# Do Civil Wars influence voter participation? A case study from Nepal *

MGTECON614 Final Project Report

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**Abstract**

The Nepalese Civil War that began in 1996 was a turning point for the tiny Himalayan Kingdom. It saw the abolition of the 240-year-old monarchy and paved the way for Nepal to become a republic. The 10-year-long war's legacy remains a topic of debate among academics and the general public, with much attention on the casualties and destruction it caused. However, there is a broad consensus that the war raised political awareness and engagement among the population. Several economics and political science papers concur that civil wars can increase political participation in post-conflict democratic political contexts. These studies typically use datasets from surveys from specific regions in the country. We, on the other hand, analyze national-level election data from pre- and post-war periods. Viewing the war as a natural experiment, with high-conflict and low-conflict regions serving as treatment and control groups, we employ modern variants of Difference-in-Differences methods to estimate the war's impact. Our findings show that in the aftermath of the war, high-conflict regions saw an increase in voter turnout. Furthermore, leveraging district-level data, we capture the variation in effects across different regions and observe heterogeneity in treatment effects over time, offering deeper insights into the political effects of the civil war.

## 1 Introduction

**Civil Wars** are a watershed event for any nation. They change the country's social, economic, and political trajectory. Irrespective of the nature and magnitude of the change, civil wars have an ugly side. They result in mass casualties, destruction of properties and infrastructures, and migration crises. Understanding the factors that cause wars or are affected by wars can help policymakers take action to prevent conflicts. In this regard, tools from causal are particularly valuable, as they can effectively model the cause-effect relationships between various variables in play. Additionally, causal studies provide insights into post-war changes. The findings can guide the country's rebuilding process.

In this report, I study the effects of civil war in Nepal. More specifically, I intend to measure the influence of the war on people's participation in elections. The conflict, also referred to as the People's War, officially started in 1996 after the Communist Party of Nepal (CPN)- Maoists had decided to launch an armed revolution to realize their objectives of ending the feudal system of governance and bringing about equality (Do and Iyer, 2010). After the attack, the CPN-Maoists engaged in small-scale combats against the army and police. The fighting mostly took place in the rural regions. A turning point came in 2001. Nine members of the royal family, including the king, queen, and prince, were killed in the "Royal Massacre." In the aftermath of the massacre, the government, with support from the newly crowned king, escalated its efforts to bring an end to the Maoist insurgency. Subsequently, there was a big upsurge in violence and casualties (See figure 4). In 2005, the then-king, citing the failure of political parties to stabilize the situation, dissolved the parliament, arrested the major political figures, and seized power. Political leaders were highly critical of the king's move. In a surprise turn of events, they decided to join hands with the Maoists to restore democracy. The major parties decided to launch a nationwide movement against the king. After about a month of intense fighting, the king gave up power in April 2006. Soon after, the major parties signed a peace agreement with the Maoists, formally ending the Civil War.

The general public and intellectuals have varying opinions about the impacts of the civil war. The restoration of democracy was a landmark achievement. There has been an uptick in the involvement of marginalized communities in both private and public sectors. However, politically, the country is still unstable. Since 2006, the

*I would like to thank Chandra Bhandari of Yale Economic Growth Center for providing the election data.

government has changed 14 times. As per statistics from the World Bank, pre and post-war economic growths are comparable. Nevertheless, there is an agreement among the people across the political spectrum that the conflict has led the populace to exercise their political rights more actively. To empirically evaluate this view, I measure the degree to which the civil war has impacted people's participation in the national elections. Using variants of the Difference-in-Differences (DiD) method, I compare the voter turnout rates before and after the civil war in high and low-conflict regions. My experiments and analysis show that the high-conflict areas saw an increase in voter turnout in the post-conflict elections compared to low-conflict areas.

# 2 Related Work

Civil wars and their political impacts have been well-studied in economics and political science. Bellows and Miguel (2009) show that Sierra Leoneans whose household members experienced more intense war violence are more likely to vote and join political groups. Likewise, Blattman (2009) find that Ugandan combatants who were coerced to join the rebel forces are more likely to take local political leadership positions. On the other hand, Alacevich and Zejcirovic (2020) shows that violence against civilians during the Bosnian civil war depressed voter turnouts. There are also scholarly works that have studied the Nepalese Civil War. Gilligan et al. (2014) find that voter turnout increased significantly in households that participated in the war.

