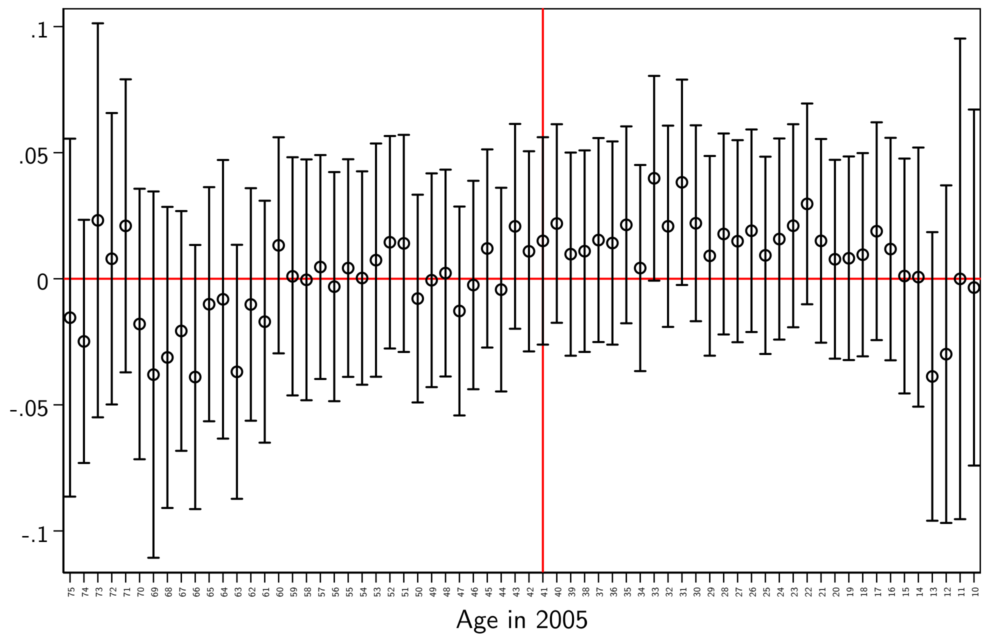
Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in agriculture in 2005. The excluded cohort is composed by individuals with 76 years or more in 2005. 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

