Series Name: WPS
Paper No.: 116
Issue Date: 14 Apr 2020

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Center for Effective Global Action

Working Paper Series

Center for Effective Global Action
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Does Revolution Work? Evidence from Nepal's People's War *

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February 4, 2020

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Abstract

In 2015, after a decade-long conflict and nine years of negotiation, Nepal promulgated a constitution that replaced its 240-year-old monarchy by a federal republic. The subsequent 2017 local elections ushered more than 30,000 first-time politicians into office. Using a census of 3.68 million Nepalis (2.56 million of whom are of voting age) covering eleven districts, party nomination lists and party candidate selection committee surveys, electoral data and information on conflict incidence, we document that castes that were historically excluded from political representation achieved representation without a significant representation-ability trade-off: improved social representation among politicians is accompanied by positive selection on education and income. Triangulating across multiple data sources, we show that the entry of the revolutionary Maoist group as a post-conflict mainstream party played an important role. Finally, political representation of non-elite castes improved their policy inclusion as measured by individual access to earthquake reconstruction transfers. These gains, however, vary with the extent of social connections to the elected mayor and point to a continuing need to balance power by supporting institutions that provide all citizens political voice.

* *Authors' Note*: We thank Chandra Bhandari, Anastasiia Faikina, Prakat Khati, Binod Paudel, Ofir Reich, Daniela Philipson, Keshar Shahi, Satish Wasti, and Aaron Wolf for excellent research assistance and Thomas van der Aarssen and Kelsey Reiff for outstanding project management. Alberto Alesina, Eli Berman, Renee Bowen, Davide Cantoni, Ernesto Dal Bó, James Fearon, Francesco Trebbi, Gaurav Khanna, John Porten, Devesh Rustagi, Gerard Padró-i-Miquel, Barbara F. Walter, and many other colleagues provided insightful feedback. We thank seminar audiences at Columbia, Goethe University, Ludwig Maximillian University, Harvard, Stanford, LSE, and UCSD. We acknowledge funding from the International Growth Center and the Innovations for Poverty Action Peace and Recovery initiative. We thank Christopher Paik and Mario Chacon for sharing the 1992 election returns data and John Porten for sharing some recordings of the Informal Sector Service Center (INSEC) violence data.

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1 Introduction

Revolutions aim to change the ruling class and to redress political inequalities. They occur frequently and, if successful, fundamentally alter institutions (Skocpol, 1979; Huntington, 2006). When they lead to democratization, the resulting political institutions prove remarkably durable. Eleven of the 63 revolutions that occurred between 1950 and 2006 ended in democracy and only one reverted to autocracy (Albertus and Menaldo, 2014). While cross-country evidence is striking in its suggestion that revolutions create real potential for democratic consolidation, why this is so is less clear. In particular, our knowledge of whether and how revolutions redress historical inequities in political representation and ultimately affect policy outcomes remains limited (Blattman and Miguel, 2010).

In this paper, we use administrative and electoral data from Nepal for three broad purposes. First, we quantify the extent of ethnic inclusion in post-conflict local elections and evaluate political selection on multiple proxies of competence. Second, we evaluate the role of armed conflict and, in particular, the how the transition of the main revolutionary group into mainstream politics post-conflict enabled political inclusion. [1] Third, we examine whether political inclusion for non-elite castes enables policy inclusion as measured by the distribution of government reconstruction assistance in the wake of a devastating earthquake.

These issues have been difficult to answer for multiple reasons. Micro census data – needed to quantify the extent of political representation afforded to different population groups – is seldom available for lower income countries. Data on internal party selection processes is similarly rare. And, finally, it is an additional challenge to identify the causal impact of ethnic favoritism in public policy as the socioeconomic characteristics of ethnic groups that do and do not gain political representation typically differ in ways that are also predictive of their eligibility for public policies (related empirical studies that seek to identify the causal link between identity and policy include Chandra (2006); Chattopadhyay and Duflo (2004); Pande (2003); Dunning and Nilekani (2013); Burgess et al. (2015); Jensenius (2015)).

Nepal's political history, and a unique set of administrative datasets, enables progress on these fronts. For most of the 20th century, Nepal suffered political instability rooted in deep economic and political inequalities between castes and remained under the thumb of a powerful monarch. Following failed attempts at peaceful democratization, the Maoist People's

[1] On the last, Matanock and Staniland (2018) estimate that when signatories to negotiated peace settlements agree to establish political parties, the chance of enduring democratic peace increases by 80% (also see Weinstein (2006); Manning and Smith (2016))

War began in 1996. The war concluded in 2006 with the definitive end of the 240-year-old monarchy and the introduction of an interim constitution. The Maoist's fundamental objective to replace the caste-based monarchy with a federal multiparty democracy, was realized with the promulgation of a federal constitution and local elections in 2017.

Prior to the elections, a devastating earthquake in 2015 damaged houses of over 750,000 Nepali households. To identify affected households, the government conducted a full census in 11 crisis-hit districts in early 2016. The census has 3,680,772 Nepalis of whom 2,562,008 who are 18 or older. It provides an important source of population data from just before the first local elections under the new constitution in 2017 while the beneficiary database enable us to examine how targeting changed after elections.

We merge this census with 2017 electoral data, including candidate nomination lists from the three main political parties. The election data cover 20,408 nominees, 15,523 candidates, and 4,029 elected representatives. We pair these data with person-level data on beneficiaries for national reconstruction grants, using a close election regression discontinuity design, to assess whether local politicians enable households from their ethnic group to access grants more easily. To measure local variation in exposure to the revolution we use data on conflict incidence from the Informal Sector Service Center. Finally, we also have data from a survey of 700 party selection committee members that we conducted. These data allow, to the best of our knowledge, the first comprehensive examination of the nature of political selection, including the role of parties and citizens, in a post-conflict, low-income setting.

These data allow us to contribute to multiple core research questions in political economy. First: do post-revolution elections improve political representation of historically underrepresented groups who led the struggle? Using our matched census politician dataset we provide evidence of significant representation of non-elite caste groups. We then examine whether these gains in political inclusion come at the expense of political ability. While inclusion is often cited as a core tenet of democracies (Dahl, 1973; Pitkin, 1967), we lack an understanding of whether new democracies, emerging from violent revolution can yield both representative and competent representatives. Contrary to expectations given Nepal's low GDP and limited experience with democracy, we find that the newly elected cadre of representatives in Nepal are positively selected (in terms of income, education, assets, and ability) relative to the population, yet they closely represent the caste and gender characteristics of Nepal's society. These patterns bear a qualitative resemblance to those documented in Sweden in Dal Bó et al. (2017), which the authors appropriately describe as an 'exemplar of democracy.' They also look notably different from patterns documented in the United States in Thompson et al. (2019), where the cadre of federal representatives are highly educated relative to population but derive disproportionately from elite backgrounds.

So, how did these gains in political inclusion come about? We evaluate the role of the armed uprising and, in particular, the Maoist rebel group which subsequently entered mainstream politics. First, we leverage variation in exposure to the Maoist revolution across localities. In 2017, relative to 1992 elections, political power transitions from elite to non-elite castes were more frequent in communities that saw Maoist activity: power transferred from elite to non-elite caste politicians in 19% of conflict-affected localities, as compared to only 16% of non-conflict localities. This is reflected in the political power of the Maoist party: conflict-affected localities were 6 percentage points more likely to elect a Maoist party candidate as ward chairperson. Semi-structured interviews with party members further highlight that during the People's War the Maoists invested in raising political awareness, promoting political participation of non-elite castes, and cultivating a set of leaders who could contest office after the conflict.[2] Returning to our matched politician-census sample, we show that these differences in caste representation by party are also present in that sample. Importantly, we continue to see positive selection on our proxies for competence in Maoist conflict areas, suggesting that the party had access to a deep pool of candidates in these areas.

In Nepal, as in many low-income democracies, parties play a critical role in distilling the pool of potential candidates and, therefore, in setting terms for political representation. We show that parties had access to different nominee pools: While 60% of nominees considered for candidacy for municipal positions by the Maoists are from non-elite castes, only 42% and 26% are for the center party (Marxist-Leninist) and the right party (Nepali Congress) respectively.

We also conducted what is, to the best of our knowledge, the first representative survey of party selection committee members. Committee members are both unrepresentative of the population and even of politicians (70% of committee members come from elite castes) and highly positively selected on education, income, and ability. The Maoist party, however, has a significantly higher share of non-elite members. We measure committee members implicit bias against leadership of non-elite castes using an Implicit Association Test. A non-negligible proportion (25%) of committee members demonstrate moderate to severe bias

[2]It is also worth noting that the Maoist party led the demand for a federal democracy with electoral quotas for women and minorities.

against non-elite castes. Importantly, non-elite committee members have relatively lower caste bias compared to their elite counterparts. This is potentially another reason for why Maoist party expanded inclusion.

Did political inclusion yield policy inclusion for non-elite castes? We evaluate this by studying the distribution of housing reconstruction grants comparing localities barely won by a candidate from a non-elite caste. In general, citizens from elite castes receive more post-earthquake reconstruction assistance, even after controlling for objective grant eligibility. Among non-elite castes, this access gap is closed for a subset: those who share the same caste, last name, and constituency as a mayor (which we term as belonging to the Mayor's 'clan'). That is, having a clan member elected to office appears to completely remediate the access disadvantage for non-elite castes, but provides no additional benefit to the already elite castes. We use a close elections regression discontinuity to enable a causal interpretation of the policy benefits of political inclusion, finding that individuals who had a clan member win mayoral office are more likely to receive earthquake reconstruction grants.

Our findings are consistent with a growing body of empirical work that suggests that group identity is a salient dimension of politics in lower income settings (Padró-i-Miquel, 2007; Pande, 2003; Chattopadhyay and Duflo, 2004; Cruz et al., 2017). Kramon and Posner (2013) provide a list of 50 of the leading studies on distributive politics. Of these, we count eight that provide direct evidence that the ethnicity, gender, or caste of politicians relates to the allocation of government services. The idea that the identity of politicians influences policy selection underpins citizen candidate models of representative democracy (Besley and Coate, 1997). By examining the salience of ethnicity in a post-conflict setting, we also speak to the grievance-based literature that examines the link between ethnic divisions and conflict. Finally, our work also points to the importance of supporting democratic electoral institutions with other institutions that allow for grievance redressal and reduce the potential for elite capture of the policy process.

The rest of the paper proceeds as follows. Section 2 describes the economic, political, and social context relevant to the Maoist Movement. Section 3 describes our data. Section 5 reports results on conflict and inclusion. Section 4 describes patterns of political selection. Section 6 documents preferential access to earthquake reconstruction grants by family members of politicians and by historically elite castes. Section 7 concludes.

2 Context: Nepal and the People's War

Nepal, a landlocked country in South Asia, is the 17th poorest country in the world with a GDP per capita of 730 USD in 2018. Urbanization rates remain low at 20 percent, and a quarter of Nepal's population lives in extreme poverty (less than 1.9 USD a day).

While a country of minorities, comprising 125 different ethnic groups speaking 123 languages (Census, 2011), the historical legacies of a codified caste system remain active. In 1854 the Muluki Ain (Legal Code) system enhanced the monarch's control by providing hierarchical caste categories for all Nepalis (where the monarch belonged to the elite Brahmin/Rajput caste). Historically, the three elite castes Bahun (Brahmin), Chhetri, and Newar castes (BCN) - which comprise 35 percent of the population - have wielded significant administrative and political power while the indigenous ethnic (Janjatis) and out-caste (Dalits) groups remained marginalized. On the eve of the civil war in 1995-96, the poverty rates within elite castes (BCN) were half those of non-elite castes (Dalits and Janjatis) (20-30% v/s 50-55%) (BS 2005, based on NLSS-I). These inequities were a driving force of Nepal's People's war.

2.1 Nepal's Recent Political History

Nepal's political liberalization involved several false starts. In 1960, a coup re-established monarchic rule under a partyless 'Panchayat' system. This system continued until 1990, from where we provide more detailed context.

A. The 1990 People's Movement

A popular uprising in 1990, called the People's Movement, forced the monarchy to form a new constitution that allowed for a first round of party-based elections at the central level in 1991 and at the local level in 1992. Unlike subsequent Constitutions, the 1990 Constitution made no explicit aims at inclusion (Lawoti, 2007, p. 57).The two major political parties were the Nepali Congress and the left-wing CPN-UML. The electoral front of the Communist Party (Unity Center) – United Nepal People's Front (UNPF) – was not allowed to participate in the 1991 elections.[3]

During this period, the political system remained fragile: with three separate parliamentary governments formed between 1990 and 1996. Strikingly elite representation, both in politics

[3]Many of the people who came to power were former Panchayat members who had joined the Nepali Congress which won the election in 1991 and formed the Government. The Prime Minister from the Nepali Congress, G.P. Koirala, vocally opposed political participation by leftists.

and the bureaucracy, increased, to the frustration of the People's Movement.[4] This created a fertile setting for revolution (Acemoglu and Robinson, 2005), ultimately in the form of the 1996 Maoist uprising. In 1994, the Communist Party of Nepal (Unity Centre) and its electoral front split. In 1995, one faction renamed itself as the Communist Party of Nepal (Maoist) and declared that for "the true liberation of the people, all efforts must be concentrated for the development of a people's war that would usher in the new people's democratic form of government". The group officially gave up on participating in parliamentary elections. In September 1995, the 'Plan for the Historic Initiation of the People's War' was adopted by the Central Committee of the party.

B. 1996 - 2007: The People's War

In 1996 the Maoists launched their armed uprising, popularly known as the People's War. This uprising lasted until 2006, with three major players involved: the monarchy, the Maoists, and the two mainstream parties (Nepali Congress and United Marxist-Leninist) (Weinstein, 2006). The monarchy wanted to retain full control over the political processes. The mainstream parties sought a constitutional monarchy with a constituent assembly, with UML more committed to the ideal of inclusion. The Maoists wanted a full republic with no role for the Monarchy. From 1996-2001, violence was mostly local, until, in 2001, the monarchy retaliated with the full force of the state: 85% of the 17,800 battle deaths occurred from 2001-2006 (Gilligan et al., 2014). The conflict ended with a Peace Agreement in 2007 in the form of a 19-point statement signed by the Maoists and mainstream parties. This agreement laid the foundations for the modern republic.

C. 2008 - 2015: The Struggle to Promulgate a Constitution

After the peace agreement, on January 15, 2007, the government created an interim constitution, which provided for a constituent assembly that was to draft the new constitution with a deadline of 2010. Disagreements led to the assembly missing the deadline and, because of continued failure, the assembly was dissolved in November 2013. A new assembly was subsequently elected, which again failed to write a constitution.

D. 2015-2017: Earthquake and Elections

In April 2015, a devastating earthquake affected one-third of Nepal's population with over 800,000 homes partially or fully destroyed. Arguably, this event combined with a substantial

[4] During the largely ceremonial Panchayat parliament of the 1980s, Bahuns and Chhtetris occupied around 50% of seats. Their share increased to 55% in 1991, and 63% in 1994 (Vollan, 2015). Similarly, 69% of those passing the civil services exam in 1985 were Chhetri, this rose to 81% in 1992, topping out at 98% in 2001.

degree of international political pressure led to 90% of the legislators voting in favor of a new constitution, establishing Nepal as a federal republic in September 2015. Seven provinces and 753 municipalities were created, which were further subdivided into 6742 wards.

Starting in 2017, elections were held separately for municipal and province level positions, with powers separately delegated to the two levels of government. The focus of this paper is on the three-phase municipal (and ward) elections, held between May to September 2017, which involved nearly 150,000 political candidates. In each municipality, a mayor and deputy mayor (for urban areas) and a chairperson and vice-chairperson (in rural areas) were elected. Each party was required to nominate at least one woman across the two positions. Invariably parties fielded women for the deputy mayor/vice-chairperson position. Municipalities were further subdivided into wards, composed of an elected ward chairperson and four ward members. Two ward member seats were reserved, one each for a female and for a female from the marginalized Dalit community. The elections required a plurality and those elected were to serve a five-year term.

