Developmental Legacies of Draconian Dictatorship: Evidence from the Khmer Rouge *

Donald Grasse†

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Abstract

Does mass repression have a long-term economic legacy, and if so, what explains persistence? I argue repression can undermine development by delimiting human capital. I study the aftermath of the Khmer Rouge in Cambodia. The regime implemented a campaign of violence to reorganize society, yet governing elites varied across the communist ideological spectrum. I exploit an arbitrary border that allocated villages to either the loyalist Mok or the relatively moderate Sy in Kampong Speu province. Using a regression discontinuity design, I find villages in the more extremist Southwest zone are poorer today compared to villages in the adjacent West zone, and had lower human capital immediately after the regime. Exposure to more intense repression shapes labor markets and child health, explaining intergenerational persistence. I find no conclusive evidence for other persistence channels. My findings add a novel pathway to the library of mechanisms which explain why historical coercion undermines development.

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†Political Economy of Security Postdoctoral Scholar, Center for International Studies, University of Southern California. Email: dgrasse@usc.edu

Introduction

Dictatorships often engage in mass repression to control society. Several authoritarian regimes have demographically targeted repression to purge intellectuals, the educated, or middle class members of society to weaken opposition movements. Whereas the political legacies of such repression are more often studied (Balcells, 2012; Lupu and Peisakhin, 2017; Rozenas and Zhukov, 2019), the long-run developmental consequences - and the mechanisms of persistence - are less clear (Davenport et al., 2019). Does mass repression have long-term developmental effects, and if so, why do the consequences persist?

I argue repression of educated members of society and skilled laborers undermines long-term economic development by undermining human capital. A paucity of skilled intellectuals in the aftermath of state violence places communities on diverging development paths: places more adversely impacted compensate for low-education levels with behaviors that reinforce low income - such as underinvesting in education, health, and specialized training - since doing so is too costly when starting from a level of extreme poverty and low education. The consequence of mass repression is a poverty trap.

Identifying the long-term effect of repression on economic welfare is challenging because state violence is strategically allocated. Both cross-national and within-country analyses may be biased by intervening events, diverging pre-trends, or the endogeneity of repression to local economic conditions (Sun, 2019).

I surmount identification issues by exploiting an administrative redistricting during the Democratic Kampuchea (DK) regime in Cambodia, which placed similar, nearby villages into the control of radically different cadres. DK divided a single combat theater into two governing zones, the West and the Southwest, along National Highway 4 (NR4) in Kampong

Speu province. Villages on either side of the natural border were then governed by either Ta Mok in the Southwest zone - a brutal loyalist to the extreme doctrine of the dictator Pol Pot - or Sy in the West, who was a relatively more moderate communist.[1] Conditional on village proximity to the border, villages were arbitrarily assigned exposure to more or less intense state repression.

Using a geographic regression discontinuity design, I find villages in the more repressive zone are significantly poorer today (0.42σ, 20% of the control group mean). The results replicate while using administrative and nighttime lights data, at the village and individual level, and at different points in time. The estimates suggest a persistent wealth gap between former zones. The results are robust to alternative estimation windows, weighting kernels, and are not likely to be an artifact of spatial noise (Kelly, 2020).

Next, I evaluate channels of persistence. I argue repression that demographically targets the educated, which is not uncommon in authoritarian contexts or under coerced labor regimes more generally, creates a skill gap between generations, leaving a lacuna of trained and schooled individuals in a locality. The consequences reverberate overtime through a poverty trap mechanism, wherein people in poverty take actions that keep them poor because of constraints created by their lower income status.

I show evidence consistent with the poverty trap explanation, wherein the human capital shock from the regime's repression reinforces behavior that keeps income lower in affected areas. I find literacy and education rates are much lower in the former Southwest ($0.50\ \sigma$) in 1998. Specifically, I show age cohorts whose secondary schooling years overlapped with the Khmer Rouge experience the largest drop in education in the former Southwest (extreme)

[1] I use moderate and relatively moderate interchangeably in some places. Note that Sy was moderate in comparison to extremists within Pol Pot's regime; since he was a communist insurgent, he cannot be considered a moderate in an absolute sense.

zone. Consistent with qualitative evidence that links generational skill gaps to contemporary Cambodian poverty (Jeong, 2014; Kerbo, 2014), I find persons living in the former Southwest are more likely to be informally employed, earn less, and have lower productivity. Further, I show intergenerational consequences by finding child health is lower in the Southwest, which is a key predictor of future socioeconomic status.

I draw from a variety of data sources to evaluate other causal mechanisms linking poverty to historical repression. Scholarship on the developmental legacies of coercive institutions suggest several persistence channels, including institutional path dependence (political competition, public goods provision (Dell, 2010), conflict over property rights (Guardado, 2018)), and cultural persistence (social trust (Lowes and Montero, 2020)).

Using data on elections, newly collected data on land disputes, survey data on community trust, and georeferenced data on public goods access, I find no evidence of persistence via commonly cited pathways. The finding suggests poverty traps are a unique channel that may be added to the library of mechanisms linking coercion to contemporary development.

My study contributes to three sets of literature. First, I add to debates about the legacies of state repression (Balcells, 2012; Lupu and Peisakhin, 2017; Rozenas and Zhukov, 2019). As Davenport et al. (2019) recently argue, "substantially more research is needed to uncover whether and how repression hurts economies." Research on the developmental impact of repression is divided. Some show positive impacts of state violence for decedents of victims and surrounding communities (Becker et al., 2020; Toews and Vézina, 2020), while others show null (Charnysh and Finkel, 2017; Rogall and Yanagizawa-Drott, 2013) or negative long-term effects (Acemoglu, Hassan and Robinson, 2011; Lichter, Löffler and Siegloch, 2021; Meng and Qian, 2009; Naumenko, 2019; Zeng and Eisenman, 2018).

My study shows repression can cause underdevelopment when victims are targeted in a way that changes underlying factors of production - specifically human capital. I highlight how the state's objectives during repression determine the direction of the relationship. The argument is also related to the large literature on the economic consequences of civil war, where scholars debate whether civil conflict can improve economic well-being by reducing inequality (Scheidel, 2018), or if it undermines development by reducing human capital (Blattman and Miguel, 2010; Chamarbagwala and Morán, 2011; Justino, 2011).

Next, my findings elucidate the mechanisms by which coercive institutions have persistent economic effects (Cirone and Pepinsky, 2021; Simpser, Slater and Wittenberg, 2018). The durable impacts of historical institutions have been well-established, but the pathways by which defunct coercive regimes continue to shape development are ambiguous. Using a variety of data sources, I test several plausible candidate causal pathways to show the uniqueness of the poverty trap mechanism. Understanding persistence channels is critically important because it implies much different solutions to persistence; for instance, technical interventions such as cash transfers may better address poverty traps, whereas fundamental reforms are required to address institutional path dependence.

Finally, my study highlights the long-term importance of regional executives in dictatorships (Carter and Hassan, 2021; Reuter and Robertson, 2012; Rundlett and Svolik, 2016). Authoritarian politics scholars have increasingly highlighted the importance of subnational administration in autocracies, especially how dictators delegate control to loyalists. My study shows the consequences of regional executive loyalty in repressive regimes are substantial and persistent, providing an additional normative impetus for understanding how autocrats manage agency problems with their subnational subordinates.

State Repression and Economic Development

Repression is the "original sin" of dictatorship (Svolik, 2012, p.10). State violence has clear short-term economic implications: population transfers, mass killings, or detentions impact local labor markets along with individuals and their families. However, since such violence is transitory, effects may only persist if the fundamentals of economic growth - land, labor, capital, or social and formal institutions - change as a result of repression.

Since the economic legacy of repression is contingent on changes in factors of production, scholars have found mixed evidence in a variety of contexts. Some show positive impacts of state violence for decedents of victims and surrounding communities due to changing preferences (Becker et al., 2020) or relocation (Toews and Vézina, 2020). Genocide may increase development in the short-run through property theft (Charnysh and Finkel, 2017), or Malthusian channels (Rogall and Yanagizawa-Drott, 2013), however, effects do not persist. Others document negative legacies, either leveraging instrumental variables (Meng and Qian, 2009; Naumenko, 2019; Zeng and Eisenman, 2018) or selection on observables (Acemoglu, Hassan and Robinson, 2011) for identification.

Understanding the legacy of repression on development requires a particular focus on the technology of coercion along with who the state is attempting to victimize. Transitory episodes of mass arrests that target citizens indiscriminately may not permanently alter underlying factors of production, whereas lethal repression that targets persons based on certain socioeconomic traits may have more lasting effects by changing the composition of the labor force, creating multiple developmental equilibria.

A common form of demographically targeted repression is coercion of educators, educational institutions, and middle income persons. Several authoritarian regimes have demographically targeted repression in a manner intended to eliminate higher income or educated segments of society. Franquist Spain purged public school teachers (Balcells and Villamil, 2020) as did Mao Zedong's Anti-Rightist Campaign in China (Zeng and Eisenman, 2018). Francisco Macias Nguema's rule of Equatorial Guinea included the closure of all private schools and the use of repression to support coerced labor (Fegley, 1981). Joseph Stalin's dekulakization was intended to "break the back of the independent peasantry" (Naimark, 2010, p.54), and targeted more middle-income peasants. In the early stages of genocide, the Ottoman Empire and Nazi Germany both targeted intellectuals within minority groups.

Even less extreme dictatorships have targeted skilled workers and educators. Argentina's last dictatorship targeted secondary schools and architects, due to the regime's belief that persons in these sectors produced subversives (Rock, 1993, p. 228-230). Pinochet's dictatorship in Chile similarly defunded universities, creating a crunch on higher education (Bautista et al., 2020).

Repression of the educated, however, is not a thing of the past: Hungary, Turkey, and Zimbabwe have all engaged in state repression of higher education and teachers.[2] Outside of dictatorships, insurgent groups including the Islamic State (IS), the Free Aceh Movement (GAM), the Shining Path, the Taliban, and anglophone separatists in Cameroon, have similarly repressed educated persons and formalized schooling.

Repression that demographically targets more educated, intellectual, and professional

[2]Suzy Hansen. " 'The Era of People Like You Is Over': How Turkey Purged Its Intellectuals." New York Times. July 24, 2019. `https://www.nytimes.com/2019/07/24/magazine/the-era-of-people-like-you-is-over-how-turkey-purged-its-intellectuals.html`. Jennifer Rankin. "'How dictatorship works': Hungarian academic quits in censorship row." The Guardian. 11-30-2021. `https://www.theguardian.com/world/2021/nov/30/hungarian-academic-andrea-peto-quits-in-censorship-row`. Barbara Wall. "Teachers flee poverty and repression : Zimbabwe brain drain." New York Times. 02-12-2002. `https://www.nytimes.com/2002/02/12/news/teachers-flee-poverty-and-repression-zimbabwe-brain-drain.html`.

classes may directly undermine human capital in a locality by eliminating the learned members of society, causing developmental divergences through poverty traps. Poverty traps are situations where poverty is so extreme that individuals cannot afford to take poverty-reducing actions. For instance, if education levels are already low and individuals are poor, the opportunity cost of seeking additional training may be larger than the return to schooling, since another year spent in school means a year out of the labor market (Azariadis and Drazen, 1990). Alternatively, low income and education may force an individual into a low-earning job, since the effort required to find alternative means of employment are too expensive for the already poor. Poverty may lead individuals to become unhealthy, and worse health could reinforce low income (Banerjee and Duflo, 2011). This explanation posits that multiple developmental equilibria exist, and that a locality or person may find themselves in one equilibrium versus another due to path-dependent processes sprung by historical factors.

Repression may undermine development through a variety of other mechanisms. Coercion can change social capital (Nunn and Wantchekon, 2011; Lowes and Montero, 2020; Lichter, Löffler and Siegloch, 2021), formal government institutions (Acemoglu, Johnson and Robinson, 2001), local elite strength (Dell, 2010), or cause property conflict (Guardado, 2018), hindering development. The variety of possible mechanisms and related papers are displayed in Table 1.

Context: Democratic Kampuchea (DK)

I study a historically important case of demographically targeted repression: the Democratic Kampuchea (DK) regime in Cambodia. During the regime's short tenure of less than four

Table 1: Causes of Persistent Underdevelopment from Coercive Institutions*

Category	Theory	Literature	Empirical Implications
Multiple Equilibria	Poverty trap	Present paper	Lower human capital intergenerational poverty
Institutions		Acemoglu, Johnson, and Robinson (2001) Dell (2010) Guardado (2018)	Elite capture, Property conflict, Fewer public goods
Culture	Social Capital	Nunn and Wantchekon (2011), Lowes and Montero (2020) Lichter, Löffler and Siegloch (2021)	Difference in generalized trust†

† Scholars are divided on the direction of the trust effect after exposure to coercive institutions; Lowes and Montero (2020) argue the legacy of violence after the Congo Free State increased trust, in line with the large literature on civil conflict legacies, whereas Nunn and Wantchekon (2011) and Lichter, Löffler and Siegloch (2021) argue coercion reduced trust in the long-term.
Three categories drawn from Nunn (2014).

years, nearly one in five Cambodians are estimated to have died. Due to the gravity of the event, it is important to understand the impacts of the DK regime in its own right.

Aside from its intrinsic importance, the DK case is of interest because it presents an opportunity to uniquely identify multiple equilibria - poverty traps - as the causal mechanism connecting state repression to long-term development. The observable implications of poverty traps could be explained by institutional or cultural changes that occur as a result of state violence. Many coercive regimes institute extractive rules of the game that outlast the regime, are controlled by the same economic elites overtime, and reshape cultural norms. These forces may link patterns of individual behavior that reinforce poverty, such as under-investing in health and education, rather than poverty traps, which are individual feedback loops. Figure 1 outlines the logic: in all three subfigures, poverty in the past shapes poverty in the future (poverty+t), but in Panels B and C the repression shapes poverty overtime through its impact on culture and institutions.

In the DK case, institutional and cultural persistence are implausible explanations for the persistence of poverty from repression at the subnational level. The typical institutions-based story is implausible because formal rules created by DK did not survive the regime, and the extreme faction of DK was supplanted by the moderate faction, now represented by the Cambodian People's Party (CPP). Next, since the identifying variation I explore is in terms of intensity rather than existence, it is unlikely that cultural norms sharply diverge based on subnational exposure to violence: to the extent experiencing horrific violence can alter fundamental beliefs about the trustworthiness of others, some exposure to mass repression is likely sufficient to generate changes in trust. In Section 6, I examine the plausibility of all three causal diagrams outlined in Figure 1.

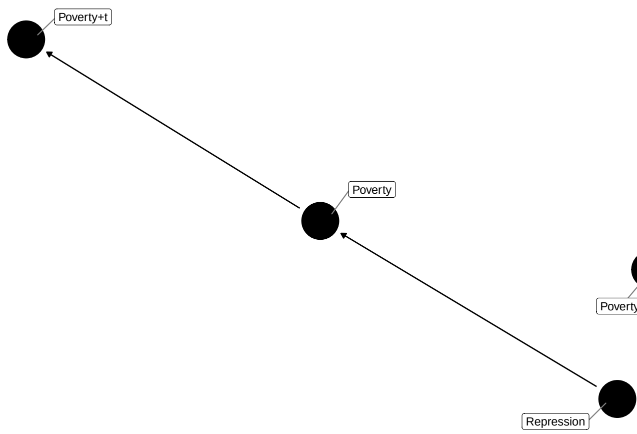
In the next four subsections, I explain the historical context behind the regime, motivating the identification strategy and the channel of persistence.

DK: Administration and Legacy

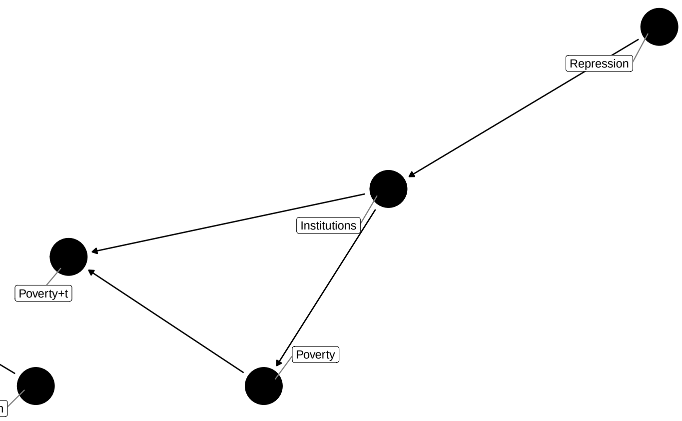
From 1975-1979, DK abolished private property and currency, collectivized agriculture, closed formal schools, and forced citizens into highly stratified labor groups according to their age, sex, residence, and educational background. The regime's development strategy

Figure 1: Theoretical Pathways Linking Repression to Long-run Poverty

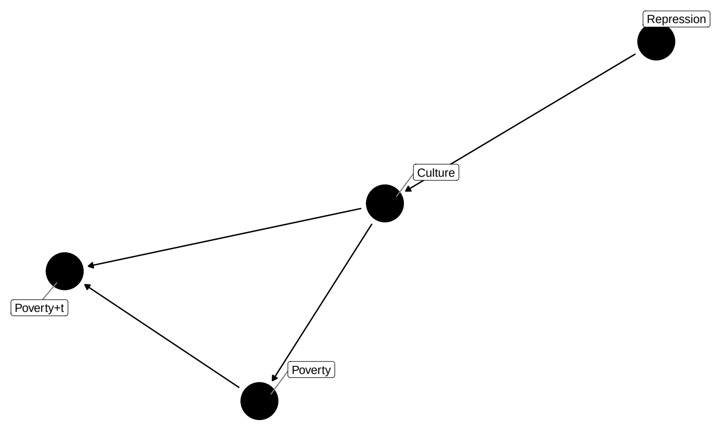
(a) Poverty Trap (Multiple Equilibria)



(b) Institutional Path Dependence



(c) Cultural Persistence



Notes: Directed Acyclic Graphs diagraming competing causal pathways linking repression to long-run poverty. Multiple equilibria via the poverty trap, wherein repression causes poverty which feedbacks into itself over time, is depicted in Panel A. Institutional and Cultural channels (Panels B and C) illustrate paths where poverty feeds into itself, but culture and institutions explain persistent effects. Persistence is denoted with the Poverty+t for any t$>$ 0.

hinged on a significant increase in rice production, which would be supported by building irrigation infrastructure through forced labor. Nominally, the regime pursued a mass literacy campaign, but labor requirements and the purging of former educators served a cross purpose. The regime relied on coercion to enact its social reorganization (Becker, 1998; Kiernan, 2008; Vickery, 1984).

The DK regime was ideologically fragmented on a spectrum of moderate communists to repressive extremists. Fissures were consequential; after capturing Phnom Penh, it took months for combat commanders to come together to form a government. The fractionalization across ideology was highly regionalized: during the civil war from 1970-1975, commanders operated largely in isolation, even wearing different uniforms.

DK Zones: The Southwest and West

To manage tensions between regional commanders, the central party leadership divided the country into several different zones, which closely overlapped with combat theaters and at times ignored pre-existing provincial boundaries. The leaders of zones were called zone secretaries. Zones were organized with rigid hierarchy internally, but the ability of the central government to coordinate policy between zones was constrained by the influence of the zone secretaries within their territory (Vickery, 1984, p.68). Mass killing directives were handed down by Party leadership, but zone secretaries ultimately carried out orders (Ea, 2005, p.126). Since secretaries had a great deal of de facto authority, the implementation of regime mandates varied across zones based on the idiosyncrasies of personal leadership (Becker, 1998, p.176).

I focus on a salient border that divided very different commanders: Mok in the Southwest and Sy in the West. Mok and Sy shared jurisdiction during the civil war, and their two respective zones were one area of operation during the civil war. After a major dispute concerning the brutality of Mok's approach to the revolution, their jurisdiction was divided into two separate zones which they commanded in isolation, divided along National Road 4 (NR4).

The border road - NR4 - was constructed cheaply by the United States in the 1950s, with the goal of connecting the port city of Sihanoukville to the capital Phnom Penh in the least costly way possible. In Congressional hearings about the US's construction of the road, officials concede "[t]he principal justification was a political justification" unrelated to economics: the United States constructed the road as a favor to France and as a way to reduce Cambodian dependency on Vietnam for trade. Indeed, one engineer remarked "[t]he decision to give support to the construction of this highway in the first instance was not based on detailed studies of such matters as the volume of traffic and the precise economic benefits expected to result, nor indeed were they considered to be the determining factors under the circumstances" (House of Representatives, 1961). Consistent with a lack of meticulous planning, the road quickly fell into disrepair, straining the US-Cambodian relationship (Howland and Kennedy, 1999).[3]

Whereas the idea of the road was driven by political considerations, the exact location was less of a reflection of local economics and more of a matter of convenience. Figure 2 maps the Southwest and West zone. Binding geographic constraints outside of Kampong Speu (dashed lines) caused the road to bisect the province. The simplest route to connect the port and the capital was through a narrow stretch of flat land, across Kampong Speu. Building the road slightly differently would have led to the route to cross over elevated terrain (dark shading), adding cost and complexity to the project. As such, the location of the highway is largely arbitrary within Kampong Speu, since the terrain features that

[3]Prince Sihanouk was so "disgusted" with the roads conditions he once took a helicopter after hitting potholes on a drive. Time Magazine. July 1961. Accessed January 20, 2022. `http://content.time.com/time/subscriber/article/0,33009,897811,00.html`

induced the road to be built in such a way are beyond the borders of the province. Within Kampong Speu, terrain, river, and road access appear largely similar on either side of NR4.

