War and Work : Labor Market impacts of Nepalese Civil War

Suhishan Bhandari

July 29, 2025

Abstract

This paper studies the labor market consequences of Nepalese Civil War (1996 -2006 A.D.). Using two rounds of Nepal Labor Force Survey (NLFS) data, the article uses Doubly Robust DiD to assess the effect of conflict intensity (as proxied by conflict deaths) on employment measures. Being in a conflict-intense region had minimal effect on the probability of being employed, although these regions saw reduced work hours and self-employment hours. Urban areas have starker negative employment effects than rural areas.

1 Introduction

Nepal experienced a decade-long Civil War from 1996 to 2006 A.D. which claimed more than 13,000 lives and sustained countless injuries (Lawoti, 2009). The Nepalses Civil War, also termed the Maoist Insurgency, was an armed struggle between the Communist Part of Nepal (Maoist) and the Government of the then Kingdom of Nepal. The conflict brought widespread destruction: damaging infrastructure, shutting down industries and banks, disrupting local governance, and conscription of young individuals. The paper aims to estimate the labor market implications of conflict, analyzing the relationship between conflict intensity and employment.

The literature on Maoist Insurgency has mainly focued either on proximate causes of conflict incidence such as poverty and inequality (Nepal et al., 2011; Do and Iyer, 2010), or on national-level economic consequences like GDP and Tourism. The microeconomic consequences of the Nepalese Civil war, which includes effects on education and earnings, is understudied and unclear. Given the widespread destruction of infrastructure, conscription of adolescents by the Maoists, the use of extreme force by the government, and an overall air uncertainity, it is almost certain that economic activity, and by extension, the labor market were profoundly affected.

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 resulted in a positive effect. The research seeks to empirically examine this relationship.

I use Nepal Labor Force Survey I (NLFS I, 1998) and NLFS II, 2008 for individual-level employment data, and Uppsala Conflict Data Program (UCDP) for measures on conflict causalties. To estimate the causal effect, a repeated cross-section Difference-in-Differences (DiD) approach is employed, using 1998 A.D. 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, afore-mentioned doubly robust DiD estimator is used to control for covariates. This is different for 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 indentifying the sources of conflict, namely what factors lead to presence or absence of conflict or with variation in conflict intensity (as measured by casualties). To do so, researchers have relied on a range of theoretical frameworks including growth theory, models of information assymetry 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 microeconomic 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 et al. (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 dominoe 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 the political economy perspective and 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 empirical evidence were the papers by Bohara et al. (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 et al. (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)). The other two studies focus on the consequences of conflict. Valente (2014) finds, counterintuitively, 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 the 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 the extortion of local resources.

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 uncertainity, and d) many banks were looted and destroyed (Lawoti, 2009). Additionally, the Maoists destroyed 1,683 or 43 percent of Village Development Committees(VDC) buildings along with police posts, airports, electricty 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 increasing unemployment. Labor supply disruption is further excacerbated by the fact that many who fight in the war are either killed or become life-longed disabled. Labor Supply also may be quantitatively smaller in conflict-afflicted areas due to high volumes of emigration, where, an INSEC report from 2008 reports 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 hypotheses is equally 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 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 area and variables

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

1. NLFS records detailed microeconomic data on employment, such as hours worked in the past 7 days, type of work a person is involved in, reasons for inactivity, any education or training received and key variables pertinent to labor market analysis.
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). This allows us to draw not only sample-level insights but also to make population-level inferences about Nepal's labor market.

Labor Market data from NLFS is merged with conflict-event data from Uppsala Conflict Data Program (UCDP), collected and maintained by Uppsala University Sweden. [1]. UCDP provides detailed and timed records of all casualties during the Nepalses Civil war 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. [2] 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.

The main variables used in my analysis along with their description is provided in the following table.

