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Escalation of civil war in Nepal: The role of poverty, inequality and caste polarisation

Hari Sharma & John Gibson

Abstract

A growing literature examines effects of poverty, inequality and polarisation on civil war. Few studies examine effects at very local levels despite considerable spatial heterogeneity in many civil wars. We study Nepal's civil war, which escalated sharply from 2001, using geo-coded data on 15,000 conflict deaths. We also use small-area estimation to form poverty and inequality estimates for almost 4000 localities. Contrary to prior findings, it appears that higher local poverty rates reduced the risk of conflict and the number of deaths. This negative association is explained by the shift in strategy by the rebels, to target richer middle class and urban areas so as to access resources as a way to win the war. We also find that local relative wealth inequality is associated with escalation of the civil conflict, suggesting that relative wellbeing affects decisions about rebellion and conflict. Caste polarisation also raises odds of conflict and the number of deaths, especially where the dominant caste groups were larger. In a society where individual identity and alliances are defined by a discriminatory and unequal caste system, the probability of conflict is likely to be higher.

Keywords: Civil war, inequality, polarisation, poverty, small-area estimation, Nepal

JEL codes: D74, I32, O53

1. Introduction

Civil war is detrimental to development of a country. Understanding why conflict escalates and the propagation mechanisms that prolong conflict are important concerns for designing policies and institutions that can further the peaceful coexistence of people. Many studies explore causes of civil war at nation level (Sambanis, 2002; Taydas & Peksen, 2012), thus treating it as an outcome whose driving factors are homogeneous within a country. Yet civil war rarely spreads over the entire state and is often locally concentrated. Drivers of conflict are also usually not homogeneous across the state (Cederman & Gleditsch, 2009). The “Naxal” movement in India and conflict in Mindanao are typical examples of these localised conflicts (Eastin, 2018; Gomes, 2015; Hoelscher et al., 2012; Khanna & Zimmermann, 2017). A particular concern is that studying civil conflict at overly-aggregated levels may distort understanding of how conflict escalates and persists (Cederman & Gleditsch, 2009).

In this paper we use disaggregated administrative data on civil war deaths for almost 4000 localities in Nepal. We also use small-area estimation techniques to link survey and census data in order to construct welfare indicators for each of these localities. We use these data to explore the effects of poverty, inequality and caste polarisation on the escalation of Nepal’s civil conflict between 2001 and 2005. We believe there is much to gain from such granular-level study when conflict and its determinants are spatially heterogeneous.

Nepal’s civil war that ran from 1996 to 2006 is typical of such heterogeneous conflict. It was low intensity and localized for five years (1996-2000), with conflict-related deaths in fewer than 500 localities (of 3982 nationally; localities are also known as VDCs or Village Development Committees, and used to be called *panchayats*). Of 15,000 conflict-related deaths or disappearances from 1996 to 2006, fewer than 15% happened in the first five years (Figure 1). In 2001 the rebels changed their strategy and (unrelatedly) King Birendra and his family were murdered by the crown prince who then committed suicide. The new king mobilised the Nepalese Army throughout the country in 2001 to support the police force as

part of the ‘Global War on Terror’ (Sharma, 2006a). After that, the conflict spread to almost 60% of localities, and 85% of all conflict-related deaths occurred from 2001 to 2005 (Joshi & Pyakurel, 2015). Yet even with this escalation the conflict was unevenly experienced; out of about 2300 localities with conflict deaths from 2001-2005, only 661 (261) had five (ten) or more deaths. The conflict was heterogeneous, with not all localities (which we will also term ‘villages’ at some points) affected to the same extent.

(Figure 1 about here)

An important issue for researchers studying heterogeneous conflicts is the appropriate level of spatial aggregation. If raw data on conflict deaths can be geo-coded, researchers can aggregate to any level. Survey estimates used in conflict models, such as for inequality and poverty, were traditionally available only at the first or second sub-national level (such as provinces and districts) but modern small-area estimation techniques linking census data to surveys give welfare estimates at the very local, village level (Elbers et al, 2003). Therefore, the administrative level for which data are easily available matters less now for choosing the right aggregation level (Cederman & Gleditsch, 2009). The prior studies of Nepal’s civil war mostly use district level data. Sharma & Gibson (2019) note this may not be desirable as death rates varied far more within districts than between districts. Moreover, a district covers 2000 km², on average, which is 55-times larger than the average locality, so a lot of fine detail may be lost in district data. Poverty and related characteristics such as caste and the local environment also can vary significantly within districts (CBS, 1996). Likewise, spatial factors such as forest cover and elevation are heterogeneous within districts, and these factors may make some localities more vulnerable to conflict than others (Braithwaite, 2006, 2010). For these reasons we model the escalation of Nepal’s civil war at the locality level, using both cross-sectional and panel analyses for almost 4000 localities.

In contrast, prior studies of causes and effects of the civil conflict in Nepal mostly use

district-level data. Do & Iyer (2010) explored effects of district-level poverty on the conflict. Related studies examine effects of horizontal inequality, relative deprivation, polarisation, civic participation and social capital (Bohara et al., 2006; Deraniyagala, 2005; Murshed & Gates, 2005; and Sharma 2006b). Holtermann (2016) considers the relative capacity of rebels to escalate conflict. The data used in these studies is district level or even more aggregated. In terms of consequences of the conflict, Adhikari (2012), Pivovarova & Swee (2015), De Juan & Pierskalla (2016), and Shrestha (2017) examine effects on internal displacement, on schooling, on political trust and on emigration. While outcome measures in these studies are often at a more disaggregated level, such as from household survey data, the conflict rates are calculated at the district level and so smooth over much of the heterogeneity in the conflict.

Perhaps the closest study to ours is Nepal et al. (2011), who use data for 3860 villages to examine effects of inequality and poverty on conflict intensity. There are three concerns about this study. Like us, they use data from the Informal Sector Service Centre (INSEC), a NGO that monitored human rights violations by both government and Maoist forces, whose data are considered the most reliable source on the conflict (Joshi and Pyakurel, 2015). Yet Nepal et al. (2011) only geo-coded 2623 deaths between 1996 and 2003, which is just 28% of the total conflict deaths recorded by INSEC in that period. In contrast, we geo-coded 97% of the 15,021 deaths covered in the full decade-long INSEC dataset. If the missed deaths are not random, the findings from Nepal et al. (2011) may be distorted. Second, their data end in 2003 so over 4000 conflict-related deaths in 2004 and 2005 are ignored by their analysis. Finally, their research design is purely cross-sectional (as are other studies on Nepal also), and so cannot inform about the conflict escalation that occurred from 2001 onwards.

We find a negative effect of local poverty rates on the risk of conflict and the number of deaths. The poverty rates are for each locality, from small-area estimates linking detailed welfare indicators from the National Living Standards Survey to spatial coverage of the 2001

National Population Census. Other studies for Nepal, like Do & Iyer (2010), Sharma (2006a), and Hatlebakk (2010) find district-level poverty rates are positively related to conflict but this may be from overly-aggregated data disguising patterns seen at more local levels. Our results are consistent with what is proposed by Boulding (1962) and found (for Liberia) by Hegre et al. (2009), that rebel groups protect zones of influence and take conflict to the government strongholds as the rebels get stronger. In Nepal the Maoist rebels made a major strategic shift in 2001, to target urban areas and the middle class, so as to access resources and to garner greater support as a way to win the war. More generally, our results support the agnostic view that, notwithstanding the fact that internal conflict is more likely in poor countries (Theisen, 2008, Braithwaite et al., 2016), poverty is neither a necessary nor a sufficient condition for the escalation of internal conflict (Tollefsen, 2017; Verwimp et al., 2019).

As opposed to patterns for poverty, greater relative inequality was a major cause of conflict escalating. This finding may support the idea that people weigh relative wellbeing more highly than absolute wellbeing, so worsening inequality can heighten social tension and provoke violence (Koubi & Böhmelt, 2014). It also seems that polarisation by caste mattered to the escalation of the conflict. The struggle by *Dalits* (‘untouchables’) against “dominant classes” (the *Brahmin/Chhetri*, *Thakuries* and *Newars* castes) during the civil war is largely unnoticed in the empirical literature on causes of the conflict. Yet *Dalit* activists were active even before the civil war and later joined with Maoists to oppose caste-based discrimination (Bownas, 2015). To understand the effect of caste dynamics in Nepal we developed a caste-based polarisation index which goes well beyond the previous polarisation measures used by Nepal et al. (2011). More generally, our results suggest that a polarised society with a “dominant caste” is prone to conflict when a minority discriminated-against group gets some support from rebels. Our results also illustrate that when individual identity and alliances are defined by a discriminatory caste system, as in Nepal, conflict is likely to occur.

Overall, the data, method and range of covariates in this paper go well beyond prior papers relating to Nepal. While other studies use cross-sectional analysis, we use time and spatial fixed effects to account for heterogeneity over time and space. We model conflict and conflict intensity in two ways; whether a death(s) occurred in a locality in a given year (using a logit model), and how many deaths per locality each year (using a negative binomial model). The rest of the paper is as follows: section 2 provides background on Nepal's civil war, and the data collection and empirical strategy are discussed in section 3. The findings are reported in section 4 and the conclusions are presented in section 5.

2. Nepal's civil conflict (1996-2006)

In the lead-up to the civil war, 1990 was an important milestone in the social and political transformation of modern Nepal, with steps to restore democracy, and increase political freedom, social mobility and economic advancement. Yet, the transition to democracy was marked by corruption and weak institutions, and increased power of traditional elite dominant groups. Social and economic transformations gave greater freedom to middle class and “dominant caste” populations but marginalized, indigenous and socially excluded communities were side-lined from this improvement.¹ In fact, political participation and access to employment, healthcare and education for these communities failed to take off. Thus, while the national poverty rate was 42% in 1996 (CBS, 1996), it was far higher in the marginalized far-west and mid-west regions, at 58% and 62%, and also much higher for *Dalit* communities and for the class known as *Janjaties*.² Elite capture of the centre and rising poverty in rural areas created grievances and resentment towards the state.

