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Abstract

As part of its Cold War counterinsurgency operations in Southeast Asia, the U.S. government conducted a "Secret War" in Laos from 1964-1973. This war constituted one of the most intensive 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 economic development, using highly disaggregated and newly available data on bombing campaigns, satellite imagery and development outcomes. We find a negative, significant and economically meaningful impact of bombings on nighttime lights, expenditures and poverty rates. Almost 50 years after the conflict officially ended, bombed regions are poorer today and are growing at slower rates than unbombed areas. A one standard deviation increase in the total pounds of bombs dropped is associated with a 9.3% fall in GDP per capita. To deal with the potential endogeneity of bombing, we use as instruments the distance to the Vietnamese Ho Chi Minh Trail as well as US military airbases outside Laos. Using census data at the village and individual levels, we show the deleterious impact of UXOs in terms of health, as well as education, structural transformation and rural-urban migration.

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

Keywords: conflict, Laos, Cold War, UXO, Development, growth, health, Human Capital, structural transformation, migration

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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 U.S. government conducted a "Secret War" in Laos from 1964-1973. This war constituted one of the most intensive 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 economic development, using highly disaggregated and newly available data on bombing campaigns, satellite imagery and development outcomes. We find a negative, significant and economically meaningful impact of bombings on nighttime lights, expenditures and poverty rates. Almost 50 years after the conflict officially ended, bombed regions are poorer today and are growing at slower rates than unbombed areas. A one standard deviation increase in the total pounds of bombs dropped is associated with a 9.3% fall in GDP per capita. To deal with the potential endogeneity of bombing, we use as instruments the distance to the Vietnamese Ho Chi Minh Trail as well as US military airbases *outside* Laos. Using census data at the village and *individual* levels, we show the deleterious impact of UXOs in terms of health, as well as education, structural transformation and rural-urban migration.

Keywords: Conflict, Laos, Persistence, Cold War, Counterinsurgency, 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"
- Lao proverb[1]

1 Introduction

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 are 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.

To make progress on this important question, we focus on the Lao People's Democratic Republic (Laos). Today Laos is one of the poorest countries in the world, where almost a quarter of the population lives under extreme poverty and 80% survive on less than $2.50 dollars per day. Due to the US military intervention during the Laotian Civil War (1959-1975), Laos is also one of the most heavily bombed countries 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 nowadays one of the most contaminated countries in the world in terms of UXO (Unexploded Ordnance).[4] In this paper we ask whether conflict 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 production function.[5] Theoretically, Rohner, Thoenig, and Zilibotti (2013) and Acemoglu and Wolitzky (2014) have formally demonstrated how societies can enter into 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—remains largely unexplored. We look at this relationship in the context of Laos, finding a negative and significant effect between conflict and economic development. In particular, we stress

[1] Quoted in Conboy (1995).

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

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

[4] This does *not* mean that the 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. The survey also noted the small number of studies looking at socioeconomic effects.

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

the role of UXOs in generating these persistent effects, and how they affect health, human capital accumulation, structural transformation and migration patterns.

To test this hypothesis and its potential mechanisms of transmission, we combine novel data on the incidence of conflict with key 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 more than 10,000 villages and 561,000 individuals, allowing us to explore both the spatial and temporal dimensions 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 way. 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 even the district (and 141 districts) levels.[7] Similarly, when aggregating the data for different years, we include time fixed effects. 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 key 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 Demilitarized Zone), distance to the Vietnam border and distance to the nearest district capital. 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 33% decrease in nightlights with respect to their mean (-0.0231/0.0683), an effect that corresponds to a 9.3% fall in GDP per capita, a sizable decrease.

Still, OLS and even Fixed Effects estimates might be biased, as bombing was presumably 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 bombed

[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] Helping us to bypass potential endogenous border formation concerns.

more intensely.[8] Using quantile regressions, we show that the effect is concentrated among the higher parts of the distribution, consistent with the former case. Still, to tackle this potential endogeneity issue, we employ an Instrumental Variables (IV) identification strategy. Our first instrument is the distance to the Ho Chi Minh Trail, in particular, the part that was unknown to Americans at the time—mostly constituted by underground tunnels. This instrument thus exploits the asymmetric information inherent to 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 and was not known to the Laotians at the time. We believe that the location of these bases in South Vietnam, Thailand and Japan can be viewed as largely exogenous to the posterior Laotian conflict, as detailed in the historical background and Section 4.3.

Our IV estimates confirm the baseline OLS and FEs findings. First, we find a negative and strong relationship between both distance to the Ho Chi Minh Trail and the nearest US air base and bombings. 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. The results are robust to using geographic and location controls, as well as netting out fixed effects.[9]

To further test the validity of our findings—as well as to explore potential mechanisms of transmission, we use data from the national censuses, both at the village and individual levels. We divide the sample between villages that are above and below the median in terms of number of bombs received. We find that in the former people have lower expenditures and higher poverty rates, meaning that the nightlights results translate into relevant development outcomes. We also 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 accidents panel starting in 1950. We find more accidents in more heavily bombed areas from the 1960s to today.

But the negative effects of conflict appear to transcend the direct effects of UXO contamination, hampering other key economic investments. At a first pass, we observe that bombed areas are less dense today. They also have *lower* levels of human capital, in terms of literacy and health. Affected villages also appear to have worse public goods provision, in terms of electricity and water supplies. We complement these

[8] We show, among others, that our results hold after controlling for population in 1960, *before* the conflict started.

[9] We also test for potential spatial spillovers, but find little evidence for them (cf. Chiovelli, Michalopoulos, and Papaioannou (2018)).

aggregate findings with an analysis of the data at the *individual* level. To this end, we use a difference-in-differences specification, where we identify off the level of exposure to conflict for individuals from different cohorts, born in different provinces. 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). In modern times, now that these individuals have entered the labor market, they have a lower probability of being employed as a whole. Furthermore, even when employed, they are *more* likely to be working in agriculture, and less in services. Hence, conflict appears to have negatively affected human capital accumulation and further delayed the structural transformation process in Laos.

Finally, we study the interaction with migration. We find that conflict decreased the rates of internal migration by around 10% with respect to the sample mean. Using a triple difference, we *decompose* the human capital and labor effects for migrants and non-migrants. We find that the negative education shock is concentrated among those who stayed (about 90% of the sample) rather than on those who moved (the remaining 10%). These results for human capital parallel those for sectoral employment, where again non-migrants are more affected. Taken together, these rural-urban migration patters help explain the negative long-run development consequences of the Laotian conflict, providing lessons for other countries still grappling with the legacies of war.

1.1 Literature

Social scientists have spent considerable effort studying the causes and consequences of conflicts. 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) again stressed economic factors leading to war and advocated in particular for more research about the socioeconomic consequences of conflict, a call we take in this paper. Bauer et al. (2016) have pointed out the surprisingly positive societal consequences of war, via increased cooperation, predominantly in the short run.

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). Similarly, 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 (Dincecco & Onorato, 2018), while Becker et al. (2019)

show causal evidence for this key link for Germany. Researchers have even stressed a Malthusian mechanism during war, 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 war.

In spite of its credence in policy and development circles, the "Conflict Trap" hypothesis advocated by Collier has not been formally tested in the literature. 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, in essence, a contemporaneous exercise. Rohner et al. (2013) and Acemoglu and Wolitzky (2014) already provide a sound *theoretical* foundation for conflict traps. Still, to the best of our knowledge, no paper in economics has tested the other direction of the conflict trap hypothesis empirically, as we do here in Laos, where war literally fell from the sky.

The major surveys on conflict in economics stress the incidence 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).[10] Some of the most closely related papers to the present work study conflict in Mozambique, Cambodia and Colombia. Chiovelli et al. (2018), stress the large economic benefits of *clearing* the landmines left after the Mozambican Civil War (1977-1992). Lin (2017) looks at the problem of UXOs in Cambodia, which shares a border with Laos, finding that agricultural land (especially for rice) has become less productive due to UXOs. 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 hypothesize that this channel could be playing an important role in the Laotian case as well.

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. In turn, Tur-Prats and Valencia Caicedo

[10] 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. Different from this earlier contribution, we use here highly disaggregated data, at the grid cell and village levels, which allows us to take province, and even district fixed effects (N=584 vs. N=2,216 & 10,522).

(2020) examine the cultural and political consequences of the Spanish Civil War. Closer to the area of interest, Dell and Querubin (2018) find causal effects of the Vietnam bombing on anti-American sentiment. 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. More broadly, this article is also related to the large literature on long-term economic persistence, recently summarized by Nunn (2009, 2014, 2020), Spolaore and Wacziarg (2013), and Michalopoulos and Papaioannou (2017). Here we focus on conflict as a source of long-term economic persistence, in a developing country context.

We contribute threefold to the conflict literature. First, we stress the special role of UXOs in generating the lingering aftereffects of conflict, harming not only health directly, but also *other* key 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* cost of conflict. Lastly, we study human capital accumulation, public good provision, structural transformation and rural-urban migration, as transmission channels of the negative effect of conflict on long-term development and growth.

The rest of the paper is organized as follows. The next section covers the relevant historical background. We then present the data and the empirical strategy in Sections 3 and 4, followed by the main empirical results in Section 5—divided into OLS, FEs and IV estimates. Section 6 contains the mechanisms of transmission. We conclude with the main lessons of the study along with their potential relevance for policy.

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. 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), described later.[11] Laos was essentially seen through the lens of President Eisenhower's "Domino Theory" of the Cold War, according to which if one country fell to Communism in the region, it could precipitate the fall of others. Accordingly, the US intervened in

[11] 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, under Pol Pot. For more details, see Iwanowsky and Madestam (2019).

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.

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 added 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." 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 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 US troops. In 1964, the US conducted its first reconnaissance aerial missions and on June 9 President Lyndon B. Johnson authorized the bombing of 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 lion share of the war was carried by external military forces.[12]

A series of covert military operations by the CIA and the US Air Division were deployed in Laos and Vietnam, including Operation Steel Tiger, Operation Tiger Hound, and Operation Commando Hunt. Aside from the Plain of Jars, the US heavily bombed southeast Laos, given its proximity to the Ho Chi Minh Trail. Figure 6. 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, putting an end to the conflict, forcing King Savang Vatthana's abdication, and proclaiming the Lao People's Democratic Republic.

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

As a result of the war 200,000 people or one tenth of the Laotian population was killed. It is estimated that twice as many were wounded and as many as 300,000 people were forcibly displaced. Officially, 728 Americans, mostly CIA operators died in Laos (see, for instance, Kurlantzick (2017)). In total, over 270 million cluster bombs were dropped in the country, about a third of which did not explode. Approximately 50,000 Laotians, most of them civilians–especially children–have been killed or injured by such artifacts. Less than 1% of these munitions have been cleared, making this the number one development issue in the country (Boddington & Chanthavongsa, 2008). Still, very little is invested in clearance, around 4.9 million dollars a year, when 13.3 million dollars were spent in bombing during the war daily.[13]

The broader Vietnam War, also known as the Second Indochina War, was fought between North and South Vietnam from 1955 to 1975.[14] We only provide a brief sketch here, referring the reader to Miguel and Roland (2011) and Dell and Querubin (2018) for more details. 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. The US was heavily involved in the confrontation, sending a total of almost three million troops to Vietnam and dropping 7.5 million tons of bombs in the Indochinese peninsula. Aside from Vietnam, the US bombed Cambodia and Laos to stop the flow of troops and resources to North Vietnam in operations such as Menu and Freedom Deal. Almost 60,000 US troops were killed in Vietnam, while the Vietnamese military casualties were in the order of three million. The fall of Saigon in 1975 and the overall defeat of South Vietnam and its allies constitute a defining moment in modern American history.

3 Data

In this section we describe the different sources and levels of aggregation of the main variables used in the empirical analysis. Namely, we use information at the synthetic grid cell, village and individual levels.

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

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

[14] The first Indochina War, pitting the French against the Viet Minh, lasted from 1946 to 1954.

cells of 10km-by-10km. In Figure 2, we present the synthetic grid and the principal administrative divisions of the country, consisting of 18 provinces and 141 districts. This level of disaggregation allows us to net out fixed effects at the province and even the district levels, an important step forward relative to the existing literature (see Montalvo and Reynal-Querol (2017) and Harari and Ferrara (2018) for similar approaches in Africa). We collate information on economic activity and historical bombing, geographic and location controls at this level, 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 3 Panel A illustrates 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,[15] 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, seen in Figure 3 Panel B. This previously classified data consists of a daily panel of individual operations with the exact coordinates of each deployment. It includes 1,635,759 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.

Geographic Controls To account for potential geographical confounders, we use geophysical, and weather information from DIVA-GIS and World Clim 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.

[15] As opposed to total lights, the measure of stable lights excludes ephemeral events, such as fires and water reflections. This noise is identified and replaced with zeros by the NOAA.

Location Controls To control for spatial confounders of conflict or 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 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 for our examination, giving us a more granular picture of the whole country. All the information comes from The Lao DECIDE info platform, an initiative of the Laotian Government to improve access to official data.[16] Panel A of Figure A-2 presents the geographical distribution of the 10,522 villages reported in 2005. This represents an even *higher* level of disaggregation than the grid cells described above. We employ information on development outcomes, UXO contamination, urbanization, human capital and public good provision at the village level.

One important limitation of this data is that there is no official demarcation of village boundaries in Laos.[17] To bypass this constraint, we constructed a synthetic set of village boundaries based on Thiessen / Voronoi polygons. The rationale for using this method of border assignment is to define an area around each village within which we can calculate the historical intensity of the conflict.[18] Panel 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.

Development Outcomes We complement our analysis of nightlight data using more direct measures of development outcomes. 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.

[16]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.

[17]Citing textually from the census reports: 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."

[18]We use this method based on the coordinates reported in each census. 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).

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

Urbanization and Human Capital We study the role of conflict on additional outcomes at this level of disaggregation. In particular, we look at the influence of historical conflict on 1) population density, measured as the log of the population at the village level divided by its area in square kilometers; 2) the fraction of households with disabled people and 3) the fraction of literate households.

Public Goods Provision Finally, we explore the role of conflict on the provision of public goods. We focus our analysis in three specific indicator variables: The presence of primary schools, the availability of electricity and water supply.[19]

3.3 Individual-level Data

We zoom into individual-level information to estimate the long-term impact of conflict on individual outcomes and the potential effects on human capital and structural transformation. We used two data-sets to perform this analysis. First, we use a 10% sample of the micro-level data of the 2005 Census. This sample includes around 561,000 *individual* observations and comes from the IPUMS project for Laos. We focus on 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. 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).

3.4 Historical Maps

Our empirical identification strategy exploits the typical information asymmetries that occur during conflict. In particular, we use the fact that neither the U.S. nor the Laotian Communist forces perfectly knew the location of their enemies at the time. For this part of the analysis, we rely on two historical maps. From the U.S. perspective, we

[19] We also use information on the the average travel time in minutes to the closest primary school.

digitized 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.[20] This information that was *not* available to the Communist forces 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. From the perspective of the Communist forces, we digitized a map of the hidden parts of the Ho Chi Minh Trail, consisting of a complex set of underground paths, that was *unknown* to the U.S. forces and which is nowadays proudly exhibited in the Highway 9 War Museum in Laos.[21] We present the original maps in Appendix Figure A-1.

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. Finally, we include a comprehensive set of geographical and location controls at the grid cell level X_g that account for arguably exogenous but potentially confounding factors at the grid cell level, as described in Section 3.1. The parameter of interest in this model is γ_τ and represents the conditional and long-term correlation between historical conflict and economic activity at year τ.

[20] 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.

[21] 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.

4.2 Fixed-effects Models: Within Variation in Conflict

The high degree of disaggregation of our data, allows us to control for time invariant characteristics at the province or district levels, which may be correlated with contemporaneous economic activity or the historical presence of conflict. In order to do this, we include a full set of province o district fixed effects in Equation (1), which allows us to exploit the within-district or within-province variation in the intensity of conflict. To account for the spatial correlation of these groups of observations we cluster our standard errors at the same level of the fixed effects.[22]

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

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

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 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.

4.3 IV Models: Addressing the Endogeneity of Bombing

Since bombing was costly, more productive places may have been targeted during the war. If that was the case, our coefficients would be underestimating the long-term impact of conflict, since historical and persistent economic activity would be a key omitted variable. On the contrary, if bombing campaigns targeted already poor and isolated areas, and those areas remain poor today, we might be overestimating the role of conflict on economic development.[23]

To tackle this potential source of endogeneity, 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 conflict. The idea here is to use a variable $Z_{g,d}$ that would be predictive of historical bombing but that was not directly correlated with economic activity today. Specifically, we run first stage equations of the form,

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

[22] Either 18 provinces or 144 districts.

