War and Work: Labor Market Impact of the Nepalese Civil War

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Abstract

1 Introduction

Nepal experienced a decade-long Civil War from 1996 to 2006 A.D. which inflicted countless injuries and claimed more than 13,000 lives (Lawoti 2009). The Nepalese Civil War, also termed the Maoist Insurgency, was an armed struggle between the Communist Party of Nepal (Maoists) and the Nepalese Government. The conflict brought widespread destruction: damaged infrastructure, banks and industry closure, local government disruption, and conscription of young individuals into armed conflict. The paper aims to estimate the labor market implications of this violent conflict.

The literature on Maoist Insurgency has focused either on proximate causes of conflict incidence such as poverty and inequality (Nepal, Bohara, and Gawande 2011; Do and Iyer 2010), or on the effects on national GDP and tourism. The micro-economic consequences of the Nepalese Civil war, which includes effects on education and earnings, is understudied and unclear. Given the conflict's disruptive and violent nature, from adolescent conscription to the use of extreme force by the government, it is likely that economic activity, and by extension, was profoundly affected by the conflict.

The estimand in question is: *How does increased conflict intensity, measured by the number of conflict-related deaths per 10,000 people, impact a person's likelihood of being employed?* While it may be reasonable to assume *a priori* that conflict likely has a negative effect on employment, the Maoist movement's emphasis on the inclusion of marginalized communities and empowerment of women may have had a positive effect.

I use Nepal Labor Force Survey I (NLFS I, 1998) and Nepal Labor Force Survey II (NLFS II, 2008) for individual-level data on employment, and Uppsala Conflict Data Program (UCDP) for measures on conflict casualties. To estimate the causal effect, a repeated cross-section Difference-in-Differences (DiD) approach is used, where 1998 A.D. serves as the pre-conflict period and 2008 A.D. as the post-conflict period. The analysis is restricted to districts that reported zero conflict-related casualties in 1998. A continuous treatment DiD design is adopted, since by 2008, nearly all districts in Nepal had experienced some level of conflict, leaving no truly untreated units. To bolster the credibility of the Strong Parallel Trends (SPT) assumption, Doubly robust DiD estimator is used to control for covariates. This is different from TWFE DiD used in Menon and Van der Meulen Rodgers (2015) and the conventional DiD used in Valente (2014), two studies that have used survey data to gauge the economic consequences of the Nepalese Civil War.

Section 2 provides a brief review of the current literature on conflict causes and consequences, Section 3 sketches a simple theory linking conflict and the labor market, Section 4 describes the data and the variables used, Section 5 provides an extensive discussion on the methodology, its robustness and credibility (and absence thereof), Section 6 displays and summarizes the main results and Section 7 concludes.

2 Literature Review

The first studies on conflict and economic performance used cross-country measures on prosperity like GDP and GDP per capita (Blattman and Miguel 2010). These cross country analyses have largely focused on identifying the sources of conflict, namely what factors led to the presence/absence of conflict or variation in conflict intensity (as measured by casualties). To do so, researchers have relied on a range of theoretical frameworks including endogenous growth theory, models of information asymmetry and theories of ethno-linguistic fractionalizations. As for economic legacies, the literature has viewed evidence under two frameworks: a) The neoclassical growth theory framework which posits that conflict disrupts economic performance by affecting factors of production, technology and institutions, but implies no lasting change in equilibrium following a one-time shock; and b) Poverty Trap or endogenous growth models which suggest that conflicts can have persistent effects on future economic development.

The limited within-country micro-economic literature, which is also the scope of this paper, has relied on cross-sectional data and Difference-in-Differences method to justify causal identification of post-war legacy. Justino and Verwimp (2013) estimate that 20 percent of the Rwandan population fell into poverty following the Rwandan genocide. Using panel data on child nutrition, Alderman, Hoddinott, and Kinsey (2006) find that young children exposed to war-related malnutrition in Zimbabwe were significantly shorter as adults. In the context of Tajikistan, Shemyakina (2011) reports that girls whose

homes were destroyed in the civil war were less likely to obtain secondary education, with long-term domino effect on later-life wages. These results support the poverty-trap framework where exposure to conflict has affected people's long-term health, education and employment.

The literature on the Nepalese Civil War has largely followed a qualitative approach: some studies explore the conflict through a political economy perspective, underlying its role in the evolution of Nepal's political history, while others employ ethnographic methods with small, targeted samples to test their hypotheses (Lawoti and Pahara 2010). The first papers to prioritize large-scale empirical evidence were the papers by Bohara, Mitchell, and Nepal (2006) and Do and Iyer (2010). Their district-level analyses highlighted that the magnitude of violence depended on political and geographical opportunities for violence, for instance, mountainous terrain and dense forests.

Building on this empirical vein, I have identified three studies that use rigorous causal methods to examine the causes and consequence of the conflict. On the causes, Nepal, Bohara, and Gawande (2011) find that local jurisdictions in Nepal with higher inequality experienced more killings whereas poverty itself did not predict violence (in contrast to (Do and Iyer 2010)). Two other studies focus on the consequences of conflict. Valente (2014) finds, counter-intuitively, that conflict casualties were associated with an increase in female educational attainment while Menon and Van der Meulen Rodgers (2015) find, in a similar vein, that the likelihood of women's employment rose as a result of the conflict. While these two studies do use Difference-in-Differences, it is worth noting that the literature on DiD was not as refined as it is now. The reliance on Two way fixed effects (TWFE) with covariates by Menon and Van der Meulen Rodgers (2015) for example, may not credibly identify causal effects (Goodman-Bacon 2021).