3 Data

Our analysis builds on a major data collection and collation exercise around the 2017 local elections which we describe below. Appendix A provides additional details regarding the data, how we deal with the reorganization of administrative units across time, and how data sets are merged.

3.1 Population and Politician Data

Administrative population data: In early 2016, the Government of Nepal conducted a census in 11 earthquake-affected districts to identify housing reconstruction needs. Through a partnership with Nepal's National Reconstruction Authority (NRA), we received access to these individual-level census data, including individual-level information on caste, education, household income, household pre- and post-earthquake assets, and level of housing damage. The data include 3,680,772 Nepalis, 2,562,008 of whom are 18 or older and so eligible to vote. For much of our analysis, we focus on the voting-eligible population.

2017 politician data: We have collected electoral data for the 148,362 candidates who stood for municipal and ward-level elections in 2017 across Nepal. For our 11 census districts we collected lists of all citizens considered by party selection committees as candidate nominees for the three largest political parties - Nepali Congress, Communist Party of Nepal-United Marxist-Leninist (UML), and Maoist Centre. These lists were collected directly from district party leaders within six months of the election. Party documentation of nominees for municipal-level positions was well-kept and complete, however, nominee data for ward positions was often incomplete. As a result, we focus on municipal positions when examining candidate selection by party committees. In total, these data consist of 22,179 potential nominees, 18,626 candidates, and 4,920 representatives.

Our aim is to merge these politician-level data with census data. The data, however, lack any unique identifier to do so. We therefore use fuzzy matching algorithms to match on name, location, age, gender, and parent's names from the voter list. This yields a match rate of roughly 80% of the politicians to the census data, yielding a sample of 16,614 nominees, 14,219 candidates, and 3,767 representatives across the three largest parties.

1992 politician data: As a (pre-conflict) baseline to compare representation in the 2017 elections, we use electoral data from the 1992 local elections for mayoral positions. Chacón and Paik (2017) digitized data from this election, including candidate names and corresponding vote totals.[5]

The administrative structures have changed substantially since the introduction of the new Constitution. What were 4,000 Village Development Committees (VDCs) across 75 districts have been converted into 6,500 wards within 753 municipalities and 77 districts. We collected data matching the former VDCs to current wards and municipalities. However, because of the nature of conversion from the old to new structure, their is imperfect match from VDCs to wards. To address this concern, we use GIS software to create a cleaner crosswalk between VDCs and wards to allow for a constant geographic unit of analysis over time. This described in greater detail in Appendix C.

Identifying politician caste: For our fuzzy matched politicians we directly obtain caste from the census data. However, we lack caste data for the 1992 politicians and for 2017 politicians outside of the 11 census districts. Caste is fundamentally linked with surname. We use the 3,680,772 individuals in the census for whom we observe both surname and caste to build a prediction model that links surnames to castes. Appendix B describes the prediction model and how we validate it out of sample. We use this prediction model to infer the

[5] Digitization of the electoral outcomes data from 1997 is ongoing.

caste from politician surname for those not matched to census data directly.

We classify castes as elite or non-elite following the method based on histories of political power that Vollan (2015) proposed. Using the 125 caste classification in the 2011 census, a caste is defined as non-elite if it consistently wins seats equal to or less than 60% of its share in the population in the Constituent Assembly (CA) elections over the period 1991 to 2013.[6] An important caste category are the Janajatis, who are local indigenous groups that were placed into the caste ordering by Hindu monarchs. Some Janajati castes are elite, while others are non-elite.

Identifying politician clans: Finally, while lack systematic information on politician's parents and family, we are able to identify their local clans. We define a clan as the set of people sharing the same surname, caste, and living in the same municipality. From this, we identify 8,569 clans.

Measuring politician ability: Our (fuzzy) matched sample provides background covariates on political hopefuls. We identify three relevant covariates for ability: education, household income, and household assets, and also estimate ability as the residual from a Mincer regression following Besley et al. (2017). Specifically, we estimate the regression $Income_i = f(Educ_i, Age_i) + \beta_1 Female_i + \gamma_w + \varepsilon_i$, where $Educ$ is a dummy variable for having more than ten years of education, Age is a categorical variable with five year age bins, $Female_i$ is a dummy variable equal to one for women, and γ_w are ward fixed effects. Function f represents the fact that the specification includes a dummy for each subgroup and every possible double and triple interaction. We restrict the sample to the over 18 population. We transform the residual from this regression into a z-score to assist with interpretation: The standardized residual is used to measure the distribution of ability in the over 18 (voting eligible) population.

3.2 Beneficiary Data

Housing grant beneficiary data: The National Reconstruction Authority further provided household-level data on receipt of reconstruction grants across three tranches (up to March 2018). These data include tranche and timing of grant receipt along with amount received. Across these 11 districts, 501,866 households were beneficiaries of reconstruction

[6] Vollan (2015) considers only First Past the Post (FPTP) seats not affected by quotas. He is comprehensive in explaining his judgements for each group, notes that the definition is highly robust to using either a 60% or 90% threshold.

grants.

We match these beneficiary data to the census data, which also includes indicators of housing damage and corresponding assigned damage grade. We are able to match 95% of the beneficiaries to the census data.

3.3 Political Party Data

Survey of party selection committees: Local party selection committees are responsible for the selection of whom to nominate for candidacy in elections. They are comprised of senior party officials and carry substantial importance in determining election options. Selection committees exist at two level: the district or regional level which selects candidates for municipal positions and the municipality level which selects candidates for ward positions

In 2019, we surveyed a sample of party selection committee members for the three major parties - CPN (Maoist), CPN (UML), and Nepali Congress. Conducting this survey required considerable cooperation given the seniority of party members being surveyed. We randomly sampled 883 party committee members across 110 municipalities in the eleven districts.[7] The survey had a response rate of 79.84% and a final sample size of 705. Appendix Table A3 reports predictors of successfully interviewed candidates. Coverage is uniform across genders, parties, and districts (with the exception of a higher success rate in Kavre district). In Section 6 and appendix D we describe this survey in more detail.

3.4 Conflict Data

Maoist conflict violence data: To measure local exposure to the conflict, we use Informal Sector Service Sector (INSEC) data on whether a casualty (death or injury) occurred within each locality Village Development Council (VDC) throughout the conflict.[8] These VDC level data are merged to the GIS crosswalk between VDCs and wards to identify which present-day wards most directly experienced violent conflict during the People's War.

[7] We first collected lists of all committee members from each party, including party position of each member. We took a stratified random sample of committee members, stratifying on party, committee type, committee, and decision-making status. The probability of inclusion varied by committee type and party position. First, we sampled all titled committee members from the district and regional selection committees. Only the UML had non-titled committee members, but given that they had larger committees, we yield a similar sample size. We were further informed that non-titled committee members had very little influence in these committees. Second, for the municipal committees, we took a random sample of two titled committee members and one non-titled committee member from each committee.

[8] We create the conflict variables at VDC level to be able to match the electoral outcomes in 1992 and 1997 to conflict.

4 Descriptive representation in the 2017 elections

The 2017 elections ushered in thousands of novice political hopefuls and representatives, providing an opportunity to understand political selection without the constraints and calculations from incumbency. Using the matched census and politician data, we descriptively map patterns of political selection to understand who becomes a politician in a low income country following a massive decentralization of political authority.

4.1 Selection on Caste

Figure 1 uses the matched 2017 census and politician data to graph the distributions of population and candidate caste identity. We separately report the caste composition of unelected candidates and elected representatives across three political positions: all municipal positions (mayor and deputy mayor), ward chair positions, and all ward member positions (including reserved seats).

The left-most and central panel considers candidates for the two municipal positions and ward chairperson. Together, these three positions are the most important political positions. In both cases, we see that all caste groups gained political representation, except for the non-elite Dalits. That said, the two elite castes of Brahmin and Chhetri are over-represented amongst the candidate pool. Among municipal positions, over-representation of Chhetris, but not Brahmins, is accentuated by voter choices. Less than 25% of non-elected but over 30% of elected political positions come from the elite Chhetri caste. In contrast, the fraction of elected Brahmins matches their population share. Amng ward chairpersons, both Brahmins and Chhetris remain over-represented.

The right-most panel considers ward members. Strikingly, the ward member caste distribution is characterized by significant over-representation of the most marginalized caste group of Dalits. The latter reflects the fact that 25% of ward member positions are reserved for female Dalits.

4.2 Selection on Measures of Competence

The census data provides multiple, albeit imperfect, correlates of individual competence: ability (measured as the residual from mincer regression of income on education, gender, and age, as described in the data section), education and income. Figure 2 shows overlapping histograms for the population and elected representatives in both municipal positions and ward chair positions. It reports separate distributions for elite and non-elite caste groups.

It is evident that the population distribution across all three measures of competence vary by caste eliteness. Relative to elite castes, non-elite castes have lower levels of ability, education and household income. Given this, is the over-representation of elite castes, in part, a consequence of voter selection on (apparent) measures of competence?

A comparison of the politician distribution by caste eliteness offers a nuanced answer. First, relative to the population, all elected politicians are selected positively. In the case of municipal representatives, the extent of positive selection is greater for non-elite castes, such that roughly 35% of both elite and non-elite caste politicians are drawn from the highest ability group. Second, non-elite caste candidates are positively selected on these variables relative to the population distribution for both non-elite and elite castes. Put simply, candidates from non-elite castes are generally better educated than the elite caste population. Appendix Figure A3 examines selection by each local government position: we see only one clear violation of this pattern, for deputy mayors, a position overwhelmingly held by women as the result of quotas.

4.3 Selection on Clan

Does the positive selection of politicians on these measures of competence reflect their characteristics or their family's characteristics? To fully assess the quality of political selection, we need to know whether politicians come from a representative set of not only caste, but also of economic backgrounds. Ideally, we would consider the demographics of their parents or siblings to assess this, as in Dal Bó et al. (2017) and Thompson et al. (2019). However, our data do not allow us to identify family relations for non-cohabitating citizens. Instead, we compare the background of candidates relative to members of their 'clan', defined as all individuals who simultaneously share the same surname, belong to the same caste, and live in the same municipality (or ward) as their municipality (or ward) representatives. This is a very natural unit of social identification in Nepal. We identify roughly 90,000 clans in our population of over 3 million.

Figure 3 compares the clans of politicians (separated by elite caste status) and the comparable population along the three dimensions of ability, education and income. Unlike with elected representatives, their clan members closely resemble the general population. These patterns are identical across elite and non-elite politicians and municipal and ward representatives.

By contrast, we know from Figure 2 that politicians from both groups are positively selected relative to both the population. It follows that politicians, irrespective of their caste, are positively selected relative to their clan.

4.4 Regression estimates

Finally, we use a set of basic descriptive regressions to evaluate the trade-off between caste representation and competence. To evaluate the determinants of selection from the general voting age (over 18) population into politics, we estimate:

$$Y_{ic} = \beta_0 + \beta_1 Elite_{ic} + \beta_2 Female_{ic} + \delta \sum X_{ic} + \gamma_c + \varepsilon'_{ic} \tag{1}$$

where Y_{ic} is a dummy variable equal to one for individual i in constituency c who is selected. We consider two measures: selection into candidacy and selection into political office. We include constituency fixed effects, γ_c. X_{ic} is the vector of competence measures; we transform the measures of education and income by first recoding each category as the midpoint of the values contained in that bin and then transforming the measure to a z-score. The asset index is also transformed into a z-score.

We can interpret specification 1 according to the taxonomy given in Dal Bó et al. (2017). If Nepal's political system is 'elitist' (or 'historically deterministic'), then $\beta_1 > 0$ even after adding additional covariates to account for ability, education and wealth. By contrast, in an 'elitist meritocracy', wherein elites disproportionately win office only because they are disproportionately educated and wealthy, after controlling for competence, β_1 should be close to zero. In a fully inclusive meritocracy, by contrast, β_1 should always be zero.

Panel A in Table 1 estimates the correlates of selection into municipal positions. Columns (1)-(3) consider predictors of winning a ticket. Based on population means we see that three in every 10,000 citizens are selected as candidates on a party ticket. Without accounting for competence (column 1), being from an elite caste raises this probability to five in every 10,000. Controlling for ability and education (column 2) and education, income, and assets (column 3) halves this advantage. Thus, while being from an elite caste does convey some advantage in terms of selection by political parties into candidacy, this advantage is attenuated by proxies of competence, namely education and income. In selecting candidates, parties appear to focus on competence, and disproportionately draw from elite castes, in part, because they have higher levels of education and income. Panel B shows a similar pattern for ward chairperson. Here, the base probability of being selected as a candidate is higher (reflecting the larger number of positions) at 12.6 in every 10,000. For elite castes, this rises to 17 in every 10,000.

Columns (4)-(6) estimate the correlates of winning a seat. The probability that any citizen is elected to municipal local office is six out of every 10,000 and this doubles among elite castes to twelve out of every 10,000. A similar pattern to representative selection emerges as with candidate selection: the estimate of β_1 (the advantage in selection from being from a elite caste) is substantially reduced when controlling for education and ability (column 5), and education, income and assets (column 6). This suggests that voters make selections in largely the same fashion as political parties, prioritizing both competence and elite status. We see a similar pattern in Panel B for ward chairperson.

Overall, while belonging to an elite caste positively predicts political representation a substantial part of the relevance of caste is explained by proxies for competence (education, ability, income, and assets).

5 Tracing Pathways: From the People's War to Political Inclusion

Political selection in local elections conducted under the new 2017 constitution in Nepal expanded descriptive representation of non-elite caste groups with no significant evidence of an ability-competence trade-off.

We triangulate across multiple types of evidence to evaluate the argument that the People's War, followed by the entry of the Maoists as an independent political party, played an important role in enabling this. First, we show a significant correlation between the likelihood that an area experienced conflict during the People's War and the subsequent electoral success of the Maoist party. Next, we provide evidence of two ways in which non-elite castes gained access to political power: party-level differences in candidate selection along caste lines, and differences in voters' electoral preferences across conflict and non-conflict areas.

5.1 Did conflict-affected areas see more political inclusion?

Past work suggests that conflict-affected areas are likely to differ in ways fundamental to political representation, such as levels of collective action and pro-sociality (Gilligan et al., 2014). We use multiple datasets to evaluate the role of the People's War in shaping subsequent inclusion. First, we use electoral data spanning all of Nepal to examine the relationship between conflict incidence and violence. Next, we use our census micro-data (available for 11 districts) to provide corroborative evidence on caste inclusion and to also examine implications for other measures of politician competence.

A. Conflict and Political Selection: All Nepal analysis

Here, our main data challenge is over-time changes in the relevant geographic units. Following the promulgation of the constitution in 2015, Nepal introduced comprehensive changes in its local governance system. Prior to the new constitution, the local electoral unit in Nepal were village development committees (VDCs).[9] Under the new constitution, the principal local electoral unit is the municipality, which is subdivided into wards. The conflict and 1992 election data are available at the VDC-level, while 2017 elections data are at the municipality and ward level.

We address this issue in two steps. First, we identify a comparable electoral position. In terms of job allocation the ward chairperson in the 2017 election is most comparable to the VDC head. They both serve populations of roughly the same size, and have similar functions in the government apparatus. Next, we use spatial information on changing boundaries to construct a common geographic unit that can be traced over time. The procedure for this is discussed in detail in Appendix C. The resulting data comprise the intersection of the spatial boundaries that relate the 1997 VDCs and to the 2017 wards, and yields 7,399 unique geographic units, which we label polygons. We merge the 2017 and 1992 election data and violence data to these polygons.

