Terrorism and Regional Development: Evidence from Peru's Internal War

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Abstract

How do regions recover from civil conflict? This paper studies Peru's internal armed conflict (1980–2000), which claimed approximately 69,000 lives, using district-level census data spanning 36 years with a pre-conflict baseline. Conflict districts did not simply return to their pre-war state: their populations are 2–3 years younger, with elderly shares 2.4–3.3 percentage points lower, the mark of persistent cohort displacement. Human capital converged substantially, with the literacy gap narrowing by 66%. Economic activity shows extensive-margin catch-up, with conflict districts now more likely to have detectable night-time luminosity. Dominant-perpetrator estimates differ substantially, though imprecisely and with a specification-dependent literacy pattern: Sendero Luminoso areas show pronounced demographic restructuring and weak educational recovery, while state-violence areas show no significant mean-age or migration shift, lower dependency ratios, and strong literacy gains, consistent with Sendero's documented targeting of local authorities. Recovery is achievable, but the demographic transformation persists a generation later.

JEL Codes: D74, O15, O18, R11, J24

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1 Introduction

How do regions recover from sustained internal conflict? Beyond immediate casualties, war damages infrastructure, displaces populations, and disrupts schooling, yet the long-run consequences remain poorly understood. Do affected areas eventually recover, or do conflict shocks produce permanent divergence? What mechanisms drive recovery when it occurs: return migration, demographic replacement, or in-situ rebuilding? And does recovery in one dimension (population, education, infrastructure) translate into recovery in others (economic activity, living standards)?

This paper addresses these questions by examining Peru's internal armed conflict (1980–2000), one of Latin America's most destructive civil wars. The conflict between the Maoist insurgency Sendero Luminoso (Shining Path), the smaller Túpac Amaru Revolutionary Movement (MRTA), and Peruvian state forces claimed approximately 69,000 lives and forced approximately 600,000 people to leave their homes, generating large-scale internal displacement concentrated in the rural highlands (Comisión de la Verdad y Reconciliación, 2003, Anexo 2 and Tomo VI). The paper constructs a district-level panel spanning 36 years, from the 1981 pre-conflict census through post-conflict censuses in 1993, 2007, and 2017, to trace the full arc of demographic, human capital, and economic trajectories in conflict-affected areas.

Three main findings emerge. First, recovery took the form of demographic transformation. High-conflict districts show substantial population recovery by 2017, but the populations inhabiting these areas today are systematically different from their pre-conflict counterparts. Residents are 2–3 years younger on average, with elderly (65+) population shares 2.4–3.3 percentage points lower and elevated shares of youth and young working-age adults. This "missing generations" pattern, made up of the cohorts who experienced conflict as adults, persists a quarter-century after Guzmán's capture: through 2017, conflict had durably reshaped the demographic structure of these areas.

Second, there is substantial *human capital convergence*. The raw literacy gap between very-high-conflict and no/low-conflict districts (0–10 victims) narrowed from 10.1 percentage points in 1993 to 3.4 percentage points in 2017, a 66% reduction. Conflict districts also achieved substantial catch-up in basic infrastructure, with gains in sanitation and housing quality that outpaced the trend in comparison districts, though electricity access lagged for much of the period. This convergence reflects both compositional effects (younger populations have higher baseline education) and improvements in educational access during reconstruction.

Third, the paper documents *economic recovery with persistent demographic scars*. Using satellite-based night-time lights as an objective measure of economic activity, the analysis finds substantial convergence on the extensive margin: conflict districts are now more likely to have detectable economic activity than comparison districts, reflecting infrastructure expansion and electrification in formerly remote areas. Full-sample estimators put the remaining per-capita activity gap close to zero, far smaller than the deficits implied by analyses restricted to economically active districts, though its exact magnitude depends on the transformation used. The combination of demographic transformation, human capital gains, and economic catch-up indicates meaningful recovery, even as the "missing generations" represent demographic change that shows no sign of reversal through 2017.

These findings, however, require careful interpretation in light of spatial spillovers. The analysis reveals that non-conflict districts near the violence epicenter also experienced negative population effects, which suggests that the entire central-southern highlands suffered demographic disruption, not only districts with documented violence. The positive coefficients estimated for conflict districts therefore measure recovery against a comparison group that was itself negatively affected, not against an unaffected counterfactual. Conflict districts outperformed their neighbors in population terms. This relative recovery is consistent with reconstruction investment and post-conflict mobility, but the district aggregates do not identify the separate contributions of return migration, new settlement, mortality, and differential fertility. The regional disruption was broader than victim counts alone suggest, and the estimates may understate the total demographic impact of the conflict on Peru's highlands. Within-province comparisons sharpen this reading. The population recovery is specific to the directly affected districts and strengthens when they are compared only with their province neighbors, whereas literacy gains and demographic rejuvenation extend across the surrounding region as regional rather than district-specific phenomena.

Beyond these aggregate patterns, the paper documents substantial heterogeneity along several dimensions. The estimates suggest potentially important perpetrator heterogeneity: in dominant-perpetrator splits, districts where state forces were the dominant source of violence show significant educational gains with no significant shift in mean age or migration (though sharply lower dependency ratios), while Sendero-dominant districts experienced pronounced demographic transformation but weaker human capital recovery. This divergence reflects different violence modalities. Sendero's Maoist ideology demanded complete destruction of existing social structures. Its systematic targeting of teachers, local officials, and educated community members created lasting barriers to institutional recovery. State counterinsurgency, though brutal, was reactive and less directed at local authorities and social leaders. Conflict duration and intensity, by contrast, are tightly entangled: every very-high-conflict district experienced prolonged violence, so short, acute exposure does not occur at the highest intensities and duration effects cannot be separated from intensity effects in this setting. And initial development conditions shape trajectories: night-time lights reveal that initially less-developed conflict districts show a much smaller relative per-capita shortfall than initially more-developed ones, producing convergence within the set of affected communities.

This paper contributes to several literatures. Relative to work on the long-run effects of civil conflict, the 36-year horizon and pre-conflict 1981 baseline are a rare combination that separates genuine recovery from regression to the mean or cohort replacement. Studies typically observe outcomes 10–15 years after a conflict ends, whereas this paper shows that demographic distortions persist well beyond that horizon even as economic and educational indicators converge. On mechanisms, the finding of substantial population turnover implies that the human capital and social networks of displaced communities can be durably lost even when population counts rebound. Methodologically, the standard log transformation of night-time lights drops zero-luminosity districts, the poorest and most marginalized, and overstates economic gaps, which full-sample estimators shrink sharply (Chen and Roth, 2024). Finally, perpetrator identity may shape long-run outcomes alongside the violence intensity that most of the literature emphasizes.

The empirical strategy exploits the dramatic spatial variation in conflict intensity across Peru's nearly 1,900 districts. A difference-in-differences design compares high-conflict districts to less-affected areas, using 1981 (pre-conflict) as the baseline and tracking outcomes through 2017. District fixed effects absorb time-invariant characteristics, while year fixed effects and geographic controls interacted with time address concerns about differential trends. The census-based findings are validated using satellite night-time lights, which provide an objective measure of economic activity independent of administrative data collection quality.

The Peruvian context offers several advantages for studying long-run conflict effects. The conflict had a clear beginning (1980) and end (approximately 2000), allowing clean temporal delineation. Census data from 1981 establishes baseline conditions before large-scale violence began. The Truth and Reconciliation Commission (Comisión de la Verdad y Reconciliación, CVR) documented violence at fine geographic resolution, enabling precise measurement of conflict exposure. And the 36-year span of the data, covering pre-conflict, conflict, and extended post-conflict periods, allows observation of recovery trajectories that shorter panels would miss.

The remainder of the paper proceeds as follows. Section 2 provides historical background on Peru's internal conflict. Section 3 describes the data sources. Section 4 presents the empirical strategy. Section 5 reports main results on population, infrastructure, and human capital outcomes. Section 6 examines spatial spillovers and their implications for interpreting the baseline estimates. Section 7 analyzes demographic mechanisms and heterogeneity by perpetrator type and conflict characteristics. Section 8 presents the night-time lights analysis of economic recovery. Section 9 concludes with implications for research and policy.

2 Historical Background

Peru's internal armed conflict (1980–2000) represents one of Latin America's most devastating insurgencies, claiming approximately 69,000 lives according to the Truth and Reconciliation Commission (Comisión de la Verdad y Reconciliación, 2003, Anexo 2). The conflict pitted Maoist guerrillas against the Peruvian state, with rural indigenous communities bearing the brunt of violence from both sides. Understanding the origins, geographic patterns, and ultimate resolution of this conflict is essential for interpreting the long-run effects examined in this study.

2.1 Origins of the Conflict

The Shining Path (Sendero Luminoso) emerged from the provincial University of San Cristóbal de Huamanga in Ayacucho, one of Peru's poorest and most neglected departments (Degregori, 1990). Founded by philosophy professor Abimael Guzmán Reynoso in the late 1960s, the organization developed a rigid Maoist ideology that rejected both the Peruvian left's electoral strategies and the Soviet model in favor of protracted people's war modeled on the Chinese revolution (Palmer, 1994). Guzmán, who styled himself "Chairman Gonzalo," cultivated a personality cult and demanded absolute loyalty from followers (Stern, 1998).

The movement drew initial support from university students and teachers frustrated by Peru's persistent inequality and the failure of agrarian reform to transform rural livelihoods (McClintock, 1984). Ayacucho's isolation, both geographic and economic, created fertile ground for revolutionary mobilization. The department had among the highest poverty rates, lowest literacy levels, and weakest state presence in Peru (Degregori, 2010). When Shining Path launched its armed struggle on May 17, 1980, burning ballot boxes in the village of Chuschi on the eve of Peru's return to democracy, it did so in a region where the state had long been experienced primarily as an extractive and repressive force.

2.2 Geographic Patterns of Violence

The conflict's geographic footprint was far from random. Violence concentrated heavily in the central and southern highlands (Ayacucho, Huancavelica, Apurímac, Junín, and parts of Cusco and Puno) before spreading to other regions (Comisión de la Verdad y Reconciliación, 2003). Several factors explain this pattern. First, Shining Path deliberately targeted areas with weak state capacity, where small guerrilla columns could operate with relative impunity (Weinstein, 2007). Second, the organization exploited local grievances, particularly disputes over land, labor, and abusive local authorities (Stern, 1998). Third, the mountainous terrain of the central highlands provided natural refuge from military operations.

A clear correlation emerges between pre-conflict inequality and subsequent violence intensity. Figure 1 displays the geographic distribution of income inequality in 1981, measured before the conflict's escalation.[1] Figure 2 confirms the pattern at the district level: districts that would experience very high conflict intensity (>100 victims) had markedly higher baseline inequality than unaffected districts.

[1]The Gini coefficient is calculated from grouped income data where each observation represents an income value and the count of people earning that amount. Top-coded categories ("1,021 soles o más," etc.) are addressed by estimating a Pareto α parameter from the upper tail of the national distribution via OLS regression of log-survival on log-income, then imputing the conditional mean $E[Y|Y \geq \text{threshold}] = \frac{\alpha}{\alpha-1} \times \text{threshold}$. With imputed values in place, the Gini is computed using the Lorenz curve approach: sorting by income, calculating cumulative population shares (p) and cumulative income shares (L), then applying the trapezoidal rule to estimate the area under the Lorenz curve, where Gini $= 1 - 2 \times$ (Lorenz area). The estimated Pareto α was 2.86, yielding a multiplier of 1.54 for top-coded values. Coverage includes 22 of 25 departments (88%). Loreto, San Martín, and Apurímac are not covered in the 1981 census income tabulations used here.

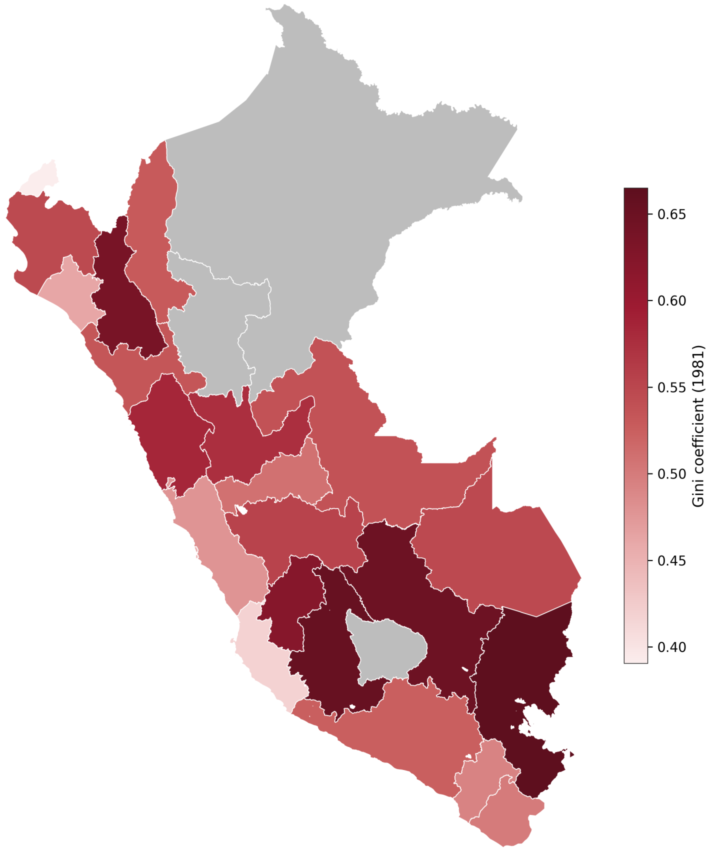


Figure 1: Pre-Conflict Income Inequality by Department, Peru 1981

Notes: Department-level Gini coefficients from grouped income data in the 1981 census. Gray areas (Loreto, San Martín, Apurímac) are not covered in the 1981 census income tabulations used here. See text for the Gini calculation methodology.

The overlap between poverty and inequality in pre-conflict Peru is pronounced. The five poorest departments (Cajamarca, Puno, Huancavelica, Ayacucho, and Cusco, all with mean incomes below 35 soles per capita) are also among the six most unequal, with Gini coefficients ranging from 0.63 to 0.67 (Table A1 in Appendix). Three of them, Ayacucho, Huancavelica, and Cusco, lie in the highland belt that would become the epicenter of Shining Path violence. In contrast, coastal departments exhibited both higher incomes and lower inequality: Tumbes (Gini 0.39), Ica (0.42), Lima (0.48), and Lambayeque (0.46).

The district-level patterns are equally clear (Table A2 in Appendix). The ten poorest districts are concentrated entirely in Ayacucho, Huancavelica, Cusco, and Puno, the departments that would experience the most devastating violence. Chuschi in Ayacucho, where Shining Path launched its armed struggle by burning ballot boxes on May 17, 1980, ranks among the ten most unequal districts in Peru (Gini 0.89), despite being among the poorest (mean income of just 6 soles per capita). This combination of extreme poverty and inequality in the conflict's birthplace reflects the social conditions that enabled revolutionary mobilization.

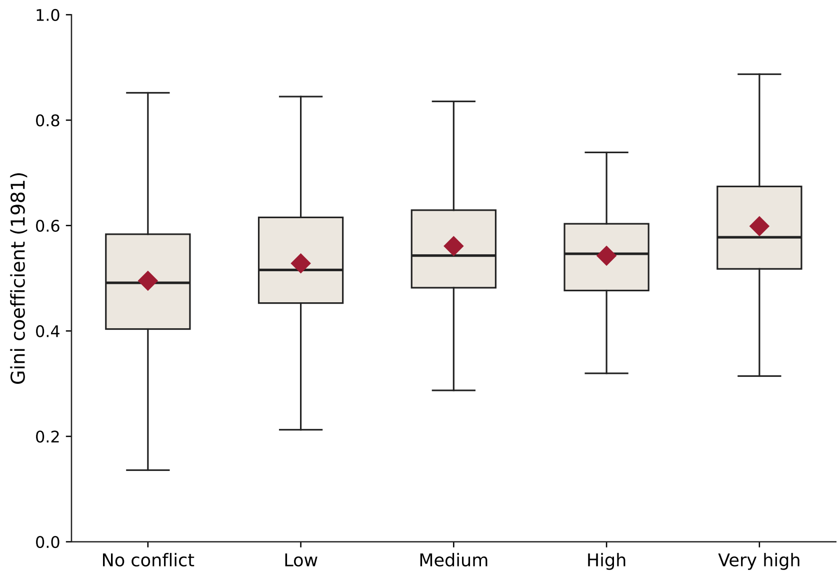


Figure 2: District Income Inequality by Subsequent Conflict Intensity

Notes: District-level Gini coefficients (1981) grouped by subsequent conflict intensity (CVR-documented victims, 1980–2000). Boxes show the interquartile range with the median, and cranberry diamonds mark group means. Categories: Low (1–10 victims), Medium (11–50), High (51–100), Very high (>100).

This correlation between inequality and violence, while not establishing causality, is consistent with theoretical accounts emphasizing grievance-based mobilization (Gurr, 1970). Shining Path's rhetoric explicitly targeted class enemies (landlords, merchants, local officials) and promised radical redistribution (Degregori, 1990). In highly unequal communities, such appeals may have found receptive audiences, or at minimum, populations unwilling to actively resist guerrilla presence. The correlation also reflects the overlap between inequality, indigenous identity, and historical marginalization: the same highland departments that exhibited high inequality were predominantly Quechua-speaking, had experienced centuries of exploitation under colonial and republican rule, and remained largely excluded from the benefits of modernization (Thorp and Bertram, 1991).

The conflict evolved through distinct phases (Comisión de la Verdad y Reconciliación, 2003). The initial period (1980–1982) saw Shining Path consolidate control in rural Ayacucho through a combination of political work and selective violence against perceived enemies. The militarization phase (1983–1989) began when the government declared emergency zones and deployed the armed forces, leading to massive human rights violations as both insurgents and counterinsurgents targeted civilian populations. The urban phase (1989–1992) brought car bombings and assassinations to Lima, culminating in the devastating Tarata bombing of 1992. Throughout, the conflict's epicenter remained the central highlands, though violence spread to the Upper Huallaga Valley (coca-growing region) and eventually metropolitan Lima.

2.3 State Response and Human Rights Violations

The Peruvian state's response to Shining Path was characterized by initial neglect followed by indiscriminate repression (Mauceri, 1995). President Fernando Belaúnde Terry (1980–1985) initially dismissed the insurgency as cattle rustlers or delinquents, allowing Shining Path to consolidate control over much of rural Ayacucho. When the military was finally deployed in December 1982, commanders implemented counterinsurgency strategies that treated entire communities as enemy combatants (Comisión de la Verdad y Reconciliación, 2003).

The declaration of emergency zones suspended constitutional rights and granted military commanders authority over civilian governance. In these areas, which eventually covered much of the highlands, arbitrary detention, torture, extrajudicial execution, and forced disappearance became routine (Burt, 2006). The military's failure to distinguish between guerrillas and civilians, compounded by linguistic barriers, cultural prejudice against indigenous populations, and pressure to produce results, generated massive civilian casualties. The CVR attributed approximately 37% of conflict deaths to state forces, alongside the 54% attributed to Shining Path (Comisión de la Verdad y Reconciliación, 2003, Anexo 2 and Conclusiones Generales).

The armed forces' abuses proved counterproductive, alienating communities that might otherwise have supported counterinsurgency efforts and providing Shining Path with recruitment opportunities (Degregori, 2010). Only in the late 1980s did the military begin developing more sophisticated approaches, including support for peasant self-defense patrols (rondas campesinas) that would prove central to eventual victory (Starn, 1999). These community-based organizations, armed and supported by the military but rooted in preexisting traditions of communal governance, provided an alternative to both Shining Path's authoritarian control and the state's distant and often abusive presence.

2.4 End of Conflict and Persistence

The conflict's turning point came on September 12, 1992, when a specialized police intelligence unit captured Abimael Guzmán in Lima (Roncagliolo, 2007). The arrest decapitated an organization built around Guzmán's cult of personality and ideological authority. Within months, much of Shining Path's leadership was imprisoned, and the organization fragmented into competing factions. Guzmán's subsequent call for peace negotiations from prison further demoralized remaining fighters (Comisión de la Verdad y Reconciliación, 2003).

The smaller Túpac Amaru Revolutionary Movement (MRTA), which had operated primarily in the central jungle and urban areas with a more conventional leftist ideology, also collapsed in the 1990s. Its final dramatic act, the seizure of the Japanese ambassador's residence in December 1996, ended with a military assault that killed all fourteen hostage-takers (Stern, 1998). By the late 1990s, organized insurgent activity had effectively ceased outside a few remote areas.

However, the conflict's legacy persists. The Apurímac, Ene, and Mantaro River Valleys (VRAEM) remain under emergency rule, with remnant Shining Path factions, now largely transformed into drug trafficking organizations, continuing low-level operations (Méndez and Granados, 2019). More broadly, the conflict left deep scars on affected communities: destroyed infrastructure, displaced populations, fractured social trust, and unresolved trauma (Theidon, 2013). The approximately 69,000 estimated deaths and disappearances represent only the most visible cost. The CVR documented widespread sexual violence, forced disappearance, and the destruction of entire communities. Three-quarters of victims were rural, Quechua-speaking, and poor, the same populations that had been marginalized before the conflict and would face the greatest challenges in recovery afterward (Comisión de la Verdad y Reconciliación, 2003).

3 Data

This study combines four data sources: population censuses spanning four decades, violence records from Peru's Truth and Reconciliation Commission, geographic characteristics, and satellite-derived night-time lights. The resulting panel tracks 1,677 districts across census years 1981, 1993, 2007, and 2017.

3.1 Population Census Data

The paper uses district-level data from Peru's four national population censuses conducted in 1981, 1993, 2007, and 2017 by the National Institute of Statistics and Informatics (INEI). The 1981 census provides the critical baseline. Although the Shining Path insurgency launched its armed struggle in May 1980 with attacks in Ayacucho, violence remained localized and small in scale until the conflict's militarization in 1983, so the 1981 census precedes the overwhelming majority of documented violence.[2] The 1993 census captures conditions shortly after the decisive turning point produced by Abimael Guzmán's capture in September 1992. The 2007 and 2017 censuses measure medium and long-run recovery.

From these censuses, the analysis constructs measures of population size, age structure, educational attainment, labor force composition, migration patterns, and linguistic identity. Age-specific population shares allow construction of dependency ratios and identification of demographic dividend dynamics. Educational variables include literacy rates and shares with primary, secondary, and higher education. Occupational data permit classification into high-skill, white-collar, manual, and elementary categories. Migration is measured as the share of residents born outside the district. Indigenous identity is proxied by mother tongue, distinguishing Quechua, Aymara, and other native language speakers from Spanish speakers.

District boundaries changed across censuses due to administrative redistricting. Boundaries are harmonized to 2017 definitions using INEI concordance tables, aggregating split districts and tracking merged units. This yields an unbalanced panel of 1,505 districts in 1981, 1,631 in 1993, 1,651 in 2007, and 1,677 in 2017, totaling 6,464 district-year observations. Table 1 summarizes the panel structure by year and conflict status.

Table 1: Panel Structure: Districts by Year and Conflict Status

	1981	1993	2007	2017	Total
Very high (>100)	39	50	50	50	189
High (51–100)	33	45	45	45	168
Medium (11–50)	94	153	162	163	572
Low (1–10)	263	423	443	443	1572
No conflict	1076	960	951	976	3963
Total	1505	1631	1651	1677	6464

Notes: Conflict intensity based on CVR-documented victims 1980–2000: Very high (>100), High (51–100), Medium (11–50), Low (1–10). Any conflict = 1+ victims. Unbalanced panel due to district creation through administrative redistricting. Conflict status is time-invariant (assigned based on total 1980–2000 violence exposure). Changes in district counts across years reflect boundary harmonization to 2017 definitions.

3.2 Violence Data

Conflict exposure is measured using the database compiled by Peru's Truth and Reconciliation Commission (Comisión de la Verdad y Reconciliación, CVR), which documented

[2] Throughout the paper, "pre-conflict baseline" is shorthand for this pre-escalation baseline: the 1981 census follows Sendero's May 1980 launch but predates the escalation to large-scale violence.

human rights violations during 1980–2000. The CVR's statistical estimate puts total deaths and disappearances at approximately 69,000 (Comisión de la Verdad y Reconciliación, 2003, Anexo 2). The documented case-level records used in this paper, compiled through testimonies, forensic investigations, and cross-referenced administrative records, are geocoded to the district where the violation occurred.