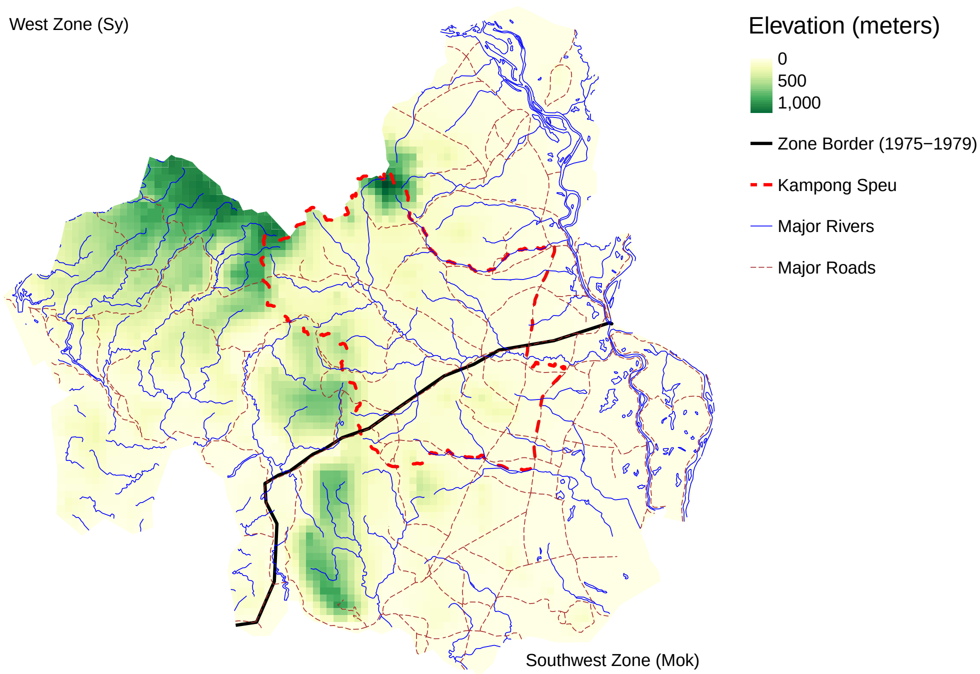
The road was a natural choice for a border for DK since it provided a visible marker to divide rivals. Clear lines of demarcation of authority between areas was important because zone leaders were conflictual - trespassing on zones were known to cause skirmishes between troops in places were lines were less clear, such as the boundary between the Southwestern and Eastern zone (Vickery, 1984, p.77). One natural solution to this problem was the use of natural landmarks as borders, like roads, which DK also used to divide smaller Damban regions such as Damban 1 and 4 in the Northwest zone (Vickery, 1984, p.111), or rivers, such as the Mekong, which divided the North-Central and East Zone in Kampong Cham.

Repression in the Southwest versus West

Both primary and secondary sources, along with descriptive quantitive evidence, point to a difference in repression intensity between the West and Southwest zones. Whereas Mok is credited with being among the most ruthless towards "new people" - individuals who were educated, urbanites, or in other ways connected to the Lon Nol or Sihanouk regime - Sy in comparison was less brutally violent towards these groups.

Sy and Mok are illustrative of the ideological divide within DK, which shaped how violent and repressive their rule was during the regime (Becker, 1998; Commission, 1984). Sy was an intellectual, member of old reformist socialist groups, and less ruthless than the more extreme factions. In contrast to Mok and other extremists, he believed old regime members could be incorporated into DK rather than executed. During the civil war, interviewees report "Sangha Hoeun and Chou Chet [Sy] re-educated and taught these people [Lon Nol

Figure 2: West and Southwest Zones During Democratic Kampuchea Regime



Note: Zone border from Yale Genocide Studies Program `https://gsp.yale.edu/dk-zones-english`. Shading shows elevation (in meters) in grid cells across the zones. Red dashed line is the provincial boundary of Kampong Speu, which was salient pre and post (but not during) the DK era. The thick black line shows the border between the West and Southwest zone, drawn over National Road 4, which was only a political border during the DK era. Brown dashed lines are major roads, thin blue lines are rivers.

soldiers]. I saw this; they did not kill them. But Mok did kill such people, and he became angry with what the other two were doing" (Kiernan, 1989).

Mok executed the moderate communist Sangha Hoeun, which created a strong division between him and Sy: an interviewee reported Sy "...didn't agree with that [the execution of Sangha Hoeun] so he was transferred and the Southwest Zone was divided into two, and the Western Zone created" (Kiernan, 1980*a*). Consistent with Sy's approach of incorporating old regime members rather than executing them, party meeting reports in 1977 indicate that a "fair number" of cooperatives were staffed by individuals who were not members of the peasant class in Sector 32 of the West (Carney, 1992, p.86). Sector 32 of the West was Sy's headquarters, which covered the half of Kampong Speu that was split into his zone. Staffing cooperatives with non-peasants is suggestive of Sy choosing to incorporate the social groups that Mok executed into government [4]

Primary source interviews corroborate the qualitative differences in cruel repression between Mok and Sy. One interviewee remarked "Mok was cruel since 1971-1972. Different from Chou Chet [Sy] and Phouk Chlag. Mok was fierce (khlang), a killer (Kiernan, 1980*b*)."[5] A former Communist Party of Kampuchea (CPK) district chief expanded upon how the differences in ferociousness - *khlang* - impacted the intensity of DK cruelty: he said Sy was "not very harsh (khlang)...Sy didn't set targets: when he took me to Tonle Sap, on the boat with me, he said 'friend, grow 1,000 ha of rice here, if there is enough water. If water is short, well, it depends on the concrete situation.' " (Kiernan, 1980*c*). Given the excessive death caused by unrealistic project goals during the regime, this distinction suggests a critical difference in repression intensity. One interviewee who lived in Sector 32 of the West - Sy's headquarters -

[4]Further detail on both secretaries in SI H.1.

[5]Chou Chet was another nome de guerre of Sy.

reports "no killings" in 1975, and described the area as "softer" since "they didn't kill many people in R32" (Kiernan, 1980*d*).

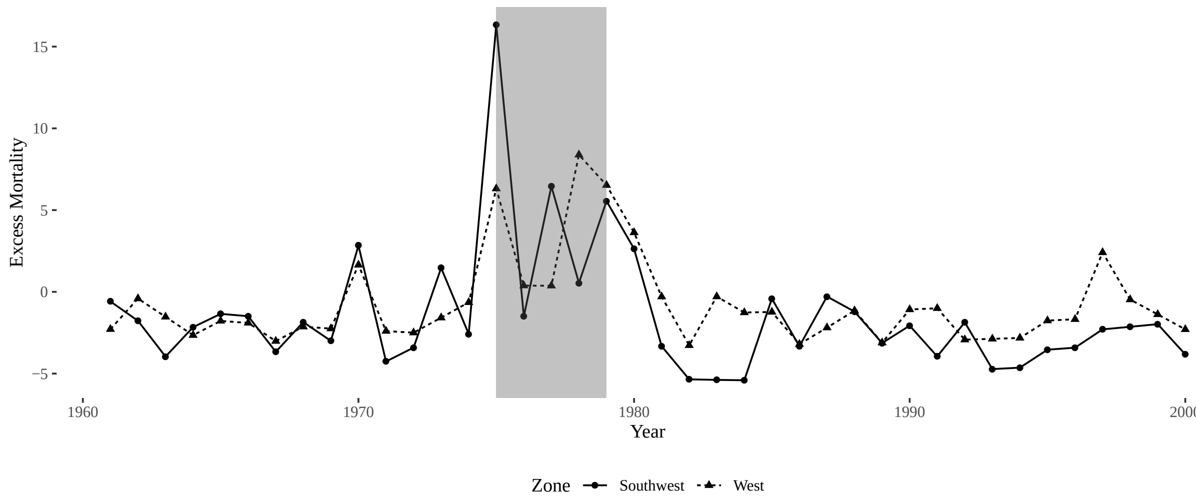
Meanwhile, the Southwest committed most to the development of cooperatives according to the revolution's ideology (Kiernan, 2008, p.87-90). The zone was the "power core" of the regime (Vickery, 1984, p.86). Mok staffed his zone with close family members, who would remain loyal to his orders. Sector 33, run by Mok's son, exemplifies the pattern: the area, in modern Kampong Speu province, was "the toughest sanctuary of the Khmer Rouge movement" (Vickery, 1984, p.98); affiliates of the old regime were forced to work in the fields (Vickery, 1984, p.93) and refugee reports suggest "new people" received less rations (Vickery, 1984, p.99). A US embassy report quoted a refuge who said "[a]n error, if discovered, means death in the south" (Kiernan, 2008, p.194).

Descriptive evidence is consistent with interviewee accounts of the differences between Mok and Sy. I use data on sibling deaths from the 2000 Demographic Health Survey round to estimate annual mortality trends by zone in Kampong Speu. I develop a predictive model of mortality based on gender, age, and residence (out of sample) and then use the model to compute expected mortalities by year. Figure 3 plots the difference between observed and expected mortalities by zone. In 1975, there is a differential spike in excess mortality in the Southwest, which corresponds with the year Pol Pot gave the order to begin murdering the educated and intellectuals indiscriminately (Kiernan, 2008).[6]

To be clear, the West was not free of repression. Refugees report enforcement of the DK's family separation policy, executions, and starvation (Kiernan, 1980*e*,*b*). From the reports that families were separated, one can reasonably infer education and labor policies did not

[6] The increase in excess mortality in the West coincides with the year that Sy was expelled from the zone.

Figure 3: Estimated Mortality Trends by Zone



Note: Shaded region denotes Khmer Rouge period (1975-1979). Vertical axis is the difference between total and expected mortality. Horizontal axis is the year of reported death. Data from 2000 DHS survey round in Cambodia. Details on estimation of excess mortality in SI E.5.

sharply differ between Sy and Mok: indeed, such a difference would be such an affront to the official DK line it would have been easily observed and broadly recorded. The distinction between governance cannot be understood as night and day, violent or not. Instead, the difference between Sy and Mok is better characterized as a difference in the *intensive margin* of violence.

Long-run Poverty

Poverty has persisted since DK-era repression (Kerbo, 2014). A key dimension of the poverty trap in Cambodia is characterized by a generational skill gap caused by executions. Inter-generational transfers of knowledge were either severely inhibited or eliminated due to the execution of middle aged intelligentsia, educators, and skilled workers (Jeong, 2014). The paucity of educated mentors pushed individuals into precarious lines of work with lower economic returns which did not require education to obtain. Therefore, many worked on family farms without seeking specialized training or higher forms of education after the regime (Islam et al., 2016), a trend which continues to drive poverty across the country (Kerbo, 2014).

Research Design

Data

I study the degree of local poverty and economic activity at the village (phum) level in Kampong Speu province. Villages are the smallest unit; in Kampong Speu province, the median size of a village was 401 persons and 78 households in 1998. The compact size of villages provide a reasonable approximation of households distance to the border that separated the West and Southwest.[7]

I compare the Southwest and the West within Kampong Speu for three reasons. First, the regions represent the ideological polarization within the regime; Mok was the staunchest ally of the party's genocidal faction, and Sy was a typical moderate communist. Second, the border between zones did not overlap with other political boundaries unlike other DK zones, meaning a discrete change in the outcomes can be attributed to different zone leadership rather than differences between provinces. This mitigates the "compound treatment

[7]Households tend to cluster towards village centers. Census data provides coordinates for village centroids, which I use to measure latitude-longitude and distance to the border. See SI E.3 for visualization of village boundaries.

problem" commonly found in research designs that rely on geography. Third, the density of observations within a narrow bandwidth around the border means villages in the Southwest are being compared to an appropriate counterfactual, which is not true at other boundaries where villages are further from borders, or where the natural borders were excessively wide, like divisions created using the Mekong River.

Poverty data is from the Cambodian National Poverty Identification System (IDPoor). The data is collected in 2011 through a 16 question household survey conducted by elected village representatives who use questions regarding assets, living standards, means of transport, employment, education, and health to score household poverty on a continuous scale which is subsequently used to construct poverty categories. I measure the percentage of poor households. Further detail on the data collection process of IDPoor is available in SI E.1.

Second, I use data on the nighttime luminosity of villages to estimate GDP within a 2 km x 2 km grid cell surrounding the village center (Ghosh et al., 2010). Luminosity proxies both formal and informal economic activity, which is important given the role of informal commerce. I use the inverse hyperbolic sine (IHS) transformation to account for skewness and zeros.[8]

Empirical Strategy

The nature of assignment into the Southwest versus West suggests a regression discontinuity (RD) approach which compares modern outcomes between nearby villages on either side of

[8] IHS of y is $ln(y + \sqrt{1 + y^2})$

the boundary. The RD estimator is:

$$(1) \qquad y_v = \alpha + \gamma \text{SW Zone}_v + f(\text{geographic location}_v) + \sum_{s=1}^{n} seg_v^s + \varepsilon_v \;\; for \;\; v \in bw$$

where y_v is the outcome of interest, SW Zone$_v$ is a binary indicator scored 1 if a village was in the Southwest and 0 otherwise. $f(\text{geographic location}_v)$ is the forcing variable, which I define as the distance between the village v and the border that divided the Southwest and West.[9] I evaluate equation (1) using distance in a linear and quadratic form.

I follow Dell (2010) and include boundary segment fixed effects $\sum_{s=1}^{n} seg_v^s$, which are computed by splitting the border into n segments s and then scoring 1 if a village is closest to segment s. Segment fixed effects compare villages that lie in the same neighborhood around the border, avoiding imprecise comparisons that may occur if villages have similar absolute distances at extreme ends of the boundary.[10]

The robust error term is ε_v. I adjust standard errors for spatial heteroskedasticity and autocorrelation (HAC), following the data-driven procedure developed by Kelly (2020) for selecting a HAC spatial kernel based on the spatial structure of each respective outcome. I estimate equation (1) within narrow MSE optimal bandwidths bw (Calonico, Cattaneo and Titiunik, 2014), however results are robust to alternative bandwidth choices. I include the distance to the provincial capital as an adjusting covariate in some regressions to account for proximity to the provincial center.

The RD approach is advantageous relative to a selection on observables strategy. Since

[9] A problem with distance as a forcing variable is that proximity to a line may not be a strong correlate of the outcome of interest, meaning local linear regressions fitted on either side of the discontinuity may fit the data in a noisy way, producing inconsistent or biased estimates. However, since distance to a highway is economically important, the use of a univariate assignment variable is theoretically justified.

[10] For segments, I use the boundary points, spaced approximately 10 kilometers apart.

DK demographically targeted repression against the more well-off, repression levels are likely correlated with positive developmental trajectories, leading to an upward biased estimate of the effect on repression. Since administrative microdata before the regime was destroyed by DK cadres, one cannot adequately adjust for pre-existing development levels.

Since my RD design compares villages which were arbitrarily split into more or less extreme administrative zones, in expectation, confounding factors ought to be similar between villages within a narrow bandwidth, conditional on location. So long as the design assumptions hold, my strategy identifies a local average treatment effect (LATE) of exposure to an extreme DK administrator. I turn to discussing these assumptions now.

Design Assumptions and Inferential Threats

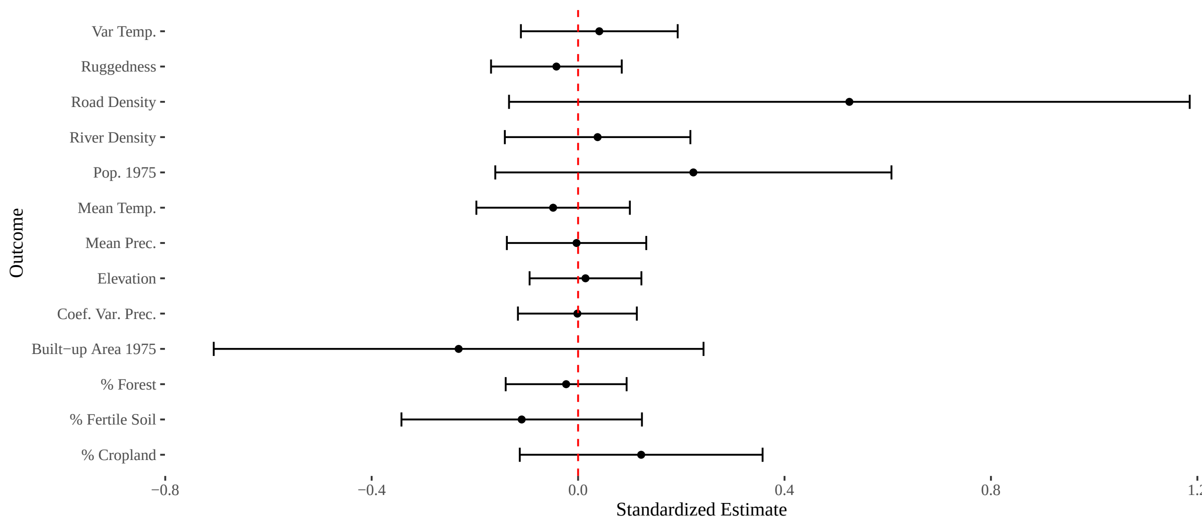
My design relies on two core assumptions: the smoothness of confounders at the discontinuity, and the absence of strategic line drawing to sort observations in a particular way.

Balance Tests

The assumption that confounders are smooth at the discontinuity is reasonable given the arbitrary placement of the road with respect to Kampong Speu. The historical record suggests one confounding feature: the Pol Pot faction wished to divide territory in a way to give Mok control over more productive areas and Sy with less well-endowed land, a goal that would be accomplished by splitting the relatively soil-poor Kampong Speu in two, leaving Mok with the entirety of the soil-rich Kampot province and leaving Sy with the more desolate Koh Kong and the more rugged areas in the far-north of Kampong Speu (Chandler, Kiernan and Boua, 1988; Vickery, 1984).

Geographic variables are "slow moving" in the sense that they vary little within small bandwidths; given the arbitrary placement of the road, there is no reason to believe differences in productivity are sharp at the discontinuity despite the fact Mok was given more rich endowments in the far South outside of Kampong Speu.

Figure 4: Balance Tests: 1×1 Kilometer Grid Cells



Note: Unit of analysis is the 1x1 kilometer grid cell. Outcomes standardized reported in horizontal axis, vertical axis refers to each respective outcome. Spatial heteroskedasticity and autocorrelation consistent standard errors used to construct equivalence confidence interval (ECI). Equivalence range selected using the sensitivity approach $\epsilon \pm .36\sigma$. The null hypothesis is that areas *differ* from one another with at least a magnitude of .36 σ (Hartman, 2021).

I test balance on agro-economic, climatic, and topographic area when crossing from one side of the border to another on 1x1 kilometer grid cells. Figure 4 shows the mean and variance of temperature and rainfall, forest and cropland cover, ruggedness, elevation, and soil fertility are similar on either side of the boundary. Critically, since the Cambodian economy was agriculture based in the lead-up to the Khmer Rouge, the similarity of factors of production on either side of the border suggest villages had similar access to sources of productive income.

DK destroyed micro data from the 1962 Cambodian census, making tests of balance on predetermined socioeconomic variables difficult. I use three data sources to probe for pre-existing economic differences from satellite data: estimated population, built-up areas, and road networks in 1975. As Figure 4 shows the equivalence confidence interval contains zero for these outcomes, however, the substantive size of the estimate could suggest some degree of initial imbalance. There is no reason to regard this imbalance as systematic evidence of manipulation rather than chance: first, it would make little sense for a border to be strategically drawn to give built-up areas - the locations DK was most concerned about repressing - to a moderate. Second, to the extent road density could be higher in the former Southwest, increased market access should *boost* development for former-Southwest villages, suggesting bias in the opposite direction of my main prediction. Balance tests are substantively similar with nonparametric estimator within an MSE optimal bandwidth (SI A.1).

Sorting Test

Another possibility is that the road was chosen as the border because it would give Mok more authority. This concern is somewhat mitigated by the fact that the border was a natural landmark: had DK drawn a particular line, the potential for strategic line drawing would be more first order. If it was the case NR4 was chosen strategically with respect to localities, one would expect a discontinuity in the number of villages at the boundary, specifically with more villages under the authority of Mok rather than Sy. I test for strategic sorting of villages along the border, and I find the density of the running variable is continuous (SI A.2).