Did patterns of political representation look different in conflict-affected areas as compared to non-conflict areas in the 2017 elections? We estimate the following regressions:

$$\Delta Y_p = \beta_0 + \beta_1 Violence_p + \varepsilon_p \qquad (2)$$

where $Violence$ is an indicator variable that equals 1 if the polygon p belonged to a VDC recording any type of casualty or injury during the People's War. As described in Section 3 above, these violence data come from the widely used INSEC database. Indicator variables at the polygon-level, like violence, take a value of one if the polygon belongs to a VDC that experienced violence, and zero otherwise. Continuous variables get assigned through an

[9] There were municipal elections in 1997 but not in 1992. However, municipalities comprised a higher and non-overlapping geographic unit than the VDCs.

area-weighting rule. For instance, if there were 10 candidates from a new ward in 2017 elections and a polygon constitutes 50 percent area of this ward, then the number of candidates for the polygon is 5. Since we code the entire VDC to be affected by conflict at the same time, we cluster standard errors at this level.

A key challenge in interpreting the results is the endogeneity of conflict. Several papers investigate the predictors of local conflict during the People's War, typically using the same measures of conflict used here. Pre-conflict and geographic characteristics that authors have found predictive of conflict include poverty levels (Do and Iyer, 2010), favorable terrain for hiding e.g., mountains and forests (Bohara et al., 2006) and low road density (Acharya, 2009)). However, the evidence on whether ethnic polarization, land inequality, and prior political participation affected violence is mixed.[10]

Our main outcomes - change in number of candidates by caste category - are estimated using a difference-in-difference approach. That is, we ask whether, relative to non-conflict areas, areas that saw conflict during the People's war saw greater representation for non-elite castes. By comparing changes over time in political selection for a given geographic unit, we account for time-invariant location characteristics that may have influenced whether a locality saw conflict. To the best of our knowledge, this is the first exercise for Nepal political outcomes that examines the effects of conflict while ruling out location specific confounders. That said, we currently do not control for time-varying, locality-specific characteristics that could be correlated with conflict onset. Hence, we see the evidence as informative of potential pathways between conflict history and political selection in 2017 but as also stopping short of providing unequivocal causal evidence.

The results are presented in Table 2. Being exposed to violence is associated with an increase in political competition in terms of the number of candidates that run by 1.7 percentage points (column 1). This increase reflects a steeper rise in the number of non-elite candidates (column 2) and, a relatively lower increase in the number of elite candidates (column 3).

[10] Macours (2011) studies how conflict erupted, despite Nepal's healthy economic growth in the period prior to the conflict. She finds that, during this period, economic gains were much smaller for the (near) landless, relative to the landed. She also finds that recruitment via forced abductions was more common in districts where inequality between the landed and the landless had previously increased. Mitra and Mitra (2018) also find that poorer districts are more likely to see conflict and argue that this is an agreement between Nepal's disenfranchised and the Maoists whereby they would be empowered should the Maoists prevail. Murshed and Gates (2005) find that inequality (measured as the difference between the district average and the average in Kathmandu) in life expectancy, schooling, HDI, Landlessness, Road density, and natural resources, all robustly predict the number of battle deaths.

Taken together, while 64 percent of non-violent polygons saw a transition from being governed by an elite mayor to a non-elite one, 68.4 percent of violent ones saw such a transition (column 4). By contrast, there is no such difference between violence and non-violent polygons in transitions from non-elite to elite castes.

In examining the party identity of candidates, we consider cross-sectional regressions as the Maoist party did not exist prior to conflict. Maoists held mayoral positions in 62.6% in non-violent polygons and 73.9% of ward chair positions in violent polygons (column 6). This increase in Maoist representation is fairly evenly divided between Maoist ward chairs coming from elite and non-elite castes (columns 7 and 8). Overall, the results suggest a greater increase in representation afforded to non-elite castes in VDCs that experienced conflict, and that alongside the Maoist party gained increased representation in these areas. We now turn to our micro-data in the subsample of 11 districts to further interrogate this relationship.

B. Conflict and Selection: Administrative data analysis

Figure 4 uses the matched 2017 census and politician data to show the distribution of caste identity for the population and unelected and elected ward chair candidates. We show this for four groups: VDCs that did and did not experience conflict separated for Maoist politicians relative to all others. The striking feature in the upper right panel is that non-elite Janjatis are over-represented among Maoist ward chairpersons, but only in conflict-affected VDCs. Further, this over-representation of non-elite castes is driven in large part by voter selection: there is greater representation amongst those elected than just those nominated. Comparing across all panels, we see that it is only in conflict-affected VDCs amongst Maoist politicians where we see over-representation of non-elite castes. Consistent with our all-Nepal analysis, we continue to see that conflict areas where the Maoist party won is driving the overall increase non-elite ward chairpersons described earlier.

We can also examine implications for measures of politician competence. Figure 5 shows the distribution of ability, as measured in the residual from a Mincer regression, for the population and Maoist and non-Maoist politicians across conflict-affected and non-conflict VDCs. The top right quadrant suggests that the greater inclusion of non-elite castes amongst Maoist politicians in conflict-affected VDCs may have been at the cost of politician ability. However, Maoist politicians in these areas are still positively selected relative toe the population, just to a lesser degree than in non-conflict areas and in comparison to selection by other parties. Additionally, looking across all quadrants, politicians are positively selected on ability everywhere. Similar findings hold for other measures of competence. [11]

5.2 Did politician selection patterns vary by party?

In Nepal, as in many developing countries, candidates for the 2017 elections were not selected through open primaries, but rather by intra-party protocols. Thus, a key part of understanding the reduced form relationship between conflict incidence and the subsequent increases in political representation afforded to non-elite castes is to evaluate whether the Maoist party, as accorded with the ideological aims of their movement, behaved differently in candidate selection.

Administrative data analysis

A first piece of evidence comes from expanding our matched politician census data sample to also include the lists of all citizens considered for party tickets. These data are only complete, however, for municipal positions, so subsequent analyses will subset to these positions.

Figure 6 shows the distribution of caste identity for the population, candidates considered for, but not awarded, party tickets, unelected candidates, and elected representatives for Maoist politicians and non-Maoist politicians separately. The bottom panel shows that the Maoist party selection committee chose from a (relatively) very deep pool of non-elite potential nominees and that the party selection committee seems to have made choices such that the distribution of Maoist candidates over-represents elite castes, whereas the distribution of Maoist unsuccessful political hopefuls over-represents non-elite Janjatis. Thus, unlike Maoists voters who favored non-elite candidates, Maoist selection committee members selected elite caste candidates as a higher share of the available pool of same caste candidates.

In Figure 7, we consider the distribution of ability, education, and income separately for the general population, potential candidates (those nominated but not selected for tickets), unelected candidates, and elected representatives. Once again, we see that a substantial degree of selection occurs at the nomination stage. The distribution of nominees much more closely resembles that of the population. For example, while about 26.4% of the population is illiterate, only about 16.6% of nominees are illiterate. This is true across all parties. Paired

[11] Table A6 summarizes reports the predictors of winning a party ticket (panel A) and of winning office (panel B) for a ward chair seat separately for each of the three main parties - Maoists (Columns 1 and 2), UML (Columns 3 and 4), and Nepali Congress (Columns 5 and 6). While historical elitism does convey some advantage in the selection process before accounting for measures of competence, this advantage disappears after adding proxies to the regression for all parties but the UML at the ward chair level.

with Figure 6 above, this may suggest that the selection committee culled the less competent potential candidates and this group overrepresented non-elite castes.

B.Selection Committee Survey

From March-August 2019, we conducted a representative survey of selection committee members from the three main parties (United Marxist-Leninist, Maoist Centre, and Nepali Congress) across the 11 census districts. While committee structure varied by party, all parties had different selection committees for municipal and ward candidates.[12] We collected committee member lists from party leadership in each district, including each member's position within the committee and then randomly sampled from these lists, stratifying on position and committee type.[13] We classify committee members into influential and non-influential members, with influential committee members being those who held a specifically nominated position. We have a final sample of 699 committee members.[14] Appendix Table A3 demonstrates the representativeness of this final sample and balance across respondents and nonrespondents.

During the survey, committee members were first asked to complete an Implicit Association Test (described below). They were then orally administered a questionnaire regarding their experiences in the party, their experiences on the selection committee, and their perceptions over the characteristics needed for nomination. Following the survey questionnaire, a short semi-structured interview was conducted around their perceptions of conflict-affected areas.

B.1 Who do selection committees descriptively represent?

Table 3 summarizes the demographic composition separately for committee members and politicians. The comparisons are stark and, in part, reflect the presence of gender and caste quotas for elected positions but not selection committee members: only 9% of selection committee members are women, as opposed to 40% of politicians, and 70% come from an elite

[12]The United Marxist Leninist and Maoist parties both had district-level selection committees that chose candidates for municipal positions and municipality-level selection committees that decided on candidates for ward positions. The Nepali Congress party had district-level selection committees that chose candidates for municipal positions and regional selection committees which oversaw the selection of ward candidates across several municipalities.

[13]From these lists, we sampled as follows:(i) all district committee members;(ii) all influential committee members in the Nepali Congress regional committees; (iii) two randomly sampled influential committee members in the UML and Maoist municipal committees; (iv) one randomly sampled committee members from all remaining unsampled committee members in both regional and municipal committees.

[14]Of the 883 selection committee members sampled, 705 were successfully interviewed, yielding a response rate of roughly 80%. Six observations were removed because of data incompleteness and duplication, yielding a final sample of 699 committee members.

caste. Committee members have, on average, 10.6 years of education, and score 2.4 standard deviations above the mean in the general population on the ability score. By contrast, politicians have on average only 3.7 years of education and score only 0.2 standard deviations higher on the ability score. Similarly, incomes of committee members are more than double those of politicians.

Cross-party differences in committee membership are also informative. Relative to the Nepali Congress, both the Maoist and UML parties have three times more female committee members (10% versus 3%). In terms of caste, the Maoist party has the highest fraction of non-elite members, roughly 10-15 percentage points higher than UML and Nepali Congress.

B.Does committee member caste identity predict bias in selection? Evidence from IATs

Given party differences in selection committee member characteristics, we now ask whether a committee member's caste identity predicts the extent of his/her bias against non-elite castes in leadership positions. If yes, this would point to another mechanism through which the post-conflict entry of the Maoist party into mainstream politics influenced political representation.

To evaluate this possibility, our survey implemented a single-attribute implicit association test (IAT) (Penke et al., 2006). The IAT uses the categorization of words to the left or to the right of a computer or tablet screen to provide a measurement of the strength of the association between two concepts in this case, caste and leadership. Each respondent was presented with two sets of stimuli. The first set included elite caste Brahmin surnames (e.g., Paudel, Tiwari, Adhikari) and non-elite caste Tamang surnames (e.g., Waiba, Moktan, Bomjon), and the second set included words related to leadership (e.g., decisive, ambitious, self-confident). Words appear one at a time at the center of the screen, and the respondent was instructed to categorize them as fast as possible to the left or the right according to different labels displayed on the top of the screen (for instance, on the right the label "Brahmin and on the left the label "Tamang).

To calculate an implicit association score, two types of tasks are used: in the first task, the respondent was are instructed to categorize Brahmin names and leadership categories to one side of the screen and, on the opposite side of the screen, categorize Tamang names (order compatible task), while in the second task, individuals are instructed to categorize to one side of the screen Tamang names and leadership and to the opposite side of the screen Brahmin names (order incompatible task).[15] The idea behind this measure is that if committee members are biased against non-elite castes (Tamangs) being leaders, then it will be harder and take longer for them to associate (i.e. categorize) Tamang names with leadership words. To measure bias, we calculated for each respondent the difference in time on average it took to categorize Brahmin and leadership together from the time on average it took to categorize Tamang and leadership together.[16] This average difference is then normalized by the standard deviation across all trials to create a final respondent-level, standardized measure of bias (Greenwald et al., 2003).

Table 4 reports predictors of implicit caste bias. The data clearly reject the null of no bias (constant, column 1). Elite committee members are also 0.6σ more biased than than non-elite members, even after controlling for income, age, and marital status. We do not see different degrees of bias among high ranking committee members (columns 3 and 4) or among members who serve on the municipal selection, as opposed to the ward selection, committee (columns 5 and 6).

Appendix Figure **??** plots the distribution of IAT scores by committee member caste; a positive value indicates a slower association of non-elite castes with leadership compared to elite castes and a score greater than 0.35 is conventionally noted as signifying moderate to severe bias (Greenwald et al., 2003). For both committee members from elite and non-elite castes the mean IAT score is positive. The average caste bias across committee members is 0.137 σ, and on average 35.4% of selection committee members achieving scores that signify moderate to severe bias against non-elite castes. However, Figure **??** shows that the distributions across elite and non-elite committee members are different, with an average difference of 0.07 σ, suggesting non-elite castes have less bias than those from elite castes (mean of 0.09 as compared to 0.16).

[15] Respondents were asked to complete a total of five rounds as follows:
Randomization of Brahmin/Tamang to right or left
Round 1: Brahmin/Tamang, 10 trials
Randomization of Leadership to right or left
Round 2: Brahmin/Tamang; Leader, 20 trials
Round 3: Brahmin/Tamang; Leader, 20 trials (identical to round 2)
Round 4: Tamang/Brahmin; Leader, 20 trials (reverse to round 2)
Round 5: Tamang/Brahmin; Leader, 20 trials (identical to round 4)

[16] This difference is calculated by taking the difference in average time to correctly categorize responses in rounds 2 and 3 and rounds 4 and 5. Following common practices, we eliminate trials with latencies ¿ 10,000ms and ¡ 300ms. We further drop respondents if more than 10% of trials have latency ¡ 300 ms or more than 10% of trials have ¿ 3000 ms.

5.3 Qualitative evidence

Our final piece of evidence comes from semi-structured interviews, conducted with a subset of party selection committee members at the end of the short survey administered post IAT. Party members were asked open-ended questions on how conflict-affected and non-conflict affected areas differed with respect to voter turnout, the number of candidates, victory margin, and likelihood of non-elite caste candidates being elected[17].

The most oft-cited reasons for differences in conflict-affected areas amongst Maoist and UML party members were greater political participation by non-elite castes and heightened political consciousness. For instance, one respondent pointed to increased awareness around caste bias and discrimination in conflict-affected areas as raising non-elite caste engagement in political spaces. A Maoist party member emphasized that non-elite castes became empowered to raise their voices in conflict-affected areas. Further, these gains in political participation and consciousness were largely attributed to the Maoist party and the aims of the revolution. Other related reasons for differences by conflict include stronger norms of inclusion, altered perceptions of marginalized groups, and direct actions taken by the Maoist party. Some indicative quotes from our selection committee survey include:

> The likelihood [that non-elite castes will be elected] was higher in conflict affected areas because the revolution made people aware of discrimination based on caste. Marginalized groups have become more active and conscious politically. The revolution uplifted people's political and social consciousness. In conflict affected areas, participation in politics has broadened.
> *Male Party Member, UML Party*

> The Maoists started their struggle for empowerment of oppressed groups and Janajatis. For example, the discriminatory practice of untouchability .. has ended now, thanks to the revolution....Because Maoists fought for the welfare of the lower class and represent marginalized groups, their likelihood of winning was higher in conflict affected areas.
> *Male Party Member, Maoist Party*

[17] Respondents were asked: As you know, the levels of conflict during 1996 to 2006 varied across Nepal. In the 2017 elections, what is your impression of how areas with more conflict differed? Specifically, relative to low conflict areas do you think the following were higher or lower in high conflict areas relative to low conflict: (i) voter turnout; (ii) number of candidates; (iii) victory margin; (iv) likelihood that candidates from non-elite castes were elected as ward chairperson

These explanations focused on increased political inclusion of non-elite groups were more frequently reported by Maoist and UML party members. Nepali Congress Party members reported in equal numbers that it was the continued political control of Maoists and specifically Maoist coercion in the polling booth that drove differences between conflict and non-conflict-affected areas:

> In conflict affected areas, the Maoists continued using their tactics of intimidating and threatening political leaders from other political parties. Due to this, politicians from other political parties were reluctant to stand in the election.
> *Male Party Member, Nepali Congress Party*

In Appendix Table A8 we provide the frequency of each response category by political party. In line with the quantitative evidence, these qualitative interviews provide three key insights. First, the focus on political participation of non-elite citizens may underlie the earlier finding that increased representation in conflict-affected areas was driven in large part by voters. Second, there is consensus across all parties that the Maoists were largely responsible for changes in patterns of political selection, particularly in conflict-affected areas. Third, there is contention about whether this influence was through empowerment or coercion.

