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COLLATERAL DAMAGE: THE LEGACY OF THE SECRET WAR IN LAOS*

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We investigate the long-term impact of conflict on economic development, focusing on the US 'Secret War' in Laos (1964–73). Our study employs multiple empirical strategies and data on bombing campaigns, satellite imagery, and development indicators to demonstrate that regions heavily bombed during this period experienced lower economic development almost fifty years after the conflict officially ended. A one-standard-deviation increase in bombing intensity is associated with a 7.1% decrease in GDP per capita. We demonstrate the persistent effects of bombing campaigns on human capital accumulation, structural transformation and migration patterns, stressing the role of unexploded ordnance contamination as the primary mechanism of transmission of these effects.

When buffalos fight, it is the grass that suffers.

Laotian proverb[1]

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

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[1] Quoted in Conboy (1995).

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

[3] Voigtländer and Voth (2013), Gennaioli and Voth (2015), Dincecco and Onorato (2018) and Becker *et al.* (2019) even found *positive* effects in the longer run.

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To scrutinise the long-term legacies of conflict, we focus on the Lao People's Democratic Republic (Laos), a country of more than seven million people in the Indochinese Peninsula. Today Laos is one of the poorest countries in the world. Almost a quarter of the population lives under extreme poverty; 80% survives on less than $2.50 dollars per day (PPP 2005) and 70% lives in rural areas. Because of the US military intervention during the Laotian Civil War (1959–75), Laos is also the most heavily bombed country in human history. It is estimated that during nine years, from 1964 to 1973, the country received approximately one bomb every eight minutes, a third of which did not explode. As a result, Laos is one of the most contaminated countries in the world in terms of unexploded ordnances (UXOs), presenting a major threat to civilians.[4] In this paper we ask whether this legacy of war can be one of the fundamental drivers of Laos' chronic underdevelopment.

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

To test this hypothesis and its transmission mechanisms, we combine novel grid-cell-level data on the incidence of conflict with fine-grained economic indicators. We employ information on more than 1.6 million bombing missions that have recently been 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. These comprehensive data are available for 10,522 villages and 560,480 individuals, allowing us to explore both the spatial and temporal dimensions of conflict. To this end, we estimate Ordinary Least Squares (OLS), fixed-effect and Instrumental Variable (IV) models at a high degree of spatial disaggregation, as well as difference-in-differences (DiD) models that take into account the timing of conflict. We also make use of administrative data on geo-located UXO accidents from the National Regulatory Authority for Mine Action in Laos (NRA) covering *daily* incidents from 1950 to 2011, which we incorporate in a structural equation model (SEM) to test this main mechanism of transmission.[6]

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

[5] See Dasgupta and Ray (1986), Azariadis and Drazen (1990), the survey by Kraay and McKenzie (2014) and, most recently, Balboni *et al.* (2020).

[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.

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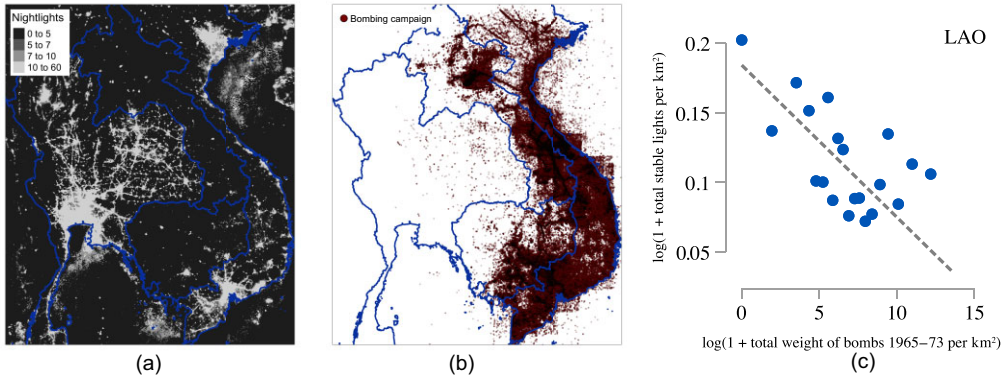


Fig. 1. *Indochina: Stable Lights and US Bombing Events from 1965 and 1973.*
Notes: Panel (a) displays the Indochina peninsula and the 2013 stable nightlights in grayscale. Country borders are displayed using a continuous line. Panel (b) displays the Indochina peninsula and the US Bombing Campaigns in the region from 1965 to 1973 in a dot distribution map. Each dot represents a single campaign. Country borders are displayed using a continuous line. Panel (c) presents a bin-scatter for Laos between Luminosity and Bombing intensity, controlling for province-fixed effects, year-fixed effects, and geographical and location covariates.

We conduct the empirical analysis in the following manner. First, we partition the country into 2,216 artificial grid cells of $0.1^\circ \times 0.1^\circ$,[7] which allows us to control—using fixed effects—for time-invariant characteristics at the province (Laos has eighteen provinces) and district (and 141 districts) levels.[8] Similarly, when aggregating the data for different years, we include time fixed effects, to control for potential trends during various cross sections. We also take into account in our estimates the potential effect of a large set of geographic and location characteristics at the grid-cell level, including altitude, ruggedness, temperature, precipitation, latitude and longitude—which are standard in the literature of conflict. Additionally, we control for other characteristics relevant for this particular context, such as the distance to the 17th parallel (the Vietnamese Demilitarised Zone), distance to the Vietnam border and distance to the nearest population centre, to get closer to a causal estimate of the bombing effect. OLS results reveal a negative and significant relationship between conflict incidence (intensity of bombing) and income (nightlights). A summary of this negative relationship can be seen in Figure 1. In terms of magnitudes, we find that a one-SD increase in bombs leads to approximately a 7.1% fall in GDP per capita.[9]

Still, OLS and fixed-effect estimates might be biased, as bombing was probably not random. More productive places could have been targeted—since bombing was a costly activity—or some already poor and isolated areas might have been attacked more intensely. Using quantile regressions, we show that the effect is concentrated at the upper tail of the nightlight distribution, suggesting the former case.[10] To tackle this potential endogeneity issue, we employ an IV strategy. Intuitively, we exploit the asymmetric information that is inherent in violent confrontations.

[7] In the Cartesian plane, this is equivalent to 11.1×11.1 km^2 grid cells at the equator.
[8] This grid-cell analysis also helps us to bypass potential endogenous border formation concerns.
[9] See footnote 38 in Section 4.2 below for details behind this estimate.
[10] Moreover, our baseline results are robust to controlling for pre-conflict population density in 1960 as well as to dropping lower- and upper-tail observations from the nightlight distribution. See Section 4.3 below for these and additional exercises.

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Our first instrument is the distance to the Vietnamese Ho Chi Minh Trail—mostly constituted by underground tunnels and obeying the dynamics of the broader Indochinese confrontation. Additionally, we use the distance to the nearest US air base *outside* Laos established *before* the beginning of the conflict started in the 1960s. This sensitive information comes from declassified CIA documents. We believe that the location of these bases in South Vietnam and Thailand can be viewed as largely exogenous to the eventual Laotian conflict, as detailed in Sections 1 and 3.3.

Our IV estimates confirm the baseline OLS and fixed-effect findings. First, we find a negative and strong relationship between bombing intensity and both distances to the Ho Chi Minh Trail and the nearest US air base. We also estimate a quadratic relationship in the first stage, to allow for heterogeneous effects, as in Dieterle and Snell (2016). Using these instruments, we again find a negative and highly significant relationship between the number of bombs dropped and lights in 1993, 2003 and 2013. In our preferred specification, we obtain a (standardised) coefficient for bombs of −0.109 (i.e., a 10% fall), which now has a more causal interpretation. We also test for spatial spillovers, but find little evidence for them.

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

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

[11] We observe no significant effect on manufacturing.