[23] Our quantile regression estimates in Figure 5 suggest that this is *not* the case, and that we are more likely experiencing a downward bias.

where the index notation and controls are analogous to Equation (1), and ρ_d are province or district fixed effects. Notice, however, that following Dieterle and Snell (2016) we have included a second degree polynomial $f\left(Z_{g,d}\right)$ on the instrument, to account the potential non-linearities on the intensity of bombing.[24] We propose two instruments based on the asymmetries of the conflict: the distance to the hidden part of the Ho Chi Minh Trail, and the proximity to US air bases outside Laos.

Instrument 1: Distance to the Ho Chi Minh Trail We exploit the fact that the location of the Ho Chi Minh Trail, was not entirely known to US authorities at the time. 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. We focus here precisely on the part of the trail that was not visible from the air, mostly consisting on tunnels and hidden paths.[25] We present an example of the original maps used in Appendix Figure A-1 and our digitization of them in Figure 6.

Instrument 2: Distance to US air Bases Outside Laos For the second instrument, we use distance to the closest American base *outside* Laos, mostly in South Vietnam, Thailand and Japan. We also consider bases built *before* the onset of the conflict, in 1960. We view these 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 bases.[26] 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.[27] Figure 6 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

Additionally, we exploit cohort and yearly variation in the degree of exposure to conflict. For this, we employ individual-level data from the 2005 Census described in detail in

[24]Still, our results are robust to using linear instruments.

[25]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).

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

[27]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.

Section 3.3. We exploit the differential impact of conflict across provinces (of birth) for different cohorts. In particular, we estimate the following econometric specification,

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

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 close to 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 the bombing on birth cohort k.

For cohorts k in their schooling years and those younger than them, (γ_k) is an unbiased measure of the impact of conflict if there are no omitted time-varying and province-specific characteristics correlated with conflict incidence. We verify the plausibility of this assumption by checking whether the bombing helps to explain the change in years of schooling for cohorts that were too old (i.e those older than 17 years old in 1964) to have changed their schooling decisions by the conflict.

4.4.1 Triple Differences: Migration Decomposition

Lastly, we calculate the triple interaction effect of the timing of conflict and migration, decomposing the human capital accumulation and labor effects between migrants and non-migrants. In particular we run:

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

where p indexes province of birth, k cohort of birth, and d_{ipk} is an indicator variable equal to one if individual i from cohort k who was born in province p. $B_p \equiv \log(1 + \text{Bombs 1964-1973})_p$ and M_i is an indicator variable equal to one if individual i is a long term migrant.[28]

[28] We define as long term migrants those individuals who in 2005 report living in a province different to the one they were born.

5 Baseline Results

5.1 OLS Results

Before running any regression, Figure 1 shows 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. This combination leads to the bin-scatter on the right, where we pool all of our nightlight observations.[29] There we can already see a negative and significant (linear) association between these two variables (net of location controls, province and year fixed effects). In what follows we test the robustness of this finding, estimating OLS, Fixed Effects and IV models.

We begin our empirical 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% confidence level. This holds true after controlling for basic geographic controls, in Column 2, and a larger set of 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 war. Only ruggedness enters negatively and significant consistently, in terms of geographic controls. With respect to the location variables, the distances to the Demilitarized Zone, Vietnam and the closest provincial capital, appear all negative and broadly significant. Though potentially important, they do not alter our coefficient of interest. We repeat the exercise using instead lights in 2003, in Columns 4 to 6, which leaves the result almost unchanged, just slightly larger. The same holds true for lights in 2013, in Columns 7 to 9, where the coefficients emerge larger in magnitude, in the order of 5%. In terms of controls, temperature emerges positively in the full specifications. Overall, it seems that areas that were bombed during the war are poorer (less lit) in modern times, all the way up to 2013.

For robustness, we introduce two important controls. 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-2, 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 this level of disaggregation. Additionally, we control for roads. This is most probably a "bad control" in the language of (Angrist & Pischke, 2008). Still, our result is unaffected by

[29] We report the relationships for individual years and different specifications next.

this addition and, if anything, increase slightly, in Table A-3.[30]

For robustness, we re-estimate our model dropping outliers in terms of Luminosity: without upper, lower or both tails (reported in Table A-5, Panel B). Similarly, we aggregate up at the district level, which leaves the results unchanged, in Table A-5, Panel A. We also show, in Table A-4 that the effect is concentrated on rural areas, which we explore later in the mechanisms section.[31] We also test for potential spillovers in Table A-6 following the model of Lee and Yu (2010). In terms of potential spatial correlation, there seems to be none in 1993 and some for the later years.[32] 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*, different from what Chiovelli et al. (2018) find for Mozambique.

Table 2 looks at the potential 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 postwar scenarios.

5.2 Fixed Effects Results

The next set of results introduce province and district fixed effects, to control for time invariant characteristics—such as ecological zones—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 disaggregation. 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. The negative relationship remains strong after adding location controls in Column 4. The negative and significant coefficients are present when we add district fixed effects, in Column 5, and when we control for location characteristics,

[30] To complete this empirical exercise, we show the impact of our independent variable of interest, bombs, on the bad control, roads, in Table A-10, following Pei, Pischke, and Schwandt (2019).

[31] We thank Sascha Becker, for suggesting these tests.

[32] Which justifies our later clustering at the fixed effect level.

in Column 6. Again, the negative results are present for the three years: 1993, 2003, and 2013 in Panels A, B and C, respectively. 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 a more local (within province and *even* district) level.

Figure 4 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 across the board, perhaps suggesting a non-linear fit. The second row presents the plots for the specification for the specification with controls and district fixed effects. Again, the relationship is strongly negative, and now appears more linear.

Finally, we pool all observations to estimate the specification in Equation (2). We now include year fixed effects in all specifications. 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, and 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 coefficient is -0.025, which is similar to the previous fixed effects results, and even the OLS estimates presented before.

To interpret the economic meaning of our estimates, 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 9.3% fall in GDP per capita.[33] This sizable decrease gives some empirical support to the Conflict Trap hypothesis in the aggregate, suggesting an S-shaped factor accumulation function, resulting in a poverty trap. 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 and within district levels.

[33] To reach this estimate, we compute the relative size of our coefficient with respect to the sample mean as $\frac{-0.0231}{0.0683}$, then we use Henderson et al. (2012) estimated elasticity of GDP to lights of 0.277, and calculate the corresponding GDP fall as $\frac{-0.0231}{0.0683} \times 0.277 = -0.093$.

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.[34] 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 5. We see that the OLS effect is working at around the 70th percentile of the distribution. This holds true for 1993, and if anything is even higher for the later years. This suggests that the estimates presented so far are potentially downward biased. Regardless of the direction of the bias, it is important to present unbiased estimates of the effect of interest. To this end, we employ an Instrumental Variables strategy, as described in Section 5.3. Recall that we have two instruments: the distance from the Ho Chi Minh Trail and the proximity to the US air bases outside Laos. Figure 6 depicts both of these instruments in a map, with Laos depicted in grid cells.

5.3.1 First Stage Results

Before reporting any regression, we plot the unconditional relationship between bombing and the two instruments, along with a quadratic fit. As can be seen in Figure 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. Most of the observations appear less than 100 kilometers from the trail, suggesting the more localized nature of this first instrument. Something similar occurs with the relationship between bombs and distance to the nearest US base outside Laos, in Figure 7 Panel B. 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 use a quadratic first stage (plotted in the figures), allowing for heterogeneous effects as in Dieterle and Snell (2016), and estimating Equation (3).

Table 5 Panel C reports the first stages of our instruments, for distance to Ho Chi Minh in Panel 5A and distance to the closest US air base in Panel 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. 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

[34] We find some evidence for this case in Table A-10 with respect to roads.

than 10 in all cases.

For completeness, Table A-7 reports the first stage tables for the two instruments with the full set of controls, province and district fixed effects. The first stage estimates for the distance to the Ho Chi Mihn Trail instrument, are presented in Table A-7, Panel A. The coefficient for the bombing regression is strongly negative throughout, and the corresponding F-statistics are always above the critical value of 10. The quadratic term is less robust. In the case of distance to the nearest US base, in Panel B, both the linear and quadratic coefficients are significant, the first positively and the second negatively, largely confirming the concave relationship.[35]

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 even very local variation. A similar negative and significant relationship appears for the second instrument, in Table 5B. In this case, the magnitude increases in the last specification.

Reduced form estimates are presented in Table 5 Panel B. These are positive and significant for the distance to Ho Chi Minh Trail instrument, suggesting that places become richer the farther away they are from this area. The quadratic terms are insignificant in this case. For distance to US air bases, in the Panel B of Table 5B the distance coefficient is now negative and significant across the board. The quadratic term is now positive and significant, confirming the non-linear nature of the effect for this variable.

Table A-8 contains the second stage results for our two instruments, by year. The results for the first instrument (distance to the Ho Chi Minh Trail) can be seen in Table A-8, Panel A. The effect of bombings on light is negative and strongly significant. This is true across the board, in the specifications with geographic and location controls (Column 1), province fixed effects (Column 2) and district fixed effects (Column 3). For the second instrument (distance to US bases), the effect of bombing on nightlights appears negative and significant a the 1% level in Panel B, Column 1, for lights in 1993, 2003 and 2013, in Panels A, B, and C, respectively. The estimates preserve the sign in Column 2, with province fixed effects. When including district fixed effects, the

[35]The relationship is largely unchanged in Column 2, but loses significance in Column 3, with district fixed effects. We interpret this last result as an indication that the airbase instrument is capturing more global variation. Though recall that the first stage is strongly significant in the pooled sample.

coefficients cease to be significant, confirming the more global nature of this instrument.

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 coefficient is -0.0915 which is very similar to the last coefficient for distance to Ho Chi Minh in Table 5. The Sargan over identification tests suggest that the instruments are valid for the first and third specifications of Panel A. Lastly, we run the IV regressions for the the South and the North of the country separately in Table A-9 finding slightly larger coefficients in the former case.

In general, the magnitudes appear larger than in the corresponding OLS specifications, which is consistent with our previous interpretation of them as underestimates.[36] The difference between the OLS and IV results can also 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) and (Becker, 2016) for a more in-depth discussion. In this set-up, though Laos was heavily bombed, some areas suffered disproportionately. This distribution is illustrated in Figure A-3 where we run the IV analysis, dropping one district at a time. Overall, the IV estimates confirm the negative effects of conflict for long-term development, explored further in the next section.

6 Mechanisms

In this section we look at transmission channels of the main effect. To this end we use Census data from 2005 and 2011, available at the village level.[37] We further employ individual-level data from the 2005 Census in Section 6.5. We first validate the nightlight results, using expenditure and poverty data, and then look at UXO contamination, expanding on its pernicious direct and indirect development effects, as suggested by Unruh, Heynen, and Hossler (2003).

[36]The IV estimates are very similar to those that account for spillovers in Table A-6.

[37]This data is even more disaggregated than the pixel level data employed before. To be able to map it, we use Thiessen polygons to represent village level boundaries, otherwise not available for Laos. See Figure A-2 for an illustration.

6.1 Expenditure and Poverty

We begin the analysis by looking at whether the effects observed on nightlights also translate into relevant development outcomes. We find that indeed, in areas that were bombed, people report lower expenditures. Figure A-5 shows the distributions for areas above (shifted to the left) and below (shifted to the right) the median for bombing. Consistent with this, they also have a higher poverty incidence, as can be seen in Panel B of this same figure. Table 7 reports the corresponding estimates. Overall, the information for the census corroborates the negative impact of bombing not only on lights, but also on expenditure and poverty incidence.

6.2 UXO Contamination

We turn now to UXO contamination, our main mechanism of transmission. We find first a very high correlation between bombing campaigns and agricultural land that has been contaminated by UXOs (Figure A-4, Panel A). These (almost linear) results at the extensive margin are also present at the intensive margin, in Panel B. The relationship is again very tight. Using the sample split, in Figure 8 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.

To further explore the UXO channel, we use a geo-located panel data with *daily* data on UXO accidents from 1950 to 2011. Figure 3, Panel C depicts this data geographically by number of accidents. We see a high prevalence of counts at the grid cell level in the Plain of Jars (in the central northern part of the country) and near the Ho Chi Minh Trail, 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 9. First we observe no relationship between UXO accidents during the 1950s and the total number of bombs dropped (in Panel A). This is expected, since bombing campaigns started in 1964, suggesting no pre-trends. The relationship between bombs and UXO accidents becomes positive and significant for 1960. This relationship decreases slightly, but is still visible 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.

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 findings. 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

II and Figure 9 Panel B). Second, we control for the total number of UXO accidents in our regression of lights on bombs, a bad control (in Table 9). 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. Still, interestingly, it does not fully reduce the magnitude or alter the significance of our main findings. Under a bad controls framework (Angrist & Pischke, 2008), we take this as an indication that the bombing effect is working through other potential mechanisms *aside* UXO contamination.

6.3 Urbanization, Health and Literacy

In light of the previous results, we examine the potential relationship between bombing and *other* economic outcomes, such as urbanization, literacy and health, going beyond UXO accidents. First, we find that areas that were bombed are *less* densely populated than bombed areas (Figure 8, Panel C). The estimated coefficient is negative, sizable and significant with and without controls and province fixed effects (Table 8, Panel A). From these findings, it does not appear that Laos experienced a population boom after the war, or at least these numbers have stabilized in the long run.

With regards to health, we focus on disability status, which is closely related to the UXO accidents reported before. In many cases, when bombs explode, they maim or gravely injury the victims. This tragic reality is evident in our analysis, in Figure 8, 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).

We continue the analysis by looking at other human capital indicators. We find that in areas that were bombed, literacy levels are *lower* than in areas that were not. This is evident in the distributions, divided by median number of bombs, as well as in the corresponding regressions (Figure 8, Panel D and and Table 8, Panel C). The coefficient remains negative and significant throughout. We examine this channel of transmission using finer-grained data in Section 6.5.

6.4 Public Goods Provision

Beyond the aforementioned outcomes, we expand our analysis by focusing on public good provision as a potential mechanism of transmission.[38] We hypothesize that

[38]We thank Jared Rubin for suggesting looking at public goods as mechanisms of transmission.

providing these services to the population could be costlier and more difficult in the presence of UXOs. Using the same 2005 Census information, in Table 10, we find that villages that were bombed more historically have significantly less access to electricity now. This holds with and without the full set of controls, as well as including province fixed effects (Columns 1 to 3). We find a similar pattern when looking at water supply (Columns 4 to 6). Villages that were bombed have significantly less access to this vital supply, suggesting a potential state capacity avenue of our main effects.

6.5 Human Capital Accumulation, Structural Transformation and Migration

Motivated by the previous findings at the village level, we zoom into the role of human capital accumulation, the process of structural transformation and the special role of migration, exploiting the timing of conflict. To this end, we employ the *individual* level data from the 2005 Census and empirical specifications detailed in Section 4.4.

6.5.1 Years of Schooling

Our main results for years of schooling are presented in Figure 10. 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 when 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, 10 to 14, reaching a trough for the 15 to 19 and 10 to 19 year old categories. The most affected cohorts receive 0.2 years of schooling less, or 5% with an average of four (see Table A-1 for such descriptive statistics). 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-6). They also follow the same broad pattern—though the coefficients are smaller—when we use the number of bombs rather than UXO accidents (not reported).[39] 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. Our results are in line with those for Guatemala, Peru and Colombia

[39] We also look at the provision of schools in Table A-11, which is inconclusive with respect to mean travel time to the next school and negative, but ultimately insignificant with respect to villages having a primary school. As best, it does not appear that the results are entirely driven by the supply side.

(Chamarbagwala & Morán, 2011; Leon, 2012; Fergusson et al., 2020).[40]

6.5.2 Sectoral Employment and Structural Transformation

To complete the individual-level analysis, we proceed with structural transformation.[41] 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 11.[42] 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 extensive margin of employment to an analysis of occupational structure in terms of agriculture, industry and services. We find, using the same modern cutoff, a hump-shaped relationship for agricultural employment, in Figure 12. Recall that we already showed that the effects are concentrated on rural areas (Table A-4). It appears now that people that are from 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 12, 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%. We find no significant impact on the probability of being employed in the manufacturing sector (Figure 12, Panel C). The results by sector also hold when using quinquennial, as opposed to yearly variation, Figure A-8. The results for agriculture are in consonance with the findings by Lin (2017) for rice in Cambodia.

6.5.3 Migration

Lastly, we look at migration as a potential mechanism of persistent poverty, 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 land. Hence, the effect of conflict on

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

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

[42] Similar results using quinquennia instead of years are reported in Figure A-7.

migration is an empirical question. To this end, 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. They are in the order of 11% for the whole sample. This fact suggests that our baseline estimates are not likely to be driven by this factor. 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).[43]

We proceed the analysis by looking directly at how the probability of migrating is affected by conflict, estimating Equation (4). Recall that we had already controlled for this factor (a potentially bad control) in the human capital accumulation regressions. We present the results in Figure 13. We find now, if anything, that cohorts affected by conflict have a *lower* probability to migrate internally. The effect is statistically significant and in the order of -0.01, or 10% with respect to the sample mean.