6 Did descriptive representation enable substantive representation?

Finally, we turn to the policy implications of these changes and ask: Consistent with the Maoist rhetoric, did descriptive representation for non-elite castes in 2017 enable substantive representation for them? We consider a private-transfer program – beneficiary access to reconstruction grants for earthquake damage. The reconstruction program is particularly useful for two reasons. First, it was the largest and most important social program overseen by the newly-elected politicians immediately upon their entry into office in 2017. Second, eligibility for grants is supposed to be objectively based on the degree of damage as assessed by an engineer so that the identity of a politician should not affect their distribution.

6.1 Political connections and earthquake housing benefits

Under the Rural Housing Reconstruction Program (RHRP), reconstruction cash grants were to be provided to eligible beneficiaries to aid construction of earthquake-resistant houses. Beneficiary selection was stated to be based only on the extent of damage as assessed by engineers in the 2016 census. From the engineering assessment, each household received a damage grade on a scale of 1-5. Grants were given to those with a damage grade of at least three. In the census we see that 533,182 households received a damage grade of three or higher. To receive the grant, applicants had to provide proof of home-ownership and bank account. The household then submitted and had approved a formal application to the ward. Money was released in three tranches: the first 50,000 Nepali rupee (about $500) installment was intended to build an earthquake-resistant foundation. The second installment was for 150,000 rupees (about $1,500), and the third installment was for 100,000-300,000 rupees (about $1,000-$3,000) in total. A government engineer needed to sign off on the construction work at each phase, before the next installment was released.

The government started signing contracts with households in July 2016. By December 2016, roughly 450,000 households had received their first installment. After the elections, local representatives, specifically mayors, were empowered to determine earthquake relief eligibility and oversee the disbursement of the second and third tranches.[18] Formally, they are part of complaint hearing committees that make recommendations to engineers regarding tranche disbursements. Informally, they also influence tranche disbursements and their timing.

A. Basic estimates

If earthquake reconstruction grant eligibility is truly programmatic, then after controlling for the degree of damage and the feasibility of reconstruction, a household's caste identity and whether they belong to the same clan of a politician should not predict probability of grant receipt.

To test this, we use the matched sample of politicians and the voting age census population to estimate variants of the following equation:

$$\begin{aligned} Relief\ Transfers_i = {} & \beta_0 + \beta_1 Elite_i + \beta_2 Mayor's\ Group_i \\ & + \beta_3 Elite_i \times Mayor's\ Group_i + \beta_4 Damage\ Grade_i \\ & + \beta_5 Feasible_i + \beta_6 \boldsymbol{X}_i \varepsilon_i, \end{aligned} \tag{3}$$

[18] In July 2017 (when local elections were underway) NRA announced deadlines for disbursement of the Housing Reconstruction Grant. The deadline for signing the grant agreement was November 2017 and for disbursement of the first tranche as January 2018. Thus, a high priority for citizens just after the election was to apply for benefits (or file for reconsideration of status if their initial application had been refused). For those how had already received their first installment, they sought to file claims for the second or third installment.

where $Relief\ Transfers_i$ are cumulative reconstruction transfers received by household i, $Elite_i$ is a dummy variable equal to one for households from an elite caste, and $Mayor'sGroup_i$ is a dummy variable equal to one for households belonging to the mayor's caste in some specifications or the mayor's clan in other specifications. $Damage\ Grade_i$ and $Feasible_i$ are controls for the damage grade and the feasibility of reconstruction assessed during the census. Officially, $Damage\ Grade_i$ and $Feasibility_i$ entirely determine eligibility. Standard errors are clustered at the municipality level.

Table 5 reports estimates corresponding to specification (3). We consider two related outcomes: total relief transfers (columns 1-4) and receipt of second or third tranche of benefits (columns 5-8).

On average, households in 11 earthquake-affected districts received around 86,387 rupees worth of reconstruction grants and, relatedly, are more likely to have received their second/third tranche of payments.[19] Those from elite castes, however, are estimated to receive an additional 10,096 rupees, even after controlling for damage grade and feasibility (column 1). Columns (2) and (3) show that while belonging to the Mayor's clan but not caste increases relief transfers. The same is true for tranches (columns 6 and 7).

In columns (4) and (8) we see that these benefits to political connection only exist for non-elite mayor clans. Thus politically connected members of a non-elite clan do as well as elite castes. Put differently, while it appears that elite castes benefit disproportionately, independent of whether they are connected to a politician, non-elite castes need a connection to a politician in order to receive favorable treatment. While we cannot rule out the possibility that clan membership is informative of characteristics like information flow, this finding is suggestive of incipient distributional politics.

6.1.1 Non-elite representatives and caste/clan distribution: regression discontinuity estimates

If municipalities that elect non-elite castes as mayor systematically differ, then Table 5 estimates may not capture the causal impact of belonging to a mayor's clan on benefit receipts. We, therefore, compare transfers received by clan members of candidates who barely won to transfers received by clan members of those who barely lost.

[19] 1,633,412 individuals over 18 received some transfer and the average receipt was 135,498 among those receiving transfers.

Two features make our setting suited to this type of analysis. First, caste and clan identity are observable and have been shown to play a large role in shaping political relationships (Chandra, 2006; Besley et al., 2011; Jensenius, 2015; Dunning and Nilekani, 2013). Second, because we are using a census, we have a substantial amount of data in elections very close to the winning threshold. Specifically, we estimate:

$$TE = \lim_{x \downarrow 0} E[Y_{mic}|x_{ic}] - \lim_{x \uparrow 0} E[Y_{mic}|x_{ic}], \tag{4}$$

where Y_{mic} is a measure of earthquake transfers to member m of candidate i's clan in constituency c. x_{ic} is candidate i's vote share minus the runner-up's (winner's) vote share for the winner (runner-up) in constituency c. All regressions use the local linear polynomial on both sides of the cutoff and employ triangular weights. We cluster standard errors at the clan level, which is the effective unit of treatment. We also perform placebo tests, comparing the second and third place candidates.

In the first row, we report a standard regression discontinuity specification with local linear polynomials on either side of the threshold (row 1). In the second row, we report 'bias-corrected'estimates, based on specifications that employ quadratic polynomials on either side of the threshold, as suggested by Calonico et al. (2014). Last, in the third row, we report the same estimates with standard errors adjusted using the method suggested in Calonico et al. (2014).[20]

Table 6 presents the regression discontinuity estimates. Being the clan member of a barely elected mayor results in an additional 21,855 Rs. worth of transfers (column 1). It also increases the number of tranches received by 0.276 (column 2). We find no comparable effect when considering the runner up with the third place finisher. The evidence indicates that mayors are able to successfully direct earthquake reconstruction grants to their clan members, providing direct evidence that politician identity matters for service delivery outcomes.

Figure 8 reports the cumulative shares of the adult population that received the first (top panel) and the second and third (bottom panel) tranches of grants separately for the mayor's clan (red line) and for the runner-up's clan (blue line). Three features of the figure reinforce that the identity of the mayor causally affects earthquake reconstruction grants. First, near the 0% vote margin cut-off, for the first tranche, which was awarded before the election, the identity of the politician is irrelevant for grant receipts. Second, for the second and third

[20]Estimates obtained using several other widely-used regression discontinuity specifications are similar. Figure 8 further supports a causal interpretation of these estimates.

tranches, a gap opens between the mayor and the runner up's caste immediately after the election. This gap is localized to clans whose relatives contested close elections. It is also notable that this gap persists nearly a year after the election. This suggests that mayoral interference in the distribution of grants is fundamental, and not just speeding up the delivery of grants for mayor's relatives, but creating a durable gap.

7 Conclusion

Combining census data from a new federal democracy with electoral and party data, we examine post-revolution patterns of political representation. Following the People's war and the enactment of a new, federal Constitution in 2015, Nepalese local politics became more inclusive in terms of ethnic composition, particularly in places that witnessed direct conflict. Using electoral and conflict data and surveys of selection committee members, we argue that the transition of the Maoist armed group into mainstream politics played an important role.

After the revolution, the caste distribution of elected politicians largely resembled the population they represent but was positively selected on education and ability. These changes in caste representation matter for policy outcomes: historically non-elite caste members receive greater reconstruction assistance, but only when they are politically connected (belong to the Mayor's clan).

Studying the political institutions that emerge from conflict, and especially the extent to which they succeed in redressing caste-based grievances, carries an additional benefit. It provides information about the likelihood that such institutions will endure and provide public services more equitably. Nepal's conflict is clearly rooted in the country's long history of caste-based economic and political inequality enforced by a powerful monarchy. The Maoists fundamental goal was to move toward a federal system that leveled the political playing field for different castes. Our data indicate that the institutions that emerged from the conflict are achieving some of these ends.

Nepal is at a 'critical juncture' (Acemoglu and Robinson, 2012). While the peace agreement written in 2007 laid the groundwork for a more inclusive set of institutions, it was ultimately the earthquake of 2015 that drove elites to act. Indeed, prior to the earthquake, many were skeptical that the peace deal, by itself, could transform patterns of political power. Writing in 2008, Ghani and Lockhart (2008) observe: "The mass social mobilization that brought an end to the autocratic regime of the king created an open moment in Nepal." Yet, the same authors were cynical about the country's prospects, arguing: "Nepalese politics has long been about the capture of government resources for purposes of patronage" and that the "fragmentation of the elite, its lack of consensus on a common vision, and its apathy in implementing technical programs all reveal the disjunction between the people's aspirations and the narrow concerns of the elite.' The revolution laid the groundwork for fundamental institutional change, and the earthquake created a national emergency that forced feuding parties to agree on a new constitution. Our paper provides evidence that this 'open moment' is bringing previously excluded groups into the political space. In this sense, our data are consistent with the argument in Shefter (1977): parties forced to initially organize outside of the state can play a role in driving the transition from patronage to programmatic politics. Nonetheless, Nepal's autocratic and clientelistic political history, alongside some early signs in the data of backsliding, point to a clear need to invest in supporting institutions, including clear grievance mechanisms that can help citizens to hold these new politicians accountable.

Tables and Figures

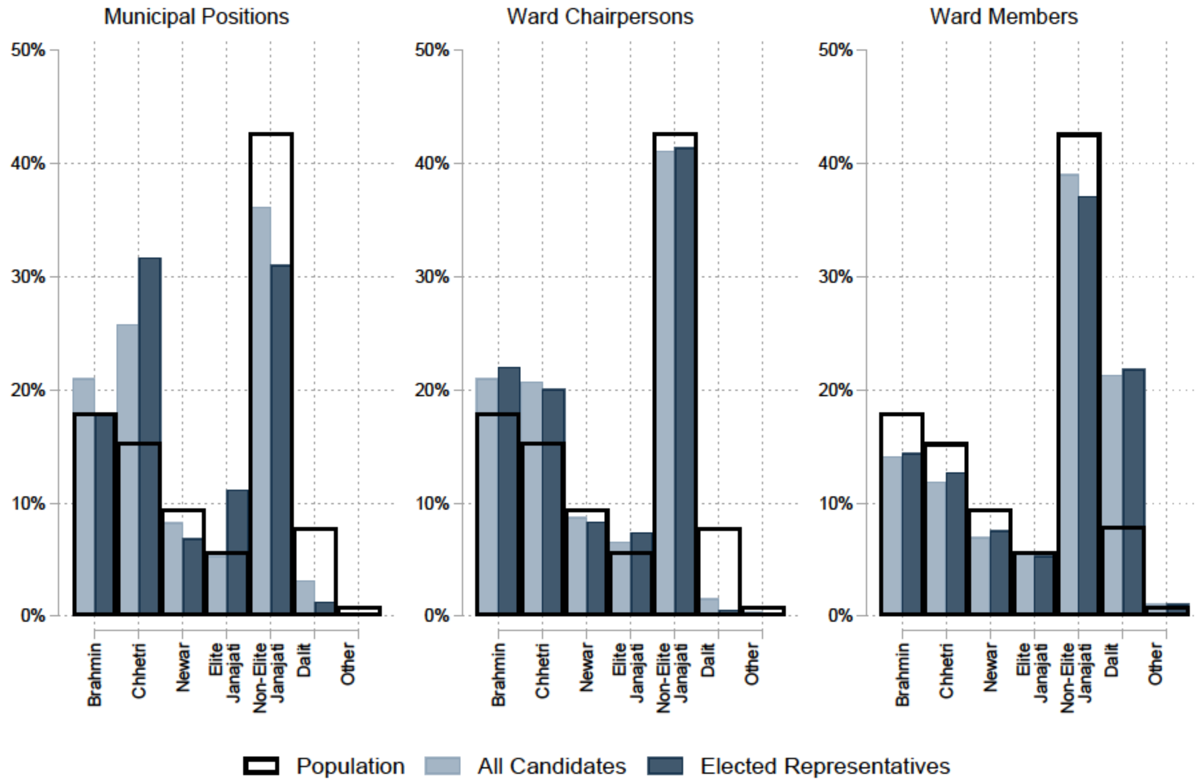

Figure 1: Caste Representation of Candidates and Politicians Relative to the Population

Notes: The figure shows the distribution of caste for the adult population in 11 districts in Nepal as well as for unelected candidates and elected representatives. The distributions are further shown across municipal positions, ward chair positions, and for all other ward members. Caste categories follow those proposed in Vollan (2015).