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

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

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

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

The main surveys on conflict in economics stress the impact of violence on developing countries (Blattman and Miguel, 2010; Bauer *et al.*, 2016; Ray and Esteban, 2017). Here we focus on the role of UXOs, which notably were not part of the analysis in Miguel and Roland (2011).[12] We discuss other differences with respect to this article in Section 6, where we focus on differential investments in demining. Other closely related papers to the present work study conflict in Mozambique, Vietnam and Cambodia. Chiovelli *et al.* (2018) stressed the large economic benefits

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

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of *clearing* the landmines left after the Mozambican Civil War (1977–92).[13] Closer to the area of interest, Dell and Querubin (2018) found causal effects of the Vietnam bombing campaign on anti-American sentiment. Lin (2020) looked at the problem of UXOs in Cambodia, which shares a border with Laos, finding that fertile agricultural land has become *less* productive due to UXOs. We find empirical support for some of these findings and provide novel identification strategies, along with mechanisms of transmission. In particular, we find that UXOs are keeping Laos more rural and restricting Laotian's mobility.

We also build on the historical conflict literature. On the political front, Fontana *et al.* (2023) showed that the Italian Civil War led to decades of political extremism, while Gagliarducci *et al.* (2020) looked at how media helped coordinate the Italian resistance during World War II. Tur-Prats and Valencia Caicedo (2020) examined the cultural and political consequences of the Spanish Civil War.[14] In terms of mechanisms, Fergusson *et al.* (2020) showed that conflict hampered structural transformation during the *La Violencia* (1948–58) period in Colombia. Though in a different context, we show that this channel plays an important role in Laos as well. In the more distant past, Feigenbaum *et al.* (2018) showed that Sherman's march during the American Civil War brought widespread capital destruction and Alix-Garcia *et al.* (2022) documented the demographic impact of the Triple Alliance War (1864–70) in South America. Here, we add to the modern literature on the impact of bombing (Redding and Sturm, 2016; Adena *et al.*, 2020; Harada *et al.*, 2020; Dericks and Koster, 2021) with a major Cold War operation. More broadly, this article is also related to the large literature on long-term economic persistence, recently summarised by Nunn (2020). Here we focus on conflict as a source of long-term underdevelopment.

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

However, these convergence dynamics can be hampered, even in the long run, if the damages extend from physical to human capital (Waldinger, 2016), which was the case in Laos. In the current context, we document how, beyond bombing, UXO contamination hampered key human capital investments, even after the ceasefire. The presence of such dangerous artefacts can alter structural transformation, urbanisation and migration patterns, generating a 'conflict trap'. Such a trap would be consistent with the more general development poverty traps (Barrett and Carter, 2013). Perhaps the most important paper on this concept shows a causal relationship between negative income shocks and increased conflict (Miguel *et al.*, 2004). Still, we know less about the converse relationship. A notable exception is the work of Abadie and Gardeazabal (2003) examining the negative impact of the ETA terrorist group on the Basque economy. Still, this synthetic control approach is essentially a contemporaneous exercise. We provide here an empirical test of the other direction of the conflict trap hypothesis in the long run, in a country

[13] Prem *et al.* (2023) provided an important counterexample, by pointing out that demining campaigns are more useful when the conflict has already stopped.

[14] It is worth noting that Laos is one of the four existing communist countries in the world along with China, Cuba and Vietnam, which precludes any meaningful electoral analysis.

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where war literally fell from the sky.[15] These harmful dynamics can be exacerbated by lower investments in demining and other productive activities, as we compare the Laotian case with that of neighbouring Cambodia and Vietnam.

The rest of the paper is organised as follows. Section 1 covers the relevant historical background. We then present the data and empirical strategy in Sections 2 and 3, followed by the main empirical results in Section 4—divided into OLS, FE, IV and DiD estimates. Section 5 contains the mechanisms of transmission and Section 6 discusses our findings more broadly. We conclude in Section 7 with the main lessons of the study along with their potential policy relevance.

1. Background

1.1. *The 'Secret War' in Laos*

The Laotian Civil War (1959–75) was a proxy conflict during the broader Cold War confrontation between the United States and the USSR (see Malis *et al.*, 2021 for a survey). It pitted the Communist Pathet Lao against the Royal Lao Government. The country was of key geostrategic interest, given the neighbouring civil war in Cambodia (1967–75) and the Vietnam War (1955–75), in what is generally known as the Second Indochina War.[16] Laos was essentially seen through the lens of President Eisenhower's 'domino theory' of the Cold War, according to which if one country fell to communism in the region, it could precipitate the downfall of others. In his words, 'If Laos were lost, the whole of Southeast Asia would follow'. Accordingly, the United States intervened in Laos, as part of its anti-communist counterinsurgency operations, though the conflict remained 'secret' in the United States at the time, as was later acknowledged. Many of the bombing campaigns in Laos obeyed the broader Indochinese confrontation, and the eventualities of the Vietnamese conflict, which informs the title of our study.

Perhaps the best summary of the situation was provided by President Barack Obama in his 2016 visit to Laos. Obama was the first US president to visit the Southeast Asian nation. In his historic visit, Obama first acknowledged that

> as the fighting raged next door in Vietnam, your neighbours and foreign powers, including the United States, intervened here. It was a secret war, and for years, the American people did not know. Even now, many Americans are not fully aware of this chapter in our history, and it's important that we remember today.

He then noted that, as a result of the Secret War,

> Over nine years—from 1964 to 1973—the United States dropped more than two million tons of bombs here in Laos—more than we dropped on Germany and Japan combined during all of World War II. It made Laos, per person, the most heavily bombed country in history.

Adding that locals recall that 'bombs fell like rain'.

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

[16] The Cambodian Civil War (1967–75) pitted the Khmer Rouge, supported by North Vietnam and the Viet Cong, against the Kingdom of Cambodia and the Khmer Republic, supported by the United States and South Vietnam. It was won by the Khmer Rouge, and led to the establishment of Democratic Kampuchea, under Pol Pot (see Bühler and Madestam, 2024; Lin, 2020). The Vietnam War was fought between North and South Vietnam from 1955 to 1975. The North Vietnamese were supported by the Soviet Union and China, while the southern Vietnamese by a coalition of countries led by the United States, including South Korea and Thailand; see Miguel and Roland (2011) and Dell and Querubin (2018). We refer the interested reader to the historical accounts by Stuart-Fox (1997), Taylor (2013) and Chandler (2018).

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

A series of covert military operations by the CIA and the US Air Division were conducted in Laos and Vietnam, including Operation Steel Tiger, Operation Tiger Hound and Operation Commando Hunt. These operations helped to give rise to the military CIA (Kurlantzick, 2017). Aside from the Plain of Jars, the United States heavily bombed southeast Laos, given its strategic proximity to the Vietnamese Ho Chi Minh Trail, where the Viet Cong enemy troops were stationed (see Figure 3 below). This area was of key geostrategic interest, as it connected South and North Vietnam. From 1964 to 1973 the United States 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 27 January 1973 to end the Vietnam War, the United States effectively pulled out of Laos. The Pathet Lao finally captured Vientiane in 1975, forcing King Savang Vatthana's abdication, putting an end to the conflict, and proclaiming the Lao People's Democratic Republic, a regime that is still in power today.

1.2. *The Aftermath of the Conflict*

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

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

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

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

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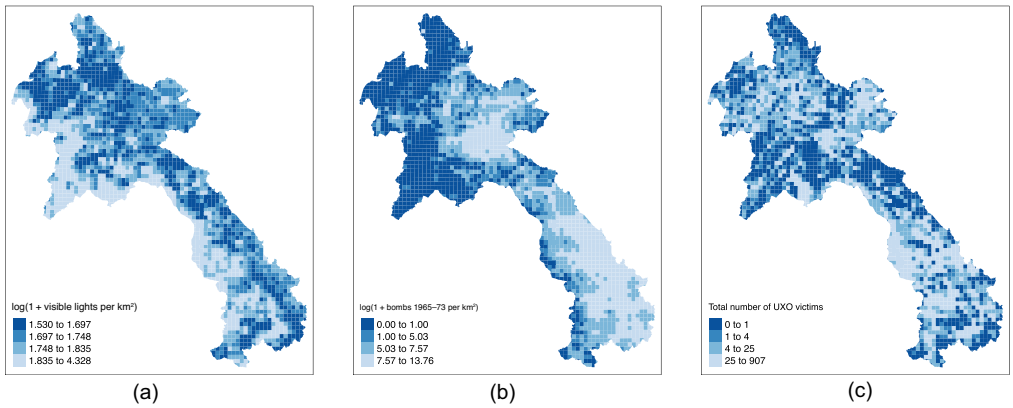


Fig. 2. *Luminosity, Bombs and UXOs.*
Notes: Panel (a) presents luminosity measured as the total sum of visible lights in 2013 per km^2 at grid-cell level (in logs). Panel (b) displays bombing intensity measured as total pounds jettisoned from 1965 to 1973 per km^2 (in logs). Panel (c) shows total number of UXO victims from 1950 to 2011.