Individual cases are aggregated to construct district-level measures of total victims, deaths, and disappearances. Perpetrator identity is recorded for most cases, enabling decomposition into violence attributed to state forces (military and police), Shining Path (Sendero Luminoso), and the Túpac Amaru Revolutionary Movement (MRTA). Following the CVR's methodology, districts are classified by dominant perpetrator when one actor accounts for more than 50% of victims.

Conflict intensity is categorized into five groups based on total victims during 1980–2000: no conflict (zero victims), low (1–10 victims), medium (11–50 victims), high (51–100 victims), and very high (more than 100 victims). Among the 1,505 districts observed in the 1981 baseline, 1,076 (71%) experienced no subsequent conflict, 263 (17%) had low intensity, 94 (6%) medium, 33 (2%) high, and 39 (3%) very high intensity. The most affected district recorded 1,064 victims. Very high-conflict districts averaged 289 victims over the two-decade period.

3.3 Geographic Covariates

Geographic characteristics come from multiple sources. Altitude and district area derive from INEI's cartographic database. Distance to Lima and distance to the nearest coast are calculated as geodesic distances from district centroids. Terrain ruggedness follows Nunn and Puga (2012), calculated as the Terrain Ruggedness Index (TRI) from 30-arc-second elevation data, which measures average elevation change between adjacent cells.

Night-time lights (NTL) serve as a proxy for economic activity. NTL data come from the simulated VIIRS (Visible Infrared Imaging Radiometer Suite) dataset of Chen et al. (2024), constructed from DMSP-OLS (Defense Meteorological Satellite Program–Operational Linescan System) and VIIRS imagery, which provides consistent 500-meter resolution annual luminosity measures from 1992–2023. Total luminosity (sum of pixel values) and mean luminosity (average per pixel) are extracted for each district in census years 1993, 2007, and 2017. NTL data are unavailable for 1981 because the series begins in 1992.

3.4 Sample Construction and Summary Statistics

The analysis sample is constructed through several steps. First, district boundaries are harmonized to 2017 definitions across all four censuses. Second, census data are merged with CVR violence records using district codes. Third, geographic covariates are attached using GIS matching of district polygons. The merged panel comprises 6,464 district-year observations. The main estimation sample contains 6,115 because the fixed-effects estimator drops 349 singleton districts observed in only one census year. Lima is included in the main specifications. Given its unique metropolitan characteristics, robustness to excluding the Lima metropolitan area is verified in Column (5) of Table 4.

Table 2 presents summary statistics for the 1981 pre-conflict baseline, comparing districts that would subsequently experience different levels of conflict exposure. A clear gradient emerges across conflict intensity categories. Very high-conflict districts were substantially more indigenous (67% vs 36% native language speakers in unaffected areas), less literate (59% vs 70%), had higher dependency ratios (106 vs 97), lower sex ratios (95 vs 102 males per 100 females), and were closer to Lima (314 km vs 557 km). Migration rates were also markedly lower in areas that would experience intense violence (18% vs 27%), indicating more isolated, less mobile populations. These pre-existing differences motivate the difference-in-differences identification strategy, which relies on within-district variation over time rather than cross-sectional comparisons.

Table 2: Summary Statistics: 1981 Pre-Conflict Baseline by Conflict Intensity

	Full Sample		No Conflict		Low		Medium		High		Very High	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Total population	10570.45	(28663.58)	7566.88	(19690.35)	19735.29	(45710.37)	14492.84	(31086.34)	23031.03	(64198.62)	11636.77	(17241.95)
Mean age (years)	24.49	(2.97)	24.58	(3.08)	24.39	(2.59)	24.17	(2.61)	23.22	(2.63)	24.55	(3.15)
Dependency ratio (%)	97.56	(16.04)	97.42	(15.79)	95.01	(16.60)	102.17	(15.94)	99.82	(16.62)	105.62	(14.29)
Sex ratio (M per 100 F)	100.81	(15.18)	101.79	(15.73)	99.01	(14.79)	97.23	(10.90)	100.26	(12.60)	95.00	(8.96)
Literacy rate (%)	69.50	(15.22)	70.44	(14.53)	70.25	(15.94)	62.67	(15.70)	64.35	(16.43)	59.09	(18.35)
Higher education (%)	2.51	(3.73)	2.23	(3.20)	3.58	(5.33)	2.58	(3.53)	2.72	(3.52)	2.84	(3.87)
High-skill occupation (%)	3.78	(4.46)	3.42	(3.94)	5.11	(5.90)	4.16	(4.74)	3.79	(4.08)	4.04	(4.84)
Agriculture (%)	70.92	(25.14)	72.97	(23.21)	62.68	(29.59)	72.57	(25.16)	65.50	(31.23)	70.54	(27.46)
Manufacturing (%)	5.18	(6.92)	5.01	(6.99)	6.44	(7.58)	4.21	(5.33)	4.34	(4.90)	4.22	(3.60)
Commerce (%)	5.58	(5.89)	5.03	(5.42)	7.27	(6.48)	5.39	(5.23)	8.62	(10.17)	7.09	(7.63)
Indigenous language (%)	40.80	(39.87)	35.77	(39.45)	46.82	(38.28)	64.03	(34.43)	60.01	(37.49)	66.88	(37.12)
Migration rate (%)	26.56	(22.11)	26.68	(21.73)	29.41	(24.86)	20.86	(18.83)	26.06	(20.67)	18.21	(16.97)
Altitude (m)	2373.81	(1337.86)	2233.30	(1348.14)	2516.76	(1378.06)	2934.26	(1028.09)	2829.61	(1048.90)	2267.36	(1261.98)
Distance to Lima (km)	483.18	(266.78)	557.50	(260.11)	381.10	(259.58)	330.42	(192.47)	309.88	(152.03)	314.26	(73.87)
Terrain ruggedness	257.19	(168.44)	272.16	(176.31)	231.98	(157.60)	232.93	(152.39)	204.66	(116.88)	253.70	(129.88)
Observations	1505		1076		263		94		33		39	

Notes: Sample restricted to the 1981 census baseline. Conflict intensity based on total CVR-documented victims 1980–2000: No conflict (0 victims), Low (1–10), Medium (11–50), High (51–100), Very high (>100). Standard deviations in parentheses. Indigenous language includes Quechua, Aymara, and other native languages. Dependency ratio = (population 0–14 + 65+) / (population 15–64) × 100.

Table 3 reports 1981 characteristics across all conflict-intensity categories, and Welch two-sample t-tests comparing no-conflict and very high-conflict districts (Table A3 in the Appendix) reveal systematic selection into conflict exposure. Very high-conflict districts had substantially lower literacy rates (-11.4 percentage points, $p < 0.001$), much higher indigenous population shares (+31 percentage points, $p < 0.001$), and lower migration rates (-8.5 percentage points, $p = 0.004$), indicating more isolated and marginalized communities. These areas were also closer to Lima (-243 km, $p < 0.001$), consistent with the conflict's geographic concentration in the central highlands rather than remote frontier regions. Demographic structure also differed: very high-conflict districts had higher dependency ratios (+8.2, $p = 0.001$), lower sex ratios (-6.8 males per 100 females, $p < 0.001$), more children (+1.3 percentage points, $p = 0.030$), and fewer working-age adults (-2.1 percentage points, $p = 0.001$).

Several baseline characteristics were statistically similar across the two groups. These comparisons describe pre-conflict level differences but do not directly test parallel trends. Population size ($p = 0.157$), mean age ($p = 0.962$), higher education ($p = 0.333$), high-skill occupations ($p = 0.435$), agricultural employment share ($p = 0.589$), manufacturing ($p = 0.205$), commerce ($p = 0.102$), altitude ($p = 0.871$), and terrain ruggedness ($p = 0.402$) show no significant differences between groups. The balance on economic structure is particularly reassuring: despite large differences in human capital and ethnic composition, the sectoral distribution of employment was virtually identical across conflict categories prior to the insurgency. The similarity in baseline sectoral employment composition reduces concern that the groups differed sharply in productive structure before the conflict, although it does not by itself establish that subsequent divergence was caused by conflict exposure.

Table 3: Pre-Conflict (1981) District Characteristics by Conflict Intensity

	High(51-100)	Low(1-10)	Medium(11-50)	No conflict	Very high (>100)	Total
Altitude (m)	2829.6	2516.8	2934.3	2233.3	2267.4	2373.8
Distance to Lima (km)	309.9	381.1	330.4	557.5	314.3	483.2
Literacy rate (%)	64.35	70.25	62.67	70.44	59.09	69.50
Mean age (years)	23.22	24.39	24.17	24.58	24.55	24.49
Total population	23031.0	19735.3	14492.9	7566.9	11636.8	10570.5

Notes: Group means in the 1981 census baseline. Very high conflict defined as >100 CVR-documented victims during 1980–2000. Formal balance tests (Welch two-sample t-tests, no conflict vs. very high) are reported in the text.

4 Empirical Strategy

This section describes the approach to identifying the long-run effects of Peru's internal conflict on district-level outcomes. The strategy exploits the dramatic spatial variation in conflict intensity across Peru's nearly 1,900 districts, comparing trajectories of high-conflict areas to less-affected districts using pre-conflict (1981) baselines.

4.1 Difference-in-Differences Specification

The main specification implements a generalized difference-in-differences design with district and year fixed effects:

$$Y_{dt} = \alpha_d + \lambda_t + \sum_{t \neq 1981} \beta_t \left(\text{VeryHighConflict}_d \times \mathbf{1}[Year = t]\right) + \varepsilon_{dt} \tag{1}$$

where Y_{dt} is the outcome in district d at census year $t \in \{1981, 1993, 2007, 2017\}$, α_d are district fixed effects absorbing all time-invariant district characteristics, λ_t are year fixed effects capturing common shocks, and $\text{VeryHighConflict}_d$ is an indicator for districts experiencing very high violence during the conflict period. The coefficients of interest, β_t, measure the differential change in outcomes for very-high-conflict districts relative to comparison districts, using 1981 as the reference period.

Conflict intensity is defined using data from Peru's Truth and Reconciliation Commission, which geocoded documented deaths and disappearances to the district level. The primary treatment indicator, $\text{VeryHighConflict}_d$, equals one for districts with more than 100 total victims: 50 districts in the 1,874-district cartographic universe, approximately the top 2.7% of the violence distribution. The harmonized census estimation panel contains up to 1,677 of these districts (Section 3). Continuous measures and alternative thresholds are examined in robustness analyses.

Standard errors are clustered at the district level to account for serial correlation within districts over time. This clustering is conservative given that treatment (conflict exposure) is assigned at the district level and does not vary over time.

4.2 Perpetrator-Specific Effects

A distinctive feature of Peru's conflict is the well-documented attribution of violence to specific perpetrators. The Truth and Reconciliation Commission assigned responsibility for each documented death or disappearance to Sendero Luminoso, state forces (military and police), MRTA, or other actors. The analysis exploits this granularity to examine whether recovery trajectories differ by perpetrator, estimating share specifications separately for each actor on the sample of conflict districts:

$$Y_{dt} = \alpha_d + \lambda_t + \sum_{t \neq 1981} \beta_t^a \left(\text{Share}_d^a \times \mathbf{1}[Year = t]\right) + \varepsilon_{dt}, \qquad a \in \{\text{Sendero}, \text{State}\} \tag{2}$$

where Share_d^a measures the percentage of victims (0–100) in district d attributed to actor a, so coefficients are per one-percentage-point increase in that perpetrator's share. The Sendero-share and state-share regressions are estimated separately rather than jointly. Districts are also categorized as Sendero-dominant (Sendero responsible for more than 50% of victims), State-dominant (state forces responsible for more than 50%), or Mixed (no single perpetrator majority), and estimate effects separately for each group.

4.3 Extended Specification with Time-Varying Controls

While district fixed effects absorb time-invariant confounders, differential trends correlated with conflict exposure remain a concern. This is addressed by interacting baseline geographic characteristics with year indicators:

$$Y_{dt} = \alpha_d + \lambda_t + \sum_{t \neq 1981} \beta_t \left(\text{VeryHighConflict}_d \times \mathbf{1}[Year = t]\right) + \sum_{t \neq 1981} \gamma_t \left(\mathbf{X}_d \times \mathbf{1}[Year = t]\right) + \varepsilon_{dt} \tag{3}$$

where $\mathbf{X}_d$ includes altitude and distance to Lima in the census specifications (Table 4, Column 4) and altitude and terrain ruggedness in the night-time-lights specifications. These controls allow for flexible differential trends by geography, addressing concerns that mountainous or remote areas, which experienced more conflict, may have followed different development trajectories regardless of violence exposure.

4.4 Identification

The difference-in-differences design requires the parallel trends assumption: absent conflict, high-violence districts would have followed similar trajectories to low-violence districts. Several features of the setting support this assumption.

Outcomes are directly observed in 1981, before significant violence began, which allows a direct assessment of baseline comparability. High-conflict districts were somewhat less literate and less developed at baseline, but these level differences are absorbed by district fixed effects, and the identifying assumption concerns trends, not levels. Because violence concentrated in the central-southern highlands, baseline geographic characteristics are interacted with year dummies, allowing flexible differential trends by location and isolating variation in conflict exposure conditional on geography.

The conflict's temporal structure reinforces this reading: most violence fell between 1983 and 1993, with the 1981 census just before escalation and the 2007 and 2017 censuses well after it ceased. And because violence spread unevenly even within the highlands, sparing many highland districts while reaching some coastal and jungle ones, within-region variation helps separate conflict effects from regional trends.

Several concerns warrant discussion. Violence was not randomly assigned. Sendero Luminoso initially targeted areas with specific characteristics: highland districts with indigenous populations, limited state presence, and historical grievances. If these characteristics independently affected development trajectories, the estimates may be biased. This is partially addressed through geographic controls and by examining heterogeneity across perpetrator types, but cannot fully rule out selection on unobservables.

Conflict induced massive displacement, and the outcome measures reflect the characteristics of district residents, not a fixed population. If higher-skilled individuals disproportionately left conflict areas and did not return, apparent effects may reflect compositional change rather than impacts on a stable population. The estimates are interpreted as effects on districts (places), not individuals, and substantial attention is devoted to documenting demographic transformation.

The Truth and Reconciliation Commission's statistical estimate put total conflict mortality at approximately 69,000, a figure subject to substantial uncertainty (Comisión de la Verdad y Reconciliación, 2003, Anexo 2). Underreporting may be more severe in remote areas or for certain perpetrators. Classical measurement error in conflict intensity would attenuate the estimates toward zero, making significant findings conservative. Non-classical error correlated with outcomes is more concerning but difficult to assess.

If conflict in one district affected outcomes in neighboring districts, through displacement, disrupted trade, or regional economic effects, treatment effects may be attenuated (if comparison districts were negatively affected) or amplified (if comparison districts benefited from displaced resources). Section 6 addresses this concern directly, using "donut" specifications that exclude potentially contaminated comparison districts and "ring" specifications that estimate spillover effects explicitly. As documented there, nearby non-conflict districts experienced negative spillovers, suggesting the baseline estimates compare conflict districts to a negatively affected comparison group rather than an unaffected counterfactual.

4.5 Night-Time Lights Specification

Census-based outcomes may suffer from differential measurement quality in conflict-affected areas. Enumerators may have had difficulty reaching remote or insecure districts, or conflict-era disruptions may have affected administrative capacity. The findings are validated using satellite-based night-time lights (NTL), which provide an objective measure of economic activity independent of ground-based data collection.

NTL data are available from 1992 onward, precluding direct comparison with the 1981 baseline. NTL specifications therefore use 1993 as the reference year:

$$g(\mathrm{NTL}_{dt}^{k}) = \alpha_d + \lambda_t + \sum_{t\in\{2007,2017\}} \beta_t \left(\mathrm{VeryHighConflict}_d \times \mathbf{1}[Year = t]\right) + \varepsilon_{dt} \tag{4}$$

where $k \in \{\mathrm{total}, \mathrm{per\ capita}\}$ indexes the NTL outcome and $g(\cdot)$ denotes the transformation or conditional-mean specification used in the relevant table (log, IHS, $\log(x + c)$, percentile rank, or Poisson pseudo-maximum-likelihood). This specification identifies differential NTL growth in conflict districts relative to 1993 levels. While pre-conflict NTL baselines cannot be established, comparing NTL trajectories to census-based outcomes provides a consistency check and allows examination of economic activity measures less subject to administrative data limitations.

The analysis examines two NTL outcomes, along with an indicator for any detected luminosity. Total luminosity (log of pixel sum) measures aggregate light output within district boundaries. NTL per capita (log of total NTL divided by population) combines satellite and census data to measure economic output per person, directly testing whether demographic recovery translated into proportionate economic gains.

4.6 Robustness Specifications

Several alternative specifications probe the sensitivity of the findings. First, alternative conflict measures are examined: an any-conflict indicator and the continuous log of victim counts (Table A4), with qualitatively similar population results.

Second, specifications with province-by-year fixed effects absorb province-specific time trends and identify effects from within-province variation in conflict exposure. These are displayed prominently in Section 5.3.

Third, Lima experienced relatively little conflict but dominates national aggregates. Results are robust to excluding the Lima metropolitan area.

Fourth, effects are allowed to differ by the temporal profile of violence, meaning above-median death versus disappearance shares and long versus short conflict duration, noting that duration is not separable from intensity at the highest exposure levels (Section 7.4).

Fifth, spatial spillovers are examined using "donut" specifications that progressively exclude non-conflict districts within 25, 50, 75, and 100 km of very-high-conflict districts, and "ring" specifications that directly estimate effects on these nearby districts. These tests assess whether the comparison group is contaminated by refugee absorption or regional economic disruption, and allow us to bound the magnitude of any violations of the Stable Unit Treatment Value Assumption (SUTVA).

5 Main Results

This section documents the central findings on long-run recovery in conflict-affected districts. It examines population trajectories, dose-response patterns across conflict intensity levels, and convergence in human capital and infrastructure outcomes.

5.1 Population Recovery

Table 4 presents the core results using 1981, the pre-conflict census, as the reference year. Coefficients measure how very-high-conflict districts evolved relative to comparison districts from this baseline.[3]

[3]Throughout the results, "comparison districts" denotes the omitted group of the regression at hand. In specifications with a single very-high-conflict indicator, meaning Columns (1), (4), and (5) of Table 4 and most outcome tables, this group is every district below the very-high threshold, including lower-intensity conflict districts. Only specifications that include all intensity indicators (Column 3) use no-conflict districts as the omitted group. Unqualified references to "conflict districts" in the results denote the very-high-conflict treatment group; districts with any documented victims are identified explicitly as such.

Table 4: Effect of Conflict on Log Population

	(1) Very High	(2) High+VHigh	(3) All	(4) Geo×	(5) Excl Lima
Very High × 1993	0.496**	0.506**	0.549**	0.485**	0.347*
	(0.250)	(0.251)	(0.252)	(0.234)	(0.179)
Very High × 2007	0.668***	0.678***	0.729***	0.660***	0.524***
	(0.250)	(0.250)	(0.252)	(0.230)	(0.178)
Very High × 2017	0.593**	0.600**	0.637**	0.606**	0.443**
	(0.268)	(0.268)	(0.270)	(0.240)	(0.196)
High × 1993		0.348*	0.391*		
		(0.205)	(0.206)		
High × 2007		0.330	0.381*		
		(0.209)	(0.210)		
High × 2017		0.248	0.285		
		(0.222)	(0.224)		
Medium × 1993			0.126		
			(0.125)		
Medium × 2007			0.167		
			(0.124)		
Medium × 2017			0.080		
			(0.128)		
Low × 1993			0.136		
			(0.084)		
Low × 2007			0.147*		
			(0.086)		
Low × 2017			0.129		
			(0.090)		
Observations	6115	6115	6115	6047	5514
Adjusted R^2	0.819	0.819	0.819	0.831	0.814

Notes: Standard errors clustered at district level in parentheses. Omitted comparison group: all districts below the >100-victim threshold in Columns (1), (4), and (5), districts with 50 or fewer victims in Column (2), and no-conflict districts in Column (3). Reference year: 1981 (pre-conflict). Column (4) includes altitude and distance to Lima interacted with year FE. *** p<0.01, ** p<0.05, * p<0.10.

Contrary to expectations of persistent population loss, very-high-conflict districts experienced faster population growth than comparison districts. Column (1) shows that by 1993, very-high-conflict districts had grown 0.50 log points more than districts below the threshold relative to 1981 (p = 0.048). This differential peaked at 0.67 log points in 2007 (p = 0.008) and remained at 0.59 log points by 2017 (p = 0.027). In percentage terms, conflict districts grew roughly 65–95 percent more than comparison districts across the three post-baseline census comparisons. By 2017, covering the full 36-year horizon, the differential was approximately 81 percent.

These positive coefficients warrant careful interpretation. As Section 6 documents, non-conflict districts near the epicenter also lost population relative to distant comparison areas. The baseline estimates therefore compare conflict districts to a comparison group that was itself negatively affected, so they capture relative recovery within a disrupted region rather than recovery to a pre-conflict trajectory. The paper returns to this point after presenting the spillover analysis.

Figure 3 illustrates this trajectory visually. The event study shows coefficients rising sharply from zero in 1981 (the normalized pre-conflict baseline) to positive and statistically significant values that persist through 2017. The shaded confidence region excludes zero for most of the post-conflict period, and there is no indication of a persistent relative population-count deficit. The vertical dashed line marks Guzmán's capture in September 1992, which precipitated the collapse of the main insurgency. The 1993 census, conducted shortly thereafter, already shows substantial positive effects.

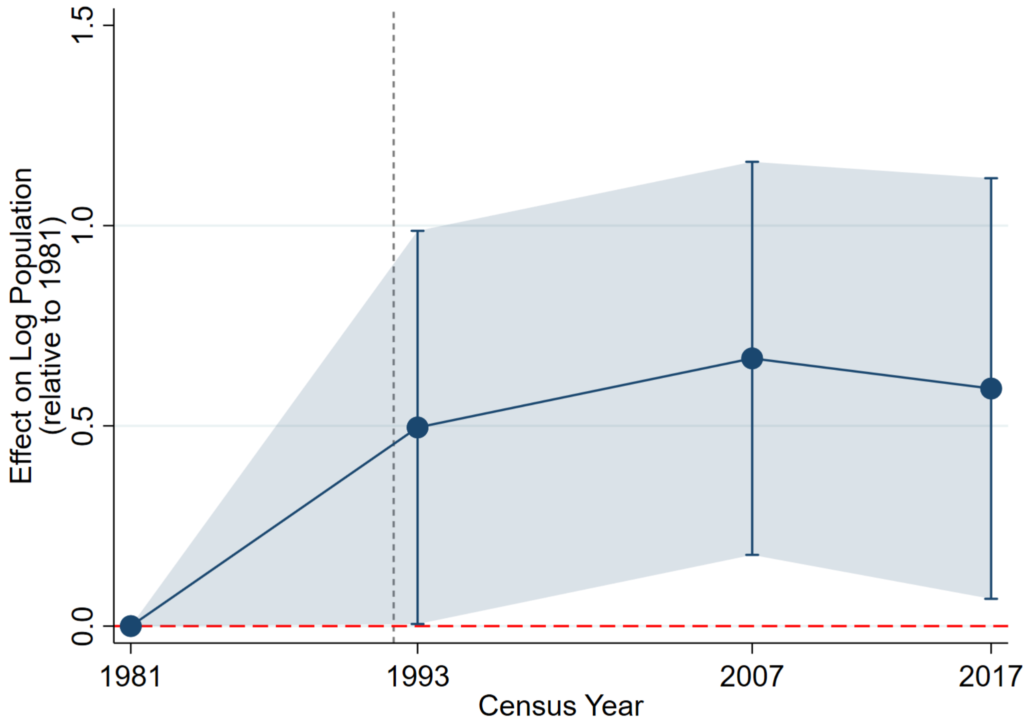


Figure 3: Event Study: Population Effects in Very High-Conflict Districts

Notes: Coefficients for very-high-conflict districts (>100 CVR-documented victims) interacted with year indicators. Reference category: 1981 (pre-conflict baseline). Shaded area and error bars represent 95% confidence intervals. Standard errors clustered at district level. Dashed vertical line marks Guzmán's capture (September 1992).