3   Underlying Theory

Violent conflict disrupts regional economic activity in numerous ways : destruction of infrastructure, reduced mobility, conscription of able-bodied individuals into state or rebel forces, reduced tourism due to insecurity and overall, extortion of local resources for state or rebel benefit.

Concerning the labor market, the impact of a violent conflict on regional labor market outcomes may follow two stylized paths:

1. **Labor Demand Path**: During Nepal's Civil Conflict a) tourist arrival declined in Nepal, b) investment in manufacturing and service industries declined due to poor law and order, c) firms faced extortions, closures and uncertainty, and d) many banks were looted and/or destroyed (Lawoti 2009). Additionally, the Maoists

destroyed 1,683 Village Development Committees (VDC) buildings (43% of total) along with police posts, airports, electricity stations, and bridges (Lawoti 2009). With decreasing expected returns, increase in risk, and short investment horizons, it is reasonable to expect a fall in labor demand from formal and informal employers in conflict afflicted zones.

2. **Labor Supply Path**: Civil war conscription often target school-age children, disrupting their educational and career trajectories. Post war, they may find it harder to match with potential employers. Labor supply disruption is further exacerbated by the fact that many who fight in the war are either killed or become life-long disabled. Labor Supply also may be quantitatively smaller in conflict-afflicted areas due to high volumes of emigration. An INSEC 2008 (Informal Sector Service Centre 2008) report details that between 2002 and 2004, $50,365$ were displaced in Nepal: $3,837$ and $21,320$ people by the state and the Maoists respectively, whereas $25,199$ persons emigrated from fear and terror.

It is important to note that for both of these paths, an alternative income effect hypothesis is also plausible. Regarding labor demand, if local firms, in response to lower returns, offer higher wages to attract workers and stimulate economic activity in efforts for survival, conflict-afflicted zones may actually have more employment than their peaceful counterparts. In a similar vein, if displaced men are replaced by women in the workforce, or if higher wages tempt some men to stay, labor supply, again, may be higher in conflicted afflicted regions. The proposed emancipation of historically oppressed groups such as the Dalits, other socio-ethnic minorities, and women, may have had positive effects on employment by reducing discriminatory practices in the society and the workforce.

4   Data and Variables

This research relies on data that covers both labor market characteristics and conflict-related events in Nepal. For labor market information, I use two rounds of Nepal Labor Force Survey: NLFS 1[1] which was conducted in 1998 A.D. and NLFS 2[2] from 2008 A.D. The usage of NLFS is amenable to our analysis in two ways:

1. NLFS records detailed micro-economic data on employment: hours worked in the past 7 days, type of work a person is involved in, reasons for inactivity, any education or training received and other key variables pertinent to labor market analysis.

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[1]https://microdata.nsonepal.gov.np/index.php/catalog/1/related-materials
[2]https://microdata.nsonepal.gov.np/index.php/catalog/2/related-materials

2. The NLFS is a nationally representative survey, with large sample sizes obtained through a two-stage stratified sampling procedure based on Probability Proportional to Size (PPS).

Labor Market data from NLFS is merged with conflict-event data from Uppsala Conflict Data Program (UCDP), collected and maintained by Uppsala University, Sweden[3]. UCDP provides detailed and timed records of all casualties with Geo-spatial information on the district of incidence, number of deaths (with lower and upper bound estimates), who died – Maoists, civilians or the police officials, and the dyadic context of the conflict i.e. who initiated the conflict as reported by the source.

Since the main variable of interest is work, the definition and scope of what is deemed work must be clear, especially in a developing economy like Nepal. The scope of work in NLFS is based on ILO standards and 1993 System of National Accounts (SNA). The example of activities which count as work include: wage job, any business operated by the person, agriculture, milling and other food processing, handicrafts, construction and major repairs, fetching water, collecting firewood, and other work activities[4]. A key caveat in classifying work activities involves the inclusion of tasks such as collecting firewood and fetching water. In rural Nepal, where a significant share of the population must perform these tasks for household survival, extending the production boundary to count these activities as employment may distort labor market estimates. All work-related measures in this paper exclude people *exclusively* involved in collecting firewood and fetching water.

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[3]`https://ucdp.uu.se/`
[4]For more detail, see NLFS I or NLFS II Report's section on Work.

Table 1: Variables and Description

Variable	Description
Usually Employed	A person is assumed usually employed when they have worked more than 180 days (NLFS I) or more than or equal to 6 full months (NLFS II)
Currently Employed	There are two situations in which a person can be defined as being currently employed. Either the person is actually working in the reference week (here the last 7 days), or he or she has an attachment to a job or business but did not work during the reference week.
Currently Self Employed	As a subset of currently employed, a person is currently self-employed if she fulfills working in the categories of work defined unde the self-employment category such as agriculture, handicraft, food processing at home for sale, etc.
Work Hours (cont)	The number of hours worked in the last 7 days.
Work Hours – Self Emp (cont)	The number of self employment hours in the last 7 days.
Conflict Deaths (cont)	From the UCDP dataset, the best estimate of the number of people that died in a conflict between Maoist Insurgents and the Government of Nepal between 1996 and 2006 A.D. (for every district)
Conflict Deaths per 10000 population (cont)	Conflict Deaths standardized to population of every district (population metrics from Nepal's 2001 Census)
Age (cont)	Age of the people surveyd
Ever Attented School	A categorical variable indicating whether the person surveyed ever attended school.
Year of education (cont)	Total years of completed years of schooling, among those who did attend school i.e. among ever attended school = 1.
Years of education for all (cont)	Completed Years of schooling whereby those who never attended school are coded as 0.
Hindu	If a person surveyed identifies as Hindu.
Brahmin/Chhetri	If a person surveyed belongs to either Brahmin or Chhetri Caste i.e. the privileged class.
Male	If a person is male.
Married	A variable indicating whether a person is currently married.
Household Size	The size of the household that a person belongs to. Members from the same household have the same household size.
Urban	Whether a person's household resides in an urban or a rural area.