Baseline Results

Table 2 contains results from equation (1), which shows a substantively large and statistically significant difference between villages in the Southwest and West. Columns 1-4 refer to the poverty outcome whereas 5-8 refer to night lights. Columns 1-2 and 5-6 use a linear forcing variable, and Columns 3-4 and 7-8 use the squared term. Descriptive RD plots are in SI E.6.[11]

The results imply a meaningful increase in poverty and reduction in luminosity at the discontinuity. Conservative estimates in Columns 1 and 3 suggest poverty increased by 4% - .41 standard deviations and 20% of the control average - in the Southwest. Meanwhile, nighttime lights decreased by .6 standard deviations in the Southwest, which is consistent with the increase in poverty, and is robust to alternative aggregation techniques (SI B.6). The inclusion of segment fixed effects and alternative functional forms of the running variable do not meaningfully impact the estimates, nor does adjusting for distance to Chbar Mon, the provincial capital.

[11] For full model results see SI F.

Table 2: Effect of Southwest on Village Development

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%Poverty				IHS Luminosity			
$\mathbb{1}$ SW	4.53*	4.43*	5.81**	4.96*	−.68***	−.69***	−.48**	−.64***
	(1.76)	(1.77)	(2.07)	(2.04)	(0.13)	(0.14)	(0.17)	(0.15)
Effective N	334	324	502	484	422	389	452	568
Bandwidth	6.34	5.98	10.99	10.62	8.9	7.95	9.64	12.79
μ Control	20.95	20.95	20.95	20.95	.43	.43	.43	.43
σ DV	10.55	10.55	10.55	10.55	.63	.63	.63	.63
Segment FE	-	✓	-	✓	-	✓	-	✓
Dist. Capital Covariate	-	✓	-	✓	-	✓	-	✓
Linear	✓	✓	-	-	✓	✓	-	-
Quadratic	-	-	✓	✓	-	-	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: % Poverty is the count of level 1 and level 2 poverty divided by the number of households per village as measured by IDPoor in 2011. Nighttime lights are the inverse hyperbolic sine of the sum of estimated GDP from luminosity in a 2x2 kilometer grid cell surrounding the village centroid. See Appendix Table F.1 for the partial derivatives and uncertainty for adjusting covariates.

Threats to Inference

Confounding (Observable and Unobservable): Sensitivity Analysis

Although regression discontinuity is a credible research design, my study is observational, and adjusting for pre-existing covariates may be important to account for precision or omitted variable bias. First, I show results are robust to covariate adjustment: including the density of roads and built-up area in 1975 does not meaningfully impact the estimates (SI C.1). Second, I do a sensitivity analysis to assess how severe unobservable selection would need to be in order to overturn the main findings (Cinelli and Hazlett, 2020). In general, I find an unobservable feature would need to explain at least 10% of the residual variation in exposure to Mok and modern development. Since such a confounder would need to be up to four times stronger than built up area in 1975, a strong predictor, it is implausible that a covariate so large is driving the finding (SI B.4).

Road Effect: A Placebo Case Study

Roads themselves may be engines of commerce. To the extent distance to a road matters for development, my main specification flexibly controls for this by including a polynomial in village proximity to the highway. Since my focus is on the local discontinuity in development driven by being on one side of the road versus the other, for the road to explain away the main result, it must be the case that being on one side determines a change in development.

Roads may divide areas which follow different developmental trajectories due to separation and isolation from one another, in which case, a spatial discontinuity in development may emerge by virtue of the border being a road rather than differences in administration. I test this possibility using National Road 3 (NR3) in Kampot Province as a placebo case study. NR3 bisected Kampot in a similar way as NR4, but the entire province was in the Southwest zone during DK. Available qualitative evidence suggests the road separated different communities before the regime; "[i]n some places the line of demarcation between the two kinds of peasantry was apparently quite clear...north of the road running between Chhouk and Kampot the population was isolated, hostile to everything urban, and, incidentally, revolutionary from long before 1970, while south of that road the peasants interacted with the market, were familiar with urban ways, and considered themselves part of wider Cambodian society" (Vickery, 1984, p.4).

I find no evidence of a discontinuity along NR3, suggesting that roads do not generically predict discrete shifts in development across space. The absence of an effect in the context of NR 3 increases our confidence that the main finding is driven by the administrative boundary NR 4 represented rather than the fact it is a road (SI B.5).

Civil Conflict Legacy: Falsification Test

The legacy could be driven by civil conflict legacies rather than state repression. This explanation is implausible, since both zones were one combat theater during the civil war (1970-1975). Civil war violence outside of state repression must change underlying factors of production to have a persistent effect (Blattman and Miguel, 2010). In Cambodia, the most plausible way this could occur would be if explosive remnants of war (ERW, landmines or bombs) were differently allocated between zones, degrading land (Lin, 2020). I find no evidence of differential ERW (SI B.5).

Robustness

I probe the robustness of my findings in several ways.

DHS Wealth Data To validate my measure of poverty at the village level with administrative data, I replicate my findings using survey data at the individual level collected by the Demographic Health Survey from 2000-2014. I show rural household wealth is lower in the former Southwest (SI B.1).

Two-Dimensional Forcing Variable Nonlinear spatial trends could be mistaken for discrete change in income levels if the univariate forcing variable masks higher-order changes across latitude-longitude space. I include a two-dimensional forcing variable (SI B.1) and estimate the RD along border points to account for this (SI B.2).

Power Analysis One may be concerned that the number of observations is small in a narrow neighborhood, reducing the statistical power of the tests. Since the effect size I uncover is substantial, not many observations are required. I show that I have sufficient power within an MSE optimal bandwidth to detect the main effects (SI B.3).

Falsification Test Spatial autocorrelation could explain the finding if village development clusters geographically. I show the bias-corrected CCT standard errors are robust to spatial noise simulations which create synthetic outcome data following the same spatial structure of the true data (Kelly, 2020) (SI B.2)

Donut RD I estimate a series of donut-hole RDs, dropping observations close to the border, and find similar results even after 10% of the data is dropped (SI B.8). The result guards against the possibility that when approaching the road, villages experience a differential positive development shock unrelated to DK.

Mechanisms

Repression and Poverty Traps: Conceptual Framework

Violence targeted at higher educated segments of society creates a skill gap between generations, leaving younger people without mentors who can transfer skills and knowledge. This type of violence can be found across autocracies and coerced labor regimes: autocrats prefer low-skilled loyalists to competent persons to extend their survival (Egorov and Sonin, 2011) and under coerced labor, principals are more violent towards productive and skilled persons, who have a larger outside option (Acemoglu and Wolitzky, 2011). The mechanism I study is therefore plausible in other contexts.

In the next sections, I show how poverty becomes self-perpetuating and persistent due to repression: a poverty trap. Educational attainment is lower in the former Southwest, with a particularly strong drop among the age cohort whose secondary schooling years were interrupted by the regime. This created an intergenerational poverty trap in two ways. Individuals in the Southwest were pushed into informal employment, which earns less income. The evidence is consistent with a model of poverty wherein individuals at time t remain poor in $t+1$ because their low income forces them into making decisions that reinforce their poverty, such as working low-earning jobs (Banerjee and Duflo, 2011). Further, children born after the regime in the Southwest have worse health outcomes, which strongly predicts future income. This evidence highlights the intergenerational nature of the poverty trap: although children born in the former Southwest were never repressed by DK, they face deprivation because their parents were driven into poverty, perpetuating the cycle.

Human Capital Declined After DK

First, I evaluate whether trends in schooling by age changed in the Southwest zone. If human capital differentially declined in the Southwest due to the Khmer Rouge, one should observe relatively similar levels of schooling among age cohorts who finished schooling before the regime along with a sharp decline in schooling among villagers whose school-age years overlapped with the regime. I test this argument using a difference-in-differences design leveraging microdata on individual schooling and age from Cambodian Labor Force Surveys in 2000/2001. The common trends assumption is plausible in this setting, since all villagers educated before DK were in the same province, meaning the institutional differences between regions only emerged after the regime. I placebo test this assumption, regressing schooling on a series of separate cohort dummies among persons past schooling age in 1975, finding no evidence of large or significant breaks in educational trends (SI D.6).

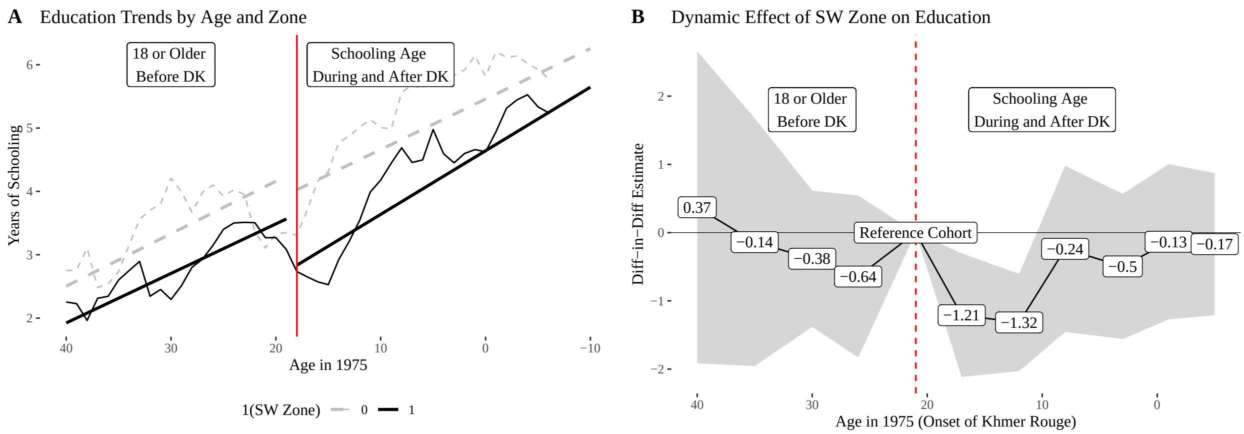
I estimate the following model.

$$y_{i,(v),(c)} = \sum_{c \neq 20-24}^{C} \beta_c \big(\text{Cohort}_{i,(c)} \times \mathbb{1}\{SW_{i,(v)}\}\big) + \mu_v + \lambda_{iy} + \sum_{k=1}^{K} \alpha_k x_i^k + \epsilon_{i,(v),(c)} \tag{2}$$

The outcome is years of schooling, $y_{i,(v),(c)}$, measured for individual i in village v among age cohort c. The coefficients of interest are β_c, which capture the differential effect of an individual living in the Southwest zone in an age cohort who would have had primary or secondary schooling after DK, relative to the age cohort who would have completed primary or secondary schooling before the regime (aged 20-24 in 1975). Note β_c captures both pre-trends in educational differences among older cohorts and the dynamic effect of having overlapped with Mok's rule during schooling age. I include birth-decade-by-commune fixed effects λ_{iy} which absorb decadal educational trends over space, village fixed-effects (μ_v) to adjust for village-invariant factors, and K individual controls $\sum_{k=1}^{K} \alpha_k x_i^k$ including age and its square and respondent gender. Standard errors are clustered at the village.

Figure 5 graphically displays the identification approach and results. Panel A shows the average years of schooling by cohort per zone, illustrating a (fitted) parallel trend in the pre period. Education levels then sharply decline in the former Southwest zone among 12-17 year olds (in 1975 years). Panel B corroborates the descriptive trend, showing the absence of a difference among older age cohorts between zones and a transitory decline in

Figure 5: Educational Attainment by Age Cohort and Zone



Note: X-axis records birth cohorts in reference to 1975 - individuals born in 1985 are scored -10 whereas birth in 1965 is 10. Y-axis is years of education completed. Controls include, age, age^2, gender, decade-by-commune fixed effects, village fixed effects. Panel A is the raw trend - averages of schooling by age cohorts and zone, with the five year moving average and linear fit separated by the pre- and post-period Panel B plots difference-in-differences coefficients (β_c per equation (2)). See Table F.2 in appendix for partial derivatives and uncertainty for adjusting covariates.

educational attainment for persons who were schooling age when the regime began. The evidence suggests schooling fell among school-aged Cambodians in the Southwest.

If human capital decline persists overtime, one should observe lower human capital levels at the village level between zones. Table 3 shows the share of persons who have never attended school increases, whereas the literacy rate (of those over 15 years of age) declines. The estimates are largely commensurate with one another; whereas the percentage of persons who never attended school increases by 7% in the baseline, the share of literate persons over 15 declines by 8%. The results are substantively large, near .5 σ in the baseline estimates. In SI D.1, I show years of education decline by a year on average, and school attendance declines by 6% in 1998. The result is robust to adjusting for distance to schools (SI D.2).

The education gap persists into 2008 through tertiary and secondary education (SI D.4).

Table 3: Human Capital: Education and Literacy in 1998

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%No Educ.				Lit. Rate			
$\mathbb{1}$ SW Zone	7.58^{**}	3.55	7.39^{**}	$4.46^{\dagger}$	-8.02^{**}	$-4.85^{\dagger}$	-7.85^{*}	$-5.46^{\dagger}$
	(2.45)	(2.2)	(2.65)	(2.5)	(2.65)	(2.59)	(3.07)	(2.86)
Effective N	310	316	552	440	308	290	442	412
Bandwidth	5.69	5.95	12.89	9.80	5.62	4.99	9.87	8.95
μ Control	50.48	50.48	50.48	50.48	62.88	62.88	62.88	62.88
σ DV	14.85	14.85	14.85	14.85	17.03	17.03	17.03	17.03
Segment FE	-	✓	-	✓	-	✓	-	✓
Dist. Capital Covariate	-	✓	-	✓	-	✓	-	✓
Linear	✓	✓	-	-	✓	✓	-	-
Quadratic	-	-	✓	✓	-	-	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$

Note: See Table 2. Outcomes are percentage of the population without education and percentage over the age of 15 who can read and write. See Table F.3 for full model results.

The impacts of repression on schooling could vary by gender: parents may invest less in schooling daughters in the aftermath of repression, pushing female family members into care-taking roles instead of education. The pattern of lower educational attainment for females is consistent across Cambodia. Notably, this mechanism would not be a rival account to a poverty trap, rather, it would be a dimension by which the poverty trap is perpetuated. I find no consistent evidence of this pattern (SI D.5).

Labor Market Outcomes

Qualitative evidence suggests the absence of educated and skilled persons drove individuals to work in low-paying jobs (Jeong, 2014). In the Cambodian context, less schooling strongly predicts individuals being "own account workers" - self employed, typically working agricultural jobs on small-scale family farms or in otherwise informal roles. This line of work is highly labor intensive, has a low level of productivity, and involves low levels of skill and technology (Arnold, 2008). If the decline in education caused by DK repression reshaped local labor markets by pushing individuals into low-earning informal agricultural work, one may expect an increase in the probability an individual is an own-account worker and a commensurate decline in earnings and productivity.

Table 4 shows findings consistent with this pattern. Rural persons in the Southwest are far more likely to be own account workers - self-employed informal laborers (column (1)). Consistent with broader patterns of employment and earnings, column (2) shows lower income from work as well. Finally, column (3) shows earnings per hour are also lower, meaning productivity for workers also diminishes. The evidence is consistent with qualitative accounts of how state repression shaped labor markets and workers in the wake of the human capital shock from the regime. In SI D.8, I show own-account workers are less educated and earn less.

Intergenerational Consequences

Economic impacts can reverberate across generations by reducing child health. Childhood health determines later-life income levels and is partially determined by maternal economic well-being (Bleakley, 2010). I evaluate how the DK shock impacted subsequent generations

Table 4: Labor Market Effects of Repression

	(1) Pr(Self Employed)	(2) IHS(Income)	(3) Productivity
$\mathbb{1}$ SW	$0.12^{\dagger}$	-0.68^{**}	-8.67^{*}
	(0.07)	(0.24)	(4.17)
	[0.08]	$[0.22]^{**}$	$[3.65]^{*}$
Effective N	235	285	411
Bandwidth	9.7	12.8	19.2
N Villages	16	20	30
Covariates	✓	✓	✓
σ DV	0.45	0.86	8.81

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$

Note: Unit of analysis is employed working aged (11-59) individuals. Data from 2000-2001 Labor Force Survey. Pr(Self Employed) is scored 1 for persons who are own account workers. Income is individual wages, remuneration, earnings, tips reported from the last month in 10,000 riels, and productivity is riels divided by working hours. Estimates are obtained using Calonico, Cattaneo and Titiunik (2014) nonparametric RD within MSE optimal bandwidths and a triangular kernel. Covariates in local linear regressions include survey wave fixed effects, age, age squared, and gender of individual. Robust errors clustered at the village reported in (); wild cluster bootstrapped errors reported in []. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$. See Appendix Table F.4 for full model results.

by exploring the health of children between zones with four rounds (2000, 2005, 2010, 2014) of Demographic Health Survey (DHS) data. Parents who lost schooling and were therefore poor as a result of Mok's rule may have less healthy children as a result of their low income. Finding worse health outcomes for youth may highlight how repression creates persistent, negative human capital consequences beyond schooling and across generations that were never exposed to violence.

DHS randomly selects a subset of respondents and measures three critical dimensions of child health for persons aged 3-5: height for age (a measure of stunting), weight for age (a measure of wasting), and weight for height (a measure of being underweight). I create an index of health scores using the first principal component of these measures and evaluate

Table 5: Intergenerational Effects: Child Health Between Zones

Outcome	(1) Health Index	(2) Height/Age	(3) Weight/Age	(4) Weight/Height
$\mathbb{1}$ SW	-0.88^{***}	0.10	-0.59^{**}	-1.11^{***}
	(0.26)	(0.17)	(0.19)	(0.16)
	$[0.34]^{*}$	[0.17]	$[0.22]^{*}$	$[0.34]^{***}$
N. Individuals	243	298	243	195
N. Clusters	29	36	29	23
Bandwidth	11.05	11.55	11.21	9.34
Covariates	✓	✓	✓	✓
SD DV	1.38	1.26	0.99	0.98

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Unit of analysis is the 3-5 year old individual from the 2000-2014 DHS survey waves - the children of the generation exposed to the Khmer Rouge. Health index (Column 1) is the first principal component of individual health measures. Height/Age is the standard deviations from the median of individual height for age (stunting), Weight/Age is standard deviations from the median of weight for age (wasting), Weight/Height is standard deviations from the median of weight for height (underweight). Analysis within rural households to maximize comparability. Controls include the age of the mother, its square, and survey fixed effects. Robust standard errors clustered at the survey area reported in parentheses. Cluster standard errors reported in parentheses, wild cluster bootstraps reported in brackets. See Appendix Table F.5 for full model results.

each measure individually, and then estimate a version of equation (1) which includes wave year fixed effects and maternal controls among rural households to maximize comparability.

Table 5 shows the health index declines by nearly 0.8 σ. The effect is driven by underweight and wasting children, rather than stunting, which suggests childhood food poverty drives health differences. In SI D.7 I show the effect is orders of magnitude larger for mothers without formal schooling, and that the difference between zones attenuates when mothers have some education, suggesting the education shock from the regime plays a crucial role in explaining health differences.

Alternative Mechanisms

Social Capital

Cultural persistence via social trust has been shown to be an important persistence channel linking coerced labor to modern development. (Lowes and Montero, 2020; Lichter, Löffler and Siegloch, 2021; Nunn and Wantchekon, 2011). I use data from Cambodia's Violence Against Women survey, which asks respondent's three questions about communal trust and social cohesion including (1) "Do neighbours in COMMUNITY NAME generally tend to know each other well?", (2) "If there were a street fight in COMMUNITY NAME would people generally do something to stop it?" and (3) "If someone in your family suddenly fell ill or had an accident, would your neighbours offer to help?" I code 1 if a respondent answers "yes" and 0 otherwise. There is little variation across villages in different zones along these dimensions, with respondent's reporting affirmative answers at high and nearly identical rates between zones (Table 6). This suggests social capital cannot explain the developmental divergence.

Table 6: Social Cohesion and Trust

Zone	Know Neighbors	Help Fight	Help Sick	N
SW	1.00	1.00	0.96	80
W	1.00	0.93	0.99	120

Source: WHO Women's Health and Life Experiences Survey. Outcomes are the share of respondents reporting that they know their neighbors well (Know Neighbors), whether the respondent believes people in the community would provide help if a fight broke out on the street (Help Fight) and whether neighbors would help if one become sick or had an accident (Help Sick). Each cell reports the proportion of respondents who reply in the affirmative divided by total respondents. SW is the Southwest zone and W is the West zone.

Property Rights

Weak property rights institutions are another channel commonly cited in the literature (Acemoglu, Johnson and Robinson, 2001; Dell, 2010). Since neither the DK ban on private property nor collectivization has persisted, it is unlikely formal institutional persistence explains contemporary maldevelopment. However, the destruction of records of land ownership could have increased the contestability of land, creating tenure insecurity and poverty. Social conflict as a result of extractive institutions has been shown to be a crucial persistence mechanism (Guardado, 2018).

To measure respect for property rights, I collect data on the count of village land disputes from Commune Database Online. This measure captures a highly salient aspect of respect for property in the Cambodian context, where the highly agrarian economy has seen increasing poverty due to land grabs and unclear titling (Kerbo, 2014). I find no difference in land disputes at the discontinuity (Table 7).

Table 7: Land Disputes

	Levels (1)	IHS (2)	Binary (3)
$\mathbb{1}$ SW	0.5499 (1.0794)	0.2405 (0.2179)	0.1094 (0.0692)
N	607	631	615
BW	14.5	15.3	14.7

Note: RD estimates evaluating changes in land disputes. Outcomes are level of land disputes in 2008-2010 reported by the Commune Database Online. Column (1) is the count (Levels), column (2) is the inverse hyperbolic sine of the count (IHS) and column (3) is a binary indicator for any dispute (Binary). Standard errors reported in parentheses.