[1] `https://ucdp.uu.se/`

[2] For 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	0.45	0	1
Work Hours	32.1	25.3	0	84
Self Employed Work Hours	22.6	24.8	0	84
Conflict Deaths	107.4	67.3	0	328
Conflict Deaths per 10000 population	5.14	4.6	0	22.2
Age (cont)	31.4	12.01	15	59
Ever Attented School	0.48	0.5	0	1
Year of education (cont)	8.72	3.75	0	18
Years of education for all (cont)	5.7	5.14	0	18
Hindu	0.84	0.36	0	1
Brahmin/Chhetri	0.33	0.47	0	1
Male	0.47	0.5	0	1
Married	0.71	0.46	0	1
Household Size	5.6	2.67	1	29
Urban	0.58	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[3]. Under the standard parallel trends assumption, the canonical DiD framework estimates the Average Treatment Effect on the Treated (ATT) as:

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

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

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[4]:

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 41 districts.

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

$$E[\Delta Y|D = d] - E[\Delta Y|D = d_L] = ATT(d|d) - ATT(d_L|d_L)$$

   (a) This specification compares the outcome evolution of districts exposed to treatment intensity d 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, 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. This is a much stronger assumption than in

[4] The following subsection is highly influenced by (Callaway et al., 2024). Please refer to it for further exposition and explanation

binary-treatment DiD designs and requires invoking Strong Parallel Trends (SPT) (Callaway et al., 2024).Under strong parallel trends we have[5]:

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

(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:

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

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)* 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.[6]

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	3.01
$E[D=d]$	0	11.3

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

The sample size for pre-period and post-period, with classification into treatment and control groups is shown in Table 5:

[5]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.

[6]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 low population area do not signify the same impact.

Table 4: Conflict Deaths per 10,000 population regressed on Treatment Status

	Dependent variable:
	Conflict Deaths per 10,000 population (std)
Treatment (1/0)	1.811
	(0.212)
Constant	−0.463
	(0.107)
Observations	43
R^2	0.640
Adjusted R^2	0.631
Note:	(std) represents standardized variables

Table 5: Sample Size Classificaiton

	1998 (pre-period)	2008 (post-period)
$E[D = d_L]$	21279	25824
$E[D = d]$	1521	1953

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 the absence of conflict, 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, hindu, brahmin chhetri, sex, marital status, household size, urban/rural status, and if the person ever attended school. Table 6 presents group-wise averages for these variables in 1998 A.D. along with their normalized differences[7] (Imbens and Rubin, 2015).

	Norm. Diff	Treated Mean	Control Mean
Age	0.03	31.66	31.35
Years of Education (All)	-0.62	2.48	5.17
Years of Education (If attended school)	-0.63	6.32	8.38
Hindu (1/0)	0.26	0.93	0.85
Brahmin/Chhetri(1/0)	0.54	0.58	0.32
Male	-0.14	0.42	0.49
Married	0.05	0.74	0.72
Household Size	-0.07	5.57	5.74
Urban	-0.75	0.25	0.60
Ever Attended School	-0.46	0.39	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 imblance between high and low conflict afflicted regions is by examining changes in observable characteristics over time. Table 7 shows the 1998-2008 trend for some observable covariates.

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

	Control trend	Treatment trend
Age	0.30	0.38
Years of Education (All)	1.27	1.76
Years of Education (If attended school)	0.73	1.24
Hindu (1/0)	-0.01	-0.05
Brahmin/Chhetri(1/0)	-0.02	-0.07
Male	-0.02	0.01
Married	-0.03	-0.01
Household Size	-0.19	0.36
Urban	0.01	-0.07
Ever Attended School	0.09	0.18

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 Doubly Robust DiD

A useful way to account for covariate imbalances is the doubly robust DiD estimator from SantâAnna 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 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 covariates, obtains propensity scores for the probability of being treated, and reweights the changes in outcome to ensure that treatment and control groups are similar on covariates.