Panel A: Non-Migrants



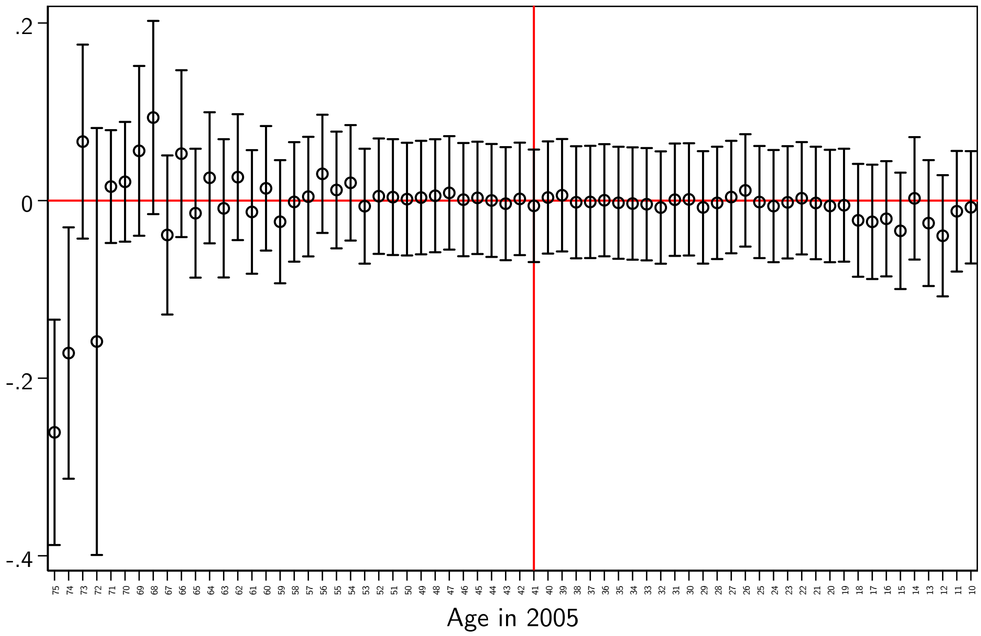
Panel B: Migrants



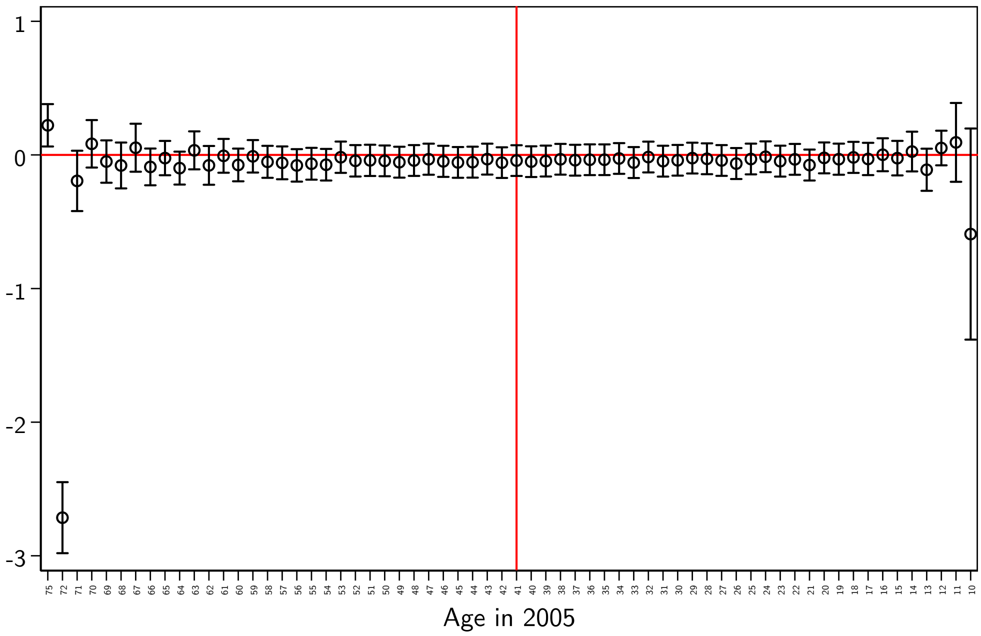
Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in services in 2005. The excluded cohort is composed by individuals with 76 years or more in 2005. 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-19: Impact of Bombing on the Probability of Working in Manufacturing by Migration Status