Political Legacy

A third class of explanations relates to the political dominance of former regime elites; historical coercive institutions may create politically uncompetitive environments, which outlast initial conditions. As explained, this mechanism is unlikely, as Mok and his cadres were driven from the region during Vietnam's invasion. I measure the competitiveness of commune council elections in 2012 and 2017 (Herfindahl index, higher values represent less competitiveness) and the vote share for the ruling Cambodian People's Party (CPP) in 2012/2017. Data is only reported at the commune level, of which there are 87 in Kampong Speu. Since the units are much larger than villages, I include all communes in the RD, but also include district fixed effects to absorb spatial heterogeneity.

Table 8: Commune Council Elections (2012/2017)

Outcome	Competitiveness		CPP Vote Share	
	(1)	(2)	(3)	(4)
$\mathbb{1}$ SW Zone	-2.74	-3.61*	-2.82	-0.04
	(2.89)	(1.59)	(3.69)	(0.03)
District FE	✓	✓	✓	✓
Election Year	2012	2017	2012	2017
N	87	87	87	87

Note: RD estimates evaluating the political impact of the Southwest zone on commune council elections. Competitiveness is the share of vote shares squared (higher values mean more concentration, lower values more competitive.) CPP vote share is the count of votes to CPP, the dominant ruling party, out of total votes. SHAC errors reported in parentheses.

Results in Table 8 show local elections are largely similar between zones. To the extent competitiveness of elections are different, elections appeared more competitive in the Southwest in 2017, where vote shares were less concentrated by 3.6 points. As such, political competition and partisan support are unlikely explanations. Another observable implication of elite capture and corruption - a key persistence mechanism in the study of extractive institutional persistence - is lower levels of public goods. In Table C.2, I show villages on either side of the border have similar access to hospitals, schools, and commune centers.

Migration

Migration could explain my findings if a substantial proportion of wealthy individuals fled the (former) Southwest zone after the regime for the West. While this would not invalidate the design, it would mean the primary persistence channel was selective migration of more well-off civilians rather than an intergenerational human capital shock.

I treat migration as a post-treatment variable, and back out how large selective migration would need to be in order to explain the result under weak assumptions and a conservative trimming exercise. Selective migrants would need to occupy the entire top 25% of the wealth distribution in the rural West to explain the result - an implausibly high proportion considering low rates of rural-rural migration (See SI C.4 C.1) for results and SI G for explanation).

Conclusion

Does mass repression have a developmental legacy? If so, why do the consequences persist overtime? I argue mass repression which demographically targets the educated and intellectuals can destroy human capital in more intensely repressed localities, creating a poverty trap. I find evidence by exploiting an administrative redistricting which arbitrarily placed villages under very different rulers during the Khmer Rouge regime, creating quasi-random variation in the intensive margin of state repression. I show substantial impacts on wealth, household poverty, and human capital at the individual and village level, which spillover to the next generation via health. Whereas evidence is consistent with a poverty trap, I find no evidence in support of other important persistence channels linking coercive regimes to long-run development.

The results show the legacy of increased exposure to repression at the intensive rather than the extensive margin. Since villages in the former West zone were also repressed, albeit less severely, the counterfactual of what development would have looked like absent any repression is not estimated. However, as in Dell (2010), the intensive margin estimates presented here are likely a lower bound on the impact of Khmer Rouge rule at the extensive margin. Assuming the human capital destroyed in the West was more destructive to long-run development than the absence of any repression, my results showing more intense repression led to 0.40σ increase in poverty and a 0.50σ reduction in human capital are conservative estimates of how much total wealth was lost from repression. The results are on par with the developmental impact of King Leopold's concessions in the Congo (Lowes and Montero, 2020).

My study shows that state repression can create multiple developmental equilibria across space, adding human capital shocks to the library of mechanisms that may link coercive institutions to worse development in the modern day (Gailmard, 2021). My study also shows when other theories of persistence do not generalize, and provides a within-case explanation that is plausible in contexts where governing institutions eradicate well-off or intellectual groups. Since coerced labor institutions throughout history use more violence against the highly capable, and since several dictatorships and insurgencies throughout history have targeted intellectuals, the channel I identify may be at play in many other settings, which are key avenues for future research.

The findings suggest a focus on the technology of coercion and the targets of repression is a useful starting point for making sense of developmental impacts of state violence. Since DK executed higher class civilians, factors of production changed in a way that created poverty cycles. However, as other research has shown, the impacts of repression on the economy are not homogenous or unidirectional. Unpacking how and why repression shapes poverty in the long-term is not only crucial to understanding the roots of development and consequences of conflict, it can also help scholars begin to understand why autocrats choose certain tools over others to control populations. Recent work by Sun (2019) is a start in this direction, illustrating how the impact of repression on wages determines the state's counterinsurgency strategy. New avenues may interrogate why the state would chose a repression strategy that destroys wealth, or the conditions wherein the negative economic impact of repression may spur "repression traps," wherein by creating conditions favorable for insurgent recruiting through violence, the state is forced to further rely on violence (Davenport et al., 2019).

Future scholarship may consider whether or how the lingering impacts of autocratic repression moderates the effects of democratic transitions on development. Sequencing of events may shape the effect of repression in the long-term; the Cambodian case is one where repression was followed by occupation and more dictatorship. Studying how the legacy of repression on development may change - or stay the same - after regime change may further elucidate mechanisms of, or solutions to, the developmental legacy of draconian dictatorships.

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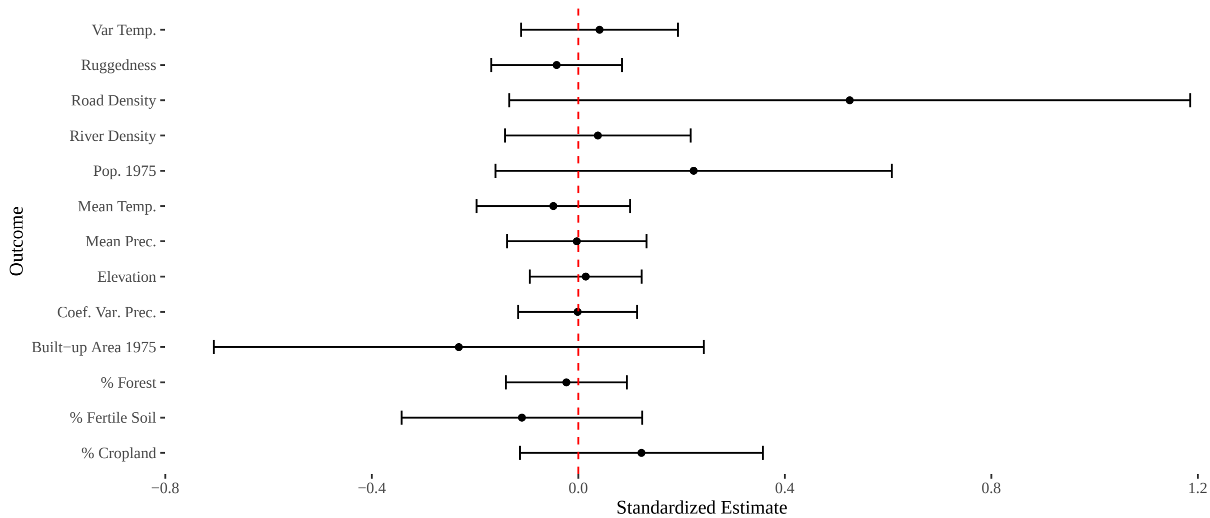
Appendices: Online A-D, Dataverse ONLY E-I

Contents

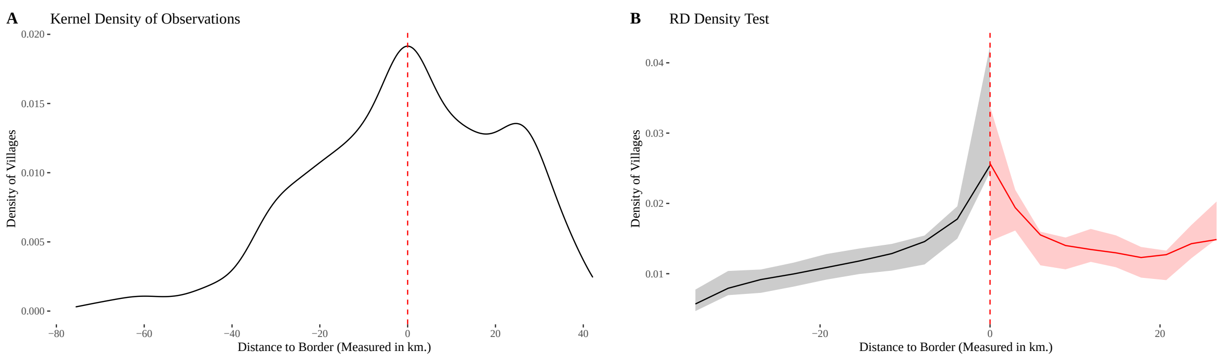
A Identification Checks: Online Appendix

Figure A.1: Balance Tests



Note: Outcomes standardized reported in horizontal axis, vertical axis refers to each respective outcome. Spatial heteroskedasticity and autocorrelation consistent standard errors used to construct equivalence confidence interval (ECI). Equivalence range selected using the sensitivity approach $\epsilon \pm .36\sigma$. Estimates using nonparametric RD within MSE optimal bandwidth.

Figure A.2: Density Test



Note: Kernel density of observations by running variable in Panel A. Test for discontinuity in density in Panel B showing smoothness of observations at the cutpoint.

B Robustness: Online Appendix

Table B.1: DHS Wealth

	(1) Levels	(2) Logs	(3) Categories
$\mathbb{1}$ SW	-0.80***	-0.42***	-1.23***
	(0.16)	(0.92)	(0.36)
Bandwidth	8.93	9.19	10.32
Effective N	3155	3155	3567

Outcome is the DHS wealth index constructed from the first principal component of household assets. Unit of analysis is the rural individual. Adjusting covariates include gender, age, age squared, and survey wave fixed effects. Column (1) reports the outcome measured in levels, Column (2) reports the natural log of the index, and Column (3) shows the outcome according to categories (quintiles).

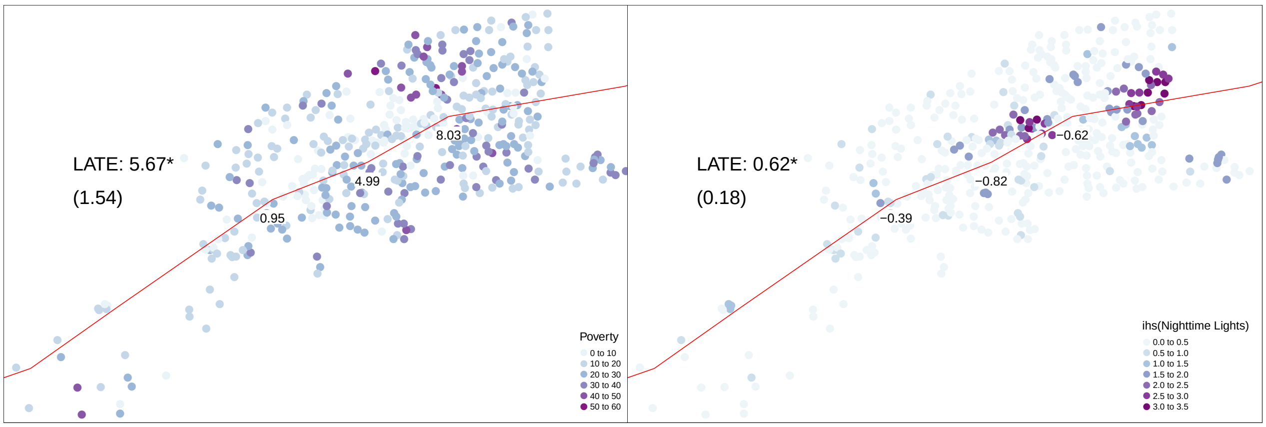
Table B.2: Baseline Results: Multidimensional Forcing Variable

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%Poverty				IHS Luminosity			
$\mathbb{1}$ SW	5.45**	5.75**	6.37***	5.16***	−0.72***	−0.8***	−0.7***	−0.57***
	(1.8)	(1.85)	(1.43)	(1.45)	(0.12)	(0.13)	(0.11)	(0.1)
Effective N	334	324	502	484	422	389	452	568
Bandwidth	6.34	5.98	10.99	10.62	8.9	7.95	9.64	12.79
μ Control	20.95	20.95	20.95	20.95	0.43	0.43	0.43	0.43
σ DV	10.55	10.55	10.55	10.55	0.63	0.63	0.63	0.63

RD results using a polynomial in latitude-longitude space as the forcing variable. Linear forcing variable models latitude and longitude, denoted as x and y, as: $x + y + xy$. Squared model uses: $x + y + xy + x^2 + y^2 + xy^2 + yx^2 + y^2x^2$.

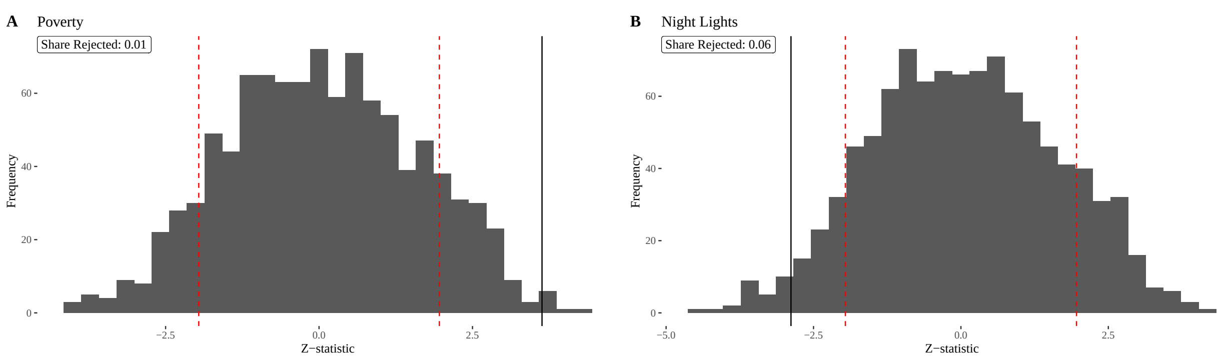
Figure B.1: Treatment Effect Curve

(a) Poverty (b) Luminosity



Notes: RD estimates along border points (reported at each particular point) and aggregated LATE (reported in upper left corner). Standard error computed via the bootstrap. Each dot represents a village with associated shading corresponding to level of poverty or luminosity respectively.

Figure B.2: Noise Simulations



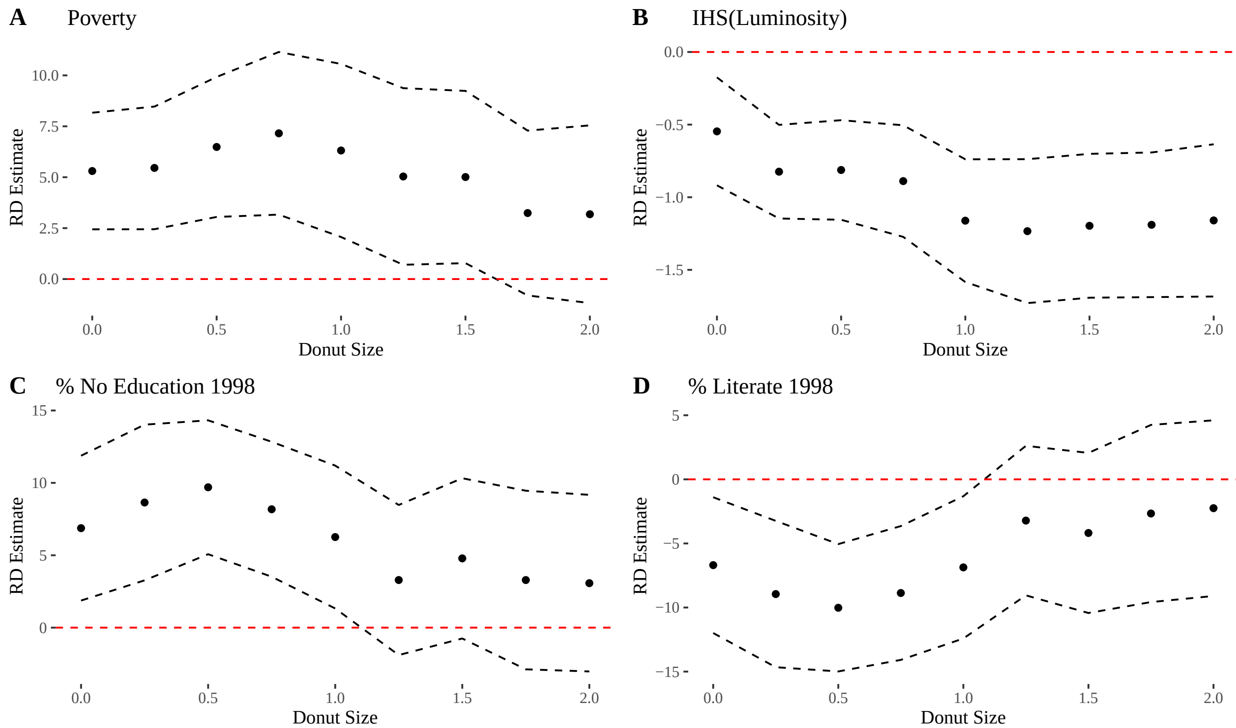
Note: Histograms of z-statistics from CCT robust standard errors. Outcome is simulated spatial noise for each respective outcome. Vertical red line is the z-statistic using the true data. Upper right corner is the proportion of z-statistics from simulations that are more extreme than the estimates from the true data.

Table B.3: Power Analysis:

	Power Against				
Kernel	H0: $\tau = 0$	0.2*τ	0.5*τ	.8 *τ	$\tau = \widehat{\tau}$
		Panel A: Poverty			
Uniform:	.05	.089	0.304	0 .638	0.824
Triangular:	.05	0.129	0.532	0.904	0.983
		Panel B: Luminosity			
Uniform:	.05	0.145	0.609	0 .947	0.994
Triangular:	.05	0.117	0.47	0 .854	0.965

Note: Power analysis of nonparametric robust bias-corrected regression discontinuity design for primary outcomes of interest (poverty and luminosity). Each column shows the power of the test against various null hypotheses based on the hypothesized effect size. The column to the furthest to the right reports the power against assuming the effect size detected in the study is the true value of τ, moving to the left the size of τ is decreasing. Power analysis includes border segment fixed effects.

Figure B.3: Excluding Observations Near Threshold



Note: Estimation using CCT nonparametric approach and confidence intervals. Size of donut-hole expands at .25 kilometer increments starting with .5 kilometers. Each estimate drops additional data.