¹ Dominant castes are *Brahmin*, *Chhetri* (including *Thakuries*) and *Newars* who traditionally received favour from the King and state, and are regarded as higher class.

² *Janjaties* are indigenous communities that are battling to restore their cultural, linguistic, religious and land ownership rights. They were landless and worked as slaves for the dominant castes for many years. *Dalits* are considered as untouchable and historically they were slaves and constitutionally not free to own physical assets. Although caste-based discrimination is criminalised in the constitution of Nepal it is still practised, including in the capital city Kathmandu.

In 1996, the Communist Party of Nepal (CPM-Maoist) formally declared war against the state so as to replace the constitutional monarchy with rules enforcing equality (Gobyn, 2009). The Maoist movement benefitted from the resentments created by rising social and political inequality and by poverty, and caste and ethnic discrimination so it drew major support from poor regions like the far west and mid-western regions. The opportunity cost of conflict is lower in poor regions, and it is relatively easier to recruit poor people who may harbour greater resentment against the government and thus be more likely to join a rebel group. The rebels also benefitted from remoteness and the presence of dense forest and mountains, which favoured guerrilla war tactics. In the early stages of the conflict, rebel activity concentrated mainly in the poorest and most underdeveloped regions of the mid-west and far-western parts of Nepal (Figure 2). Indeed, until 2000, conflict was largely limited to western Nepal, with only 493 villages having conflict-related deaths and 1693 people killed.

(Figure 2 about here)

In 2001, it became clear to the rebels that a struggle against the state that was limited to poor and remote regions was unlikely to succeed. Instead, they needed to capture urban areas and gain middle class support, both as a source of resources to fund rebellion and as a gateway to seizing the cities as a way to win the war (Gobyn, 2009). Rapid expansion of Maoist cadres and increased activities in new areas also precipitated this need to form a new war strategy. The second national Maoist convention in February 2001 adopted a new approach and decided to wage large-scale war to win over the middle class and gain access to urban areas (Davis et al., 2012; Gates & Miklian, 2010; Gobyn, 2009; Nayak, 2007). This strategic shift is also known as the “*Prachanda Path*” (Ogura, 2008). This reformulation of the Maoist war strategy aimed to destabilise the central power of the state, instigate revolt within the security forces, and garner support of mainstream political forces such as civil society and the urban population in order to win the war (Nayak, 2007).

Not long after this change in strategy by the rebels, the unexpected Royal Massacre in June 2001 (a murder-suicide) contributed to an escalation of the civil war. The new King, Gyanendra Shah initiated the formation of an armed police force and mobilisation of the army to control the rising Maoist insurgency (Davis et al., 2012). The deployment of armed police and the Royal Nepalese army to restrict the rising Maoist influence contributed to an escalation in the civil conflict (Nayak, 2007).

The spread in conflict from 2001 is shown in Figure 3, with almost 60% of localities (specifically, 2280 out of 3982) experiencing conflict-related deaths between 2001 and 2005. Thus, 2001 is seen as a major milestone in the history of Nepal's armed conflict, with a rapid spread out from rural western regions to begin challenging the government in the urban areas and cities in the richer central and eastern parts of the country (Holtermann, 2016; Nayak, 2007). Yet even with this spread there was a lot of heterogeneity in conflict intensity, as most conflict-affected localities had fewer than 15 deaths over this five year period (three per year, on average) with more localized hotspots in areas that had more than 40 people killed per locality over the five-year period (Figure 3b).

(Figure 3 about here)

At least some of this heterogeneity in deaths was due to the hit-and-run war tactics of the rebels, that killed many civilians and led to increasing human rights abuse from both sides (Nayak, 2007). The escalation of armed conflict also destabilized the economy and increased unemployment, which further fuelled the intensity of the conflict as rebels gained popularity and support from the unemployed. The extent of escalation is shown by the fact that the Maoist rebels eventually controlled half of all districts (Pivovarov & Swee, 2015), and repeatedly challenged the Nepalese Army and police force. From this greater position of strength, the rebels called for a ceasefire in 2005 to enable their participation in peace talks with seven major political parties. These peace talks marked the beginning of a new chapter

in Nepal's politics as the popular uprising and demonstrations by the Nepali population against the King in 2006 brought an end to both the civil conflict and the Monarchy. The peace agreement formally ended a decade-long civil war that cost over 15,000 lives.

3. Data and Empirical Methods

Our conflict data are from INSEC, an NGO who maintained a database of over 15,000 conflict-related deaths during the civil war period of 1996 to 2006. The INSEC database has detailed information about type of victim (civilians, rebels, military), the perpetrators, place and date of death, place of residence and victim age. We used this database to geocode the place where each victim was killed. For 97% of victims we could link to the locality (among all the 3982 VDCs in Nepal). In addition to deaths, we count disappearances that were never relocated as deaths. Thus, we have a comprehensive measure of the changing location of the civil war conflict in Nepal, that eclipses previous geo-coding efforts (e.g. Nepal, 2011).

The shift in the rebels strategy from early 2001 and the militarization after the Royal Massacre in June 2001 created a sharp change in the extent and location of the conflict. This is seen in the comparison of Figures 2 and 3 and in the far greater number of conflict-affected villages and conflict deaths from 2001 onwards seen in Figure 1. Given this dramatic shift, we argue that conflict from 2001 was substantially different to what had occurred in the five years prior, and indeed was a shift that changed the structure of Nepal's politics. Thus, our models focus on this new phase of conflict, by considering the changing risk of a locality being conflict-affected and the changing number of conflict deaths in each year from 2001 to 2005. We allow an impact from the past by using conflict data from 1996 to 2000 as one of several explanatory factors for the location and intensity of conflict in the 2001-05 period.

Our other sources of data include an extract from the tenth national population and housing census in 2001. Microdata are provided for what is roughly a one-in-ten sample on age, education, literacy, international migration, household assets and so on (CBS, 2001), and

we use these data to construct control variables. Our forest cover and elevation data are locality-level averages from *AidData* (Goodman et al. 2019). Night time lights, from satellite observation, are used to measure local economic activity (Gibson et al. 2020). The variables of main interest are poverty rates, a caste-based polarisation index, and inequality (overall, in terms of assets, and also looking at relative inequality amongst the poor), all measured at the local level. The computation of these variables is discussed in the following sub-sections.

3.1 Survey to census imputation of small area poverty

Poverty and inequality may be important drivers of conflict escalation. The maps in Figures 2 and 3 highlight the heterogeneous nature of the conflict, and suggest the need for local measures of poverty. Previous conflict-related research on Nepal uses district level poverty estimates, from the 1996 Nepal Living Standards Survey (NLSS). However, this survey has limited spatial coverage because the sample of just over 3300 households is from only 275 localities, less than seven percent of the total. So using these data directly makes researchers choose either to focus on a small subset of localities or to use poverty rates calculated at a spatially aggregated level that may disguise much of the heterogeneity. Also, the NLSS sample is designed to be representative at the ecological zone level (five zones) and not at the district level where the sample is too small (often just 12 or 24 households drawn from one or two villages in a district).

While the NLSS is spatially limited, the 2001 census extract covers over 0.5 million households and represents every locality. The drawback of the census is that it lacks information on consumption and so cannot be directly used to calculate poverty. However, the small-area-estimation (SAE) method of Elbers, Lanjouw and Lanjouw (2003) [hereafter, ELL] combines the spatial coverage of the census with the topical detail of the living standards survey to let us calculate poverty rates for every locality. Consider the following linear model of per capita consumption:

$$Y_{ch} = \beta X_{ch} + u_{ch} \quad (1)$$

for household h living in cluster c . The vector of predictor variables X_{ch} is restricted to those that have comparable distributions across the census and survey. A key feature of the ELL method is attention to the spatial characteristics of the disturbance term u_{ch} which has two independent components:

$$u_{ch} = \eta_c + e_{ch} \quad (2)$$

where η_c is the cluster effect and e_{ch} is a household-specific random error term. The cluster effect captures the unobserved similarities in consumption for households surveyed in the same locality, which if unaccounted for would lead to distorted measures of uncertainty when the predicted consumption for each census household is used to calculate local poverty rates. The ELL method involves estimating a “beta model” of consumption and an “alpha model” of the household-specific random error (details are reported in Appendix A.1 and A.2).

In the simulation stage, the estimated parameters from the alpha and beta models are applied to the X_{ch} characteristics of each household in the census. For each simulation, a set of $\tilde{\beta}$ and $\tilde{\alpha}$ are drawn, and the simulated value of the cluster specific variance $\tilde{\sigma}_c^2$ is obtained and used to calculate the household-specific variance $\tilde{\sigma}_{ch}^2$ for each census household. Then $\tilde{\eta}_c$ and \tilde{e}_{ch} are drawn from the corresponding distribution and the consumption for each census household \tilde{Y}_{ch} is then imputed as:

$$\tilde{Y}_{ch} = X_{ch}\tilde{\beta}_{GLS} + \tilde{\eta}_c + \tilde{e}_{ch} \quad (3)$$

By repeating the simulation 200 times we create a new set of coefficients and disturbance terms each time. The mean value of all 200 simulated consumption values is calculated for each census household and is used to calculate locality-level poverty rates, while the standard deviation for the 200 simulations provides an estimate of the standard error. Generally, ELL estimates at locality level have similar precision to that of survey estimates at district level.

The average poverty rate from the ELL simulations is 35.0%. This is midway between

survey estimates of 41.8% in 1996 and 30.8% in 2004 (CBS, 2004). Our estimate matches these, as it relates to 2001 (we use census data from that year); a linear decline in poverty between 1996 and 2004 would give a rate of 35% for 2001. Of note is that the poverty rate varies greatly over space, with a lot of within-district heterogeneity. Figure 4 shows this heterogeneity, contrasting the mean poverty rate in the district with the lowest and highest rates. For instance, *Dhading* district in central Nepal has a mean poverty rate of 31.8 % with a lowest poverty rate of 21.3% and a highest rate of 54.0%. This variation in poverty rates is seen in all regions. The fact that some localities may be more vulnerable to conflict than others, due to differences in their poverty rates, would be obscured if the more aggregated poverty rates, such as from the district level, were used.