Most papers analyzing the political impacts of civil wars, including the ones cited above, carry out their study at the individual level. Data used in the analysis come from household surveys conducted in specific regions. Hence, the studies do not illustrate the impact of the wars on a macro level. In this report, I conduct the analyses using district-level elections and demographics data. The incidence of civil war in Nepal can be viewed as a natural experiment, thereby allowing us to apply quasi-experimental methods to model the changes brought upon by the civil war.

# 3 Dataset

## 3.1 Description of the Raw Data

Data on the incident type and victim count comes from Joshi and Pyakurel (2015). Informal Sector Service Center, a human rights group working in Nepal, compiled the raw dataset.

Election data for 1991, 1994, 1999, 2008, and 2013, the years the election took place, comes from the Election Commission of Nepal, the government body responsible for conducting elections. In Nepal, the elections take place at the constituency level. For this study, we aggregated the data at the district level. The number of constituencies and their geographic boundaries change over time, which makes it harder to conduct the analysis at the constituency level. However, the boundaries and the number of districts have stayed the same.

The source of district-wise eligible voter population (adults 18 years and above) and the total population statistics is the nationwide census conducted by the Central Bureau of Statistics. The bureau carries out a census every ten years. Hence, demographic data is available for 1991, 2001, and 2011. The relevant estimates for the non-election years: 1994, 1999, 2008, and 2013 were calculated using the population growth rates provided in the census.

## 3.2 Model variables

1. **Outcome (Y)**: The outcome of interest is the "Voter Turnout Rate." It is equal to the ratio of total votes cast to the total number of eligible voters, the population of adults above 18 years of age.

2. **Time (t)**: The years in which elections took place: 1991, 1994, 1999, 2001, 2008.

3. **State (i)**: In our case, this represents district.

4. **Interaction/treatment indicator($D$)**: Dummy variable that is 1 if the district i is treated at time t. Treated districts are those where the conflict intensity is high.

5. **Treatment time (G)**: The year when the civil war started in each district. We do not have data on when the war began in each district. Instead, we look at the count of civil war-related incidents in each district and perform a Quandt Likelihood Ratio (QLR) Test to detect structural breaks. The treatment year corresponds to the first time period in which the detected break is significant. For all cases, the treatment years were $1999, 2000, 2001$.

The classification of a district as a high or low-conflict region is based on the Nepal government's categorization. The scheme looks at factors such as total casualties, property damages, and the total number of reported confrontations between rebel and security forces. Out of 75, 32 districts are classified as high-conflict regions. Hatlebakk (2007) qualitatively studies the other classification schemes and finds that the government's categorization is reliable. Figure 1 presents a graphical summary of war-related victim counts in high and low-conflict districts.