Table B.4: Sensitivity Analysis

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Outcome: *Poverty*						
$\mathbb{1}$ SW:	3.486	1.783	1.956	1.2%	10.2%	0%
df = 328	*Bound (4x Built Area 1975)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 9.4\%$, $R^2_{D\sim Z\|\mathbf{X}} = 15.2\%$					
Outcome: *Luminosity*						
$\mathbb{1}$ SW:	-0.574	0.14	-4.113	4.2%	18.9%	10.4%
df = 383	*Bound (4x Built Area 1975)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 28\%$, $R^2_{D\sim Z\|\mathbf{X}} = 15.4\%$					
Outcome: *Literacy Rate*						
$\mathbb{1}$ SW	-7.262	2.648	-2.743	2.4%	14.4%	4.3%
df = 311	*Bound (4x Built Area 1975)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0\%$, $R^2_{D\sim Z\|\mathbf{X}} = 4.2\%$					
Outcome: *No Educ.*						
$\mathbb{1}$ SW	7.42	2.5	2.968	2.8%	15.7%	5.6%
df = 303	*Bound (4x Built Area 1975)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 1.2\%$, $R^2_{D\sim Z\|\mathbf{X}} = 4.7\%$					

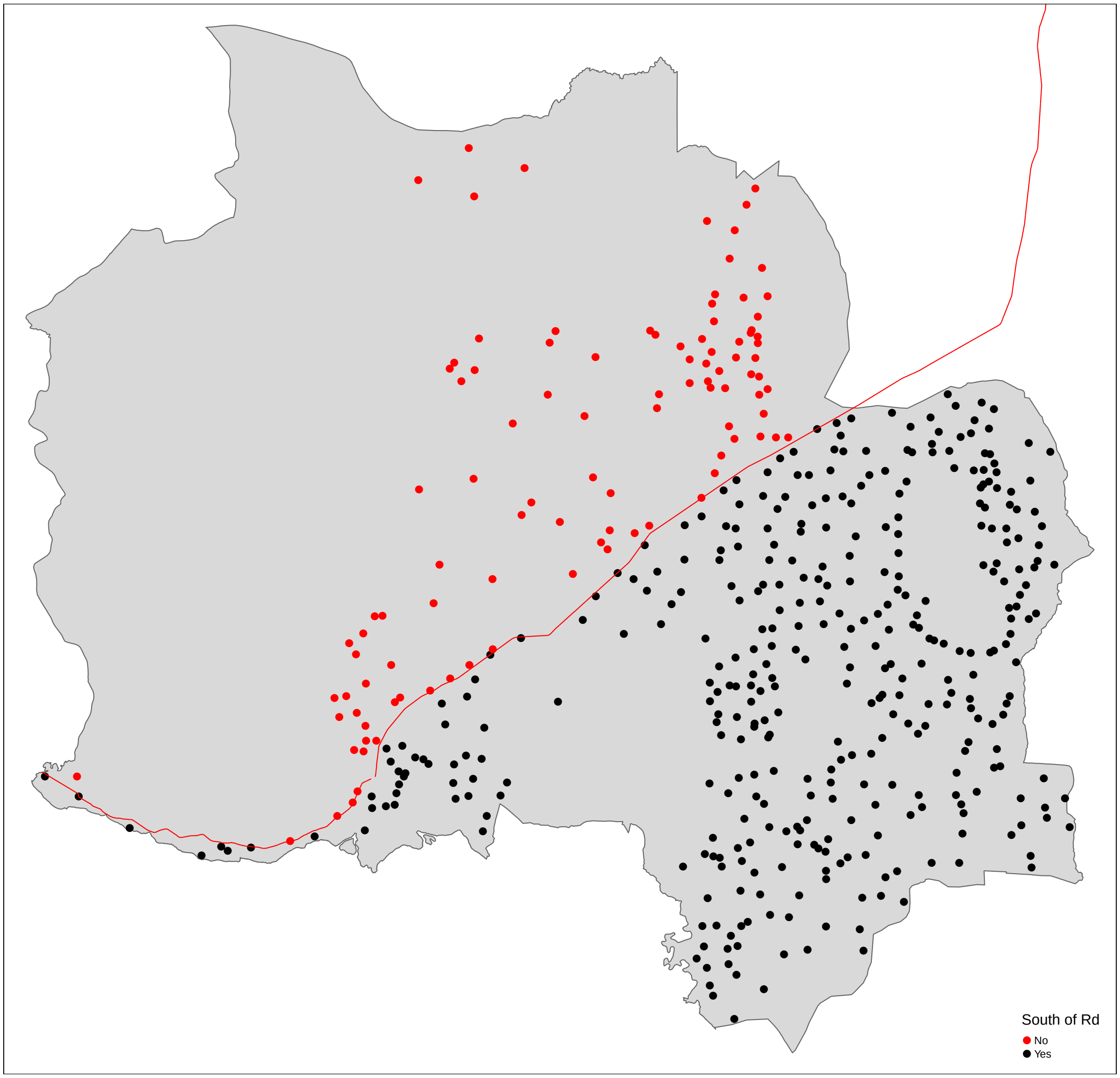
Sensitivity analysis results adjusting for road density and density of built up areas in 2 x 2 kilometer grids surrounding village centers. "Est." column is the estimate, "S.E." is the standard error, "t-value" is the t-statistic. $R^2_{Y\sim D|\mathbf{X}}$ reports how much residual variation in treatment exposure unobserved confounder would need to explain in order to erase the effect of treatment conditional on the unobserved confounder explaining all of the left out variance in the outcome of interest. $RV_{q=1}$ is the robustness value for bringing the estimate of Southwest to zero. Unobserved confounders that explain less than the robustness value's worth of both exposure to the Southwest zone and the outcome of interest are not sufficiently strong to explain away the observed effect.

Table B.5: National Road 3 Placebo: Kampot Province

Outcome	(1) Night Lights	(2) Poverty	(3) No Educ.	(4) Literacy
$\mathbb{1}$ South	-0.14	-1.15	-2.61	1.88
	(0.13)	(1.48)	(2.42)	(2.69)
Effective N	162	112	134	146
Bandwidth	7831.48	5009.04	6427	6974.87
μ Control	0.28	17.11	53.59	56.79
σ DV	0.5	7.38	12.57	14.2

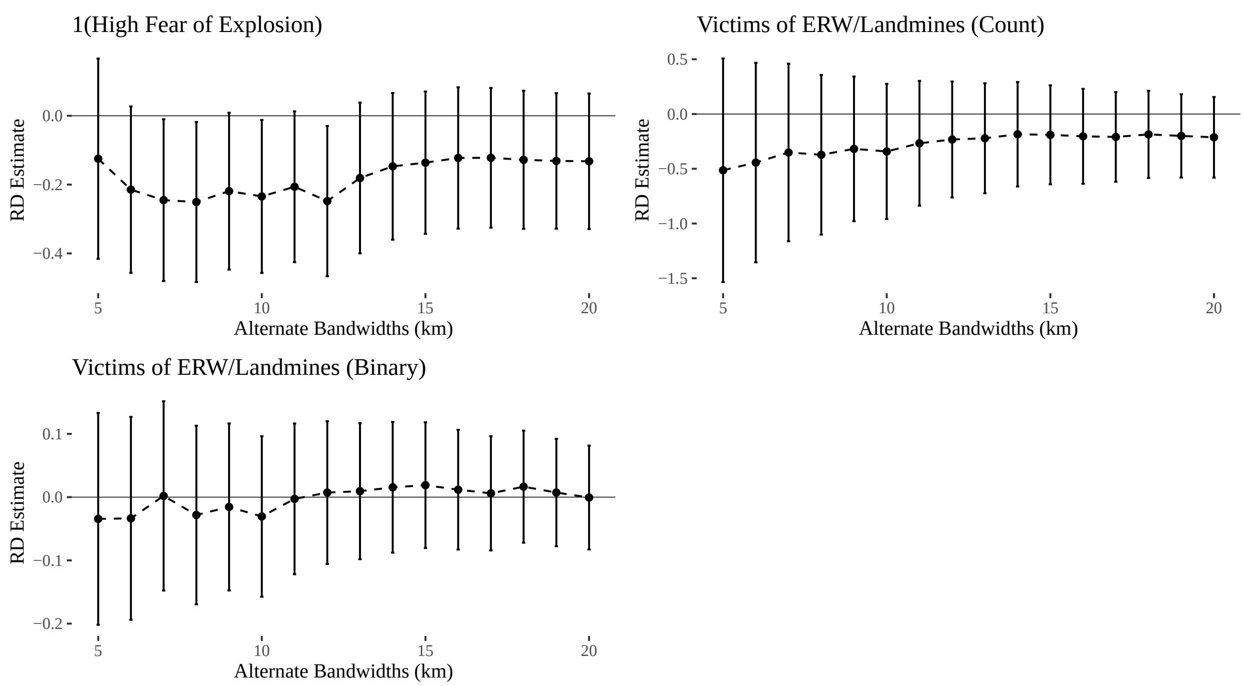
$\mathbb{1}$ South is a binary indicator for a village being South of National Road 3 within Kampot province (See Figure B.4 for reference). All villages within Kampot province, which was entirely in the Southwest Zone during the DK and civil war period (1970-1979).

Figure B.4: Road Placebo: National Highway 3



Note: Map showing the province and villages used for the National Highway 3 placebo test.

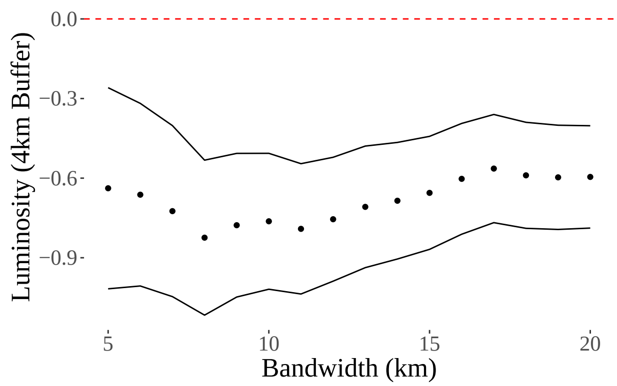
Figure B.5: Explosive Remnants of War (ERW) and Landmine Exposure: Post 2000



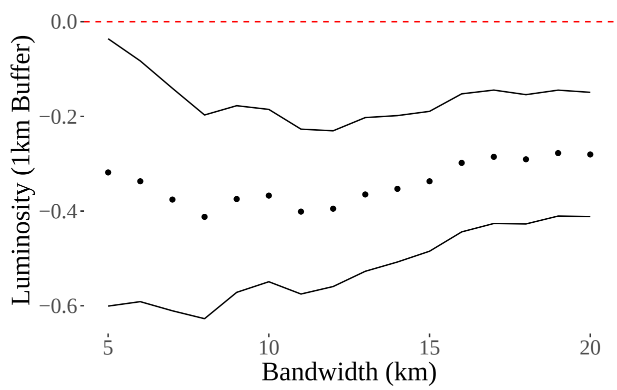
Note: 95% CCT robust confidence intervals shaded around estimates, uniform kernel, alternative bandwidths

Figure B.6: Luminosity: Other Aggregation Grids

(a) Nighttime Lights (4km)

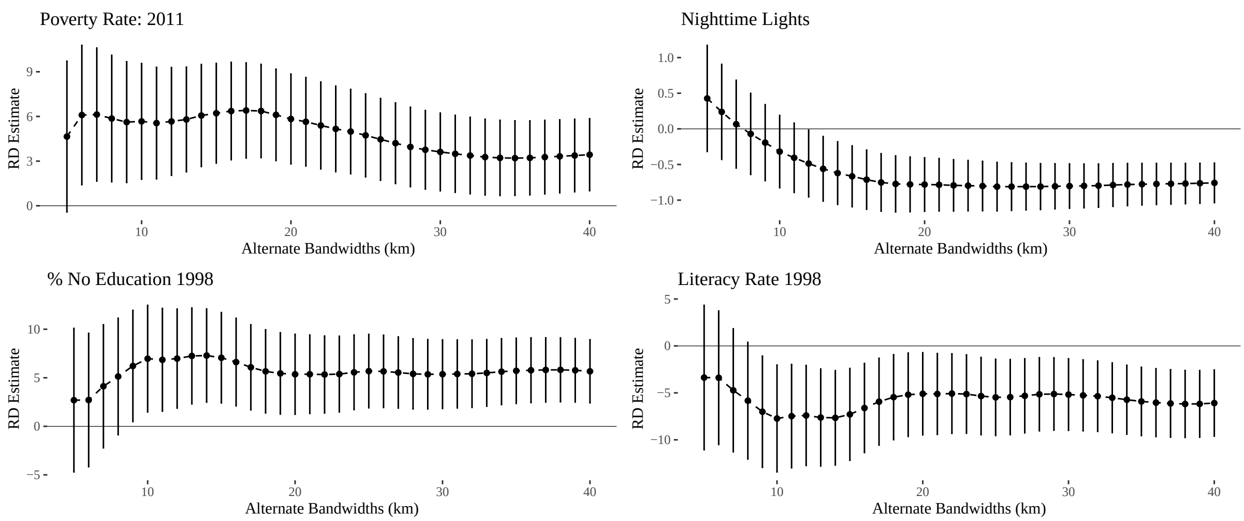


(b) Nighttime Lights (1km)



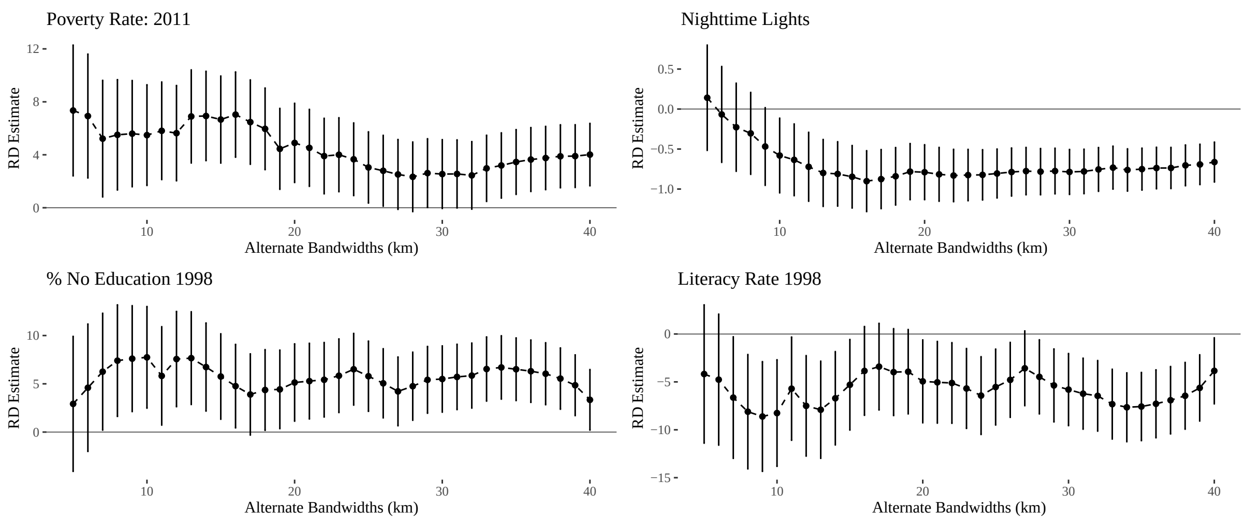
Notes: Semi-parametric RD estimates at alternative bandwidths. Panel A shows the results where a 4 km buffer is created around villages to compute luminosity. Panel B shows results where a narrower 1 km buffer is used to compute luminosity. SHAC standard errors used to construct 95% confidence bands.

Figure B.7: Nonparametric RD: Alternative Bandwidths, Triangular Kernel



Note: Estimation using CCT nonparametric approach and confidence intervals at alternative bandwidths with triangular kernel.

Figure B.8: Nonparametric RD: Alternative Bandwidths, Uniform Kernel



Note: Estimation using CCT nonparametric approach and confidence intervals at alternative bandwidths with uniform kernel.

C Alternative Explanations: Online Appendix

Table C.1: Effect of Southwest on Village Development (Covariate Adjusted)

Outcome	(1)	(2)	(3)	(4)
	%Poverty		IHS Luminosity	
SW	$3.21^{\dagger}$	4.36^{*}	-0.53^{***}	-0.53^{***}
	(1.71)	(2.03)	(0.12)	(0.13)
Effective N	340	505	439	618
Bandwidth	6.58	11.12	9.31	14.37
μ Control	20.95	20.95	0.43	0.43
σ DV	10.55	10.55	0.63	0.63
Segment FE	✓	✓	✓	✓
Dist. Capital Covariate	✓	✓	✓	✓
Pre-DK covariates	✓	✓	✓	✓
Linear	✓	-	✓	-

Note: % Poverty is the count of level 1 and level 2 poverty divided by the number of households per village as measured by IDPoor in 2011. Nighttime lights are the inverse hyperbolic sine of the sum of estimated GDP from luminosity in a 2x2 kilometer grid cell surrounding the village centroid. Estimates include the following pre-DK covariates: distance to the provincial capital, the sum of built up area around the grid cell surrounding the village in 1975, road density in the grid cell surrounding the village.

Table C.2: Public Goods Access

Outcome: Distance to:	Hospital (1)	School (2)	Commune Center (3)
$\mathbb{1}$ SW	-0.0788	-0.0039	0.3503
	(0.8141)	(0.1538)	(0.6218)
N	398	457	397
BW	8.2	9.9	8.5

Notes: See Table 2. Outcomes are village distance to nearest public good (kilometers)

Table C.3: International Migration (Commune)

	(1)	(2)	(3)	(4)
$\mathbb{1}$ SW	0.11	0.07	-0.21	-0.09
	(0.10)	(0.13)	(0.13)	(0.19)
N.	87	87	87	87
Effective N.	87	87	21	21
Bandwidth	-	-	7.46	7.46

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

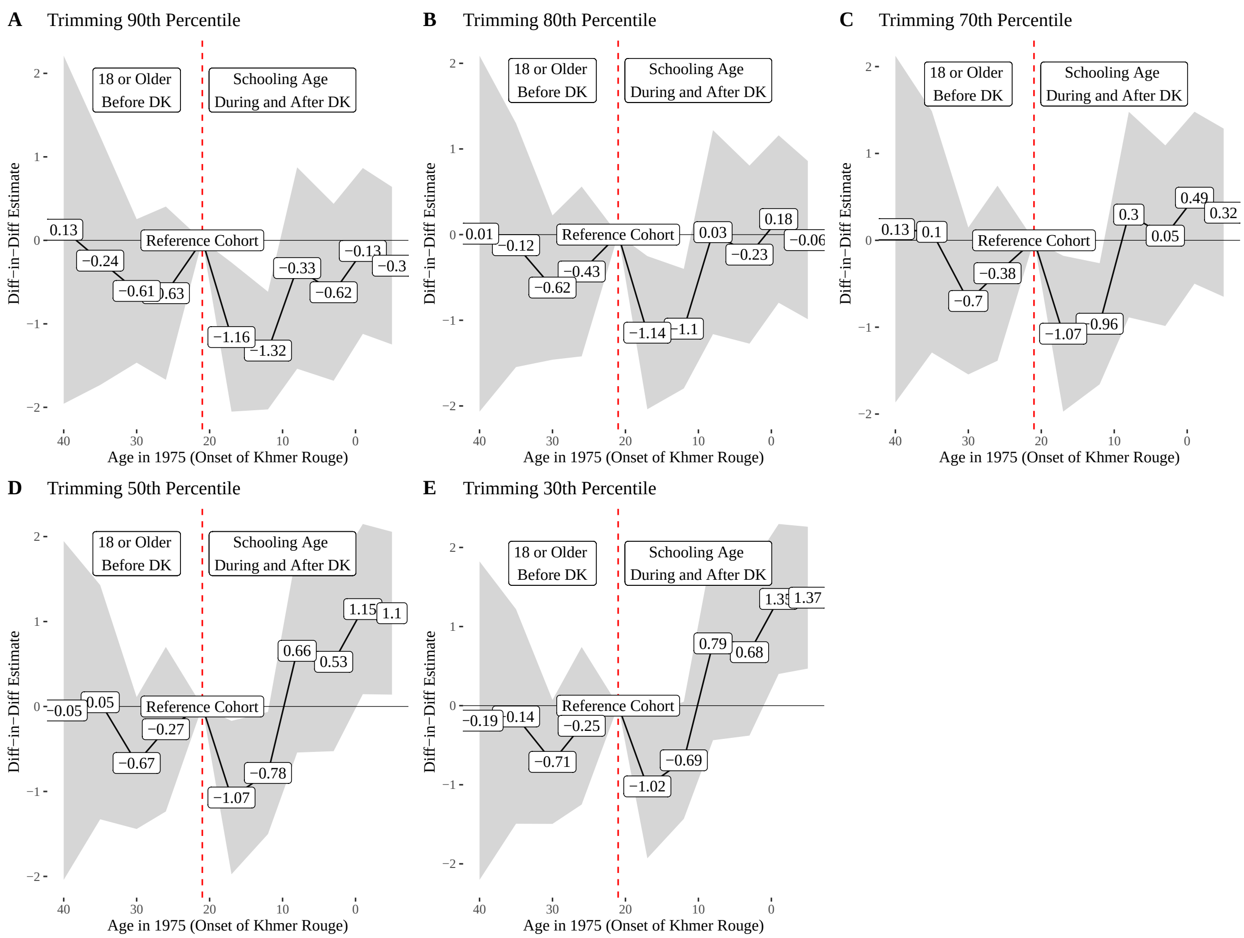
Robust standard errors reported in parentheses. Distance to boundary and its interaction with SW omitted from table for space. Outcome is the share of the population that is international migrants per commune.

Table C.4: Results from Trimming: Wealth

	(1)	(2)	(3)	(4)	(5)	(6)
$x\%$	95	90	85	80	75	70
$\mathbb{1}$ SW	-0.26***	-0.25***	-0.22***	-0.18***	-0.14**	-0.09
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)
BW	9125.75	9191.93	9307.24	9764.86	10200.60	11031.62
Total N	13100	13063	12936	12733	12505	12280
Effective N	3152	3138	3103	3148	3352	3388

Note: Outcome is DHS wealth data. Each column drops a percentile of top wealthiest persons in the West zone - e.g. Column (1) drops the top 5% wealthiest from the West zone and retains the bottom 95%, Column (2) drops the top 10% and retains the bottom 90%, ect.

Figure C.1: Event Studies Trimming Upper Education Percentiles



Note: Robust errors clustered at the village. Each panel drops top percentile of schooled persons from the West zone.