(Figure 4 about here)

3.2 Household Assets indicator for inequality:

Inequality indexes are often used in empirical models of conflict (Koubi & Böhmelt, 2014). Prior studies for Nepal use the Gini index (e.g., Nepal et al., 2011) but we go beyond this by using two indexes. The first measures relative inequality amongst the poor, using their squared proportionate shortfall from the poverty line. The second index uses census data for 20 household assets. Assets are good long-run indicators of household wealth, and are easier for survey respondents to report (McKenzie, 2005). We use the first principal component score Y for household i given the assets vector X , which is the linear combination of:

$$Y_i = a_1 \left(\frac{x_1 - \bar{x}_1}{s_1} \right) + a_2 \left(\frac{x_2 - \bar{x}_2}{s_2} \right) + \dots + a_k \left(\frac{x_k - \bar{x}_k}{s_k} \right) \quad (4)$$

for $a = (a_1, a_2 \dots \dots a_k)$ coefficients, and \bar{x}_k and s_k means and standard deviations of ownership rates for the k^{th} asset. The first principal component score provides the maximum discrimination as assets that vary most across households get the largest weighting.

Given that Y_i can take negative values (as the mean is zero across all households), we cannot use measures of inequality like the Gini coefficient that are only defined for positive

values. Instead, our measure of relative inequality for locality l is estimated as:

$$IN_l = \frac{\sigma_l}{\sqrt{\lambda}} \quad (5)$$

which is the ratio of the standard deviation of the first principal component score σ_l to the eigenvalue λ , which is also the variance of Y_i across all households in the sample. In other words, if IN_l is greater than one then locality l has more inequality in the asset index than is apparent for the whole population, and vice versa (McKenzie, 2005).

3.3 Ethnic polarisation index

Polarisation is a term used to define the relative strength of two or more groups in society (Esteban & Ray 1994; Wolfson 1994). Reynal-Querol (2002) formed a polarisation index related to conflict and Montalvo & Reynal-Querol (2005) specifically consider effects of ethnic polarisation on civil wars. Other studies also note the impact of racial, religious and language diversity on civil war (Denny & Walter, 2014; Esteban et al., 2012). Yet the caste-based diversity prevalent in South Asia receives little attention despite caste discrimination being a major cause of the rise of the Maoist movement in India (Gomes, 2015). The caste system is also dominant in Nepal with so-called “lower castes”, especially *Dalits* and *Janjaties*, discriminated against. For example, *Dalits* comprise 80% of the ultra-poor of Nepal and are subjected to bonded labour, slavery, trafficking and other forms of extreme exploitation. Goyal et al. (2005) note that during the civil war, the army and the police force regularly punished *Dalits* without any evidence of their involvement with the Maoists, and often carried out sexual and physical abuse against women from this community.

To capture effects of local caste polarisation we formed a Reynal-Querol (RQ) index:

$$RQ = 1 - \sum_{i=1}^N \left[\frac{0.5 - \pi_i}{0.5} \right]^2 \pi_i \quad (6)$$

where π_i is the share of each caste group (for N groups) in a locality. The RQ index captures distance of a group from a $(1/2, 0, \dots, 0, 1/2)$ bipolar distribution. For example, a locality with

two individuals has distance zero if both belong to the same group, and is otherwise one. To construct an RQ index we identify six different groups, following the caste classification of Nepal's 2006 DHS survey (Bennett et al., 2008). Those of *Brahmin*, *Chhetri* and *Newars* caste are one group, and are considered the dominant group. *Dalits* are one group. The *Janjaties* from the hills ecological zone are one group and from the *terai* (lowlands) are another. The *Dalits* and *Janjaties* groups are considered the dominated group. We put other castes from the *terai* ecological zone into one group, and all other remaining castes that do not belong to any of the above classifications into one group. Our polarisation index is motivated by the fact that conflict is more likely to occur if a large minority group faces a large majority group. Therefore, the RQ Index is able to capture conflict effects when there are two major contesting groups in a society (Montalvo & Reynal-Querol, 2005).

3.4 Econometric Model

We have data for all 3982 localities in Nepal for the 2001 to 2005 period. We develop two dependent variables: to explain the probability of conflict we use a binary measure of whether a locality had any conflict deaths in a given year and to explain the intensity of conflict we use a count variable of the total number of deaths in the locality in each year. Our econometric specification to investigate the correlates of conflict is as follows:

$$Conflict_{it} = X_i\beta_n + V_i b_n + M_{it}\theta_n + conflict_{96-00} + \alpha_z + \delta_t + e_{it} \quad (7)$$

The binary conflict outcome and intensity of conflict are denoted by $Conflict_{it}$. We use X_i to represent variables of interest, such as the poverty rate, inequality and polarisation, which are measured at one point in time. The time-invariant control variables are denoted by V_i , while time-variant controls are denoted by M_{it} . The coefficient vectors to estimate are β , θ and b , while e_{it} is an error term that we initially treat as independent and identically distributed (iid) across panels and time with variance (σ^2). We later use a spatial autoregressive model as a robustness check, relaxing these error assumptions. We also use time fixed effects for each

year and 15 zonal (or 75 district) fixed effects for variation over space, denoted by δ_t and α_z .

We use a logistic regression model for the binary conflict outcome, and a negative binomial regression model for the count data to deal with the over-dispersion in conflict deaths.

Control variables:

When measuring effects on conflict of our main variables, it is important to control for confounders that may correlate with variables of interest and outcomes. Previous studies, such as Ware (2005) and Miller & Ritter (2014), highlight emigration as both a cause and an effect of conflict. For example, remittances may finance rebel activities or alternatively may reduce grievances if they serve as additional income in the absence of state support (Regan & Frank, 2014). Emigration may have a direct effect by allowing an outlet for young people (who may otherwise be recruited by rebels). To control for demographic and human capital effects, we include the share of the working age population (aged 15 to 59) and the share of those people with at least basic education (≥ 8 years of school). Rebels may more easily recruit in less educated areas if people feel future prospects are limited. Our migration, working age and education control variables are measured from the 2001 Census.

The risk of conflict often increases with distance from the capital city as the state may particularly fortify their headquarters. Another spatial effect is that rebels often concentrate near international borders (Buhaug et al., 2009; Cederman et al., 2009). To control for these effects, we include distance to the capital city (*Kathmandu*) and to the Indian border (which has free movement unlike Nepal's other borders) calculated using *ArcGIS* software.

Some studies highlight the role of geographic attributes like forest cover and elevation in influencing conflict (Buhaug et al., 2009; Cederman et al., 2009). In guerrilla war, rebels may shelter in forests and high elevation areas, that are strongholds for them, to plan timely attacks on government forces. Considering this, we include forest cover and elevation in our model. In Nepal, villages located in very high elevations have only small populations and so

may have experienced less conflict. We include a mountainous region dummy variable for localities above 2800 metres elevation. Urbanization, industrialization and socioeconomic development also influence conflict but data on these factors at subnational level are sparse so we use locality-level satellite-detected night time light data as a proxy, as lights provide a reasonable measure of local economic activity (Henderson et al., 2012).

Nepal's conflict took a sudden turn in 2001, moving well beyond the original areas but there was no ceasefire in these areas, which still had conflict. So following Bleaney and Dimico (2011), we use an indicator for whether there was any conflict in the locality in 1996 to 2000 as a control variable. Any drivers of this prior conflict, including poverty, are thus controlled for by inclusion of this control variable and so our specification implicitly gets at the change in the risk of conflict, controlling for baseline characteristics (including spatial fixed effects at region or district level). With our main variables of interest measured in 2001, reverse causation from the escalated conflict in the 2001-2005 period can also be ruled out.

4. Results and discussion

The definitions and summary statistics for all variables are reported in Table 1. Our main results are reported in Table 2, using six models – three for the risk of conflict (logit models) and three for the number of deaths (negative binomial models). The models differ by type of fixed effects (for 15 regional zones or for 75 districts) and whether the caste polarisation rate is interacted with the local population share of the dominant caste groups. Two further tables are presented after the main results, to show the robustness of the main findings to replacing the panel specification with either cross-sectional models or with spatial spillover models.

(Table 1 about here)

Effects of poverty and inequality

Poverty is often considered as a major driver of conflict, as poor people may harbour grievances against the state and may have less to lose from involvement with rebels. Yet it is

unclear whether relationships that seem to hold in aggregate data also hold at the very local level (Tollefsen, 2017). At least for Nepal, conflict seems higher in localities with a lower poverty rate, contrary to what prior studies based on district level data have suggested. Using the results in column 1 of Table 2, where unobserved factors are controlled for at the zonal level, for every ten percentage point increase in the locality poverty rate (just under a one standard deviation change), the risk of conflict would decrease by 4.2 percentage points (the effect is statistically significant at the $p < 0.01$ level). In terms of the expected number of conflict deaths, the results in column 2 suggest there would be 0.2 fewer deaths per locality with a ten percentage point higher poverty rate. These results suggest that during the escalation of the conflict, wealthier areas had more risk than did poorer areas, as their families and assets were the direct targets of some of the violence.

(Table 2 about here)

These results are consistent with the concept of support and target value proposed by Boulding (1962).³ Rebel groups first protect their primary zone of influence and then take the conflict to the government's stronghold areas, which has strategic importance to the rebels in terms of what they need in order to win the war (Hegre et al., 2009). At the beginning of the civil conflict in Nepal (1996-2000), the Maoist armed movement was restricted to the poor and underdeveloped region of the country, where they have gained the people's support and strengthened their rebel forces. After transforming into a formidable fighting force (year 2000 onwards), the Maoists shifted the war strategy and targeted areas in order to win middle class support, both as a source of resources and as a gateway to the cities or urban areas (Gobyn, 2009; Holtermann, 2016). The Maoists realised that their traditional way of struggle was unlikely to win a war if they lacked middle-class support (Nayak, 2007).