We further analyze the triple interaction with migration, following Equation (5). The pattern for non-migrants resembles the one described before in terms of significance and magnitudes. Namely, individuals affected by conflict appear to receive significantly less years of schooling, as seen in Figure 14, Panel A. The effect for migrants, however, is reversed, in Panel B. These people appear now to have acquired significantly *more* years of schooling, offering a glimmer of hope. The effect is large, in the order of almost 0.5 years, but concentrated on a (fairly) small part of the sample.

The results for human capital parallel those for labor, with respect to the migration decomposition. Initially, we find that the negative impact on the probability of working is concentrated among non-migrants, in Figure A-9. We can see, in Figure 15, Panel A that non-migrants are more likely to be working in agriculture. This effect is not present for migrants, in Panel B. We present similar decompositions for manufacturing and services in the Appendix, in the interest of space. We find no impact for manufacturing, by migrating status in Figure A-10 and the effect of services appears concentrated on non-migrants again in Figure A-11. This decomposition 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 contributions to this literature).

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

[43]Which we also check empirically, not shown.

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 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 take decades to return to normal. Moreover, it appears that migration, or the lack thereof, is exacerbating these trends. The decomposition results are in line with the heterogenous effects, showing a larger impact on rural areas. Our findings for Laos are also consistent with those for *La Violencia* conflict in Colombia (Fergusson et al., 2020) and WWII in Austria (Eder, 2016). We learn from the Laotian context how these key economic variables interact with UXO contamination, affecting human development for decades.

7 Conclusions

In this paper 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 Ho Chi Mihn Trail and proximity to US air bases outside of Laos, suggesting a causal effect. We use census data at the village level to show how our results on nightlights extend to relevant development outcomes such as poverty rates, literacy and health. We use this same data and a daily panel of UXO accidents to show how war has affected the local population in terms of health. Combining this information with individual-level census data, and exploiting yearly variation, we show that UXO contamination led to decreased human capital accumulation, hindered structural transformation and dampened rural-urban migration in the long run.

We contribute to the literature on conflict, by showing the negative and sizable *economic* impact of a war that formally ended decades ago. Though potentially obvious *ex post*, we do not think that this empirical finding was part of the prevalent economic consensus, on the aftereffects of historical conflict—providing a relevant counterpoint to the existing literature and empirical support to the Conflict Trap hypothesis. We also single out UXO contamination as a key element in the persistently negative impact of conflict. Since conflict officially ended, people have been affected directly through UXO accidents as well as *indirectly* through lower education and less labor mobility into modern sectors and urban centers. This pernicious combination of factors, among others, helps explain why Laos remains one of the poorest countries in the world today.

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 was the case in Mozambique (Chiovelli et al., 2018) and is now the case in places like Colombia. The problem of UXO is not contained to Laos and extends to neighboring Cambodia (Lin, 2017) and Vietnam, in the Indochina Peninsula.[44] Though unexploded mines are a thing of the past in European countries that fought WWII, they are still a pressing issue in the Balkan countries, Afghanistan and Iraq. Local political leaders and advisors can learn from the results presented with regards to 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 lingering consequences of historical conflict. 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 costs against their more immediate political and strategic objectives.

[44] To the best of our knowledge, there is no empirical study examining the impact of UXOs in Vietnam, suggesting a potential avenue for future research.

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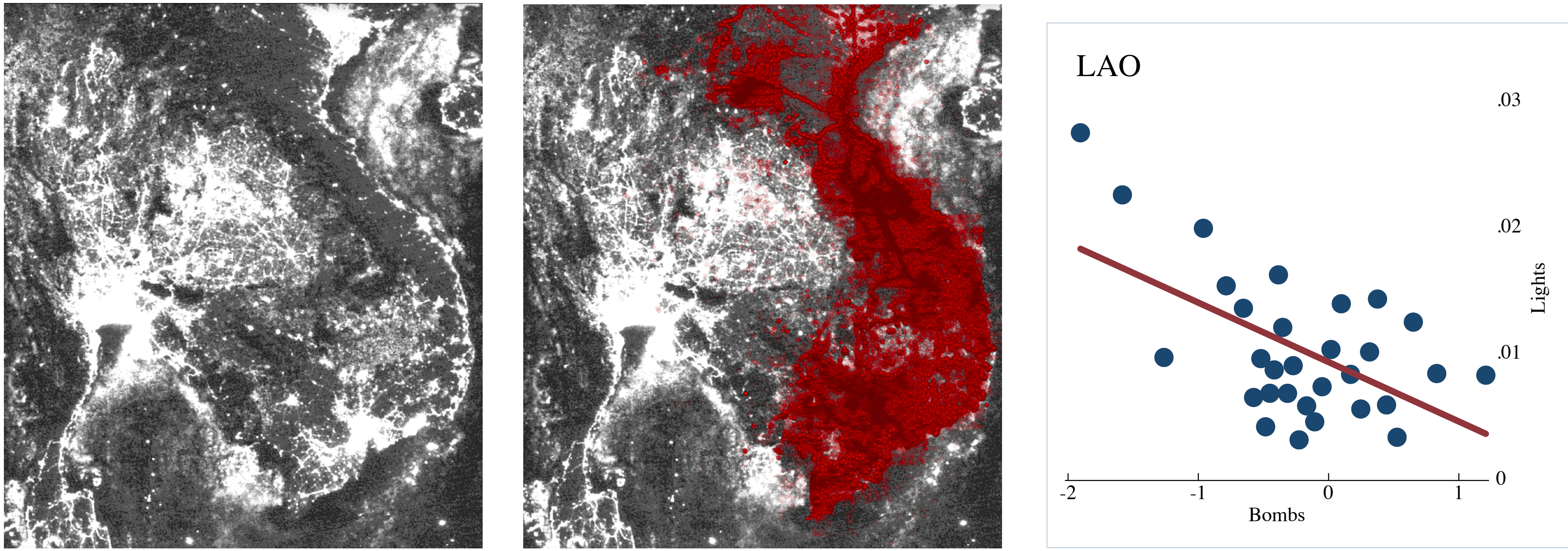
Figure 1: Indochina: Stable Lights in 2013 and US Bombing Events from 1965 and 1973

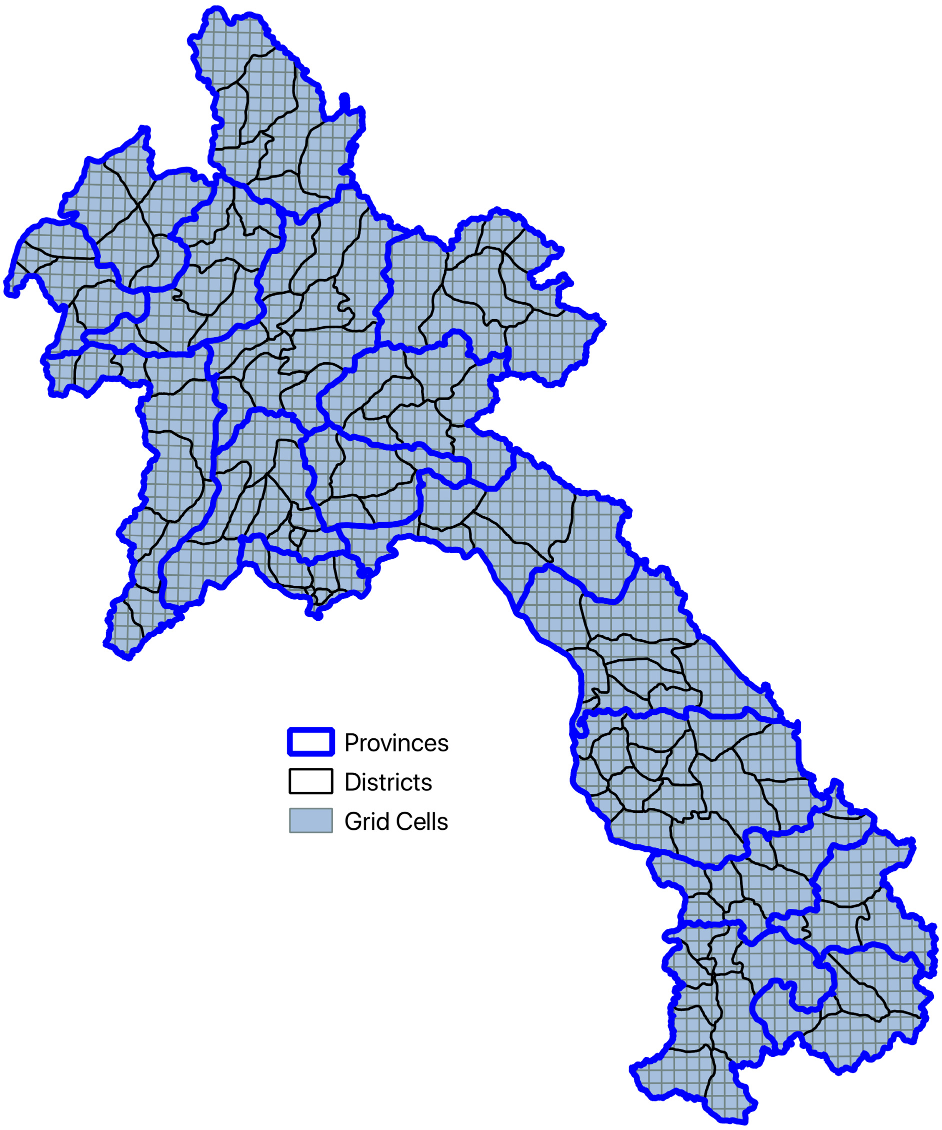


Panel A: Stable lights in 2013.

Panel B: US Bombing Events from 1965 to 1973.

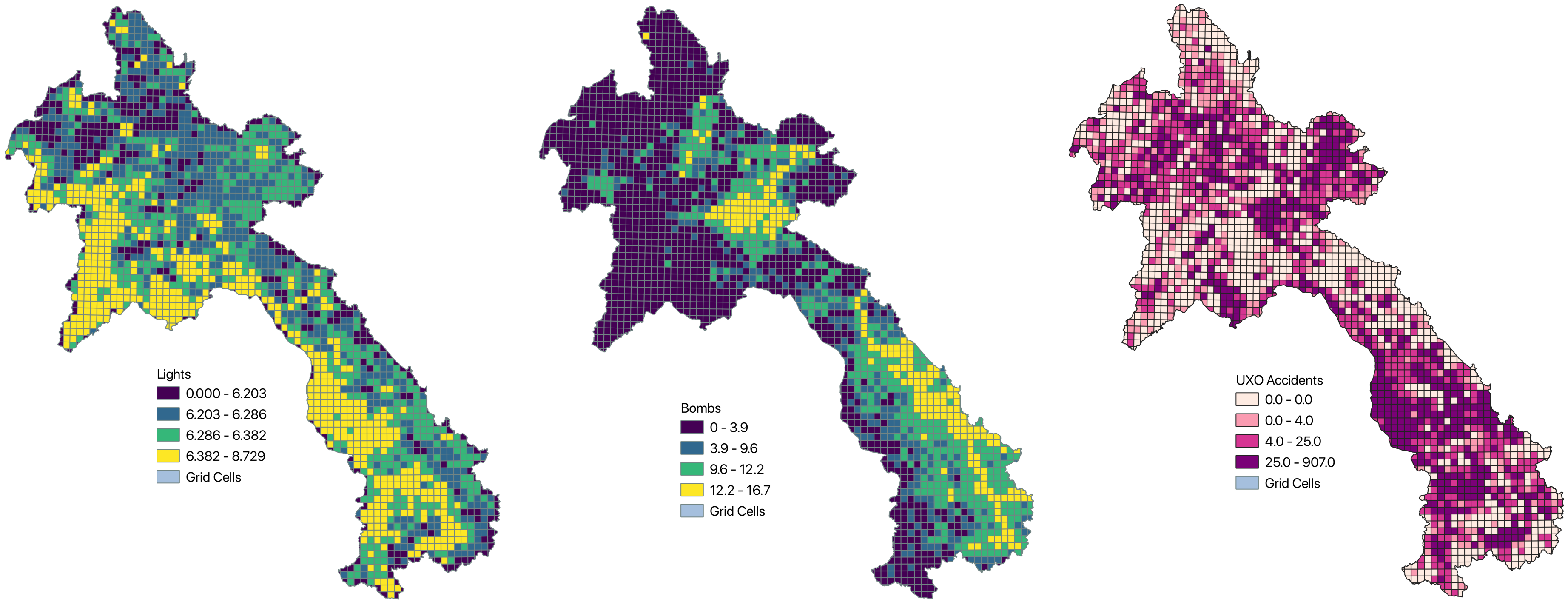
Panel C: Bin-scatter controlling for province fixed effects year fixed effects and location controls.

Figure 2: Grid cell Level Analysis: Grid cells of 10km × 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 3: Luminosity, Bombs and UXO

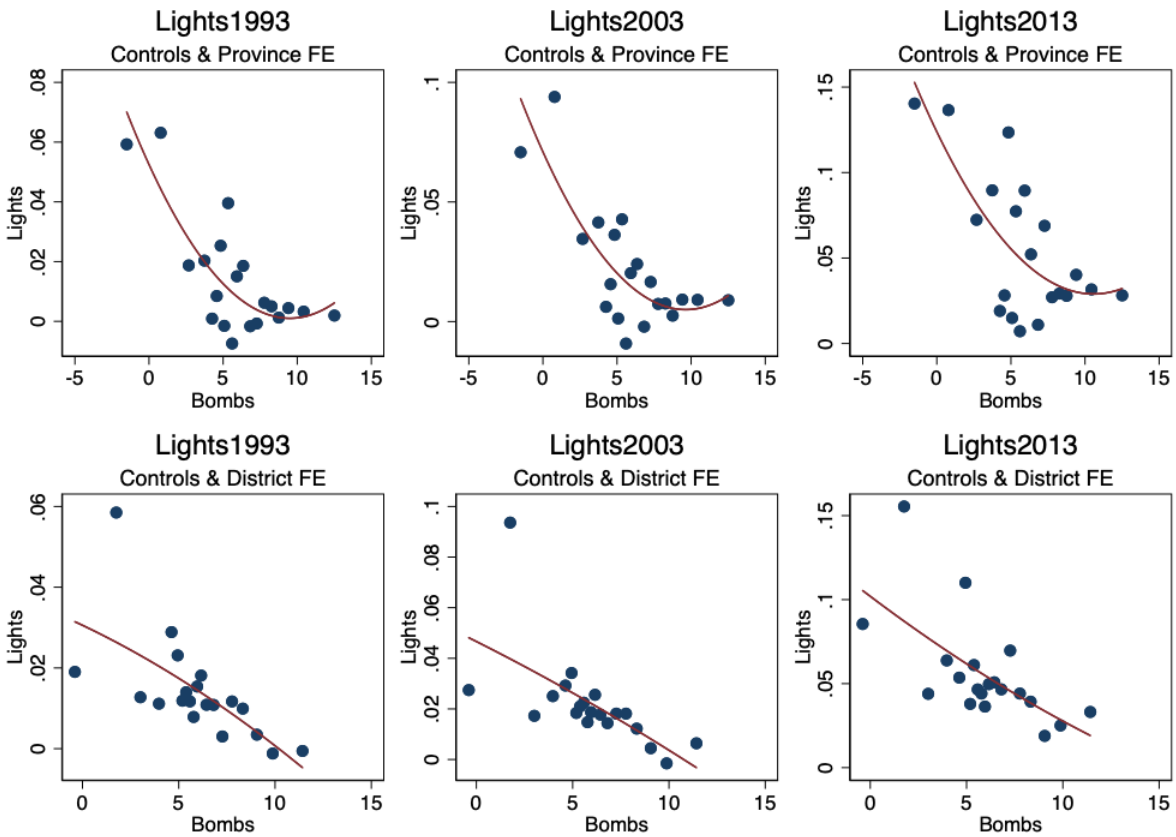


Panel A: Luminosity measured as the total sum of lights (stable and unstable) in 2013 at the grid cell level (in logs).

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

Panel C: UXO victims from 1950 to 2011.