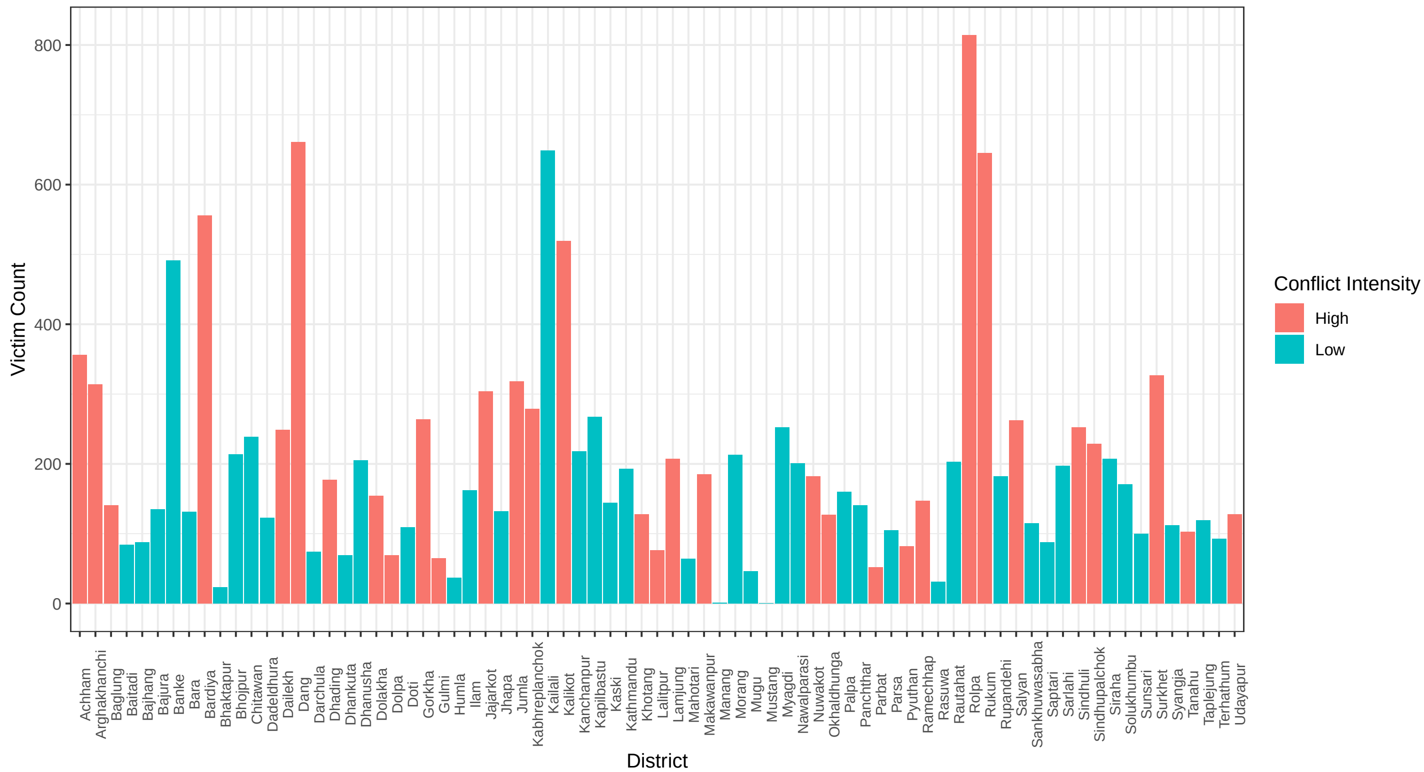


Figure 1: Tally of civil war-related incidents in the 75 districts. Classification of a district into high/low conflict zone is based on the Nepal government's categorization

# 4 Methods

We briefly describe the key details associated with difference-in-differences (Roth et al., 2023).

## 4.1 Canonical Difference-in-Differences (DiD)

Canonical DiD consists of two periods: pre-treatment (t=1) and post-treatment (t=2). The quantity of interest is the average treatment effect on the treated (ATT), which is given by,

$$\tau = \mathbb{E}\left[Y_{i,2}(1) - Y_{i,2}(0) | D_i = 1\right] \tag{1}$$

To enable the estimation of $\tau$, we make two key assumptions:

1. **Parallel trends** This assumes that if not for the treatment, the treated units would have evolved just like the control units. Mathematically,

$$\mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) | D_i = 1\right] = \mathbb{E}\left[Y_{i,2}(0) - Y_{i,1}(0) | D_i = 0\right] \tag{2}$$

2. **No anticipatory effects** This states that the effect of the treatment is observed after it is applied. Mathematically,

$$Y_{i,1}(0) = Y_{i,1}(1) \text{ for all i with } D_i = 1 \tag{3}$$

Imposing the two assumptions, the ATT can be estimated as follows:

$$\hat{\tau} = \frac{1}{n_1} \sum_{i=1,i:D_i=1}^{n_1} (Y_{i,2} - Y_{i,1}) - \frac{1}{n_0} \sum_{i=1,i:D_i=0}^{n_0} (Y_{i,2} - Y_{i,1}) \tag{4}$$

where $n_1$ = number of treated units and $n_0$ = number of control units .

## 4.2 TWFE

TWFE is an extension of the canonical two-period DiD model for panel datasets with multiple treatment years and units. The basic model is,

$$Y_{i,t} = \omega + \tau D_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{5}$$

In the above model, $\alpha_i$ and $\gamma_t$ are state (district) and time-fixed effects respectively. The coefficient of interest is $\tau$. In settings with exactly two periods, the $\hat{\tau}$ obtained via regression is equal to the value obtained using the difference in means equations in 4.