In our context, it is both equally plausbile 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. [8]

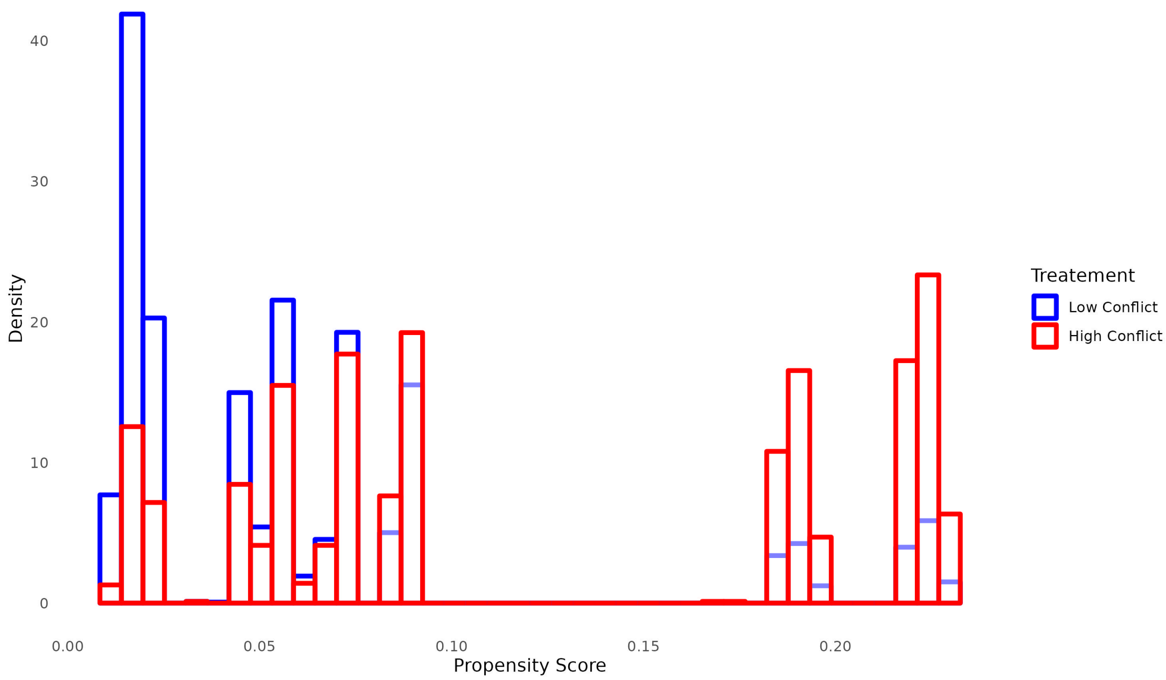
Table 8 presents the results from the propensity score model, showing that covariates such as ethnicity, sex, and urban/rural status are strong predictors of exposure to high-conflict intensity. The corresponding overlap in estimated propensity scores is displayed in Figure 1, where we can see good common 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.

[8] For more on Doubly Robust methods, with practical examples and good intuition, see Baker et al. (2025)

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

	Dependent variable:
	Treatment (high-conflict)
Age	0.001
	(0.003)
Hindu	0.320
	(0.478)
Brahmin/Chhetri	1.091
	(0.248)
Sex	−0.205
	(0.055)
Marital Status	0.010
	(0.107)
Urban	−1.557
	(0.427)
Constant	−2.711
	(0.482)
Observations	22,708
Log Likelihood	−4,991.217
Akaike Inf. Crit.	9,996.433
Note:	Standard errors are psu-clustered

Figure 1: Propensity Score Overlap



6 Main Results[9]

Table 9 reports the Doubly Robust DiD estimates for five outcome variables. Individuals affected highly by conflict are estimated to be less likely to be *usually employed* i.e. employed for more than 6 months in the past year, while there are no differences in *currently employed* and *currently self-employed* metrics. 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 5.3 hours less on average than the comparsion group. This is a decrease in -0.21 standard deviations in the standardize scale and represents 16% of the mean. There is likewise a -4.35 hours effect on self-employment, a 0.18 standard deviations decrease and represents 19% reduction from the mean.