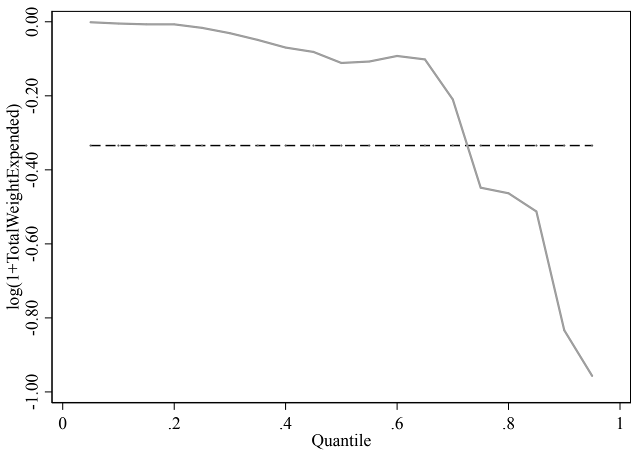
Figure 4: Bin-scatters of Lights on Bombs at the Grid Cell Level by Year



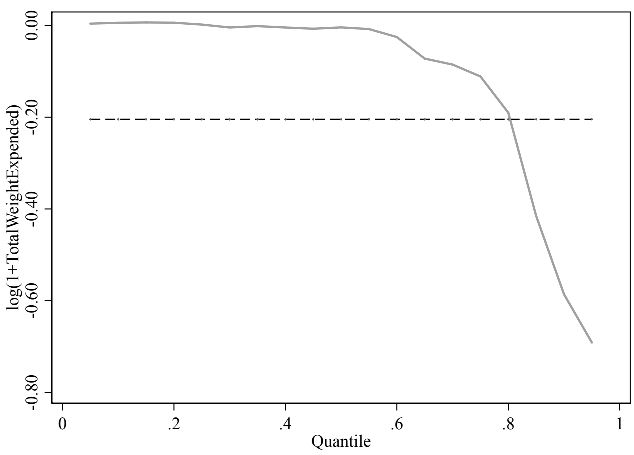
Notes: This figure depicts the relationship between Bombs and Luminosity using satellite data for each year separately. All panels are bin-scatters with overlapping quadratic fits of the underlying data. All figures control for location and geographical covariates. The first row includes province fixed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

Figure 5: OLS and Quantile Regression Coefficients by Year

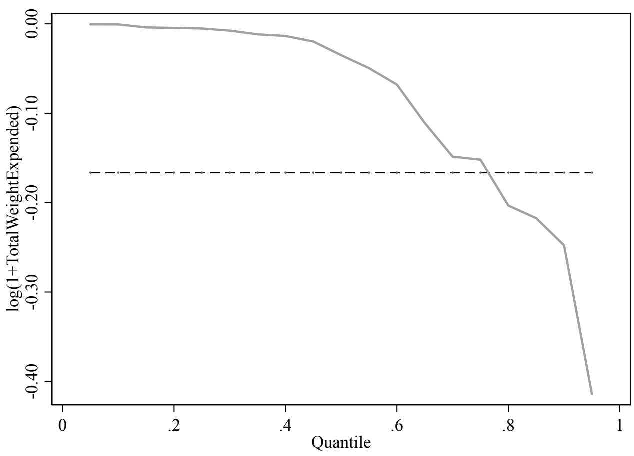
Panel A: Lights in 1993



Panel B: Lights in 2003

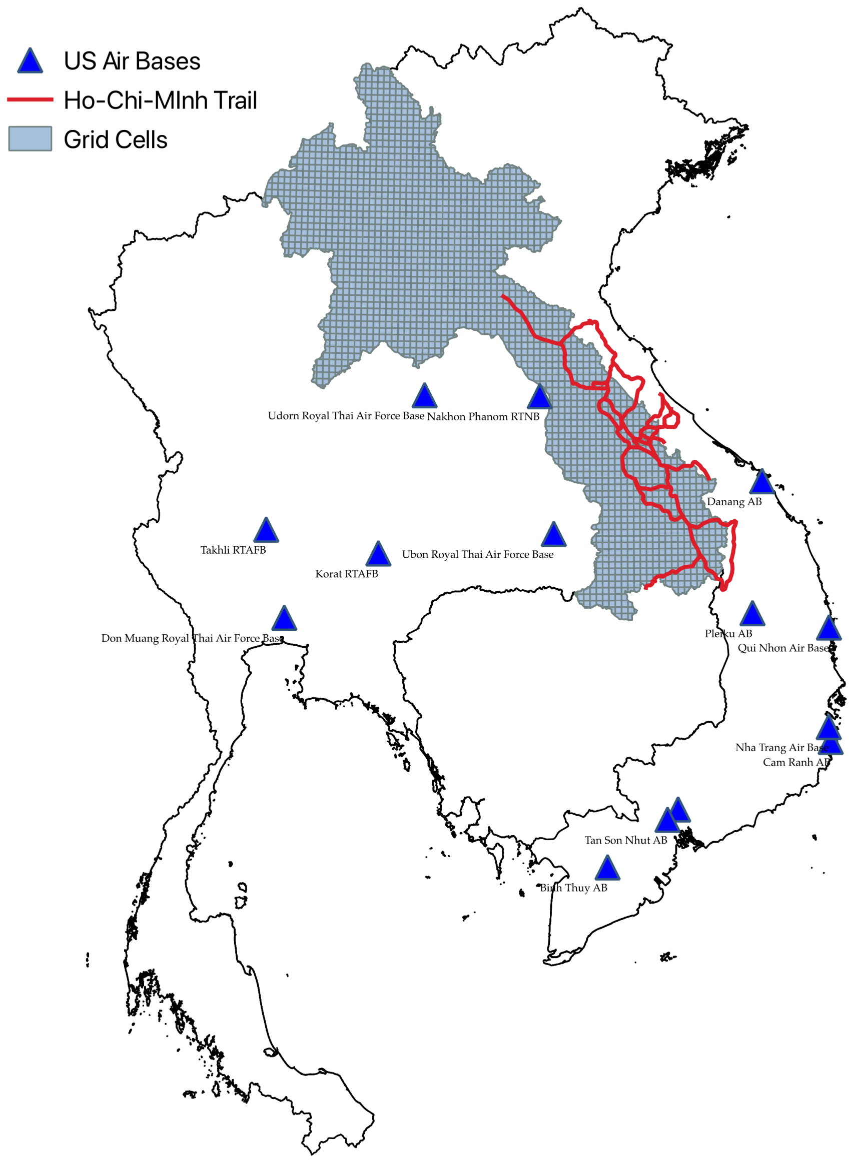


Panel C: Lights in 2013



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.

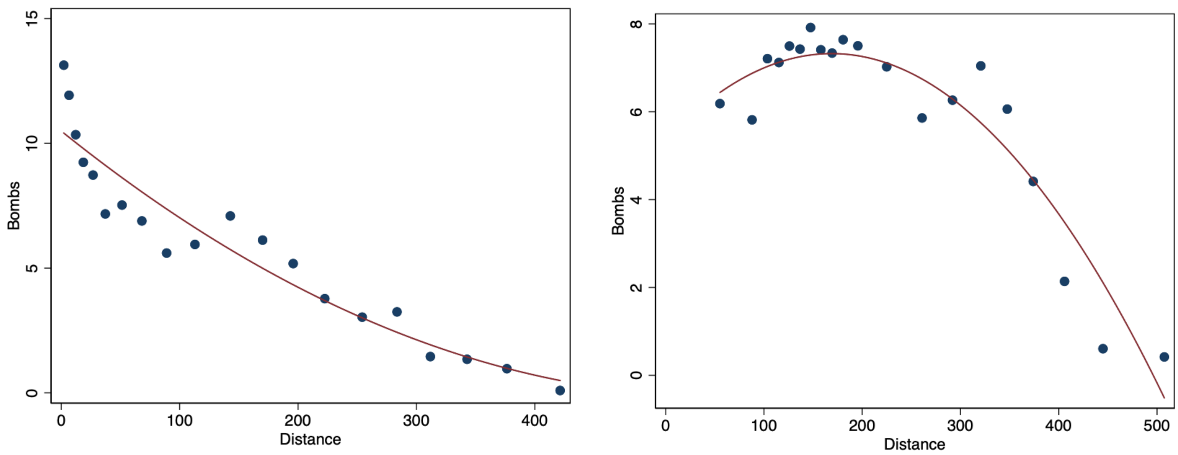
Figure 6: US Air Bases Outside Laos and the Ho Chi Minh Trail



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-1.

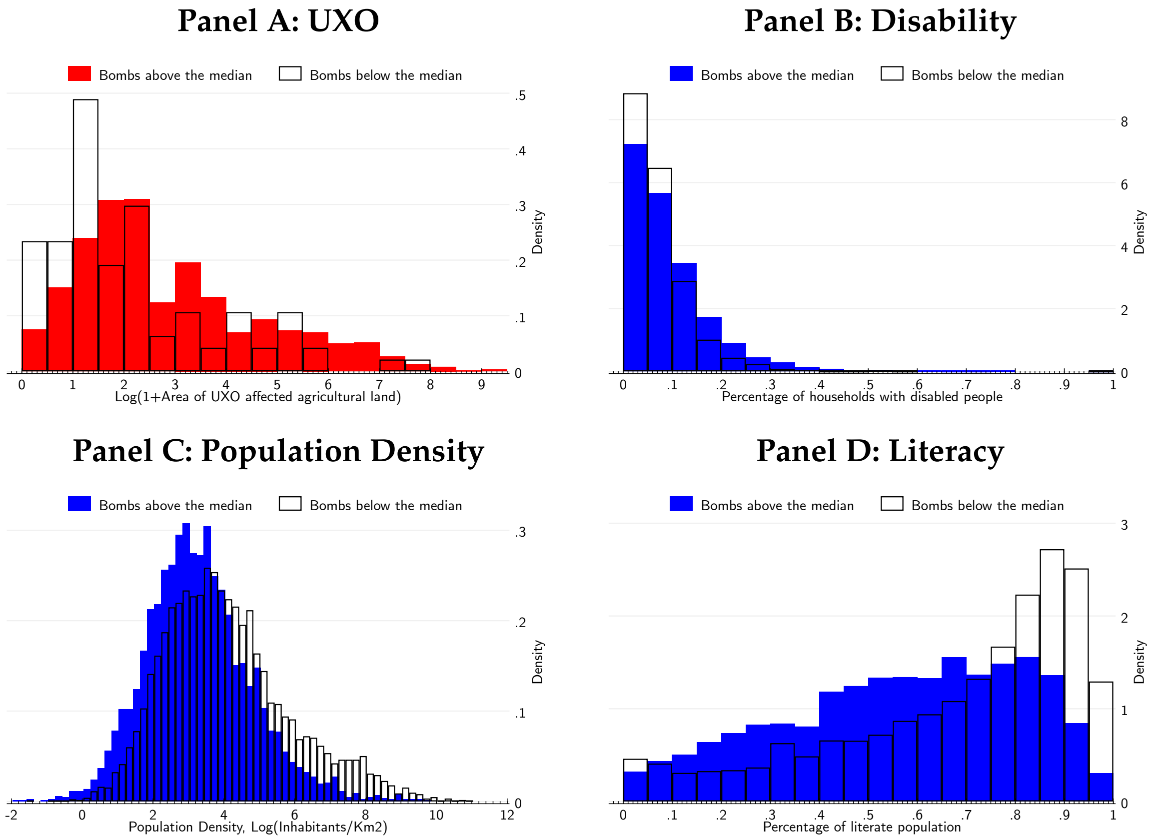
Figure 7: Bin-scatters for the First Stages

Panel A Distance to Ho Chi Minh Trail **Panel B** Distance to Closest US Air Base



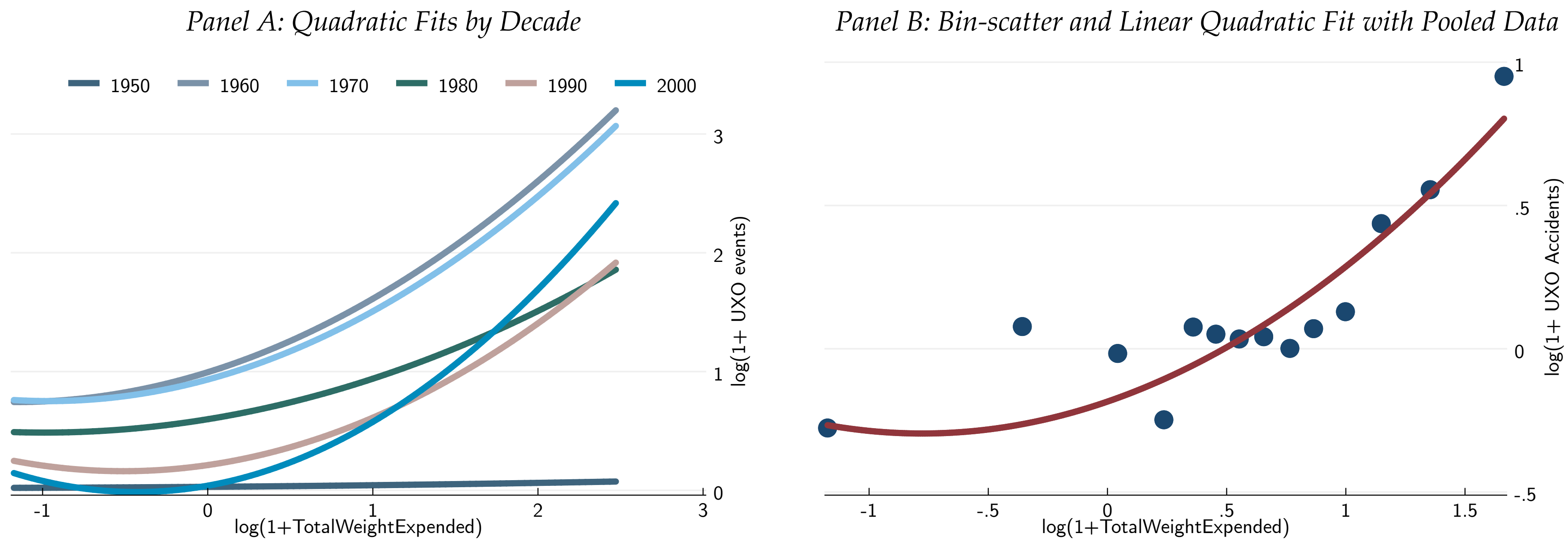
Notes: This figure depicts the relationship between Bombs and the euclidean distance specified in each panel. Both panels are bin-scatters with overlapping quadratic fits of the underlying data.

Figure 8: Mechanisms of Transmission: Distributional Comparisons



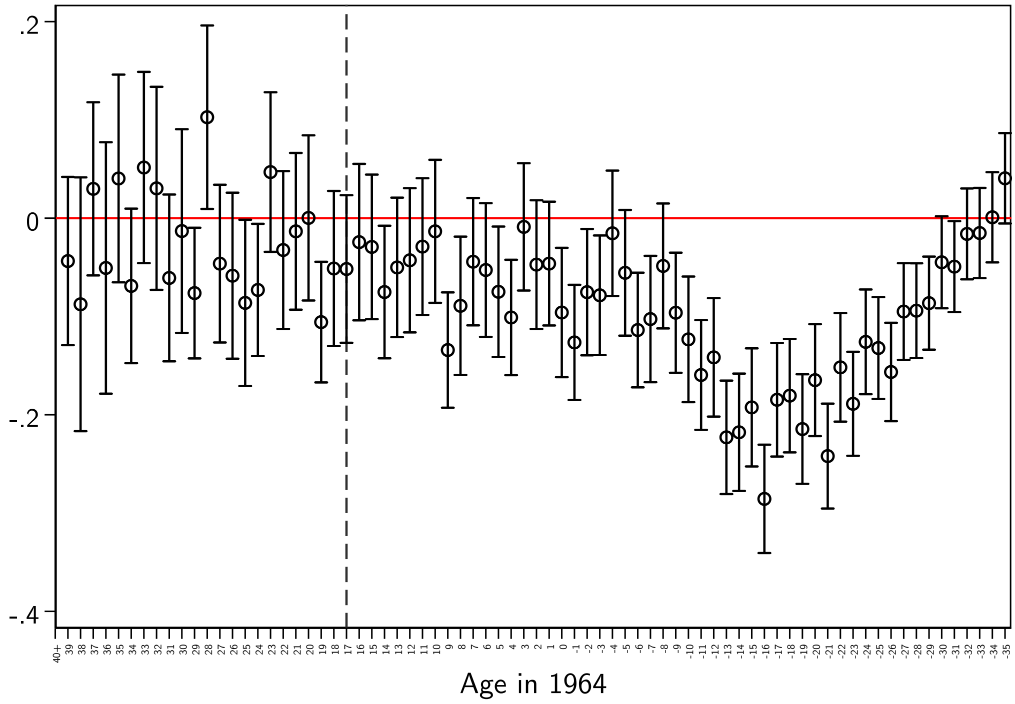
Notes: This figure presents the empirical distribution of the variables specified in each panel by the level of bombing intensity (above or below the median of bombs).