## 4.3 TWFE with covariates

The basic TWFE model can be used as a baseline. As a next step, we add covariates, $X_{it}$ to the model. The resulting DiD regression is given by

$$Y_{i,t} = \omega + \tau D_{i,t} + \beta X_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{6}$$

In our case, $X_{it}$ corresponds to the literacy rate of district i at time t. Literacy rate can be a valid covariate because it is unaffected by the treatment. Some schools in high-conflict regions shut down due to conflict-related activities. However, people continued to receive education in their homes. Additionally, many students ended up enrolling in schools in low-conflict parts.

## 4.4 Difference-in-differences for staggered treatments (Callaway and Sant'Anna (2021))

In staggered treatment settings, we make the following assumptions:

1. **Parallel trends for staggered setting** Denote $Y_{i,t}(\infty)$ as the outcome for unit i that does not get treatment at time t. Then, for all $t, t' \geq g_{min} - 1$ and $g_{min} = \min g_1, g_2, \cdots, g_n$,

$$\mathbb{E}\left[Y_{i,t}(\infty) - Y_{i,t'}(\infty) | G_i = g\right] = \mathbb{E}\left[Y_{i,t}(\infty) - Y_{i,t'}(\infty) | G_i = g'\right] \tag{7}$$

The above assumption says that outcomes would have evolved in parallel for different time periods had treatment not been provided.

2. **No-anticipation for staggered settings** For all i and $t < g$,

$$Y_{i,t}(g) = Y_{i,t}(\infty) \tag{8}$$

This says that the treatment effects manifest only after the first treatment time period.

Under the above assumptions, the estimator is given by,

$$\hat{\tau}_{g,t} = \frac{1}{N_g} \sum_{i:G_i=g} [Y_{i,t} - Y_{i,g-1}] - \frac{1}{N_{\bar{G}}} \sum_{i:G_i \in \bar{G}} [Y_{i,t} - Y_{i,g-1}] \tag{9}$$

In the above equation, $\bar{G}$ can denote either the never-treated-units, $\{\infty\}$ or not-yet-treated-units, $\{g' : g' > t\}$

Likewise, we can compute a weighted average of the staggered $\hat{\tau}_{g,t}$. For l periods after treatment adoption,

$$\hat{\tau}_l^w = \sum_g w_g \hat{\tau}_{g,g+l} \tag{10}$$

### 4.5 Justification for using DiD

The major reason for using DiD is that the data does not come from a randomized experiment. Difference-in-differences cancel changes brought upon by other confounding variables in the treated units over time. Similarly, the first treatment year in our dataset is 1999. If we look at figure 2, we see that in the period 1991 - 1999, the turnout rates in the high and low-conflict regions are roughly parallel.