Panel A: Non-Migrants

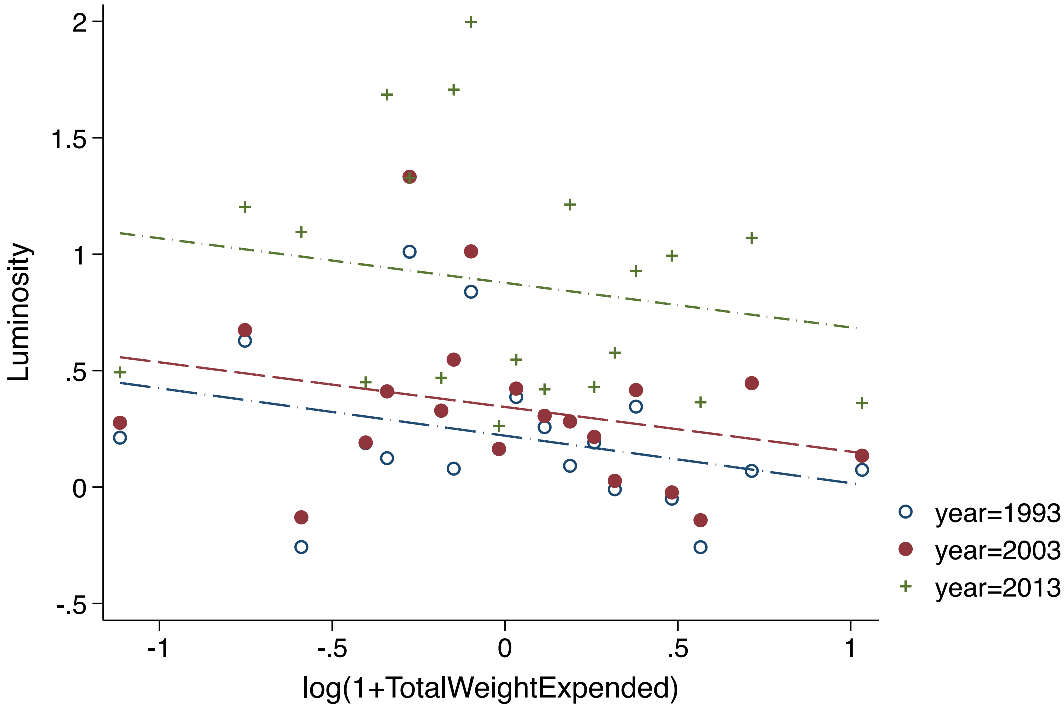


Panel B: Migrants



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.

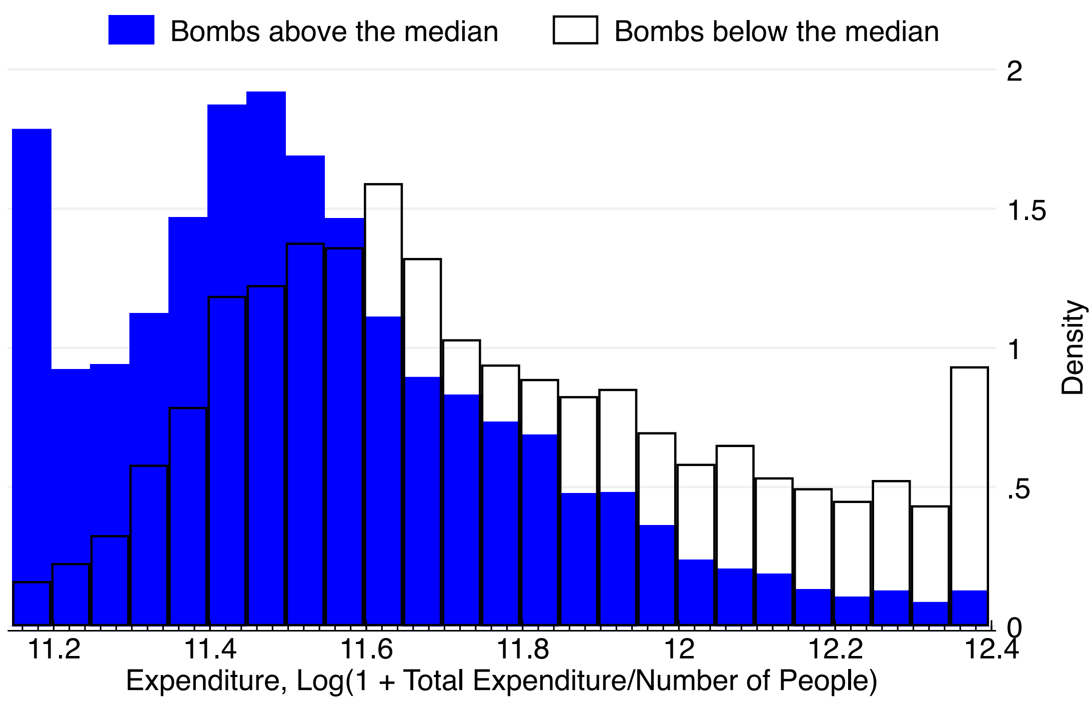
Figure A-20: Luminosity & Bombs: Bin-scatters at the District Level by Year