Column (3) of Table 4 incorporates all conflict intensity levels simultaneously and reveals a clear dose-response: the population gains are concentrated in the most heavily affected districts. Very-high-conflict districts grew 0.55–0.73 log points more than no-conflict districts (significant at the 5 percent level), and high-conflict districts 0.29–0.39 log points (significant at the 10 percent level in 1993 and 2007), while low- and medium-conflict districts show small differences (0.08–0.17 log points) that are at most marginally significant. Results are robust to including geographic controls interacted with year fixed effects (Column 4) and to excluding Lima (Column 5).

Inference with few treated districts. Because the very-high-conflict group comprises only 50 districts, cluster-robust standard errors could overstate precision. They are therefore complemented with randomization inference, randomly reassigning the very-high-conflict label across districts (holding the number of treated districts fixed) and re-estimating the effect 500 times. The observed coefficients exceed those of nearly all placebo assignments:

the randomization-inference p-values are 0.034 (1993), 0.006 (2007), and 0.024 (2017) (Table A8, Panel A), confirming that the population gains are not an artifact of the small treated group.

Pre-conflict comparability. A single pre-conflict census (1981) precludes a direct test of differential pre-trends in population. The 1981 census's retrospective migration questions, which record each resident's district of birth and place of residence in 1976, instead allow comparing *pre-conflict* demographic dynamics across districts. Table 5 formalizes this evidence. The flow margins relevant for pre-trends are balanced: very-high-conflict districts are statistically indistinguishable from the rest in the share of residents living in the same province in 1976 and in 1976–1981 in-migration from other provinces, with or without department fixed effects and geographic controls. The stock of lifetime migrants (share born in another district) is lower in very-high-conflict districts, significantly so once geographic controls are added (-8.0 percentage points). This reflects the long-standing isolation already documented in the baseline comparisons of Table 2, a level difference absorbed by district fixed effects. What matters for identification is that migration *dynamics* in the five years before the conflict's escalation show no differential trajectory.

Table 5: Pre-Conflict Migration Balance, 1976–1981

	Same province 1976 (%)			Inflow 1976–81 (%)		Born other district (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Raw	Dept FE	+Geo	Dept FE	+Geo	Dept FE	+Geo
Very High Conflict	0.349	0.438	1.111	-0.438	-1.111	-2.646	-7.990***
	(1.320)	(1.003)	(0.769)	(1.003)	(0.769)	(2.758)	(1.941)
Observations	1505	1505	1149	1505	1149	1505	1149
Adjusted R^2	-0.001	0.115	0.135	0.115	0.135	0.216	0.305

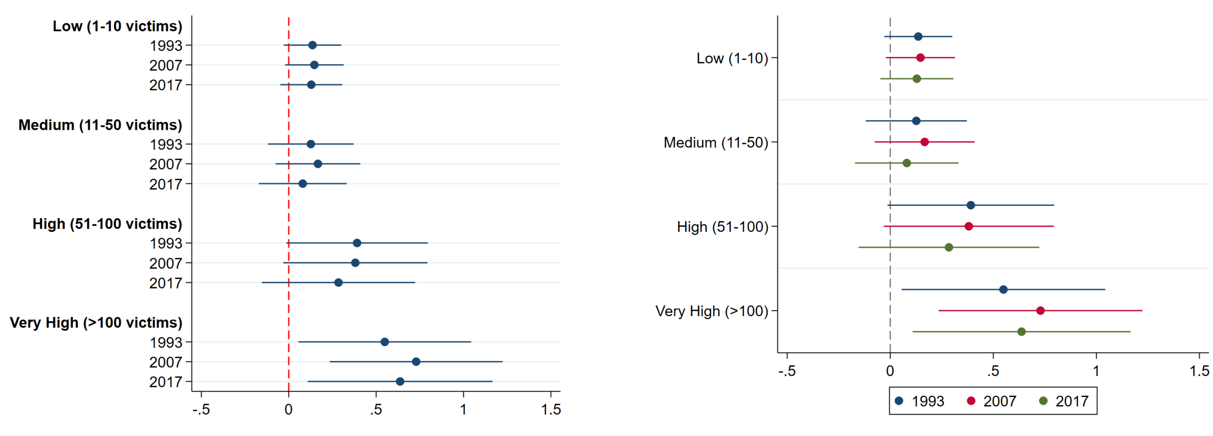
Notes: 1981 census cross-section (1,505 districts). Outcomes from the census's retrospective questions, defined over residents with a reported 1976 residence: share who lived in the same province in 1976 and its constructed complement, the share who arrived from another province during 1976–1981 (Inflow, equal to 100 minus the same-province share up to a negligible abroad share, which is why Columns (4)–(5) mirror Columns (2)–(3)), plus the share born outside the current district (lifetime migrants). "+Geo" adds altitude, distance to Lima, and terrain ruggedness (available for 1,149 districts). Standard errors clustered at the department level (22 clusters) in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

5.2 Dose-Response Patterns

A key test for causal interpretation is whether effects scale with conflict intensity. If violence causally affects development trajectories, larger effects would be expected in more severely affected districts. Figure 4 presents coefficient plots that facilitate visual comparison across intensity levels and time periods.

Panel (a) of Figure 4 displays effects organized by conflict intensity, with separate coefficients for each census year within intensity categories. Several patterns emerge. First, all coefficients are positive, but only the very-high category excludes zero at the 95% level. The high-conflict estimates are marginally significant at the 10% level in 1993 and 2007, and low- and medium-conflict estimates are small and imprecise. Second, effects are broadly stable over time within each intensity category, with a mild peak in 2007. Third, point estimates increase with intensity, from 0.13–0.15 log points for low-conflict to 0.55–0.73 for very-high-conflict districts, though confidence intervals overlap substantially.

Panel (b) of Figure 4 overlays the three census-year estimates within each intensity category, using color to facilitate comparison across years. This visualization highlights that 2007 effects tend to be largest, with 2017 effects showing slight attenuation. The pattern suggests that population differentials peaked roughly 15 years after Guzmán's capture before moderating somewhat.



(a) By conflict intensity

(b) By census year

Figure 4: Population Effects by Conflict Intensity and Time Period

Notes: Both panels show coefficients from the full dose-response specification (Table 4, Column 3) with all intensity levels included simultaneously. Panel (a) organizes results by intensity category. Panel (b) uses color to distinguish years (blue = 1993, red = 2007, green = 2017). Reference: no-conflict districts, 1981. 95% confidence intervals shown. Standard errors clustered at district level.

This pattern, a rising gradient in point estimates with statistical significance concentrated at the top of the intensity distribution, admits two interpretations. Under a causal reading, recovery dynamics scale with the severity of the shock: the displacement-and-repopulation cycle that generates relative population growth operates mainly where violence was intense enough to empty communities. Alternatively, the uniformly positive point estimates may partly reflect selection: districts that experienced any conflict shared unobserved characteristics (geographic remoteness, pre-existing growth potential, targeting by post-conflict development programs) that drove differential trajectories independent of violence intensity.

5.3 Within-Province Comparisons

A demanding version of the identification concern is that very-high-conflict districts differ from the national pool of comparison districts in unobserved ways correlated with regional development trends. Table 6 addresses this by replacing year fixed effects with province-by-year fixed effects, so that each very-high-conflict district is compared only with districts in its own province in the same census year.

Table 6: Within-Province Comparisons

	Log Population		Literacy Rate		Mean Age	
	(1)	(2)	(3)	(4)	(5)	(6)
	Base	Prov.×Yr	Base	Prov.×Yr	Base	Prov.×Yr
Very High × 1993	0.496**	0.877**	0.885	-2.699	-1.928**	-0.142
	(0.250)	(0.399)	(2.183)	(2.502)	(0.753)	(0.683)
Very High × 2007	0.668***	1.051***	5.260**	-2.978	-3.095***	-0.719
	(0.250)	(0.394)	(2.358)	(2.541)	(0.739)	(0.669)
Very High × 2017	0.593**	1.040***	6.966***	-1.978	-2.823***	-0.929
	(0.268)	(0.386)	(2.457)	(2.637)	(0.782)	(0.745)
Observations	6115	6112	6115	6112	6115	6112
Adjusted R^2	0.819	0.838	0.711	0.824	0.822	0.861

Notes: "Base" columns include district and census-year fixed effects (as in Table 4), with all districts below the very-high threshold as the omitted comparison group. "Prov.×Yr" columns replace year fixed effects with province-by-year fixed effects, so very-high-conflict districts are compared only with below-threshold districts in the same province in the same year. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

The population result strengthens under this much more local comparison: coefficients rise to 0.88–1.05 log points, all significant at the 5% level or better. Because same-province neighbors are disproportionately the spillover districts shown in Section 6 to have lost population, the sharper within-province contrast is exactly what the spillover results predict.

Literacy and mean age behave differently. Within provinces, the literacy effect turns statistically insignificant (point estimates of −2.0 to −3.0 percentage points) and the mean-age effect attenuates to insignificance (−0.1 to −0.9 years). Read alongside Section 6.4, which documents that nearby non-conflict districts also gained literacy (+6.1 points by 2017) and became younger, this pattern indicates that the human capital and demographic changes diffused across the affected region rather than stopping at the boundaries of directly victimized districts. The literacy convergence documented below is therefore best understood as a regional phenomenon concentrated in conflict-affected provinces, not an advantage of victimized districts over their immediate neighbors. The population recovery, by contrast, is district-specific.

5.4 Human Capital Convergence

Table 7 examines effects on educational attainment, revealing a pattern of dramatic convergence in basic literacy alongside persistent deficits in higher education.

Table 7: Effect of Very High Conflict on Human Capital

	(1) Literacy	(2) Primary	(3) Secondary	(4) Higher Ed	(5) High Skill
Very High × 1993	0.885	3.484**	-1.860	-1.625**	-2.730***
	(2.183)	(1.546)	(1.136)	(0.704)	(0.871)
Very High × 2007	5.260**	5.386***	-1.128	-4.260***	-0.715
	(2.358)	(1.539)	(1.232)	(0.918)	(0.840)
Very High × 2017	6.966***	2.390*	0.484	-2.875***	-0.770
	(2.457)	(1.425)	(1.388)	(1.023)	(0.799)
Observations	6115	6115	6115	6115	6115
Adjusted R^2	0.711	0.882	0.788	0.775	0.544

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Very high conflict = >100 victims. Omitted comparison group: all districts below the very-high threshold. Reference year: 1981. Outcomes in percentage points. *** p<0.01, ** p<0.05, * p<0.10.

Literacy rates in very-high-conflict districts improved substantially relative to comparison districts. The 1993 coefficient of 0.9 percentage points is not statistically significant, but effects grow to 5.3 percentage points by 2007 ($p < 0.05$) and 7.0 percentage points by 2017 ($p < 0.01$). This represents substantial catch-up: relative to the trend in districts below the very-high threshold, conflict districts that started with lower literacy in 1981 gained 7 percentage points over nearly four decades. Table 8 contextualizes these gains in raw means: the literacy gap between very high conflict and no/low conflict districts narrowed from 10.1 percentage points in 1993 to 3.4 percentage points in 2017, a reduction of 66%.

The pattern for higher education in Table 7 diverges sharply. Very-high-conflict districts show a deficit of 4.3 percentage points in higher education by 2007, moderating to 2.9 percentage points by 2017, with both estimates significant at the 1% level. This suggests that while basic education expanded dramatically, pathways to university remained disrupted by conflict's destruction of institutional infrastructure.

These divergent patterns are consistent with post-conflict reconstruction efforts that prioritized basic literacy through community schools and adult education campaigns, interventions deliverable without heavy infrastructure, while pathways to higher education required longer-term institutional rebuilding that lagged behind. Recall from Section 5.3 that these literacy gains extend to same-province neighbors: they are a feature of the conflict-affected region as a whole rather than of victimized districts relative to adjacent ones.

Table 8: Literacy Rate Convergence: 1993–2017

	1993		2017	
	Mean	Std. Dev.	Mean	Std. Dev.
Very High Conflict	67.3	12.8	80.7	5.4
No/Low Conflict	77.4	11.3	84.1	6.2
Gap	10.1 pp		3.4 pp	
Gap Closed	6.7 pp (66%)			

Notes: No/Low Conflict = districts with 0–10 CVR-documented victims. N = 50 very high conflict districts, 1,383–1,419 no/low conflict districts depending on year.

5.5 Infrastructure Recovery

Table 9 examines six infrastructure and housing quality indicators drawn from census housing modules. The results reveal substantial relative gains in sanitation and housing quality alongside a persistent electricity deficit.

Sanitation coverage improved sharply relative to the comparison-district trend: +13.6 percentage points by 2007 and +9.9 percentage points by 2017, both significant at the 1% level, after a negligible 1993 effect (−1.1 pp). Public water network effects, by contrast, are never statistically significant: negative through 2007 (−3.7 and −4.5 pp) and positive only in the 2017 point estimate (+3.9 pp).

Housing quality indicators in Table 9 show consistent relative gains. Conflict districts exhibit persistently higher rates of quality wall construction: 6.9 percentage points more brick or cement block walls in 1993 ($p < 0.01$), 6.3 percentage points in 2007 ($p < 0.05$), and 6.3 percentage points in 2017 ($p < 0.05$). Dirt-floor prevalence declines by 1–3 percentage points across the periods, though no estimate is statistically significant.

Electricity and public sewage lag. Electricity access fell significantly behind the comparison trend during reconstruction (−6.7 pp in 1993 at $p < 0.10$, and −11.9 pp in 2007 at $p < 0.01$) and the gap closed only partially by 2017 (−2.5 pp, insignificant). Public sewage connections, the most infrastructure-intensive sanitation option, show small negative and insignificant effects in all years, indicating that the sanitation gains come from improved latrines and septic systems rather than full sewage infrastructure.

Table 9: Effect of Very High Conflict on Infrastructure and Housing Quality

	(1) Electricity	(2) Water	(3) Sewage	(4) Sanitation	(5) Brick Walls	(6) Dirt Floor
Very High × 1993	-6.696*	-3.717	-0.306	-1.146	6.929***	-1.204
	(4.008)	(3.379)	(2.068)	(2.992)	(2.271)	(2.827)
Very High × 2007	-11.912***	-4.519	-1.004	13.620***	6.306**	-1.862
	(4.086)	(3.685)	(2.542)	(2.788)	(2.525)	(2.791)
Very High × 2017	-2.463	3.882	-1.277	9.937***	6.316**	-3.176
	(3.987)	(4.337)	(3.184)	(2.666)	(3.098)	(3.070)
Observations	6115	6115	6115	6115	6115	6115
Adjusted R^2	0.730	0.650	0.736	0.785	0.808	0.841

Notes: Standard errors clustered at district level in parentheses. All outcomes are percentages (0–100). Electricity = % households with electric lighting. Water = % with public water network. Sewage = % with public sewage connection. Sanitation = % with any sanitation facility. Brick Walls = % with brick or cement block walls. Dirt Floor = % with earth floors. Omitted comparison group: all districts below the very-high threshold. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

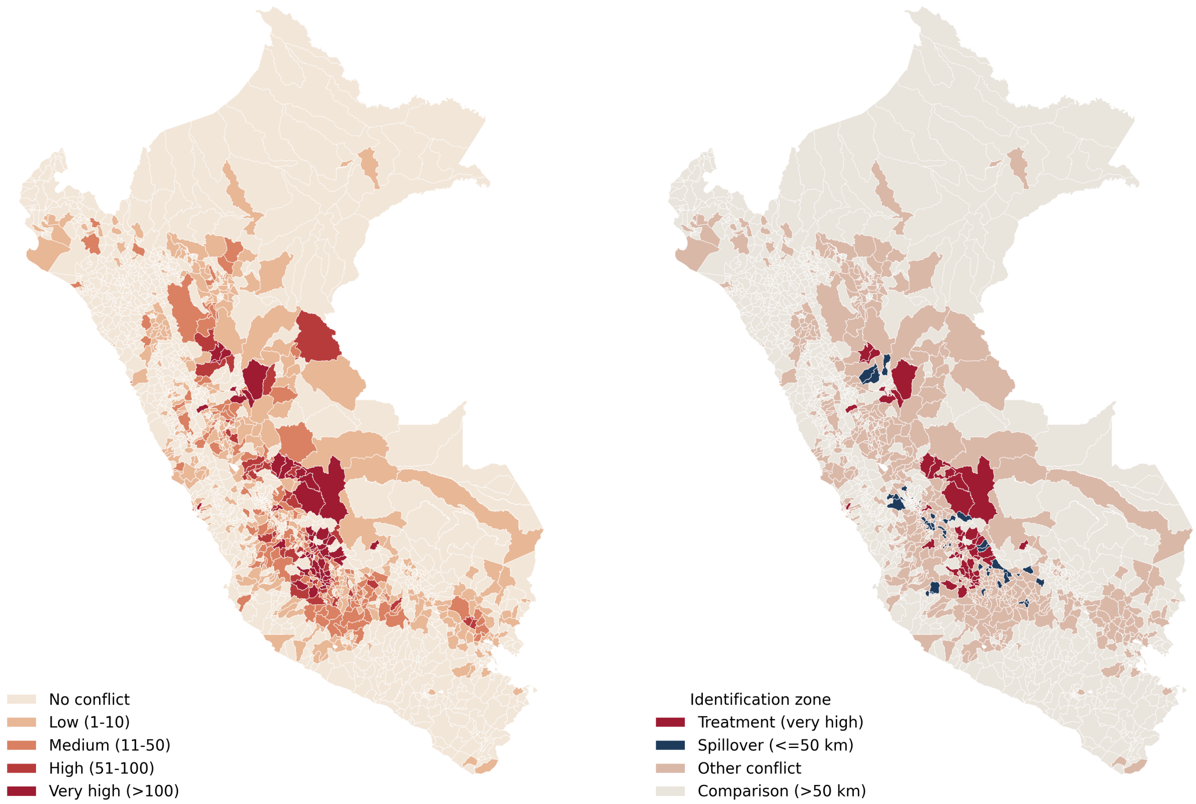
These sanitation and housing gains are consistent with deliberate policy responses rather than purely organic development. Peru's post-conflict programs, including the poverty-targeted social investment fund FONCODES (Fondo de Cooperación para el Desarrollo Social), the food assistance program PRONAA (Programa Nacional de Asistencia Alimentaria), and various international aid programs, operated intensively in the poor highland areas where the conflict had concentrated, although program allocation is not observed directly. The timing of effects is consistent with this interpretation: sanitation gains emerged strongly by 2007, approximately 15 years after Guzmán's capture, in line with the lag required for planning and implementing large-scale water and sanitation projects.

6 Spatial Spillovers

A potential threat to the identification strategy arises if conflict affected neighboring districts through displacement or regional economic disruption, violating the Stable Unit Treatment Value Assumption (SUTVA). If displaced populations from conflict districts migrated to nearby non-conflict areas, the comparison group would be "treated" by refugee inflows, potentially biasing estimates toward zero. Conversely, if conflict disrupted regional economies more broadly, the comparison group may have experienced negative spillovers, causing the estimates to understate the total regional impact of violence. This section examines these possibilities through spatial analysis.

6.1 Geographic Distribution of Conflict

Figure 5a displays the geographic distribution of conflict intensity across Peru's 1,874 districts. Violence was heavily concentrated in the central-southern highlands. Of the 50 very-high-conflict districts (>100 CVR-documented victims), 41 are located in Ayacucho (32), Junín (7), and Huancavelica (2), with the remainder in Huánuco (5), San Martín (2), Lima (1), and Ucayali (1). The remaining 651 conflict districts (1–100 victims) form a periphery around this core, while the coast, northern highlands, and Amazon basin remained largely unaffected.



(a) Violence intensity by district

(b) Spillover zones

Figure 5: Geographic Distribution of Conflict and Potential Spillover Zones

Notes: Panel (a) shows conflict intensity based on CVR-documented victims (deaths and disappearances): Very High = >100 victims (50 districts), High = 51–100 (45 districts), Medium = 11–50 (163 districts), Low = 1–10 (443 districts), and No conflict = 0 victims (1,173 districts). Panel (b) shows the spillover design: treatment = the 50 very-high-conflict districts (cranberry), spillover = non-conflict districts within 50 km of a treatment district (53 districts, navy), comparison = non-conflict districts beyond 50 km (1,120 districts, gray). Other conflict districts (1–100 victims) appear in a muted tone.

This spatial concentration raises immediate concerns about spillovers. Figure 5b identifies potential spillover zones by calculating each non-conflict district's distance to the nearest very-high-conflict district. The blue-shaded spillover zones form a clear ring around the conflict epicenter, concentrated in the highland departments adjacent to Ayacucho.

Figure 6 provides a detailed view of the conflict epicenter and surrounding spillover zones. The concentration of violence in Ayacucho and adjacent provinces is pronounced, as is the ring of spillover districts (blue) surrounding the conflict core. This spatial structure motivates the robustness tests: if these nearby non-conflict districts absorbed displaced populations or suffered from regional economic disruption, they constitute a contaminated comparison group.

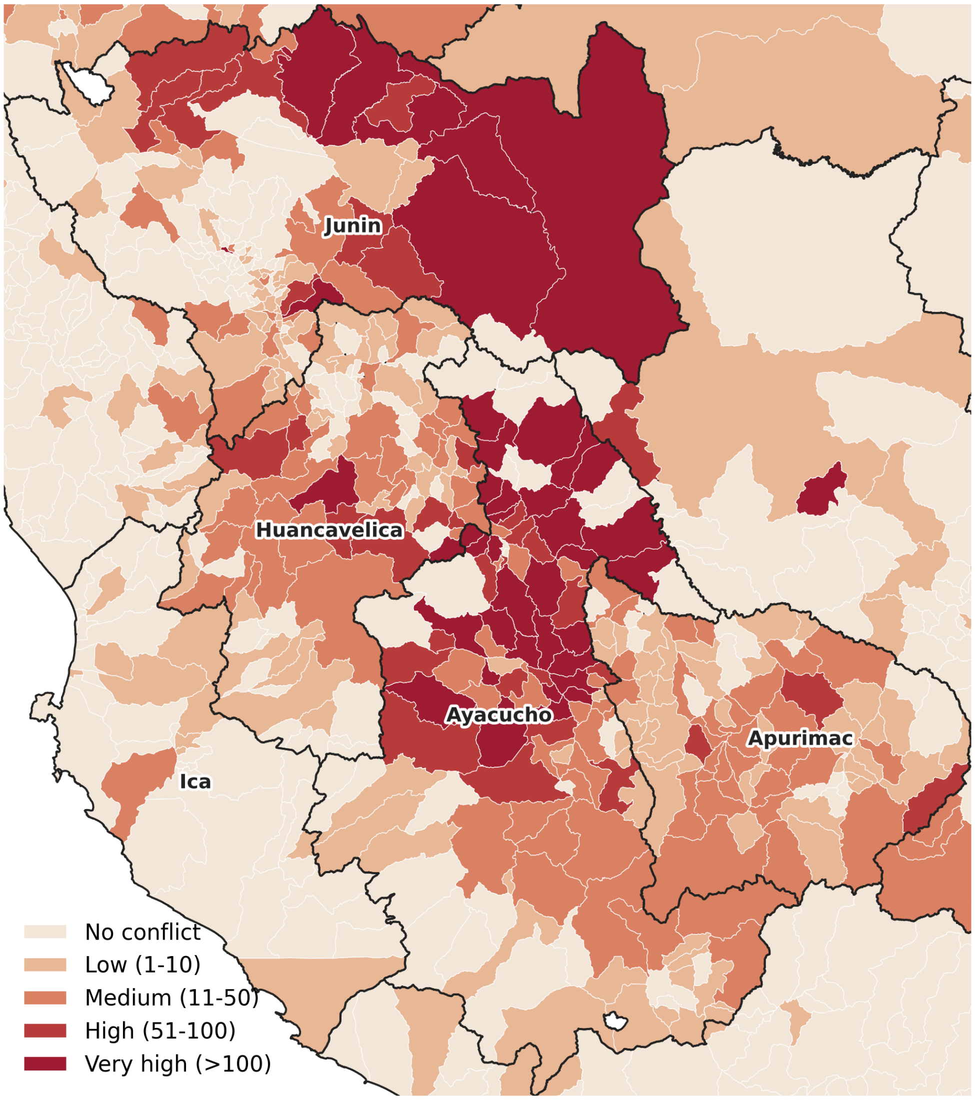


Figure 6: Conflict Epicenter: Central-Southern Highlands

Notes: Zoomed view of Ayacucho, Huancavelica, Apurímac, Junín, and neighboring departments. Department boundaries shown in black. Ayacucho, Junín, and Huancavelica together contain 41 of the 50 very-high-conflict districts, and the wider region shown accounts for the majority of all conflict-related violence.