Table 2: Table of Summary Statistics

	Mean	SD	Min	Max
Usually Employed	0.71	0.45	0	1
Currently Employed	0.73	0.44	0	1
Currently Self Employed	0.57	0.50	0	1
Work Hours	31.94	25.3	0	84
Self Employed Work Hours	22.42	24.8	0	84
Conflict Deaths	109	65.4	26	328
Conflict Deaths per 10000 population	5.57	4.7	0.832	22.2
Age (cont)	31.56	12.02	15	59
Ever Attended School	0.58	0.49	0	1
Year of education (cont)	8.72	3.81	0	18
Years of education for all (cont)	5.73	5.17	0	18
Hindu	0.85	0.36	0	1
Brahmin/Chhetri	0.33	0.47	0	1
Male	0.47	0.5	0	1
Married	0.70	0.46	0	1
Household Size	5.65	2.69	1	29
Urban	0.57	0.49	0	1

5 Empirical Method

This paper employs Difference-in-Difference to gauge the causal impact of Nepal's Maoist Civil War on the likelihood of employment. Let Y denote whether an individual is usually employed, and D denote treatment status (1 if treated, 0 otherwise), where treatment is based on the level of conflict-related casualties in a given district [5]. Let $t = 1$ and $t = 2$ represent the pre-period of 1998 A.D. and post-period of 2008 A.D respectively. Under the standard parallel trends assumption, the canonical DiD framework estimates the Average Treatment Effect on the Treated (ATT) as:

$$ATT = (E[Y_{i,t=2}|D=1] - E[Y_{i,t=1}|D=1]) - (E[Y_{i,t=2}|D=0] - E[Y_{i,t=1}|D=0]) \quad (1)$$

While the canonical DiD setup serves as a useful tool for preliminary analysis, estimating ATT in this empirical context requires much stronger assumptions and more appropriate estimators. The limitations of the standard approach along with the proposed methodological adjustments is discussed in the subsections that follow.

5.1 Classification into Treatment and Control

There are two major difficulties in classifying Nepal's districts into conflicted-afflicted (treatment) and not-conflict-afflicted (control) groups:

1. The first concern pertains to the use of 1998 Nepal Labor Force Survey (NLFS 1) as the pre-treatment period. Since the Civil War began in 1996, several districts had already experienced substantial conflict-related casualties by 1998.

2. By the end of the conflict in 2008, very few districts (e.g. Manang and Mustang) remained untouched by violence. Nearly all districts had experienced some degree of conflict, which the literature refers as no untreated units classification.

I attend to the concerns in the following ways[6]

1. I filter the sample to only those districts that had 0 conflict casualties up until the end of 1998 A.D. This limits the sample to 38 districts. (Districts like Manang and Mustang are excluded in the analysis.)

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[5]The mechanism behind treatment assignment is explained in the following section

[6]The following subsection is highly influenced by (Callaway, Goodman-Bacon, and Sant'Anna 2024). Please refer to it for further exposition and explanation

2. Given that conflict intensity, measured as conflict casualties per population, is a continuous metric, the canonical DiD non-parametric estimator for ATT must be adapted to[7]:

$$E[\Delta Y | D = d_H] - E[\Delta Y | D = d_L] = ATT(d_H | d_H) - ATT(d_L | d_L) \qquad (2)$$

(a) This specification compares the outcome evolution of districts exposed to high treatment intensity d_H with those exposed to the lowest observed treatment intensity d_L, since no districts remained entirely untreated. The estimator captures the average causal effect of moving from d_L to d_H, but includes a potential selection bias term. That is, it assumes that the change in outcomes for units with treatment d_L serves as the valid counterfactual for those with higher treatment d_H. This is a much stronger assumption than in binary-treatment DiD designs and requires invoking Strong Parallel Trends (SPT) (Callaway, Goodman-Bacon, and Sant'Anna 2024). Under strong parallel trends we have:

$$E[\Delta Y | D = d_H] - E[\Delta Y | D = d_L] = E[Y_{t=2}(d_H) - Y_{t=2}(d_L) | D > 0] \qquad (3)$$

(b) The SPT assumes that lower dose groups are valid counterfactuals for higher dose groups. While this is a strong assumption, the plausibility of SPT can be improved by conditioning on observed covariates X.

If these arguments are summarized and constellated, we can estimate Average Treatment Effect on the treated (ATT) in our empirical context as:

$$ATT_x(d_H) = E[Y_{t=2}(d_H) - Y_{t=2}(d_L) | X = x, D > 0] \qquad (4)$$

As noted earlier, the empirical design follows what the DiD literature refers to as a no untreated units specification. In this setup, I compare units that are "more treated" (d_H) to units that are "less treated" (d_L). This is evidenced from table 3, where differences in the dose of treatment (here, conflict-related deaths per 10000 population) is shown. Districts with conflict casualty rates above the 75th percentile are classified as "more treated" (treatment group), while those below this threshold are considered "less treated" (control group). The regression results in table 4 indicate that, under this classification, more-treated districts experienced conflict casualties that were 1.8 standard deviations higher than those in less-treated districts[8].