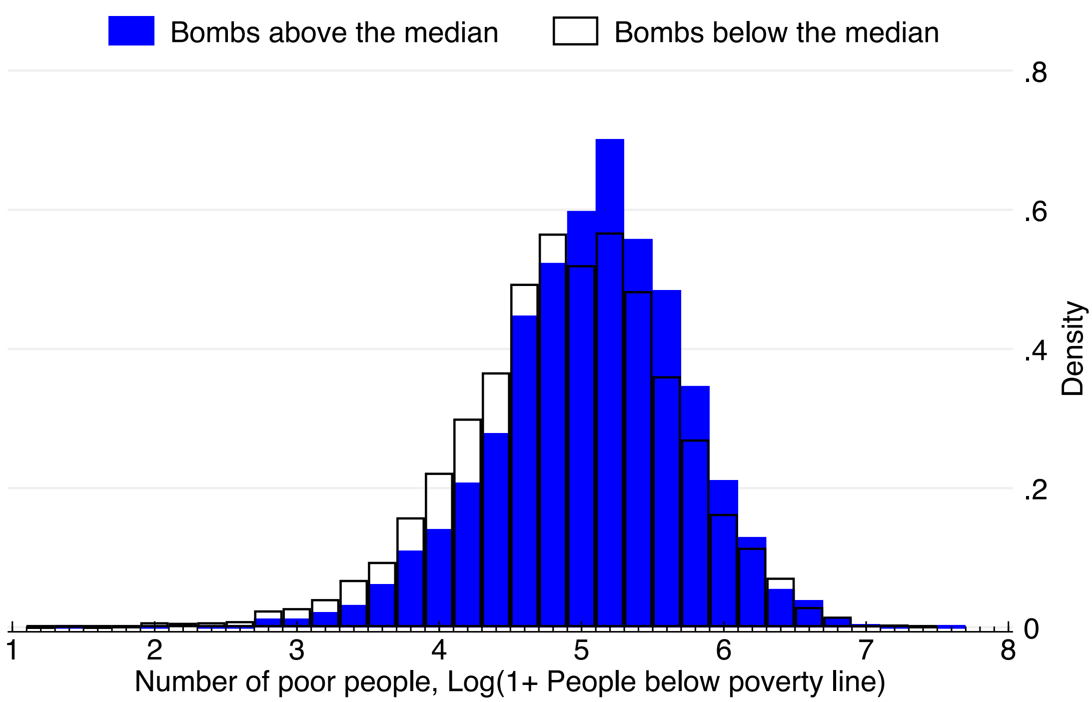
Notes: Figure presents the linear relationship between luminosity and bombing intensity. $\log(1 + \text{TotalWeightExpended})$ is standardized. Observations are at the district level. To replicate the main specification in Miguel and Roland (2011) all bin-scatters control for population in 1960, district area, province fixed effects, average rainfall, average temperature, latitude of the district centroid and absolute distance to the demilitarized zone (DMZ or parallel 17th)

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).

Online Appendix: Tables

Table A-1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: Grid cell level data				
Bombs, (log$(1 +$ Total Weight in pounds Jettisoned 1965-1973 per Km^2))	5.944	5.063	0	18.458
Total Luminosity 1993 (log$(1 +$ Total Lights 2013 per Km^2))	0.03	0.281	0	5.549
Total Luminosity, 2003 (log$(1 +$ Total Lights 2003 per Km^2))	0.049	0.344	0	5.7
Total Luminosity, 2013 (log$(1 +$ Total Lights 1993 per Km^2))	0.126	0.539	0	6.558
Luminosity, 1993 (log$(1 +$ Stable Lights 1993 per Km^2))	0.014	0.166	0	3.955
Luminosity, 2003 (log$(1 +$ Stable Lights 2003 per Km^2))	0.022	0.2	0	4.104
Luminosity 2013 (log$(1 +$ Stable Lights 2013 per Km^2))	0.056	0.315	0	4.954
Luminosity Growth, 1993-2003	0.008	0.071	-0.085	1.758
Luminosity Growth, 2003-2013	0.034	0.181	-1.758	3.94
Luminosity Growth, 1993-2013	0.042	0.213	-0.085	3.94
Panel B: Micro level data				
- Years of Schooling	4.319	3.927	0	13
- Migrant	0.114	0.318	0	1
- Employed	0.663	0.473	0	1
– Agriculture	0.807	0.395	0	1
– Services	0.219	0.413	0	1
– Manufacturing	0.179	0.383	0	1
Panel C: Village level data				
- Average farm size per household (m^2)	2.05	8.019	0.02	436.87
- Area potentially suitable for cultivation (km^2)	2.527	1.952	0	11.156
- Percentage of households with disabled people	0.079	0.073	0	1
- Average number of people with disabilities	36.44	37.955	0	640.680
- Village has electricity	0.353	0.478	0	1
- Village has water supply	0.064	0.245	0	1
- Village has road access	0.664	0.472	0	1
- Village has a primary school	0.802	0.399	0	1

Notes: Grid cell level data refers to synthetic squares of 10km $\times$ 10km.