2. Data

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

2.1. *Synthetic Grid-Cell-Level Data*

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

2.1.1. *Economic activity*

We use nighttime light satellite data as a proxy of economic activity following Henderson *et al.* (2012). Our data come from the fourth version of the DMSP-OLS nighttime lights time series, collected by the National Oceanic and Atmospheric Administration since 1992 (National Centers for Environmental Information, 2013). We aggregate up these lights at the grid-cell level. Figure 2(a) depicts nightlights in 2013. We use the information on lights at 30 arc seconds for 1993, 2003 and 2013, accounting for the impact of conflict after approximately twenty, thirty and forty years. To reduce the measurement error and make the interpretation of our coefficients easier, we employ stable lights, and use a conventional logarithmic transformation of one plus

[20] Online Appendix Table A-1 presents the summary statistics for the key variables.
[21] In Online Appendix Figure A-1, we present the synthetic grid and the principal administrative divisions of the country, consisting of eighteen provinces and 141 districts.

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the sum of light intensity divided by the area of the grid cell in square kilometres.[22] We refer to this measure as lights or luminosity interchangeably.

2.1.2. *Historical bombing*

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

2.1.3. *Geographic and location controls*

To account for potential geographic confounders, we use geophysical and weather information from DIVA-GIS (Hijmans *et al.*, 2017) and WorldClim spatial data (Fick and Hijmans, 2017). We aggregate information on average altitude, temperature and precipitation within each grid cell. We also use terrain ruggedness from Nunn and Puga (2012). To control for spatial confounders of conflict and additional geographic determinants of economic activity, we use the latitude and longitude of each grid cell as supplementary controls. Furthermore, we include the Euclidean distance to the closest portion of the Vietnam border as well as the distance from the cell to the nearest populated centre from Natural Earth (2009).[23] Finally, we also include the distance to the 17th parallel (the Vietnamese Demilitarised Zone), a potentially powerful predictor of bombing intensity during the Vietnam War, used as an instrument by Miguel and Roland (2011).

2.2. *Village-Level Data*

Information at the village level consists of two geo-located censuses: the Population Census of 2005 and the Agricultural Census of 2011 (Government of Lao PDR, 2020a,b). These are the two most recent censuses digitised and available for Laos, giving us an even more granular picture of the whole country encompassing about 10,522 villages.[24] All of the information comes from the Lao DECIDE info platform, an initiative of the Laotian Government to improve access to official data.[25] We employ information on UXO contamination, human capital levels,

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

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

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

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

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development outcomes, urbanisation and public goods provision at the village level, detailed next. An important limitation of these data is that there is no official demarcation of village boundaries in Laos. To bypass this constraint, we constructed a synthetic set of village boundaries based on Thiessen/Voronoi polygons and the coordinates of administrative centres.[26]

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 one if there is any agricultural land contaminated by UXOs at the village level, as well as the official estimate of the total area in hectares affected by it. For the latter, we use the log transformation of one plus the total number of hectares contaminated. The mere inclusion of these variables in the census highlights the importance of this phenomenon in Laos (National Regulatory Authority for UXO/Mine Action in Lao PDR, 2015).

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

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

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

2.3. *Individual-Level Data*

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

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

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2.4. *Historical Maps*

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

3. Empirical Strategy

3.1. *OLS Models: Cross-Sectional Variation*

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

$$\text{Luminosity}_{g,d,t=\tau} = \gamma_\tau \cdot \log(1 + \text{Bombs 1964–73})_{g,d} + \boldsymbol{X}'_g \Gamma + \xi_{g,t=\tau}, \tag{1}$$

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 (1), $\text{Bombs 1964–73}_{g,d}$ is the total weight in pounds jettisoned within grid cell g in district d from 1965 to 1973 per square kilometre, while $\text{Luminosity}_{g,d,t=\tau}$ represents the log of one plus the total number of stable lights per square kilometre within the same grid cell g.[28] We include a comprehensive set of geographical and location controls at the grid-cell level X_g that account for exogenous, but potentially confounding factors at this level of disaggregation, as described in Section 2.1. These include average altitude, temperature, precipitation, ruggedness, latitude, longitude, distance to the closest portion of the Vietnam border, distance to the nearest population centre and the distance to the 17th parallel (the Vietnamese Demilitarised Zone).[29] The parameter of interest in this model is γ_τ and represents the conditional long-term correlation between historical conflict and economic activity at year τ. In this formulation, econometric identification comes from the fact that bombs are lagged in time with respect to lights, but there could still be other omitted variables to interpret the estimates causally. To improve upon these potential challenges, we turn next to fixed-effect models.

3.2. *Fixed-Effect Models: Within-Province, District and Year Variation*

The high degree of disaggregation of our data allows us to control for time-invariant characteristics at the province and district levels, which may be correlated with contemporaneous economic

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

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

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

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activity or the historical prevalence of conflict. To this end, we include a full set of province or district fixed effects in (1), which permits us to exploit the within-district or within-province variation in the intensity of conflict. Relative to the OLS specification, this estimation allows us to control for potentially omitted characteristics for which we did not have information before.

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

$$\text{Luminosity}_{g,d,t} = \alpha_d + \delta_t + \gamma \cdot \log(1 + \text{Bombs 1964–73})_{g,d} + \boldsymbol{X}_g'\Gamma + \xi_{g,t}. \quad (2)$$

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

We present multiple methods of inference accounting for alternative serial and geographic interdependence of the error term $\xi_{g,t}$. For example, we document our results for different levels of clustering (grid, district and province) and distance thresholds (100, 200, 300, 500, 1,000 and 1,500 km), as in Conley (1999). In addition, we explicitly estimate potential spatial spillovers in the unobserved component of our regressions following Lee and Yu (2010).[30]

3.3. *IV Models: Addressing the Endogeneity of Bombing*

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

$$\log(1 + \text{Bombs 1964–73})_{g,d} = \rho_d + \beta \cdot f(Z_{g,d}) + \boldsymbol{X}_g'\Pi + \varepsilon_{g,d}, \quad (3)$$

where the index notation and controls are analogous to (1), and the ρ_d are province or district fixed effects. We include a second-degree polynomial $f(Z_{g,d})$ for the instrument to account for the potential non-linearities on the intensity of bombing, as in Dieterle and Snell (2016), though we also report linear specifications. We propose two instruments based on the informational asymmetries of conflict: the distance to the hidden part of the Vietnamese Ho Chi Minh Trail, and the proximity to US air bases outside Laos, built before the conflict started. We also combine both instruments in the analysis.

For the first instrument, the distance to the Ho Chi Minh Trail (HCMT), we use the Euclidean distance from the grid cell's centroid to the closest part of the trail. The 'trail', which actually consisted of a series of paths, roads and tunnels, constituted the main supply route to and from North Vietnam, and a key reason for why this country was able to withhold the American

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

[31] See Section 4.4 below for empirical evidence on this.