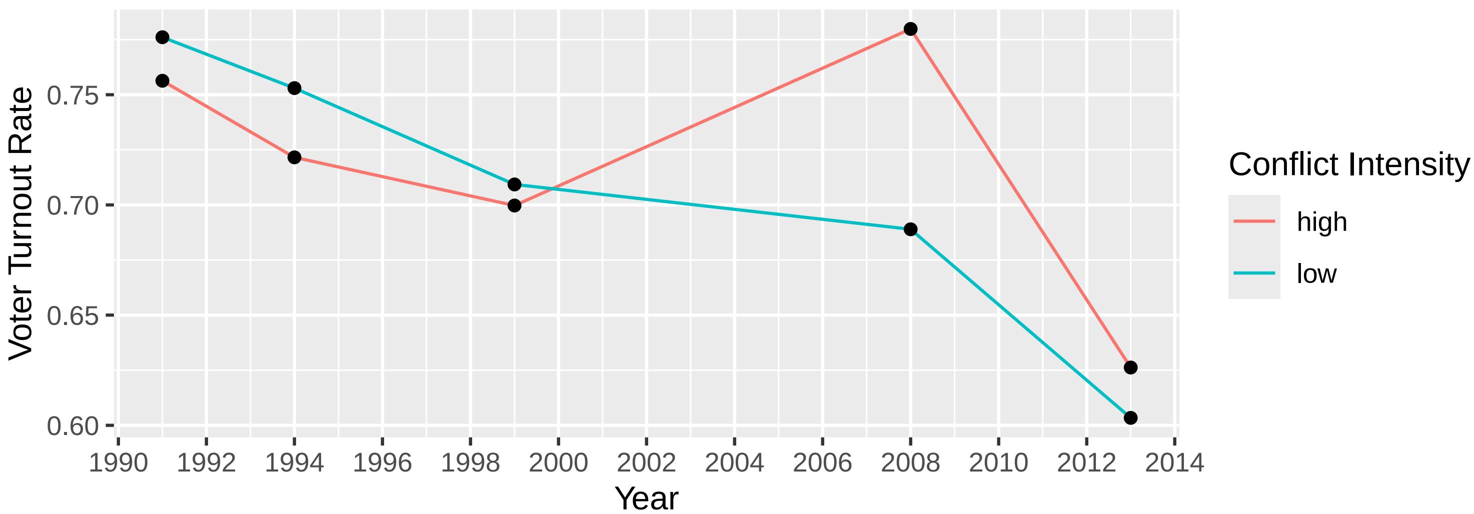


Figure 2: Voter turnout rates for 5 different elections. In the 2008 elections, after the conclusion of the civil war, high-conflict regions saw a big increase in voter turnout rate. In the year 2013, the participation rate went down for both high and low-conflict regions. This drop is because a large swathes of adults left Nepal for employment opportunities abroad

## 5 Empirical Results

All codes were implemented in R. The TWFE models were implemented using the lm function. Meanwhile, the staggered DiD method was implemented using the DiD package.

| | **Basic TWFE** (5) | **TWFE with covariates**(6) | **Aggregated** $\hat{\tau}_{g,t}$ (10) |
|---|---|---|---|
| Intercept ($\omega$) | 0.789 *** | 0.713 *** | |
| | (0.032) | (0.051) | |
| interaction ($\tau$) | 0.063 *** | 0.055 *** | 0.060 * |
| | (0.014) | (0.015) | (0.017) |
| literacy rate ($\beta$) | | 0.311 | |
| | | (0.162) | |

Table 1: Summary of DiD results

Table 1 shows the results of applying variants of the TWFE models. For the non-staggered models, the interaction term coefficient is statistically significant. Since our treatment is staggered, we apply the Goodman-Bacon decomposition (Goodman-Bacon (2021)) to understand the effect of different comparison groups.

As per the decomposition (table 2)The overall estimate of $\hat{\tau}$ is driven by comparison between treatment and control groups. About 10% of the estimate is attributed to the comparison between earlier and later treated groups, indicating the heterogeneity in treatment effects at different times. To further unpack this, we use the Callaway-Sant'Anna (CS) estimator.

| Comparison | Weight | Average Estimate |
|---|---|---|
| Earlier vs Later Treated | 0.05185 | 0.02756 |
| Later vs Earlier Treated | 0.04499 | -0.04550 |
| Treated vs Untreated | 0.90316 | 0.07064 |

Table 2: Goodman-Bacon decomposition of TWFE estimates

As evident from figure 3, there is variation in the magnitude of the effect by years of exposure. We observe the strongest effect in the 2008 elections, corresponding to time 7, 8, and 9 years in the figure. This observation makes sense because it was the first election after the war. Meanwhile, in the 2013 elections, we see a drop in the effect size. The effect is statistically significant in districts where the war started in 1999 (t=14 in figure 3); these districts are the ones where the civil war first started.