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[7]I follow the conventional potential outcomes framework as outlines in (Baker et al. 2025) and use similar notation. For notational reference, please check this paper.

[8]Conflict casualties per 10,000 population is used instead of raw conflict casualties information to relativize the magnitude of the impact of conflict. This is done because high death toll in a highly populated district and high death toll in a lowly populated district do not signify the same impact.

Table 3: d and d_L i.e High and Low-dose groups conflict intensity

	1998 (pre-period)	2008 (post-period)
$E[D = d_L]$	0	3.34
$E[D = d_H]$	0	11.8

Note: The values in the table are Conflict Deaths between 1996 and 2008 per 10,000 population (population metrics from 2001 Census)

Table 4: Sample Size Classification

	1998 (pre-period)	2008 (post-period)
$E[D = d_L]$	$18,660$	$22,618$
$E[D = d_H]$	1287	1756

Table 5: Conflict Deaths per 10,000 population regressed on Treatment Status

	Dependent variable:
	Conflict Deaths per 10,000 population (std)
Treatment (1/0)	1.803
	(0.222)
Constant	-0.475
	(0.114)
Observations	38
R^2	0.648
Adjusted R^2	0.638

Note: (std) represents standardized variables

5.2 Strong Parallel Trends and DiD with Covariates

In the previous section, I noted that estimating the causal effect of conflict intensity (as proxied by conflict-related deaths) on employment requires strengthening the parallel trends assumption. Specifically, this implies that districts with lower conflict intensity (low-dose) must serve as valid counterfactuals for districts with higher conflict intensity (high-dose). However, this assumption becomes implausible if these two groups differ systematically in observable characteristics that influence employment outcomes. For eg: let's suppose that during 1998 A.D. (the pre-period), individual employment status was strongly associated with years of education or ethnic background. If this relationship

would've persisted in low-conflict areas, and if highly-afflicted and low-afflicted districts differ along these dimensions, then the parallel trends assumption may fail to hold. In such a case, the observed trends in low-afflicted districts cannot serve as untreated potential outcome for highly afflicted districts. Therefore, as emphasized by (Baker et al. 2025), checking balance in observable determinants of $Y_i, t(d_L)$ is a sensible way to evaluate the validity of parallel trends (in this case strong parallel trends).

I assess for balance in the following variables : a person' age, years of education, whether a person is Hindu, whether a person belongs to Brahmin/Chhetri ethnicity, a person's sex, marital status, household size and whether the person lived in an urban or rural area. Table 6 presents group-wise averages for these variables in 1998 A.D. along with their normalized differences[9].

	Norm. Diff	Treated Mean	Control Mean
Age	0.03	31.73	31.38
Years of Education (All)	-0.68	2.31	5.23
Years of Education (If attended school)	-0.74	6.07	8.45
Hindu (1/0)	0.18	0.92	0.86
Brahmin/Chhetri(1/0)	0.43	0.54	0.33
Male	-0.15	0.41	0.49
Married	0.04	0.73	0.71
Household Size	-0.14	5.44	5.76
Urban	-0.94	0.18	0.60
Ever Attended School	-0.49	0.38	0.62

Table 6: Covariate Balance Statistics

There are meaningful imbalances in several baseline (pre-period) variables. Imbens and Rubin (2015) suggest that a normalized difference exceeding $|0.25|$ indicates substantive imbalance between treatment and control groups. According to this heuristic, highly afflicted and less afflicted regions differed in completed years of education, if they ever attended school, composition of Hindus and Brahmin/Chhetris, as well as urban/rural residency. This imbalance highlights two important points:

1. Conflict incidence is probably not exogenous. There are systematic differences in pre-conflict observable characteristics like education, ethnic composition and rurality, which may predict conflict incidence.

2. There is a risk of parallel trends violation if areas starting out with different education level or ethnic composition would have followed different employment trends in conflict's absence.

Another way to assess imbalance between high and low conflict afflicted regions is by

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[9]Norm Diff $= \frac{\bar{X}_T - \bar{X}_C}{\sqrt{0.5(SD_T^2 + SD_C^2)}}$

examining changes in observable characteristics over time. Table 7 shows the 1998-2008 trend for some observable covariates.

	Control trend	Treatment trend
Age	0.28	0.33
Years of Education (All)	1.23	1.91
Years of Education (If attended school)	0.64	1.31
Hindu (1/0)	-0.02	-0.05
Brahmin/Chhetri(1/0)	-0.02	-0.07
Male	-0.02	0.02
Married	-0.02	-0.01
Household Size	-0.20	0.51
Urban	0.01	-0.02
Ever Attended School	0.09	0.19

Table 7: Covariate Balance Statistics for trends/differences (2008 - 1998)

As with baseline covariates, there are some meaningful differences in trends. For instance, more-afflicted districts saw greater increases in completed years of schooling and school attendance. Household size also rose in treated districts, while it declined in controls. Trend imbalance is useful if differences are meaningful contributors to untreated (here less-treated) potential outcomes $\Delta Y_{i,t}(d_L)$. For example, it is plausible that increase in completed years of schooling may affect employment. As such, using such a variable as a covariate seems sensible. However, if covariate itself is influenced by treatment, controlling for it may bias the estimate. This is true for educational measures, which were likely influenced by conflict, and its inclusion may introduce bias. In summary, while exogenous covariate changes may indicate a violation of parallel trends, change in endogenous covariates may reflect a consequence of the treatment itself, and as such may not be appropriate controls.