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invasion. We view the trail as an important strategic bombing target for the United States, but also one more related to the internal dynamics of the neighbouring Vietnamese conflict. The idea here is that Laotian bombings due to the proximity of the HCMT constitutes collateral damage from the broader Indochinese confrontation. Importantly, we control for distance to Vietnam and its Demilitarised Zone, as well as for road access in our IV estimates. Furthermore, we focus here on the part of the trail that was not visible from the air, mostly consisting of tunnels and hidden paths, which we see as plausibly exogenous, and less related to other types of visible infrastructure, assuaging potential exclusion-restriction concerns.[32] For instance, we examine the relationship with roads empirically in Online Appendix Table A-17. The general intuition is to exploit the asymmetric information, inherent in conflict, in particular the part that was unknown to US soldiers at the time.

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

3.4. *Difference-in-Differences: The Timing of Conflict*

As an alternative identification strategy, we exploit cohort and yearly variation in the degree of exposure to conflict. This strategy allows us to move beyond the purely spatial identification of the main effect, to look at its temporal dynamics. Namely, we employ individual-level data from the 2005 Census detailed in Section 2.3. We exploit the differential impact of bombing intensity across provinces (of birth) for different cohorts. This allows us to bypass some of

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

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

[34] Data come from page 81 of the report 'USAF Plans and Operations in Southeast Asia 1965' by the USAF Historical Division Liaison Office in 1966, a declassified document since 16 May 2006.

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

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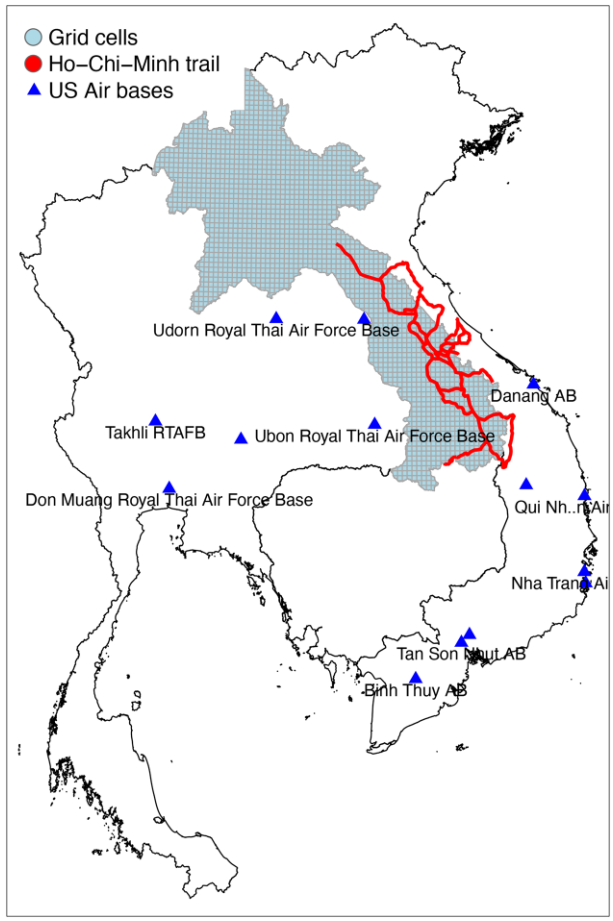


Fig. 3. *US Air Bases outside Laos and the Ho Chi Minh Trail.*
Notes: This figure presents the map of Thailand, Cambodia, Vietnam and Laos and the grid-cell partition used in the empirical analysis. In triangles, it depicts the locations of US air bases outside Laos and the georeferencing of the Vietnamese Ho Chi Minh Trail. Information was digitised based on historical maps presented in Online Appendix Figure A-3.

the potential concerns, even of the IV estimates. In particular, we estimate the econometric specification:

$$y_{i,p,k} = \delta_k + \lambda_p + \sum_k \gamma_k(\log(1 + \text{Bombs 1964–73})_p \times d_{i,p,k}) + \boldsymbol{X}_i'\Gamma + \epsilon_{i,p,k}, \quad (4)$$

where y_{ipk} represents educational attainment or labour market outcomes of individual i, born at province p belonging to cohort k in 1964. Here we look at educational outcomes around the outset of the war, and labour outcomes approximately forty years later. As before, Bombs 1964–73_p corresponds to the total weight in pounds jettisoned in province p from 1965 to 1973 per square kilometre. Similarly, d_{ipk} is a set of dummy variables that equals 1 if individual i was born in province p and belongs to cohort k, and 0 otherwise. We include a full set of province λ_p and

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cohort δ_k fixed effects and individual controls X_i, such as sex and long-term migration status. The coefficients of interest are the difference-in-differences estimates γ_k of the average impact of bombing on birth cohort k. For cohorts k in their schooling years and younger, γ_k is an unbiased measure of the impact of bombing if there are no omitted time-varying and province-specific characteristics correlated with conflict incidence.[36] We see this as an important and complementary way of identifying the effect of conflict.

4. Baseline Results

4.1. *OLS Results*

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

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

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

Table 2 looks at the effect on growth rates, instead of levels. We use the same control set as before and now look at *changes* in nightlights. It does *not* seem that bombed areas are growing significantly more, but quite the opposite. This is true when considering growth rates from 1993 to 2003 in columns (1) to (3), from 2003 to 2013 in columns (4) to (6) and from 1993 to 2013 (the longer difference) in columns (7) to (8). The coefficients are always negative, and significant at the standard levels in some specifications. Overall, it does not seem that bombed areas are experiencing a growth boom in Laos, as has occurred in other commonly studied postwar scenarios. Instead the results are more consistent with a conflict trap dynamic. Some fundamental variables such as human capital investments and labour outcomes might have recovered, as we show later, but we still do not observe convergence in growth rates, perhaps due to more permanent changes in human capital acquisition and settlement patterns, as we examine in Section 5.

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

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Table 1. *OLS Estimates: Luminosity and Bombs.*

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

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

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

Dependent variable	Luminosity growth 1993–2003			Luminosity growth 2003–13			Luminosity growth 1993–2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bombs	−0.001	−0.004	−0.005	−0.010	−0.018**	0.006	−0.015*	−0.026***	−0.007
	(0.003)	(0.003)	(0.004)	(0.007)	(0.007)	(0.010)	(0.009)	(0.010)	(0.012)
Altitude		−0.019**	−0.033		−0.057***	−0.235***		−0.093***	−0.302***
		(0.008)	(0.025)		(0.022)	(0.054)		(0.027)	(0.067)
Ruggedness		−0.014***	−0.015***		−0.024**	−0.028***		−0.049***	−0.054***
		(0.003)	(0.003)		(0.009)	(0.009)		(0.012)	(0.012)
Temperature		−0.014*	−0.031		−0.016	−0.216***		−0.043	−0.284***
		(0.008)	(0.030)		(0.022)	(0.062)		(0.028)	(0.079)
Precipitation		0.002	0.004		0.009	0.036***		0.012	0.041***
		(0.003)	(0.004)		(0.006)	(0.009)		(0.008)	(0.012)
Longitude			−0.051**			−0.187***			−0.279***
			(0.024)			(0.057)			(0.070)
Latitude			−0.028			−0.112**			−0.168**
			(0.022)			(0.055)			(0.067)
Distance to DMZ			−0.018***			−0.025**			−0.058***
			(0.004)			(0.011)			(0.012)
Distance to Vietnam border			−0.028***			−0.047			−0.097***
			(0.010)			(0.031)			(0.035)
Distance to population centre			−0.016***			−0.059***			−0.088***
			(0.003)			(0.009)			(0.011)
Observations	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216	2,216
R^2	0.092	0.114	0.136	0.203	0.235	0.274	0.135	0.186	0.242

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

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Table 3. *Fixed-Effect Estimates: Luminosity and Bombs.*

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

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

4.2. *Fixed-Effect Results*

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

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

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Table 4. *Fixed-Effect Estimates: Pooled OLS of Luminosity on Bombs.*

Dependent variable	Luminosity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bombs	−0.037***	−0.044***	−0.038***	−0.024**	−0.050***	−0.044***	−0.020**
	(0.007)	(0.007)	(0.011)	(0.009)	(0.011)	(0.011)	(0.009)
Geographical controls		Yes	Yes	Yes	Yes	Yes	Yes
Location controls					Yes	Yes	Yes
Province fixed effects			Yes			Yes	
District 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^2	0.034	0.097	0.206	0.409	0.172	0.241	0.417