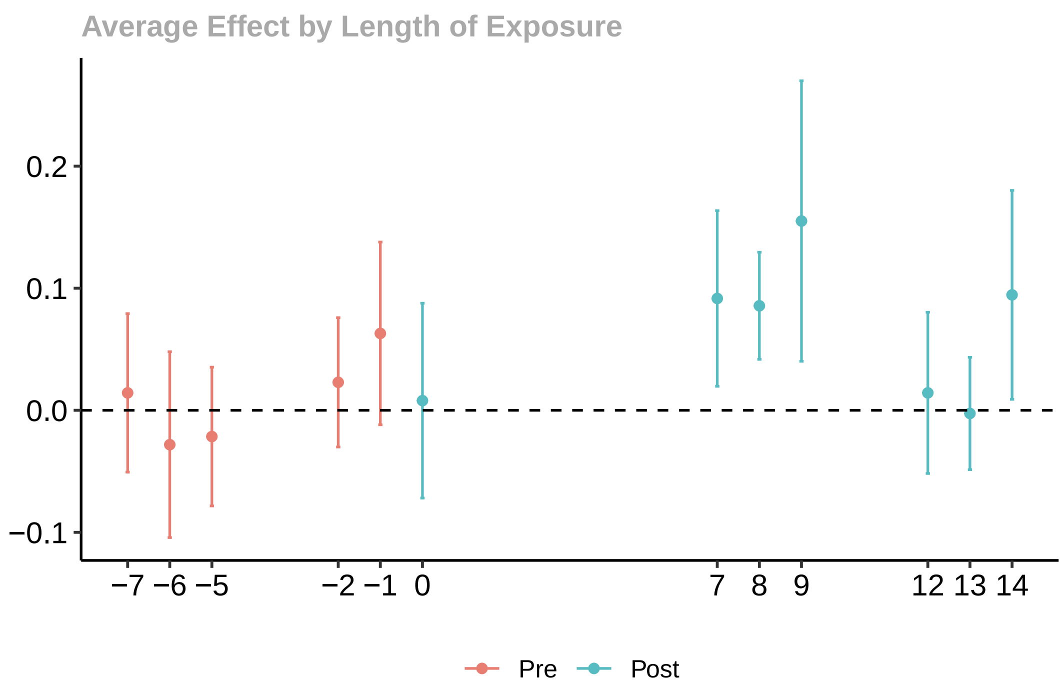


Figure 3: $\hat{ATT}(t, g)$ by length of exposure

**Robustness Check** In the above tables, we use the Nepal government's categorization of districts as high / low-conflict regions. The categorization scheme is quite broad and may appear odd in some cases. For instance, if we look at figure 1, we see that certain low-conflict regions also have high victim counts. Hence, as a robustness check, we test the models using another categorization scheme that looks solely at casualties rate i.e. ratio of total casualties to the total population of the district. Based on this scheme, 37 out of 75 districts are classified as high-conflict zones (figure 5). The results for this categorization (table 3) also show that the war led to an increase in voter participation rates in high-conflict regions.

## 5.1 Discussion

Based on the above results, we conclude that the Nepali civil war led to an increase in voter turnout rate in high-conflict regions. However, this finding contrasts with those of Juan and Pierskalla (2016). They find that Nepali people who experienced a higher degree of violence tend to be more distrustful of the political leaders. If they're more distrustful, then they would most likely not vote in elections. Many Nepali political commentators argue that the Maoist party used voter intimidation tactics and forced citizens to vote for them. Moreover, commentators also argue that people in high-conflict regions were still fearful of the Maoists and voted to avoid any reprisals

| | **Basic TWFE** (5) | **TWFE with covariates**(6) | **Aggregated** $\tau_{g,t}$ (10) |
|---|---|---|---|
| Intercept ($\omega$) | 0.788 *** | 0.723 *** | |
| | (0.033) | (0.053) | |
| interaction ($\tau$) | 0.059 *** | 0.049 ** | 0.061 * |
| | (0.015) | (0.016) | (0.016) |
| literacy rate ($\beta$) | | 0.27 | |
| | | (0.17) | |

Table 3: Summary of DiD results when using casualty counts to choose treatment/control districts

that could follow if Maoists were to lose. However, in the 2008 elections, Maoists won at least 1 constituency in 59 out of 75 districts, including many low-conflict districts. A more likely possibility is that the Nepalese people were dissatisfied with the older political parties and viewed the Maoist party as the harbinger of a new Democratic Nepal. Hence, they decided to vote overwhelmingly for the Maoists. Developing models that take into account the candidates running in the elections would be able to give a more decisive estimate of the influence of political parties.

Another factor to consider in the analysis is migration and displacement. Singh et al. (2007) estimate that around 200, 000 people left their homes in war-torn regions. It is possible that some individuals may have traveled back to their hometowns, where they were registered to vote, during the elections. However, it is unlikely that a significant portion of them made the travel. It is costly for the migrants, most of whom are in the low-income group, to travel.