³ In the context of civil war in Nepal, 'support level' relates to the condition in which a rebel group gained the support of the population in the form of financial contributions, army recruits, and the provision of places to hide. In contrast the 'target level' refers to places and actions that had strategic importance to the rebel group, such as winning the support of the middle class, strategic locations for war, and sources of finance.

Our two indicators of local inequality – overall asset inequality and relative inequality amongst the poor – are positively associated with risk of conflict and the intensity of the conflict. For instance, a standard deviation increase in the inequality index based on household assets would raise the risk of conflict by about six percentage points, and the expected number of deaths by about 0.3 per locality per year. These effects are precisely measured, regardless of whether unobserved factors are controlled for with fixed effects at the zonal level or the district level. The effects are smaller for relative inequality amongst the poor, with a standard deviation increase associated with about 0.1 more deaths per locality per year and this effect becomes imprecise if district fixed effects are used. Nevertheless, the fact that conflict was, overall, less likely in poor areas but that greater inequality, overall and amongst the poor, saw more conflict suggests that relative position in a (local) society may matter – if some people judge that they are in a lower position than others, even amongst the poor, it may lead to a sense of unfairness that plays a role in heightening social tensions.

Although we lack data on land ownership there is likely to be a link between the inequality measures, conflict, and patterns of land ownership. At about the time the conflict escalated, almost one-half (44%) of households were marginal landowners who owned less than 0.5 ha of land (Deraniyagala, 2005; Macours, 2010). Therefore, the Maoists' demand for greater land equality, where they confiscated lands from landlords and redistributed to the poor who had little or no land, was an important source of their popularity and helped them to gather support, at the expense of support for the government.

Effect of caste polarisation

In localities with greater polarisation in terms of caste, there was more risk of conflict and greater intensity of conflict. According to the results in column 2 of Table 2, a standard deviation increase in local caste polarisation would increase the expected number of conflict deaths by 0.1 per locality per year. Although effects of caste are rarely examined our result is

consistent with other findings that diversity based on race, identity, ethnicity, and linguistics plays a key role in escalating civil war (Bosker & de Ree, 2014; Cederman et al., 2009; Nepal et al., 2011; Janus & Riera-Crichton, 2015). In Nepalese society, identity of an individual and alliances they form are defined by the pre-existing caste system, which is still prevalent in almost every part of the country.

To further explore effects of caste-based polarisation and the influence of dominant castes (*Brahmin, Chhetri* and *Newars*), we interact these two variables, with the results in the last two columns of Table 2. The larger the share of the dominant group (the ones doing the caste-based discriminatory practices) and the greater the polarisation, the higher the odds of conflict and the intensity of conflict. This result is consistent with the idea that discriminatory practices carried out by the dominant caste against minority groups contributed to the escalation of conflict. If membership growth for the Maoists and increased Maoist rebel activities were partly due to the exclusionary, caste-based discriminatory practices against *Dalits* and *Janjaties* it suggests that the rebels benefitted from local grievances in polarised villages. In particular, the rebels may have gathered support from the two dominated groups to make common-cause in their fight against the caste-based discriminatory practices.

Robustness check

We use two different approaches to check whether our main findings are robust. The first is to recast the model as cross-sectional, by collapsing the annual variation from 2001 to 2005. In other words, our first dependent variable is redefined as a dummy for whether a locality had any conflict deaths from 2001 to 2005, and the second dependent variable is the total number of those deaths. For time-varying controls (forest cover and night lights) we use the average of their values from 2001 to 2005. In Table 3, Model 1 presents the results where the polarisation index, the poverty rate and the inequality indicators are all directly included, and in Model 2 the polarisation index is interacted with the dominant caste population share.

The main finding that the risk of conflict and the number of conflict deaths is lower in localities with a higher poverty rate persists when the temporal variation has been suppressed. For example, a locality with a ten percentage point higher poverty rate (slightly less than one standard deviation) would expect 0.3 fewer deaths (one-tenth of the mean number) than an otherwise similar locality. A higher degree of caste polarisation for a locality is associated with that locality having more conflict deaths, and when this is interacted with the local share of the population who are from the dominant caste, it appears that it is especially the more polarised localities where the dominant caste had a larger share of the population that had more conflict deaths. The two types of inequality that we measure are both associated with a greater number of conflict deaths, while the overall inequality in terms of the asset index is also associated with greater risk of conflict. The main patterns amongst the control variables also persist; conflict is more likely and more intense in forested areas and in places that had prior conflict, and is more likely but not more intense in localities further from Kathmandu. Conversely, the risk of, and intensity of, conflict was lower in localities that had higher prior emigration, in high mountain areas, and in more educated areas.

(Table 3 about here)

Our second sensitivity analysis relaxes an assumption that is inherent when using typical regression approaches, that the conflict events in one locality are independent in space from events in other (neighbouring) localities. The diffusion aspect of conflict over space and time, either at national or local level, receives little attention (Schutte & Weidmann, 2011). There are a range of spatial spillover models available (LeSage & Pace, 2009; Fischer & Getis, 2009) but they are only rarely used to study conflict (Anselin & O'Loughlin, 1992; Ayana et al., 2016). If spillovers are ignored it may lead to estimation bias, and also to incorrect inferences if errors are wrongly treated as independent. These issues likely matter to the escalation of conflict in Nepal because there was considerable clustering in the conflict

deaths, with a statistically significant global Moran statistic ($I= 159.6$) for the relationship between deaths in a locality and deaths in neighbouring localities.

To allow for spatial spillovers we use a spatial autoregressive model (SAR), where the spatial lag of the dependent variable (the average in neighbouring localities) is included as an additional regressor.⁴ This lag structure allows for spatial spillovers because if a change in covariate X causes a local change in the outcome, that may affect outcomes of neighbours; in turn, the change in the outcome for the neighbours affects the outcomes of their neighbours, including the original area. For both the risk of conflict and conflict intensity (which is measured as number of deaths per thousand of population), the coefficient on the spatially lagged dependent variable is 0.26 and is statistically significant at the $p<0.01$ level. Thus there is strong evidence of spatial spillovers in conflict.

With spillover and feedback effects, the impact of a change in a covariate in locality i on outcomes in locality j may differ for each i - j combination. These various impacts can be decomposed into direct and indirect components, following LeSage and Pace (2009):

- *Direct effect*: the effect of a change in a covariate in locality i on the dependent variable in locality i , averaged over all 3982 localities
- *Total effect*: the effect of the same change in the covariate in all localities on the dependent variable in locality i , averaged over all localities
- *Indirect effect*: the difference between the total effect and direct effect.⁵

Table 4 presents the result for this decomposition, which shows similar patterns to the main results in Table 2. In particular, poverty still has a negative effect on the risk of conflict and the intensity of the conflict while local inequality (of assets) has positive effects on conflict, especially through the direct channel. While caste polarisation is still associated with a greater

⁴ Due to the simultaneity, this model is estimated with generalized spatial two-stage least squares (GS2SLS), using the estimator developed by Drukker et al. (2013). If we include a spatial lag of the error term this variable is statistically insignificant ($p < 0.22$) and other coefficients are similar to those that contribute to Table 4..

⁵ An intuitive discussion and example of these direct, indirect and total effects is provided in Gibson (2019).

risk of conflict, it has a weakly negative effect on conflict intensity (deaths), in contrast to the results that did not allow for spillovers. Another change from the earlier results is that the inequality amongst the poor has no impact on conflict intensity, but still makes the risk of conflict higher. The patterns of impacts from the control variables are largely as they were from the models that did not account for spillovers. The results in Table 4 suggest most of our findings are robust to using a more general spatial model and so our conclusion about the conflict escalating into non-poor areas from 2001 onwards continues to hold.

(Table 4 about here)

5. Conclusion

This study has investigated escalation of civil conflict at the local level. A sizable literature examines effects of poverty, inequality, and polarisation on civil war, yet little attention is paid to how these relationships hold at local levels. For Nepal, we consider that locality-level indicators of conflict and the driving forces of conflict are more appropriate than indicators at the more aggregated district level that has been the focus of most previous studies because the conflict (and some of its correlates) was spatially heterogeneous. Indeed, there was more than three times as much variation in conflict death rates within districts than between districts (Sharma & Gibson, 2019) so district-level data may disguise key patterns.

In order to construct our locality-level database, we geocoded 97% of conflict-related deaths, eclipsing prior efforts such as Nepal et al. (2011) that geo-coded just 28% of deaths. We also use small-area estimation methods to combine the spatial coverage of a census with the topical coverage of a living standards survey, to form poverty and inequality indicators for almost 4000 localities. We also use an extract from the census to calculate a polarisation index based on caste, which is very important in South Asia. With this database that goes far beyond what prior studies for Nepal have used, we estimate panel, cross-sectional and spatial

spillover models of the likelihood of a locality being affected by conflict and the intensity of the conflict, in terms of the number of deaths.

We find across all of our models that poverty was negatively associated with conflict. The fact that the conflict escalated in localities with lower poverty rates is consistent with the shift in the Maoist war tactics in 2001, known as the “Prachanda Path”, to target richer areas so as to gain resources, destabilise the central power of the state, instigate revolt within the security forces, and garner support of mainstream political forces such as the urban middle class. This shift is also consistent with the concept of support and target value proposed by Boulding (1962); rebel groups protect zones of influence and take conflict to the government strongholds as the rebels get stronger. Our major finding also suggests that care is needed in interpreting results of prior studies like Do and Iyer (2010) that found a positive association between poverty and conflict; spatial aggregation may have contributed to this result.

While conflict escalation was less likely in poor areas, it was more likely in unequal and caste-polarised areas. These results point to the possible role of an unequal local society breeding a sense of unfairness that plays a role in heightening social tension and provoking violence. Such factors may especially matter where individual identities and the alliances they form are affected by the pre-existing caste system which was highly discriminatory to some groups. That conflict-related deaths were higher in polarised localities where dominant caste members were a larger share of the population may also suggest that the common-cause that the rebels sought with dominated groups like the *Dalits* may have conditioned patterns of conflict, as suppressed groups harbour grievances and want vengeance. Both hostility and antagonism were an outcome of the discriminatory practices of the dominant group. With a better understanding of the important role of local inequality and caste polarisation in raising the probability of conflict and the intensity of that conflict, it may be possible to design better institutions that can help further the peaceful coexistence of people.