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

	(1)	(2)	(3)
Panel A: Dependent Variable		$\log(1 + Lights/Km2)$	
Bombs	-0.0363***	-0.0319**	-0.0248**
	(0.0059)	(0.0141)	(0.0096)
R-squared	0.0701	0.0404	0.0199
Panel B: Dependent Variable		$\log\left(Lights/Km2 + \sqrt{(Lights/Km2)^2 + 1}\right)$	
Bombs	-0.0443***	-0.0388**	-0.0307**
	(0.0071)	(0.0171)	(0.0118)
R-squared	0.0709	0.0405	0.0203
Panel C: Dependent Variable		$\log(0.0001 + Lights/Km2)$	
Bombs	-0.2318***	-0.2049*	-0.1300*
	(0.0362)	(0.1034)	(0.0736)
R-squared	0.1486	0.0978	0.0689
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 grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. 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-3: Conley Standard Errors: Pooled OLS of Luminosity on Bombs

Dependent Variable	Luminosity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Threshold of influence	Cluster	$\leq$ 100 Km	$\leq$ 200 Km	$\leq$ 300 Km	$\leq$ 500 Km	$\leq$ 1000 Km	$\leq$ 1500 Km
Bombs	-0.0217**	-0.0217***	-0.0217**	-0.0217**	-0.0217**	-0.0217***	-0.0217***
	(0.0095)	(0.0078)	(0.0088)	(0.0094)	(0.0086)	(0.0063)	(0.0056)
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Districts Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Districts	141	141	141	141	141	141	141
Observations	6,648	6,648	6,648	6,648	6,648	6,648	6,648
R-squared	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126	0.3126

Notes: Observations are at the grid cell $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. Conley standard errors in parentheses, using as the threshold reported in each column. Column 1 report cluster standard errors at the district level for reference. *** p<0.01, ** p<0.05, * p<0.1

Table A-4: Testing for Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
	Luminosity 1993		Luminosity 2003		Luminosity 2013	
	Coeff	Spillover	Coeff	Spillover	Coeff	Spillover
Bombs	-0.03191***	0.01136	-0.04192***	0.01576	-0.07823***	0.05627***
	(0.00684)	(0.00934)	(0.00820)	(0.01120)	(0.01263)	(0.01725)
Geographical Controls		Yes		Yes		Yes
Location Controls		Yes		Yes		Yes
Observations		2,216		2,216		2,216
Moran's test p-value		0.841		0.00121		0.00111
Direct effects of Bombs		-0.0319***		-0.0419***		-0.0782***
		(0.00684)		(0.0103)		(0.0113)
Indirect effects of neighbours' Bombs		0.0105		0.0145**		0.0518***
		(0.00614)		(0.00736)		(0.0126)
Total effects of Bombs		-0.0214***		-0.0274***		-0.0264**
		(0.00860)		(0.00820)		(0.0159)

Notes: Observations are at the grid cell $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. This table presents the estimates of an 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 in matrix notation for the main equation and the error term:

$$\mathbf{y}_{mt} = \lambda_0 \boldsymbol{W}_n \left(\boldsymbol{Bombs} \right) + \boldsymbol{X'\beta} + \boldsymbol{U}_{mt}$$
$$\boldsymbol{U}_{mt} = \sigma_e \boldsymbol{W}_n \boldsymbol{U}_{mt} + \boldsymbol{V}_{mt},\ \boldsymbol{V}_{mt} \sim N(0,1)$$

Where $\boldsymbol{W}_n$ is an adjacency matrix between grid cells which entries are equal to $1/distance_{i,j}$. *** p<0.01, ** p<0.05, * p<0.1