My analysis has several limitations. Firstly, the selection of treatment year. I have applied the LQR test to detect breaks in the tally of war-related incidents in each district and choose the treatment year. Essentially, I am selecting the year when the war escalated as the treatment year. Hence, even though the war officially started in 1996, 1999 is used as the first treatment year. Likewise, war-related incident counts do not capture the complexities of the effects of the war. For example, it ignores other effects such property damages, and population displacement. A better scheme would be to look at the chronology of war-related incidents and changes in each region comprehensively and select the treatment year. Secondly, the covariate choices are limited. The only covariate I take into account is the literacy rate. There are several other plausible variables to consider. For instance, accessibility to transportation facilities and road networks. The rate at which transport facilities grew in different parts of Nepal is not the same. Remote parts saw a rapid rise relative to urban areas that were already well-connected. Another important factor to consider is the economic status of the districts. Most of the high-conflict districts are economically backward. It could be the case that the desire to improve economic well-being made people go to the polls. However, economic adversity could have also acted the other way around. Rosenstone (1982) find that economic adversity increases the opportunity costs of political participation and reduces people's participation in politics.

## 6 Conclusion and Ongoing Work

Using TWFE models for both staggered and non-staggered treatments, we find that voter turnouts in the post-conflict general elections increased in the high-conflict regions. The finding that in the aftermath of civil conflicts, the general populace tends to exercise their political rights more actively is also consistent with the conclusions of Bellows and Miguel (2009) and Gilligan et al. (2014). As discussed in the previous section, the current analysis is not free of limitations, and we are working to address them. We are compiling the occurrences of war-related incidents in each district to better inform the selection of starting treatment year. Likewise, we are also gathering more co-variates, especially those that capture the economic conditions and remoteness of the districts.

All in all, applying difference-in-differences methods to natural experiment data can help produce valuable insights on the large-scale impacts of civil wars.

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# 7 Appendix

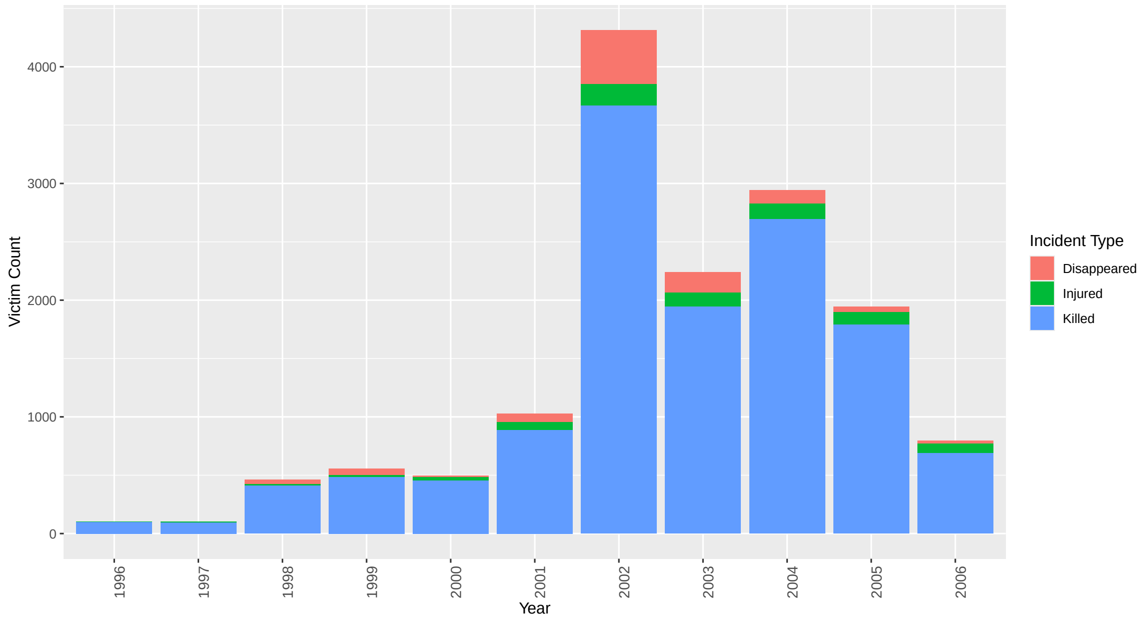


Figure 4: Tally of the total number of civil war-related incidents from 1996 to 2006. There was a sudden uptick in the number of incidents after 2001, the year when the Royal Massacre took place.