References

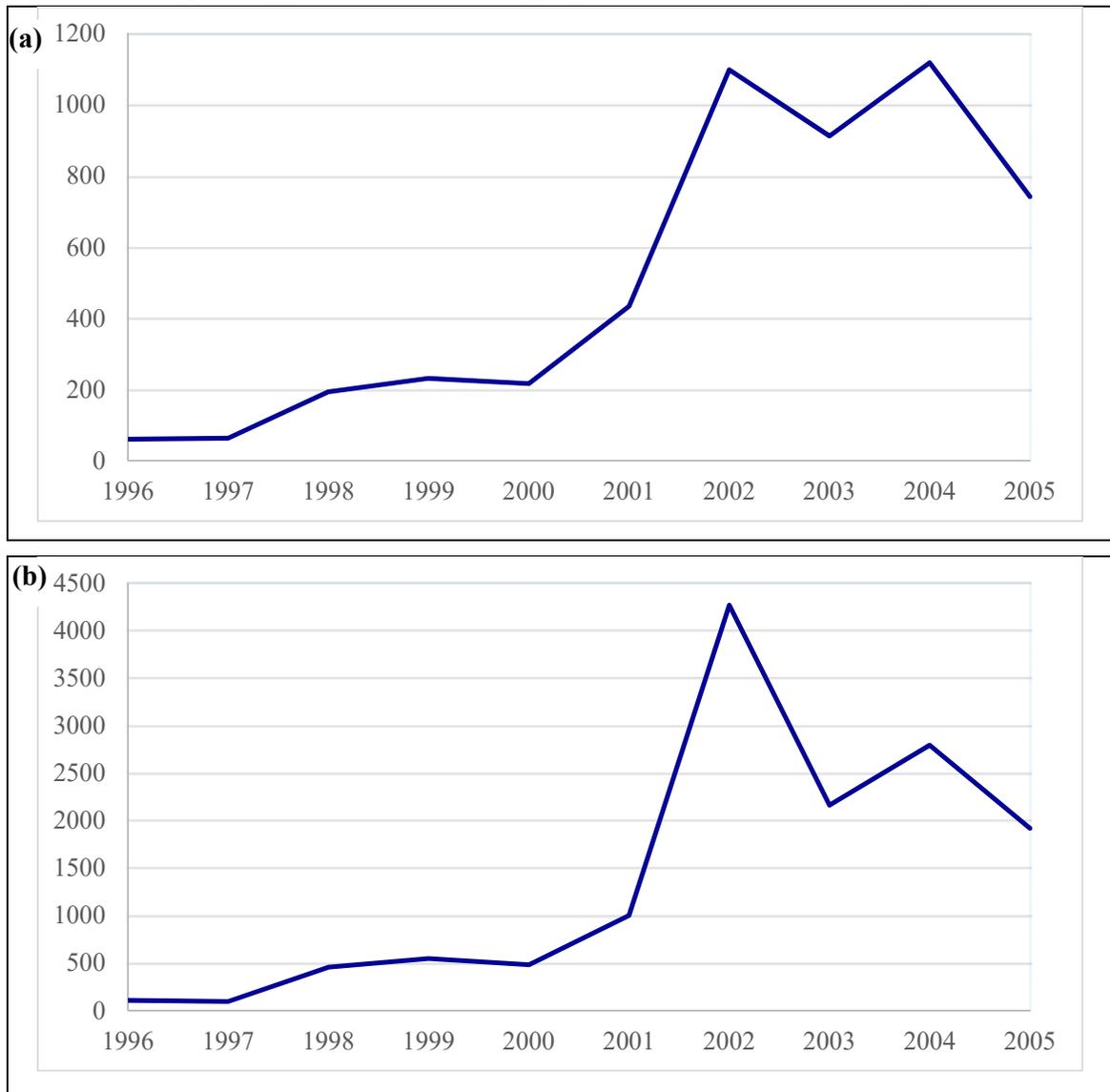
- Adhikari, P. (2012). The plight of the forgotten ones: Civil war and forced migration. *International Studies Quarterly*, 56(3), 590-606.
- Anselin, L., & O'Loughlin, J. (1992). Geography of international conflict and cooperation: spatial dependence and regional context in Africa. *The New Geopolitics*, 39-75.
- Ayana, E. K., Ceccato, P., Fisher, J. R., & DeFries, R. (2016). Examining the relationship between environmental factors and conflict in pastoralist areas of East Africa. *Science of The Total Environment*, 557, 601-611.
- Bennett, L., Dahal, D. R., & Govindasamy, P. (2008). Caste, Ethnic and Regional Identity in Nepal: Further Analysis of the 2006 Nepal Demographic and Health Survey. Calverton, Maryland, USA: Macro International Inc.
- Bleaney, M., & Dimico, A. (2011). How different are the correlates of onset and continuation of civil wars?. *Journal of Peace Research*, 48(2), 145-155.
- Bohara, A. K., Mitchell, N. J., & 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.
- Bosker, M., & de Ree, J. (2014). Ethnicity and the spread of civil war. *Journal of Development Economics*, 108, 206-221.
- Boulding, Kenneth. 1962. *Conflict and Defense: A General Theory*. New York: Harper.
- Bownas, R. A. (2015). Dalits and Maoists in Nepal's civil war: between synergy and co-optation. *Contemporary South Asia*, 23(4), 409-425.
- Braithwaite, A., Dasandi, N., & Hudson, D. (2016). Does poverty cause conflict? Isolating the causal origins of the conflict trap. *Conflict Management and Peace Science*, 33(1), 45-66.
- Braithwaite, A. (2006). The geographic spread of militarized disputes. *Journal of Peace Research*, 43(5), 507-522.
- Braithwaite, A. (2010). Resisting infection: How state capacity conditions conflict contagion. *Journal of Peace Research*, 47(3), 311-319.
- Buhaug, H., & Gleditsch, K. S. (2008). Contagion or confusion? Why conflicts cluster in space. *International Studies Quarterly*, 52(2), 215-233.
- Buhaug, H., Gates, S., & Lujala, P. (2009). Geography, rebel capability, and the duration of civil conflict. *Journal of Conflict Resolution*, 53(4), 544-569.
- Central Bureau of Statistics [CBS] (1996). Nepal Living Standard Survey I 1996: Statistical Report, Vol 1 and 2. Kathmandu: Central Bureau of Statistics.
- Central Bureau of Statistics [CBS] (2004). Nepal Living Standard Survey II 2004: Statistical Report, Vol 1 and 2. Kathmandu: Central Bureau of Statistics.
- Central Bureau of Statistics [CBS] (2001). National Population Census 2001, Report on Nepal's Tenth Census. Government of Nepal. Kathmandu.
- Cederman, L. E., Buhaug, H., & Rød, J. K. (2009). Ethno-nationalist dyads and civil war: A GIS-based analysis. *Journal of Conflict Resolution*, 53(4), 496-525.

- Cederman, L., & Gleditsch, K. (2009). Introduction to Special Issue on “Disaggregating Civil War”. *Journal of Conflict Resolution*, 53(4), 487-495.
- Davis, Paul K., Eric V. Larson, Zachary Haldeman, Mustafa Oguz, and Yashodhara Rana. (2012). Public Support for the Maoists in Nepal. In *Understanding and Influencing Public Support for Insurgency and Terrorism* (pp. 119-150). Rand National Defense Research Institute, Santa Monica.
- De Juan, A., & Pierskalla, J. H. (2016). Civil war violence and political trust: Microlevel evidence from Nepal. *Conflict Management and Peace Science*, 33(1), 67-88.
- Denny, E. K., & Walter, B. F. (2014). Ethnicity and civil war. *Journal of Peace Research*, 51(2), 199-212.
- Deraniyagala, S. (2005). The political economy of civil conflict in Nepal. *Oxford Development Studies*, 33(1), 47-62.
- Do, Q. T., & Iyer, L. (2010). Geography, poverty and conflict in Nepal. *Journal of Peace Research*, 47(6), 735-748.
- Drukker, D. M., Prucha, I. R., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*, 13(2), 221-241.
- Eastin, J. (2018). Hell and high water: Precipitation shocks and conflict violence in the Philippines. *Political Geography*, 63, 116-134.
- Elbers, C., Lanjouw, J. O., & Lanjouw, P. (2003). Micro-level estimation of poverty and inequality. *Econometrica*, 71(1), 355-364.
- Esteban, J., Mayoral, L., & Ray, D. (2012). Ethnicity and conflict: An empirical study. *American Economic Review*, 102(4), 1310-42.
- Esteban, J. M., & Ray, D. (1994). On the measurement of polarisation. *Econometrica*, 62(4), 819-851.
- Fischer, M. M., & Getis, A. (Eds.). (2009). *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*. Springer Science & Business Media.
- Gates, S., & Miklian, J. (2010). Strategic Revolutionary Phases of the Maoist Insurgency in Nepal. *Unpublished manuscript*.
- Gibson, J. (2019). Are You Estimating the Right Thing? An Editor Reflects. *Applied Economic Perspectives and Policy*, 41(3), 329-350.
- Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). Night lights in economics: Sources and uses. *Working Paper 2020-01* Centre for the Study of African Economies, University of Oxford.
- Gobyn, W. (2009). From war to peace: The Nepalese Maoists's strategic and ideological thinking. *Studies in Conflict & Terrorism*, 32(5), 420-438.
- Gomes, J. F. (2015). The political economy of the Maoist conflict in India: an empirical analysis. *World Development*, 68, 96-123.
- Goodman, S., BenYishay, A., Lv, Z., & Runfola, D. (2019). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & Geosciences*, 122, 103-112.