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

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Luminosity					
Bombs	-0.0226***	-0.0266***	-0.0202**	-0.0278***	-0.0218**
	(0.0030)	(0.0032)	(0.0093)	(0.0049)	(0.0099)
Population density in 1960	0.3327***	0.3111***	0.3059***	0.2997***	0.2985***
	(0.0476)	(0.0500)	(0.0618)	(0.0492)	(0.0613)
Geographical Controls		Yes	Yes	Yes	Yes
Location Controls				Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects			Yes		Yes
Number of Provinces			18		18
Observations	6,648	6,648	6,648	6,648	6,648
R-squared	0.1037	0.1126	0.0968	0.1271	0.0989

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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. Robust standard errors in parentheses, if province fixed effects are present standard errors clustered at that level. *** p<0.01, ** p<0.05, * p<0.1

Table A-6: Controlling for the Number of Roads in 2013 (Bad Control)

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Luminosity					
Bombs	-0.0278***	-0.0278***	-0.0324**	-0.0384***	-0.0322**
	(0.0034)	(0.0033)	(0.0131)	(0.0057)	(0.0131)
Number of roads	0.0090***	0.0064***	0.0012	0.0046**	0.0008
	(0.0020)	(0.0021)	(0.0037)	(0.0021)	(0.0039)
Geographical Controls		Yes	Yes	Yes	Yes
Location Controls				Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects			Yes		Yes
Number of Provinces			18		18
Observations	6,648	6,648	6,648	6,648	6,648
R-squared	0.0200	0.0474	0.0324	0.0709	0.0404

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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Variable Bombs is standardized. Robust standard errors in parentheses, if province fixed effects are present standard errors clustered at that 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	-0.0366***	-0.0056***	-0.2612***	-0.0497***
	(0.0039)	(0.0010)	(0.0403)	(0.0109)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	6,648	6,581	550	483
R-squared	0.1192	0.0862	0.2017	0.1507
Dep Var Mean	0.0306	0.00992	0.370	0.135
Panel B: Observations at the district × year level				
Bombs	-0.0828***	-0.0765***	-0.1348***	-0.1169***
	(0.0195)	(0.0143)	(0.0390)	(0.0282)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Observations	423	418	195	190
R-squared	0.4541	0.3601	0.4659	0.3893
Dep Var Mean	0.0805	0.0583	0.175	0.128

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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Robust standard errors in parenthesis. If fixed effects are present, standard errors are clustered at that level.

Table A-8: Heterogeneous Results: Urban Rural Divide

	(1)	(2)	(3)
Dependent variable: Luminosity			
	All	Urban	Rural
Bombs	-0.0277**	0.0037	-0.0259**
	(0.0106)	(0.0030)	(0.0118)
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	780	5,868
R-squared	0.0757	0.0399	0.0791

Notes: Observations are at the grid cell $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer.Variable Bombs is standardized. Robust standard errors in parentheses, if province fixed effects are present standard errors clustered at that level. *** p<0.01, ** p<0.05, * p<0.1

Table A-9: Instrumental Variables: First Stages

Table A8-A: *Instrument: Distance to the Ho Chi Minh Trail*

	(1)	(2)	(3)
Dependent Variable		Bombs	
Distance to the Ho Chi Minh	-0.0066***	-0.0108***	-0.0200***
	(0.0007)	(0.0035)	(0.0030)
(Distance to the Ho Chi Minh)^2	-0.0055***	0.0052	0.0146*
	(0.0015)	(0.0071)	(0.0076)
Altitude	0.0008***	0.0008**	0.0004***
	(0.0002)	(0.0003)	(0.0001)
Ruggedness	-0.0829	-0.1874	0.0355
	(0.1196)	(0.2885)	(0.1695)
Temperature	0.1011***	0.1781***	0.1207***
	(0.0335)	(0.0557)	(0.0297)
Precipitation	-0.0018***	0.0025	-0.0013
	(0.0005)	(0.0017)	(0.0016)
Distance to DMZ	-0.0189	-0.1838	-0.1328
	(0.0213)	(0.1347)	(0.1952)
Latitude	0.1793***	0.2020	0.4473
	(0.0538)	(0.2413)	(0.3708)
Longitude	-0.1307*	-0.0540	-0.0373
	(0.0717)	(0.2457)	(0.5042)
Distance to the Vietnam Border	-0.0001	0.0007	0.0035
	(0.0009)	(0.0036)	(0.0058)
Distance to the closest capital	0.0039***	0.0054***	0.0039**
	(0.0003)	(0.0009)	(0.0017)
Observations	2,216	2,216	2,216
R-squared	0.5626	0.2427	0.1348
F	430.3	20.68	12.42
R-squared Adj	0.560	0.239	0.130
Number of Provinces		18	
Number of Districts			141