5.3   Estimator: Doubly Robust DiD

A useful way to account for covariate imbalances is the doubly robust DiD estimator from (Sant'Anna and Zhao 2020). This estimator uses both outcome-regression (regression adjustment, RA) and Inverse Probability Weighting (IPW) approaches. In the outcome regression approach, outcome changes for untreated units (here, less-treated) are regressed on covariates, and the fitted model thus achieved is use to predict treated units' trends. This provides a counterfactual trend for treated units, which is then subtracted from the actual trend to get the treatment effect.

The IPW procedure, on the other hand, models treatment assignment on observed co-variates, obtains propensity scores for the probability of being treated, and re-weights the changes in outcome to ensure that treatment and control groups are similar on covariates.

In our context, it is both equally plausible that imbalance in urban status, sex, religion and ethnicity in 1998 A.D. affects employment trends and how such imbalances are the reason some have higher conflict intensity than others. The former concern is addressed by RA and the latter is dealt by IPW. The doubly robust DiD accounts for both such potential violations of parallel trends, and offers protection even if either one of the model is misspecified[10].

Table 8 presents the results from the propensity score model, showing that covariates such as ethnicity, sex, and urban/rural status are strong predictors of exposure to high-conflict intensity. The corresponding overlap in estimated propensity scores is displayed in Figure 1, where we can see good common support and overlap between treated and control groups. This overlap suggests that treatment and control groups are sufficiently comparable, and we can make meaningful inferences from the Doubly robust DiD estimates in Section 6.

Table 8: Propensity Score Regression on observed covariates (1998 NLFS)

	Dependent variable:
	Treatment (high-conflict)
Hindu	−0.317
	(0.508)
Brahmin/Chhetri	0.542*
	(0.287)
Sex	−0.197***
	(0.057)
Poverty Rate	0.048***
	(0.012)
Urban	−1.345**
	(0.530)
Constant	−3.944***
	(0.726)
Observations	19,902
Log Likelihood	−3,719.054
Akaike Inf. Crit.	7,450.108
Note:	Standard errors are psu-clustered

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[10]For more on Doubly Robust methods, with practical examples and good intuition, see Baker et al. (2025)
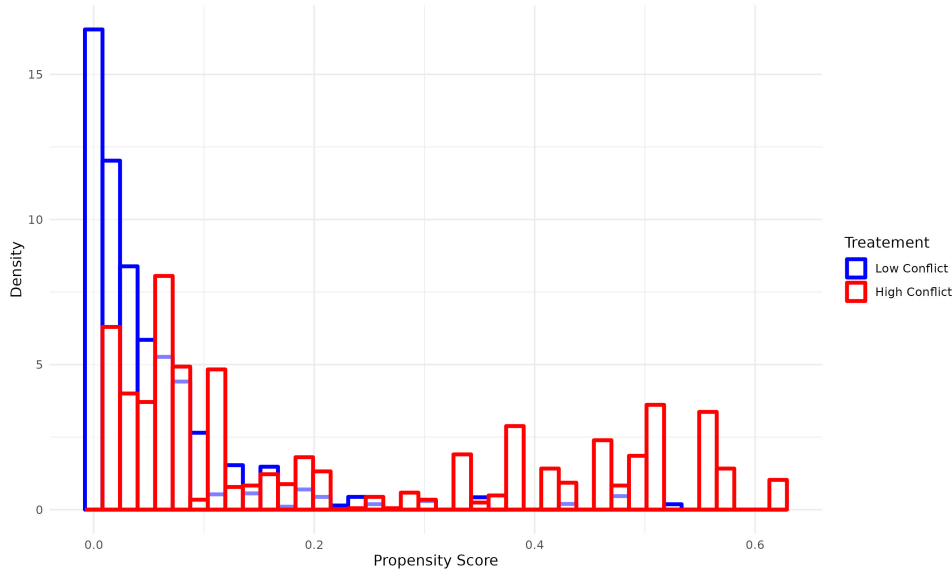
Figure 1: This figure shows the distribution of propensity scores for low and high-conflict regions, based on regression from Table 8.

6   Estimates

Table 9 reports the Doubly Robust DiD[11] estimates for five outcome variables. Being in a high-conflict district has no effect on a person's status of being usually employed(employed for more than six months in the past year). We do see negative employment effects on short-term employment metrics like the status of being currently-employed or currently-self employed (pertaining to the reference period of last 7 days). More importantly, conflict intensity has a large negative effect on an individual's work hours, with individuals in high conflict-afflicted regions estimated to work 4.7 hours less on average than the comparison group. This is a decrease in -0.18 standard deviations on the standardize scale. There is likewise a -4.29 hours effect on self-employment, a 0.17 standard deviations decrease.