6.2 Donut Specifications

The first robustness test excludes potentially contaminated comparison districts using "donut" specifications. If spillovers to nearby districts bias the baseline estimates, excluding these districts should change the coefficients. Table 10 presents results progressively excluding non-conflict districts within 25, 50, 75, and 100 km of any very-high-conflict district.

Table 10: Donut Specifications: Excluding Districts Near Conflict Zones

	Full Sample	Donut 25km	Donut 50km	Donut 75km	Donut 100km
Panel A: Log Population					
Very High × 1993	0.496**	0.486*	0.481*	0.475*	0.480*
	(0.250)	(0.251)	(0.251)	(0.251)	(0.251)
Very High × 2007	0.668***	0.656***	0.644**	0.637**	0.636**
	(0.250)	(0.251)	(0.251)	(0.251)	(0.251)
Very High × 2017	0.593**	0.580**	0.553**	0.538**	0.522*
	(0.268)	(0.268)	(0.268)	(0.268)	(0.269)
Observations	6115	5700	5268	5052	4617
Panel B: Literacy Rate					
Very High × 1993	0.885	1.041	0.862	0.913	1.111
	(2.183)	(2.185)	(2.186)	(2.187)	(2.189)
Very High × 2007	5.260**	5.704**	5.935**	6.120***	6.473***
	(2.358)	(2.359)	(2.361)	(2.361)	(2.364)
Very High × 2017	6.966***	7.446***	7.739***	8.032***	8.461***
	(2.457)	(2.458)	(2.460)	(2.460)	(2.463)
Observations	6115	5700	5268	5052	4617

Notes: Standard errors clustered at district level in parentheses. Donut X km excludes non-conflict districts within X km of any very-high-conflict district. All specifications include district and year fixed effects. Omitted comparison group: all remaining districts below the very-high threshold (lower-intensity conflict districts plus non-conflict districts beyond the donut radius). Reference year: 1981 (pre-conflict baseline). *** p<0.01, ** p<0.05, * p<0.10.

Panel A of Table 10 shows that population effects are reasonably stable across donut specifications. The 2017 coefficient declines from 0.593 in the full sample to 0.522 when excluding districts within 100 km, a reduction of approximately 12%. This modest attenuation is consistent with negative population spillovers in nearby non-conflict districts: including those negatively affected districts in the comparison group increases the estimated relative growth of very-high-conflict districts. The core finding of relative population growth in conflict districts is unchanged.

Panel B shows the opposite pattern for literacy. The 2017 literacy effect *increases* from 7.0 percentage points in the full sample to 8.5 percentage points in the 100 km donut, a gain of approximately 21%. This suggests that nearby non-conflict districts experienced positive literacy spillovers, perhaps through access to educational programs that targeted the broader conflict-affected region. Excluding these districts reveals even larger convergence in conflict areas relative to the remaining below-threshold comparison districts.

Figure 7 visualizes coefficient stability across donut specifications for the 2017 population effect. Point estimates decline modestly as the donut radius expands, but confidence intervals overlap substantially across all specifications. The effect remains positive and economically meaningful even when the comparison group excludes non-conflict districts within 100 km of a very-high-conflict district.

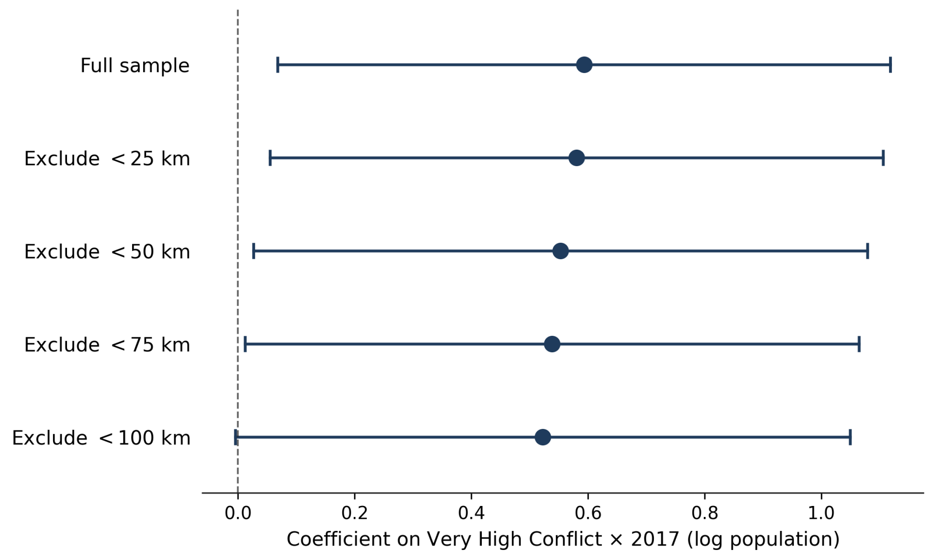


Figure 7: Stability of Long-Run Population Effect Across Donut Specifications

Notes: Coefficient on Very High Conflict $\times$ 2017 from specifications progressively excluding non-conflict districts within 25, 50, 75, and 100 km of conflict zones. Horizontal bars show 95% confidence intervals. Standard errors clustered at district level.

6.3 Ring Specifications

Rather than simply excluding potential spillover districts, spillover effects can be estimated directly by including indicators for non-conflict districts within specified distances of conflict zones. This "ring" specification allows us to test whether nearby districts experienced population changes consistent with refugee absorption (positive spillovers) or regional economic disruption (negative spillovers).

Table 11 presents results from specifications that simultaneously estimate effects on conflict districts and spillover zones. The findings run contrary to expectations.

Table 11: Ring Analysis: Direct Conflict and Spillover Effects

	Ring 25km	Ring 50km	Ring 75km	Ring 100km
Very High × 1993	0.486*	0.481*	0.475*	0.480*
	(0.251)	(0.251)	(0.251)	(0.251)
Very High × 2007	0.656***	0.644**	0.637**	0.636**
	(0.251)	(0.251)	(0.251)	(0.251)
Very High × 2017	0.580**	0.553**	0.538**	0.522*
	(0.268)	(0.268)	(0.268)	(0.269)
Spillover (25 km) × 1993	-0.158			
	(0.134)			
Spillover (25 km) × 2007	-0.185			
	(0.132)			
Spillover (25 km) × 2017	-0.193			
	(0.142)			
Spillover (50 km) × 1993		-0.160		
		(0.103)		
Spillover (50 km) × 2007		-0.219**		
		(0.104)		
Spillover (50 km) × 2017		-0.323***		
		(0.108)		
Spillover (75 km) × 1993			-0.170*	
			(0.091)	
Spillover (75 km) × 2007			-0.228**	
			(0.093)	
Spillover (75 km) × 2017			-0.348***	
			(0.096)	
Spillover (100 km) × 1993				-0.092
				(0.079)
Spillover (100 km) × 2007				-0.159**
				(0.081)
Spillover (100 km) × 2017				-0.301***
				(0.084)
Observations	6115	6115	6115	6115

Notes: Dependent variable: log population. Standard errors clustered at district level in parentheses. Spillover = non-conflict districts within specified distance of any very-high-conflict district. Omitted comparison group: all districts that are neither very-high-conflict nor in the spillover ring (non-conflict districts beyond the ring plus lower-intensity conflict districts). Reference year: 1981. Joint F-tests for the spillover coefficients are reported in Table A8, Panel B. *** p<0.01, ** p<0.05, * p<0.10.

Contrary to the hypothesis that nearby districts absorbed displaced populations, the estimates show negative spillover effects that grow over time. In the 50 km ring specification (Column 2), spillover districts experienced population declines of 0.16 log points by 1993 ($p = 0.121$), 0.22 log points by 2007 ($p = 0.035$), and 0.32 log points by 2017 ($p = 0.003$). The joint F-test strongly rejects the null of zero spillovers ($F = 10.60$, $p < 0.001$, Table A8, Panel B). Effects are even larger in the 75 km ring, with 2017 spillovers reaching -0.35 log points.

Figure 8 visualizes the divergent trajectories of conflict and spillover districts. While very-high-conflict districts show persistent positive effects relative to distant comparison areas, spillover districts show persistent negative effects that deepen over time. By 2017, the gap between conflict districts ($+0.55$) and spillover districts (-0.32) reaches 0.88 log points, roughly 140 percent in proportional terms.

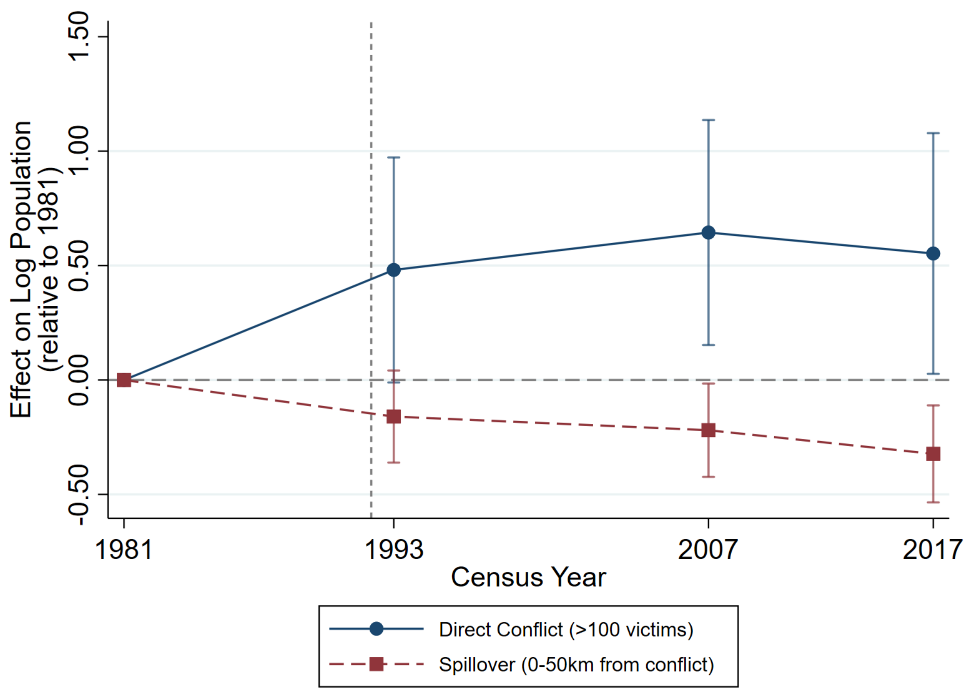


Figure 8: Event Study: Direct Conflict vs. Spillover Effects

Notes: Coefficients from ring specification with 50 km spillover zone. Direct conflict = very-high-conflict districts (>100 victims). Spillover = non-conflict districts within 50 km of conflict. Omitted group: lower-intensity conflict districts plus non-conflict districts more than 50 km from a very-high-conflict district. Reference year: 1981. 95% confidence intervals shown. Standard errors clustered at district level. Dashed vertical line marks Guzmán's capture (September 1992).

6.4 Spillover Effects Across Outcomes

Table 12 examines spillover effects across multiple outcomes, revealing heterogeneous patterns that point to the mechanisms at work.

Table 12: Direct and Spillover Effects on Multiple Outcomes

	(1) Log Pop	(2) Literacy	(3) Migration	(4) Mean Age	(5) Indigenous
Direct Conflict Effects					
× 1993	0.481*	0.862	9.104***	-1.992***	4.617
	(0.251)	(2.187)	(2.989)	(0.754)	(3.686)
× 2007	0.644**	5.935**	10.433**	-3.257***	4.064
	(0.251)	(2.361)	(4.246)	(0.740)	(3.658)
× 2017	0.553**	7.739***	6.276***	-2.851***	2.814
	(0.268)	(2.460)	(2.306)	(0.784)	(3.695)
Spillover Effects (0–50km)					
× 1993	-0.160	0.787	1.356	-0.641**	-5.330**
	(0.103)	(1.119)	(1.999)	(0.305)	(2.391)
× 2007	-0.219**	5.509***	4.583*	-1.292***	-7.350***
	(0.104)	(1.166)	(2.579)	(0.322)	(2.374)
× 2017	-0.323***	6.065***	5.777***	-0.395	-5.203**
	(0.108)	(1.173)	(1.908)	(0.356)	(2.381)
Observations	6115	6115	6115	6115	6115
Adjusted R^2	0.820	0.719	0.535	0.823	0.895

Notes: Standard errors clustered at district level in parentheses. Spillover = non-conflict districts within 50 km of very-high-conflict districts. Omitted comparison group: all districts that are neither very-high-conflict nor in the 50 km spillover ring. Reference year: 1981. All specifications include district and year fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Column 1 confirms the negative population spillovers documented above. Yet Columns 2–3 reveal that spillover districts experienced *positive* effects on literacy (+6.1 pp by 2017, $p < 0.001$) and migration rates (+5.8 pp by 2017, $p < 0.01$). Column 4 shows spillover districts became younger, with mean age declining by 1.3 years by 2007 ($p < 0.001$). Column 5 indicates a decline in indigenous language speakers in spillover areas (−7.4 pp by 2007, $p < 0.01$).

This pattern of population loss combined with gains in literacy, migration, and youth is consistent with selective out-migration. Spillover districts lost population, but the remaining (or subsequently arriving) residents had higher human capital. This compositional upgrading may reflect several mechanisms: educated residents had greater capacity to relocate away from the conflict-affected region. Return migrants brought skills acquired in Lima or other destinations. Or post-conflict development programs attracted human capital to the broader region even as total population declined.

6.5 Recovery Relative to a Disrupted Comparison Group

The negative population spillovers are large and rule out the most obvious SUTVA concern, that the comparison group was inflated by refugee absorption. Instead, the evidence suggests that conflict disrupted the broader regional economy, affecting districts well beyond those experiencing direct violence.

Several mechanisms could explain these patterns. First, conflict may have disrupted regional trade networks, markets, and supply chains, depressing economic activity throughout the central highlands and inducing out-migration even from areas without direct violence. Second, fear and uncertainty may have extended beyond conflict zones, with households avoiding the entire region rather than just specific violent districts. Third, displaced populations may have bypassed nearby rural districts entirely, migrating directly to Lima and coastal cities where economic opportunities were concentrated. The 50 km spillover ring may have been "too close to violence" to attract displaced households seeking safety and employment.

These findings reshape the interpretation of the main results. Because nearby comparison districts also experienced negative population effects, the difference-in-differences estimates compare conflict districts to a negatively affected comparison group, not to an unaffected counterfactual. The positive coefficients in Table 4 therefore represent recovery relative to neighbors who also suffered, not absolute recovery to pre-conflict trajectories.

Both conflict districts and their immediate neighbors experienced the regional disruption of war, yet only the conflict districts recovered. The aggregates do not identify the mechanism, though reconstruction investment that favored districts with documented violence is one candidate, and program allocation is not observed directly. Spillover districts continued to lose population.

This interpretation has three important implications:

First, the baseline estimates likely *understate* the total regional impact of violence. The true effect of conflict on Peru's central highlands, measured against unaffected counterfactual districts, would be more negative than the estimates suggest, because the comparison group was itself harmed.

Second, the positive coefficients for conflict districts reflect relative recovery within a disrupted region, consistent with a role for policy intervention. Peru implemented return, repopulation, and collective-reparation initiatives for conflict-affected communities (Comisión de la Verdad y Reconciliación, 2003, Tomo IX), and spillover districts, lacking documented violence to justify prioritization, would have received less attention under such criteria. Because this paper does not observe the geographic allocation or timing of those programs, it cannot estimate their contribution to the reported coefficients.

Third, the divergent trajectories of conflict and spillover districts are consistent with policy mattering: if reconstruction investment followed documented violence, conflict districts recovered while equally disrupted neighbors continued to decline. This reading fits the infrastructure and human capital gains documented in Section 5, though establishing the policy channel would require direct data on program allocation.

Figure 9 summarizes the identification strategy visually. Treatment districts (very-high-conflict, in red) are compared to distant comparison districts (gray), with the spillover zone (blue) either excluded in donut specifications or explicitly modeled in ring specifications. The spatial concentration of both conflict and spillovers in the central highlands points to the importance of accounting for regional effects when estimating the long-run consequences of localized violence.

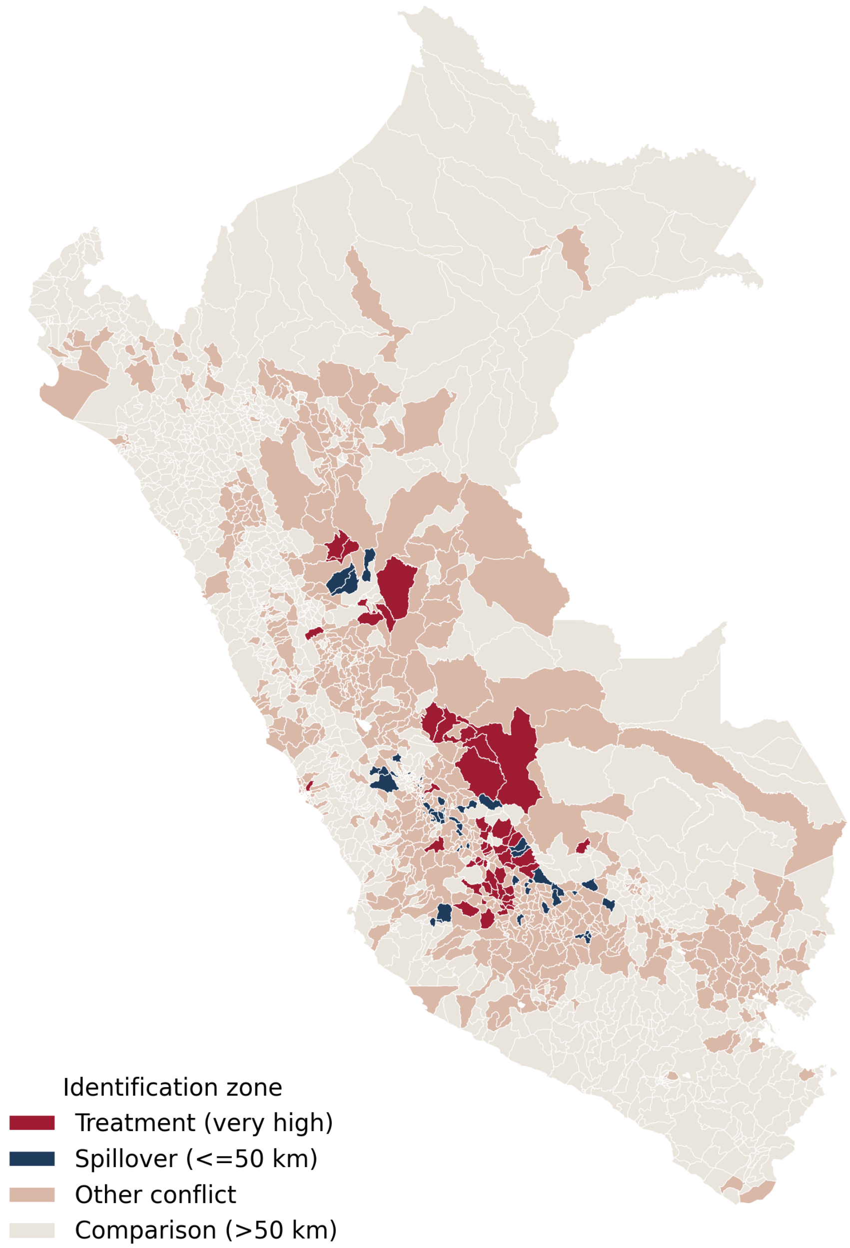


Figure 9: Identification Strategy: Treatment, Spillover, and Comparison Groups

Notes: Treatment = very-high-conflict districts with >100 CVR-documented victims (50 districts). Spillover = non-conflict districts within 50 km of treatment (53 districts). Comparison = non-conflict districts >50 km from treatment (1,120 districts). Other conflict districts (1–100 victims) shown in a muted tone.

7 Mechanisms and Heterogeneity

The population recovery and human capital convergence documented in Section 5 raise important questions about underlying mechanisms. This section examines demographic transformation as the primary channel through which recovery occurred, then explores heterogeneity by perpetrator type, conflict duration, and geographic region.

7.1 Age Structure Transformation

Table 13 reveals systematic demographic changes that point to mechanisms behind population recovery. Conflict districts became significantly younger, with important implications for long-run economic potential.

Table 13: Effect of Very High Conflict on Demographics

	(1) Mean Age	(2) Dep Ratio	(3) Sex Ratio	(4) Children %	(5) Working Age %
Very High × 1993	-1.928**	-6.167**	3.530*	0.917	1.516*
	(0.753)	(2.752)	(2.078)	(1.063)	(0.778)
Very High × 2007	-3.095***	-1.415	4.316**	3.444***	-0.221
	(0.739)	(2.451)	(2.030)	(0.973)	(0.709)
Very High × 2017	-2.823***	-7.456***	2.210	1.658*	1.685***
	(0.782)	(2.218)	(1.930)	(0.958)	(0.648)
Observations	6115	6115	6115	6115	6115
Adjusted R^2	0.822	0.731	0.413	0.816	0.736

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Very high conflict = >100 victims. Omitted comparison group: all districts below the very-high threshold. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

Mean age in very-high-conflict districts declined by 1.9 years relative to comparison districts by 1993 ($p = 0.011$), 3.1 years by 2007 ($p < 0.001$), and 2.8 years by 2017 ($p < 0.001$). This persistent demographic shift reflects compositional changes rather than differential aging rates.

The child population share (ages 0–14) increased by 3.4 percentage points in 2007 ($p < 0.001$), while the dependency ratio declined by 7.5 percentage points by 2017 ($p < 0.001$). This combination creates demographic conditions consistent with a potential demographic dividend: age structures with more workers per dependent could support faster economic growth in coming decades. This dividend reflects both a large elderly-share deficit and a more modest working-age surplus. The elderly (65+) population share is 2.4–3.3 percentage points lower in conflict districts (Table A14), representing the cohorts most exposed to conflict-era violence and displacement.

Sex ratios in Table 13 shift toward men in the post-conflict decades: +3.5 males per 100 females in 1993 ($p < 0.10$) and +4.3 in 2007 ($p < 0.05$), with the 2017 estimate (+2.2) no longer statistically significant. The direction is unexpected. Despite violence that fell disproportionately on men, the sex composition of these districts moved toward men relative to comparison trends, narrowing their baseline female surplus, a pattern consistent with male-dominated labor in-migration during reconstruction. The differential fades by 2017.