D Human Capital Mechanism: Online Appendix

Table D.1: Human Capital in 1998: Years of Schooling and Attendance

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Yrs Educ.				Attendance Rate			
SW	-1.1^{**}	-0.58	-1.1^{*}	$-0.69^{\dagger}$	-6.02^{**}	-4.64^{*}	-7.79^{**}	-3.42
	(0.41)	(0.39)	(0.43)	(0.38)	(2.15)	(2.16)	(2.43)	(2.29)
Effective N	312	285	442	439	355	313	597	476
Bandwidth	5.78	4.85	9.87	9.66	7.13	5.85	14.27	10.78
μ Control	4.16	4.16	4.16	4.16	30.07	30.07	30.07	30.07
σ DV	1.9	1.9	1.9	1.9	12.8	12.8	12.8	12.8
Segment FE	-	✓	-	✓	-	✓	-	✓
Dist. Capital Covariate	-	✓	-	✓	-	✓	-	✓
Linear	✓	✓	-	-	✓	✓	-	-
Quadratic	-	-	✓	✓	-	-	✓	✓

Note: Yrs. Educ. is the average years of education in a village. Attendance Rate is the share of persons who are enrolled in school below 25 (i.e. schooling aged). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table D.2: Human Capital in 1998: Adjusting for Distance to Schools

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Literacy Rate		% No Educ.		Yrs. Educ.		Attendance Rate	
$\mathbb{1}$ SW	-4.94^{*}	-5.62^{*}	4.23^{*}	5.15^{*}	$-0.62^{\dagger}$	-0.76^{*}	-5.14^{*}	$-4.21^{\dagger}$
	(2.44)	(2.71)	(2.11)	(2.41)	(0.37)	(0.37)	(2.08)	(2.3)
Effective N	302	424	313	430	286	436	313	451
Bandwidth	5343.89	9249.23	5847.32	9352.39	4860.19	9592.27	5843.17	10170.76
μ Control	62.88	62.88	50.48	50.48	4.16	4.16	30.07	30.07
σ DV	17.03	17.03	14.85	14.85	1.9	1.9	12.8	12.8

Note: Literacy Rate is the percentage of persons over 15 who can read write. % No Educ. is the percentage of people who have no schooling. Yrs. Educ. is the average years of education in a village. Attendance Rate is the share of persons who are enrolled in school below 25 (i.e. schooling aged). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table D.3: School Outcomes

School Outcome	Staff/Student Ratio				Students Per Classroom			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$ Southwest	-0.28	-0.15	-0.30	-0.22	-0.38	-1.33	-2.89	-4.43
	(0.35)	(0.42)	(0.51)	(0.59)	(2.32)	(2.71)	(3.65)	(3.74)
N	495	495	495	495	495	495	495	495
Polynomial	-	✓	-	✓	-	✓	-	✓
Segment FE	-	-	✓	✓	-	-	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Robust standard errors reported in parentheses. Data collected at the school level. Staff/student ratio is the number of employees in the school divided by the number of students. Students per classroom is the number of students divided by the number of rooms in the school.

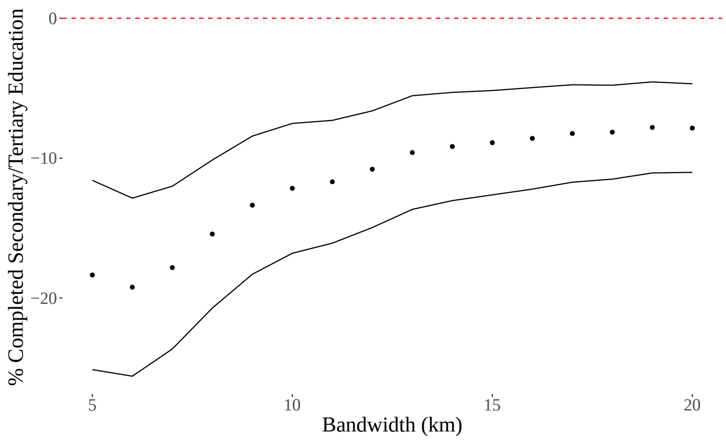
Table D.4: Schooling Persistence: 2008 Census

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attendance Rate		Yrs. School		Literacy Rate		% No Educ.	
SW	-1.61	$-2.25^{\dagger}$	-0.13	-0.24	-1.29	-2.27	-0.82^{**}	-1.15^{*}
	(1.24)	(1.23)	(0.12)	(0.15)	(1.89)	(2.18)	(0.3)	(0.47)
Effective N	336	612	294	391	358	569	405	710
Bandwidth	6.48	14.11	5.03	8.04	7.17	12.8	8.49	17.1
μ Control	29.77	29.77	5.16	5.16	75.04	75.04	1.18	1.18
σ DV	6.46	6.46	0.65	0.65	14.07	14.07	2.13	2.13

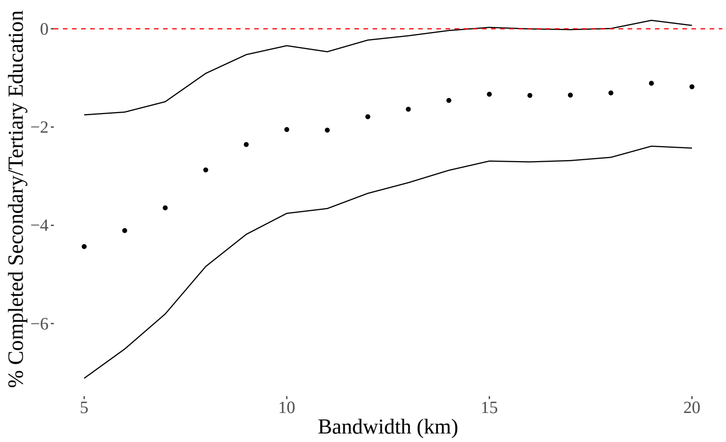
Note: Unit of analysis is the village. SHAC standard errors reported in parentheses.

Figure D.1: Tertiary and Secondary Education (All Data)

(a) Tertiary and Secondary Education



(b) Tertiary and Secondary Education (Dropping Outliers)



Notes: Parametric RD estimates at alternative bandwidths. Panel A shows results using all villages. Panel B shows results where outlying positive observations (highly educated villages) are dropped from the analysis. Horizontal axis reports different evaluation bandwidths. SHAC standard errors used to construct 95% confidence bands.

Table D.5: Education Differences by Gender: 1998 Census

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Males	%No Educ. Males				Lit. Rate Males			
SW	6.83^{**}	$3.98^{\dagger}$	$4.31^{\dagger}$	3.77	-5.49^{*}	-3.23	-5.86^{*}	$-4.59^{\dagger}$
	(2.23)	(2.06)	(2.39)	(2.38)	(2.25)	(2.13)	(2.66)	(2.49)
Effective N	320	311	624	452	317	321	528	435
Bandwidth	6157.66	5758.35	15246.56	10249.45	6003.24	6214.12	11983.37	9554.23
B: Females	%No Educ. Females				Lit. Rate Females			
SW	8.33^{**}	3.81	8.35^{**}	$4.95^{\dagger}$	-9.41^{**}	-4.53	-10.82^{**}	$-6.4^{\dagger}$
	(2.77)	(2.49)	(2.95)	(2.77)	(3.18)	(3.15)	(3.7)	(3.42)
Effective N	306	312	507	434	309	279	413	412
Bandwidth	5526.79	5808.96	11714.12	9432.27	5632.18	4690.57	8993.07	8951.34
C: Gap	%No Educ. Gender Gap				Lit. Rate Gender Gap			
SW	$3.33^{\dagger}$	1.64	$3.8^{\dagger}$	2.48	-1.38	-1.2	-1.52	-1.51
	(1.97)	(1.94)	(2.13)	(2.06)	(0.85)	(0.89)	(1)	(0.97)
Effective N	310	314	447	460	440	417	611	668
Bandwidth	5658.08	5893.41	10076.75	10401.42	9786.66	9125.82	14902.86	16266.69

RD estimates using education by gender as the outcomes of interest. Panel A studies the rates of no education and literacy by males, and Panel B by females. Panel C studies the gender gap in these outcomes, defined as the difference between human capital rates by group. Overall, I find little to no evidence of differential gender effects.

Table D.6: Placebo Tests: Cohort Analysis

	(1)	(2)	(3)	(4)
SW $\times$ $\mathbb{1}$(DK age <= 35)	-0.49			
	(1.37)			
SW $\times$ $\mathbb{1}$(DK age <= 30)		-0.58		
		(0.81)		
SW $\times$ $\mathbb{1}$(DK age <= 25)			0.13	
			(0.66)	
SW $\times$ $\mathbb{1}$(DK age <= 20)				0.42
				(1.08)
N.	537	537	537	537
SD DV	3.5	3.5	3.5	3.5
Village FE	✓	✓	✓	✓
Commune by Decade FE	✓	✓	✓	✓
Gender FE	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Village clustered errors reported in parentheses. Outcome is the years of schooling. Sample is individuals who were over 18 years old in 1975, meaning they would have completed schooling before the DK regime began.

Table D.7: Child Health Between Zones by Maternal Education Level

Outcome	(1) Health Index	(2) Height/Age	(3) Weight/Age	(4) Weight/Height
	Panel A: Mothers with No Education			
$\mathbb{1}$ SW	-2.52^{***}	-0.73	-1.74^{**}	-2.77^{***}
	(0.73)	(0.85)	(0.53)	(0.44)
	$[0.97]^{*}$	[0.80]	$[0.69]^{*}$	$[0.54]^{***}$
Bandwidth	12.90	9.32	13.33	9.57
N. Individuals	73	65	73	59
N. Clusters	27	25	27	21
	Panel B: Mothers with Education			
$\mathbb{1}$ SW	-0.30	0.11	-0.22	-0.90^{***}
	(0.40)	(0.22)	(0.29)	(0.15)
	[0.36]	[0.19]	[0.27]	$[0.42]^{*}$
Bandwidth	15.97	10.25	15.56	10.565
N. Individuals	233	184	232	160
N. Clusters	38	29	37	24
Controls	✓	✓	✓	✓
SD DV	1.38	1.26	0.99	0.98

Note: Unit of analysis is the 3-5 year old individual from the 2000-2014 DHS survey waves - the children of the generation exposed to the Khmer Rouge. Health index (Column 1) is the first principal component of individual health measures. Height/Age is the standard deviations from the median of individual height for age (stunting), Weight/Age is standard deviations from the median of weight for age (wasting), Weight/Height is standard deviations from the median of weight for height (underweight). Analysis within rural households to maximize comparability. Controls include the age of the mother and its square and survey year fixed effects. Robust standard errors clustered at the survey area reported in parentheses. Panel A studies children with mothers without education. Panel B studies children of mothers with at least some education. Clustered standard errors, clustered by survey area, reported in parentheses. Wild cluster bootstrapped errors in brackets. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table D.8: Schooling, Self Employment, and Income

	(1) Self Employment	(2) Income	(3) Income
Years of School	-0.03^{***}		
	(0.00)		
Age	4.44^{***}	-0.19	1.64
	(0.42)	(0.92)	(1.72)
Age^2	-2.75^{***}	1.67^{*}	0.69
	(0.41)	(0.82)	(1.13)
Rural	0.09^{**}	-0.29^{***}	-0.24^{***}
	(0.03)	(0.06)	(0.07)
Female	0.00	-0.02	-0.00
	(0.03)	(0.05)	(0.06)
Self Employed		-0.51^{***}	-0.86^{**}
		(0.06)	(0.28)
N.	975	975	975
Adj. R^2	0.23	0.11	0.09
Estimator	OLS	OLS	2SLS

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Labor Force Survey. Unit of analysis is employed working aged (11-59) individuals. Data from 2000-2001 Labor Force Survey. Pr(Self Employed) is scored 1 for persons who are own account workers. Income is individual wages, remuneration, earnings, tips reported from the last month in 10,000 riels, and productivity is riels divided by working hours.

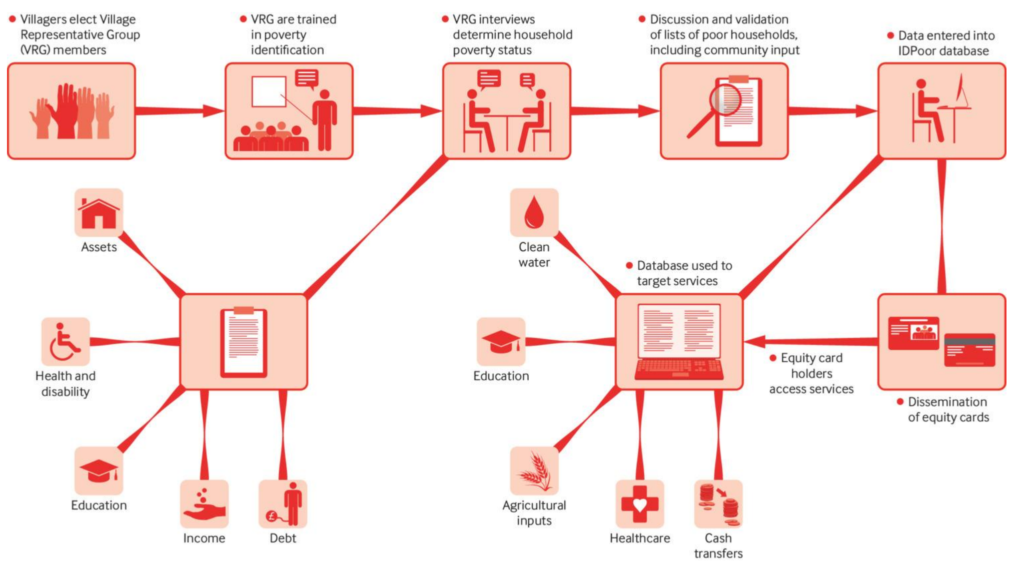
E Data: Dataverse Only

E.1 IDPoor

IDPoor provides a comprehensive measure of poverty in Cambodia. By combining household assets, education levels, and using community consultations, several dimensions of poverty are captured and validated (Kaba et al., 2018). For example, a measure of consumption alone may not account for individuals who consume the same amount but have different investments or assets.

IDPoor data collection process pictured in Figure E.1 from Kaba et al. (2018). Poor level 1 refers to the extreme poverty, with level 2 referring to poor. Those not in poverty are considered average by national standards or better off. By way of illustration, interviewers observe the building material of the roof of the household and score 8 it is made of soft materials (palm leaves or thatch), and 0 if its constructed with concrete. I measure the poverty rate of each village as the sum of households in category 1 or 2 divided by the total number of households to avoid capturing population differences.

Figure E.1: IDPoor Data Collection Process



Note: Flow chart downloaded from Kaba et al. (2018).

During the process of data collection, the Ministry of Planning (MOP) monitors the implementation of the process. Once a list of poor households is drafted, the list is published and open to the community to enable validation of the list (Kaba et al., 2018). Indeed, "World Bank assessment determined that, on average, surveyed households rated the accuracy and implementation of the IDPoor process as high" (Kaba et al., 2018).

E.2 Spatial Data

Mean Temperature: Average temperature per grid cell from 1970-2000 Fick and Hijmans (2017)
Seasonality Temperature: Standard deviation temperature between months times 100 Fick and Hijmans (2017)
Mean Precipitation: Average annual precipitation Fick and Hijmans (2017)
Coefficient of Variation: Average divided by standard deviation Fick and Hijmans (2017)
Elevation: Sea level elevation Farr et al. (2007)
Ruggedness: Standard deviation of elevation from Shaver, Carter and Shawa (2019)
% Crop Land: Percentage of grid cell classified as crop land Shaver, Carter and Shawa (2019)
Distance to Roads: Distance to nearest road
Distance to Rivers: Distance to nearest river
Built up Area: Global Human Settlement Pesaresi et al. (2016)
Population 1975: Global Human Settlement Pesaresi et al. (2016)

E.3 Summary Statistics (Pretreatment Covariates)

Table E.1: Summary Statistics (Spatial Data)

Zone	West			Southwest		
Variable	N	Mean	SD	N	Mean	SD
Temp. Mean	1427	272.273	4.049	1442	271.055	3.709
Temp. Var	1427	957.353	68.899	1442	903.258	61.999
Prec. Mean	1427	1458.876	180.991	1442	1442.967	183.759
Prec. Var	1427	67.214	1.884	1442	65.807	2.266
Forest Land	1427	0.741	0.427	1442	0.648	0.463
Crop Land	1427	0.067	0.239	1442	0.087	0.266
Soil Fertility	1427	0.432	0.46	1442	0.369	0.46
Ruggedness	1427	41.919	75.132	1442	75.949	111.381
Elevation	1427	73.708	72.288	1442	89.318	64.537
River Density	1427	214.766	618.628	1442	170.083	561.766
Road Density	1427	231.913	633.369	1442	353.749	779.167
Population (1975)	1427	68.14	365.967	1442	105.304	457.868
Built-up Area (1975)	1427	0.31	3.798	1442	0.136	0.989

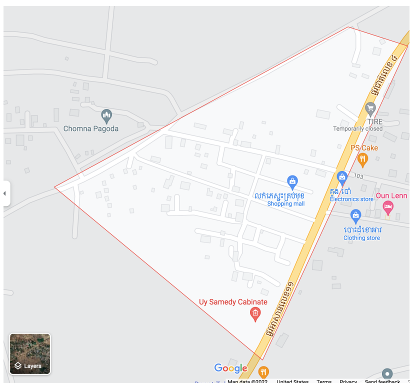
E.4 National Road 4: Google Maps Street View

Figure E.2: National Road 4 (Asian Highway 11) Street View in Kampong Speu

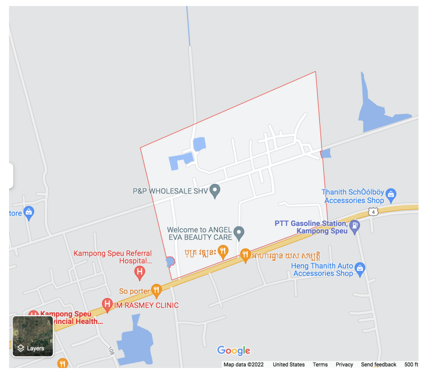
Note: Google Maps Street View of the highway (National Road 4, also known as Asian Highway 11) that separated the former West and Southwest zone. West zone shown on the left, Southwest zone shown on the right.

Figure E.3: Example Border Villages

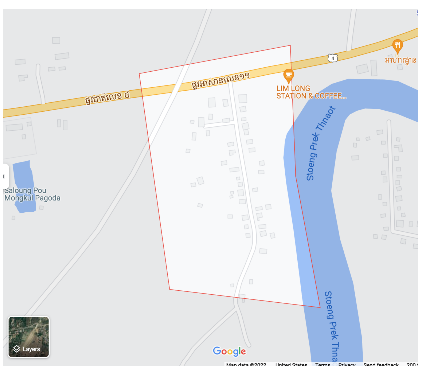
(a) Village A



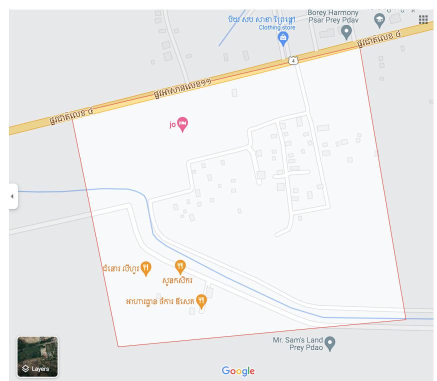
(b) Village B



(c) Village C



(d) Village D



Notes: Illustration of village polygons and their relationship to National Road 4 (the defunct border during the DK era). The maps show that in instances where village borders technically pass the road, villagers still tend to cluster towards the center, meaning classical measurement error of exposure to treatment is unlikely to significantly impact the main results.

E.5 Excess Mortality Plot

Exact mortality estimates from the Khmer Rouge are impossible to obtain due to the absence of administrative records. Despite the fact exact mortality counts cannot be computed, I obtain estimates of estimated mortality to construct a relative estimate of excess mortality overtime between Southwestern and Western Kampong Speu. I follow De Walque (2006) and use the 2000 Demographic Health Survey questionnaire, which asks respondents about (1) their siblings demographic information and (2) the year their siblings died. Notably, the data I use will only record the sibling deaths of those who survived to the year 2000. As such, estimates cannot be taken as absolute levels. However, assuming women's survival probabilities were roughly equal between zones within the province - a reasonable assumption given the excessive targeting of men - one can make a conjecture about the relative intensive of violence overtime between places using the DHS data.

Since the data contain the year siblings died, one can plot deaths over time between spaces. However, death does not necessarily mean Khmer Rouge inflicted mortality, since some siblings may have been more likely to parish for demographic reasons irrespective of regime change. To account for this, I develop a model of mortality based on age, age squared, location of residence (urban/rural), and gender. The logistic regression is as follows.

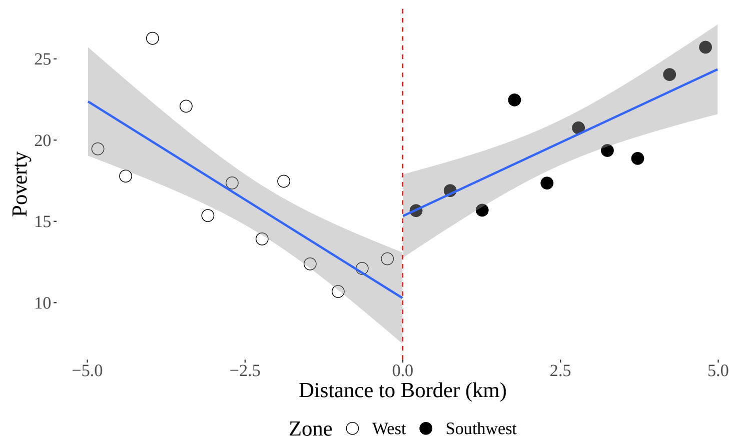
$$Pr(Y_{it} = Dead|X_{it}) = \frac{\exp(\alpha_0 + \alpha_1 Gender_i + \alpha_2 Age_{it} + \alpha_3 Age_{it}^2 + \alpha_4 \mathbb{1}Urban_i)}{1 + \exp(\alpha_0 + \alpha_1 Gender_i + \alpha_2 Age_{it} + \alpha_3 Age_{it}^2 + \alpha_4 \mathbb{1}Urban_i)}$$

I estimate the model on all siblings from the 2000 DHS survey round who were born at least before 1960 *outside* of Kampong Speu. I estimate the model outside of the province of interest to avoid overfitting. Then, I use the estimated coefficients to predict individual mortality overtime in Kampong Speu using siblings values of the predictor variables. The difference between actual mortalities in a zone-year from predicted mortality in a zone-year represents excess mortality in the zone - that is, deaths which occurred which were not predicted by an individual's demographic traits.