- Goyal, R., Dhawan, P., and Narula, S. (2005) The Missing Piece of the Puzzle: Caste Discrimination and the Conflict in Nepal, Center for Human Rights and Global Justice, NYU Law School, New York.
- Hegre, H., Østby, G., & Raleigh, C. (2009). Poverty and civil war events: A disaggregated study of Liberia. *Journal of Conflict Resolution*, 53(4), 598-623.
- Hatlebakk, M. (2010). Maoist control and level of civil conflict in Nepal. *South Asia Economic Journal*, 11(1), 99-110.
- Henderson, Vernon, Adam Storeygard, and David Weil (2012). Measuring economic growth from outer space. *American Economic Review* 102(2), 994-1028.
- Hoelscher, K., Miklian, J., & Vadlamannati, K. C. (2012). Hearts and mines: A district-level analysis of the Maoist conflict in India. *International Area Studies Review*, 15(2), 141-160.
- Holtermann, H. (2016). Relative capacity and the spread of rebellion: insights from Nepal. *Journal of Conflict Resolution*, 60(3), 501-529.
- Janus, T., & Riera-Crichton, D. (2015). Economic shocks, civil war and ethnicity. *Journal of Development Economics*, 115, 32-44.
- Joshi, M., & Pyakurel, S. R. (2015). Individual-Level Data on the Victims of Nepal's Civil War, 1996–2006: A New Dataset. *International Interactions*, 41(3), 601-619.
- Khanna, G., & Zimmermann, L. (2017). Guns and butter? Fighting violence with the promise of development. *Journal of Development Economics*, 124, 120-141.
- Koubi, V., & Böhmelt, T. (2014). Grievances, economic wealth, and civil conflict. *Journal of Peace Research*, 51(1), 19-33.
- LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Chapman and Hall/CRC.
- Macours, K. (2010). Increasing inequality and civil conflict in Nepal. *Oxford Economic Papers*, 63(1), 1-26.
- McKenzie, D. J. (2005). Measuring inequality with asset indicators. *Journal of Population Economics*, 18(2), 229-260.
- Miller, G. L., & Ritter, E. H. (2014). Emigrants and the onset of civil war. *Journal of Peace Research*, 51(1), 51-64.
- Montalvo, J. G., & Reynal-Querol, M. (2005). Ethnic polarisation, potential conflict, and civil wars. *American Economic Review*, 95(3), 796-816.
- Murshed, S. M., & Gates, S. (2005). Spatial–horizontal inequality and the Maoist insurgency in Nepal. *Review of Development Economics*, 9(1), 121-134.
- Nayak, N. (2007). The Maoist movement in Nepal and its tactical digressions: A study of strategic revolutionary phases, and future implications. *Strategic Analysis*, 31(6), 915-942.
- Nepal, M., Bohara, A. K., & Gawande, K. (2011). More inequality, more killings: the Maoist insurgency in Nepal. *American Journal of Political Science*, 55(4), 886-906.
- Ogura, K (2008). Seeking state power: The Communist Party of Nepal (Maoist). Berlin: Berghof Foundation.

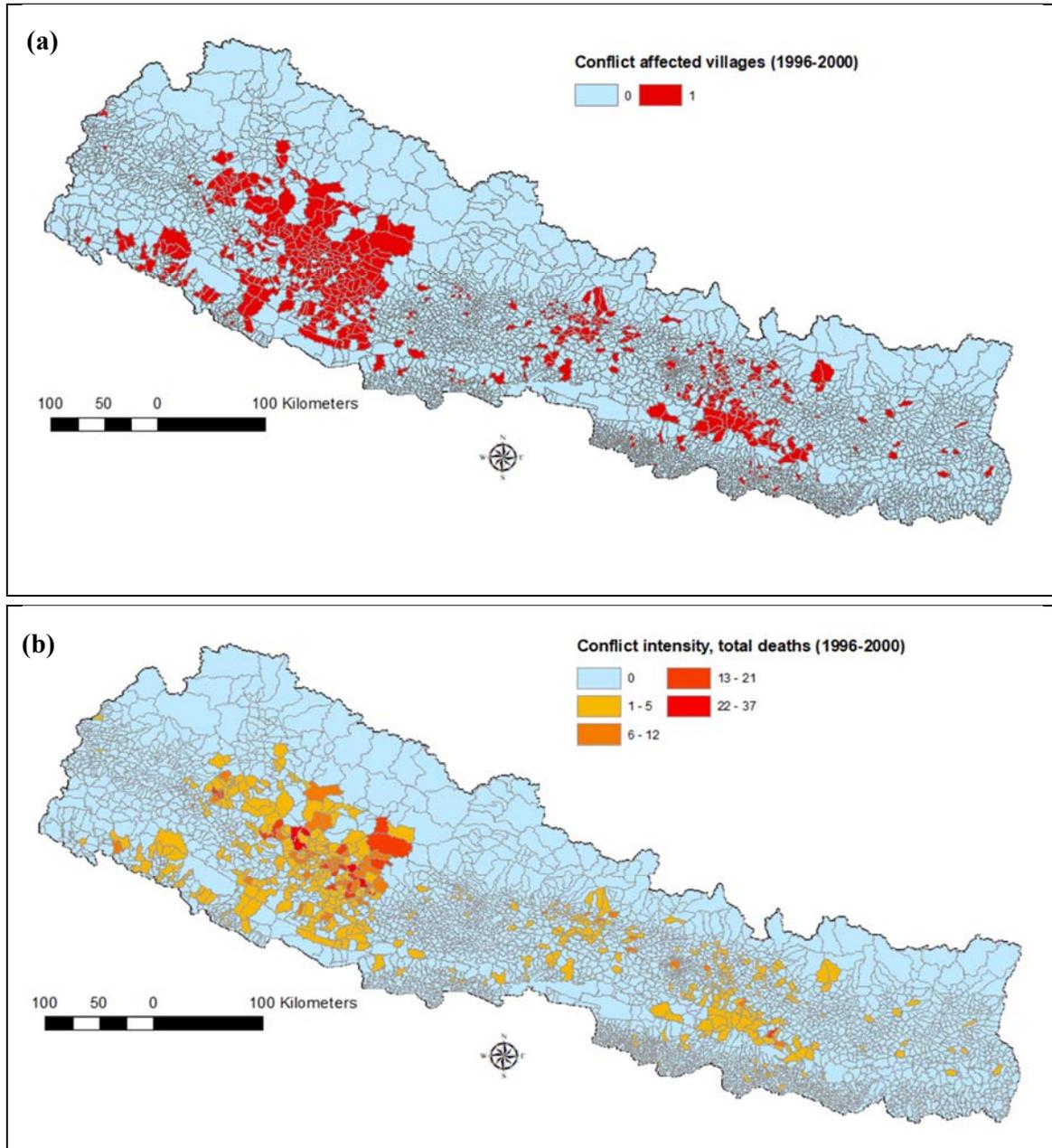
- Pivovarova, M., & Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from Nepal. *World Development*, 66, 308-321.
- Regan, P. M., & Frank, R. W. (2014). Migrant remittances and the onset of civil war. *Conflict Management and Peace Science*, 31(5), 502-520.
- Reynal-Querol, M. (2002). Ethnicity, political systems, and civil wars. *Journal of Conflict Resolution*, 46(1), 29-54.
- Sambanis, N. (2002). A review of recent advances and future directions in the quantitative literature on civil war. *Defence and Peace Economics*, 13(3), 215-243.
- Schutte, S., & Weidmann, N. B. (2011). Diffusion patterns of violence in civil wars. *Political Geography*, 30(3), 143-152.
- Sharma, H., & Gibson, J. (2019). Civil War and International Migration from Nepal: Evidence from a Spatial Durbin Model. *Working Paper in Economics 19/06*, University of Waikato.
- Sharma, K. (2006a). The political economy of civil war in Nepal. *World Development*, 34(7), 1237-1253.
- Sharma, K. (2006b). Development policy, inequity and civil war in Nepal. *Journal of International Development*, 18(4), 553-569.
- Shrestha, M. (2017). Push and pull: A study of international migration from Nepal. *Policy Research Working Paper No. 7965*, The World Bank, Washington DC.
- Taydas, Z., & Peksen, D. (2012). Can states buy peace? Social welfare spending and civil conflicts. *Journal of Peace Research*, 49(2), 273-287.
- Theisen, Ole Magnus. (2008). Blood and soil? Resource scarcity and internal armed conflict revisited. *Journal of Peace Research*, 45(6), 801-818.
- Tollefsen, A. F. (2017). Experienced poverty and local conflict violence. *Conflict Management and Peace Science*, 0738894217741618.
- Verwimp, P., Justino, P., & Brück, T. (2019). The microeconomics of violent conflict. *Journal of Development Economics*, Vol.141.
- Ware, H. (2005). Demography, migration and conflict in the Pacific. *Journal of Peace Research*, 42(4), 435-454.
- Wolfson, M. C. (1994). When inequalities diverge. *The American Economic Review*, 84(2), 353-358.