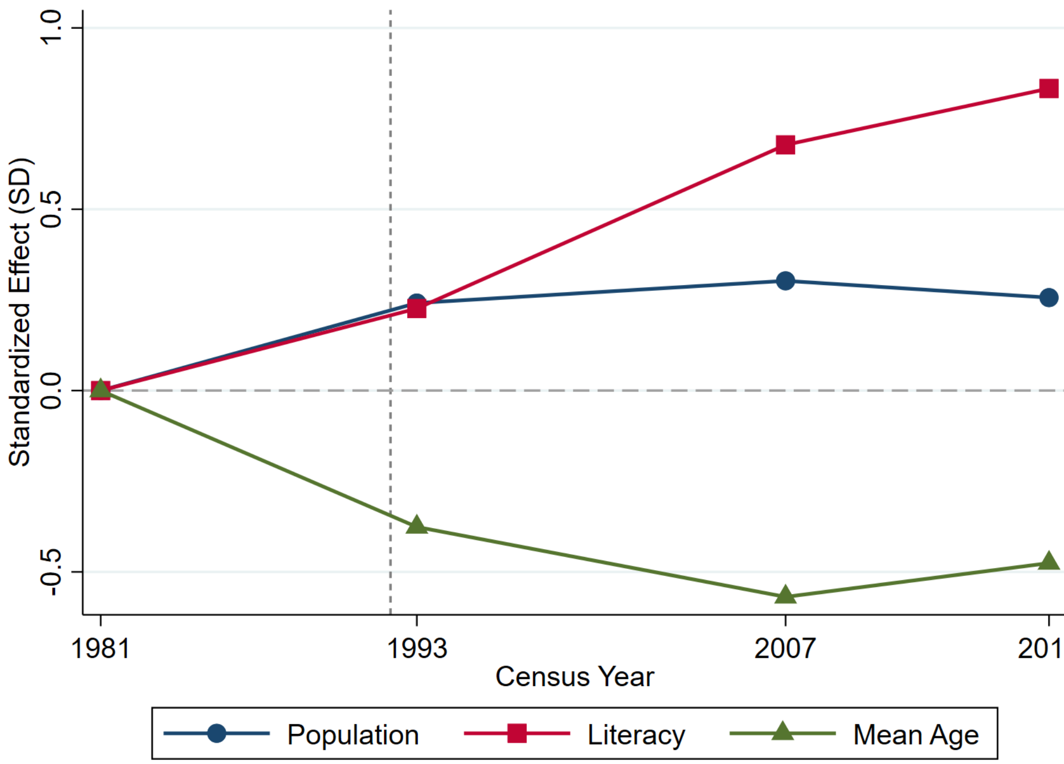


Figure 10: Standardized Effects Over Time: Population, Literacy, and Demographics

Notes: Coefficients expressed in standard deviations of each outcome, where each outcome is standardized by its pooled standard deviation across all districts and census years. Reference year: 1981. The persistent negative effect on mean age (approximately −0.4 to −0.5 SD across all periods) reflects demographic transformation: conflict districts are populated by younger cohorts, with "missing generations" among the elderly who experienced conflict-era violence and displacement.

Figure 10 places these demographic effects in comparative perspective. While literacy gains reach approximately 0.8 standard deviations by 2017, mean age shows persistent negative effects of 0.4–0.5 standard deviations across all post-conflict periods. The stability of the age effect is pronounced: unlike literacy, which shows progressive improvement, the demographic transformation was largely in place by 1993, deepened somewhat through 2007, and shows no reversal by 2017. This pattern suggests that the age structure reflects durable compositional change rather than a transitional dynamic that quickly normalizes.

7.2 Migration and Population Turnover

Table 14 examines migration patterns and cultural indicators, providing evidence of substantial population turnover during recovery.

Table 14: Effect of Very High Conflict on Migration and Culture

	(1) Migration	(2) Same Dist	(3) Indigenous	(4) Quechua	(5) Spanish
Very High × 1993	9.039***	-9.039***	5.174	2.477	-5.352
	(2.981)	(2.981)	(3.679)	(2.914)	(3.685)
Very High × 2007	9.890**	-9.890**	4.929	2.057	-5.130
	(4.238)	(4.238)	(3.649)	(2.958)	(3.654)
Very High × 2017	5.539**	-5.539**	3.368	0.512	-3.560
	(2.298)	(2.298)	(3.687)	(2.936)	(3.690)
Observations	6115	6115	6115	6115	6115
Adjusted R^2	0.534	0.534	0.894	0.894	0.894

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Migration rate = share of population not born in current district of residence. Indigenous Lang = share reporting indigenous language as mother tongue. *** p<0.01, ** p<0.05, * p<0.10.

Migration rates, the share of residents not born in their current district, were 9.0 percentage points higher in very-high-conflict districts by 1993 ($p < 0.01$) and 9.9 percentage points higher by 2007 ($p < 0.05$). Elevated mobility persisted at 5.5 percentage points by 2017 ($p < 0.05$). The share born in the same district declined by mirror-image magnitudes, implying that the 2017 population comprises substantially different individuals than the 1981 population.

Language patterns in Table 14 show no evidence of linguistic assimilation. The 2017 point estimates are positive for indigenous languages (+3.4 percentage points) and Quechua specifically (+0.5), and negative for Spanish (−3.6), but all are statistically insignificant

($p > 0.10$). Despite the substantial population turnover documented above, the linguistic composition of very-high-conflict districts did not detectably diverge from comparison districts.

These migration patterns have important implications for interpreting population recovery. The 2017 population of conflict districts comprises substantially different individuals than the 1981 population. Approximately 5.5 percentage points more are migrants compared to counterfactual trends. These patterns document substantial demographic recomposition. By 2017, very-high-conflict districts had a 5.5-percentage-point higher share of residents born outside their current district relative to the comparison trend, alongside younger age structures and lower elderly shares. The district-level census data, however, do not distinguish new settlement from return migration by former residents or their descendants, permanent non-return, mortality, or differential fertility. The evidence is therefore interpreted as persistent population turnover rather than as proof that the original communities were wholly replaced.

7.3 Heterogeneity by Perpetrator

The Peruvian conflict provides a unique setting to examine whether perpetrator identity, insurgent groups versus state forces, generates differential long-run consequences. The Truth and Reconciliation Commission documented victim-level attribution of responsibility, allowing us to classify districts by dominant perpetrator: Sendero Luminoso, state security forces, or mixed (no majority perpetrator).

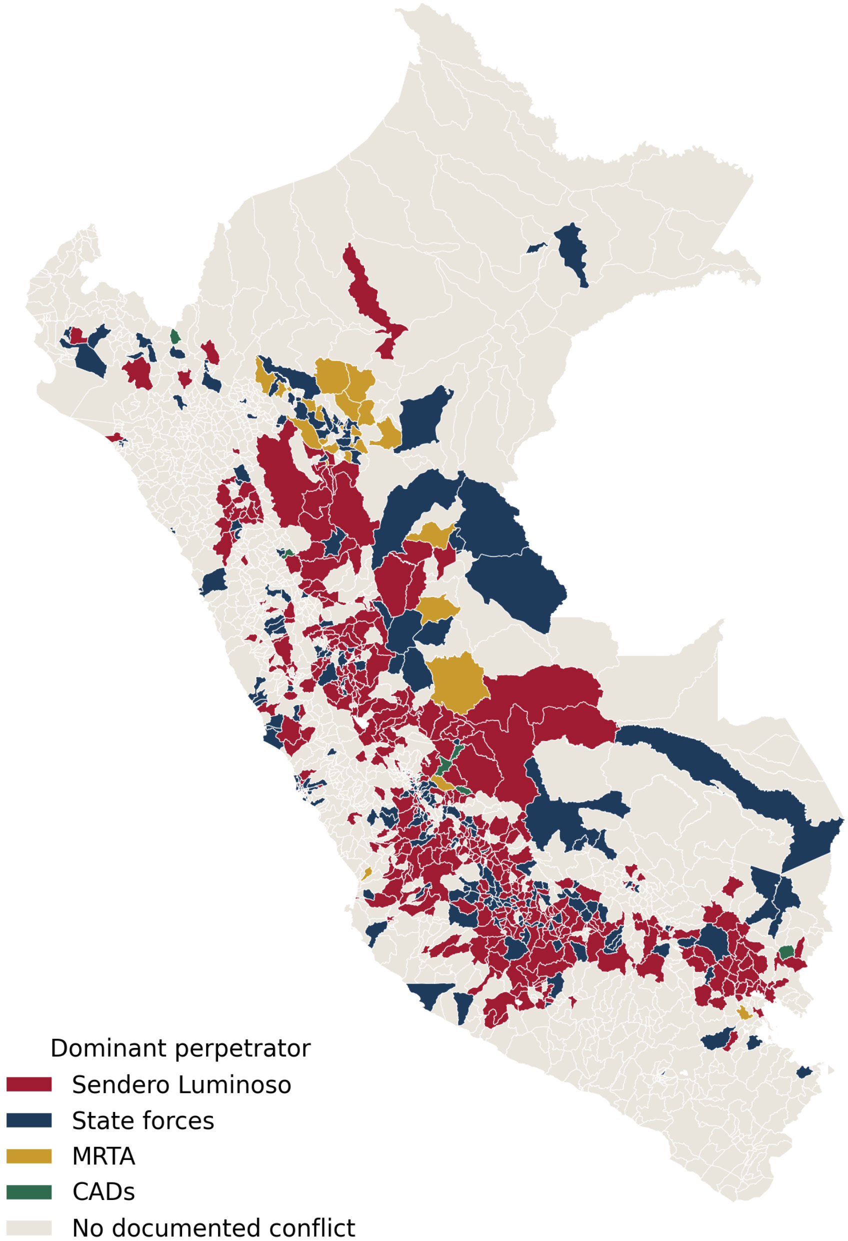


Figure 11: Conflict by Dominant Perpetrator, 1980–2000

Notes: Districts colored by the perpetrator responsible for the largest share of documented victims: Sendero Luminoso (red), state forces (blue), MRTA (gold), CADs (green, the Comités de Autodefensa or civilian self-defense committees), and no documented conflict (gray). Classification based on Truth and Reconciliation Commission victim-level data with perpetrator attribution. The Sendero-/State-dominant/Mixed grouping used in the regression tables (majority thresholds, Appendix C.1) is a coarser partition of the same attribution data.

Figure 11 reveals distinct geographic patterns by perpetrator. Sendero Luminoso-dominant districts (red) cluster in the central highlands around Ayacucho, reflecting the insurgency's Maoist strategy of rural base-building in peasant communities. State-dominant districts (blue) are more geographically dispersed, appearing along the jungle frontier and in areas of counterinsurgency operations where military forces engaged suspected insurgent strongholds. A smaller number of districts are dominated by MRTA violence (gold), concentrated in the central jungle, or by violence attributed to the CADs (green).

Table 15: Long-Run Effects by Dominant Perpetrator (2017)

	Population (log)	Literacy (%)	Mean Age (years)	Migration Rate (%)
Very High × 2017 Coefficients by Dominant Perpetrator				
Sendero Dominant	0.498*	3.836	−3.524***	6.117**
	(0.281)	(3.166)	(1.089)	(2.790)
State Dominant	1.179	10.176**	−1.405	−2.387
	(1.186)	(4.852)	(1.685)	(7.466)
Mixed Perpetrator	0.246	4.468	−0.237	12.734***
	(0.305)	(6.375)	(0.600)	(4.105)
N (Sendero)	1,276	1,276	1,276	1,276
N (State)	468	468	468	468
N (Mixed)	756	756	756	756

Notes: Coefficients from separate regressions on subsamples of conflict districts with the indicated dominant perpetrator, so each coefficient compares very-high-conflict districts with lower-intensity conflict districts of the same dominant-perpetrator type. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

The results in Table 15 reveal substantial heterogeneity. Because each perpetrator-specific regression restricts the sample to conflict districts with the indicated dominant perpetrator, the coefficients compare very-high-conflict districts with lower-intensity conflict districts of the same type. Historical evidence documents systematic Sendero attacks on local authorities, community leaders, and other institutional actors (Comisión de la Verdad y Reconciliación, 2003, Tomo II). The empirical estimates show different long-run demographic and educational profiles across dominant-perpetrator categories, but they do not directly measure the destruction or survival of local institutions. These contrasts are therefore interpreted as consistent with differences in the organization and targets of violence, rather than as a direct test of an institutional-continuity mechanism.

Sendero Luminoso. Districts where Sendero dominated exhibit the most dramatic demographic transformation, with populations 3.5 years younger than lower-intensity Sendero-dominant districts by 2017 ($p < 0.01$) and significantly elevated in-migration (+6.1 pp, $p < 0.05$), yet the weakest human capital recovery (+3.8 pp literacy, statistically insignificant). This pattern reflects Sendero's distinctive targeting strategy. Unlike conventional insurgencies that seek popular support, Sendero's Maoist ideology demanded the complete destruction of existing social structures to rebuild society from zero (Degregori, 1990).

In practice, this meant systematic targeting of precisely the individuals who embodied local human capital and institutional capacity. Teachers were executed as agents of bourgeois education. Local officials and community leaders were killed as representatives of the old order. Anyone with secondary education or professional skills was suspect as a class enemy (Comisión de la Verdad y Reconciliación, 2003, Tomo II). The Truth and Reconciliation Commission documented numerous cases of Sendero executing teachers in front of their students, destroying schools, and assassinating municipal authorities (Comisión de la Verdad y Reconciliación, 2003, Tomos II and VII).

This targeting pattern provides one historical interpretation consistent with the divergent recovery trajectories. When violence ended, Sendero-dominant communities may have lacked the human capital to reconstitute, with teachers dead or displaced and local governance severely disrupted. The elevated migration rates and younger age structures of these districts today are consistent with greater population turnover, but they do not distinguish return migration from new settlement.

State forces. State-dominant districts display a different empirical profile: no statistically significant differential in mean age (1.4 years younger) or migration (−2.4 pp), sharply lower dependency ratios (Table A12), and stronger literacy gains (+10.2 pp, $p < 0.05$) in the dominant-perpetrator specification. The educational heterogeneity is specification-dependent: the dominant-perpetrator subsamples show stronger literacy recovery in state-dominant districts, whereas the continuous perpetrator-share specifications yield the opposite literacy gradient (Appendix C.4).

Military counterinsurgency operations were often indiscriminate and brutal, and the CVR attributed 37% of all deaths to state forces, but they were not designed to destroy social structure. Soldiers conducted sweeps through suspected insurgent areas, detained and often killed young men of fighting age, and committed widespread human rights abuses (Burt, 2006). Yet they did not systematically target teachers, officials, or educated community members. State violence was reactive: it sought to eliminate insurgents, and it did not set out to remake the communities it passed through.

This pattern is consistent with a different form of post-conflict adjustment, although the available outcomes do not directly measure institutional continuity.

Mixed-perpetrator districts. Mixed-perpetrator districts show no distinctive population or literacy gains (+0.25 log points and +4.5 pp, both statistically insignificant) but the largest in-migration effect of any group (+12.7 pp, $p < 0.01$). Areas contested between Sendero and state forces experienced violence from both sides and repeated changes of territorial control, an environment consistent with extensive population turnover, though the data do not distinguish return migration from new settlement. The migration result should be read as descriptive, since the mixed category contains only twelve very-high-conflict districts, but it is consistent with contested zones experiencing churn rather than either the institutional destruction of Sendero strongholds or the in-situ persistence of state-dominant areas.

Policy implications. The point estimates suggest that perpetrator characteristics may matter alongside intensity, but the categorical differences are imprecise and the literacy pattern is specification-dependent. Two districts with identical victim counts may experience different recovery trajectories depending on who was killed, how the violence was organized, and what institutional capacity survived.

If confirmed, these patterns would carry implications for post-conflict reconstruction. Sendero-affected areas may require complete institutional rebuilding, including importing human capital from outside, since local teachers and administrators were systematically eliminated. State-affected areas may rely more on strengthening the population and organizations that remained. And contested areas, marked by wholesale population turnover, may warrant sustained attention to social cohesion even after initial reconstruction programs conclude.

7.4 Heterogeneity by Conflict Duration

Table 16 examines whether recovery differs by the temporal profile of violence: deaths versus disappearances, and long versus short duration of documented violence.

Table 16: Population Recovery by Conflict Duration

	(1) High Deaths	(2) High Disappearances	(3) Long Duration	(4) Full
Very High × 1993	0.817	0.353*	0.347	0.496**
	(1.229)	(0.205)	(0.263)	(0.250)
Very High × 2007	1.171	0.460**	0.495*	0.668***
	(1.237)	(0.204)	(0.263)	(0.250)
Very High × 2017	0.878	0.455**	0.474*	0.593**
	(1.388)	(0.213)	(0.281)	(0.268)
Observations	1247	1249	1203	6115
Adjusted R^2	0.834	0.879	0.853	0.819

Notes: High Deaths/Disappearances = above-median share of deaths (disappearances) among conflict districts. Long Duration = above-median years of documented violence among conflict districts. No short-duration column is shown because it is not estimable: every very-high-conflict district experienced above-median conflict duration, so no very-high-conflict district appears in the short-duration subsample. Columns (1)–(3) restrict the sample to conflict districts in the indicated category, so Very High coefficients compare very-high-conflict districts with other conflict districts in that category. Column (4) uses the full sample, with all districts below the very-high threshold as the comparison. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

The central lesson of the duration split is that duration and intensity cannot be separated in this setting. When conflict districts are divided at the median number of years with documented violence, every very-high-conflict district falls in the long-duration group. A short-duration column therefore cannot be estimated, since no very-high-conflict district experienced short-duration violence, and Table 16 omits it. Sustained exposure over many years is what generated the largest victim counts.

Within the long-duration subsample (Column 3), very-high-conflict districts show positive population effects of 0.35–0.50 log points relative to *other long-duration conflict districts*, marginally significant in 2007 and 2017. Column 2 shows a similar pattern within the subsample of districts with above-median disappearance shares (+0.35 to +0.46 log points). These within-subsample estimates are smaller than the full-sample effects against all below-threshold districts (Column 4), as expected when the comparison group itself experienced violence, but they point in the same direction: even among districts subjected to prolonged violence, the most intensely affected recovered in population terms.

The perfect overlap between very high intensity and long duration is itself informative:

in Peru's conflict, the most violent places were violent for many years, so any claim about "short, acute" versus "chronic" exposure at high intensities is unidentifiable from these data.

7.5 Regional Heterogeneity

Table 17 explores whether effects varied across Peru's distinct geographic regions. The comparison sets the Sierra (highlands), the conflict's epicenter, against the Selva (jungle), excluding the Costa (coast) which contained no very-high-conflict districts.

Table 17: Regional Heterogeneity: Sierra versus Selva

	Log Population			Literacy Rate		
	(1) Sierra	(2) Selva	(3) Full	(4) Sierra	(5) Selva	(6) Full
Very High × 1993	-0.076	0.983***	0.496**	1.605	-2.488	0.885
	(0.175)	(0.280)	(0.250)	(2.230)	(5.032)	(2.183)
Very High × 2007	0.108	1.096***	0.668***	6.759***	-0.591	5.260**
	(0.165)	(0.273)	(0.250)	(2.528)	(4.878)	(2.358)
Very High × 2017	0.013	1.104***	0.593**	8.795***	0.240	6.966***
	(0.185)	(0.272)	(0.268)	(2.653)	(4.789)	(2.457)
Observations	3961	738	6115	3961	738	6115
Adjusted R^2	0.815	0.841	0.819	0.722	0.626	0.711

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Costa excluded (no very-high-conflict districts). Sierra = highland departments and Selva = jungle/Amazon departments. Within each sample, the omitted comparison group is all districts below the very-high threshold. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

Population effects are concentrated entirely in the Selva (jungle): coefficients of 0.98 log points in 1993, 1.10 in 2007, and 1.10 in 2017 (all $p < 0.01$), compared to close to zero in the Sierra (highlands), where estimates range from -0.08 to $+0.11$ and never approach significance. This regional difference likely reflects distinct conflict and post-conflict dynamics. The Selva's sparse population and challenging terrain may have produced more complete initial displacement followed by aggressive resettlement during coca eradication and alternative development programs of the 1990s and 2000s. Alternative-development activities of the United States Agency for International Development (USAID) were concentrated in Amazon regions including San Martín, Huánuco, and Ucayali, where they promoted legal alternatives to coca production. These programs form part of the regional post-conflict context, although the present analysis cannot determine whether they contributed to the estimated population differential.

Literacy effects show the opposite regional pattern. Sierra districts gained 6.8 percentage points by 2007 and 8.8 by 2017 (both $p < 0.01$), while Selva point estimates are close to zero or negative (-2.5 in 1993, -0.6 in 2007, $+0.2$ in 2017) and never significant. The Sierra's denser population, more established settlement patterns, and longer history of educational infrastructure may have facilitated more effective post-conflict schooling interventions. The Sierra's proximity to major cities like Ayacucho and Huancayo also provided access to teacher training institutions and educational resources that the remote jungle lacked.

8 Night-Time Lights

The population recovery and human capital convergence documented in the preceding sections raise a natural question: did these gains translate into economic recovery? This section uses satellite-based night-time lights (NTL) data to examine economic activity in conflict-affected districts. Careful attention to sample selection reveals a more optimistic picture than initial estimates suggest: conflict districts converged substantially on the extensive margin, and full-sample transformed-outcome specifications show small negative 2017 per-capita gaps while the scale-invariant PPML estimate is statistically indistinguishable from zero.

8.1 Data and Measurement

Night-time luminosity provides an objective measure of economic activity independent of administrative data collection, making it particularly valuable for conflict-affected areas where census enumeration may have been incomplete or where informal economic activity predominates. The data are the night-time lights series of Chen et al. (2024), a simulated VIIRS-consistent annual series constructed from DMSP-OLS and VIIRS imagery, aggregated to the district level.

NTL data are available for the 1993, 2007, and 2017 census years. The 1981 census predates the start of the DMSP-OLS digital archive in 1992, so all NTL analyses use 1993 as the reference year rather than 1981. The outcomes are total NTL (sum of pixel values within district boundaries), NTL per capita (total NTL divided by census population), and an indicator for any detected luminosity.

A critical measurement issue arises from districts with zero detected luminosity. Across the three census years, 45.9% of district-year observations recorded no detectable night-time lights, predominantly in small, rural, highland districts lacking electricity infrastructure. These zero-luminosity observations disproportionately come from small, rural, high-altitude districts, but very-high-conflict exposure is statistically similar between the zero- and positive-NTL samples.

Table 18: Sample Selection in NTL Per Capita Analysis

	Dropped (Zero NTL)	Retained (Positive NTL)	*p*-value (difference)
Observations	2,256	2,659	
Share of NTL sample	45.9%	54.1%	
Mean altitude (m)	2,595	2,110	<0.001
Mean population	4,092	26,078	<0.001
Mean distance to Lima (km)	491	489	0.764
Urban share (%)	33.3	48.9	<0.001
Terrain ruggedness	288	225	<0.001
Literacy rate (%)	76.3	84.6	<0.001
Very high conflict (%)	2.6	2.8	0.647
Any conflict (%)	23.8	28.9	<0.001

Notes: Sample characteristics for district-year observations with zero versus positive NTL, with Welch *t*-test *p*-values for the difference. Dropped observations are excluded when using log(NTL per capita) but retained when using IHS or log(x+c) transformations. Estimation samples are slightly smaller (4,889 and 2,017 observations) because the fixed-effects estimator drops singleton districts. Zero-NTL district-year observations come from districts that are systematically higher altitude, smaller, and more rural, while mean distance to Lima is statistically indistinguishable across the two groups.

Table 18 documents the severity of this sample selection problem. The raw NTL sample contains 4,915 district-year observations, of which 2,256 (45.9%) are zero and 2,659 positive. The estimation samples are slightly smaller because the fixed-effects estimator drops singleton districts, meaning those observed only once and perfectly absorbed by the district fixed effect: the zero-preserving specifications retain 4,889 observations (26 singletons dropped), and the positive-only log specification retains 2,017 (642 districts appear with positive luminosity in only one census year). Zero-NTL observations come from districts that are higher altitude (2,595m versus 2,110m), much smaller (population 4,092 versus 26,078), and far less urban (33% versus 49%), though similarly distant from Lima. These are precisely the marginalized districts where conflict effects may differ most from urban or peri-urban areas.

To address this, results are presented using multiple transformations that preserve the full sample: the inverse hyperbolic sine (IHS), which handles zeros while approximating the log for large values, and log(x + c) with small constants. The IHS transformation is defined as $\text{asinh}(x) = \ln(x + \sqrt{x^2+1})$, which equals zero when $x = 0$ and approximates $\ln(2x)$ for large x, allowing zero-luminosity observations to remain in the sample. As Section 8.3 discusses, however, treatment effects estimated on IHS or $\log(x + c)$ outcomes are not unit-free percentage effects when treatment shifts the extensive margin, so their magnitudes are interpreted cautiously.

8.2 Extensive Margin: Probability of Economic Activity

The analysis first examines the extensive margin: whether districts have any detectable economic activity. This question is particularly relevant for conflict-affected areas, many of which lacked electricity and modern economic infrastructure before the conflict began.