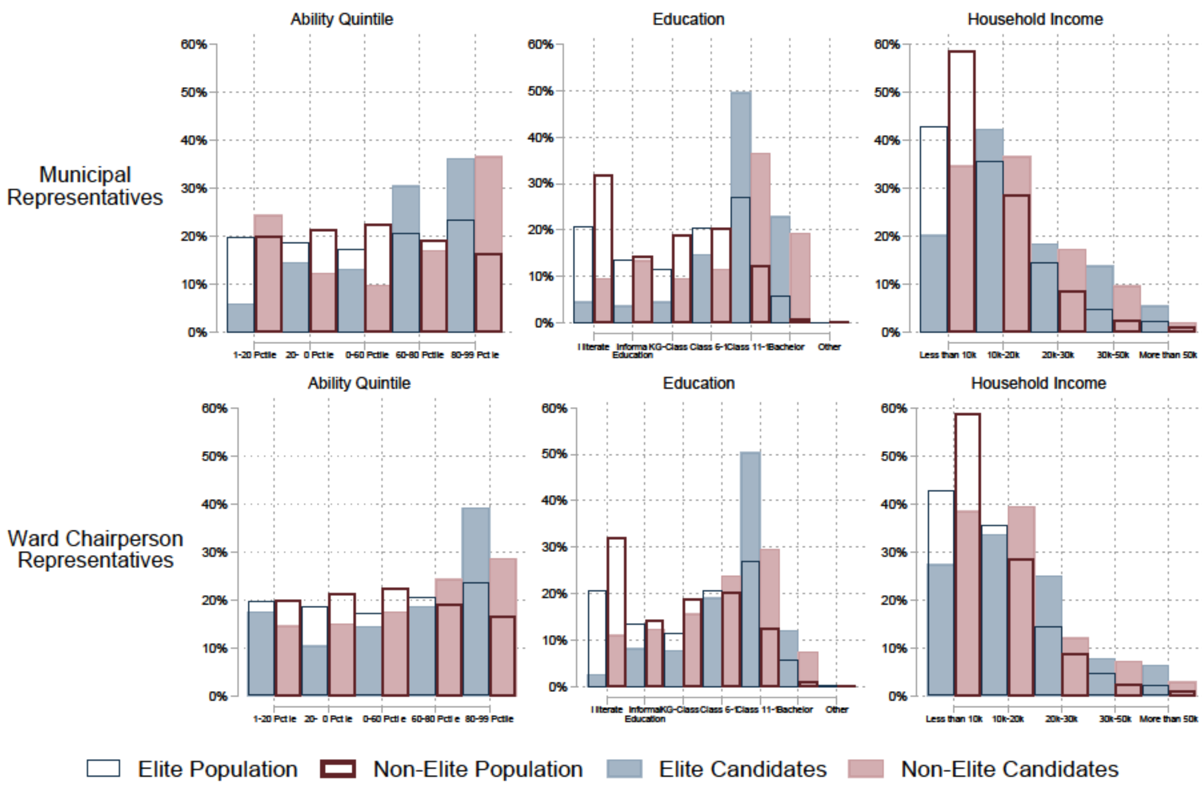

Figure 2: Distributions of measures of competence by elite caste status

Notes: The figure shows the distribution of three measures of competence - ability quintiles, education, and household income - for the adult population in 11 districts in Nepal as well as for elected representatives. Distributions are separated for elite and non-elite castes, as proposed in Vollan (2015). Elite castes include Brahmins, Chettris, Newars, and elite Janajatis. Non-elite castes include non-elite Janajatis, Dalits, and all others. Ability is measured as the residual from a mincer regression controlling for gender. Data on education and household income come from the post-disaster needs assessment census conducted in 2016. The distributions are shown for elected representatives in municipal positions and in ward chair positions.

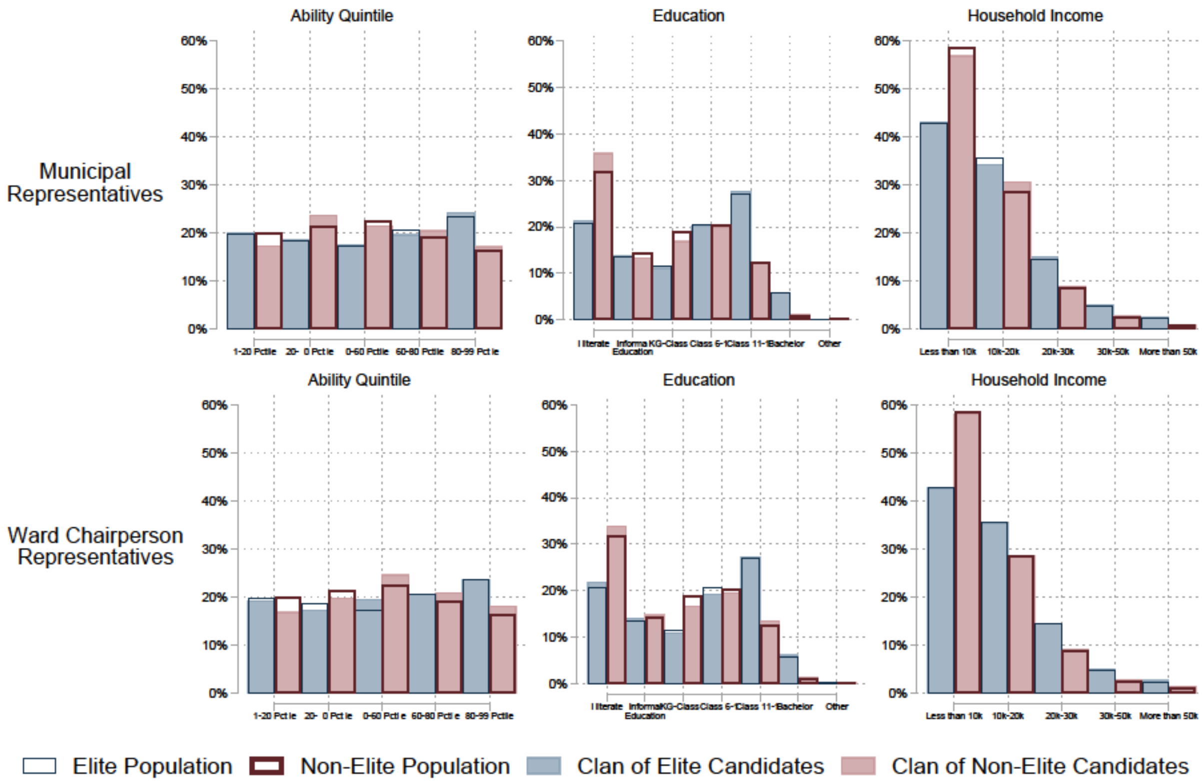

Figure 3: Distribution of measures of competence for clan members of elected representatives

Notes: The figure shows the distribution of three measures of competence - ability quintiles, education, and household income - for the adult population in 11 districts in Nepal as well as for the clans of elected representatives. Distributions are separated for elite and non-elite castes, as proposed in Vollan (2015). Elite castes include Brahmins, Chettris, Newars, and elite Janajatis. Non-elite castes include non-elite Janajatis, Dalits, and all others. Clan is defined as all those sharing the same surname, caste, and municipality as the elected representative. Ability is measured as the residual from a mincer regression controlling for gender. Data on education and household income come from the post-disaster needs assessment census conducted in 2016. The distributions are shown for the clans of elected representatives in municipal positions and in ward chair positions.

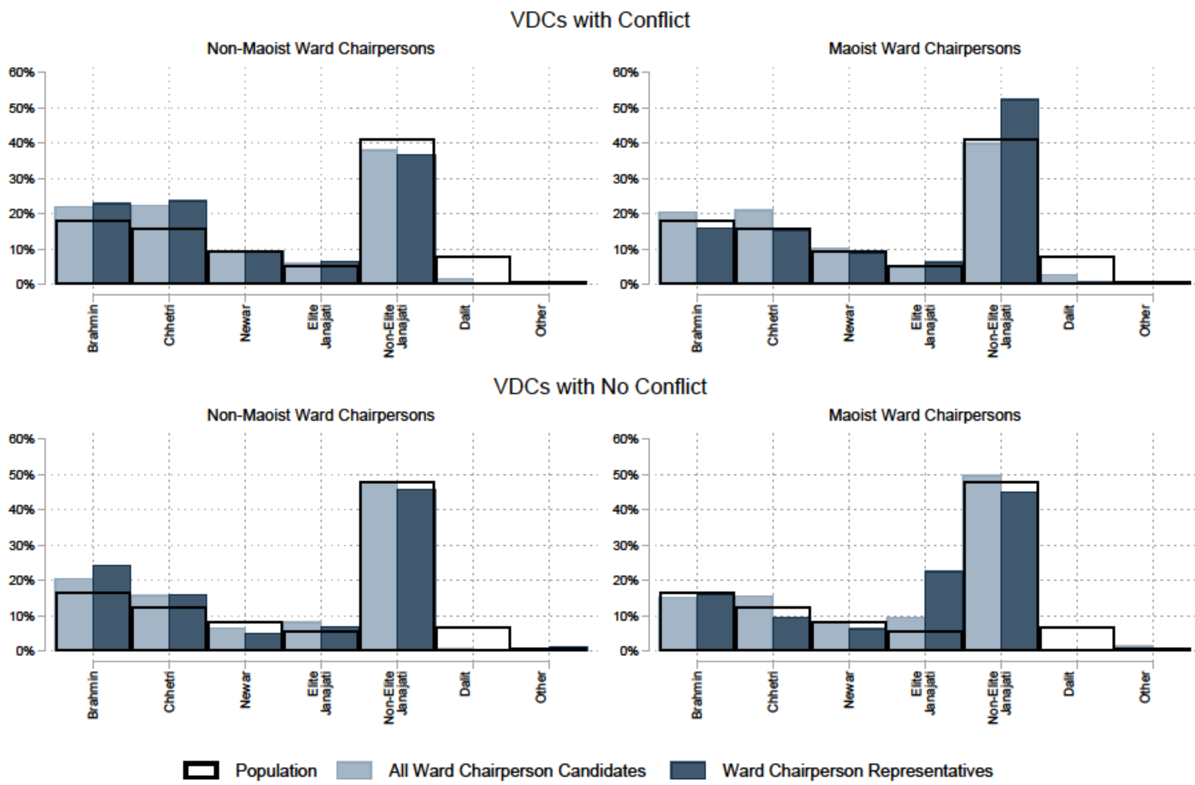

Figure 4: Conflict and Inclusion across Parties

Notes: The figure shows the distribution of caste for the population of adults in 11 districts in Nepal as well as for unelected candidates and elected representatives for ward chair positions. Village Development Committees (VDCs) were the smallest administrative unit prior to the Maoist conflict. The distributions are further shown across VDCs that did and did not experience conflict during the Maoist Revolution, as measured by whether a death occurred in the VDC from the Insec data. Additionally, these distributions are separated for Maoist politicians and politicians from the UML and Nepali Congress. Caste categories follow those proposed in Vollan (2015).

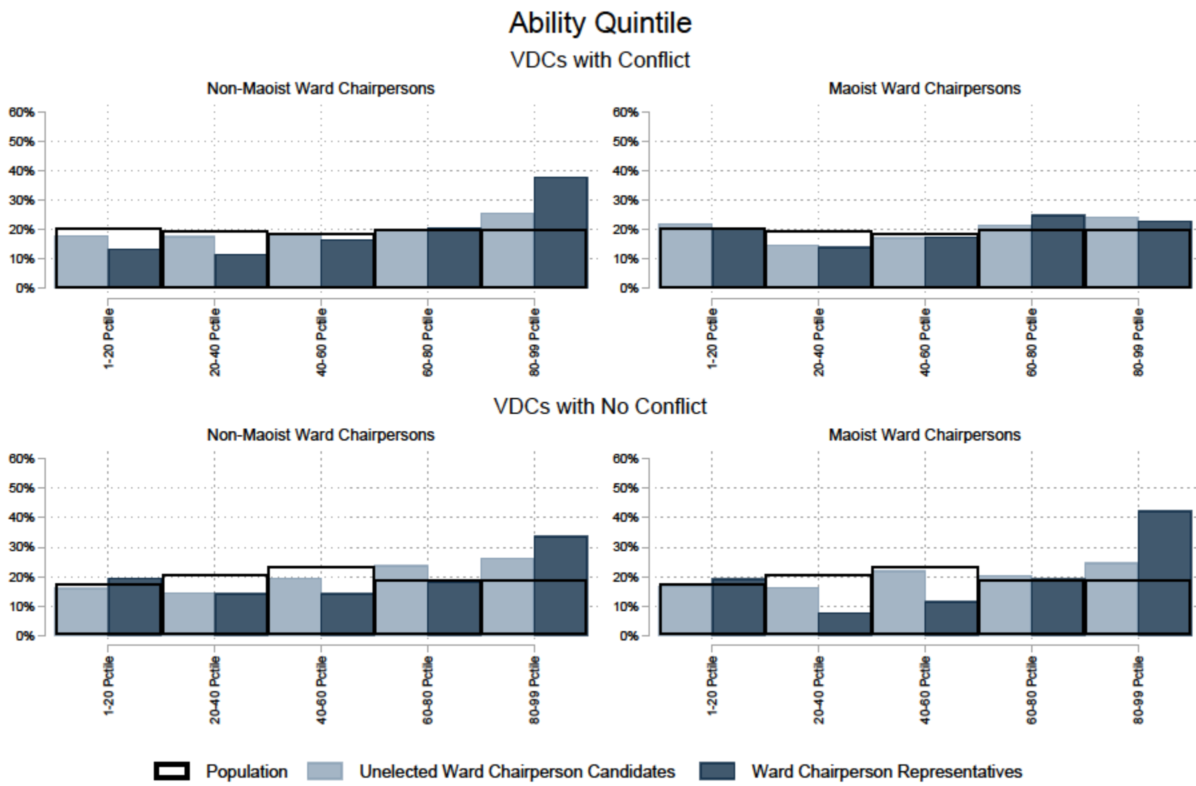

Figure 5: Conflict and Competence across Parties

Notes: The figure shows the distribution of ability, measured as the residual from a mincer regression, for the adult population in 11 districts in Nepal as well as for unelected candidates and elected representatives for ward chair positions. Village Development Committees (VDCs) were the smallest administrative unit prior to the Maoist conflict. The distributions are further shown across VDCs that did and did not experience conflict during the Maoist Revolution, as measured by whether a death occurred in the VDC from the Insec data. Additionally, these distributions are separated for Maoist politicians and politicians from the UML and Nepali Congress.

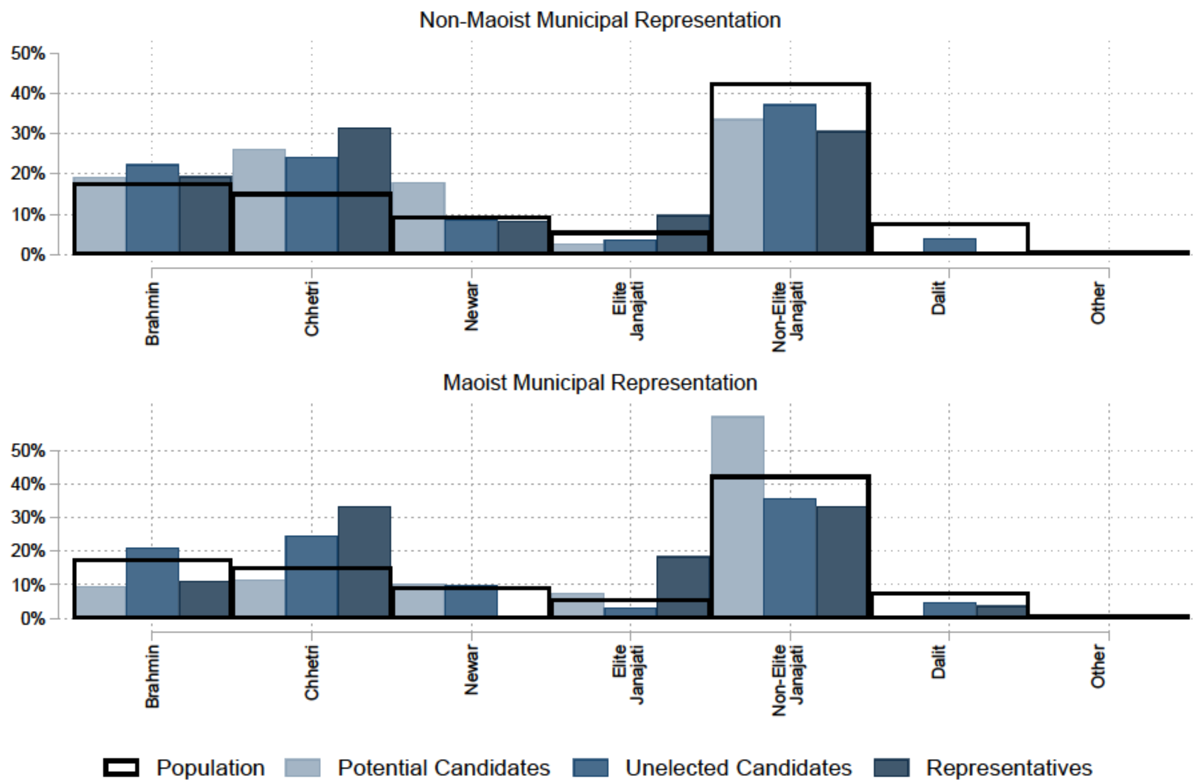

Figure 6: The Role of Voters and of Parties in Political Representation

Notes: The figure shows the distribution of caste for the adult population in 11 districts in Nepal as well as for nominees considered but not selected for candidacy, unelected candidates, and elected representatives. The distributions are shown for politicians in municipal positions, as this is the only position for which we have complete lists of potential nominees. Caste categories follow those proposed in Vollan (2015).