6.1   Accounting for Migration

As discussed in the section *Underlying Theory*, large swaths of people left conflict-heavy regions during the Civil War(Informal Sector Service Centre 2008), especially after 2001 A.D. when violence escalated. Between 2002 and 2004, 50,365 people were displaced: 3,837 and 21,320 people by the state and the Maoists respectively, whereas 25,199 persons emigrated from fear and terror (Lawoti and Pahara 2010). It is plausible to assume that

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[11] All estimates are calculated using the *drdid* package from Sant'Anna and Zhao (2020). For documentation and use, see `https://psantanna.com/DRDID/`

	ATT	se	lci	uci
Usually Employed	0.01	0.01	-0.02	0.03
Currently Employed	-0.03	0.01	-0.06	-0.01
Currently Self-employed	-0.04	0.01	-0.06	-0.01
Work Hours	-4.67	0.88	-6.40	-2.94
Work Hours (std)	-0.18	0.04	-0.25	-0.12
Self Employment Hours	-4.29	0.92	-6.10	-2.48
Self Employment Hours (std)	-0.17	0.04	-0.25	-0.10

Table 9: Doubly Robust DiD estimates of ATT

those who managed to move from high to low-intensity areas were likely the ones with the means to do so. This means the NLFS 2008 data may not fully capture region-specific labor supply, since it is already shaped by migration. As a result, our DiD estimates could be biased.

To address this, Table 10 reports DiD estimates only for those who did not move between 1996 and 2008 A.D., whom we classify I permanent residents. I excluded people if:

- They were not born in their current VDC/municipality, their last usual residence was elsewhere, and they migrated to the current place less than 12 years ago; or

- They were born in their current VDC/municipality, but had lived elsewhere, and returned less than 12 years ago.

Everyone else was treated as a permanent resident. The DiD estimates that account for migration are reported in Table 10.

	ATT	se	lci	uci
Usually Employed	-0.00	0.01	-0.03	0.02
Currently Employed	-0.04	0.01	-0.07	-0.02
Currently Self-employed	-0.05	0.01	-0.07	-0.02
Work Hours	-5.03	0.92	-6.84	-3.23
Work Hours (std)	-0.20	0.04	-0.27	-0.13
Self Employment Hours	-4.65	0.97	-6.54	-2.76
Self Employment Hours (std)	-0.19	0.04	-0.26	-0.11

Table 10: Doubly Robust DiD estimates of ATT accounting for migration

Results in Table 10 are consistent with, and in fact show stronger negative effects than, those in Table 9: individuals in high-conflict areas are even less likely to be usually or currently employed. There are similar negative effects on the number of hours worked.
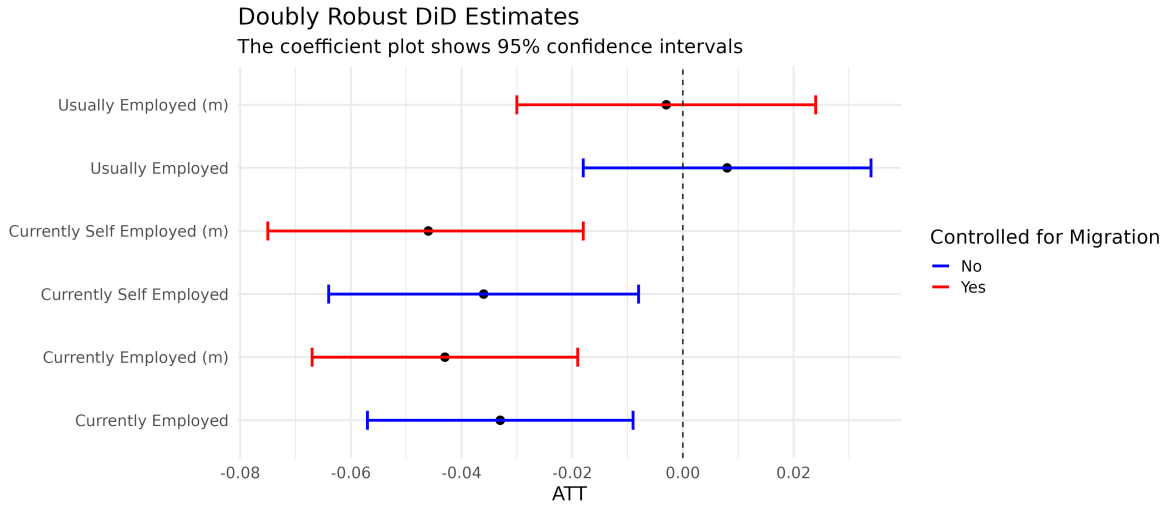
Figure 2: Coefficient plot for three employment status outcome variables classified by whether the model accounted for migration. The point estimates are the estimates from DRDID and the error bars show 95 % confidence intervals.
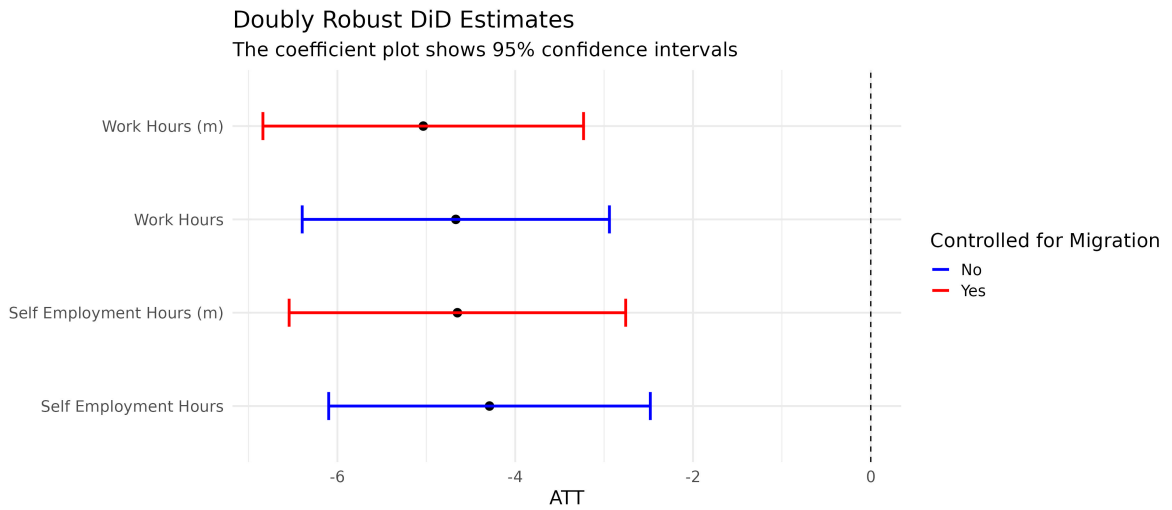