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

Finally, we pool all observations to estimate the specification in (2), where we include year fixed effects to take into account potential time differences. The results in the most basic specifications, without and with geographic controls, are presented in the first two columns of Table 4. The coefficient for bombs on lights is again negative and strongly significant. We progressively add province and district fixed effects in columns (3) and (4), as well as location controls in the last three columns. The coefficient is always negative and its significance varies from the 5% to the 1% level. In the most stringent specification, with both sets of controls, year and district fixed effects, the standardised coefficient is −0.020, similar to the more basic fixed-effects result, and the OLS estimates presented before. We proceed to interpret the economic significance of this baseline estimate. To this end, we turn to the seminal article by Henderson *et al.* (2012). We use our preferred specification in Table 4, column (7), and their baseline specification in Table 2, column (1). A one-SD increase in the total pounds of bombs dropped is associated with a 7.1% fall in GDP per capita.[38] This sizeable decrease gives some empirical support to the conflict trap hypothesis in the aggregate, suggesting an S-shaped factor accumulation function and the presence of multiple equilibria. We look more closely at factor (labour) mobility in Section 5 below. Though we present our preferred IV estimates in Section 4.4 below, the fixed-effect results imply that, to invalidate our estimates, there would have to be omitted variables working at the within-province, district and year levels.

4.3. *Robustness of the OLS and FE Specifications*

We introduce two important controls and run some additional specifications for robustness. The first one controls directly for population in 1960 at the district level to take into account potential pre-trends in this demographic variable (Halpern, 1961). As can be seen in Online Appendix Table A-5, our results are unaffected by this addition. We do not employ this control going forward, as we use district fixed effects that take care of this and other potentially relevant

[38] To reach this estimate, we compute the relative size of our coefficient with respect to the sample mean of luminosity across years as −0.020/0.078, then we use the estimated elasticity of GDP to lights of 0.277 of Henderson *et al.* (2012), and calculate the corresponding GDP fall as (−0.020/0.078) × 0.277 = −0.071.

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variables at the district level. Additionally, we control for road access in 1970, which is most probably a 'bad control' in the language of Angrist and Pischke (2008).[39] Still, our results are unaffected by this addition and, if anything, increase slightly in magnitude, as can be seen in Online Appendix Table A-6.[40] We also re-estimate our model dropping outliers in terms of luminosity: without upper, lower or both tails, as reported in Online Appendix Table A-7, panel A. Next, we show in Online Appendix Table A-8 that the effect is concentrated on rural areas, an important heterogeneity, which we explore in Section 5 below.[41] Finally, we test for potential spillovers in Online Appendix Table A-4. Following Lee and Yu (2010)—who proposed a correct estimation of a spatial auto-regressive panel data model with fixed effects—we do not find evidence of systematic spillover effects. For 1993 and 2003, for example, the effect of neighbouring grids was not statistically significant, and only until 2013 did there seem to be evidence of potentially positive spillovers. These could be the result of unlocked mobility restrictions or increases in market access due to UXO clearance (Chiovelli *et al.,* 2018). Despite this, our coefficient of interest remains negative and significant after we correct for this influence and, if anything, it is larger throughout. These results are confirmed using Conley SEs at different thresholds in Online Appendix Table A-3.

4.4. *Instrumental Variable Results*

Though robust, the results in the previous sections might still be biased. They could be underestimates of the real effect, since bombing was costly and presumably targeted key infrastructure, hampering development in the future.[42] On the contrary, the results could be biased upwards, if bombings targeted mostly poor and isolated places, such as jungle areas. To get a sense of the potential biases, we run quantile regressions, reported in Online Appendix Figure A-6. We see that the OLS effect is working at around the 70th percentile of the distribution of nightlights. This holds for 1993, and, if anything, is even higher for the later years, which provides suggestive evidence against the upward bias. To correct for such potential biases, regardless of their direction, we employ the instrumental variable strategy described in Section 3.3.

4.4.1. *First-stage results*

Before running any regression, we plot the unconditional relationship between bombing and the two instruments, along with a quadratic fit. Recall that we have two instrumental variables: the distances to the hidden part of the Vietnamese Ho Chi Minh Trail and to the nearest US air bases outside Laos, built before the war started. As can be seen in Online Appendix Figure A-7, panel A, the total number of bombs dropped is a negative function of the distance to the Ho Chi Mihn Trail. It also shows that this relationship is potentially non-linear. Many of the observations appear less than 100 km from the trail, suggesting the more localised nature of this first instrument. Panel B plots the relationship between bombs and the distance to the nearest US base outside Laos. There is a hump-shaped relationship between these two variables, with a maximum between

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

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

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

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

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100 and 200 km. To capture these non-linearities, we estimate (3) using a quadratic first stage, allowing for potential heterogeneous effects, as in Dieterle and Snell (2016).[43]

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

4.4.2. *Second-stage results*

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

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

In general, the IV magnitudes appear larger than the corresponding OLS specifications, which is consistent with our preliminary interpretation of the former as underestimates. Namely, more productive areas were probably targeted during the aerial bombing campaigns. The difference between the OLS and IV results can be driven by the fact that the latter estimate local average treatment effects, whereas the former is a potentially biased estimate of the average treatment effect; see Imbens and Angrist (1994) and Becker (2016) for a more in-depth discussion.[47] In this set-up, though Laos was heavily bombed, some areas suffered disproportionately more from the war. Since we estimate the model with province and district fixed effects, we are also capturing

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

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

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

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

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

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

	(1)	(2)	(3)
(a) *Instrument I: distance to the Ho Chi Minh Trail*			
Panel A: dependent variable is luminosity			
Model	2SLS	2SLS	2SLS
Bombs	−0.165***	−0.132***	−0.105***
	(0.040)	(0.038)	(0.027)
Panel B: dependent variable is Bombs			
Model	FS	FS	FS
Distance to the Ho Chi Minh Trail	−0.008***	−0.014***	−0.022***
	(0.001)	(0.001)	(0.002)
(Distance to the Ho Chi Minh Trail)^2	0.009***	0.022***	0.026***
	(0.001)	(0.002)	(0.003)
R^2	0.551	0.629	0.772
F-statistic	363.8	43.69	30.38
Controls that apply to both 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
(b) *Instrument II: distance to the closest US air base*			
Panel A: dependent variable is luminosity			
Model	2SLS	2SLS	2SLS
Bombs	−0.145***	−0.127***	−0.521**
	(0.031)	(0.029)	(0.210)
Panel B: dependent variable is Bombs			
Model	FS	FS	FS
Distance to US air base	0.014***	0.014***	0.004***
	(0.001)	(0.001)	(0.002)
(Distance to US air base)^2	−0.020***	−0.013***	−0.009***
	(0.001)	(0.002)	(0.003)
R^2	0.601	0.648	0.750
F-statistic	531.7	59.40	13.82
Controls that apply to both panels			
Geographical controls	Yes	Yes	Yes
Location controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects		Yes	
District fixed effects			Yes
Number of provinces		18	
Number of districts			141
Observations	6,648	6,648	6,648

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

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

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

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

a more local variation of the treatment.[48] Still, there could be additional dynamic effects from the proposed instruments. Overall, the IV estimates, despite their potential limitations, confirm the large negative effects of conflict for long-term development, along the lines of a conflict trap, something we explore further in the next section, where we also exploit the *timing* of conflict.

4.5. *Difference-in-Differences Results*

4.5.1. *Human capital: years of schooling and literacy*

In the following sections we focus on the role of human capital accumulation and the process of structural transformation, exploiting the timing of conflict. To this end, we employ individual-level data from the 2005 Census and the empirical specifications detailed in Section 3.4. Having this information allows us to bypass some of the limitations of the spatial, cross-sectional analyses presented so far, and expand on the dynamics of the bombing shock.