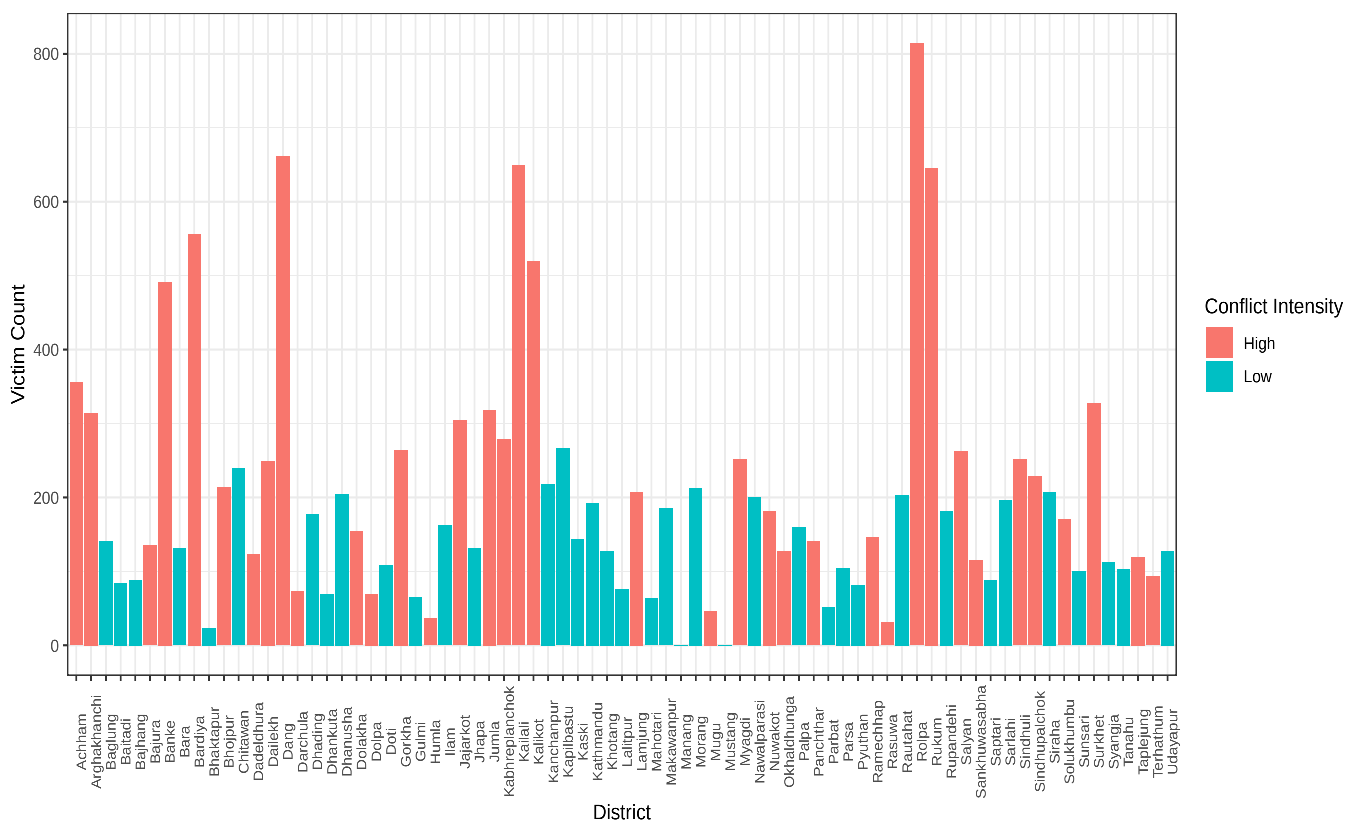


Figure 5: Tally of war-related incidents in high and low-conflict districts categorized by casualty counts