Figure 9: Panel of UXO Victims and Bombing Intensity



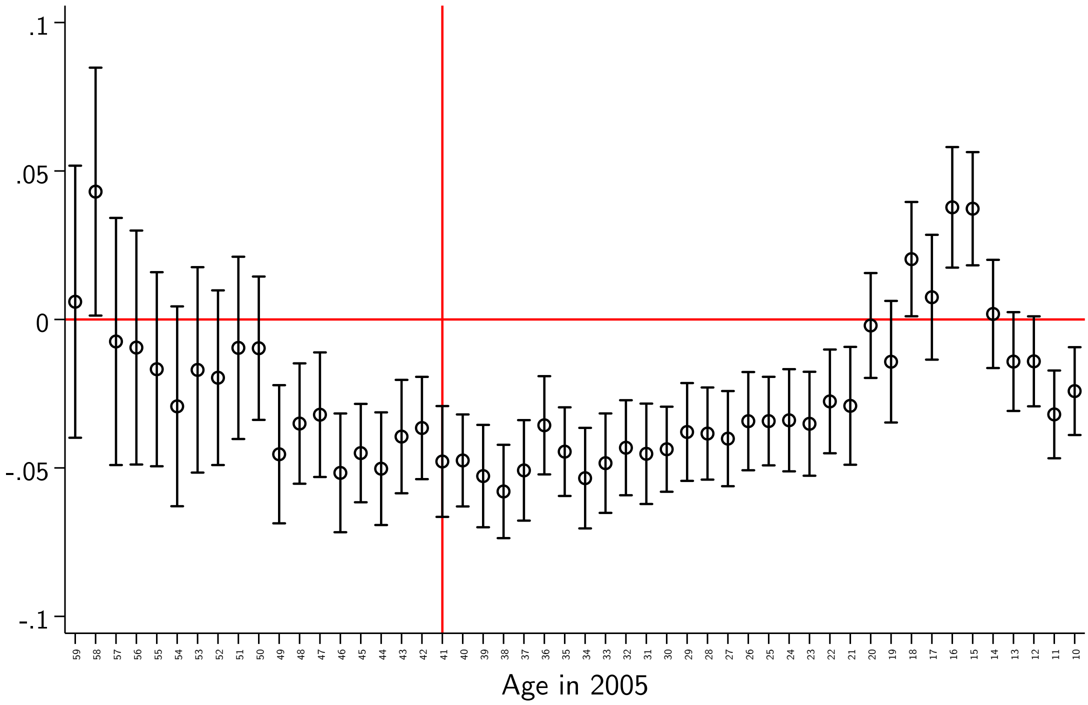
Notes: This figure presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance) and bombing intensity from 1964 to 1973. It uses panel data on daily UXO accidents and data on the bombing at the village level. Panel A presents the quadratic fits of the data by the decade of occurrence, while Panel B shows the bin-scatter of the pooled data and its quadratic fit.

Figure 10: Impact of Bombing on Years of Schooling, 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 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.

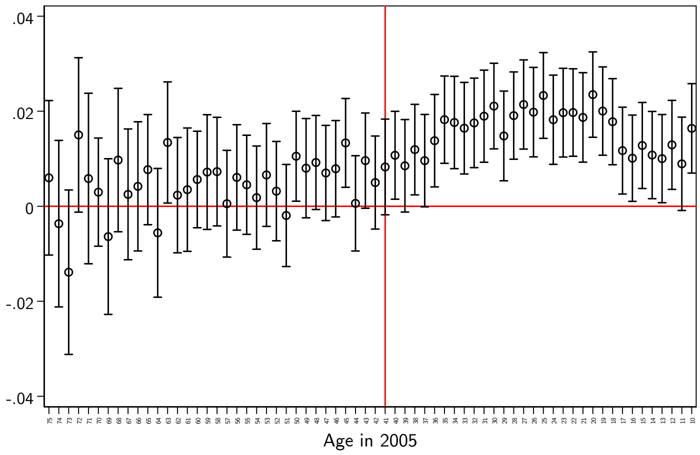
Figure 11: Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005 (yearly)



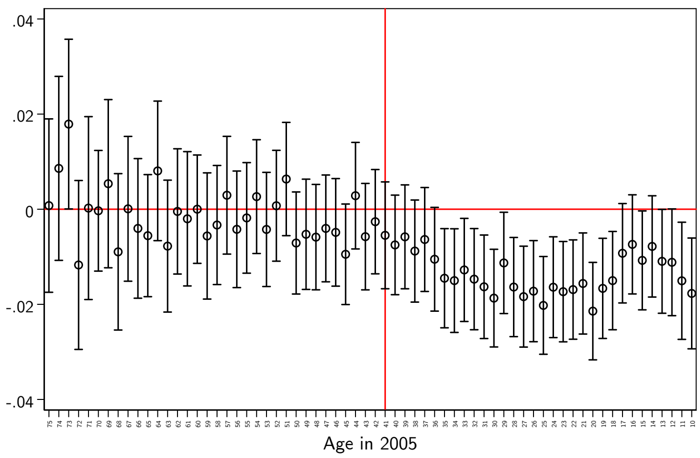
Notes: Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is an indicator of being employed. The excluded cohort is composed by individuals with 60 years or more in 2005. The 41 years old cohort marked with a vertical line as reference point since those are the individuals who were born in 1964.

Figure 12: Impact of Bombing on the Probability of Working in Agriculture, using Micro-level Data from the Population Census of 2005 (yearly)

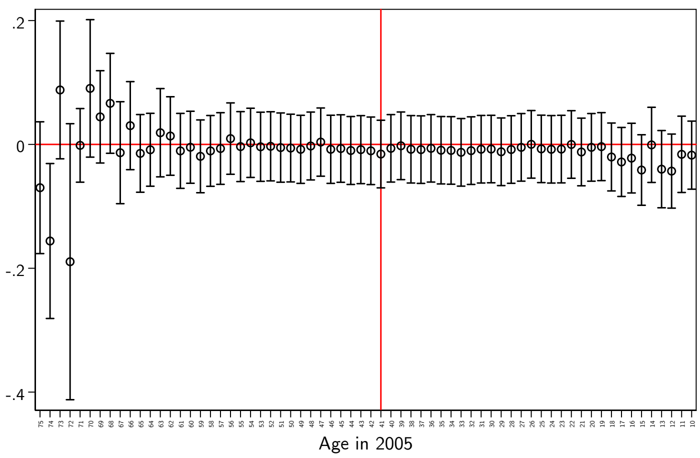
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services

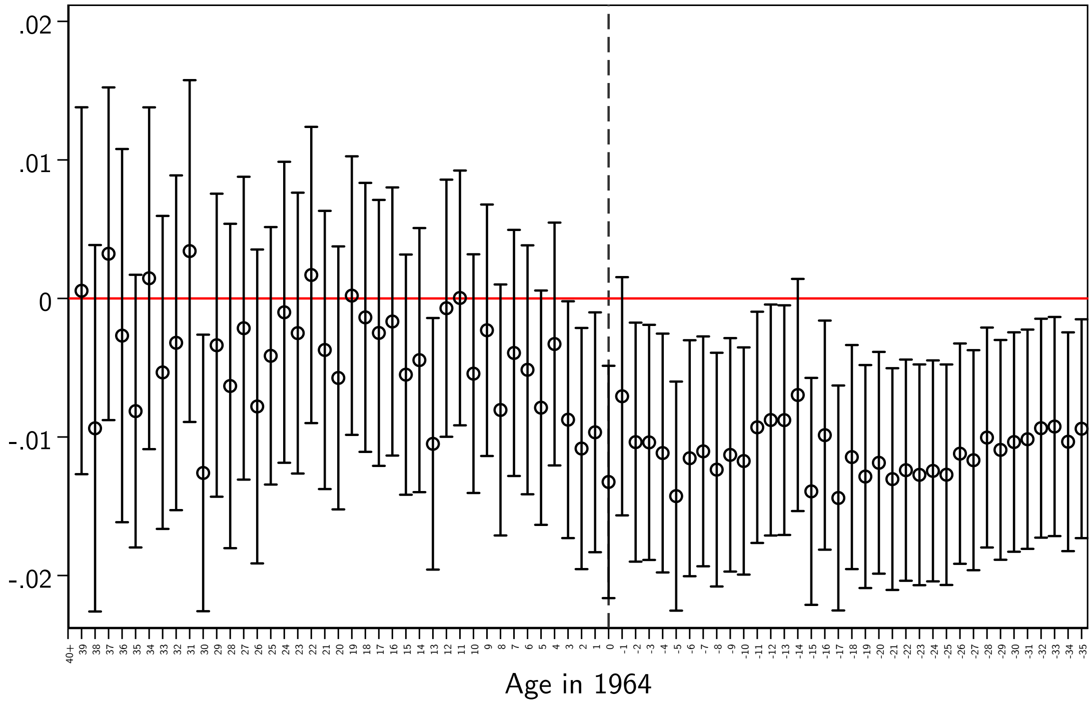


Panel C: Probability of Working in Manufacturing



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.

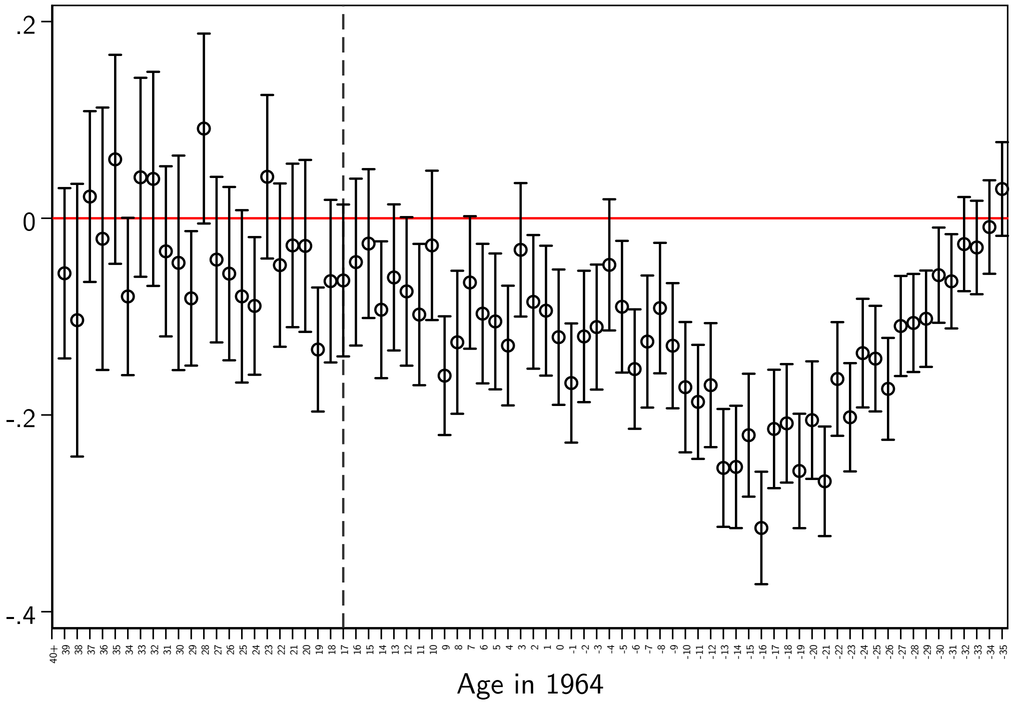
Figure 13: Impact of Bombing on the Probability of Migration, using Micro-level Data from the Population Census of 2005 (yearly)



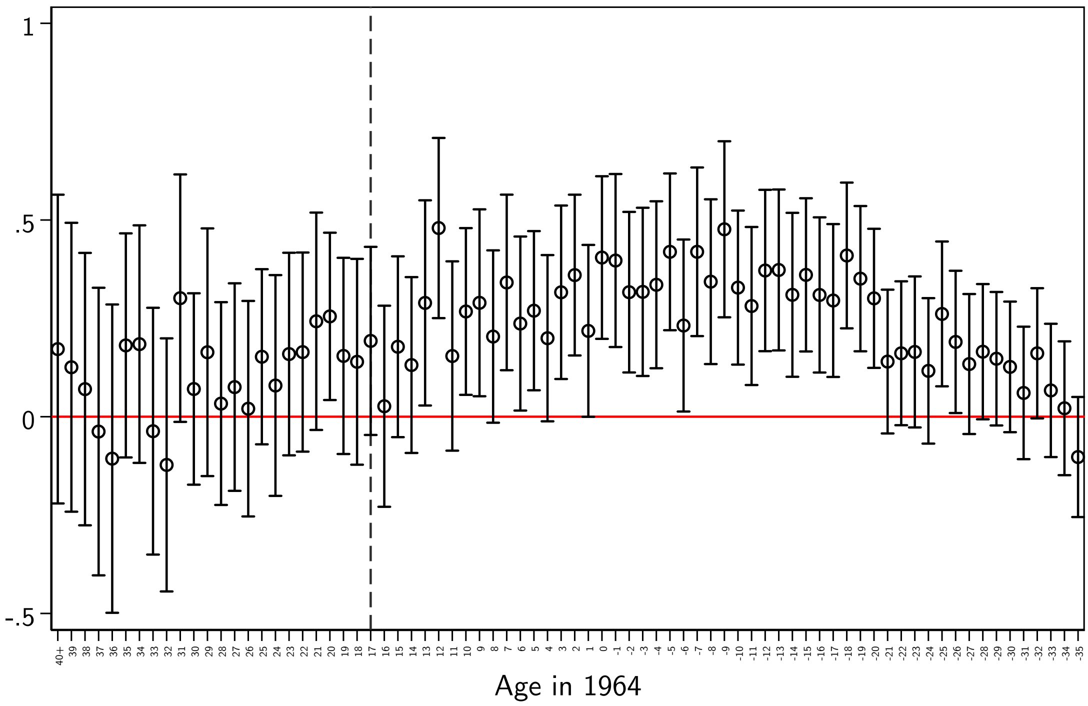
Notes: Point estimates and 95% confidence intervals corresponding to γ_k in Equation (4) when the outcome variable is an indicator of being long term migrant. We define long term migration as living in a different province to that of birth. The excluded cohort is composed by individuals with 40 years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

Figure 14: Impact of Bombing on Years of Schooling by Migration Status

Panel A: Non-Migrants



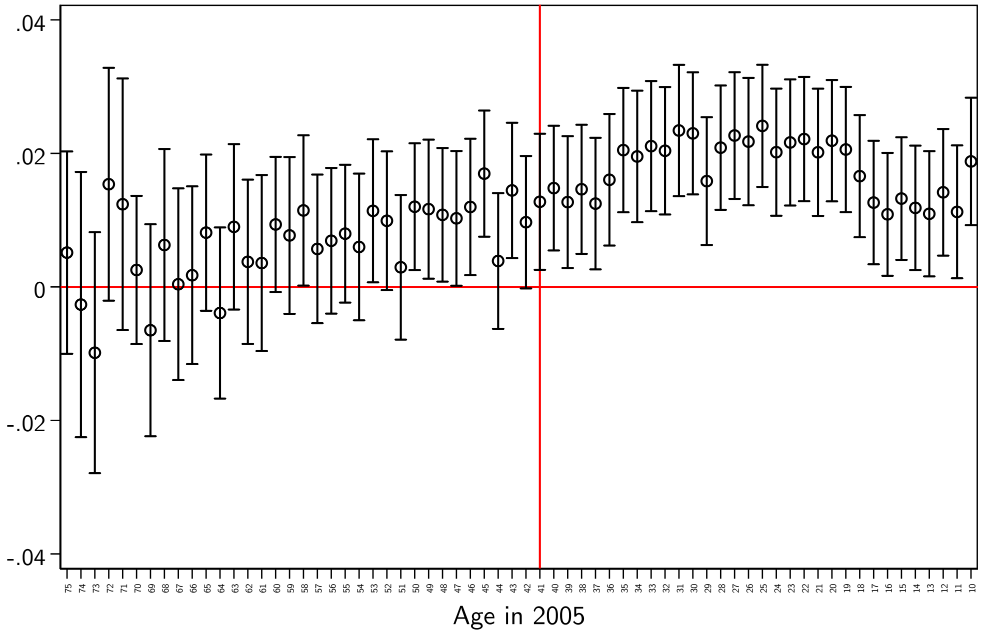
Panel B: Migrants



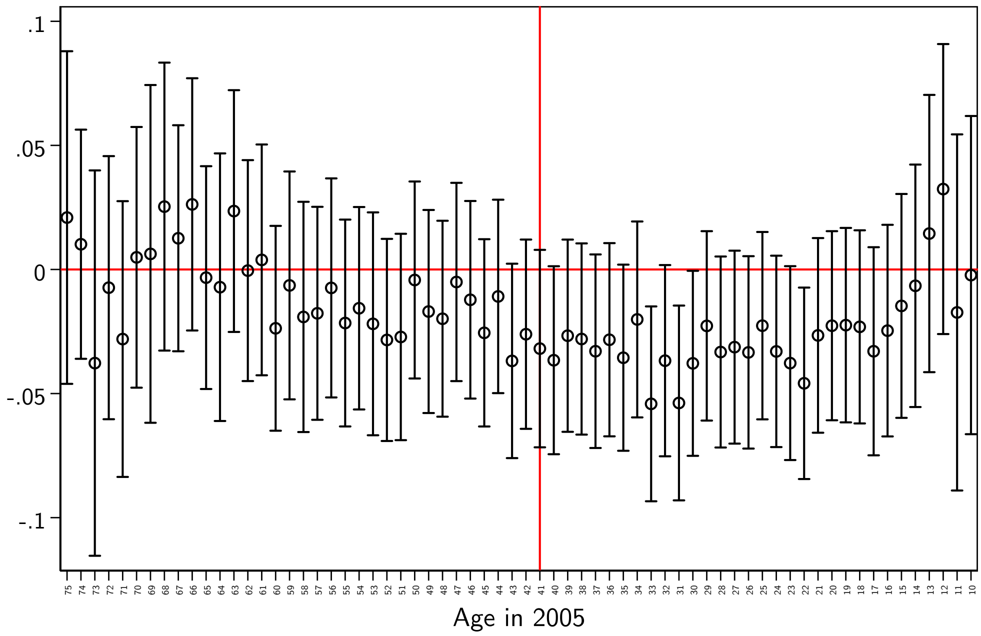
Notes: Panel A and B report the coefficients η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is years of schooling. The excluded cohort is composed by individuals with 40 years or more in 1964. The 17 years old cohort marked with a vertical line as reference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

Figure 15: 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.