Our main results for years of schooling are presented in Figure 4. Here we plot the coefficients for years of schooling for cohorts of different ages at the time the bombing started, in 1964, following (4). We observe no pre-trends with respect to this human capital variable, which is to say no significant impact of our dummy for cohorts that were too old to be affected when

[48] This is also consistent with the spillover results.

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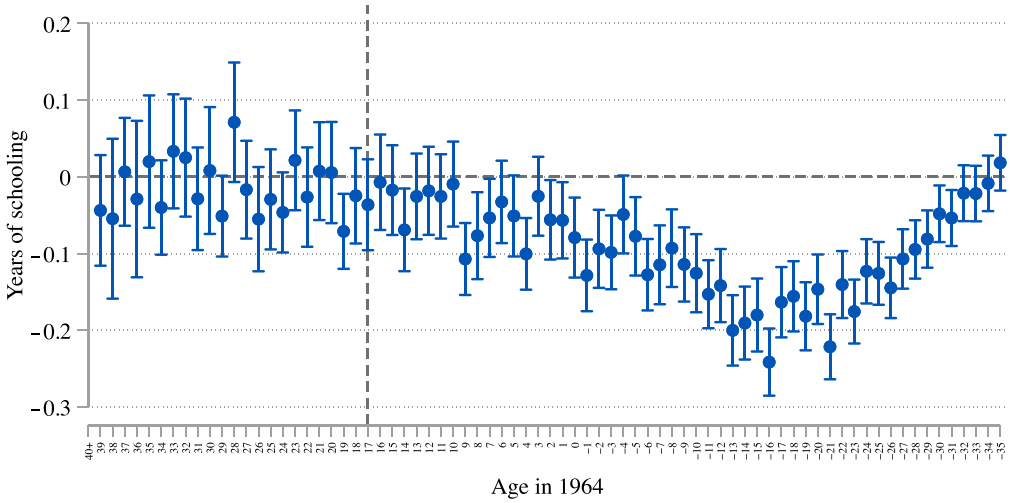


Fig. 4. *Impact of Bombing on Years of Schooling, Using Micro-Level Data from the Population Census of 2005.*

Notes: The estimation sample includes individuals from 10–98 years old in 2005. Point estimates and 95% confidence intervals are plotted for γ_k in (4) when the outcome variable is years of schooling. The excluded cohort is composed of individuals who were forty or more years old in 1964. The seventeen-year-old cohort is marked with a vertical dashed line as a reference point. It corresponds to the age that Laotians should have finished high school.

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

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

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

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

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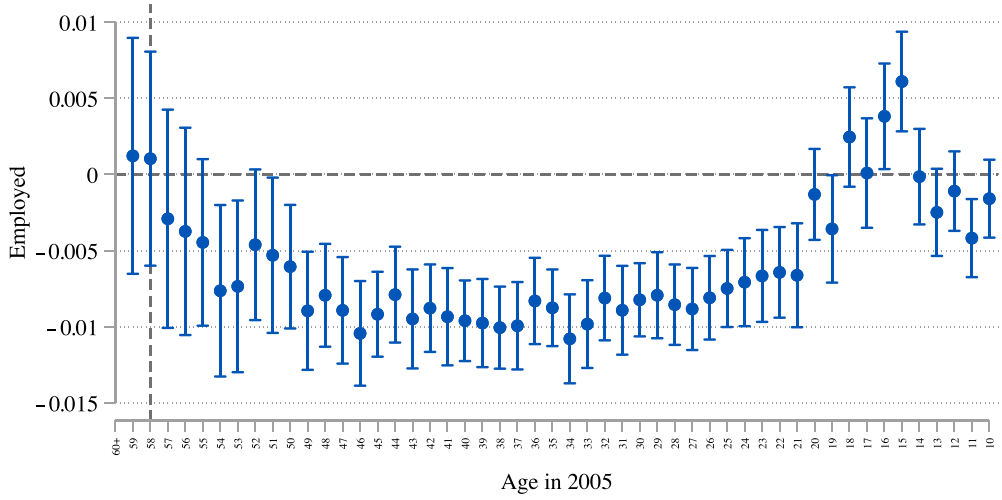


Fig. 5. *Impact of Bombing on the Probability of Employment, Using Micro-Level Data from the Population Census of 2005.*

Notes: The estimation sample includes individuals from 10–98 years old in 2005. Point estimates and 95% confidence intervals are plotted for γ_k in (4) when the outcome is an indicator of employment. The excluded cohort is people older than sixty (official age of retirement) in 2005, i.e., older than twenty in 1964. The fifty-eight-year-old cohort marked with a vertical line as a reference point is the cohort that was seventeen in 1964.

in Online Appendix Figure A-11, panel A, as well as in the corresponding regressions in Table 8, panel A. The coefficient remains negative and significant throughout. Overall, our educational results are in line with those for Guatemala, Peru and Colombia (Chamarbagwala and Morán, 2011; Leon, 2012; Fergusson *et al.*, 2020; Prem *et al.*, 2023).

4.5.2. *Sectoral employment and structural transformation*

To complement the individual-level analysis, we examine structural transformation.[51] We start by looking at the probability of being employed in modern times in Figure 5. 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: 10–14 and more than fifty-five years of age. However, we find a negative and significant dip for those between 25–49 years of age. The largest coefficients correspond to those generations with lower educational attainment in the previous set of results forty years before (i.e., those younger than seventeen years old in 1964 or younger than fifty-eight years old in 2005).

We move next from the probability of employment to an intensive margin analysis of occupational structure in terms of agriculture, industry and services. We find, using the same 2005 cutoff, a hump-shaped relationship for agricultural employment in Figure 6(a). It appears now that people from 10–41 years of age in 2005 (i.e., born after 1964) are *more* likely to be employed in agriculture during the last twelve months. The positive and significant estimates peak at 0.01

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

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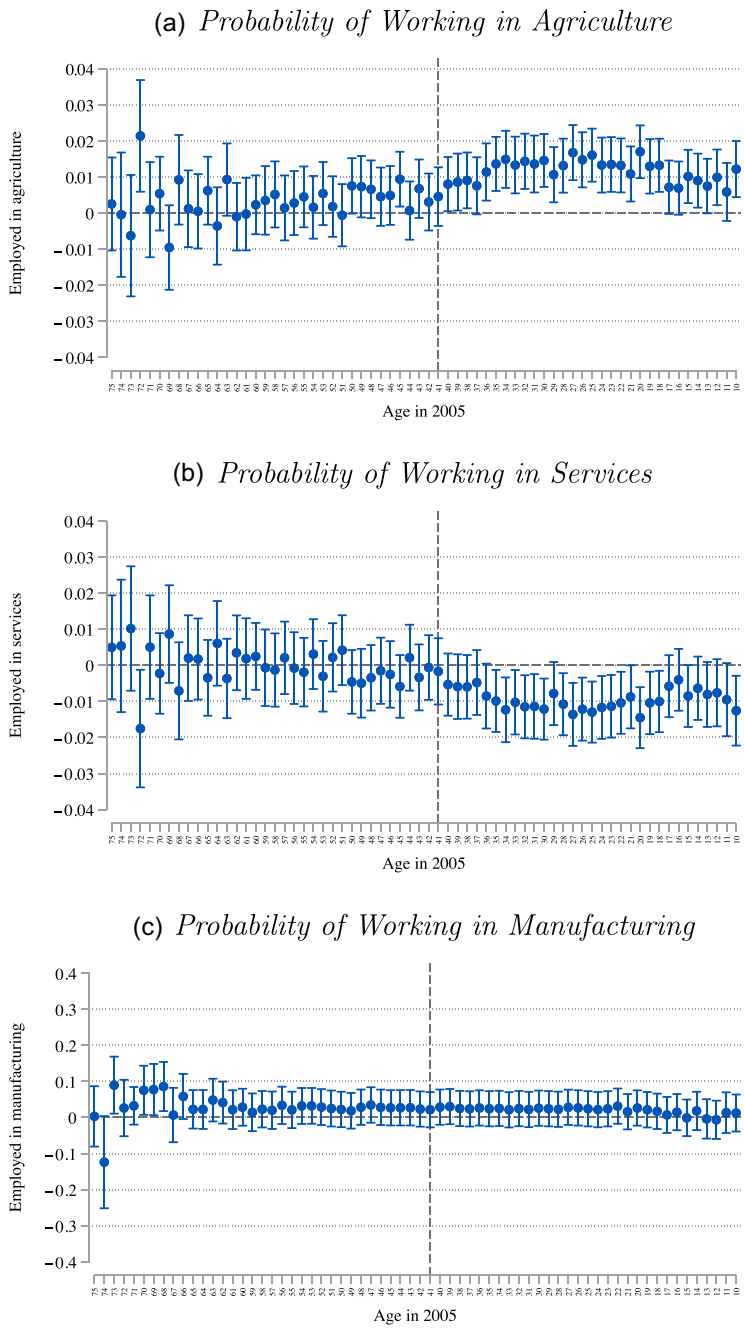