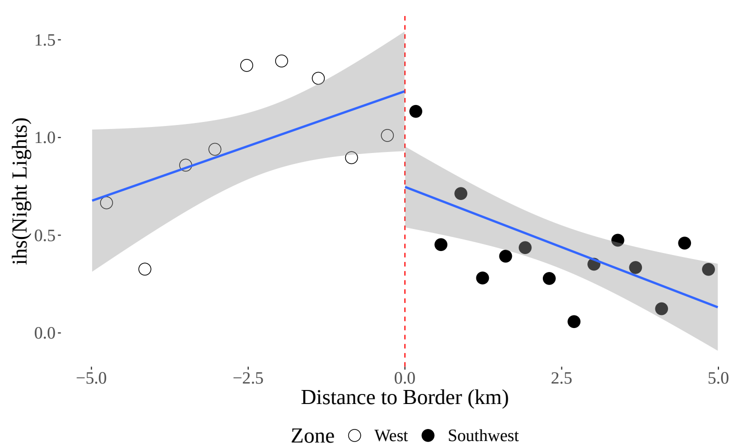
E.6 One-Dimensional RD Plots: Baseline Development

Figure E.4: One-Dimensional RD Plots: Baseline Development

(a) Poverty



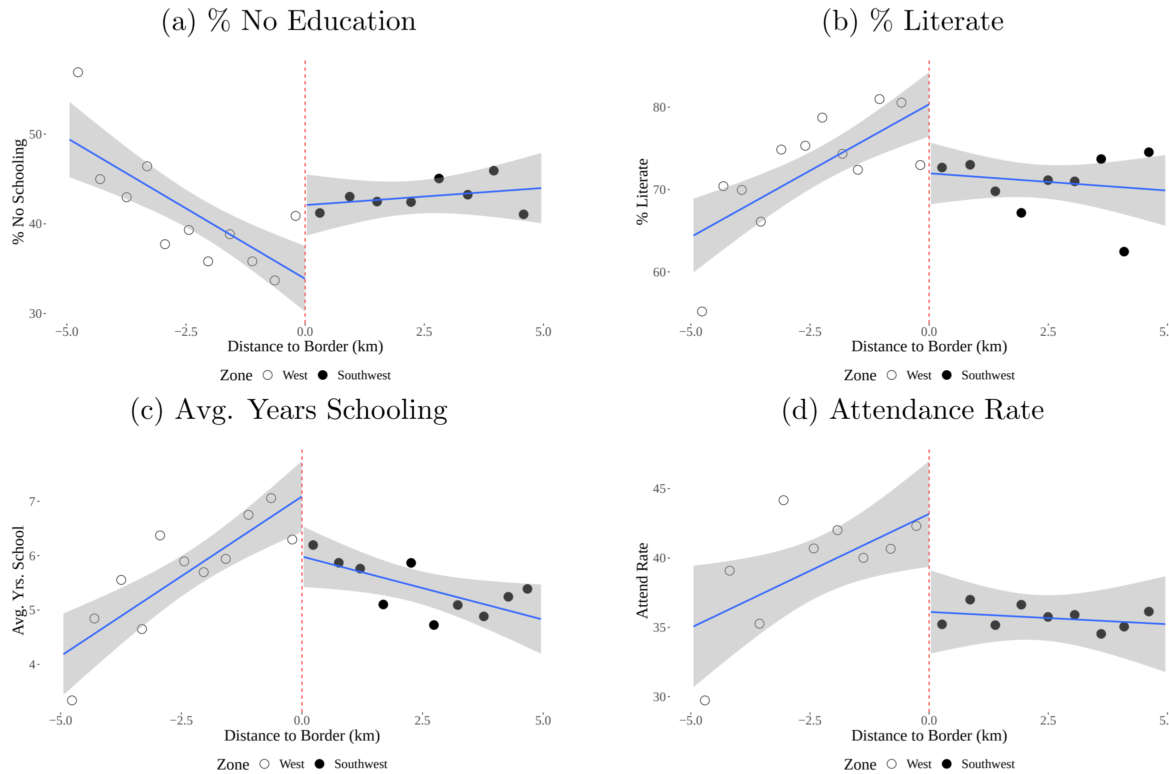
(b) Nighttime Lights



Notes: RD plots illustrating local linear regressions within a 5 kilometer bandwidth. Vertical dashed line marks 0; observations to the right are in the Southwest zone and observations to the left of the line are in the West zone. Dots represent binned averages.

E.7 One-Dimensional RD Plots: Human Capital

Figure E.5: Human Capital: 1998 Census

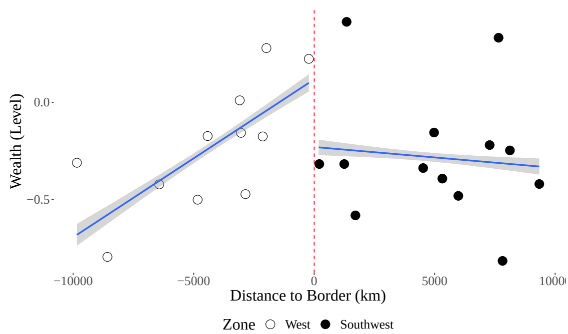


Notes: RD plots illustrating local linear regressions within a 5 kilometer bandwidth. Vertical dashed line marks 0; observations to the right are in the Southwest zone and observations to the left of the line are in the West zone. Dots represent binned averages.

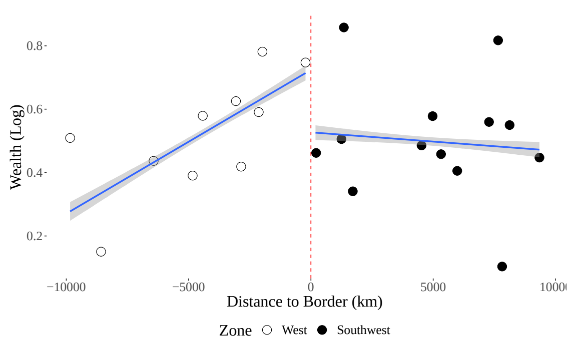
E.8 One-Dimensional RD Plots: Wealth

Figure E.6: One-Dimensional RD Plots: Rural DHS Wealth

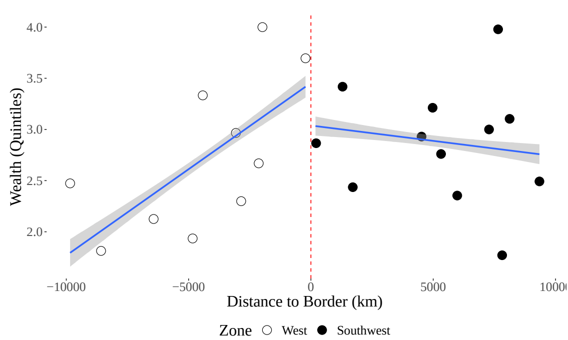
(a) Levels



(b) Logarithm



(c) Quintiles

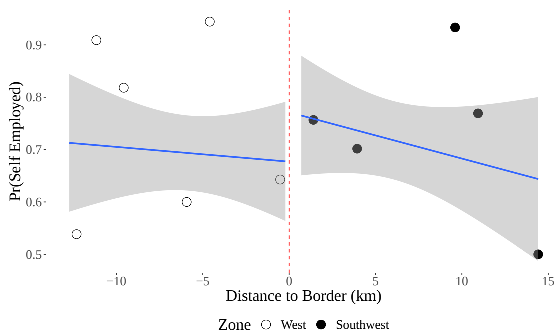


Notes: RD plots illustrating local linear regressions within a 10 kilometer bandwidth. Vertical dashed line marks 0; observations to the right are in the Southwest zone and observations to the left of the line are in the West zone. Dots represent binned averages.

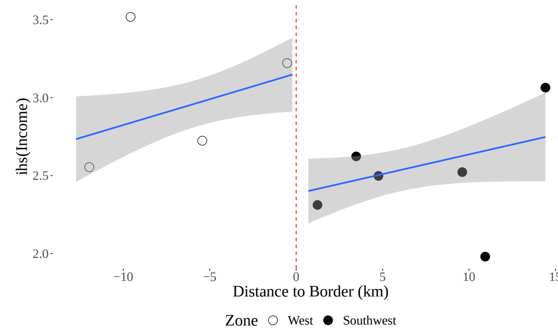
E.9 One-Dimensional RD Plots: Labor Markets

Figure E.7: Labor Force Survey (LFS) Labor Market Outcomes

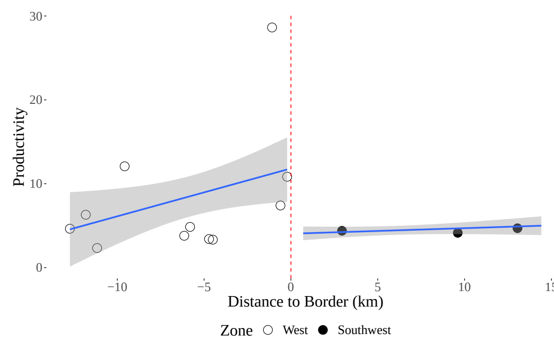
(a) Self Employment



(b) Income from Work



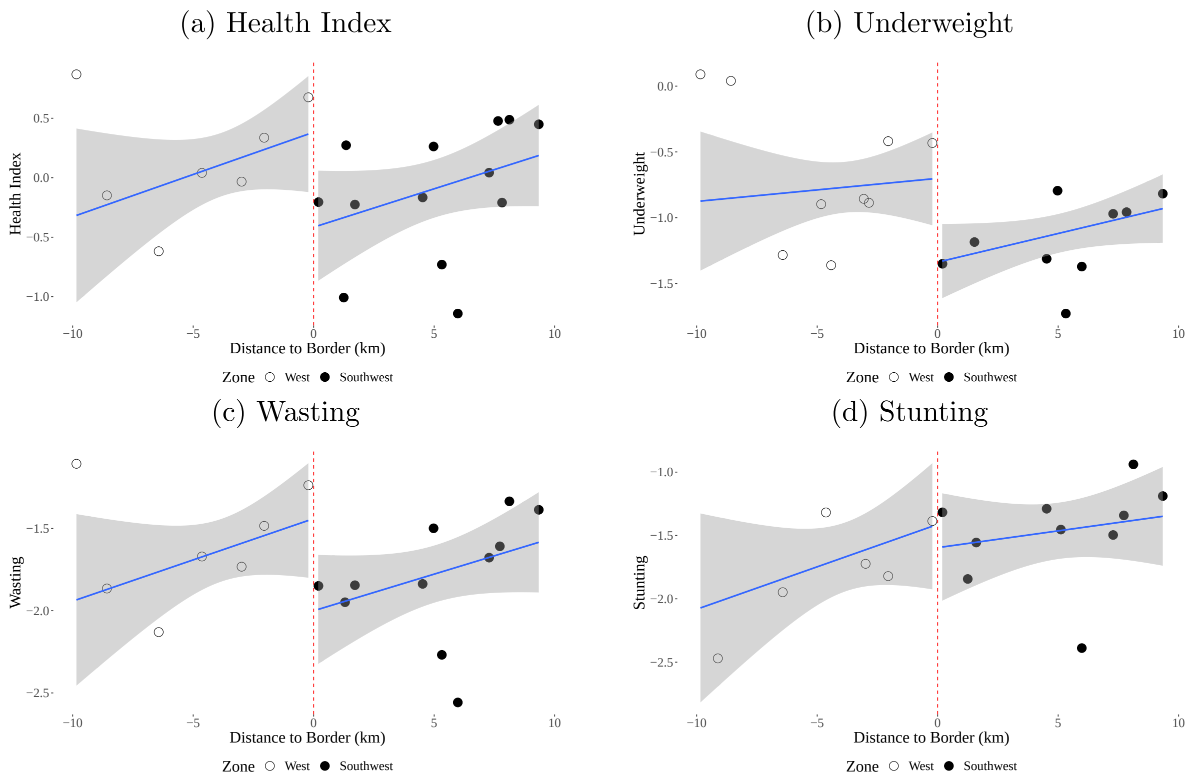
(c) Productivity



Notes: RD plots illustrating local linear regressions within a 10 kilometer bandwidth. Vertical dashed line marks 0; observations to the right are in the Southwest zone and observations to the left of the line are in the West zone. Dots represent binned averages.

E.10 One-Dimensional RD Plots: Health

Figure E.8: DHS Rural Child Health



Notes: RD plots illustrating local linear regressions within a 10 kilometer bandwidth. Vertical dashed line marks 0; observations to the right are in the Southwest zone and observations to the left of the line are in the West zone. Dots represent binned averages.

F Full Model Results

Table F.1: Full Model Results: Baseline Development Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%Poverty				IHS Luminosity			
$\mathbb{1}$ SW	4.53^{**}	4.43^{**}	5.81^{**}	4.96^{**}	-0.68^{***}	-0.69^{***}	-0.48^{*}	-0.64^{***}
	(1.66)	(1.68)	(1.91)	(1.88)	(0.16)	(0.16)	(0.23)	(0.19)
Border	-1.95^{***}	-2.22^{***}	-3.79^{***}	-3.51^{***}	0.14^{***}	0.17^{***}	0.16^{*}	0.27^{***}
	(0.38)	(0.39)	(0.70)	(0.76)	(0.02)	(0.02)	(0.07)	(0.04)
SW $\times$ Border	3.63^{***}	3.77^{***}	6.50^{***}	6.09^{***}	-0.19^{***}	-0.23^{***}	-0.35^{***}	-0.41^{***}
	(0.52)	(0.53)	(0.96)	(0.97)	(0.03)	(0.03)	(0.10)	(0.06)
Ln(Dist. Cap.)		1.27^{***}		1.20^{***}		-0.02		-0.02
		(0.28)		(0.26)		(0.03)		(0.02)
Border^2			-0.25^{***}	-0.22^{**}			0.00	0.01^{***}
			(0.07)	(0.08)			(0.01)	(0.00)
SW $\times$ Border^2			0.05	0.01			0.01	-0.00
			(0.09)	(0.10)			(0.01)	(0.00)
(Intercept)	11.05^{***}		8.99^{***}		1.27^{***}		1.28^{***}	
	(1.11)		(1.29)		(0.12)		(0.16)	
N. Villages	334	324	502	484	422	389	452	568
Segment FE	-	✓	-	✓	-	✓	-	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Results from Table 2 reproduced to show partial derivatives of adjusting covariates.

Table F.2: Full Model Results: Age Cohort Analysis

	Years of Schooling
Age	-61.87^{***}
	(13.57)
Age^2	-20.64^{*}
	(8.02)
Wave 2001	-1.05^{***}
	(0.13)
Female	-1.67^{***}
	(0.14)
SW × Age [-10, -5] in 1975	-0.17
	(0.53)
SW × Age [-5, 0] in 1975	-0.13
	(0.58)
SW × Age [0,4] in 1975	-0.50
	(0.54)
SW × Age [4,9] in 1975	-0.24
	(0.62)
SW × Age [10,14] in 1975	-1.32^{***}
	(0.36)
SW × Age [15,20] in 1975	-1.21^{**}
	(0.46)
SW × Age [21,25] in 1975	-0.64
	(0.61)
SW × Age [26, 30] in 1975	-0.38
	(0.51)
SW × Age [31,35] in 1975	-0.14
	(0.93)
SW × Age [36,40] in 1975	0.37
	(1.17)
N. Individuals	2285
N. Villages	71
Decade by Commune FE	Yes

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Results from Figure 5b reproduced to show partial derivatives of adjusting covariates.

Table F.3: Full Model Results: Human Capital: Education and Literacy in 1998

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%No Educ.				Lit. Rate			
$\mathbb{1}$ SW	7.58^{**}	3.49	7.39^{**}	4.46	-7.89^{**}	-4.85	-7.85^{*}	-5.46
	(2.47)	(2.22)	(2.66)	(2.53)	(2.66)	(2.63)	(3.09)	(2.90)
Border	-2.67^{***}	-2.63^{***}	-3.27^{***}	-4.18^{***}	3.02^{***}	3.34^{***}	3.83^{**}	4.69^{***}
	(0.60)	(0.51)	(0.78)	(0.97)	(0.65)	(0.69)	(1.18)	(1.18)
$\mathbb{1}$ SW $\times$ Border	3.00^{***}	3.38^{***}	3.64^{**}	4.83^{***}	-3.56^{***}	-4.23^{***}	-4.13^{*}	-5.16^{**}
	(0.84)	(0.72)	(1.10)	(1.35)	(0.91)	(0.96)	(1.65)	(1.68)
Ln(Cap.)		1.63^{***}		1.46^{***}		-1.45^{**}		-1.24^{**}
		(0.42)		(0.38)		(0.51)		(0.42)
Segment 1		22.32^{***}		24.69^{***}		-20.69^{***}		-25.20^{***}
		(4.20)		(3.35)		(5.12)		(3.73)
Segment 2		7.53^{***}		8.79^{***}		-6.39^{***}		-5.68^{***}
		(1.56)		(1.37)		(1.82)		(1.57)
Segment 3		0.80		0.94		-0.78		0.46
		(1.63)		(1.36)		(1.89)		(1.54)
Border^2			-0.16^{**}	-0.29^{**}			0.24	0.35^{**}
			(0.06)	(0.10)			(0.12)	(0.13)
SW $\times$ Border^2			0.22^{*}	0.35^{*}			-0.35^{*}	-0.48^{*}
			(0.09)	(0.14)			(0.17)	(0.19)
(Intercept)	34.60^{***}	19.83^{***}	34.44^{***}	19.70^{***}	80.04^{***}	93.76^{***}	80.15^{***}	92.13^{***}
	(1.77)	(4.04)	(1.91)	(3.84)	(1.90)	(4.86)	(2.20)	(4.30)
N. Villages	334	324	502	484	422	389	452	568
Segment FE	-	✓	-	✓	-	✓	-	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Results from Table 3 reproduced to show partial derivatives of adjusting covariates.

Table F.4: Labor Market Effects of Repression (Full Model Results)

	(1) Pr(Self Employed)	(2) IHS(Income)	(3) Productivity
$\mathbb{1}$ SW	0.12	-0.68^{**}	-8.67^{*}
	(0.07)	(0.24)	(4.17)
Border	-0.04^{***}	0.07	0.59
	(0.01)	(0.04)	(0.33)
Age	5.43^{***}	-4.27	-13.22
	(0.77)	(2.24)	(8.59)
Age ^{2}	-2.54^{***}	1.45	15.34^{*}
	(0.69)	(1.51)	(7.01)
Female	0.22^{**}	-0.06	1.33
	(0.07)	(0.18)	(1.06)
2000 Wave	0.11^{**}	-0.40^{*}	1.75
	(0.04)	(0.18)	(2.71)
SW $\times$ Border	0.04	-0.07	-0.51
	(0.02)	(0.04)	(0.31)
(Intercept)	0.42^{***}	3.46^{***}	10.77^{***}
	(0.03)	(0.18)	(2.08)
Effective N	235	285	411
Covariates	✓	✓	✓
SD DV	0.45	0.86	8.81

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Table 4 results from main text including the estimates and uncertainty for adjusting covariates.

Table F.5: Intergenerational Effects: Child Health Between Zones (Full Model Results)

Outcome	(1) Health Index	(2) Height/Age	(3) Weight/Age	(4) Weight/Height
$\mathbb{1}$ SW	-0.88^{***}	0.10	-0.59^{**}	-1.11^{***}
	(0.26)	(0.17)	(0.19)	(0.16)
Dist. Border	0.00^{*}	-0.00	0.00^{*}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
SW $\times$ Border	-0.00	-0.00	-0.00	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.14	-0.26	-0.11	0.07
	(0.17)	(0.16)	(0.12)	(0.11)
Age ^{2}	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
N. Individuals	243	298	243	195
N. Clusters	29	36	29	23
Bandwidth	11.05	11.55	11.21	9.34

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Table 5 results from main text including the estimates and uncertainty for adjusting covariates.

G Trimming Exercise Explanation: Dataverse Only

Migration immediately after - and during - the Khmer Rouge is an important factor to consider. The Khmer Rouge forced urbanities to move across the country. Within rural areas, villagers were forced into mobile work teams, which traveled around sectors (ie, within the administrative area directly below the zone level.) Since I investigate the legacy of the regime among villages within two sectors, the rural areas I focus may have moved during the regime, but would have moved within the geographic area of their treatment assignment (within the West or Southwest zones).