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 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 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. 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 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 5A - Instrument I: Distance to the Ho Chi Minh Trail			
	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	-0.1199***	-0.1235***	-0.0934***
	(0.0276)	(0.0331)	(0.0201)
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)
Panel C: 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 5B - Instrument II: Distance to the Closest US Air Base			
	(1)	(2)	(3)
Panel A: Dependent variable is luminosity, model:	2SLS	2SLS	2SLS
Bombs	-0.1448***	-0.1329***	-0.2651***
	(0.0336)	(0.0335)	(0.0779)
Panel B: 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)
Panel C: 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 × year level. 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 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 $\times$ year level. 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: Development Outcomes and Mechanism of Transmission

	(1)	(2)	(3)
Part I: 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
Part II: Unexploded Ordnance			
Panel C: Dependent variable is $1(\textit{Land is contaminated by UXO})$			
Bombs	0.5699***	0.5455***	0.4130***
	(0.0166)	(0.0166)	(0.0901)
R-squared	0.2164	0.2220	0.1140
Panel D: 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
Controls that apply for all panels			
Province fixed effects			Yes
Geographical Controls		Yes	Yes
Location Controls		Yes	Yes

Notes: Observations are at the village level. 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: Additional Mechanisms of Transmission

	(1)	(2)	(3)
Panel A: 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
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 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
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 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: Luminosity on Bombs and UXO Accidents

	(1)	(2)	(3)
	Luminosity 1993	Luminosity 2003	Luminosity 2013
Bombs	-0.0142**	-0.0209**	-0.0404***
	(0.0061)	(0.0083)	(0.0119)
UXO Accidents	-0.0053	-0.0046	0.0141
	(0.0104)	(0.0121)	(0.0130)
Bombs $\times$ UXO Accidents	0.0004	0.0002	-0.0049
	(0.0067)	(0.0077)	(0.0091)
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. UXO Accidents corresponds to the number of UXO events before 1993 according to the geolocated data from the NRA. Robust standard errors in parenthesis clustered at the district level.

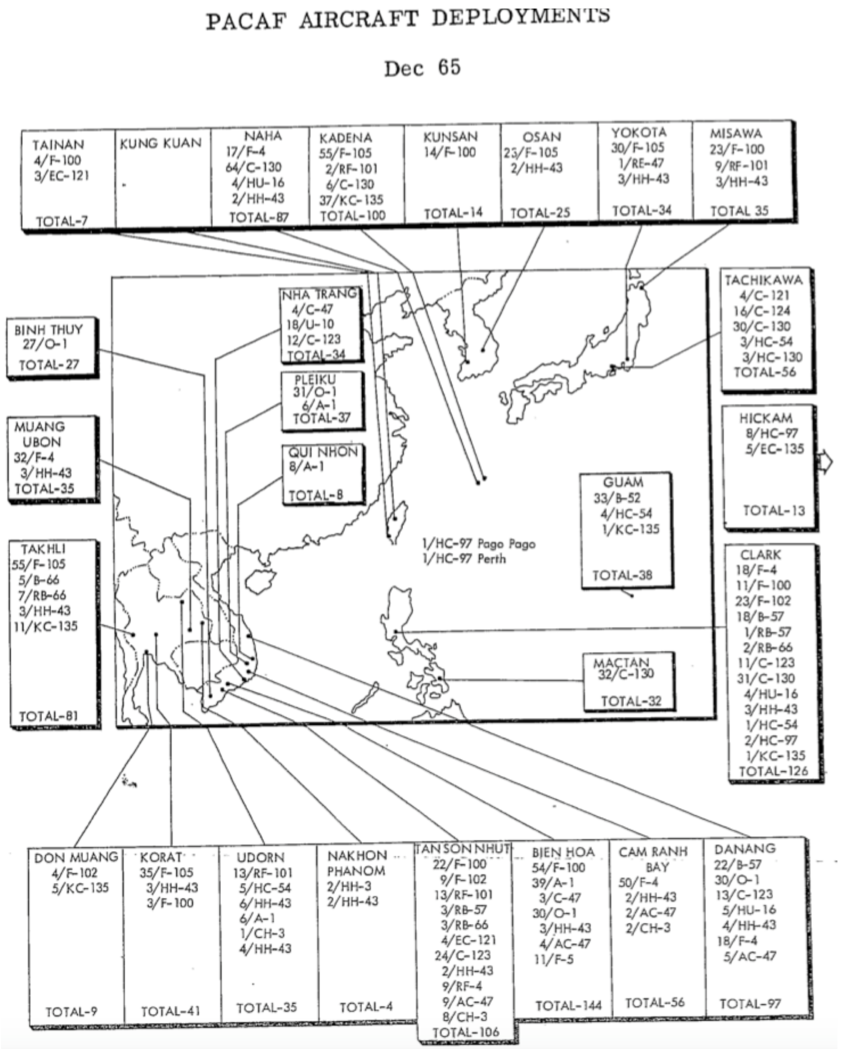
Table 10: Public Goods Provision: Electricity Access and Water Supply

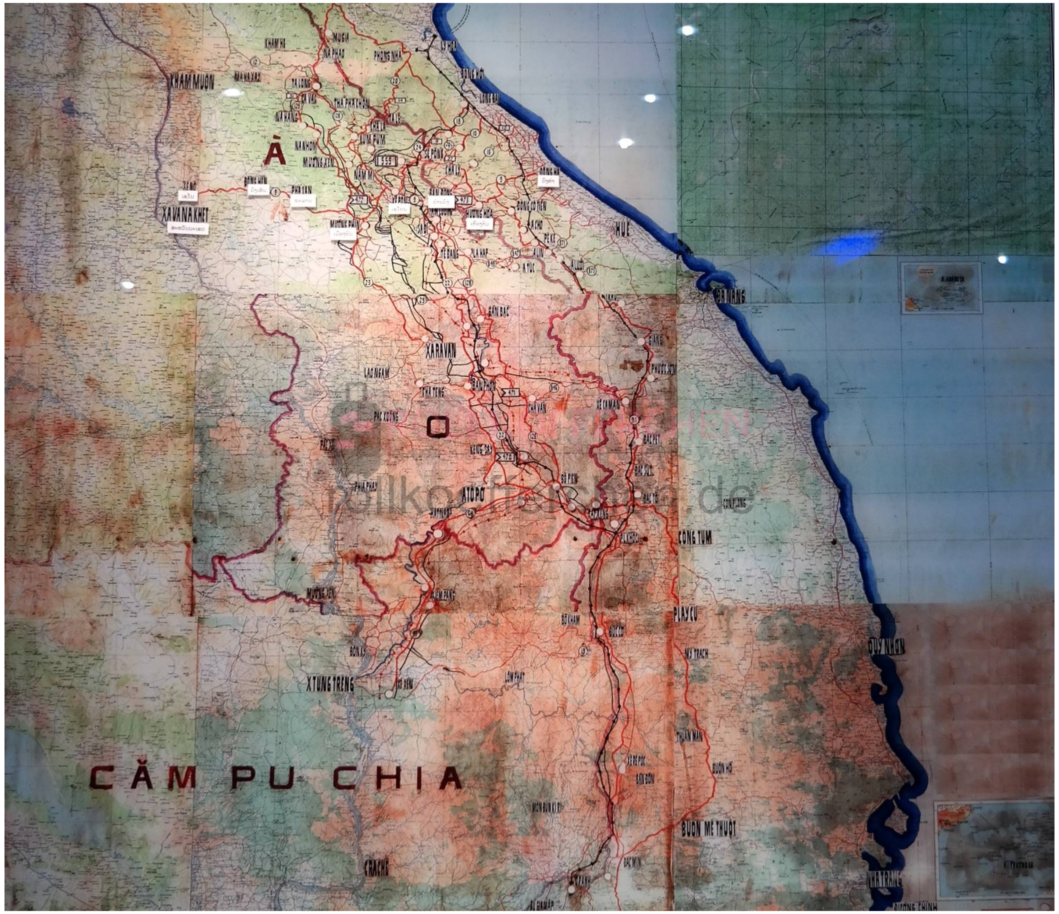
	(1)	(2)	(3)	(4)	(5)	(6)
	Village has electricity supply			Village has water supply		
Bombs	-0.1095***	-0.0881***	-0.0630***	-0.0332***	-0.0113***	-0.0119***
	(0.0043)	(0.0053)	(0.0156)	(0.0022)	(0.0025)	(0.0040)
Province FE			Yes			Yes
Full Controls		Yes	Yes		Yes	Yes
Observations	10,522	10,280	10,280	10,522	10,280	10,280
R-squared	0.0526	0.2675	0.1544	0.0184	0.0521	0.0283

Notes: 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

Online Appendix: Figures

Figure A-1: Air Bases from the Pacific Air Forces in 1965 and The Ho Chi Minh Trail



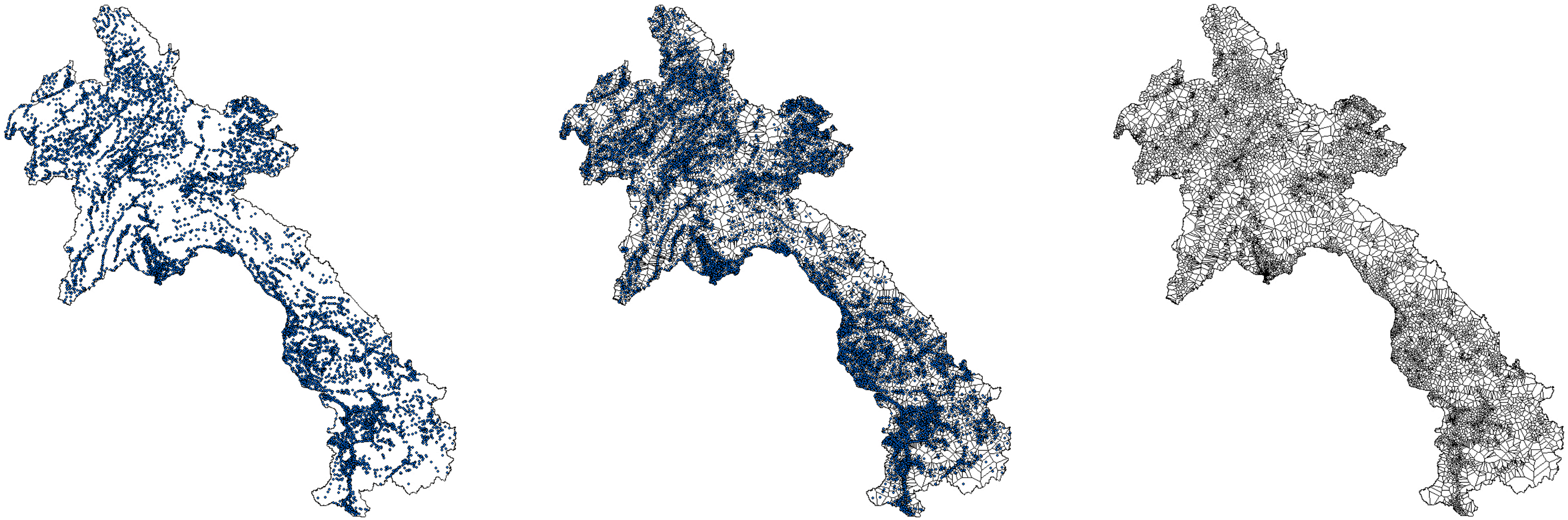


Panel A: Declassified document from the US Side

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-2: Village Level Boundary Construction

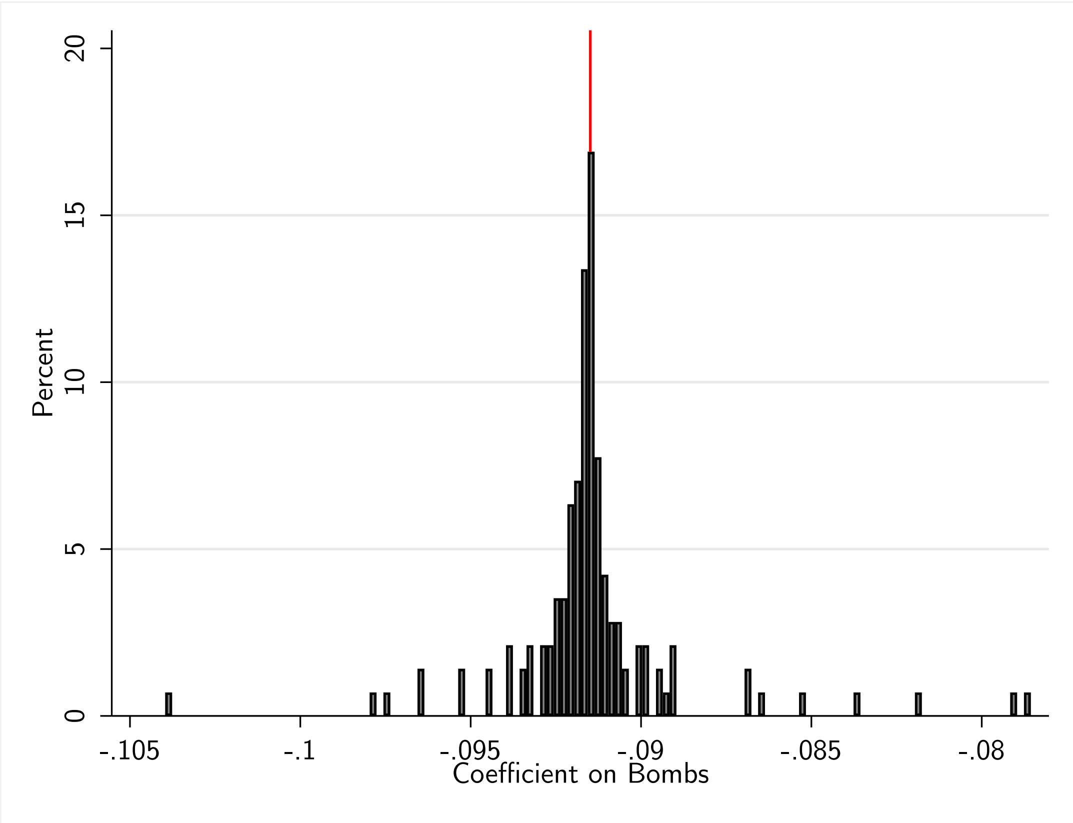


Panel A: Spatial location of villages in the census.

Panel B: Thiessen polygons.

Panel C: Implied village's boundaries.