Figure 7: The Role of Voters and of Parties in Political Selection

Notes: The figure shows the distribution of three measures of competence - ability quintiles, education, and household income - for the adult population in 11 districts in Nepal as well as for nominees considered but not selected for candidacy, unelected candidates, and elected representatives. Ability is measured as the residual from a mincer regression controlling for gender. Data on education and household income come from the post-disaster needs assessment census conducted in 2016. The distributions are shown for politicians in municipal positions, as this is the only position for which we have complete lists of potential nominees.

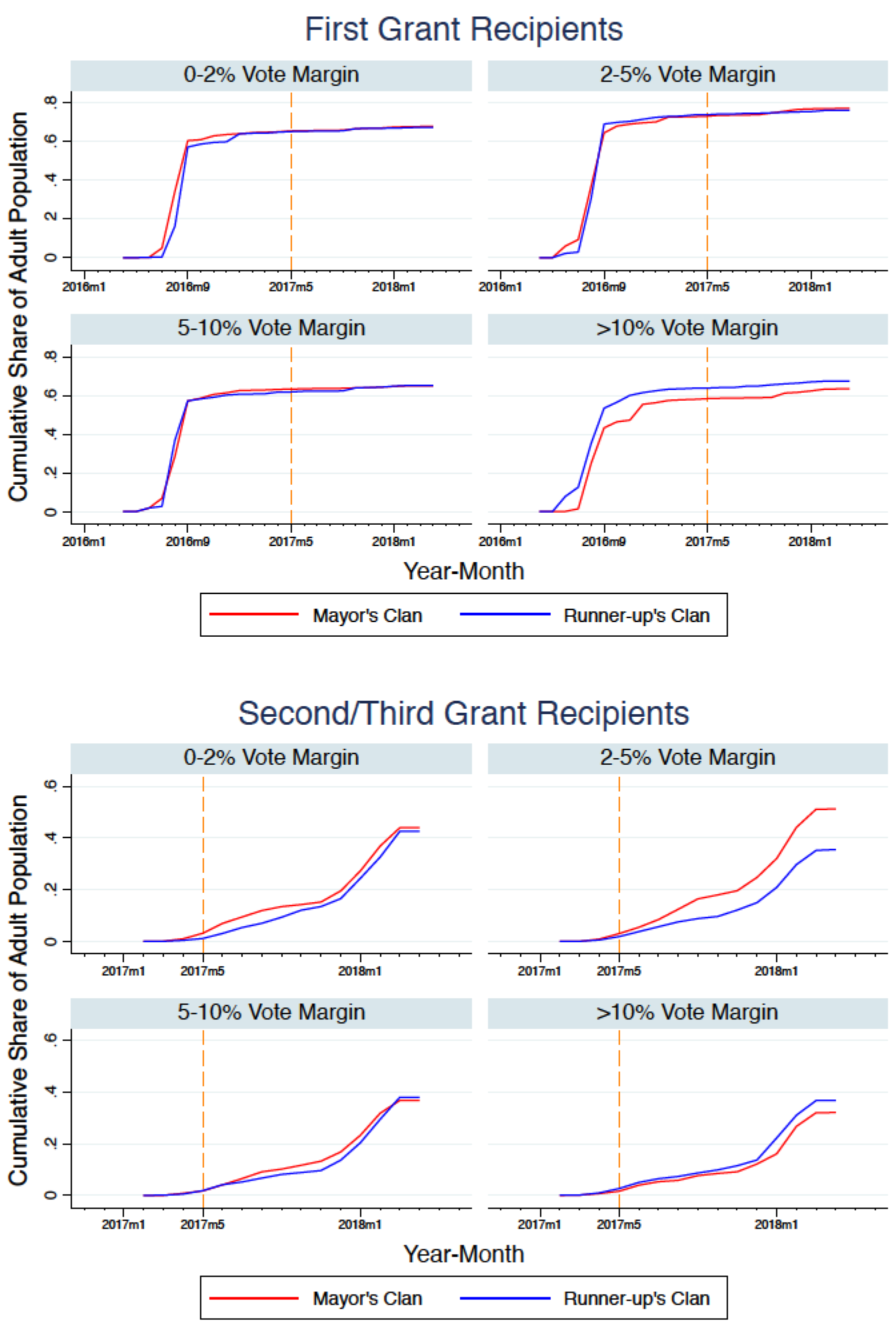

Figure 8: Mayoral Clan Identity and the Distribution of Earthquake Reconstruction Grants
Notes: The figures show the cumulative shares of the adult population who received the first and second or third tranches of grants by their relation to mayor's (red line) and runner-up's (blue line) clans and vote margins. The dashed orange line depicts the date of the first local elections.

Table 1: Eliteness, Competence, and Selection

Panel A - Historical Caste Eliteness and Winning a Party Ticket						
Dependent variable:	Muni Candidate x 100			Muni Seat x 100		
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.023***	0.010***	0.006**	0.006***	0.003***	0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Female (=1)	-0.013***	-0.005**	-0.006**	-0.000	0.002*	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Ability (z-score)		0.005***			0.002***	
		(0.001)			(0.001)	
Education (z-score)		0.025***	0.022***		0.006***	0.006***
		(0.002)	(0.002)		(0.001)	(0.001)
Income (z-score)			0.006***			0.002***
			(0.002)			(0.001)
Asset Index (z-score)			0.015***			0.003***
			(0.002)			(0.001)
# Observations	2,540,433	2,540,433	2,540,433	2,540,433	2,540,433	2,540,433
R-Squared	0.000	0.000	0.000	0.000	0.000	0.000
Mean in Population	0.035	0.035	0.035	0.006	0.006	0.006
Panel B - Historical Caste Eliteness and Winning Office						
Dependent variable:	Ward Chair Cand. x 100			Ward Chair Seat x 100		
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.053***	0.027***	0.015***	0.014***	0.005**	0.001
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Female (=1)	-0.240***	-0.225***	-0.228***	-0.057***	-0.052***	-0.053***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Ability (z-score)		0.020***			0.009***	
		(0.003)			(0.001)	
Education (z-score)		0.048***	0.038***		0.015***	0.012***
		(0.002)	(0.002)		(0.001)	(0.001)
Income (z-score)			0.018***			0.008***
			(0.003)			(0.001)
Asset Index (z-score)			0.044***			0.014***
			(0.004)			(0.002)
# Observations	2,540,433	2,540,433	2,540,433	2,540,433	2,540,433	2,540,433
R-Squared	0.001	0.002	0.002	0.000	0.000	0.001
Mean in Population	0.126	0.126	0.126	0.029	0.029	0.029

Notes: This table reports on the relationship between belonging to a historically politically included caste and the probability of becoming a candidate (Panel A) or of becoming a politicians (Panel B). All regressions include constituency fixed effects. White heteroskedasticity robust standard errors are reported in parentheses. *Levels of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2: Violence and Political Representation

	Change in No. of Cands	Change in No. of Non-elite Cands	Change in No. of Elite Cands	Elite to Non-elite	Non-Elite to Elite	Ward Chair Maoist (=1)	Ward Chair Non-elite Caste Maoist (=1)	Ward Chair Elite Caste Maoist (=1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Violence (=1)	1.300***	0.333***	0.937***	0.035***	-0.001	0.051***	0.026***	0.037***
	(0.152)	(0.063)	(0.124)	(0.013)	(0.010)	(0.014)	(0.008)	(0.012)
Mean (Violence=0)	3.798	0.957	2.665	0.145	0.080	0.167	0.042	0.120
# Observations	3504	3504	3504	3504	3504	3504	3504	3504
R-Squared	0.276	0.178	0.312	0.067	0.044	0.187	0.125	0.162

Notes: This table reports the correlation between violence and political representation. The unit of observation is a 1992 VDC (a constituency under the old structure). Violence is an indicator variable that equals to one if the 1992 VDC experienced any violence, and zero otherwise. All specifications include district fixed effects. Robust standard errors are reported in parentheses.
Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Comparing Committee Members and Politicians

Sample	# Obs.	Age (Yrs.)		Female (=1)		Included (=1)		Education (Yrs)		Ability		Income (Rs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	N	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
All Parties													
All Committee Members	699	45.082	(0.357)	0.089	(0.011)	0.699	(0.018)	10.563	(0.123)	2.419	(0.065)	37428.356	(566.069)
District Committee Members	240	46.929	(0.544)	0.083	(0.018)	0.730	(0.029)	10.855	(0.215)	2.641	(0.105)	40156.951	(940.660)
Municipal Committee Members	459	44.124	0.458	0.092	0.013	0.683	0.022	10.412	0.150	2.307	0.081	36045.455	698.857
Maoist													
All Committee Members	290	41.817	(0.529)	0.110	(0.018)	0.633	(0.029)	9.936	(0.184)	2.099	(0.105)	33967.391	(919.204)
District Committee Members	95	43.526	(0.898)	0.137	(0.035)	0.674	(0.049)	9.826	(0.328)	2.179	(0.182)	34772.727	(1646.654)
Municipal Committee Members	195	40.985	(0.648)	0.097	(0.021)	0.613	(0.035)	9.990	(0.223)	2.061	(0.129)	33590.426	(1109.611)
United Marxist - Leninist													
All Committee Members	276	47.796	(0.554)	0.094	(0.018)	0.735	(0.027)	10.804	(0.189)	2.562	(0.100)	38587.786	(857.890)
District Committee Members	45	50.227	(0.887)	0.067	(0.037)	0.756	(0.064)	12.148	(0.380)	2.804	(0.244)	41547.619	(2206.717)
Municipal Committee Members	231	47.333	(0.634)	0.100	(0.020)	0.731	(0.030)	10.548	(0.209)	2.516	(0.110)	38022.727	(928.020)
Nepali Congress													
All Committee Members	133	46.598	(0.760)	0.030	(0.015	0.767	(0.037)	11.439	(0.306)	2.828	(0.128)	42640.000	(1110.908)
District Committee Members	100	48.727	(0.793)	0.040	(0.020)	0.771	(0.043)	11.268	(0.351)	3.004	(0.134)	44623.656	(1084.616)
Municipal Committee Members	33	40.212	(1.405)	0.000	(0.000)	0.758	(0.075)	11.955	(0.627)	2.316	(0.296)	36875.000	(2762.136)
All Parties													
All Politicians	3,906	43.076	(0.166)	0.400	(0.008)	0.467	(0.008)	3.653	(0.054)	0.190	(0.017)	14099.641	(170.261)
Municipal Politicians	161	43.876	(0.787)	0.491	(0.039)	0.714	(0.036)	6.730	(0.295)	0.490	(0.097)	18944.099	(991.526)
Ward Politicians	3,745	43.042	(0.170)	0.396	(0.008)	0.457	(0.008)	3.521	(0.054)	0.177	(0.017)	13891.264	(171.592)

Notes: This table reports means of key demographics for selection committee members and for politicians. Ability is the z-score of the residual from the regression $Income_i = f(Education_i, Age_i) + \gamma_w + \varepsilon_i$, where $Education_i$ is a dummy variable equal to one for having above median education in the population, Age_i is a categorical variable with five year age bins, and γ_w are ward fixed effecs. Function f represents the fact that this specification includes a dummy for each subgroup and for every possible double and triple interaction. Standard errors are reported in parentheses.

Table 4: Correlates of Implicit Bias

Dependent variable:	Caste Bias (z-score)					
	(1)	(2)	(3)	(4)	(5)	(6)
Elite (=1)	0.065**	0.063**				
	(0.029)	(0.029)				
High Ranking Member (=1)			-0.033	-0.028		
			(0.030)	(0.030)		
Municipal Selection Committee Member (=1)					-0.005	-0.000
					(0.030)	(0.030)
Constant	0.091***	0.047	0.147***	0.056	0.138***	0.059
	(0.024)	(0.095)	(0.017)	(0.095)	(0.017)	(0.096)
Covariates	No	Yes	No	Yes	No	Yes
R-Squared	0.008	0.018	0.002	0.012	0.000	0.011
# Politicians	588	588	588	588	588	588

Notes: This table reports on the predictors bias among selection committee members as measured using an Implicit Association Test. The covariates are income, age, and marital status.
Levels of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 5: Elite Status and Receipt of Earthquake Relief Transfers

Dependent variable:	Relief Transfers (Rs.)				Second/Third Tranche (=1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elite Caste (=1)	10096.458***	10344.459***	10806.797***	11283.419***	0.047***	0.048***	0.051***	0.052***
	(1915.643)	(2053.789)	(2086.917)	(2067.355)	(0.010)	(0.011)	(0.011)	(0.011)
Mayor's Caste (=1)		-1362.487	-3416.720			-0.009	-0.020	
		(3482.275)	(3353.627)			(0.018)	(0.018)	
Mayor's Clan (=1)			12475.909**				0.065**	
			(6021.411)				(0.031)	
Mayor's Clan x Elite				-478.775				0.000
				(6243.727)				(0.030)
Mayor's Clan x Non-Elite				20447.287*				0.101*
				(10375.583)				(0.055)
# Observations	2,540,381	2,540,381	2,540,381	2,540,381	2,540,381	2,540,381	2,540,381	2,540,381
R-Squared	0.21	0.21	0.21	0.21	0.14	0.14	0.14	0.14
Mean (Non-Elite)	80459.38	80459.38	80459.38	80459.38	0.30	0.30	0.30	0.30
Mean (Not Mayor's Caste)	86593.92	86593.92	86593.92	86593.92	0.33	0.33	0.33	0.33
Mean (Not Mayor's Clan)	85302.16	85302.16	85302.16	85302.16	0.32	0.32	0.32	0.32

Notes: All regressions include damage controls. Standard errors clustered at municipality level are reported in parentheses. The dependent variable for columns 1 - 4 is the total rupee value of earthquake reconstruction grant transfers for columns 5 - 8 it is a dummy variable equal to one for households who have received at least their second tranche. *Levels of significance*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Does the Identity of Politicians Matter

Dependent variable:	Relief Benefits (Rs.)	# Tranches	Relief Benefits (Rs.)	# Tranches
	(1)	(2)	(3)	(4)
Conventional	21854.769*	0.276**	-15623.904	-0.247
	(12226.464)	(0.124)	(23179.199)	(0.219)
Bias-corrected	23250.568*	0.294**	-10698.561	-0.217
	(12226.464)	(0.124)	(23179.199)	(0.219)
Robust	23250.568	0.294	-10698.561	-0.217
	(19966.419)	(0.203)	(25434.051)	(0.242)
Sample	1st and 2nd	1st and 2nd	2nd and 3rd	2nd and 3rd
# Observations	265,980	265,980	303,227	303,227

Notes: This table reports the effect of having a clan member win office on earthquake reconstruction cash grant receipts. A person is defined as belonging to the clan of the mayor if they are in the same caste (according to the 125 caste categorizations given by the Central Bureau of Statistics of Nepal), share the same surname, and live in the same municipality as the mayor. In columns 1 and 2, the sample is restricted to clan members of the mayor or the runner up. In columns 3 and 4, the sample is restricted to the clan members of the runner up and the third place candidate. The estimation uses local linear polynomials and employs triangular weights on both sides of the cutoff. The optimal bandwidth is chosen using the method of Calonico, Cattaneo, and Titiunik (2014). Standard errors clustered at the clan level are in parentheses.
Levels of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

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Appendices

A Data

1. **Census**

    - Variables: Education, income, assets, gender, caste
    - Description: Education, gender and income were categorical in the original data. For the final analysis that uses caste/ethnicity, we follow Vollan (2015) to re-group over 100 categories in the original caste/ethnicity variable to into included and excluded castes. The asset index is created as the first principal component of household assets in pre-earthquake period, separately for rural and urban respondents. Assets in the index are: land, television, mobile phone, computer/laptop, internet, telephone, refrigerator, motorcycle, four-wheeler for personal/business use, land, availability of toilet, source of cooking, source of drinking water, source of lighting, and type of house that included surface type, foundation type, roof type, number of floors, height of house and plinth area.
    - Source: Household Registration for Housing Reconstruction Survey (HRHRS)
    - Note: Government of Nepal collected these data with help of Central Bureau of Statistics (CBS) and National Reconstruction Authority (NRA). It was a census of households conducted across 11 severely affected districts after the 2015 earthquake.