Fig. 6. *Impact of Bombing on the Probability of Working in Agriculture, Using Micro-Level Data from the Population Census of 2005 (Yearly).*

Notes: Point estimates and 95% confidence intervals are plotted for γ_k in (4) when the outcome variable is an indicator variable of working in each one of the sectors specified by each panel. The excluded cohort is composed of individuals who were seventy-six or more years old in 2005. The forty-one-year-old cohort is marked with a vertical line as a reference point since those are the individuals who were born in 1964.

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to 0.02.[52] We find the opposite when we look at services in Figure 6(b). It appears now that those aged from 10–41 years are significantly *less* likely to be employed in the service sector, by around 10% of the sample mean. We find no significant impact on the probability of being employed in the manufacturing sector in Figure 6(c).

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

5. Mechanisms of Persistence

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

5.1. *UXO Contamination*

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

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

To further explore the UXO channel, we use a geo-located panel with *daily* data on UXO accidents from 1950 to 2011 (National Regulatory Authority for UXO/Mine Action in Lao PDR, 2011). Figure 2(c) depicts these data geographically by the number of accidents. We see a high prevalence of counts at the grid-cell level in the Plain of Jars (in the central northern part of the country) and near the Ho Chi Minh Trail. We then show that bombing intensity is also highly correlated with the number of UXO accidents. To exploit the time variation available in these data and rule out the potential persistence of UXO from previous conflicts, we summarise the

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

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

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

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

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

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

Notes: Observations are at the village level. Variable *Bombs* represents the total weight in pounds jettisoned from 1965 to 1973 per square kilometre, and is standardised. Panels C and D use data from the Population Census of 2005. Panels A and B use data from the Agricultural Census of 2011. Robust SEs are reported in parentheses. *** $p < 0.01$.

evolution of such correlation by using quadratic fits by decade in Figure 7.[56] There are two main takeaways. First, we observe no relationship between UXO accidents during the 1950s and the total number of bombs dropped. As bombing campaigns started in 1964, these results suggest no pre-trends in the presence of other types of mines related to previous conflicts. Second, the relationship between bombs and UXO accidents becomes large and positive for the 1960s and the 1970s, and then starts falling progressively until the 2000s. Still, even at these lower levels, the positive association is evident and persistent: UXO accidents are concentrated in areas that have received more bombs historically.[57] This grim reality shows the continued burden of conflict on civilian victims, who are often children.

In light of the previous exercise, we examine the relationship between bombing and health outcomes. We focus on disability status, which is closely related to the UXO accident results just reported. In many cases, when landmines and UXOs explode, they maim or gravely injury the victims. This tragic reality is evident in Table 8. Households report more disabilities in areas that received more bombs. The coefficient of UXO contamination on disability is positive

[56] Results also hold using non-parametric estimations instead.
[57] See panel B of Online Appendix Figure A-10 documenting the overall correlation.

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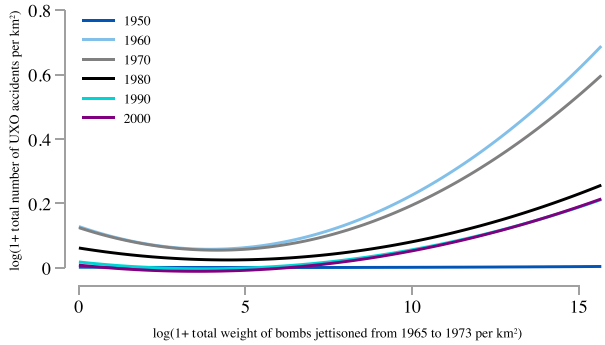


Fig. 7. *Panel of UXO Victims and Bombing Intensity with Quadratic Fits by Decade of Occurrence.* *Notes:* This figure presents the relationship between UXO victims (accidents with people killed or injured by unexploited ordinance) and bombing intensity from 1964 to 1973. It uses panel data on UXO accidents and data on the bombing at the village level. The figure shows simple quadratic fits of the raw data by decade.

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

	(1)	(2)	(3)
Panel A: dependent variable is the fraction of literate households			
Bombs	−0.057***	−0.027***	−0.024***
	(0.003)	(0.003)	(0.003)
R^2	0.050	0.258	0.451
Panel B: dependent variable is the fraction of households with disabled people			
Bombs	0.011***	0.008***	0.001
	(0.001)	(0.001)	(0.001)
R^2	0.024	0.086	0.129
Panel C: dependent variable is log*(Inhabitants/km²)*			
Bombs	−0.292***	−0.107***	−0.127***
	(0.016)	(0.018)	(0.020)
R^2	0.029	0.322	0.366
Controls that apply to all panels			
Province fixed effects			Yes
Geographical controls		Yes	Yes
Location controls		Yes	Yes
Observations	10,522	10,522	10,522

Notes: Observations are at the village level. Variable *Bombs* represents the total weight in pounds jettisoned from 1965 to 1973 per square kilometre, and is standardised. Robust SEs are reported in parentheses. *** $p < 0.01$.

and significant, except in the full specification.[58] The point estimates are also economically meaningful. A one-SD increase in the intensity of bombing is associated with about a 1.2% to 10% increase (with respect to a sample mean) in the fraction of households with disabilities. These results confirm and complement the findings from the UXO accidents presented before, showing

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

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that the bombing and the remnants of war are most likely generating persistent disabilities in the civilian population. In the next sub-section we conduct a more formal mediation analysis of the impact of UXOs on economic development.

5.1.1. *Mediation analysis: structural equation model*

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

In adopting this structural approach, we are able to evaluate the relevance of the underlying causal channels and test the empirical validity of our overarching theory using a unified methodological approach. However, this process requires additional assumptions that we deem reasonable based on the documented evidence thus far. For instance, we build on the assumption of the plausibly exogenous nature of the instruments and explicitly model the importance of geographical and location factors based on the results presented in previous sections.

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

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

[60] We refer the reader to Bollen (1989) and Mehmetoglu (2018) for a detailed treatment of this specific type of models. Note that the mediation analyses of Imai *et al.* (2011) and Acharya *et al.* (2016) are not appropriate in this context because both require observing the mediating variables (Mehmetoglu, 2018). We refer the reader to Online Appendix A for identification details on the model.