Figure 3: Coefficient plot for two continuous outcome variables classified by whether the model accounted for migration. The point estimates are the estimates from DRDID and the error bars show 95 % confidence intervals.

7 Robustness

There are some methodological and inferential concerns with the doubly robust DiD estimates in our setting:

1. Districts are split into high- and low-conflict groups based on conflict deaths per 10,000 people (above the 75th percentile = high conflict). This cutoff creates an ar-

tificial boundary, so districts with very similar conflict levels can end up in different groups.

2. Standard errors are estimated at the individual level, which means that everyone in a high-conflict region is treated as having the same exposure. This ignores district-level shocks, which is the actual source of variation (Bertrand, Duflo, and Mullainathan 2004).

While the inclusion of covariates help address potential parallel trends bias, a smaller-sample design-based analysis may address afore-mentioned concerns. For this purpose, I compare two-adjacent districts in Nepal – Gulmi and Argakhanchi – that are likely to be similar in covariates but differ considerably in conflict exposure as outlined in Table 11.

Table 11: Gulmi and Argakhanchi Conflict Deaths per 10,000 people

	1998 (pre-period)	2008 (post-period)
Gulmi d_L	0	1.92
Argakhanchi d_H	0	11.7

The choice of Gulmi and Arghakhanchi as comparison groups is based on two reasons:

1. Neither district had any casualties by 1998, but conflict deaths in Arghakhanchi rose sharply over time, reaching high levels by the end of the conflict (see Table 11).

2. Both districts lie in the western hills of Nepal and share similar ethnicity, culture, religion, and lifestyle. They are also likely to be similar in covariates by 1998, as shown in Table 12.

	Norm. Diff	Treated Mean	Control Mean
Age	-0.05	31.82	32.49
Years of Education (All)	-0.03	3.19	3.30
Years of Education (If attended school)	-0.02	6.60	6.65
Hindu (1/0)	-0.40	0.91	0.99
Brahmin/Chhetri(1/0)	0.11	0.54	0.49
Male	0.03	0.36	0.35
Married	0.14	0.77	0.70
Household Size	-0.22	5.06	5.49
Urban		0.00	0.00
Ever Attended School	-0.02	0.49	0.50

Table 12: Covariate Balance Statistics

As shown in Table 12, Gulmi and Arghakhanchi were very similar in key covariates in 1998, with only small differences in the share of the Hindu population. Similarly, Table 13 indicates no outstanding differences in their covariate trends over time. This evidence suggests that any violation of the parallel trends assumption for Gulmi and Arghakhanchi is likely to be minimal, and a conventional Difference-in-differences analysis can be carried out.

	Control trend	Treatment trend
Age	-0.82	-0.04
Years of Education (All)	2.36	2.07
Years of Education (If attended school)	1.13	1.58
Hindu (1/0)	0.00	0.09
Brahmin/Chhetri(1/0)	-0.04	0.02
Male	0.05	0.01
Married	0.00	-0.08
Household Size	-0.25	-0.27
Urban	0.00	0.00
Ever Attended School	0.23	0.15

Table 13: Covariate Balance Statistics for trends/differences (2008 - 1998)

To estimate the difference-in-differences, I use a Bayesian hurdle lognormal likelihood for the outcome variable *Work Hours*. I choose a Bayesian approach for two main reasons:

1. The distribution of Work Hours has a clear spike at zero, representing individuals who did not work. (See figure 4)

2. Work Hours is naturally bounded at zero and cannot take negative values.

The standard OLS DiD estimator does not restrict outcomes to positive values and cannot account for the probability of zeros. This is also true for doubly robust DiD methods, which rely on weighted least squares for outcome regression and inverse probability tilting for propensity scores. Since conditioning on covariates is not required in this setting, a Bayesian model with a hurdle lognormal likelihood for the outcome variable is appropriate.
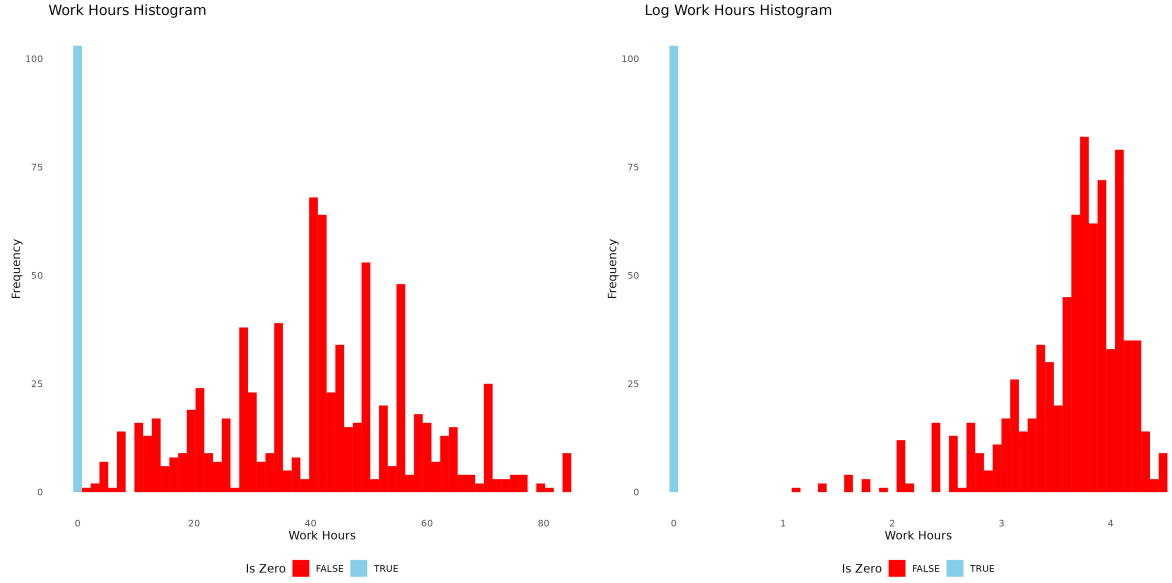
Figure 4: Histogram of variable work hours; Left : in a standard scale. Right : In the log scale.

The econometric model can be written as follows:

$$\text{wh}_i \sim \text{hurdleLognormal}(hu_i, \mu_i)$$

$$\mu_i = \alpha_{GID[i]}$$

$$hu_i = \beta_{GID[i]}$$

Priors:

$$\alpha_{GID[i]} \sim \text{lognormal}(3, 0.5)$$

$$\beta_{GID[i]} \sim \text{normal}(0, 1)$$

where, for $GID[i], i = 1, 2, 3, 4$ represents four interactions group ids: $1 = 1998$ Gulmi (low-conflict); $2 = 1998$ Arghakhanchi (high-conflict); $3 = 2008$ Gulmi (low-conflict); $4 = 2008$ Arghakhanchi (high-conflict).

Here, mu_i is the average work hours in the log scale, and hu_i represents the probability of observing 0 hours worked, which are estimated on the log and logit scales respectively.
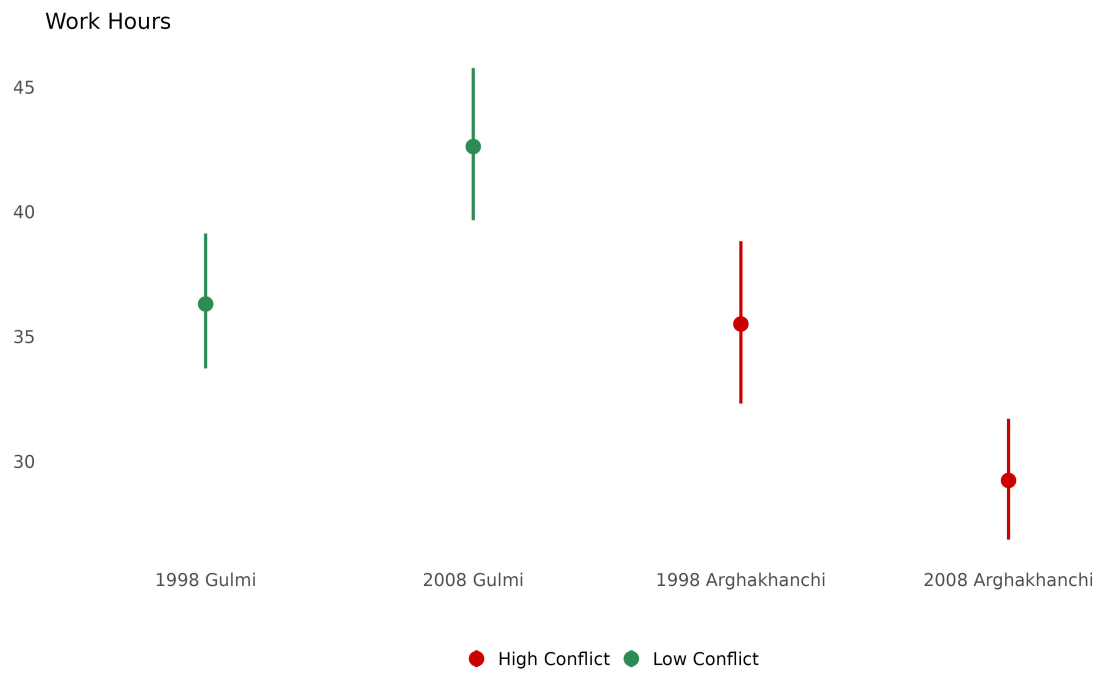
Work Hours

1998 Gulmi 2008 Gulmi 1998 Arghakhanchi 2008 Arghakhanchi

● High Conflict ● Low Conflict

Figure 5:

Probability of zero hours worked

1998 Gulmi 2008 Gulmi 1998 Arghakhanchi 2008 Arghakhanchi

● High Conflict ● Low Conflict

Figure 6:

DiD Contrasts:

Table 14: Posterior Summary of DiD contrasts (credibility intervals width = .95)

	Estimate	lci	uci
Work Hours	−12.55	−18.37	−6.61
Probability of zero (hurdle)	0.02	−0.057	0.11

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