These estimates may be contaminated by conflict-induced displacement and migration. 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). Such movements complicate the

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

	ATT	se	lci	uci
Usually Employed	-0.02	0.01	-0.04	0.01
Currently Employed	-0.03	0.01	-0.04	-0.01
Currently Self-employed	-0.01	0.01	-0.04	0.01
Work Hours	-5.32	0.71	-6.71	-3.94
Work Hours (std)	-0.21	0.03	-0.26	-0.15
Self Employment Hours	-4.35	0.76	-5.83	-2.86
Self Employment Hours (std)	-0.18	0.03	-0.24	-0.12

Table 9: Doubly Robust DiD estimates of ATT

identification of location-specific treatment effects in the sample as individuals facing employement challengs or with the means to leave may have chosen to migrate to safer places. To address for this potential bias, Table 10 presents DiD estimates based on a restricted sample that excludes individuals who either (i) were not born in their current location and migrated there within the last 12 years, or (ii) were born in their current location, left, and then returned within the same time frame. The idea is that people who migrated in the 12 years preceding 2008 may have done so due the conflict.

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. While not all migration in 12 years preceeding 2008 A.D. was necessarily because of conflict, sample restriction serves as a robustness check and provides insurance that even under strict exclusion of migrants, estimates are consistent.

	ATT	se	lci	uci
Usually Employed	-0.03	0.01	-0.05	-0.01
Currently Employed	-0.04	0.01	-0.06	-0.02
Currently Self-employed	-0.03	0.01	-0.05	-0.00
Work Hours	-5.67	0.74	-7.12	-4.23
Work Hours (std)	-0.22	0.03	-0.28	-0.17
Self Employment Hours	-4.65	0.80	-6.21	-3.09
Self Employment Hours (std)	-0.19	0.03	-0.26	-0.13

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

6.1 Discussion

A decline in average work hours can result either from fewer people finding employment or from jobs requiring fewer hours, due to higher productivity or a shift toward types of work with lower time demands. Since the likelihood of being employed is largely unchanged, the more likely explanation is the latter.

A decline in working hours is not inherently negative. From a labor supply perspective, if individuals voluntarily choose to work fewer hours in response to higher wages, while keeping their preferences constant, this may reflect rising productivity and improving economic conditions. However, when reduced hours are involuntary, maybe due to a lack of full-time opportunities or declining economic activity, the implications become concerning. In the context of Nepalese Civil War, it's difficult to interpret reductions in work hours as voluntary adjustments amid infrastructure destruction and uncertainity. Rather, the decline likely reflects a forced contraction in the availability of work, made worse by limited mobility due to fear of violence. Similarly, as alluded by Blattman and Miguel (2010), military experience is a poor substitute for education and labor market experience. The young conscripts in the Nepalese Civil War may find it harder to intergrate themselves in the labor market with reduced high-levele education and employment experience.

In terms of labor demand, being in a conflict-afflicted area is risky for firms, both in an economic sense of increased operational costs as well as the risk of physical danger. As a result, reduced investment, business closures, or relocation become plausible outcomes, which has negative effects on employment. On the other hand, if relatively underdeveloped, conflict-affected regions experienced convergence toward more developed, less-affected areas between 1998 and 2008, through shifts in industry composition, firm size, and labor demands, the productivity hypothesis cannot be ruled out.

6.2 Heterogeneous effects.

The NLFS selects equal primary sampling units from Nepal's Urban and Rural areas. The classification between an urban and rural area is based on the official classifications made by the then Ministry of Local Development, with 58 municipalities (including metropolitan and sub-metropolitan cities) classified as urban. The urban/rural classification from 1998 A.D. remained unchanged through 2008. I partition the dataset into urban-only and rural-only sample, to see effects within each. This is done for two reasons:

1. To decompose the ATT for urban and rural residing individuals.

2. The untreated counterfactual for treated units is more plausible within each subsample.

6.2.1 Urban

Table 11: Urban-only Sample Size Classification

	1998 (pre-period)	2008 (post-period)
$E[D = d_L]$	12763	15702
$E[D = d]$	386	368

The sample-size classification table shows the assymetric nature of conflict incidence, whereby, districts with high-conflict exposure contained very few urban settlements.

	ATT	se	lci	uci
Usually Employed	-0.11	0.03	-0.16	-0.06
Currently Employed	-0.13	0.03	-0.18	-0.08
Currently Self-employed	-0.17	0.03	-0.22	-0.11
Work Hours	-11.95	1.49	-14.87	-9.04
Work Hours (std)	-0.47	0.06	-0.59	-0.36
Self Employment Hours	-12.46	1.60	-15.59	-9.33
Self Employment Hours (std)	-0.52	0.07	-0.65	-0.39

Table 12: Doubly Robust DiD estimates of ATT for the urban sample

The results in Table 15 show big negative effects, both on measures on the likelihood of employment, as well as the number of hours worked.