2. **Party lists for the 2017 election**

    - Variables: Names, position, location, party
    - Description: We obtained the information of nominated individuals for candidacy for the 2017 local election from three major political parties that won 88.46% of the total seats: Nepali Congress, CPN-UML and CPN-Maoist.
    - Source: Respective party offices of Nepali Congress, CPN-UML and CPN-Maoist.
    - Note: We collected these data by visiting the respective party offices. We call this the nominee list.

3. **2017 election data**

    - Variables: Names, position, location, party, votes, rank

- Description: These data had information on individual candidates, their age, gender, party, location, position they contested for as well as 2017 election outcomes such as votes and ranks.
- Source: Election Commission of Nepal
- Note: We call this the candidate list.

4. **Demographic variables for politicians (nominees, candidates and representatives)**

    - Variabes: Education, income, assets, gender, caste/ethnicity for nominees, candidates, and politicans.
    - Description: These variables for politicians and nominees were obtained from the HRHRS census data by fuzzy matching the nominee list and the candidate list. In order to facilitate the fuzzy matching, we had also obtained the information on the spouse and parents of the politicians by scraping the 2017 voter list. That is, we extracted voter information such as the voter ID, voter name and name of parent/spouse for about 800,000 voters that was placed on the website of election commission website using Python.
    - Source: HRHRS + Nominee List + Candidate list + Voter list from the website of the Election Commission of Nepal
    - Note: The individual-level matching on names and locations was done with the help of NRA staff at their office, using a combination of the reclink2 command in Stata and manual matching.

5. **Electoral outcomes for candidates and representatives during 1992 Election**

    - Variables: Names, position, location, party, votes, rank
    - Description: These data were available only for key positions at local level. Information was available on individual candidates, their age, gender, party, location, position they contested for and 1992 election outcomes.
    - Source: Election Commission of Nepal

6. **Matching datasets over time in light of changing administrative structures**

    - Description: Administrative structures in Nepal have changed over time in Nepal over the last 3 decades. Our data come from 1992, 1996-2006, 2015 and 2017. Before 2017 the administrative structure had the following hierarchy: center, provinces, districts, Village Development Committees (VDCs) and wards. After 2017, this changed to center, provinces, districts, municipalities and wards. While the number of provinces and districts remained more or less same, VDCs and wards were transformed to municipalities and to wards. About 3915 VDCs and 36,000 wards in 1992 were transformed to 753 municipalities and 6743 wards in 2017. So, between 1992 and 2017 VDCs and wards are the closest comparable administrative tier at the local level.

- Note: We manually matched the names of VDCs over time and used the official crosswalk of their respective wards to trace the 1992 VDCs to the municipalities and wards of 2017. The table below provides an example of changes in this administrative structure. There were five types of transformations. A VDC in 1992, say VDC 1, uniquely converted into a ward in 2017, ward A1. Most of the transformations were of this type. Similarly, VDC 2 in 1992 split into multiple wards B1 and B2 in 2017. Multiple VDCs 3 and 4 of 1992 combined to form a ward C1 in 2017. Lastly, multiple VDCs in 1992 converted into multiple wards in 2017 in two ways: (i) some parts of VDCs 5 and 6 were combined into ward C2 and remaining parts of 5 and 6 were respectively converted in to C1 and C3; (ii) all of VDC 7 and a part of VDC 8 transformed to ward D1 while the other part of VDC 8 and all of VDC 9 transformed to ward D2 in 2017.

Figure A1: Crosswalk Example

VDC_92	Ward_2017	Transformation type
1	A1	Unique
2	B1	One VDC into multiple wards
2	B2	
3	C1	One Ward into multiple VDCs
4	C1	
5	C1	Multiple VDCs into multiple wards: Type 1
5	C2	
6	C2	
6	C3	
7	D1	Multiple VDCs into multiple wards: Type 2
8	D1	
8	D2	
9	D2	

B Estimating caste using surnames for the 1992 election

The 1992 Village Development Council election results do not record the caste of candidates. We therefore train a prediction model using the 2017 pdna in order to estimate the caste identify of politicians using their surnames.

Let $n_{s,c}$ be the number of individuals with the surname s who belong to caste c. For each surname, we define the set of possible castes of as $C(s) = \{c|n_{s,c} > 0\} \cup \{dummy\}$, where we include the *dummy* set of castes to stand for castes that exist in the national census grouping but that are not observed in the PDNA data. Then, for each $c \in C(s)$ we define

$$\hat{P}(caste|surname) = \frac{(n_{s,c} + 1)}{\sum_{c \in C(last)}(n_{s,c} + 1)} \tag{5}$$

The top predicted caste for a given last last name is therefore the caste with the largest number of individuals who share that name.[21] The estimated probability is therefore $\hat{P}(c|s)$.[22] We retain three predicted castes for each individual. In cases of equal number of $n_(s, c)$ for different castes, we ordered them randomly to keep the cutoff at three castes.

Within the 2017 PDNA survey, the classification accuracy using the maximum $\hat{P}(c|l)$ is 89 percent. The accuracy of one of the top 3 caste predictions being correct is 98 percent. In order for this prediction model to perform similarly in other data sets requires the assumption the individuals have the same distribution of castes conditional on surname.

We have corrected misspellings in the 1992 elections and in the 2017 PDNA. We then used these corrected names for classification. Six percent of politicians in the 1992 data were not able to be classified since their last name did not appear in the 2015 census even once. These could be misspellings.[23]

We can now estimate prediction accuracy on those 94% of individuals who are able to be classified, using the accuracy estimates $P(c|s)$. The probability that the first estimate is correct is 0.81. The probability that one of the top three predictions is correct is 0.92.

Using the same methods, where this time the spellings of last names in the census were made to accord to the names of individuals in the 2017 elections, so that almost all individuals

[21] This form for $\hat{P}(c|s)$ reflects Laplace Smoothing. For example, if 10 individuals who share a last name in the PDNA all come from the same caste, it is not with certainty (probability 1) that an 11th individual (to be predicted) would belong to the same caste.

[22] We retain three predicted castes for each individual in the 1992 data. In cases with an even number $n_{s,c}$ for two different castes, we randomly order them.

[23] It is unlikely that they are simply very rare names since, for comparison, the fraction of individuals in the census who have a name that appears only once in the entire census is only 0.03%.

(99.7 percent) are able to be classified.[24]

[24] We investigated using location as well as last name to improve classification. In this exercise, we give an upper bound on classification accuracy using last name and district. To give an upper bound on the added effect of this information, we perform an overfit estimate of the prediction accuracy with the 2015 census. For each last name and district, we take the modal caste for individuals of that last name in that district as the predicted caste. That is, instead of using $n_{l,c}$ we use the counts in each district $n_{last,district,caste}$ and perform the modal classification for each pair (last, district). We then test our prediction accuracy for all individuals in the census using their name and district. We use the entire census as both the training set and test set. Since any model using only last name and district as features must be some function f(last,district), and since we are selecting the best such function for our test data using overfitting, the accuracy of this overfit model produces a strict upper bound on accuracy of prediction using last name and district. The accuracy attained is 91 percent. This is compared to 89 percent for modal classification based on last name without using location - a 2 percent increase. Recall that there was 98% accuracy for the top 3 predictions together based on last name alone, so this is a more important margin to pursue.

C GIS Data Construction

This section describes how we employed GIS software to create a crosswalk between old and new local units in order to obtain a constant geographic unit over time for analysis. We obtained 2017 ward-level shapefile (N = 6,803[25]) from the Geographic Information Infrastructure Division at the Survey Department. For old boundaries, we use 1997 VDC-level shapefile (N = 3,982[26]) downloaded from Harvard Geospatial Library.[27][28] The choice of year 1997 for old local boundaries was determined by the availability of the shapefile.

In ArcGIS, we used the `intersect` tool to decompose the old and new boundaries into common polygons. Since shapefiles are created imperfectly, overlapping lines are often detected as distinct boundaries. As a result, when the intersect tool was deployed without allowing specifying any tolerance for imperfect coding of lines, we endd up with a total of 33,934 polygons. This is much higher than the total number of wards under the current system, which is 6,743.[29] Examining the distribution of polygon areas revealed that a lot of these values are close to zero. We infer from this that there is significant human error in the construction of these GIS shapefiles, resulting in an imperfect overlap of the two maps.

To circumvent this problem of measurement error in the construction of shape files, we use the tolerance feature in the intersect tool in Arcgis. This feature allows the user to set a tolerance level that ignores arbitrarily small differences in how shape-files are drawn.[30]. We set the tolerance feature to 0.25 km, 0.50 km, 0.75 km, and 1.00 km levels, which yield 7,399, 7,049, 6,526, and 5,922 polygons respectively. We do not want the number of polygons to be significantly less than the number of wards as this is mechanically not possible if we are deploying the intersect command properly. Since the number of polygons yielded by 0.75 km tolerance level is less than the number of wards, we can rule out 0.75 km or higher tolerance level to be useful in this case. That left 0.25 km and 0.50 km, of which we chose 0.25 km for two reasons. First, lower tolerance means we allow for less measurement error and are closer to identifying the true boundaries of polygons. Second, intersecting with 0.25km tolerance level yields more wards with an area less than the smallest polygon area from 0.50 km tolerance than for 0.25 km tolerance level. Specifically, for intersection with 0.50 km tolerance, the smallest polygon has an area of 0.487 square km and there are 78 wards with

[25] Some polygons in this shapefile are non-ward units such as national parks and conservation areas, which means the number slightly overestimates the number of wards.

[26] This number also slightly overestimates the number of 1997 vdcs for the same reason as 2.

[27] We had also acquired a similar shapefile (N = 4,051) from the Survey Department but opted against using it because of its use of different identifiers for non-contiguous areas of the same VDC.

[28] We accessed the shapefile from `hgl.harvard.edu:8080/opengeoportal` on July 10, 2019.

[29] Source: `Ministry of Federal Affairs and General Administration.` Accessed on July 10, 2019.

[30] We have used this tool in previous research: see Gulzar and Pasquale (2017)

area less than this, while for intersection with 0.25 km tolerance, the smallest area is 0.117 square km and there are only two wards smaller than this. This suggests that the 0.25km tolerance minimizes the creation of spurious polygons from the intersection, while generating a fairly accurate number of geographic units we can follow over time.

The resulting polygon-level dataset (N = 7,399) relates 1997 VDCs to 2017 wards. For each polygon in our data, that now comprises the constant geographic unit over time, we now know the corresponding 1997 VDC and the 2017 ward. Since we know the areas of each polygon, VDC, and ward, we can easily calculate what percentage of a local unit (1997 VDC or 2017 ward) comprise a particular polygon.

Once this crosswalk is constructed, we add data to from 1992 and 2017 to this crosswalk using the identifiers from those years. First, we fuzzy match the 1997 VDC names in the crossalk dataset with 1992 VDC names in 1992 elections dataset.[31][32] Second, we fuzzy match the cross-walk data with 2017 municipality names from the 2017 elections data. Third, we measure violence at the level of the polygon – the common geographic unit: "violence" gets a value of 1 if the polygon corresponds to an old VDC that experienced conflict, and zero otherwise. Since this independent variable varies at the old VDC level, we cluster standard errors in our analysis at this level. Finally, we generate other relevant variables at the level of polygon by weighting by the area of polygon. For example, if there were 100 candidates from a new ward in 2017 elections and a polygon constitutes 50 percent area of this ward, then the number of candidates for the polygon is 50.

[31]We use `reclink` command in STATA for fuzzy matching.

[32]By reviewing archival documents, we learned that the changes in local boundaries between 1992 and 1997 were minimal. Specifically, 83 VDCs were converted to 22 new municipalities. We remove these local units from our analysis because of a lack of data on the areas of these converted VDCs.

D Survey of selection committee members

In this section we describe the survey of selection committee members in more detail. We discuss the sampling strategy across different types of committees and different components of the survey. As mentioned in the paper, there were different size of committees at different geographical level across parties. The decision-making committees of UML and Maoist parties were at the level of municipality and districts for deciding candidates at ward and municipality level, respectively. Whereas, for Nepali Congress the corresponding levels were regions (geographically larger than municipality) and districts. The committee that made decisions for municipality positions were also involved in approving ward positions.

Sampling: We had a sampling frame of about 1200 respondents from the decision-making committees across three parties. A stratified sample, stratified on party, type of committee and role in decision-making, was drawn from this list. We sampled 876 respondents, of which 700 were successfully surveyed. We sampled all district committee members (about 287 respondents). Within the regional and municipal selection committees there were typically two key decision makers, chairmen and secretaries for the Nepali Congress and UML, and incharge and coordinator for the Maoist party. We sampled all of them (about 410 respondents). Finally, among the committee members of Maoists and UML we randomly sampled one municipal committee member and for Nepali Congress we randomly sampled three regional committee members (about 178 respondents). This was to account for the size of these committees to ensure representation.

Components of the survey: Each respondent was invited to participate in an interactive survey that lasted an average of 50 minutes. The survey consisted of the following components:

1. Implicit Association Test (IAT): Single Attribute Implicit Association Tests were developed using OpenSesame software. Respondents were invited to take the test on an Android tablet. Two tests were administered for the following purposes:

    - Testing for the association of gender to leadership, and
    - Testing for the association of caste to leadership.

2. Party Leadership Questionnaire (PLQ): Upon completing the IAT exercise, the respondents were invited to a structured interview that included questions on the respondents family, political career, knowledge of the courts and administrative structured set up by the Maoists during the armed conflict, their knowledge of and involvement in the

process of candidate selection in the 2017 local level elections and their views on the performance of their local government leaders. Some questions were filtered out on the basis of the respondent's party and seniority i.e., membership in district vs municipal committee. Some open-ended responses were recorded using an audio recorder.

3. Conjoint Analysis: As part of the conjoint analysis section respondents were invited to select candidates for Mayor, Deputy Mayor or Ward Chairperson from a pool of randomly generated hypothetical profiles of potential candidates. The profiles included the candidates ethnicity, gender, education and monthly income. These exercises were conducted for up to four rounds. The first two rounds were only administered to respondents who were district committee members. In the first round, they were asked to select candidates for the mayoral and deputy mayoral positions from a pool of four profiles assuming no quotas existed while in the second round, at least one of the two candidates selected by the respondent had to be a female. The last two rounds were administered to all respondents. In the third round, respondents are asked to select a candidate for ward chairperson from a pool of two profiles while in the fourth round, the exercise was repeated with the assumption that the ward in question had a history of conflict. The respondents were provided sealed envelopes with the profiles of the potential candidates and their choices were recorded in the PLQ survey form.

4. Self-Administered (Explicit Bias) Questionnaire: The questions in this section asked respondents to give their views on gender and caste in context of political leadership. The questions were printed and sealed in an envelope. Enumerators asked the respondents to read the questions and fill in the answers themselves without showing their choices to the enumerator. Once the respondents answered the questions, they were placed back in an envelope which was then sealed.