Table 19: Extensive Margin: Probability of Any Detected Night-Time Lights

	(1) Basic	(2) +Geo×
Very High × 2007	0.101	0.100
	(0.064)	(0.064)
Very High × 2017	0.190***	0.152**
	(0.070)	(0.069)
Observations	4889	4889
Adjusted R^2	0.578	0.600
Geo × Year	No	Yes

Notes: Linear probability model. Standard errors clustered at district level in parentheses. Dependent variable equals 1 if district has any detected night-time luminosity, 0 otherwise. Reference year: 1993. Column (2) includes altitude and terrain ruggedness interacted with year fixed effects to control for differential infrastructure expansion by geography. *** p<0.01, ** p<0.05, * p<0.10.

Table 19 presents linear probability models for the indicator of positive NTL. Conflict districts show significant catch-up on the extensive margin. By 2017, very-high-conflict districts were 15–19 percentage points more likely to have detectable economic activity than comparison districts relative to their 1993 baseline ($p < 0.05$ in both specifications). Given that only 25% of very-high-conflict districts had detectable NTL in 1993, this represents substantial convergence.

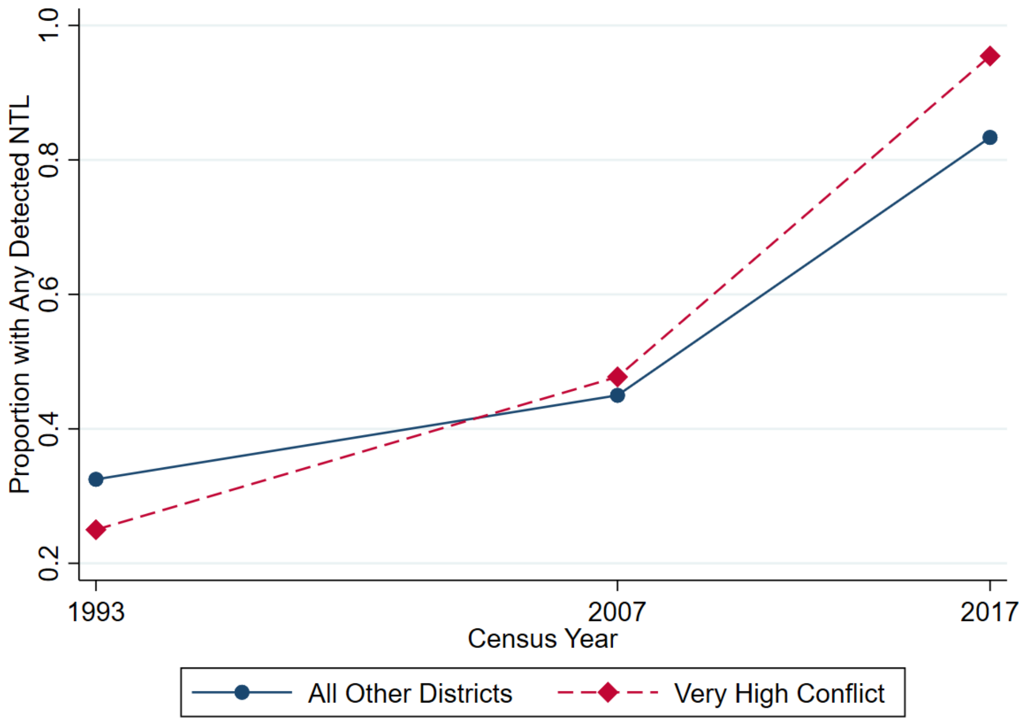


Figure 12: Extensive Margin: Probability of Any Detected Night-Time Lights Over Time

Notes: Share of districts with any detected night-time luminosity by conflict status and census year. Very high conflict districts (dashed line) started with a lower probability of detectable economic activity in 1993 (25.0% versus 32.5%) and overtook the comparison group by 2017 (95.5% versus 83.3%). This extensive-margin catch-up reflects electrification and infrastructure investment that brought previously "dark" districts into the modern economy.

Figure 12 visualizes this convergence trajectory. In 1993, very-high-conflict districts were less likely to have any detectable NTL (25.0% versus 32.5%), reflecting their remote highland locations, limited pre-conflict infrastructure, and conflict-era destruction. By 2017, the initial gap had reversed: 95.5% of very-high-conflict districts had detectable luminosity, against 83.3% of other districts.

This extensive-margin catch-up reflects the electrification of formerly dark districts. It coexists with the negative household electricity-access coefficients in Section 5.5: satellites detect any luminous infrastructure (town centers, street lighting, public facilities), which can spread even where the share of individual households with electric lighting still lags the comparison trend.

The extensive-margin story is optimistic. The share of very-high-conflict districts with detected NTL rose from 25.0% in 1993 to 95.5% in 2017. This represents meaningful economic inclusion, regardless of whether per-capita activity levels have fully converged.

8.3 Intensive Margin: NTL Per Capita

The analysis now turns to per-capita luminosity. Table 20 presents NTL per capita results using alternative transformations to assess robustness to sample selection. Only Column (1), which drops zero-luminosity observations, is a conditional intensive-margin estimate, while Columns (2)–(5) are unconditional full-sample specifications that retain zeros.

Table 20: NTL Per Capita: Robustness to Transformation Choice

	NTL Per Capita				
	(1) Log(x)	(2) IHS(x)	(3) Log(x+.01)	(4) Log(x+1)	(5) Percentile
Very High × 2007	-1.470***	-0.001***	-0.045***	-0.001***	2.084
	(0.348)	(0.000)	(0.018)	(0.000)	(2.583)
Very High × 2017	-1.346***	-0.008***	-0.225***	-0.008***	-6.220*
	(0.501)	(0.001)	(0.047)	(0.001)	(3.297)
Observations	2017	4889	4889	4889	4889
Adjusted R^2	0.601	0.338	0.613	0.367	0.698
Zero-NTL Districts	Dropped	Preserved	Preserved	Preserved	Preserved

Notes: Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Reference year: 1993. Column (1) retains only positive-NTL observations. Columns (2)–(5) preserve the full sample using transformations that accommodate zeros. IHS = inverse hyperbolic sine: $\text{asinh}(x) = \ln(x + \sqrt{x^2+1}) \approx \ln(2x)$ for large x. Percentile = within-year percentile rank (0–100). *** p<0.01, ** p<0.05, * p<0.10.

The results reveal substantial sensitivity to sample selection. The standard log specification (Column 1) shows large negative effects: -1.35 log points by 2017, implying conflict districts have approximately 74% lower NTL per capita than comparison districts. However, this estimate is based on only 2,017 observations after dropping zero-luminosity observations and the resulting singleton districts (Section 8.1), a selected sample of larger, more urban, more accessible districts.

The full-sample specifications tell a markedly different story. The IHS transformation (Column 2) yields coefficients of -0.001 in 2007 and -0.008 in 2017, and the log(x+0.01) specification (Column 3) effects of -0.045 and -0.225, small in their respective transformed units, though as discussed below these magnitudes are not unit-free percentage effects. The percentile rank specification (Column 5) shows conflict districts falling approximately 6.2 percentile points in the within-year NTL distribution by 2017 ($p < 0.10$).

The dramatic difference between Column 1 and Columns 2–5 reflects both the positive-NTL sample restriction and differences in transformation and estimand. Districts with positive NTL in all years tend to be much larger and more urban (Table 18). By restricting to this selected sample, the log specification changes the comparison sample toward substantially larger and more urban districts.

Which estimate should be believed? The disagreement across transformations is itself diagnostic. Chen and Roth (2024) show that for outcomes with zeros, the treatment effect of any log-like transformation ($\log(x+c)$, IHS) depends on the units of the outcome and cannot be interpreted as a unit-free percentage effect when treatment shifts the extensive margin, which is the source of the spread between the log, IHS, and $\log(x+c)$ estimates above. The per-capita effect is therefore estimated with Poisson pseudo-maximum-likelihood (PPML), which is scale-invariant, accommodates zeros without an arbitrary transformation, and yields a single interpretable proportional effect on the conditional mean of per-capita luminosity (Santos Silva and Tenreyro, 2006; Chen and Roth, 2024). The PPML estimates of the very-high-conflict effect on NTL per capita are $+0.0000$ (s.e. 0.250) in 2007 and -0.072 (s.e. 0.412) in 2017 (Table A8, Panel C), neither statistically distinguishable from zero, though the standard errors are wide enough that moderate gaps in either direction cannot be ruled out. The positive-only log specification produces a much larger estimated shortfall than the full-sample transformed-outcome and PPML specifications. Under the scale-invariant estimator, the data provide no statistically significant evidence of a per-capita luminosity gap.

Table 21 presents a unified comparison of demographic and economic outcomes. All columns use the full estimation sample except the positive-only log specification in Column (4).

Table 21: Demographic versus Economic Recovery: Comparison Across Samples

	Population	Economic Activity			Human Capital
	(1)	(2)	(3)	(4)	(5)
	Log Pop	IHS NTL	IHS NTL/cap	Log NTL/cap	Literacy
Very High × 2007	0.086*	-0.027	-0.001***	-1.470***	5.391***
	(0.049)	(0.207)	(0.000)	(0.348)	(0.987)
Very High × 2017	0.024	0.008	-0.008***	-1.346***	7.261***
	(0.068)	(0.241)	(0.001)	(0.501)	(1.150)
Observations	4889	4889	4889	2017	4889
Adjusted R^2	0.965	0.837	0.338	0.601	0.825

Notes: All regressions include district and year fixed effects. Columns (1)–(3) and (5) use the full estimation sample of 4,889 district-year observations with NTL data. Column (4) is the positive-only log specification with 2,017 observations. Standard errors clustered at district level in parentheses. Reference year: 1993. IHS = inverse hyperbolic sine transformation. *** p<0.01, ** p<0.05, * p<0.10.

The full-sample comparison reveals a coherent recovery pattern across dimensions. Population (Column 1) shows small positive effects of 0.02–0.09 log points, statistically insignificant by 2017. Relative to the 1993 baseline, conflict districts have maintained population parity with comparison districts. Total NTL (Column 2) shows near-zero, statistically insignificant effects (-0.03 to $+0.01$), consistent with, though not proof of, parallel trajectories in aggregate economic activity. NTL per capita (Column 3) shows small but statistically significant negative coefficients of -0.001 to -0.008 in IHS units. While per-capita economic activity remains somewhat lower, the shortfall is far smaller than the log estimates implied. Literacy (Column 5) shows large positive effects of 5–7 percentage points, highly significant, indicating that human capital has converged substantially faster than economic activity.

This pattern suggests that conflict districts experienced demographic and human capital recovery alongside meaningful though incomplete economic convergence. The population that inhabits conflict districts today is substantially more literate than the 1993 population, and while per-capita economic activity remains modestly lower in the full-sample transformed-unit estimates, the scale-invariant PPML estimator finds no statistically significant gap, nothing close to the large differences the positive-only log specification suggested.

8.4 Heterogeneity in Economic Recovery

Table 22 examines whether economic recovery varied by initial development level and perpetrator type, using the IHS transformation throughout to maintain full-sample comparability.

Table 22: NTL Per Capita Heterogeneity (IHS Transformation, Full Sample)

	By Initial Development			By Perpetrator		
	Pooled	Below Med.	Above Med.	Sendero	State	Mixed
Very High × 2007	-0.001***	-0.000	-0.004***	-0.000	-0.003**	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Very High × 2017	-0.008***	-0.005***	-0.016***	-0.005***	-0.007***	-0.003
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.004)
Observations	4889	3228	1661	1046	393	632
Adjusted R^2	0.338	0.079	0.409	0.268	0.455	0.076

Notes: Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Reference year: 1993. Low/High initial development = below/above median 1993 IHS(NTL) among all districts. Sendero/State = districts where Sendero Luminoso or state forces were responsible for majority of documented victims. IHS = inverse hyperbolic sine. *** p<0.01, ** p<0.05, * p<0.10.

Economic recovery exhibits meaningful heterogeneity along both dimensions.

Regarding initial development, initially more-developed conflict districts (above-median 1993 NTL) show larger per-capita gaps by 2017 (-0.016) than initially less-developed districts (-0.005). This pattern suggests that conflict disrupted growth trajectories more severely where there was more economic activity to lose. Initially developed districts may have experienced destruction of productive capital, displacement of skilled workers, and disruption of commercial networks that were absent in subsistence-oriented areas. Alternatively, initially underdeveloped districts may have benefited more from post-conflict reconstruction investment, which created infrastructure and economic activity where little existed before.

Regarding perpetrator type, the state-dominant gap opens earlier (-0.003 in 2007, $p < 0.05$) and reaches -0.007 by 2017 ($p < 0.01$), while the Sendero-dominant gap appears only in 2017 (-0.005, $p < 0.01$) and the mixed group shows no significant gap. All coefficients are in IHS units and compare very-high-conflict districts with lower-intensity conflict districts of the same dominant-perpetrator type. The earlier and somewhat larger state-dominant shortfall sits in tension with the human capital results from Section 7.3, where state-dominant districts showed stronger literacy gains, though by 2017 the difference between the two groups is one of timing and degree rather than sign.

Taken together, the NTL evidence revises the initial impression of economic divergence. Conflict districts converged sharply on the extensive margin, with a 15–19 percentage point differential increase in the probability of any detectable activity relative to comparison districts (the raw share rose from 25.0% to 95.5%), while full-sample estimators put the per-capita gap near zero, with the scale-invariant PPML estimate statistically indistinguishable from zero, rather than the 74 percent implied by log estimates that drop zero-luminosity districts. The remaining gaps are larger where there was more activity to lose and open earlier in state-dominant districts. The methodological lesson generalizes: log transformations of outcomes with many zeros can dramatically overstate effect magnitudes, and robustness to full-sample transformations should be routine.

9 Conclusion

This paper asks what happened to the communities Peru's internal armed conflict devastated. Drawing on four census waves over 36 years, it finds substantial recovery on several dimensions alongside a demographic transformation that fits neither a simple success nor a simple failure narrative.

The headline findings are largely encouraging. Districts that experienced the most intense violence did not become ghost towns. Their populations rebounded, their literacy rates converged toward national averages, and their infrastructure improved dramatically. By 2017, the raw literacy gap between very-high-conflict and no/low-conflict districts (0–10 victims) had narrowed by two-thirds, from 10.1 to 3.4 percentage points. Conflict areas posted gains in sanitation and housing quality that outpaced the trend in districts below the very-high-conflict threshold. Economic activity, as measured by satellite-based night-time lights, shows extensive-margin catch-up: conflict districts are now more likely to have detectable economic activity than comparison districts. These gains are real and consequential, consistent with a potential contribution of reconstruction investment and with the resilience of Peruvian communities.

Yet these findings carry an important qualification. The spillover analysis shows that non-conflict districts near the epicenter also lost population, so the comparison group was itself disrupted. The gains estimated for conflict districts are thus relative to negatively affected neighbors, and the total demographic toll on the central-southern highlands is larger than victim counts alone, or the baseline coefficients, would imply. The within-province comparisons draw the same distinction sharply: population recovery is the district-specific result, surviving and strengthening under the most local comparison, while literacy convergence and demographic rejuvenation dissolve within provinces. They are features of the conflict-affected region as a whole rather than of victimized districts relative to their immediate neighbors.

Beneath these aggregate improvements lies a more complex reality. The population composition of conflict districts differs substantially from its pre-war composition. Populations are 2–3 years younger on average, with elderly population shares 2.4–3.3 percentage points lower and substantially higher shares of young adults. This reflects substantial population turnover. The cohorts described as the "missing generations," those who experienced conflict as working-age adults, remain substantially underrepresented in these districts a generation later. With district aggregates, that absence cannot be apportioned between mortality, permanent displacement, and non-return. The communities that exist today in Ayacucho, Huancavelica, and the central highlands show a higher share of residents born outside their current district relative to comparison trends.

Economic recovery presents a mixed picture. Conflict districts show substantial catch-up on the extensive margin, the probability of having any detectable economic activity, reflecting infrastructure expansion and electrification in formerly remote areas. Per-capita economic activity remains modestly lower in the full-sample transformed-unit estimates, while the scale-invariant PPML estimator finds no statistically significant gap. Any remaining shortfall is far smaller than an analysis of only economically active districts would suggest, which shows why recovery assessments must include the poorest, most marginalized communities. The combination of human capital gains, infrastructure improvements, and extensive-margin convergence suggests that economic recovery, while incomplete, has accompanied demographic and educational gains.

These aggregate findings mask potentially important heterogeneity, though the categorical comparisons are imprecise. Districts where state forces dominated show significant literacy gains with no significant shift in mean age or migration (though sharply lower dependency ratios), while Sendero-dominant districts experienced pronounced demographic transformation, with populations roughly 3.5 years younger than lower-intensity districts with the same dominant perpetrator, but weaker educational gains. The divergence is consistent with different violence modalities: the CVR record documents Sendero targeting teachers, local officials, and educated residents as class enemies, whereas state counterinsurgency, though brutal, was largely reactive and less directed at institutional actors. These are interpretations consistent with the outcome profiles, not directly measured mechanisms.

Conflict duration and intensity prove inseparable in this setting. Every district in the most violent category experienced prolonged violence. There are no short, acute episodes at the highest intensities, so the data cannot say whether brief severe violence would have permitted faster recovery. What they do show is that even districts subjected to years of intense violence recovered in population terms, outgrowing other long-duration conflict districts by 0.35–0.50 log points.

Initial conditions also shaped recovery trajectories. Among conflict districts, those that were least developed in 1993 show the smallest relative per-capita shortfall by 2017, while more-developed ones show larger relative declines. Conflict thus induced convergence within affected areas, a leveling process that may reflect targeting of reconstruction investment toward the most marginalized communities, or differential capacity of communities to attract migrants and new settlement.

Three implications follow for policy. First, recovery timelines extend beyond a generation. Twenty-five years after Guzmán's capture, affected districts still show persistent demographic distortions, even as economic and educational gaps have narrowed substantially. Planning horizons for post-conflict reconstruction must account for these extended timeframes. Second, the patterns are consistent with returns to human capital and infrastructure investment. Peru directed reconstruction resources toward education and infrastructure in conflict-affected areas, and the observed literacy convergence, improved sanitation, and expanded economic activity are consistent with benefits from such investments, though this paper does not observe program allocation directly. The extensive-margin catch-up in night-time lights suggests that bringing basic infrastructure to formerly isolated communities accompanies measurable economic gains. Third, the nature of violence may shape recovery needs. The divergent trajectories of Sendero-dominant versus state-dominant districts, read as hypotheses consistent with the estimates, suggest that post-conflict programming could be tailored to the specific character of violence experienced, beyond its intensity or duration. Areas where insurgents systematically targeted local institutions may require complete rebuilding of human capital, including importing teachers and administrators from outside, while areas affected primarily by counterinsurgency operations may benefit more from supporting return migration and reactivating dormant institutions.

Several limitations constrain the analysis. The identification strategy relies on comparing very-high-conflict districts with districts below the >100-victim threshold before and after the war. The documented negative spillovers suggest that even the "control" districts were affected by regional disruption, complicating causal interpretation. Night-time lights, while providing an objective measure of economic activity, may imperfectly capture the agricultural, informal, and subsistence economies prevalent in rural conflict areas. The data cover populations, not individuals, and cannot distinguish whether the documented demographic changes reflect return migration, new settlement, or differential fertility and mortality among those who remained. Future research examining individual-level outcomes, migration histories, and the specific role of reconstruction programs would complement the aggregate analysis.

The Peruvian experience offers a cautiously optimistic lesson. Conflict-affected communities achieved real gains in education, infrastructure, and economic activity, showing recovery patterns consistent with benefits from sustained reconstruction investment, although its contribution is not separately identified. Yet the demographic transformation these communities underwent, the missing generations, the age-structure distortions, and the turnover of populations, marks a loss that investment had not restored a generation later. Twenty-five years after Abimael Guzmán's capture precipitated the collapse of the main insurgency, the districts that suffered most intensely are younger, more literate, and better served by sanitation infrastructure, yet also demographically transformed in ways that still bear the imprint of violence. Recovery in the sense of returning to a pre-conflict trajectory with the same communities intact may be impossible once violence reaches sufficient intensity and duration. What remains possible, and what Peru has largely achieved, is the consolidation of viable communities whose composition has changed substantially, a reality that demands realistic expectations of post-conflict policy and honors the memory of the communities the war transformed.

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A Data Construction and Additional Statistics

This appendix provides additional details on data construction, sample restrictions, and baseline characteristics.

A.1 Pre-Conflict Poverty and Inequality

Table A1 reports the department-level poverty and inequality measures from the 1981 census discussed in Section 2, ranking departments separately by mean income and by Gini coefficient.

Table A1: Poorest and Most Unequal Departments, Peru 1981 Census

Top 10 Poorest Departments					Top 10 Most Unequal Departments				
Rank	Department	Income	Gini	Population	Rank	Department	Gini	Income	Population
1	Cajamarca	29.6	0.64	205,838	1	Puno	0.67	30.0	179,106
2	Puno	30.0	0.67	179,106	2	Ayacucho	0.66	30.7	90,904
3	Huancavelica	30.5	0.63	64,289	3	Cusco	0.65	34.3	197,866
4	Ayacucho	30.7	0.66	90,904	4	Cajamarca	0.64	29.6	205,838
5	Cusco	34.3	0.65	197,866	5	Huancavelica	0.63	30.5	64,289
6	Chachapoyas	39.1	0.53	52,078	6	Huaraz	0.59	47.0	170,163
7	Huánuco	42.2	0.58	86,912	7	Huánuco	0.58	42.2	86,912
8	Huaraz	47.0	0.59	170,163	8	Huancayo	0.56	49.1	198,572
9	Huancayo	49.1	0.56	198,572	9	Tambopata	0.55	81.8	12,293
10	Chaupimarca	49.7	0.51	44,770	10	Piura	0.55	54.2	233,801

Notes: Income measured as mean income per capita in 1981 soles. Population refers to census-enumerated population in the department capital. Several rows carry the name of the department capital's province in the source tabulation rather than the department itself (Chachapoyas for Amazonas, Huaraz for Ancash, Huancayo for Junín, Chaupimarca for Pasco, Tambopata for Madre de Dios). Departments ranked by mean income (left panel) and Gini coefficient (right panel). The five poorest departments are also among the six most unequal.

Table A2 reports the district-level analogue, listing the ten poorest and the ten most unequal districts.

Table A2: Poorest and Most Unequal Districts, Peru 1981 Census

Top 10 Poorest Districts					Top 10 Most Unequal Districts				
Rank	District	Department	Income	Gini	Rank	District	Department	Gini	Income
1	Huancaraylla	Ayacucho	3.3	0.48	1	Tupac Amaru	Cusco	0.93	70.7
2	Carapo	Ayacucho	3.3	0.68	2	Layo	Cusco	0.93	38.4
3	Huayllay Grande	Huancavelica	3.4	0.43	3	Parobamba	Huaraz	0.91	128.7
4	Callanmarca	Huancavelica	3.8	0.68	4	Apata	Huancayo	0.90	132.3
5	Huaya	Ayacucho	4.3	0.59	5	Quinuabamba	Huaraz	0.90	253.6
6	Paccaritambo	Cusco	4.6	0.44	6	Macari	Puno	0.90	49.8
7	Capacmarca	Cusco	4.9	0.72	7	Pampamarca	Cusco	0.89	110.9
8	Morcolla	Ayacucho	5.0	0.46	8	Chacabamba	Huánuco	0.89	90.0
9	Ccarhuayo	Cusco	5.4	0.67	9	Coata	Puno	0.89	36.1
10	Pusi	Puno	5.7	0.69	10	Chuschi	Ayacucho	0.89	6.0

Notes: Sample restricted to districts with population >100. Income measured as mean income per capita in 1981 soles. The Department column follows the same capital-province naming convention as Table A1 (e.g., Huaraz for Ancash, Huancayo for Junín). The poorest districts are concentrated in Ayacucho, Huancavelica, Cusco, and Puno, departments that would experience intense violence. Chuschi (Ayacucho), where Shining Path launched its armed struggle on May 17, 1980, ranks among the ten most unequal districts.

A.2 Maps of Conflict Intensity

Figure A1 presents the geographic distribution of conflict intensity across Peru. The map reveals pronounced spatial concentration: violence was overwhelmingly concentrated in the central-southern highlands, with Ayacucho, Huancavelica, and Apurímac forming the epicenter. This pattern reflects Sendero Luminoso's Maoist strategy of rural base-building, which targeted isolated highland communities with weak state presence and high poverty rates.