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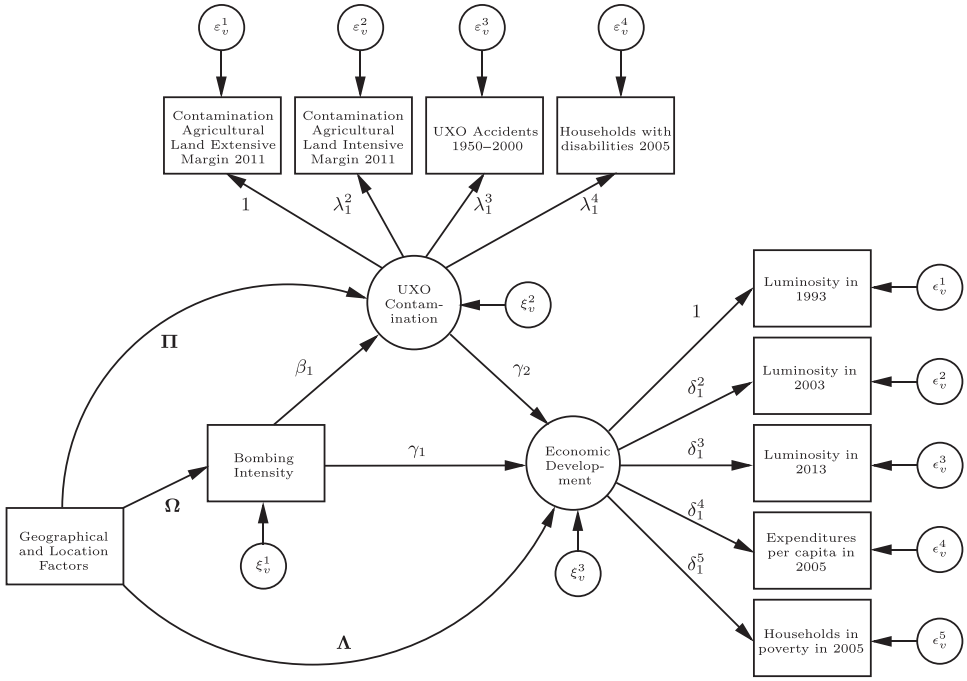


Fig. 8. *Path Diagram for the Structural Equation Model Studying UXO Contamination as a Mechanism of Transmission.*

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

economic development. Likewise, more UXO contamination emerges as a significant deterrent of economic activity.

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

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5.2. *Population Density and Rural-Urban Migration*

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

Second, we analyse migration as a potential mechanism of poverty persistence, as in Dell (2010). Conceptually, there could be two opposing effects with respect to this variable. On the one hand, conflict might have increased forced displacement, fostering internal and external migrations (Ibáñez and Vélez, 2008). On the other hand, increased transportation costs and changes in risk aversion might have induced people to stay in their territory. To empirically test this mechanism, we use the individual-level data from the 2005 Census, which crucially asked people about their province of birth and current place of residence. Using this information, we find relatively low levels of long-term migration, of the order of 11% for the whole sample. Moreover, almost 40% of internal migrants reported moving from other provinces to the capital of Vientiane. This rough estimate of rural to urban migration is consistent with the predominance of this type of population movement in Laos (Phouxay, 2010). It is important to note that, with respect to international migration, Phouxay and Tollefsen (2011) found that only 5.2% of respondents had moved abroad. Of these international migrants, 59.4% were female and 82% had moved to Thailand.

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

Overall, these results tie the findings on structural transformation with those on rural to urban migration, two fundamental pillars underpinning modern economic development according to the literature (see, for example, Lagakos, 2020 and Porzio *et al.*, 2022). It appears that migration,

[61] See Online Appendix Figure A-11, panel C for an illustration of this finding.

[62] In particular, we run a modified version of equation (4) using the triple interaction with migration as follows:

$$y_{i,p,k} = \delta_k + \lambda_p + \sum_k (B_p \times d_{i,p,k} \times M_i)\eta_k + \sum_k (B_p \times d_{i,p,k})\gamma_k + \sum_k (d_{i,p,k} \times M_i)\rho_k + \psi(B_p \times M_i) + \phi M_i + \epsilon_{i,p,k}.$$

Here M_i is an indicator variable equal to one if individual i is a long-term migrant in 2005 and zero otherwise and $B_p \equiv \log(1 + \text{Bombs 1964–73})_p$. We present the results of these estimations in Online Appendix Figures A-15 to A-19.

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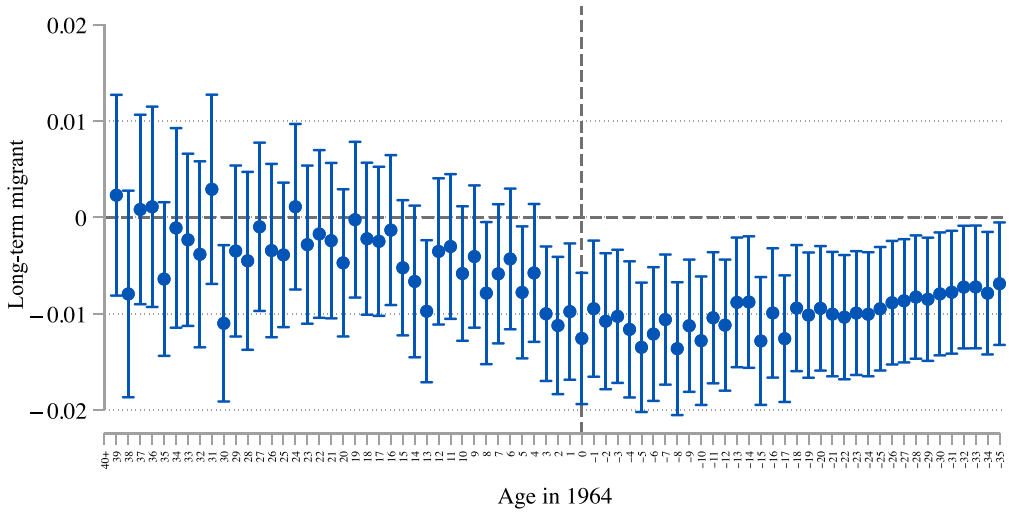


Fig. 9. *Impact of Bombing on the Probability of Migration, Using Micro-Level Data from the Population Census of 2005 (Yearly).*

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

or the lack thereof, is exacerbating the educational and structural transformation trends shown before. Though there might be selection into long-term migration, our findings are consistent with those in other contexts, such as Poland and Colombia (Becker *et al.*, 2020; Fergusson *et al.*, 2020).

6. Discussion

A natural follow-up question is whether the results for Laos extend to other contexts. In particular, our findings appear to be at odds with those of Miguel and Roland (2011) for Vietnam, where the authors found little to no economic effect after the massive bombing campaigns in that country.[63] We hypothesise that the apparent differences could emerge due to several reasons. First, there could be disparities because of the degree of disaggregation of the data used in the analysis. In our baseline regression we employ 6,648 observations and use data from 10,522 villages and more than half a million individuals, whereas in the earlier study $N = 584$. The importance of disaggregated data for the empirical analysis of conflict has been pointed out by Harari and Ferrara (2018) and Montalvo and Reynal-Querol (2021). Recall that our baseline results hold within provinces and districts, which we believe is a step forward in the literature. Still, to make the results more comparable, we aggregate up our results to the district level (i.e., focusing only

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

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on the between variation). As can be seen in the Online Appendix,[64] our results remain robustly negative to this refinement (across all years).

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

Lastly, we look at potential differences in public goods provision. We hypothesise that providing these services to the population could be costlier and more difficult in the presence of unexploded bombs.[66] Recall that there appear to be less schools in UXO-contaminated areas, in Table 9. We also find in the middle panel that villages that were bombed more historically have significantly less access to electricity now (cf. Miguel and Roland, 2011). We find a similar pattern when looking at water supply. Villages that were bombed or that suffer from UXO contamination have significantly less access to this vital supply. These findings suggest that (the lack of) state capacity might be playing an important role in perpetuating the legacies of war in Laos.[67] The fact that war was largely external to the country might have also precluded any developmental gains, such as improved fiscal capacity.

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

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

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

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

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

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

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

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

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

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

documented the deleterious impact of UXOs, especially on agricultural land, in line with our rural and structural transformation findings. Demining efforts in that country have also been small and UXO contamination remains an important issue. Outside Southeast Asia, our results also differ from those of Germany and Japan, where urban structures had been consolidated for centuries or millennia, providing important complementary evidence for more rural settings. Globally, UXO contamination remains a significant and growing threat to public health (Frost *et al.*, 2017), suggesting more settings to study this important issue, beyond a few successful cases of recovery and growth.

7. Conclusions

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

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urbanisation and poverty rates. We use this data along with a panel of UXO accidents to show how war has affected the health of the local population.

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

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

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
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