Table A8-B: *Instrument: Distance to Closest Base*

	(1)	(2)	(3)
Dependent Variable		Bombs	
Distance to closest US Air Base	0.0123***	0.0122***	0.0049
	(0.0007)	(0.0032)	(0.0038)
(Distance to closest US Air Base)^2	-0.0232***	-0.0198***	-0.0149
	(0.0012)	(0.0043)	(0.0092)
Altitude	0.0011***	0.0009**	0.0005***
	(0.0002)	(0.0003)	(0.0002)
Ruggedness	-0.4361***	-0.2349	-0.0273
	(0.1224)	(0.2837)	(0.1988)
Temperature	0.2057***	0.2146***	0.1636***
	(0.0382)	(0.0564)	(0.0360)
Precipitation	0.0011**	0.0035**	-0.0002
	(0.0006)	(0.0015)	(0.0021)
Latitude	0.0254	0.0409	0.0826
	(0.0562)	(0.1382)	(0.3207)
Longitude	0.0189	-0.0006	-0.0304
	(0.0692)	(0.1935)	(0.3576)
Distance to DMZ	-0.2281***	-0.3788**	-0.3065
	(0.0280)	(0.1674)	(0.2514)
Distance to Vietnam Border	-0.0069***	-0.0036	-0.0039
	(0.0009)	(0.0029)	(0.0046)
Distance to Closest Capital	0.0018***	0.0039***	0.0039***
	(0.0003)	(0.0011)	(0.0013)
Observations	2,216	2,216	2,216
R-squared	0.5776	0.2473	0.0581
F	523	31.89	4.410
R-squared Adj	0.576	0.244	0.0534
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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. 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. 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 A9-A Distance to the Ho Chi Minh Trail	(1)	(2)	(3)
Panel B: Dependent variable is luminosity, model:	RF	RF	RF
Distance to Ho Chi Minh Trail	0.0991***	0.1483***	0.1585***
	(0.0267)	(0.0494)	(0.0372)
Distance to Ho Chi Minh Trail^2	0.0018	-0.0108	-0.0016
	(0.0029)	(0.0066)	(0.0062)
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 A9-B Distance to the Closest US Air Base	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	RF	RF	RF
Distance to closest US air base	-0.1740***	-0.1481***	-0.1516***
	(0.0422)	(0.0383)	(0.0381)
Distance to closest US air base^2	0.0343***	0.0352***	0.0398***
	(0.0078)	(0.0083)	(0.0085)
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 $\times$ year level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. 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. 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 A10-A *Instrument: Distance to Ho Chi Minh Trail*

	(1)	(2)	(3)
Panel A: Dependent Variable Lights 1993			
Bombs	-0.0749***	-0.0783**	-0.0503**
	(0.0223)	(0.0308)	(0.0205)
Panel B: Dependent Variable Lights 2003			
Bombs	-0.1000***	-0.1049***	-0.0761***
	(0.0256)	(0.0358)	(0.0269)
Panel C: Dependent Variable Lights 2013			
Bombs	-0.1847***	-0.1875***	-0.1539***
	(0.0394)	(0.0590)	(0.0462)
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 A10-B: *Instrument: Distance to Closest Base*

	(1)	(2)	(3)
Panel A: Dependent Variable Lights 1993			
Bombs	-0.0982***	-0.0935*	-0.1233
	(0.0277)	(0.0500)	(0.0867)
Panel B: Dependent Variable Lights 2003			
Bombs	-0.1299***	-0.1262*	-0.1884
	(0.0322)	(0.0665)	(0.1237)
Panel C: Dependent Variable Lights 2013			
Bombs	-0.2064***	-0.1792*	-0.4838
	(0.0449)	(0.0980)	(0.3082)
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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. Robust standard errors in parentheses, 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	-0.1283***	-0.0985***	-0.1018***
	(0.0285)	(0.0226)	(0.0220)
Over identification test	0.0372	2.788	0.440
p-value	0.847	0.0950	0.507
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	-0.1359***	-0.1161***	-0.0910***
	(0.0302)	(0.0265)	(0.0197)
Controls that apply for all panels			
Road Access	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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. 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 standardized. 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
Bombs	-0.0940***	-0.1074**
	(0.0261)	(0.0540)
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 kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. 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 standardized. Robust standard errors in parentheses clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-14: Luminosity on Bombs and UXO Accidents (Grid Cell level)