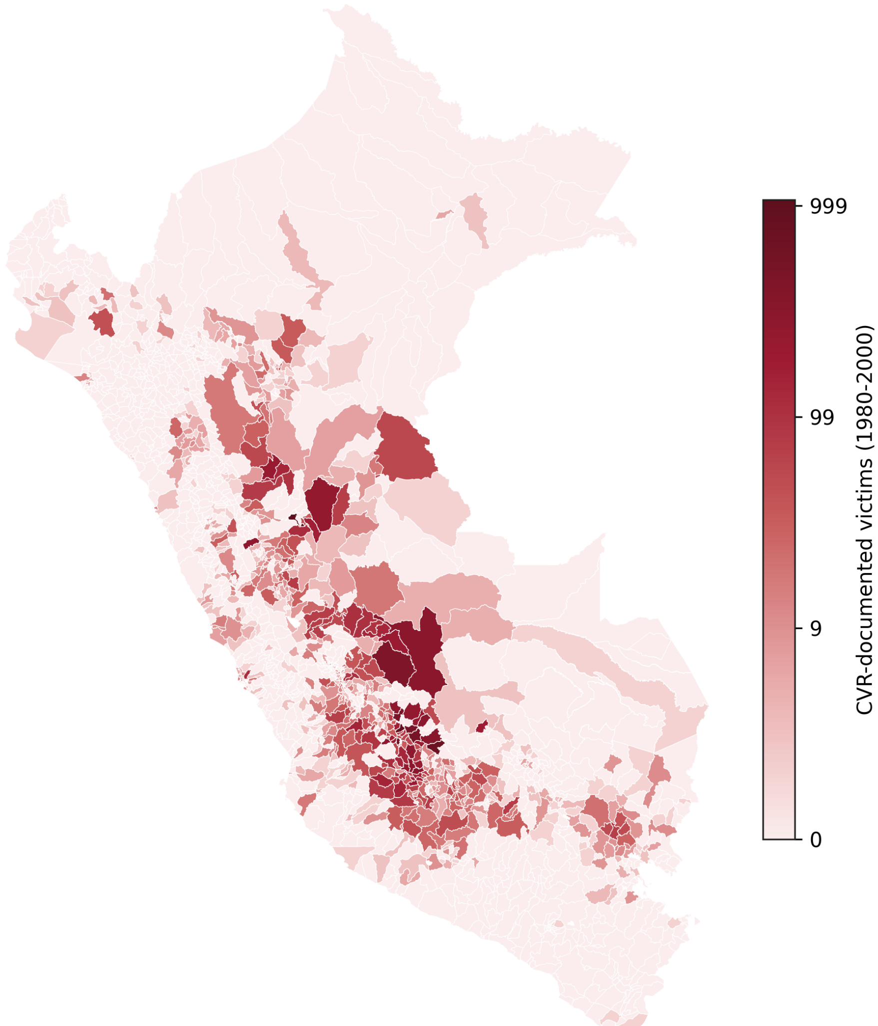

Figure A1: Geographic Distribution of Conflict Intensity

Notes: District-level total victims (log scale) from CVR documentation. Darker shading indicates higher victim counts. The central-southern highlands, particularly Ayacucho, Huancavelica, and Apurímac, experienced the most intense violence. Coastal and Amazonian regions experienced comparatively limited exposure.

Figure A2 highlights the 50 districts classified as "very high conflict" (more than 100 documented victims). These districts, representing just 2.7% of Peru's 1,874 districts, account for over 40% of all documented victims. The concentration is extreme: 41 of the 50 very-high-conflict districts lie in Ayacucho (32), Junín (7), and Huancavelica (2), centered on the Quechua-speaking highlands where Sendero Luminoso established its initial base of operations, with the remainder in Huánuco, San Martín, Lima, and Ucayali.

Figure A2: Very High Conflict Districts (>100 Victims)

Notes: Districts with more than 100 CVR-documented victims highlighted in cranberry (N=50). These districts comprise 2.7% of all Peruvian districts but account for over 40% of total documented victims. The geographic concentration in the central-southern highlands is evident.

A.3 Baseline Balance Tests

Table A3 reports the Welch two-sample t-tests underlying the balance discussion in Section 3.

Table A3: Welch Balance Tests: No Conflict versus Very High Conflict, 1981

	No Conflict	Very High	Difference	SE	p-value
Total population	7,566.9	11,636.8	4,069.9	2,825.4	0.157
Mean age (years)	24.58	24.55	−0.03	0.51	0.962
Dependency ratio (%)	97.42	105.62	8.20	2.34	0.001
Sex ratio (M per 100 F)	101.79	95.00	−6.79	1.51	0.000
Children 0–14 (%)	43.35	44.69	1.34	0.60	0.030
Working age 15–64 (%)	50.99	48.87	−2.12	0.57	0.001
Literacy rate (%)	70.44	59.09	−11.36	2.97	0.000
Higher education (%)	2.23	2.84	0.61	0.63	0.333
High-skill occupation (%)	3.42	4.04	0.62	0.78	0.435
Agriculture (%)	72.97	70.55	−2.43	4.45	0.589
Manufacturing (%)	5.01	4.22	−0.79	0.61	0.205
Commerce (%)	5.03	7.09	2.06	1.23	0.102
Indigenous language (%)	35.77	66.88	31.11	6.06	0.000
Migration rate (%)	26.68	18.22	−8.47	2.80	0.004
Born same district (%)	73.32	81.79	8.47	2.80	0.004
Altitude (m)	2,233.3	2,267.4	34.1	208.2	0.871
Distance to Lima (km)	557.5	314.3	−243.2	15.3	0.000
Terrain ruggedness	272.2	253.7	−18.5	21.8	0.402

Notes: Welch two-sample t-tests with unequal variances on the 1981 baseline, comparing no-conflict districts (N = 1,076) with very-high-conflict districts (N = 39). Difference = Very High − No Conflict.

B Robustness Checks

This appendix examines the sensitivity of the findings to alternative specifications.

B.1 Alternative Conflict Measures

The main analysis uses a binary indicator for very high conflict (>100 CVR-documented victims). Table A4 examines robustness to alternative conflict measures.

Column (1) reproduces the main specification using the very-high-conflict binary. Column (2) uses an "any conflict" indicator (1+ victims), capturing the extensive margin of violence exposure. Column (3) uses the continuous measure log(victims + 1), testing whether effects scale with intensity.

Results are robust across all specifications. The any-conflict measure yields coefficients of 0.19 log points in 1993, 0.22 in 2007, and 0.18 in 2017, significant at the 1% level in 1993 and 2007 and at the 5% level in 2017. These smaller magnitudes compared to the very-high threshold are expected: the any-conflict category includes districts with minimal exposure. The continuous specification shows that each log-unit increase in victims is associated with approximately 0.10 log points higher population across all three post-conflict censuses.

Table A4: Robustness: Alternative Conflict Intensity Measures

	(1) Very High (>100)	(2) Any (1+)	(3) Log(Victims)
× 1993	0.496**		
	(0.250)		
× 2007	0.668***		
	(0.250)		
× 2017	0.593**		
	(0.268)		
× 1993		0.192***	
		(0.073)	
× 2007		0.221***	
		(0.074)	
× 2017		0.177**	
		(0.078)	
× 1993			0.099***
			(0.026)
× 2007			0.107***
			(0.026)
× 2017			0.092***
			(0.028)
Observations	6115	6115	6115
Adjusted R^2	0.819	0.818	0.819

Notes: Standard errors clustered at district level in parentheses. Column (1): binary for >100 victims (omitted group: all districts below the threshold). Column (2): binary for any documented victims (omitted group: no-conflict districts). Column (3): log(total victims + 1), continuous measure. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

B.2 Geographic Heterogeneity

Table A5 presents results by terrain ruggedness tercile. Point estimates are larger in more rugged terrain: the 2007 coefficient reaches 0.81 log points in the middle tercile ($p < 0.10$) and 0.70 in the top tercile ($p < 0.10$), compared to 0.33 in the bottom tercile (not significant). However, confidence intervals overlap substantially.

Table A5: Population Recovery by Terrain Ruggedness

	(1) Low Rugged	(2) Med Rugged	(3) High Rugged	(4) Full Sample
Very High × 1993	0.183	0.558	0.592	0.496**
	(0.293)	(0.443)	(0.394)	(0.250)
Very High × 2007	0.331	0.809*	0.702*	0.668***
	(0.356)	(0.439)	(0.359)	(0.250)
Very High × 2017	0.280	0.807*	0.526	0.593**
	(0.370)	(0.451)	(0.440)	(0.268)
Observations	2012	2021	2014	6115
Adjusted R^2	0.820	0.800	0.811	0.819

Notes: Standard errors clustered at district level in parentheses. Ruggedness terciles based on the Terrain Ruggedness Index of Nunn and Puga (2012). Omitted group: districts below the very-high threshold within the indicated tercile. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

Table A6 examines heterogeneity by distance to the capital. Effects appear in both the close and intermediate terciles. The largest point estimates are in the tercile closest to Lima, at 0.85 log points in 2007 ($p < 0.05$) and 0.87 in 2017 ($p < 0.10$), with smaller but more uniformly significant effects at intermediate distances (0.56, 0.60, and 0.48 log points). Column (3) coefficients are omitted because no very-high-conflict districts exist in the most remote tercile, reflecting the conflict's geographic concentration in the central highlands.

Table A6: Population Recovery by Distance to Lima

	(1) Close to Lima	(2) Medium	(3) Far from Lima	(4) Full Sample
Very High × 1993	0.473	0.558**	–	0.496**
	(0.418)	(0.241)		(0.250)
Very High × 2007	0.845**	0.597**	–	0.668***
	(0.419)	(0.235)		(0.250)
Very High × 2017	0.865*	0.476*	–	0.593**
	(0.458)	(0.245)		(0.268)
Observations	2015	2014	2018	6115
Adjusted R^2	0.816	0.839	0.818	0.819

Notes: Standard errors clustered at district level in parentheses. Distance terciles based on geodesic distance to Lima center. Column (3): the Very High × Year interaction is not estimable because no very-high-conflict districts fall in the far-from-Lima tercile (all 50 lie in the two closer terciles: 22 close, 28 medium), shown as −. Omitted group: districts below the very-high threshold within the indicated tercile. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

B.3 Mechanisms: Decomposing Population Effects

Table A7 presents a mediator-by-mediator coefficient-attenuation exercise, followed by a joint specification. Column (1) reproduces the baseline specification, Columns (2)–(6) add potential mediators one at a time, and Column (7) includes them jointly.

The most dramatic attenuation comes from age structure controls (Column 5). Adding mean age and dependency ratio reduces the 2017 coefficient from 0.59 to 0.15 and renders it statistically insignificant, an attenuation of roughly three-quarters. This finding indicates that most of the population differential can be accounted for by the younger age structure of conflict districts. Conflict districts do not have significantly more people once compositional differences are accounted for. They have more young people.

Table A7: Mechanisms: Population Effects Controlling for Potential Mediators

	(1) Baseline	(2) +Urban	(3) +Migr	(4) +Educ	(5) +Age	(6) +Infra	(7) All
Very High × 1993	0.496**	-0.049	0.468*	0.503**	0.185	0.421**	-0.050
	(0.250)	(0.061)	(0.250)	(0.249)	(0.228)	(0.203)	(0.045)
Very High × 2007	0.668***	0.127**	0.637**	0.712***	0.243	0.586***	0.091**
	(0.250)	(0.052)	(0.254)	(0.246)	(0.241)	(0.205)	(0.042)
Very High × 2017	0.593**	0.000	0.576**	0.651**	0.152	0.452**	0.000
	(0.268)	(.)	(0.269)	(0.264)	(0.251)	(0.196)	(.)
Urban (%)		0.004***					0.001***
		(0.000)					(0.000)
Migration Rate (%)			0.003***				-0.000
			(0.001)				(0.000)
Literacy Rate (%)				-0.008***			-0.013***
				(0.002)			(0.002)
Mean Age					-0.133***		-0.103***
					(0.007)		(0.004)
Dependency Ratio					-0.009***		-0.006***
					(0.001)		(0.001)
Utilities Index						0.003***	0.001***
						(0.001)	(0.000)
Observations	6115	4763	6115	6115	6115	6115	4763
Adjusted R^2	0.819	0.969	0.820	0.820	0.859	0.833	0.980

Notes: Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Column (2) adds urban share, Column (3) migration rate, Column (4) literacy rate, Column (5) mean age and dependency ratio, and Column (6) utilities index. Some coefficients omitted due to collinearity. Omitted comparison group: all districts below the very-high threshold. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

B.4 Combined Effects Across Outcomes

Figure A3 presents 2017 coefficient estimates for population, literacy, and mean age, enabling direct comparison of effect magnitudes and precision across dimensions of recovery. The figure reveals a consistent pattern: population and literacy show positive and statistically significant effects, while mean age shows persistent negative effects (indicating younger populations in conflict districts).

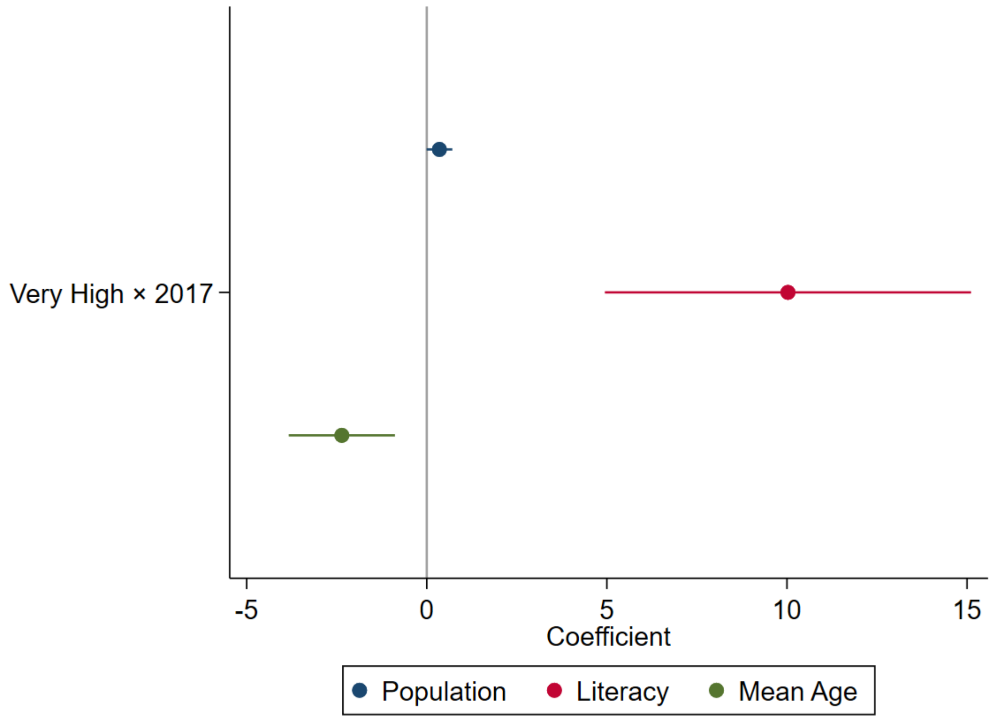

Figure A3: Combined Effects Across Outcomes (2017)

Notes: Coefficient estimates and 95% confidence intervals for very high conflict (>100 victims) interaction with 2017 indicator. All specifications include district and year fixed effects with standard errors clustered at district level. Population measured in log points. Literacy in percentage points. Mean age in years.

Figure A4 presents literacy rate trajectories from 1981 to 2017 by conflict status. Both groups show substantial literacy improvements over the 36-year period, reflecting Peru's nationwide human capital accumulation. Very-high-conflict districts started from a lower baseline in 1981, consistent with the negative selection of violence into less-developed areas. The gap narrows progressively across census years, with the steepest convergence occurring between 1993 and 2007.

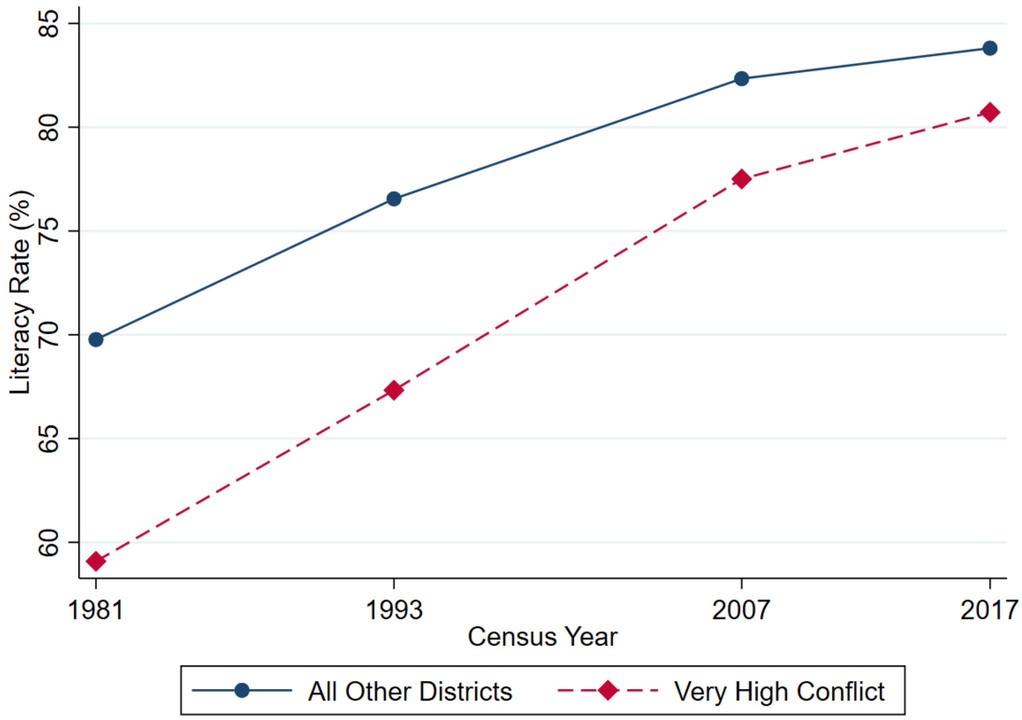

Figure A4: Literacy Rate Trajectories by Conflict Status

Notes: Mean literacy rates by census year. Very high conflict defined as districts with >100 total victims. The comparison line covers all districts below that threshold. N = 39–50 very high conflict districts and 1,466–1,627 other districts depending on year. The progressive narrowing of the gap is consistent with cohort replacement and educational expansion in conflict-affected areas.

B.5 Auxiliary Test Statistics

Table A8 collects the randomization-inference, spillover joint-test, PPML, and perpetrator test statistics referenced in the text.

Table A8: Auxiliary Test Statistics

Panel A: Randomization inference, log population (500 permutations)			
	1993	2007	2017
Estimated coefficient	0.496	0.668	0.593
Randomization-inference p-value	0.034	0.006	0.024
Panel B: Joint tests that all three spillover coefficients equal zero			
	$F(3, 1693)$		p-value
Ring 25 km	0.80		0.494
Ring 50 km	10.60		<0.001
Ring 75 km	16.66		<0.001
Ring 100 km	28.93		<0.001
Panel C: PPML and perpetrator tests			
	Coefficient	SE	p-value
PPML, NTL per capita, Very High × 2007	0.0000	0.250	1.000
PPML, NTL per capita, Very High × 2017	−0.072	0.412	0.860
Equality of State and Sendero recovery paths			0.245
Sendero share × year jointly zero, log population			0.001
Sendero share × year jointly zero, literacy			0.023
Sendero share × year jointly zero, mean age			0.012

Notes: Panel A permutes the very-high-conflict label across districts holding the number of treated districts fixed and reports the share of 500 placebo estimates at least as large in absolute value as the actual coefficient. Panel B reports joint F-tests from the ring specifications of Table 11. Panel C: the PPML rows estimate the Table 20 specification by Poisson pseudo-maximum-likelihood on NTL per capita (N = 4,125 after dropping singleton and separated observations, 1,392 district clusters). The equality row tests whether the State-dominant recovery path differs from the Sendero-dominant path in a pooled model with State interactions. The joint rows test that the three Sendero-share × year interactions are zero in the Table A13 specification for each outcome.

C Perpetrator Heterogeneity

This appendix provides detailed analysis of recovery trajectories by violence perpetrator.

C.1 Classification of Perpetrator Types

Perpetrator categories are constructed using CVR victim-level data aggregated to the district level. Sendero Dominant districts are those where more than 50% of victims were attributed to Sendero Luminoso (N=356 districts with attributed violence, 29 with very high conflict).

State Dominant districts are those where more than 50% of victims were attributed to state security forces (N=133 districts, 9 very high). Mixed Perpetrator districts are those where neither Sendero nor state forces account for a majority (N=213 districts, 12 very high). This residual category includes the small number of districts where MRTA or the CADs account for the majority of attributed victims. These counts are computed in the harmonized analysis panel, whose district universe differs marginally from the 1,874-district cartographic universe used in the maps (which contains 701 districts with documented victims): the CVR attribution file covers 832 districts, and boundary harmonization maps a small number of them differently.

Table A9 presents baseline characteristics of conflict districts by perpetrator type. Several patterns emerge. Sendero-dominant districts are smaller (mean 1981 population 9,245, versus 25,441 in state-dominant and 30,098 in mixed districts), less literate at baseline (63.0% versus 70.1% and 72.9%), and located at higher altitude (2,911 meters versus 2,394 and 2,180), consistent with the insurgency's rural highland base-building strategy. Sendero-dominant districts also record more victims on average (47.9, versus roughly 29 in the other groups).

Table A9: Baseline Characteristics of Conflict Districts by Dominant Perpetrator

	Sendero Dominant	State Dominant	Mixed Perpetrator	No Conflict (Comparison)
Total Population (1981)	9,245	25,441	30,098	7,567
Literacy Rate (%)	63.0	70.1	72.9	70.4
Mean Age (years)	24.2	24.5	24.2	24.6
Altitude (m)	2,911	2,394	2,180	2,233
Total Victims (mean)	47.9	29.9	28.8	0.0

Notes: Mean characteristics of conflict districts (1+ CVR-documented victims) by dominant perpetrator. The final column reports no-conflict districts for comparison. Violence characteristics from CVR data, baseline characteristics from the 1981 census.

C.2 Population and Literacy by Perpetrator

Table A10 presents population recovery results separately by dominant perpetrator type. Sendero-dominant districts show the clearest gains, with effects of 0.56 log points in 2007 ($p < 0.05$) and 0.50 in 2017 ($p < 0.10$). State-dominant districts show large point estimates (approximately 1.2 log points) with very wide confidence intervals, and mixed-perpetrator districts show small, statistically insignificant effects of 0.23–0.25 log points.

Table A10: Population Recovery by Dominant Perpetrator

	(1) Sendero Dom.	(2) State Dom.	(3) Mixed	(4) MRTA Present	(5) Full Sample
Very High × 1993	0.293	1.179	0.233	0.186	0.496**
	(0.252)	(1.143)	(0.285)	(0.354)	(0.250)
Very High × 2007	0.557**	1.214	0.244	0.374	0.668***
	(0.248)	(1.160)	(0.290)	(0.382)	(0.250)
Very High × 2017	0.498*	1.179	0.246	0.371	0.593**
	(0.281)	(1.186)	(0.305)	(0.376)	(0.268)
Observations	1276	468	756	318	6115
Adjusted R^2	0.814	0.881	0.871	0.869	0.819

Notes: Dependent variable is log population. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Columns 1–3 restrict the sample to conflict districts where the indicated perpetrator type accounts for the majority of victims, so coefficients compare very-high-conflict districts with lower-intensity conflict districts in the same subsample. These categories are mutually exclusive. Column 4 covers districts with any MRTA victims (not mutually exclusive). Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

Table A11 examines literacy rate trajectories by perpetrator type. State-dominant districts show literacy gains that grow from 6.1 percentage points in 2007 (not significant) to 10.2 percentage points by 2017 ($p < 0.05$). Sendero-dominant districts show small, statistically insignificant estimates that rise from −1.0 in 1993 to +3.8 percentage points by 2017. Mixed-perpetrator districts show stable, statistically insignificant estimates of 4.3–4.5 percentage points.