6.2.2 Rural

Table 13: Rural-only Sample Size Classification

	1998 (pre-period)	2008 (post-period)
$E[D = d_L]$	8516	10122
$E[D = d]$	1135	1585

The rural-only sample has better balance in sample sizes than the urban-only sample. There is little to no impact on the likelihood of being employed in rural areas, with minimal negative effects on general and self-employment work hours.

The discrepancy in ATT between urban and rural areas is stark. While an accurate estimate for the urban sample may have been hindered by assymetric balance, the few

	ATT	se	lci	uci
Usually Employed	0.01	0.01	-0.01	0.03
Currently Employed	0.00	0.01	-0.02	0.02
Currently Self-employed	0.03	0.01	0.00	0.06
Work Hours	-3.52	0.81	-5.10	-1.93
Work Hours (std)	-0.14	0.03	-0.20	-0.08
Self Employment Hours	-2.08	0.87	-3.78	-0.39
Self Employment Hours (std)	-0.09	0.04	-0.16	-0.02

Table 14: Doubly Robust DiD estimates of ATT for the rural sample

urban municipalities in high-intense districts had stark reductions in labor supply. Urban areas, unlike rural VDCs, are denser in formal businesses, government offices, and public service infrastructure. In contrast, rural livelihoods are more reliant on self-employment, agriculture, and home-based enterprises. As such, the stark difference in ATT could reflect industry-specific effects, whereby formal sectors and institutions bore the brunt of conflict. However, for true assessment, industry specific breakdown is necessary, which is beyond the scope of this paper.

6.3 Mispecification : Including Poverty Rate as a covariate.

While age, sex, relgion, ethnicity and urban/rural location as covariates may improve the comparability between high-conflict and low-conflict groups, the literature on the causes of conflict incidence show that poverty and inequality in a region increases the likelihood of conflict incidence (Do and Iyer, 2010; Nepal et al., 2011). Figure 2 shows the propensity score overlap after including poverty rate of a district (data from Do and Iyer (2010)) as a covariate in our doubly robust DiD. Compared to figure 1, the propensity score now stretches upto 0.6 which implies that inclusion of poverty aids in better prediction treatment assignment.

Figure 2: Propensity Scores Overlap (with poverty rate as covariate)