Figure 1: (a) Conflict affected villages (b) Conflict related deaths, each year



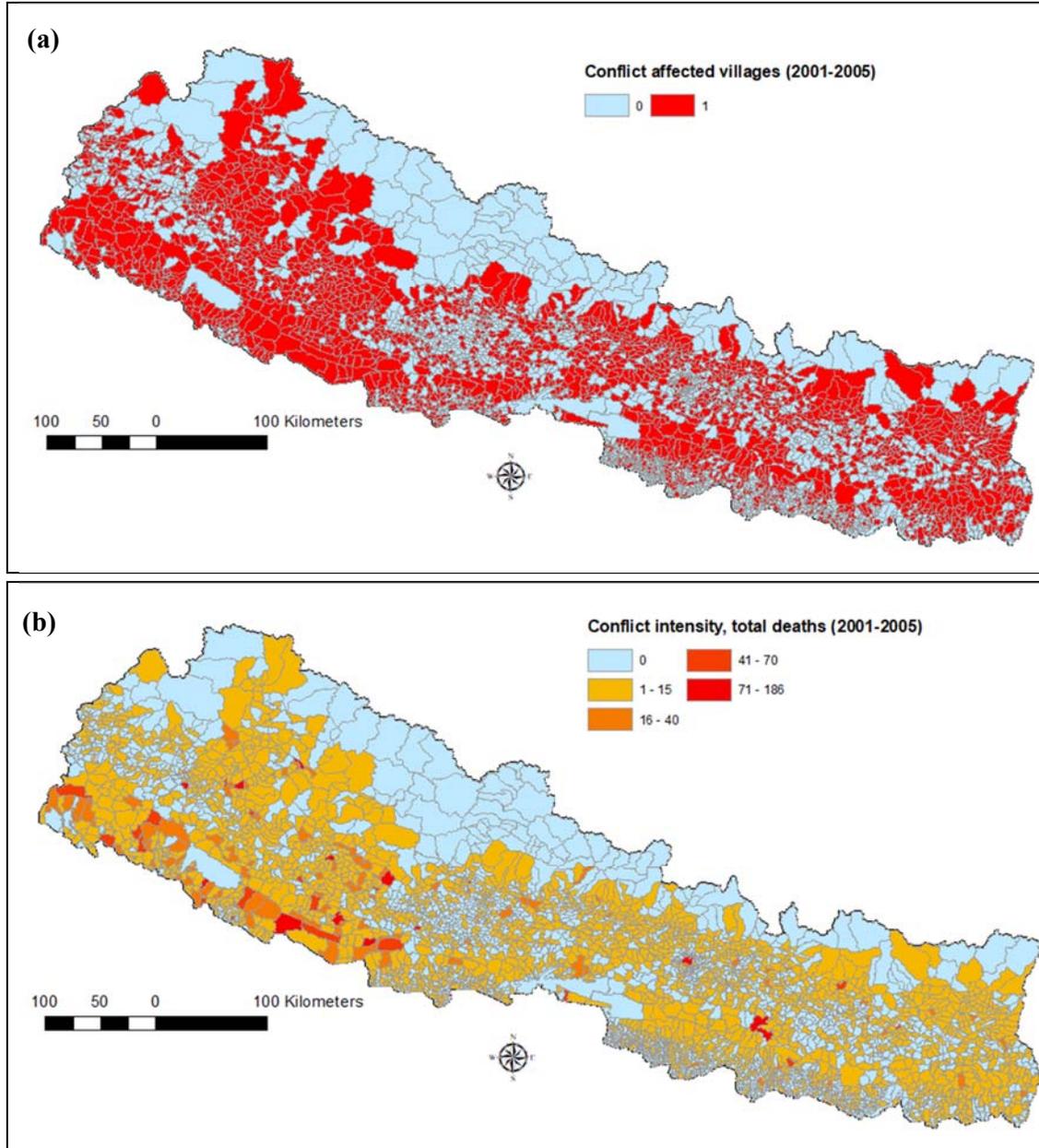
Source: Informal Sector Service Center (INSEC), Nepal.

Figure 2: Nepal's conflict (1996-2000) (a) Conflict affected villages, (b) Number of deaths



Source: INSEC, Nepal.

Figure 3: Nepal's conflict (2001-2005) (a) Conflict affected villages, (b) Number of deaths



Source: INSEC, Nepal.

Table 1: Variable Definitions and Descriptive statistics (N=3982)

	Mean	Std Dev	Min	Max
Conflict affected locality during 2001-2005 (0/1)	0.573	.495	0	1
Number of conflict victims from 2001 to 2005	3.049	9.07	0	186
Locality affected by prior conflict, 1996-2000 (0/1)	0.123	.329	0	1
Prior conflict, 1996-2000 (Number of victims)	0.425	1.945	0	37
Poverty head count rate (percentage)	35.02	11.91	14.6	90
Inequality amongst the poor (squared gap, percentage)	0.485	0.54	0.2	6.34
Inequality index (asset-based, first principal component)	0.37	0.178	0.012	1.18
Caste polarisation (RQ Index)	0.723	0.194	0	1
Share of locality who are from dominant caste (percentage)	32.86	27.32	0	100
Emigration rate, 2001 census (per 1000 population)	38.77	45.11	0	631.8
Share of forest cover relative to land cover (percentage)	40.11	32.16	0	100
Mean elevation (metres)	1096.5	970.4	64.3	5429.2
Mountainous village (=1, otherwise zero)	0.057	0.231	0	1
ln night lights DN annual value (economic activity proxy)	0.507	1.01	0	5.35
Share of working age population (ratio)	0.52	0.05	0.11	0.76
Working aged population schooled grade ≥ 8 (ratio)	0.41	0.157	0	1
Distance to Capital city (Kathmandu) (kilometres)	220.05	147.8	1	599.1
Distance to Indian border (kilometres)	48.9	36.5	0.001	195.1

Source: Author's calculation from NLSS-1996, Census 2001 and INSEC and other sources documented in text.

Note: Whether conflict-affected, number of victims, share of forest cover and local urban activity are time-varying, with averages over T=5 shown, other variables are measured in a pre-conflict year (2001 or earlier).

Table 2: Estimated effects on conflict probability and conflict intensity using logit and negative binomial models

	Zonal fixed effect		District fixed effect		Interaction model	
	Conflict	Deaths	Conflict	Deaths	Conflict	Deaths
Polarisation Index (RQ Index)	0.0565 (2.544)**	0.4910 (4.098)***	0.0436 (1.982)**	0.3387 (2.797)***	0.0488 (0.210)	0.1112 (0.631)
Poverty rate	-0.0042 (7.307)***	-0.0214 (7.149)***	-0.0015 (1.759)*	-0.0082 (1.905)*	-0.0335 (7.638)***	-0.0251 (8.016)***
Inequality amongst the poor	0.0233 (1.929)*	0.1860 (2.846)***	0.0111 (0.971)	0.0960 (1.470)	0.1596 (1.760)*	0.1805 (2.674)***
Overall inequality (asset index)	0.2925 (11.655)***	1.4383 (11.452)***	0.2706 (10.816)***	1.2903 (10.17)***	2.2058 (11.506)***	1.5902 (12.406)***
% of Dominant caste					-0.0104 (3.267)***	-0.0090 (3.712)***
% Dominant caste × RQ Index					0.0125 (2.553)**	0.0123 (3.346)***
Emigration rate	-0.0010 (8.379)***	-0.0056 (7.893)***	-0.0007 (4.858)***	-0.0040 (4.739)***	-0.0079 (8.352)***	-0.0065 (8.939)***
% of forest cover	0.0009 (4.379)***	0.0054 (5.229)***	0.0007 (3.530)***	0.0046 (4.292)***	0.0065 (4.370)***	0.0060 (5.740)***
ln (Mean elevation)	-0.0007 (0.080)	-0.0194 (0.409)	0.0150 (1.054)	0.0658 (0.877)	0.0019 (0.029)	-0.0339 (0.692)
Mountain (=1, zero otherwise)	-0.0963 (4.053)***	-0.4815 (3.865)***	-0.1052 (4.551)***	-0.5236 (4.045)***	-0.7690 (4.255)***	-0.5018 (3.938)***
ln (urban activity (night lights))	-0.0015 (0.329)	0.0271 (1.172)	0.0055 (1.134)	0.0605 (2.517)**	-0.0064 (0.180)	0.0208 (0.884)
% of working age (15-59)	0.0000 (0.001)	-0.0216 (0.050)	0.0940 (1.752)*	0.5665 (1.710)*	-0.0098 (0.017)	-0.2524 (0.550)
Working age schooled grade ≥ 8	-0.0010 (3.631)***	-0.0058 (3.602)***	0.0001 (0.311)	0.0008 (0.428)	-0.0065 (2.910)***	-0.0053 (3.118)***
Distance to capital city	0.0216 (1.377)	0.0283 (0.363)	-0.0572 (2.028)**	-0.4472 (3.397)***	0.1690 (1.420)	0.0260 (0.325)
Distance from Indian border	-0.0000 (0.003)	-0.0002 (0.114)	0.0005 (1.090)	0.0026 (1.108)	0.0004 (0.200)	0.0005 (0.316)
Prior conflict (1996-2000)	0.1273 (11.162)***	0.6325 (10.803)***	0.1112 (9.158)***	0.5716 (9.481)***	0.9753 (11.212)***	0.2129 (6.145)***
Zonal Fixed effect	Yes	Yes	No	No	Yes	Yes
District Fixed effect	No	No	Yes	Yes	No	No
Time Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	1161.95	1547.42	1431.19	2021.46	1168.43	1452.31
F-test (Chi-squared)	469.70	582.38	356.75	480.48		
Observations	19910	19910	19765	19910	19910	19910

Notes: Conflict is a binary outcome if a locality experienced conflict in a particular year, and deaths is the total number of conflict deaths each year in a locality. The cell values for the conflict columns are marginal effects (dy/dx) at mean estimated from a logit model. Cell values for the deaths columns are from a negative binomial regression model. The estimates for the binary conflict outcome in the interaction model are odds ratios. The Wald test is testing the joint significance of all explanatory variables in the model. The F-test performs the joint significance test for explanatory variables other than the fixed effects for time, for districts, and for zones. For the conflict regression, the t-statistics in () are derived from cluster-robust (for 3982 villages) standard errors; ***, **, * denote 1%, 5%, 10% statistical significance.