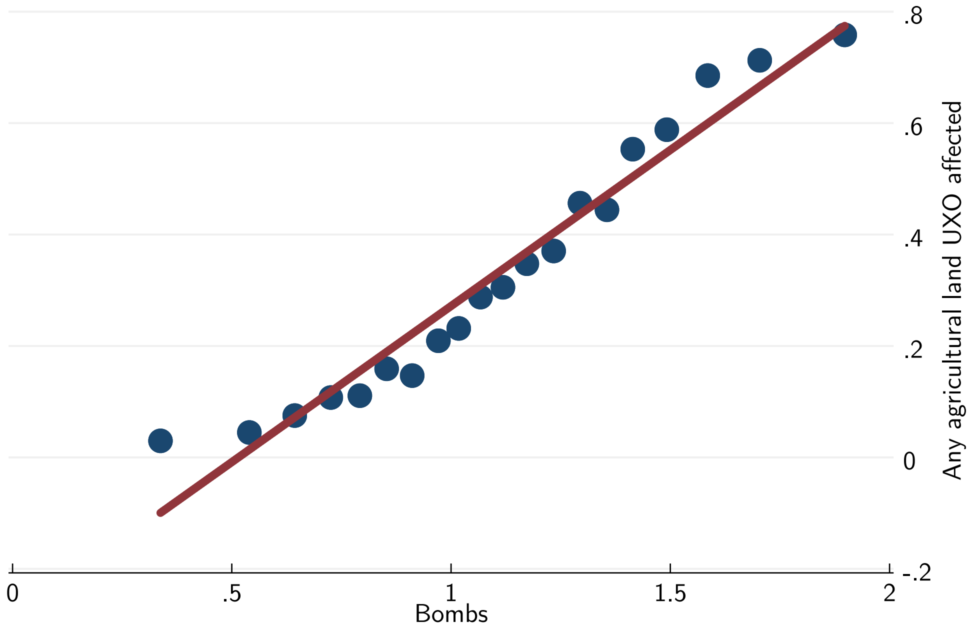
Figure A-3: Robustness IV: Distribution of Coefficients Dropping Individual Districts



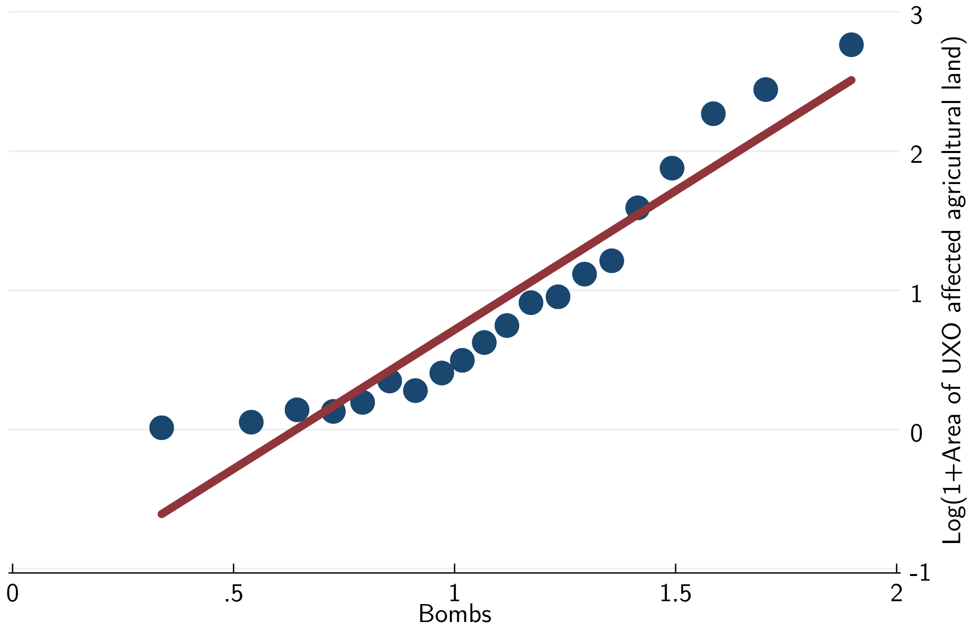
Notes: Distribution of the effect of Bombs on Lights when dropping one district at the time. The IV estimate of the pooled sample is represented by the red line.

Figure A-4: Agricultural Census 2011: Intensive and Extensive Margin of UXO Contamination

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



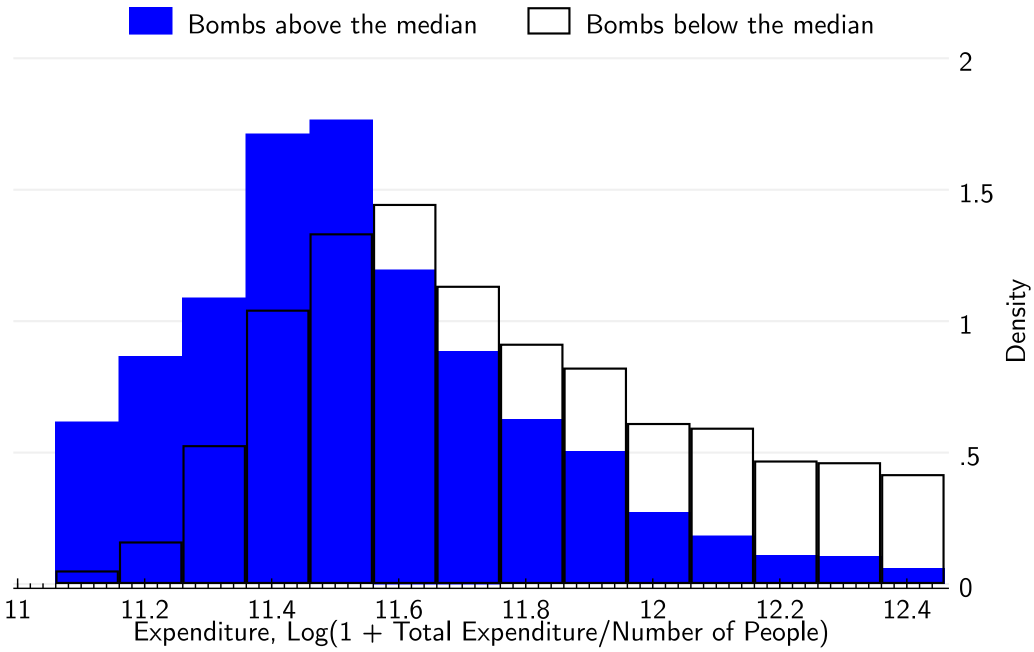
Panel B: Bin-scatter and linear fit Bombs and intensity of UXO contamination



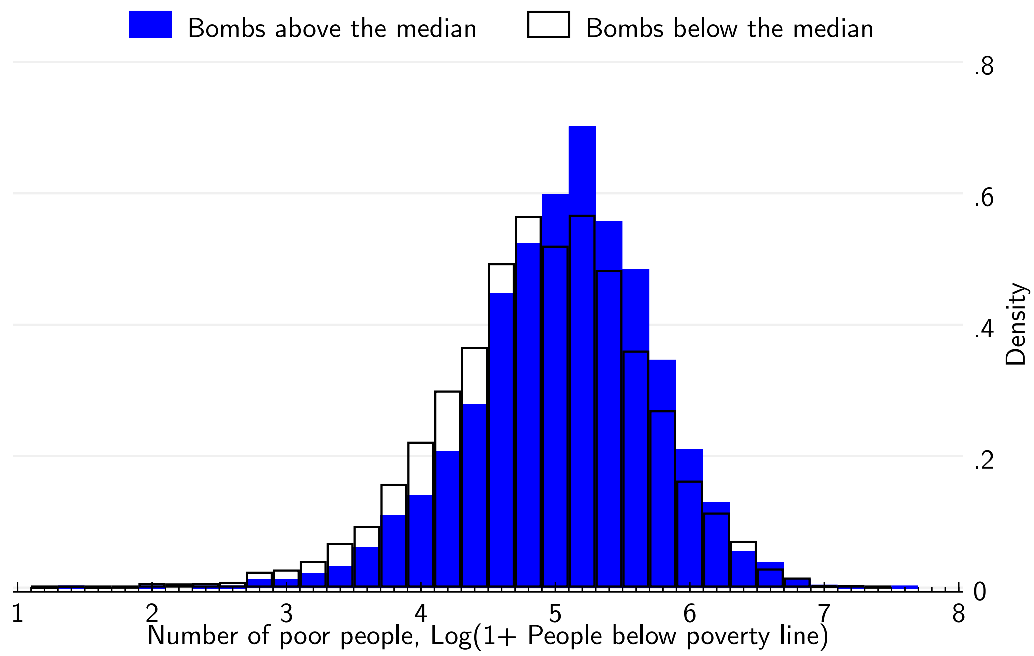
Notes: This figure presents the relationship between the intensive and the extensive margin of UXO contamination and the intensity of bombing. Both panels show bin-scatters with linear fits at the village level.

Figure A-5: Comparing Distributions for Development Outcomes

Panel A: Expenditure per capita

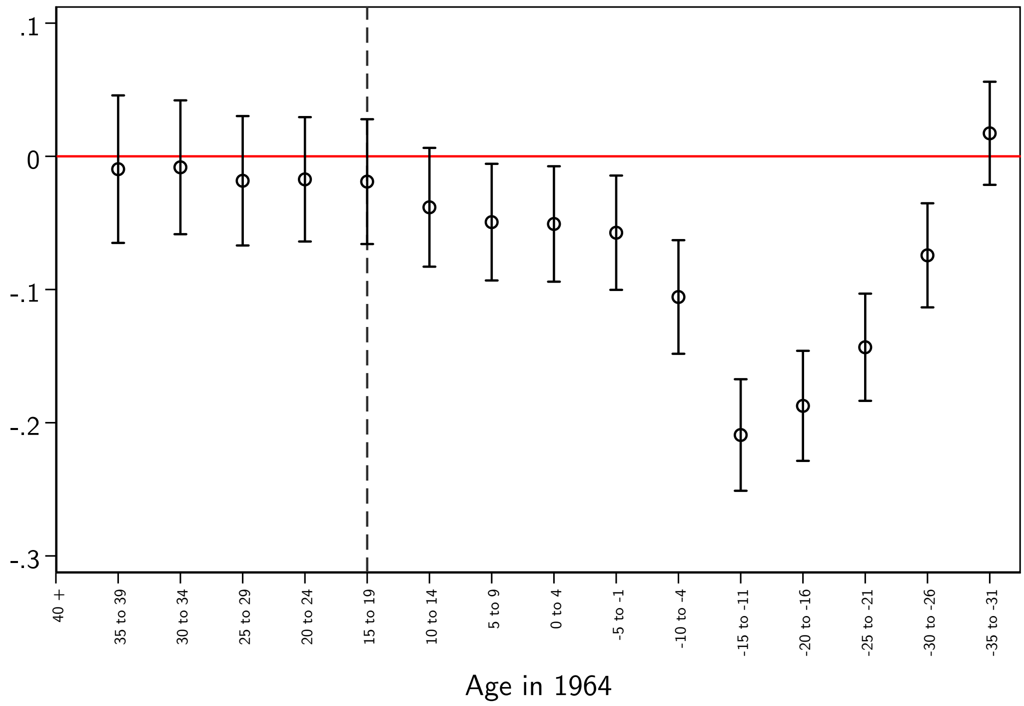


Panel B: Poverty Incidence



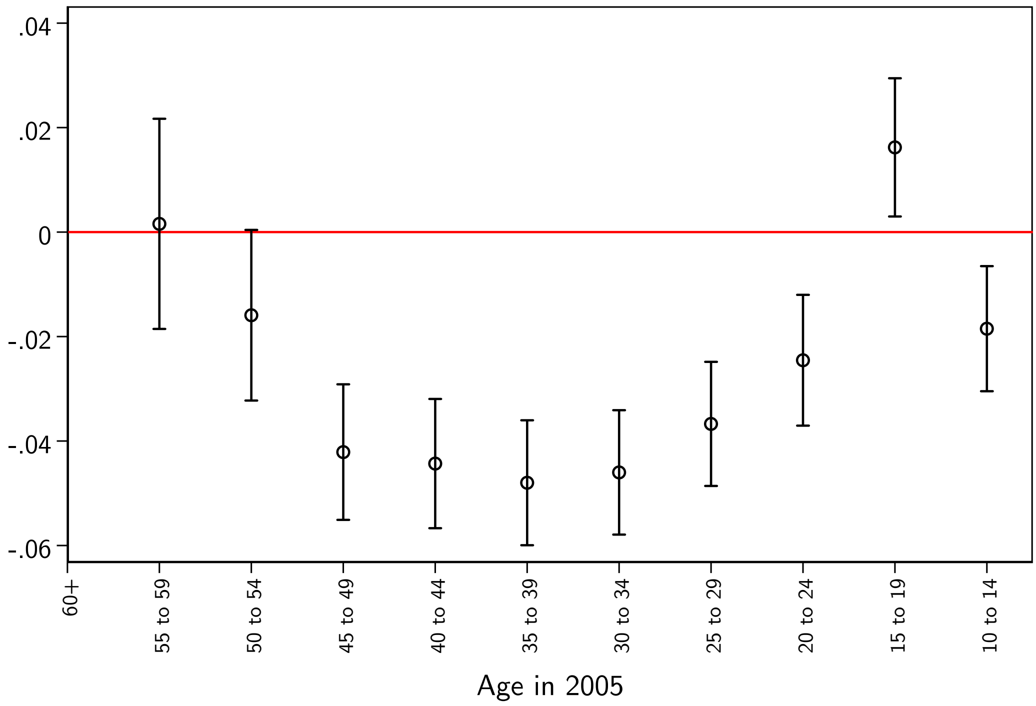
Notes: This figure presents the empirical distribution of the variables specified in each panel by the level of bombing intensity (above or below the median of bombs).

Figure A-6: 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.

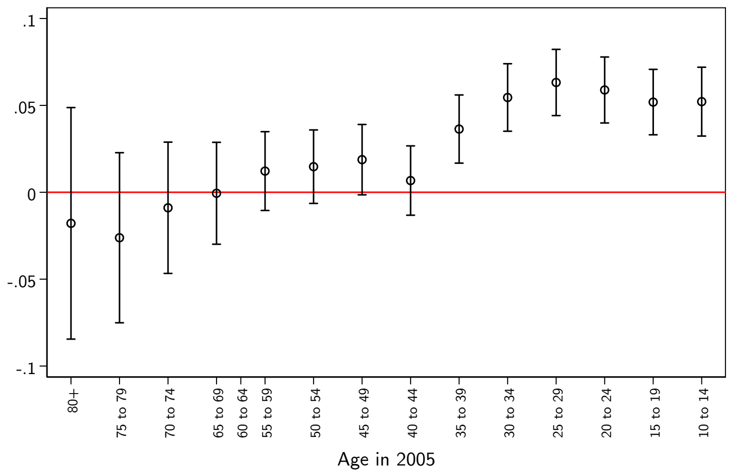
Figure A-7: Impact of Bombing on the Probability of Employment, using Micro-level Data from the Population Census of 2005 (quinquennial)



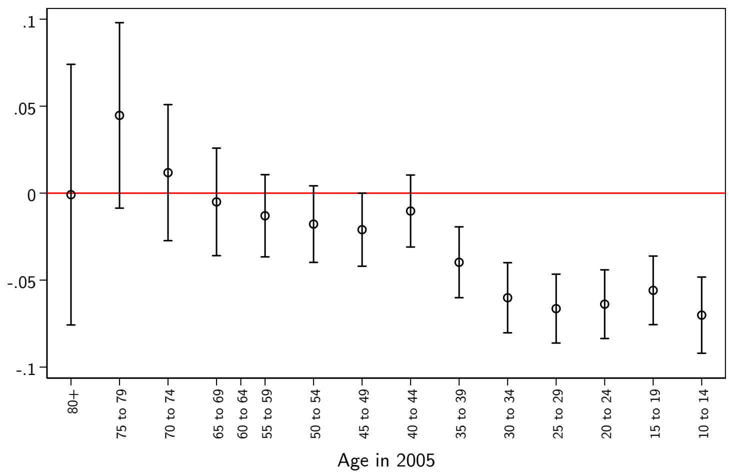
Notes: Figure reports point estimates and 95% confidence intervals of γ_k, from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors specified in the panels. The excluded cohort is composed by individuals older than 60 in 2005.