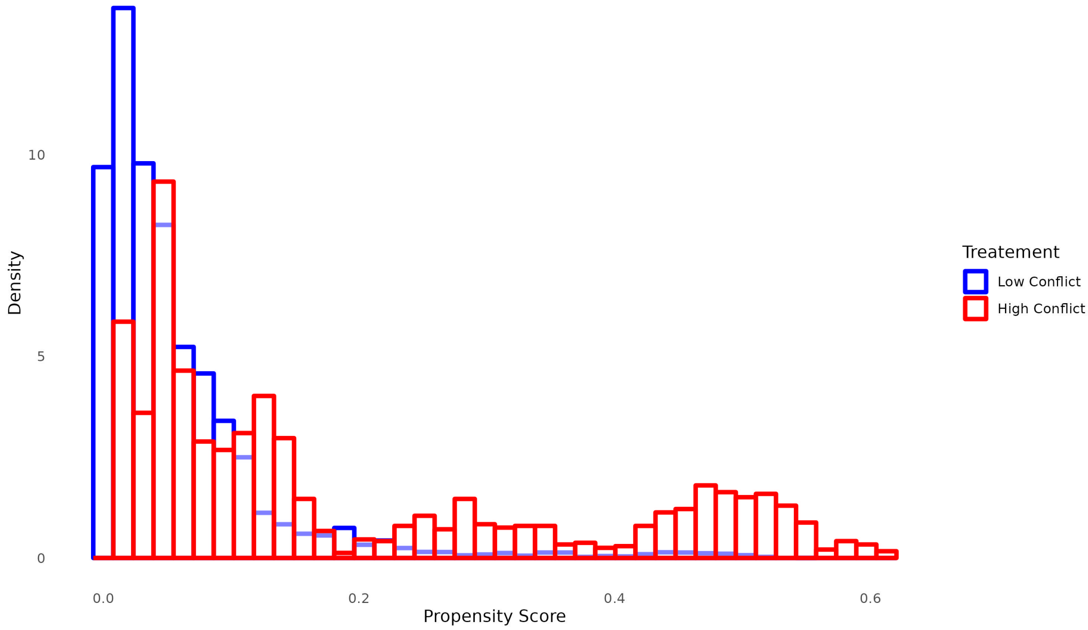


Table 15 reports the results. The ATT of conflict intensity is robust to the inclusion of district-level poverty rates as a covariate to improve balance. However, it must be noted that this procedure assigns the same district-level poverty rate to all individuals within a district, and that these rates do not vary between 1998 and 2008 A.D. ITheir main value lies in helping account for relative differences in district-level wealth.

	ATT	se	lci	uci
Usually Employed	-0.01	0.01	-0.03	0.01
Currently Employed	-0.04	0.01	-0.06	-0.01
Currently Self-employed	-0.03	0.01	-0.06	-0.00
Work Hours	-5.14	0.77	-6.65	-3.63
Work Hours (std)	-0.20	0.03	-0.26	-0.14
Self Employment Hours	-4.41	0.82	-6.02	-2.80
Self Employment Hours (std)	-0.18	0.03	-0.25	-0.12

Table 15: Doubly Robust DiD estimates of ATT (with poverty rate as covariate)

7 Conclusion

This paper investigates the labor market consequences of the Nepalese Civil War using repeated cross-section data from the 1998 and 2008 Nepal Labor Force Surveys, combined with conflict casualty data from UCDP. By leveraging a Difference-in-Differences framework and using Inverse Probability Weighted estimates to establish strong parallel trends, the study estimates the causal impact of conflict intensity on employment outcomes.

The results suggest that living in a conflict-affected district did not significantly reduce the likelihood of being employed, though individuals in highly afflicted areas tended to work fewer hours. The negative employment effect is starker in urban areas.

References

Alderman, H., Hoddinott, J., and Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford economic papers*, 58(3):450–474.

Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A., and Sant'Anna, P. H. (2025). Difference-in-differences designs: A practitioner's guide. *arXiv preprint arXiv:2503.13323*.

Blattman, C. and Miguel, E. (2010). Civil war. *Journal of Economic literature*, 48(1):3–57.

Bohara, A. K., Mitchell, N. J., and Nepal, M. (2006). Opportunity, democracy, and the exchange of political violence: A subnational analysis of conflict in nepal. *Journal of conflict resolution*, 50(1):108–128.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. (2024). Difference-in-differences with a continuous treatment. Technical report, National Bureau of Economic Research.

Do, Q.-T. and Iyer, L. (2010). Geography, poverty and conflict in nepal. *Journal of peace research*, 47(6):735–748.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of econometrics*, 225(2):254–277.

Imbens, G. W. and Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press.

Justino, P. and Verwimp, P. (2013). Poverty dynamics, violent conflict, and convergence in r wanda. *Review of Income and Wealth*, 59(1):66–90.

Lawoti, M. (2009). Violent conflict and change: Costs and benefits of the maoist rebellion in nepal. In *The Maoist Insurgency in Nepal*, pages 324–346. Routledge.

Lawoti, M. and Pahara, A. K. (2010). *The Maoist Insurgency in Nepal: Revolution in the Twenty First Century*. Routeledge, 1st edition.

Menon, N. and Van der Meulen Rodgers, Y. (2015). War and womenâs work: Evidence from the conflict in nepal. *Journal of Conflict Resolution*, 59(1):51–73.

Nepal, M., Bohara, A. K., and Gawande, K. (2011). More inequality, more killings: The maoist insurgency in nepal. *American Journal of Political Science*, 55(4):886–906.

SantâAnna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of econometrics*, 219(1):101–122.

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics*, 95(2):186–200.

Valente, C. (2014). Education and civil conflict in nepal. *The World Bank Economic Review*, 28(2):354–383.