	(1)	(2)	(3)
	Luminosity 1993	Luminosity 2003	Luminosity 2013
Bombs	-0.0143**	-0.0209**	-0.0398***
	(0.0062)	(0.0085)	(0.0120)
UXO Accidents	-0.0053	-0.0047	0.0122
	(0.0083)	(0.0098)	(0.0105)
Geographical Controls	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
Observations	2,216	2,216	2,216
Number of Districts	141	141	141

Notes: Observations are at the grid cell level. Variable Luminosity represents the log of one plus the total number of stable nightlights per square kilometer within each grid cell. Variable Bombs represents the total weight in pounds jettisoned within grid cell from 1965 to 1973 per square kilometer. UXO Accidents corresponds to the logarithm of the number of UXO events before 1993 divided by the grid area according to the geolocated data from the NRA. Robust standard errors in parenthesis clustered at the district level.

Table A-15: Luminosity on Bombs and UXO Contamination (Village Level)

Dependent variable:	Luminosity 1993		
	(1)	(2)	(3)
Bombs	-0.0369***		-0.0362***
	(0.0036)		(0.0036)
UXO Contamination		-0.0096***	-0.0020
		(0.0015)	(0.0014)
R-squared	0.2882	0.2856	0.2882
Dependent variable:	**Luminosity 2003**		
	(1)	(2)	(3)
Bombs	-0.0457***		-0.0459***
	(0.0050)		(0.0051)
UXO Contamination		-0.0091**	0.0004
		(0.0037)	(0.0038)
R-squared	0.1262	0.1235	0.1304
Dependent variable:	**Luminosity 2013**		
	(1)	(2)	(3)
Bombs	-0.0514***		-0.0511***
	(0.0089)		(0.0093)
UXO Contamination		-0.0113	-0.0007
		(0.0080)	(0.0083)
R-squared	0.3221	0.3206	0.3221
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	10,382	10,382

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

Table A-16: Agricultural Outcomes

Dependent variable:	Area potentially suitable for cultivation		
	(1)	(2)	(3)
Bombs	0.0514		-0.0160
	(0.0665)		(0.0708)
UXO Contamination		0.2054***	0.2087***
		(0.0607)	(0.0578)
R-squared	0.0250	0.0336	0.0336
Dependent variable:	**Average farm size per household**		
	(1)	(2)	(3)
Bombs	-0.4041*		-0.3659*
	(0.1949)		(0.1788)
UXO Contamination		-0.1940**	-0.1180**
		(0.0709)	(0.0510)
R-squared	0.0044	0.0033	0.0046
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	10,382	10,382

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

Table A-17: Disability

Dependent variable:	Average number of people with disabilities		
	(1)	(2)	(3)
Bombs	1.6033		1.0719
	(1.0656)		(0.8456)
UXO Contamination		1.8673**	1.6447**
		(0.8508)	(0.7425)
R-squared	0.0103	0.0114	0.0118
Dependent variable:	**Percentage of households with disabled people**		
	(1)	(2)	(3)
Bombs	0.0018		0.0006
	(0.0018)		(0.0017)
UXO Contamination		0.0037***	0.0035***
		(0.0011)	(0.0011)
R-squared	0.0257	0.0275	0.0275
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	10,382	10,382

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

Table A-18: Roads

Dependent variable:	Village has road access		
	(1)	(2)	(3)
Bombs	0.0486***		0.0462***
	(0.0154)		(0.0145)
UXO Contamination		0.0170	0.0074
		(0.0116)	(0.0113)
R-squared	0.1080	0.1033	0.1082
Province fixed effects	Yes	Yes	Yes
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Observations	10,382	10,382	10,382

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