Table A11: Literacy Recovery by Dominant Perpetrator

	(1) Sendero	(2) State	(3) Mixed	(4) Full Sample
Very High × 1993	-1.029	2.483	4.270	0.885
	(2.805)	(3.403)	(6.219)	(2.183)
Very High × 2007	2.901	6.098	4.386	5.260**
	(3.053)	(4.701)	(6.190)	(2.358)
Very High × 2017	3.836	10.176**	4.468	6.966***
	(3.166)	(4.852)	(6.375)	(2.457)
Observations	1276	468	756	6115
Adjusted R^2	0.708	0.765	0.714	0.711

Notes: Dependent variable is literacy rate (percentage). Columns 1–3 restrict the sample to conflict districts with the indicated dominant perpetrator, so coefficients compare very-high-conflict districts with lower-intensity conflict districts in the same subsample. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

C.3 Demographic Structure by Perpetrator

Table A12 examines age structure and dependency ratios by perpetrator type. Sendero-dominant very-high-conflict districts have populations that are 2.5–3.5 years younger than lower-intensity Sendero-dominant districts, with effects significant at the 5% level or better across all periods. State-dominant districts show smaller and statistically insignificant age differentials of 1.1–2.0 years, though their dependency ratios decline sharply. This divergence suggests different demographic processes across perpetrator types.

Table A12: Demographic Changes by Dominant Perpetrator

	Mean Age (years)			Dependency Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sendero	State	Full	Sendero	State	Full
Very High × 1993	-2.548**	-1.075	-1.928**	-4.370	-19.683***	-6.167**
	(1.057)	(1.519)	(0.753)	(3.768)	(5.499)	(2.752)
Very High × 2007	-3.540***	-2.012	-3.095***	-0.878	-13.379**	-1.415
	(0.960)	(1.767)	(0.739)	(3.183)	(6.569)	(2.451)
Very High × 2017	-3.524***	-1.405	-2.823***	-4.652*	-23.388***	-7.456***
	(1.089)	(1.685)	(0.782)	(2.696)	(4.117)	(2.218)
Observations	1276	468	6115	1276	468	6115
Adjusted R^2	0.818	0.853	0.822	0.742	0.778	0.731

Notes: Sendero and State columns restrict the sample to conflict districts with the indicated dominant perpetrator, so coefficients compare very-high-conflict districts with lower-intensity conflict districts in the same subsample. Full columns use the full sample with all below-threshold districts as the comparison. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

C.4 Continuous Perpetrator Effects

Table A13 presents results using continuous perpetrator share rather than categorical indicators. A consistent pattern emerges: Sendero share is negatively associated with population, while state share is positively associated. A 10 percentage point increase in Sendero's share of victims is associated with approximately 4–6% lower population ($p < 0.05$), while a 10 percentage point increase in state share is associated with approximately 5–6% higher population ($p < 0.05$).

This continuous specification is also better powered than the categorical dominant-perpetrator splits, which partition the small set of conflict districts into cells too sparse to distinguish. A formal test cannot reject equality of recovery across mutually exclusive dominant-perpetrator categories ($p = 0.245$, Table A8, Panel C), a power limitation given the sparse cells, since the State point estimate is in fact *larger* though imprecise. The continuous specification, in contrast, rejects independence of recovery from Sendero share (joint $p = 0.001$). The same gradient appears in demographic structure: a higher Sendero share is associated with a significantly younger population (joint $p = 0.012$, Table A8, Panel C). The literacy columns, in contrast, run opposite to the categorical split. Literacy rises with

Sendero share (+0.080 per point by 2017, $p < 0.01$) and falls with state share (-0.037, $p < 0.10$). The categorical and continuous specifications therefore agree on the population and age gradients but disagree on literacy, and the perpetrator-literacy contrast in the main text should be read with that caution.

Table A13: Effects of Perpetrator Share (Continuous)

	Log Population		Literacy Rate	
	(1)	(2)	(3)	(4)
	Sendero	State	Sendero	State
% Sendero × 1993	-0.0040**		0.0301*	
	(0.0017)		(0.0154)	
% Sendero × 2007	-0.0040**		0.0660***	
	(0.0017)		(0.0159)	
% Sendero × 2017	-0.0059***		0.0800***	
	(0.0018)		(0.0163)	
% State × 1993		0.0047**		-0.0192
		(0.0020)		(0.0187)
% State × 2007		0.0048**		-0.0277
		(0.0021)		(0.0195)
% State × 2017		0.0056***		-0.0365*
		(0.0022)		(0.0199)
Observations	2500	2500	2500	2500
Adjusted R^2	0.859	0.858	0.732	0.723

Notes: Sample restricted to conflict districts (1+ victims). Sendero-share and state-share specifications are estimated separately (one share at a time), not jointly. Coefficients show effect of 1 percentage point increase in the perpetrator share. All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Reference year: 1981. *** p<0.01, ** p<0.05, * p<0.10.

D Age Structure

This appendix provides detailed analysis of age structure changes and demographic mechanisms.

Table A14 provides finer-grained analysis across eight age groups. The deficits are concentrated in ages 45–54, 55–64, and 65+: significant in every census year for the two oldest groups, and from 2007 onward for ages 45–54. These age groups are not fixed birth cohorts across census years, since their membership changes with each census, but in every post-conflict census the deficit sits among residents old enough to have lived through the conflict as adults, the population most exposed to violence, displacement, and economic disruption.

In contrast, younger age groups show surpluses. The 15–24 age group shows a persistent surplus that grows from 2.1 pp in 1993 to 2.9 pp in 2017. By 2017, this age group, born between 1993 and 2002 and well after the conflict's peak, shows the largest surplus, suggesting that conflict districts became attractive destinations for young working-age migrants.

Table A14: Detailed Age Distribution Changes in Very High Conflict Districts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0-4	5-14	15-24	25-34	35-44	45-54	55-64	65+
Very High × 1993	-0.02	0.94	2.05***	1.03**	-0.12	-0.32	-1.13***	-2.43***
	(0.68)	(0.62)	(0.65)	(0.49)	(0.20)	(0.36)	(0.42)	(0.78)
Very High × 2007	0.97	2.48***	1.63***	1.02**	-0.46*	-1.15***	-1.27***	-3.22***
	(0.63)	(0.54)	(0.58)	(0.41)	(0.25)	(0.35)	(0.41)	(0.77)
Very High × 2017	0.25	1.41***	2.87***	0.91**	0.26	-0.74**	-1.61***	-3.34***
	(0.62)	(0.54)	(0.61)	(0.43)	(0.21)	(0.32)	(0.42)	(0.89)
Observations	6115	6115	6115	6115	6115	6115	6115	6115
Adjusted R^2	0.703	0.789	0.492	0.551	0.613	0.627	0.651	0.733

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. All variables measured as % of total population. VH = Very High conflict. Reference: 1981. *** p<0.01, ** p<0.05, * p<0.10.

Table A15 presents summary statistics for 1981 and 2017, comparing very-high-conflict districts with all districts below the threshold. In 1981 the two groups had nearly identical mean ages, 24.6 and 24.5 years, although they differed significantly in dependency ratios, sex ratios, and age-group shares (Table A3). Both aged substantially over the following 36 years, reflecting Peru's nationwide demographic transition, but conflict districts aged less: by 2017 their mean age was 31.2 years versus 32.9 in all other districts, a 1.7-year gap. Mean population in very-high-conflict districts also grew disproportionately (from 11,637 to 43,769, versus 10,542 to 16,714), while their raw literacy disadvantage narrowed substantially. Because this table's comparison group includes medium- and high-conflict districts, its 2017 literacy gap (3.1 percentage points) is slightly smaller than the 3.4-point gap against the stricter no/low group in Table 8.

Table A15: Demographic Summary Statistics: Baseline and Long-Run

	1981 (Pre-Conflict)		2017 (Post-Conflict)	
	Very High	All Other	Very High	All Other
Mean Age (years)	24.55	24.49	31.21	32.88
Total Population	11,637	10,542	43,769	16,714
Literacy Rate (%)	59.1	69.8	80.7	83.8

Notes: Values are means across districts in each category. Very High Conflict = >100 documented victims. All Other = every district below that threshold (including low-, medium-, and high-conflict districts).

E Additional Night-Time Lights Results

This appendix provides additional analysis of satellite-based economic activity measures, including robustness checks for sample selection and heterogeneity analysis.

E.1 Sample Selection Diagnostics

Table 18 in the main text compares the districts dropped and retained by the log transformation. Exposure to the key treatment is statistically indistinguishable across the two groups, with very-high-conflict shares of 2.6 versus 2.8 percent ($p = 0.647$), although the retained sample contains somewhat more observations with any conflict (28.9 versus 23.8 percent, $p < 0.001$). The groups differ sharply on marginalization proxies: dropped districts are higher altitude (2,595 versus 2,110 meters), more rugged (ruggedness index 288 versus 225), smaller (mean population 4,092 versus 26,078), and less literate (76.3 versus 84.6 percent), all significant at $p < 0.001$, while mean distance to Lima is nearly identical (491 versus 489 km, $p = 0.76$). The log transformation therefore discards the most marginalized segment of the sample, not very-high-conflict districts as such.

E.2 Robustness Checks

Table A16 presents total NTL results using alternative zero-preserving transformations. Total NTL and NTL per capita share exactly the same zero observations: per-capita luminosity is zero exactly when total luminosity is zero. Results are consistent across transformations.

Table A16: Total NTL: Robustness to Transformation Choice

	Total NTL		
	(1)	(2)	(3)
	IHS(x)	Log(x+.01)	Log(x+1)
Very High × 2007	-0.027	0.118	-0.016
	(0.207)	(0.375)	(0.180)
Very High × 2017	0.008	0.626	-0.029
	(0.241)	(0.441)	(0.209)
Observations	4889	4889	4889
Adjusted R^2	0.837	0.798	0.847

Notes: Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Reference year: 1993. Total NTL = sum of pixel values within district. IHS = inverse hyperbolic sine. All columns preserve zero-luminosity observations. Total NTL and NTL per capita share the same set of zero-luminosity observations. None of the coefficients is statistically significant, consistent with—though not proof of—similar growth in total economic activity across conflict and non-conflict districts. *** p<0.01, ** p<0.05, * p<0.10.

The results show no significant differential growth in total NTL between conflict and non-conflict districts. All coefficients are statistically insignificant across transformations, consistent with, though not proof of, similar absolute growth in economic activity. This contrasts with the per-capita results, where dividing by population, which grew faster in conflict districts, produces small negative effects.

Table A17 examines whether the NTL per capita results are robust to controlling for differential trends by geographic characteristics.

Table A17: NTL Per Capita with Geographic Trend Controls (IHS)

	(1) Basic	(2) +Alt×	(3) +Rugg×	(4) +Dist×
Very High × 2007	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Very High × 2017	-0.008***	-0.009***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	4889	4889	4889	4889
Adjusted R^2	0.338	0.338	0.338	0.338
Altitude × Year	No	Yes	Yes	Yes
Ruggedness × Year	No	No	Yes	Yes
Distance × Year	No	No	No	Yes

Notes: Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Reference year: 1993. Dependent variable: IHS(NTL per capita). Geographic controls interacted with year indicators allow for differential trends by altitude, ruggedness, and distance to Lima. *** p<0.01, ** p<0.05, * p<0.10.

The results are highly stable across specifications. Adding altitude, ruggedness, and distance-to-Lima trends leaves the conflict coefficients nearly unchanged. This suggests that the small per-capita gaps are not driven by differential trends correlated with geography.

E.3 Heterogeneity

Table A18 examines NTL per capita recovery by initial (1993) development level using the IHS transformation to preserve the full sample.

Table A18: NTL Per Capita by Initial Development Level (IHS, Full Sample)

	(1) Pooled	(2) Below Median	(3) Above Median
Very High × 2007	-0.001***	-0.000	-0.004***
	(0.000)	(0.000)	(0.001)
Very High × 2017	-0.008***	-0.005***	-0.016***
	(0.001)	(0.002)	(0.003)
Observations	4889	3228	1661
Adjusted R^2	0.338	0.079	0.409

Notes: Districts split at median 1993 IHS(NTL) level. Standard errors clustered at district level in parentheses. All specifications include district and year fixed effects. Reference: 1993. Dependent variable: IHS(NTL per capita). *** p<0.01, ** p<0.05, * p<0.10.

Economic recovery exhibits heterogeneity by initial conditions. Initially more-developed conflict districts (above median 1993 NTL) show larger per-capita gaps (-0.016) than initially less-developed districts (-0.005). Both groups show statistically significant gaps by 2017, but the magnitude differs substantially. This pattern suggests that conflict disrupted growth trajectories more severely where there was more economic activity to lose, though both coefficients are in IHS units rather than interpretable percentage gaps, and both are far smaller than what the log specifications that dropped zero-luminosity observations implied.

Table A19 examines whether NTL per capita recovery varies by dominant perpetrator using the IHS transformation.

Table A19: NTL Per Capita by Dominant Perpetrator (IHS, Full Sample)

	(1) Full Sample	(2) Sendero	(3) State	(4) Mixed
Very High × 2007	-0.001***	-0.000	-0.003**	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Very High × 2017	-0.008***	-0.005***	-0.007***	-0.003
	(0.001)	(0.001)	(0.002)	(0.004)
Observations	4889	1046	393	632
Adjusted R^2	0.338	0.268	0.455	0.076

Notes: Standard errors clustered at district level in parentheses. Reference year: 1993. All specifications include district and year fixed effects. Dependent variable: IHS(NTL per capita). Columns (2)–(4) restrict the sample to conflict districts with the indicated dominant perpetrator, using the CVR attribution described in Appendix C.1, so coefficients compare very-high-conflict districts with lower-intensity conflict districts in the same subsample. *** p<0.01, ** p<0.05, * p<0.10.

Economic recovery varies by perpetrator type. The state-dominant gap opens earlier (-0.003 in 2007, $p < 0.05$, reaching -0.007 by 2017, $p < 0.01$), the Sendero-dominant gap appears only in 2017 (-0.005, $p < 0.01$), and the mixed group shows no significant gap. One interpretation is that state counterinsurgency operations, which often destroyed suspected insurgent infrastructure and displaced entire communities, disrupted economic activity sooner, though the small subsamples limit what can be concluded.

E.4 NTL Summary Statistics

Table A20 presents summary statistics on NTL measures by conflict status in 2017, the most recent census year.

Table A20: NTL Summary Statistics by Conflict Status (2017)

	All Other Districts		Very High Conflict	
	Mean	SD	Mean	SD
NTL per capita	0.0146	0.0399	0.0052	0.0072
NTL (total)	274.5	977.9	173.9	414.7
Any detected NTL (%)	83.3	37.3	95.5	21.1

Notes: Cross-sectional summary statistics for 2017. Very high conflict = districts with >100 conflict victims. All other districts = every district below that threshold. NTL per capita = total NTL / population.

The summary statistics reveal several patterns. First, very-high-conflict districts have lower mean NTL per capita (0.0052 versus 0.0146), a ratio of approximately 0.36. Second, despite lower per-capita levels, conflict districts are *more* likely to have any detected NTL (95.5% versus 83.3%), consistent with the extensive-margin catch-up documented in the main text. Third, both total NTL and NTL per capita show substantial variation within each group, reflected in large standard deviations.

Figure A5 shows the distribution of IHS(NTL per capita) by conflict status in 2017. The distributions show substantial overlap between very-high-conflict districts and the comparison group plotted in the figure. While the conflict distribution is shifted slightly leftward (lower NTL per capita), the difference is modest compared to what the log-specification estimates implied. The IHS transformation's preservation of zero-luminosity districts provides a more complete picture of economic activity across all districts.

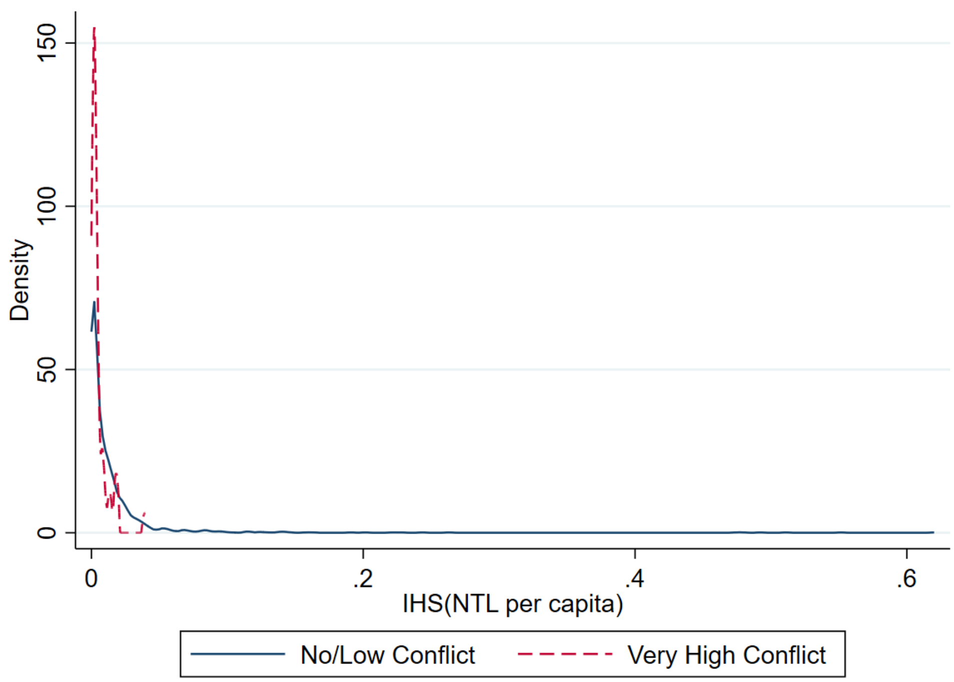

Figure A5: Distribution of Economic Activity by Conflict Status (2017)

Notes: Kernel density estimates of IHS(NTL per capita) by conflict status in 2017. The IHS transformation preserves zero-luminosity districts. Very high conflict districts show a distribution shifted slightly leftward but with substantial overlap, indicating modest rather than dramatic economic gaps.

E.5 Spatial Evolution of Night-Time Lights

Figure A6 presents the spatial evolution of night-time lights across Peru from 1992 to 2023. In 1992, only 368 districts (roughly 20% of Peru) had detectable night-time lights, concentrated along the coast and in major highland cities. By 2023, this expanded to 1,752 districts (94%), with substantial penetration into the interior highlands where the conflict was concentrated. The change panel shows that the central-southern highlands experienced large NTL gains, consistent with extensive-margin convergence in conflict-affected areas.

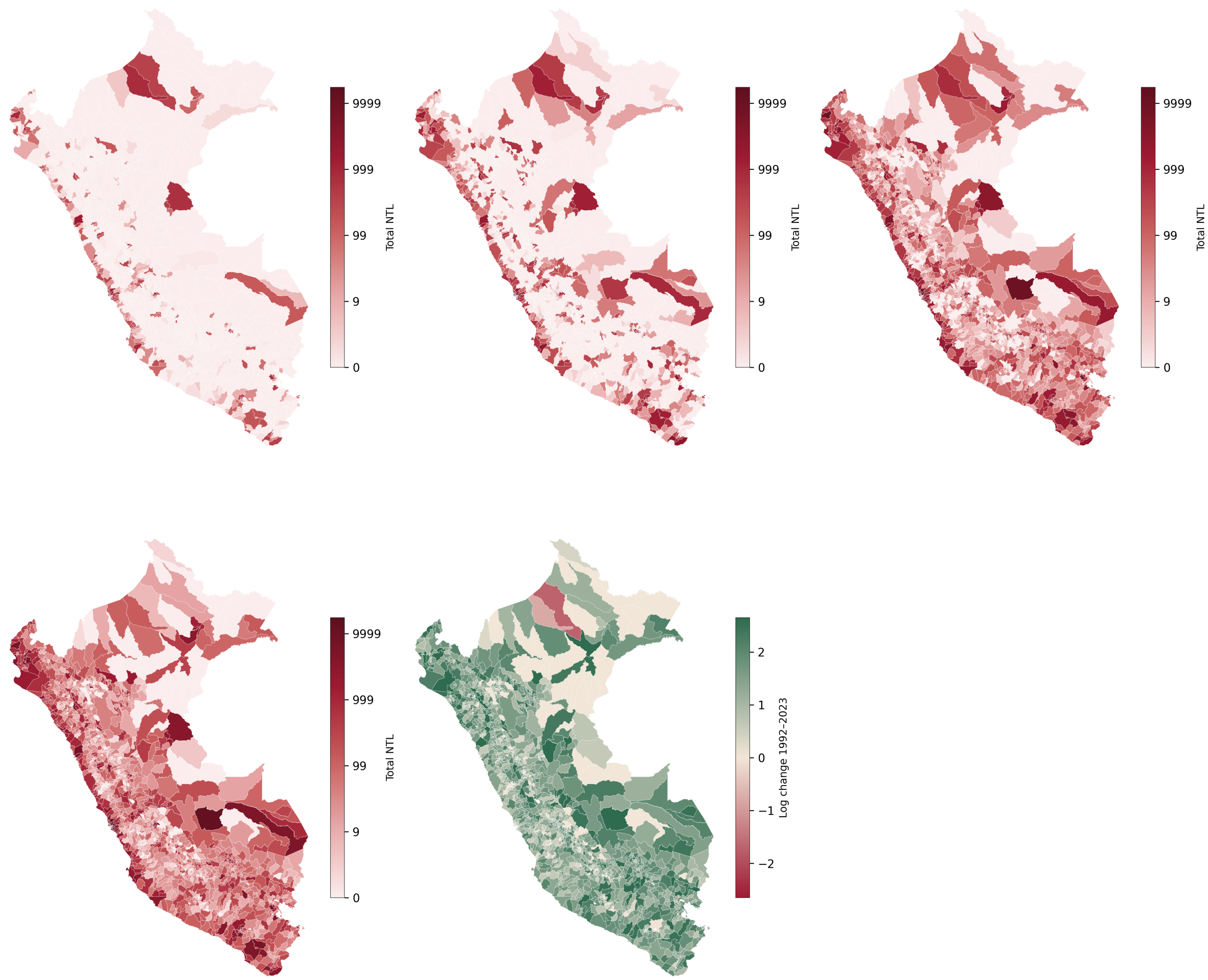

Figure A6: Peru Night-Time Lights Evolution, 1992–2023 (Log Scale)

Notes: District-level night-time lights ($\log_{10}$ scale, darker shading = higher luminosity) for 1992, 2007, 2017, and 2023, with a final panel showing the log change 1992–2023 (green = gains, cranberry = losses). Total luminosity grew from 97,311 (1992) to 781,286 (2023), and the number of districts with detectable lights rose from 368 to 1,752. Source: Chen et al. (2024) simulated VIIRS-consistent NTL series.

F Skills and Sectoral Structure

This appendix examines sectoral employment patterns.

Table A21 examines sectoral employment composition. In contrast to the substantial effects on demographics and human capital, evidence of economic restructuring is limited and transitory. The significant estimates appear in 2007: agricultural employment (which equals the primary-sector measure in these data) rises by 6.5 percentage points ($p < 0.05$) while tertiary employment falls by 5.2 percentage points ($p < 0.05$), a temporary reallocation toward primary activity that dissipates by 2017, when no coefficient is significant. Manufacturing and commerce show small, statistically insignificant changes throughout, including a -1.4 percentage point manufacturing estimate in 1993 that does not reach significance.

Table A21: Effect of Very High Conflict on Economic Structure

	(1) Agriculture	(2) Manuf.	(3) Commerce	(4) Primary	(5) Tertiary
Very High × 1993	2.979	-1.373	-0.293	2.979	-1.033
	(3.534)	(0.857)	(0.891)	(3.534)	(2.717)
Very High × 2007	6.532**	-0.381	-1.177	6.532**	-5.218**
	(3.207)	(0.730)	(0.779)	(3.207)	(2.210)
Very High × 2017	4.469	-0.009	-0.316	4.469	-3.276
	(3.063)	(0.675)	(0.817)	(3.063)	(2.227)
Observations	6115	6115	6115	6115	6115
Adjusted R^2	0.742	0.446	0.702	0.742	0.785

Notes: All specifications include district and year fixed effects. Standard errors clustered at district level in parentheses. Outcomes in percentage points. Columns (1) and (4) are identical because the primary-sector measure in these data equals agricultural employment. *** p<0.01, ** p<0.05, * p<0.10.