Table 3: Cross-sectional analyses of effects of poverty, inequality and polarisation on conflict

	Model 1		Model 2	
	Conflict	Deaths	Conflict	Deaths
Polarisation Index (RQ Index)	0.0310 (0.630)	0.5697 (3.460)***	-0.0627 (0.228)	0.2634 (1.086)
Poverty rate	-0.0062 (4.657)***	-0.0320 (6.684)***	-0.0253 (4.497)***	-0.0340 (7.096)***
Inequality amongst the poor	0.0161 (0.635)	0.2856 (2.403)**	0.0662 (0.632)	0.2620 (2.180)**
Overall inequality (asset index)	0.4993 (8.065)***	2.2332 (9.020)***	2.0427 (7.974)***	2.2192 (9.060)***
% of Dominant caste			-0.0023 (0.587)	-0.0099 (3.068)***
% Dominant caste × RQ Index			0.0055 (0.915)	0.0109 (2.143)**
Emigration rate	-0.0021 (7.241)***	-0.0077 (6.806)***	-0.0089 (7.282)***	-0.0077 (6.706)***
% of forest cover	0.0015 (3.413)***	0.0058 (3.488)***	0.0063 (3.395)***	0.0057 (3.472)***
ln (Mean elevation)	-0.0120 (0.588)	0.0742 (0.980)	-0.0594 (0.692)	0.0881 (1.155)
Mountain (=1, zero otherwise)	-0.2301 (4.302)***	-0.7514 (3.904)***	-0.9306 (4.167)***	-0.7968 (4.109)***
ln (urban activity (night lights))	-0.0175 (1.587)	0.0102 (0.224)	-0.0724 (1.586)	0.0150 (0.332)
% of working age (15-59)	-0.3715 (1.623)	-0.2963 (0.350)	-1.5726 (1.642)	-0.2666 (0.319)
Working age schooled grade ≥ 8	-0.0013 (1.919)*	-0.0061 (2.552)**	-0.0055 (1.951)*	-0.0046 (1.877)*
Distance to capital city	0.0737 (2.284)**	-0.2368 (1.234)	0.3017 (2.271)**	-0.2306 (1.201)
Distance from Indian border	0.0007 (1.083)	-0.0006 (0.255)	0.0024 (0.897)	0.0000 (0.001)
Prior conflict (1996-2000)	0.2534 (7.641)***	0.3694 (4.803)***	1.0457 (7.568)***	0.3766 (4.698)***
Zonal FE	Yes	Yes	Yes	Yes
Pseudo- R^2	0.0863	0.0536	0.0865	0.0543

Notes: Conflict is a binary outcome if a locality had any conflict deaths from 2001 to 2005, and deaths is the total number of conflict deaths from 2001 to 2005. $N=3982$. Other notes, see Table 2.

Table 4: The estimated direct, indirect and total impacts from Spatial Autoregressive models (SAR)

Impacts (dy/dx)	Conflict (Probabilities)			Conflict death rate		
	Direct	Indirect	Total	Direct	Indirect	Total
Polarisation Index	0.0369 (1.82)*	0.0095 (1.81)*	0.0464 (1.82)*	-0.0489 (1.75)*	-0.0126 (1.74)*	-0.0615 (1.75)*
Poverty rate	-0.0037 (6.65)***	-0.0001 (6.33)***	-0.0047 (6.67)***	-0.0031 (4.09)***	-0.0008 (3.97)***	-0.0039 (4.09)***
Inequality amongst the poor	0.0231 (2.13)**	0.0060 (2.12)**	0.0291 (2.13)***	-0.0016 (0.11)	-0.0004 (0.11)	-0.0021 (0.11)
Overall inequality (asset index)	0.3159 (13.15)***	0.0816 (10.29)***	0.3975 (13.01)***	0.1588 (4.79)***	0.0410 (4.58)***	0.1998 (4.78)***
Emigration rate	-0.0008 (7.4)***	-0.0002 (6.91)***	-0.001 (7.42)***	-0.0008 (5.00)***	-0.0002 (4.80)***	-0.001 (5.00)***
% of forest cover	0.0005 (2.79)***	0.0001 (2.78)***	0.0006 (2.79)***	0.0001 (0.26)	0.0000 (0.26)	0.0000 (0.26)
ln (Mean elevation)	0.0051 (0.62)	0.0013 (0.61)	0.0064 (0.62)	0.0245 (2.15)**	0.0063 (2.13)**	0.0308 (2.15)**
Mountain (=1, zero otherwise)	-0.0715 (3.51)***	-0.0185 (3.44)***	-0.0900 (3.51)***	-0.0924 (3.29)***	-0.0238 (3.23)***	-0.1162 (3.29)***
ln (urban activity (night lights))	-0.0033 (0.80)	-0.0009 (0.80)	-0.0042 (0.80)	-0.0206 (3.52)***	-0.0053 (3.44)***	-0.0259 (3.52)***
Share of working age (15-59)	0.0684 (1.39)	0.0177 (1.39)	0.086 (1.39)	0.1081 (1.60)	0.0279 (1.59)	0.1360 (1.60)
Working age schooled grade ≥ 8	-0.0008 (2.89)***	-0.0002 (2.87)***	-0.001 (2.90)***	-0.0004 (1.18)	-0.0001 (1.18)	-0.0005 (1.18)
Distance to capital city	0.0312 (2.40)**	0.0081 (2.37)**	0.0393 (2.39)**	0.0396 (2.21)**	0.0102 (2.19)**	0.0498 (2.21)**
Distance from Indian border	-0.0001 (0.36)	0.000 (0.36)	-0.0001 (0.36)	0.0001 (0.24)	0.0000 (0.24)	0.0001 (0.24)
Prior conflict (1996-2000)	0.1392 (11.89)***	0.0359 (9.83)***	0.1751 (11.85)***	0.1457 (9.06)***	0.0376 (7.95)***	0.1834 (9.03)***
Pseudo- R^2	0.1028			0.0435		

Notes: Direct, indirect and total impacts are calculated following LeSage & Pace (2009), with the coefficient estimates they are derived from available from the authors. The Spatial Autoregressive Model (SAR) uses a first order contiguity weight matrix. Zonal and Time fixed effects are also included. The t-statistics in () are from robust standard errors, ***, **, * denote 1%, 5%, 10% statistical significance. $N=19910$.

Appendix A Details on the Models Used for the ELL Survey-to-Census Imputation

Table A.1: Beta Model estimates, Covariates Selected from Backward Stepwise Regression (with removal at $p>0.1$)

	CDR	EDR	WDR	MWDR	FWDR
Mountainous village (=1, otherwise zero)	-1696.66 (2.48)**				
Hilly village (=1, otherwise zero)			3810.31 (8.45)***		
House owned by household (=1, otherwise zero)					-10155.01 (2.50)**
Literate members in HH	3038.05 (5.79)***	-523.94 (2.82)***		934.12 (3.61)***	905.01 (4.63)***
Literate male members in HH	-1547.88 (2.62)***			-537.08 (1.90)*	
Age of HH head spouse	-52.96 (3.79)***				
HH head religion (Hindu=1, otherwise zero)	-2896.29 (3.28)***		-1287.07 (1.67)*		
HH head “Upper caste” (=1, otherwise zero)	2106.67 (2.74)***			1624.39 (5.43)***	
HH head “Dalit caste” (=1, otherwise zero)	-2128.81 (3.25)***		-1913.83 (3.25)***		
HH members currently attending school	-903.35 (3.71)***				
Total poultry owned by household					-80.97 (2.40)**
Total members in non-agriculture		407.70 (1.81)*			
HH head sex (male=1; female=2)		2139.60 (2.6)***			2006.25 (2.95)***
HH head age		44.63 (2.52)**			
Source of drinking water (tub well or hand pump)		-2857.56 (5.76)***			
Members (aged ≥ 8) with primary education		1347.44 (4.18)***	961.73 (4.89)***		
HH head literate (=1, otherwise zero)		2297.52 (3.55)***			
Intercept	11431.68 (11.25)***	3958.74 (3.22)***	6222.16 (9.96)***	3581.49 (18.97)***	12232.45 (3.0)***
<i>R</i> -squared	0.1082	0.1244	0.0744	0.2003	0.2105

Notes: Estimated with NLSS data, using covariates with overlapping distribution in the Census extract. The t-statistics are in () and ***, **, * denote 1%, 5%, 10% statistically significance. The domains are the five development regions CDR= Central Development Region; EDR= Eastern Development Region; WDR=Western Development Region; MWDR= Mid-Western development Region; FWDR=Far-Western development Region. HH stands for household

Table A.2: Alpha Model estimates, Covariates Selected from Backward Stepwise Regression (with removal at $p>0.1$)

	CDR	EDR	WDR	MWDR	FWDR
Mountainous village (=1, otherwise zero)	-1.138 (3.55)***				
Literate members in HH	2.510 (4.71)***				-3.914 (3.55)***
Literate male members in HH	-1.626 (4.87)***				
HH head literate (=1, otherwise zero)		0.637 (2.81)***			
HH head sex (male=1, female=2)					-21.285 (3.14)***
Total poultry owned by HH					0.292 (2.4)***
Members (aged ≥ 8) with primary education			0.390 (3.94)***		
Literate members in HH*yhat	0.000 (1.79)*	0.000 (1.92)*		0.000 (3.61)***	0.001 (3.53)***
Literate male members in HH*yhat				0.000 (2.28)**	
HH head sex*yhat		0.000 (2.53)**			0.005 (3.43)***
HH head age*yhat		0.000 (2.06)**			
Age of HH head spouse*yhat	0.000 (5.27)***				
HH head religion* yhat	0.000 (4.86)***		0.000 (2.0)**		
HH head "Dalit caste" *yhat	0.000 (2.01)**				
HH head "Upper caste" *yhat	0.000 (4.77)**			0.000 (1.67)*	
Members with primary education*yhat		0.000 (2.77)***			
HH Members currently attending school*yhat	0.000 (4.39)***				
Source of drinking water*yhat		0.000 (1.66)*			
Total members in non-agriculture *yhat		0.000 (2.58)***			
Total poultry owned by household*yhat					0.000 (1.95)*
Total members in non-agriculture*yhat*yhat		0.000 (2.46)**			
Hilly village*yhat*yhat			0.000 (5.0)***		
HH head sex*yhat*yhat					0.000 (3.28)***

House owned by household*yhat*yhat					0.000 (4.1)***
Members attending school*yhat*yhat	0.000 (3.31)***				
HH head religion*yhat*yhat	0.000 (2.87)***		0.000 (2.26)**		
Literate members in HH*yhat*yhat	0.000 (2.46)**				0.000 (2.13)**
HH head “Upper caste” *yhat*yhat	0.000 (4.0)***				
Intercept	-5.654 (7.39)***	-7.932 (23.76)***	-10.486 (34.2)***	-8.412 (52.63)***	1.330 0.520
<i>R</i> -squared	0.1455	0.0762	0.0643	0.0558	0.1850

Notes: *yhat is an interaction of the variable with yhat, and *yhat*yhat is a interaction of the variable with square of yhat. For other notes, see Table A.1