Figure A-8: Impact of Bombing on the Probability of Working in Different Sectors, using Micro-level Data from the Population Census of 2005 (quinquennial)

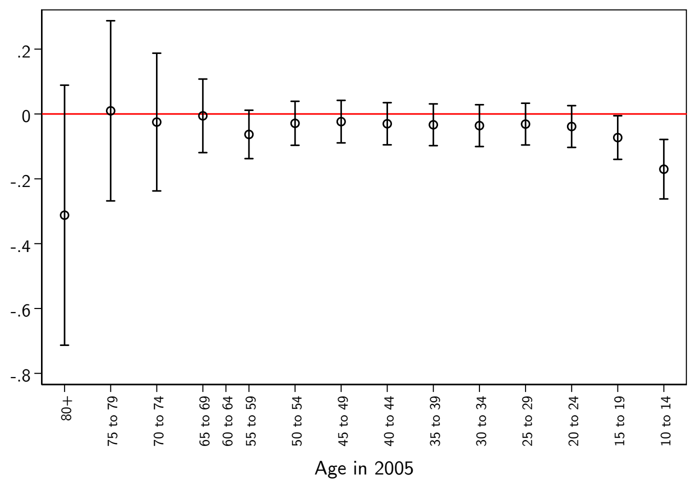
Panel A: Probability of Working in Agriculture



Panel B: Probability of Working in Services



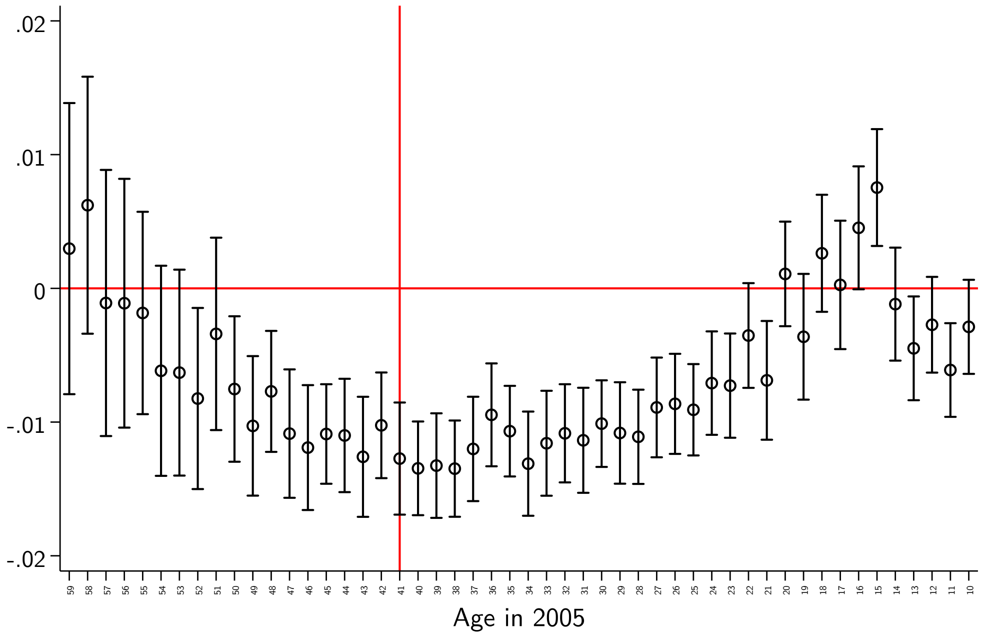
Panel C: Probability of Working in Manufacturing



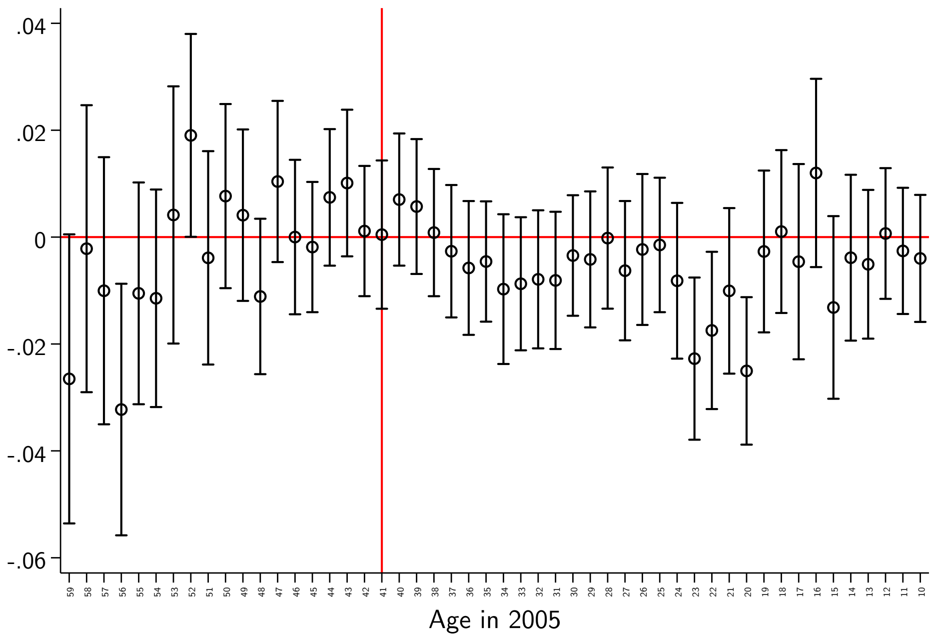
Notes: Panel A, B and C report point estimates and 95% confidence intervals γ_k from the specification in Equation (4) when the outcome variable is an indicator of being employed in each of the sectors listed in the panels. The excluded cohort is composed by individuals with 60 to 64 years old in 2005.

Figure A-9: Impact of Bombing on the Probability of Being Employed by Migration Status

Panel A: Non-Migrants



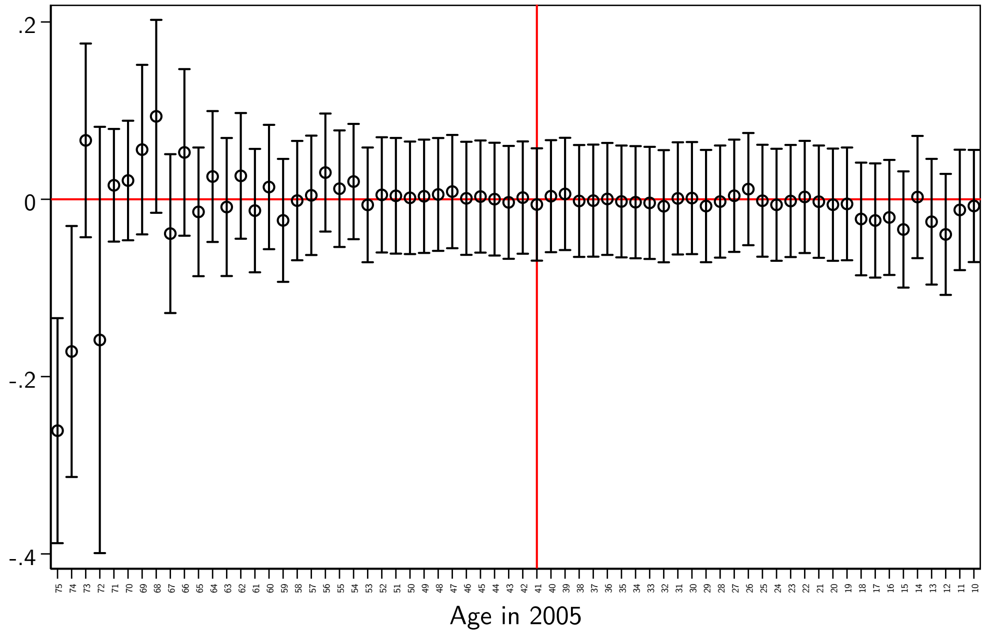
Panel B: Migrants



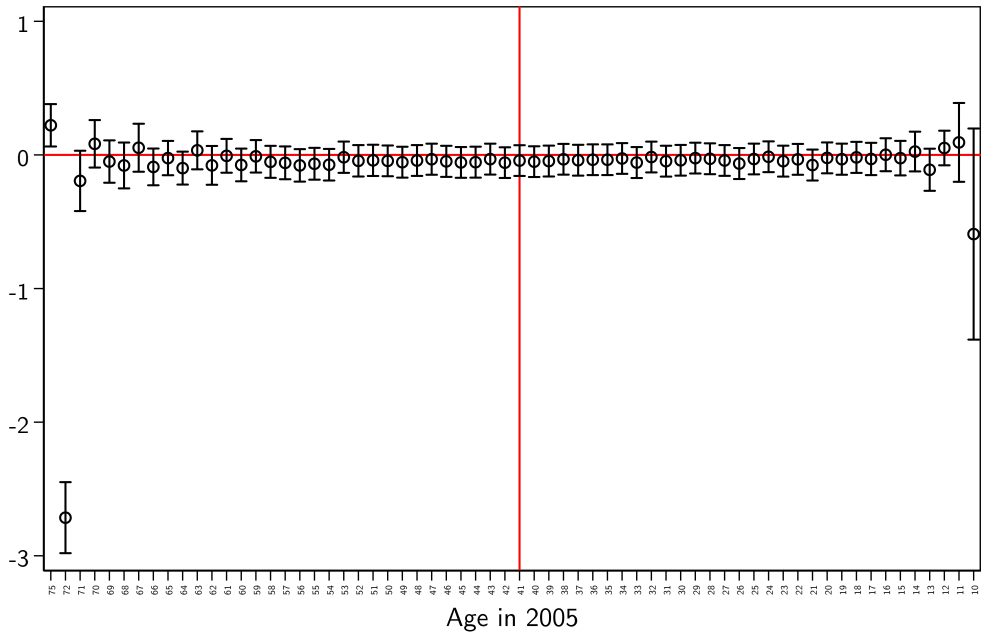
Notes: Panel A and Panel B report point estimates and 95% confidence intervals corresponding to η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed. The excluded cohort is composed by individuals with 60 years or more in 2005. 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-10: Impact of Bombing on the Probability of Working in Manufacturing by Migration Status

Panel A: Non-Migrants



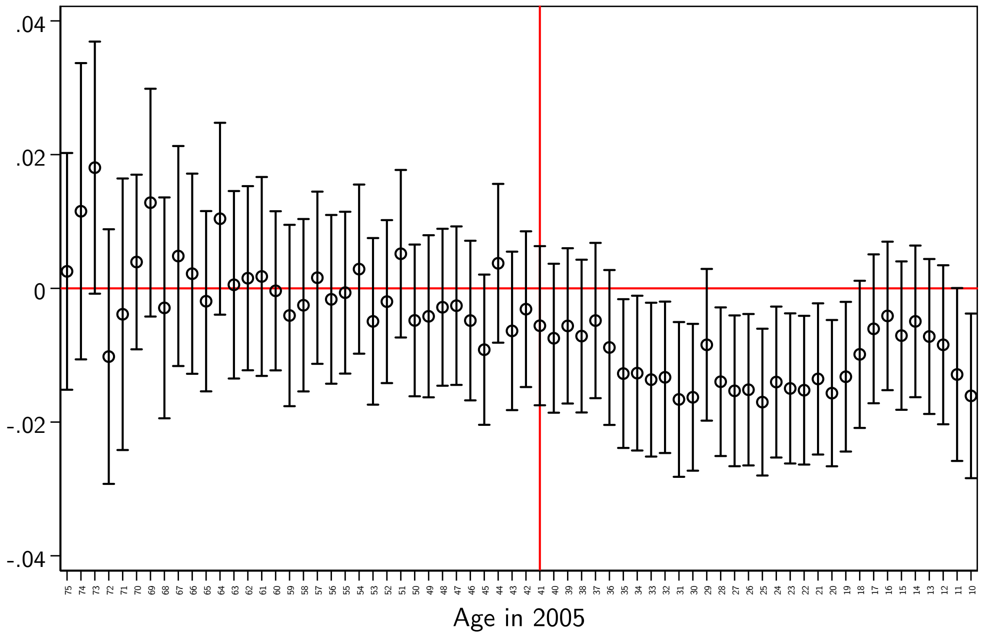
Panel B: Migrants



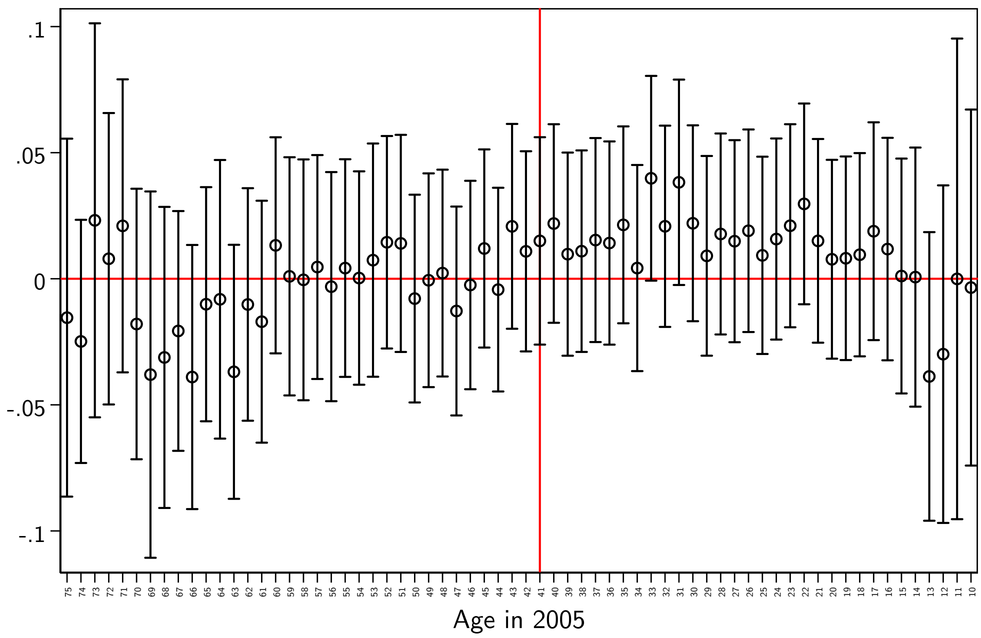
Notes: Panel A and B report the coefficients and 95% confidence intervals of η_k and γ_k, respectively, from the specification in Equation (5) when the outcome variable is an indicator of being employed in manufacturing in 2005. The excluded cohort is composed by individuals with 76 years or more in 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-11: 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.

Online Appendix: Tables

Table A-1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: Grid cell level data				
Bombs, ($\ln(1 + \text{Total Weight in pounds Jettisoned 1965-1973 per Km}^2)$)	5.944	5.063	0	18.458
Luminosity, 1993 ($\ln(1 + \text{Stable Lights 1993 per Km}^2)$)	0.014	0.166	0	3.955
Luminosity, 2003 ($\ln(1 + \text{Stable Lights 2003 per Km}^2)$)	0.022	0.2	0	4.104
Luminosity 2013 ($\ln(1 + \text{Stable Lights 2013 per Km}^2)$)	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 census 2005				
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

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

Table A-2: 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 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 $\times$ year level. 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-3: 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 $\times$ year level. 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-4: 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 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-5: Aggregating at the District Level and Excluding Observations in the Tails of the Distribution of Luminosity

	(1)	(2)	(3)	(4)
	Lights	No Upper Tail Lights	No Lower Tail Lights	No Tails Lights
Panel A: 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
Panel B: 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

Notes: Observations at the level indicated in each panel. Robust standard errors in parenthesis. If fixed effects are present, standard errors are clustered at that level.

Table A-6: 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 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:

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

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-7: Instrumental Variables: First Stages

Table A7-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 A7-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. 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-8: Instrumental Variable Estimates, by Year

Table A8-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 A8-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: Robust standard errors in parentheses, if Fixed Effects are present standard errors clustered at the level of the FE.

Table A-9: 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. 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-10: Public Goods Provision: Roads

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Roads			Length of Roads		
Bombs		0.4447***	0.2947***		2.6265***	1.6992***
		(0.0698)	(0.0634)		(0.4041)	(0.3688)
UXO Accidents	0.5776***		0.5299***	3.5267***		3.2719***
	(0.0362)		(0.0365)	(0.1982)		(0.1984)
Bombs × UXO Accidents			0.0256			0.0660
			(0.0298)			(0.1508)
Geographical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Location Controls	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,216	2,216	2,216	2,216	2,216	2,216
R-squared	0.1663	0.0876	0.1802	0.2062	0.1090	0.2210
Number of Districts	141	141	141	141	141	141

Notes: Observations are at the grid cell level. Data comes from maps of contemporaneous roads. Robust standard errors in parentheses, and clustered at the province level in columns 3 and 6. *** p<0.01, ** p<0.05, * p<0.1

Table A-11: Public Goods Provision: Educational Infrastructure

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(mean travel time in min to school)			Village has primary school		
Bombs	0.2207***	-0.0510**	-0.0983	-0.0279***	-0.0108**	0.0050
	(0.0169)	(0.0200)	(0.0829)	(0.0041)	(0.0051)	(0.0148)
Province Fixed effects			Yes			Yes
Geographical Controls		Yes	Yes		Yes	Yes
Location Controls		Yes	Yes		Yes	Yes
Observations	10,518	10,276	10,276	10,522	10,280	10,280
R-squared	0.0150	0.2534	0.1446	0.0049	0.0137	0.0142

Notes: Observations are at the village level. Data comes from the 2005 Census. Robust standard errors in parentheses, and clustered at the province level in columns 3 and 6. *** $p<0.01$, ** $p<0.05$, * $p<0.1$