That being said, some degree of internal migration could explain the result giving movement that occurred due to displacement or flight. The choice to move occurs post-treatment for many residents: after the Khmer Rouge administered repression and strictly controlled internal migration, some citizens may have sorted after the regime in ways correlated with their treatment status.

Since movement occurs post-treatment, to estimate the impact of the Southwest Zone among residents who never moved, I adopt a principal stratification framework. Consider migration $\mathcal{M} = \{0, 1\}$ where 1 means an individual has migrated (ie, lives in a place that was not their original place of birth) and 0 means the individual is living in the place they have always lived and Z = $\{0, 1\}$ where 1 denotes being exposed to the (former) Southwest Zone, which I refer to as "treatment" for brevity. Finally, a respondent's residence $R_i = \{0, 1\}$ is 1 when the person lives in the former Southwest Zone and 0 otherwise.

As in Marbach (2021), we can define 4 principal strata based on these criteria using potential outcomes notation. Let $\mathcal{M}(0)$ denote migration status under control ($Z = 0$) and $\mathcal{M}(1)$ denote migration status when assigned to the Southwest Zone ($Z = 1$).

Table G.1: Principal Strata

Types	Exposure and (Potential) Migration
Always Moves (AM)	$\mathcal{M}(0) = \mathcal{M}(1) = 1$
Never Moves (NM)	$\mathcal{M}(0) = \mathcal{M}(1) = 0$
Moves if Treated (MT)	$\mathcal{M}(0) = 0, \mathcal{M}(1) = 1$
Stay if Treated (ST)	$\mathcal{M}(0) = 1, \mathcal{M}(1) = 0$

The four strata ($S = \{AM, NM, MT, ST\}$) and labels for their types are presented in Table G.1. Qualitatively, these types are as follows:

- Always moves (AM): migrate regardless of treatment status; individuals who would have been mobile irrespective of the intensive margin of repression they were exposed to. These individuals may have preferences, income, or social ties that would have pushed them to move no matter what the Khmer Rouge did.

- Never Moves (NM): never migrate, whether repressed more or less. These individuals may have strong social ties to their place of residence, or may face very high transaction costs for moving (i.e., the entire immediate family would also need to move, lack of a car makes transportation of goods difficult, fixed assets that could be sold may be insufficient to cover for expenses, barriers to entry to new labor markets, ect).
- Moves if Treated (MT): People that migrate, but were only pushed because of Khmer Rouge repression. These persons may have gone from the Southwest zone to the nearby West zone after repression to place themselves in a more ideal labor market.
- Stays if Treated (ST): these are persons who had plans to move, or would have migrated, but did not because the Khmer Rouge shocked them into place. This could occur if income shocks were so large that assets that were going to go towards migrating had to allocated towards other expenses. Given low rural-rural migration rates and strong traditional ties to place, this subgroup is likely to be fairly small in practice.

From here, we can break down different movement types into several types displayed in Table G.2.

Table G.2: Individual Respondents Stratified by Exposure Status (Z) and Current Residency (R)

		Zone Historically	
		0	1
Residency	0	MT & NM	MT & AM
Today	1	ST & AM	ST & NM

Assumption 1: No "Stays if Treated" (Monotonicity) $\mathcal{M}_i(1) - \mathcal{M}_i(0) \geq 0 \;\; \forall \;\; i = \{1, ..., N\}$**.**

Assumption 1 says there is no type that only wants to live in the Southwest if they are exposed to mass repression. The assumption is substantively motivated and likely to be satisfied in this context. Those that wanted to leave Cambodia often did, as evidenced by the mass migration outflows from the country in the lead up to the Khmer Rouge, and the devastation wrought by violence is not likely to be a pull factor persuading otherwise mobile civilians to stay after treatment. Likewise, it makes little sense to think of a person who was satisfied staying in their home village, and was only promoted to move into the Southwest zone because they were assigned *less* repression. As such, I assume individuals will either always move regardless of repression due to factors uncorrelated with treatment, will never move, again for reasons unaffected by treatment status, or will move if repressed.

Selective migration could explain the result of the following migration patterns occurred after the Khmer Rouge: suppose MT's left the Southwest Zone due to repression and poverty, and sought to relocate somewhere nearby that had impacted less by violence. They would likely pick the parts of Kampong Speu within the West Zone, since they have preexisting ties to the province. This could explain the result if the following assumption is true.

In support of Assumption 1, I report the rates of international migration by commune in both the West and Southwest. Table C.3 shows international migration rates are similar between zones. This evidence suggests that pull factors that may attract migrants are relatively equal by area, suggesting there is nothing about having been in the Southwest zone that would lead persons who would otherwise not move to relocate to the zone.

H Background Information: Dataverse Only

H.1 Zone Commanders

Mok (Chhit Choeun) was native to Takeo province in southwestern Cambodia, where he had helped lead an insurgency during the independence era, and at one point served under Sy before becoming a commander himself. Mok's rise to power placed him in direct competition with Sy, an older leftist who harbored less extreme views about the direction of the revolution. Mok promoted his family members - including his sons, daughters, and in-laws - in positions of power throughout the Southwest (Kiernan, 2008, p. 87). Mok was charged with purging party elites who were disloyal to the regime. He survived the regime, assisting in military leadership of the Khmer Rouge insurgency after Vietnam deposed the regime.

Sy (Chou Chet) had been a politically active leftist since the 1940s, participating in independence efforts against the French (Vickery, 1984, p. 129). Sy had been the secretary of the entire Southwest during the civil war (which included the Southwest and West during the DK regime) but was demoted in 1973 in favor of Mok (Kiernan, 1989).

Sy had pro-NVA opinions (Kiernan, 2008, p. 79) which had set him apart from more nationalist hardliners closer in Pol Pot's circle. During a CPK meeting in Kampong Speu, Sy's address stood out to audience members as he did not refer to the Vietnamese as enemies and spoke of providing housing for individual families (Kiernan, 2008, p. 390). Due to the Khmer Rouge's general hostility towards Vietnam, the remarks highlighted a contrast between the ideology of Chet and the rest of DK.

Chandler (2018) avers Sy revealed an earnest assessment of the Khmer Rouge's policy failures in the autobiography DK cadres forced him to concoct as a confession while jailed in S-21.

> [I said that] the current regime was a highly dictatorial one, too rigid and severe, one that overshot the comprehension and consciousness of the people. Therefore a lot of people were muttering and moaning about how they were doing a lot of work and getting little back for it, how they couldn't get together with their families, couldn't rest, never had any fun, and so on.

Although the passage is presented as a dialogue that was almost certainly fictitious, as the party forced the biography to be a confession of crimes including collaboration with the CIA and the Vietnamese, the remark is consistent with what was reported about Sy: he was a more moderate leader who was skeptical of the regime's brutal approach.

H.2 Educational System Before, During, and After DK

Cambodia inherited its contemporary educational system from French colonization (Ayres, 2000). The Cambodian educational system was expanding prior to the onset of the civil war and the Khmer Rouge regime. The national government dedicated a large share of the budget to education, and in 1969 the country boasted "3202 primary schools, 163 secondary schools, and nine universities" (Ayres, 1999).

When the Khmer Rouge took power, traditional teachers were targeted for purges. 90% of schools were destroyed (Clayton, 1998). Whereas the regime attempted to provide education, schooling was subordinate to labor and occurred in irregular settings, such as fields and stables. Teachers were not "new people," the regime instead favored "base people" as educators, who had little to no experience. Students lacked supplies due to general resource shortages during the DK period (Ayres, 1999). Within a year of the Khmer Rouge's downfall, school reopening was attempted. Vietnam focused on quantity rather than quality, which failed to address the dilapidated school infrastructure or limited teaching corps (Ayres, 2000, p. 148).

I Genocide Intensity: Dataverse Only

This section of the appendix presents indirect evidence that exposure to increased genocide intensity is correlated with contemporary development. I leverage data on the location of mass graves in Kampong Speu to construct a gravity-based measure of exposure to genocide. Then, I estimate the relationship between development (poverty and luminosity) and the intensity of genocide exposure instrumented by zone.

I.1 Measuring Genocide Intensity

The data on mass graves is from the Cambodia Genocide Program Geographic Database. The data was collected by a team of researchers who, through interviews with locals and archival documents, excavated mass graves during the DK era. The data include an estimated 1 million bodies and over 300 mass grave locations, with 16 of those locations residing in Kampong Speu. The Khmer Rouge era included deaths from other events, including a mass bombing campaign during the civil war. However, traditional Cambodian practices included cremation at the time, and many of those killed in bombings would have been incinerated. Cremation and other traditional practices were banned during the DK regime, meaning mass graves filled with bodies are most likely attributable to Khmer Rouge activity. Forensic evidence breaking down who in the graves were victims of execution versus other causes of death, such as starvation, is unavailable. Nonetheless, starvation was a DK tactic to cheaply eliminate political rivals - to the extent the data include both sets of deaths, it may still capture the degree of DK brutality (Etcheson, 2000).

Mass grave sites were almost always constructed near security centers - indeed, most are within a kilometer of a security center. Security centers were managed at the zone level, meaning the head of the each respective zone would have retained authority over who to send to these centers and what to do with them, including torture, re-education, release, or execution (Etcheson, 2000).

One concern with attributing a village's geographic proximity to mass grave sites to genocide intensity is population transfers that occurred during the DK regime. One may reasonably object that a village near a mass grave with hundreds of bodies may have had few residents of that village buried in the grave, since people were forced to migrate internally during the regime to perform forced labor. As such, my measure may contain some error.

A key advantage of my approach is that I study a very localized instance of the genocide, which allows me to circumvent this empirical problem. The Southwest zone was subject to a mass population transfer, but it was an outflow of residents towards the Northwest zone, which was considered the breadbasket of the regime (Kiernan, 2008, p. 390). To the extent the mass graves may measure genocide exposure with error, it is likely an underrepresentation in the Southwest zone, since residents forced to move to the Northwest zone may have died there instead of the Southwest.

Nonetheless, population movements occurred within zones overtime. The Khmer Rouge formed mobile work teams who would perform tasks within their zone to construct irrigation canals. A resident may therefore be buried within their zone, but could have been executed near a village that they were not from, and very far from their village of birth.

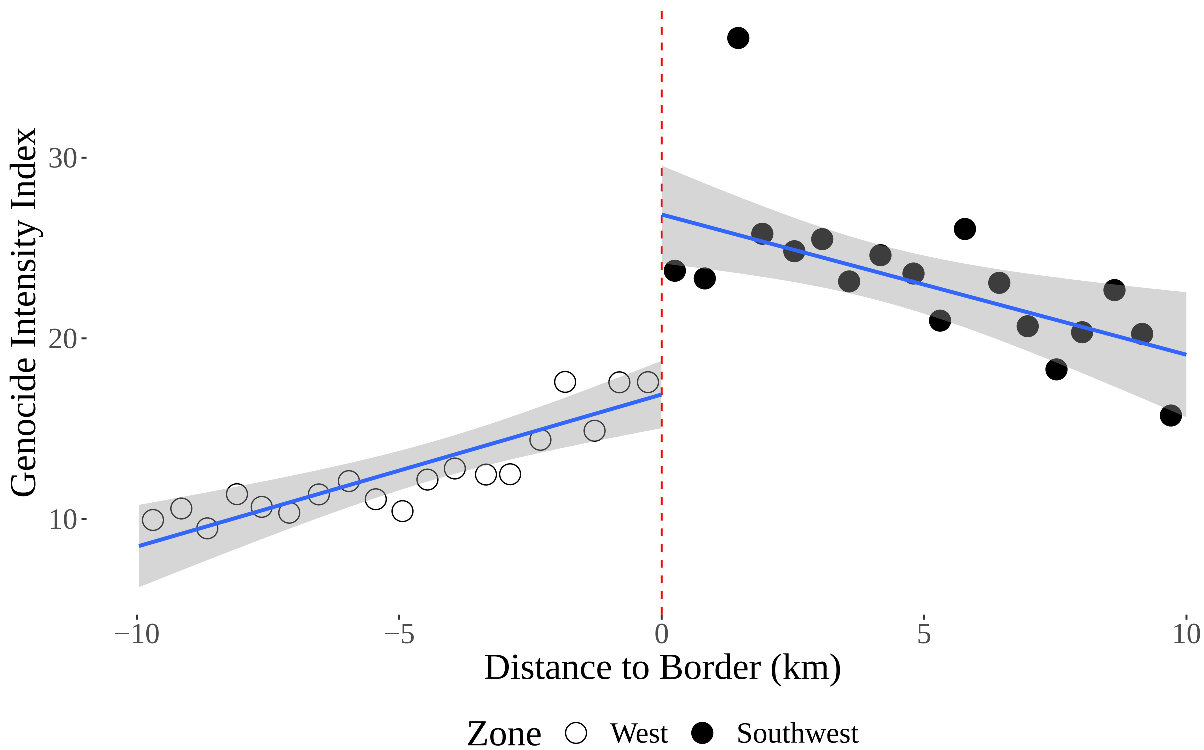
To address this issue, I adopt a gravity based measure of genocide exposure. The intuition behind the measure is that villages that are closer to more large mass graves were likely more exposed to mass killing themselves. The assumption is reasonable, since a villager living near a security center who was accused of some sort of wrongdoing could be sent to a security center to be executed at a lower cost compared to a village who was far from a prison.

$$\text{Genocide Intensity}_v = \sum_{j \in J_z} \left(1 + distance(\text{Village}_v, \text{Mass Grave}_j)^{-1} \times \frac{\text{Bodies}_j}{\sum_{j \in J_z} \text{Bodies}_j} \right)$$

First, I compute the distance between a village v and each mass grave j within the province/zone z. I add 1 to prevent very proximate mass graves from having excessive influence, and take the inverse of the quantity, so larger values represent being closer to a grave and smaller values representing more distance. Second, for each grave, I multiple this quantity by a weight which equals the proportion of total bodies in zone grave j holds. Third, I sum these values together for each mass grave to obtain a final measure of genocide intensity for each village. Finally, to ease interpretation, I scale the variable from 0-100 as follows.

$$\left(\frac{\text{Genocide Intensity}_v - min(\text{Genocide Intensity})}{max(\text{Genocide Intensity}) - min(\text{Genocide Intensity})} \right) \times 100$$

Figure I.1: Genocide Intensity in Kampong Speu Province

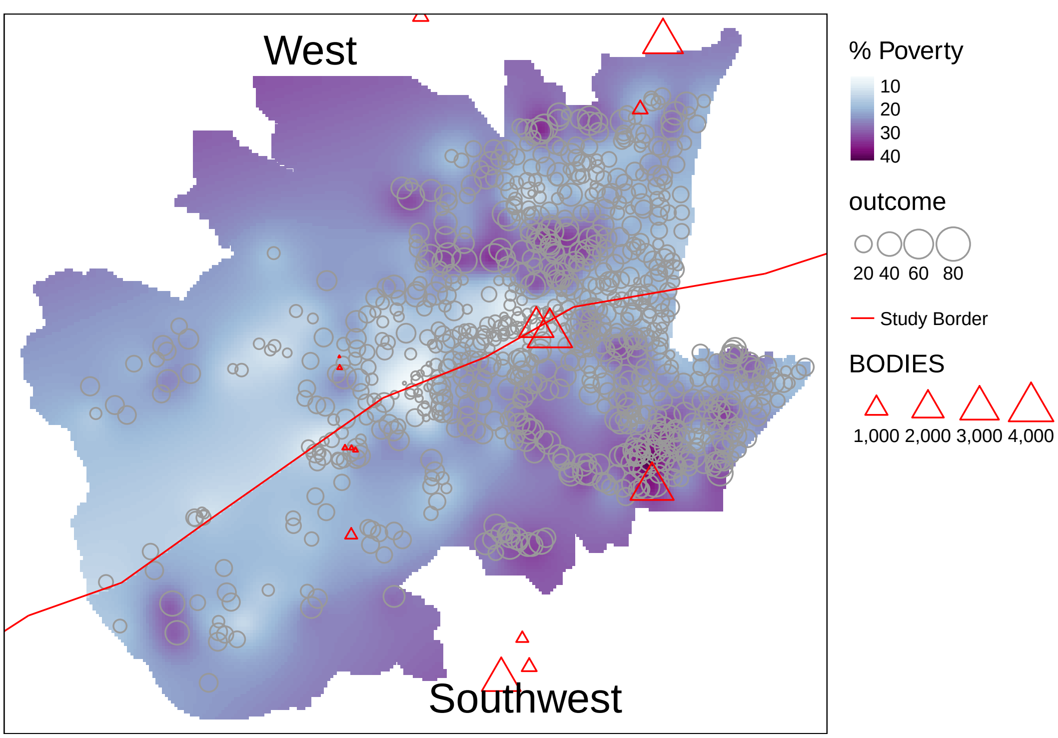


The measure represents a village's exposure to genocidal violence at the intensive rather than the extensive margin - we cannot gleam from the measure whether a village had executions or not, but it does capture the intensity of mass killing surrounding the village. While imprecise, population transfers outside of the Southwest suggest the measure will be biased against the hypothesized positive effect of the Southwest zone on genocide intensity. Another bias concern may be that the location of mass graves covary with distance to the capital. To partial out the distance to the capital, I adjust for this covariate in my estimates.

Figure I.1 plots the discrete increase in genocide intensity moving from the West to the Southwest zone.

Figure I.2 displays predicted poverty across space, actual poverty rates in 2011 at the village level, and the location and size of mass grave sites.

Figure I.2: Poverty and Mass Repression in Kampong Speu Province



Note: Dots are village locations, shaded regions are predicted values using ordinary kriging, Red line shows the border dividing the Southwest and West. Boxes with triangles are mass graves, sized to represent the estimated number of bodies found within them.

I.2 Estimating Genocide Intensity

One approach to unpacking the effect of genocide intensity and development would be regressing development directly on the measure of exposure. However, this will likely yield biased estimates. The location of mass graves was not randomly assigned; the Khmer Rouge disproportionately executed educated persons and former officials. This suggests that proximity to mass violence would be positively correlated with past development. If it was the case that genocide has a negative effect on development, and that places which were exposed more to genocide were more developed beforehand, one may recover a positive or zero coefficient from regressing development on repression due to the omission of unobservable, pre-DK factors.

To estimate the first order effect of zone assignment on genocide intensity, along with the influence of genocide intensity on development, I use the following two-staged least squares (instrumental variable) approach.

$$\text{Genocide Intensity}_{cv} = \alpha_c + \delta \mathbb{1}(\text{Southwest Zone}_{cv)} + \sum_{k=1}^{K} \zeta^k X_v^k + \varepsilon_{cv}$$

$$out_{cv} = \alpha_c + \beta \widehat{\text{Genocide Intensity}}_{cv} + \sum_{k=1}^{K} \zeta^k X_v^k + \eta_{cv}$$

The first stage estimates the impact of zone assignment on genocide intensity. The parameter δ captures the average difference between genocide intensity between the Southwest and the West, net of the K covariates X (distance to Chbar Mon and Phnom Penh). I include fixed effects for commune (α_c) which absorbs differences between administrative units and compares villages in a similar environment.

The second stage uses the predicted increase in genocide intensity to estimate the relationship between increased concentration of violence around a village and development. For both equations, standard errors are clustered at the commune, of which there are 87, to account for serial correlation induced by the fixed effects.

The key identifying assumption is zone assignment does not effect development through any channel outside of its effect on genocide intensity, after conditioning on covariates. While this assumption cannot be proven, it is reasonable in this context. As discussed in the main text, there is a dearth of qualitative evidence suggesting the zones differed along non-repression based dimensions.

Table I.1: Genocide Intensity Results

	Genocide Intensity	Household Poverty	Village Luminosity
$\mathbb{1}$(Southwest)	12.84***		
	(2.39)		
$\widehat{\text{Genocide}}$		0.33**	−0.04***
		(0.12)	(0.01)
N. Villages	1359	1359	1359
N. Clusters	87	87	87
Estimator	First Stage	2SLS	2SLS
SD DV	12.04	10.55	0.76
Commune FE	✓	✓	✓
Covariates	✓	✓	✓

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Models include commune fixed effects and covariatates adjusting for distance to Phnom Penh and Chbar Mon. Robust standard errors clustered at the commune reported in parentheses.

I.3 Genocide Intensity Results

Results reported in Table I.1 show villages in the Southwest zone experience a standard deviation increase in genocide intensity. The result corresponds with qualitative accounts that the Southwest zone was the "toughest sanctuary of the Khmer Rouge movement."

The 2SLS results show a similar pattern. Remarkably, a standard deviation increase in genocide intensity corresponds with a 3.9% increase in poverty, which is fairly close to the RD benchmark of 4.53% in the main text. The luminosity results trend in the same direction, albeit at a smaller magnitude than the RD results. Overall, the evidence suggests villages exposed more to the genocide by virtue of being in the Southwest zone are less developed today.

The results provide evidence consistent with the account that genocide exposure from the Southwest zone reduced contemporary economic development. If it was the case that the Southwest zone indicator was not correlated with genocide intensity, and that instrumented genocide intensity did not predict development, the argument in the paper would be implausible. Nonetheless, I caution that the result does not establish with certainty that repression directly causes poverty.

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