E Figures and Tables

Table A1: Balance Tests - Matching the Census Data to Party Lists

	Unique matches (1)		Unmatched (2)		Difference (1)-(2)
Variable	N	Mean/SE	N	Mean/SE	
Age	13754	43.108	4407	43.182	-0.074
		(0.096)		(0.173)	
Female (=1)	15386	0.351	5565	0.356	-0.004
		(0.004)		(0.006)	
Votes Received	13754	422.009	4407	491.841	-69.831***
		(6.166)		(14.824)	
Municipality Position (=1)	15386	0.076	5565	0.110	-0.034***
		(0.002)		(0.004)	
Ward Chair Position (=1)	15386	0.244	5565	0.297	-0.052***
		(0.003)		(0.006)	
Ward Member Position (=1)	15386	0.536	5565	0.444	0.092***
		(0.004)		(0.007)	
Dalit Ward Member Position (=1)	15386	0.144	5565	0.150	-0.006
		(0.003)		(0.005)	
CPN (UML) = 1	15386	0.287	5565	0.284	0.003
		(0.004)		(0.006)	
CPN (M) = 1	15386	0.248	5565	0.276	-0.029***
		(0.003)		(0.006)	
Nepali Congress = 1	15386	0.250	5565	0.247	0.003
		(0.003)		(0.006)	
Other Political Parties = 1	15386	0.215	5565	0.193	0.022***
		(0.003)		(0.005)	

Notes: The value displayed for t-tests are the differences in the means across the groups.
Levels of significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A2: Political Selection by Position

	Population	Mayor	Deputy Mayor	Ward Chair	Ward Member	Female Member	Dalit Female Member
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female (=1)	0.49	0.05	0.84	0.02	0.02	1.00	1.00
	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Elite Caste (=1)	0.62	0.67	0.63	0.70	0.66	0.67	0.04
	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Dominant Caste (=1)	0.47	0.59	0.62	0.57	0.48	0.50	0.02
	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Education (years)	2.89	5.96	5.56	4.91	3.41	2.45	1.64
	(0.00)	(0.17)	(0.19)	(0.06)	(0.04)	(0.05)	(0.05)
Income (Rupees)	12341.61	17277.43	16169.15	15578.24	12883.30	12954.95	10621.37
	(5.12)	(569.27)	(570.96)	(197.45)	(130.40)	(180.12)	(170.87)
Assets (Z-Score)	-0.00	0.02	0.02	0.01	-0.00	0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Age (years)	43.06	45.85	39.47	45.27	44.51	40.28	39.70
	(0.01)	(0.49)	(0.50)	(0.19)	(0.15)	(0.19)	(0.22)
# Observations	3680772	483	402	3208	5683	2778	2237

Notes:

Table A3: Sampling Attrition Tests

Dependent variable:	Successfully Interviewed (=1)				
	(1)	(2)	(3)	(4)	(5)
Female (=1)	0.005				0.008
	(0.048)				(0.049)
Maoist (=1)		-0.021			-0.033
		(0.030)			(0.031)
Nepali Congress (=1)		0.007			-0.029
		(0.037)			(0.047)
District Committee			0.039		0.049
			(0.027)		(0.035)
Dolakha				0.081	0.075
				(0.055)	(0.056)
Gorkha				-0.070	-0.074
				(0.063)	(0.062)
Kavrepalanchowk				0.091*	0.089*
				(0.052)	(0.051)
Makwanpur				-0.048	-0.059
				(0.064)	(0.064)
Nuwakot				0.022	0.020
				(0.059)	(0.059)
Okhaldhunga				-0.042	-0.044
				(0.068)	(0.068)
Ramechhap				0.067	0.059
				(0.060)	(0.060)
Rasuwa				0.004	-0.009
				(0.071)	(0.071)
Sindhuli				-0.042	-0.046
				(0.063)	(0.063)
Sindhupalchowk				-0.006	-0.010
				(0.060)	(0.060)
Constant	0.798***	0.806***	0.783***	0.792***	0.797***
	(0.014)	(0.021)	(0.018)	(0.041)	(0.044)
Omitted Category	Male	UML	Muni. Comms.	Dhading	All Cols 1 -4
R-Squared	0.00	0.00	0.00	0.02	0.02
# Observations	883	883	883	883	883

Notes: This table reports on the predictors of successfully interviewing a party selection committee member. 705 of the 883 party selection committee members sampled were successfully interviewed, yielding a success rate of 79.84%. Summary statistics describing the sample are reported in Table 3.
Levels of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A4: Political Selection By Position and By Caste

	Voting Population		Mayor		Deputy Mayor		Ward Chair		Ward Member		Female Member	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Age (Years)												
Elite	44.616	(0.135)	49.725	(1.096)	39.203	(1.150)	46.824	(0.461)	45.589	(0.365)	41.418	(0.456)
Non-elite	41.751	(0.124)	48.519	(1.507)	37.316	(2.110)	43.897	(0.564)	43.887	(0.399)	38.707	(0.484)
Difference	2.864	(0.183)	1.207	(1.863)	1.887	(2.403)	2.927	(0.729)	1.702	(0.541)	2.712	(0.665)
Female												
Elite	0.499	(0.000)	0.020	(0.016)	0.922	(0.030)	0.000	(0.002)	0.013	(0.004)	1.000	(0.000)
Non-elite	0.498	(0.000)	0.000	(0.022)	1.000	(0.055)	0.003	(0.002)	0.011	(0.004)	1.000	(0.000)
Difference	0.001	(0.001)	0.020	(0.027)	-0.078	(0.062)	-0.003	(0.003)	0.002	(0.006)	0.000	(0.000)
Dominant Caste												
Elite	0.589	(0.000)	0.686	(0.058)	0.625	(0.058)	0.628	(0.021)	0.584	(0.016)	0.579	(0.023)
Non-elite	0.658	(0.000)	0.926	(0.079)	0.842	(0.107)	0.849	(0.026)	0.769	(0.017)	0.775	(0.024)
Difference	-0.069	(0.001)	-0.240	(0.098)	-0.217	(0.122)	-0.221	(0.033)	-0.186	(0.024)	-0.196	(0.033)
Education (Years)												
Elite	3.817	(0.003)	7.814	(0.485)	6.141	(0.479)	6.174	(0.166)	4.482	(0.108)	3.190	(0.134)
Non-elite	2.339	(0.003)	5.333	(0.666)	7.789	(0.879)	4.390	(0.203)	3.106	(0.118)	1.963	(0.142)
Difference	1.479	(0.004)	2.480	(0.824)	-1.649	(1.002)	1.783	(0.262)	1.376	(0.161)	1.227	(0.195)
Ability - Mincer Wage Residual (Z-score)												
Elite	0.089	(0.001)	0.890	(0.290)	0.252	(0.137)	0.584	(0.069)	0.236	(0.041)	0.203	(0.061)
Non-elite	-0.090	(0.001)	0.292	(0.366)	0.258	(0.224)	0.340	(0.086)	0.060	(0.045)	0.071	(0.062)
Difference	0.179	(0.001)	0.598	(0.467)	-0.007	(0.262)	0.244	(0.111)	0.175	(0.061)	0.132	(0.087)
Income (Rupees)												
Elite	14113.243	(8.698)	24705.882	(1890.704)	15781.250	(1317.838)	18995.434	(584.881)	14791.169	(348.041)	14817.518	(494.720)
Non-elite	11008.135	(8.857)	15740.741	(2598.524)	18684.211	(2418.663)	14880.137	(716.330)	12414.530	(380.263)	12245.179	(526.413)
Difference	3105.108	(12.414)	8965.142	(3213.579)	-2902.961	(2754.383)	4115.297	(924.778)	2376.640	(515.492)	2572.339	(722.398)
Asset Index (Z-score)												
Elite	0.177	(0.001)	1.053	(0.295)	0.590	(0.168)	0.776	(0.075)	0.301	(0.036)	0.356	(0.056)
Non-elite	-0.182	(0.001)	0.632	(0.406)	0.129	(0.308)	0.287	(0.092)	-0.058	(0.040)	-0.098	(0.059)
Difference	0.360	(0.001)	0.421	(0.502)	0.460	(0.351)	0.489	(0.118)	0.360	(0.054)	0.454	(0.081)
# Observations	2,195,297		78		83		732		1,549		782	

Notes: This table reports means of key demographics for the voting age population, and for politicians at each level of Nepal's local government separately for included and excluded castes. Ability is the z-score of the residual from the regression $Income_i = f(Education_i, Age_i) + \gamma_w + \varepsilon_i$, where $Education_i$ is a dummy variable equal to one for having above median education, Age_i is a categorical variable with five year age bins, and γ_w are ward fixed effecs. Function f represents the fact that this specificaton includes a dummy for each subgroup and for every possible double and triple interaction. Standard errors are reported in parentheses.

Table A5: Political Selection by Position and Party

	Mayor		Deputy Mayor		Ward Chair		Ward Member		Female Member		Dalit Female Member	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Age (Years)												
Maoists	47.250	(2.068)	36.000	(1.726)	43.220	(0.753)	43.458	(0.591)	39.247	(0.630)	38.229	(0.739)
UML	50.475	(1.135)	39.730	(1.497)	46.142	(0.497)	45.352	(0.382)	40.533	(0.491)	39.714	(0.577)
Congress	49.125	(1.715)	39.300	(1.875)	46.450	(0.688)	44.798	(0.507)	40.203	(0.654)	40.881	(0.743)
Diff: UML - Maoist	3.225	(2.359)	3.730	(2.284)	2.922	(0.902)	1.894	(0.704)	1.285	(0.799)	1.485	(0.938)
Diff: Congress - Maoist	1.875	(2.687)	3.300	(2.549)	3.230	(1.020)	1.339	(0.779)	0.956	(0.908)	2.652	(1.048)
Female												
Maoist	0.000	(0.000)	0.800	(0.105)	0.000	(0.000)	0.022	(0.008)	1.000	(0.000)	1.000	(0.000)
UML	0.025	(0.025)	0.973	(0.027)	0.003	(0.003)	0.010	(0.004)	1.000	(0.000)	1.000	(0.000)
Congress	0.000	(0.000)	0.967	(0.033)	0.000	(0.000)	0.008	(0.004)	1.000	(0.000)	1.000	(0.000)
Diff: UML - Maoist	0.025	(0.025)	0.173	(0.109)	0.003	(0.003)	-0.012	(0.009)	0.000	(0.000)	0.000	(0.000)
Diff: Congress - Maoist	0.000	(0.000)	0.167	(0.110)	0.000	(0.000)	-0.013	(0.009)	0.000	(0.000)	0.000	(0.000)
Elite Caste												
Maoist	0.417	(0.145)	0.867	(0.089)	0.500	(0.041)	0.433	(0.028)	0.462	(0.038)	0.022	(0.012)
UML	0.700	(0.074)	0.757	(0.072)	0.661	(0.027)	0.561	(0.019)	0.577	(0.026)	0.025	(0.009)
Congress	0.750	(0.090)	0.733	(0.082)	0.603	(0.031)	0.583	(0.022)	0.523	(0.032)	0.015	(0.009)
Diff: UML - Maoist	0.283	(0.163)	-0.110	(0.115)	0.161	(0.049)	0.128	(0.033)	0.115	(0.046)	0.003	(0.015)
Diff: Congress - Maoist	0.333	(0.171)	-0.133	(0.122)	0.103	(0.051)	0.150	(0.036)	0.061	(0.050)	-0.007	(0.015)
Dominant Caste												
Maoist	0.667	(0.139)	0.800	(0.105)	0.747	(0.036)	0.715	(0.025)	0.730	(0.034)	0.057	(0.020)
UML	0.775	(0.067)	0.703	(0.077)	0.687	(0.026)	0.641	(0.018)	0.606	(0.026)	0.025	(0.009)
Congress	0.792	(0.085)	0.567	(0.092)	0.723	(0.028)	0.669	(0.021)	0.701	(0.030)	0.045	(0.015)
Diff: UML - Maoist	0.108	(0.154)	-0.097	(0.130)	-0.060	(0.044)	-0.074	(0.031)	-0.124	(0.043)	-0.033	(0.021)
Diff: Congress - Maoist	0.125	(0.163)	-0.233	(0.140)	-0.024	(0.046)	-0.046	(0.033)	-0.029	(0.045)	-0.012	(0.025)
Education (Years)												
Maoists	5.208	(1.054)	5.733	(1.035)	5.123	(0.292)	3.652	(0.168)	2.092	(0.176)	1.650	(0.177)
UML	7.875	(0.530)	7.027	(0.652)	5.684	(0.207)	3.892	(0.125)	2.874	(0.157)	2.054	(0.151)
Congress	6.542	(0.749)	6.233	(0.691)	5.416	(0.220)	3.951	(0.144)	2.660	(0.181)	1.284	(0.131)
Diff: UML - Maoist	2.667	(1.179)	1.294	(1.223)	0.560	(0.357)	0.240	(0.209)	0.782	(0.235)	0.404	(0.233)
Diff: Congress - Maoist	1.333	(1.293)	0.500	(1.245)	0.292	(0.365)	0.299	(0.221)	0.568	(0.252)	-0.366	(0.220)
Ability - Mincer Wage Residual (Z-score)												
Maoists	0.201	(0.573)	0.098	(0.183)	0.183	(0.094)	0.162	(0.069)	0.116	(0.094)	-0.213	(0.078)
UML	0.658	(0.357)	0.222	(0.209)	0.505	(0.080)	0.143	(0.046)	0.132	(0.065)	-0.125	(0.059)
Congress	0.874	(0.360)	0.369	(0.191)	0.666	(0.104)	0.184	(0.051)	0.167	(0.078)	-0.185	(0.058)
Diff: UML - Maoist	0.458	(0.675)	0.124	(0.278)	0.321	(0.124)	-0.020	(0.083)	0.016	(0.114)	0.088	(0.098)
Diff: Congress - Maoist	0.673	(0.677)	0.271	(0.265)	0.483	(0.140)	0.021	(0.086)	0.051	(0.122)	0.028	(0.097)
Income (Rupees)												
Maoists	21250.000	(3806.519)	15333.333	(2375.063)	15133.333	(878.598)	13544.892	(559.244)	12587.209	(773.316)	10107.143	(639.221)
UML	22750.000	(2574.563)	15945.946	(1865.470)	17674.051	(663.392)	14123.932	(388.501)	14263.456	(555.170)	11769.231	(521.117)
Congress	20416.667	(2286.611)	18000.000	(1884.292)	18534.137	(871.430)	13425.358	(450.741)	13381.743	(616.904)	10348.259	(489.188)
Diff: UML - Maoist	1500.000	(4595.428)	612.613	(3020.083)	2540.717	(1100.919)	579.040	(680.945)	1676.247	(951.962)	1662.088	(824.722)
Diff: Congress - Maoist	-833.333	(4440.515)	2666.667	(3031.746)	3400.803	(1237.467)	-119.534	(718.277)	794.533	(989.236)	241.116	(804.927)
Asset Index (Z-score)												
Maoists	0.029	(0.178)	-0.121	(0.225)	0.091	(0.086)	-0.209	(0.035)	-0.272	(0.042)	-0.318	(0.043)
UML	0.936	(0.338)	0.464	(0.211)	0.403	(0.083)	0.002	(0.037)	0.035	(0.059)	-0.189	(0.040)
Congress	0.358	(0.266)	0.169	(0.175)	0.347	(0.078)	-0.045	(0.036)	-0.043	(0.056)	-0.276	(0.044)
Diff: UML - Maoist	0.908	(0.382)	0.585	(0.308)	0.312	(0.119)	0.211	(0.051)	0.307	(0.073)	0.129	(0.058)
Diff: Congress - Maoist	0.330	(0.320)	0.290	(0.285)	0.256	(0.116)	0.164	(0.050)	0.228	(0.070)	0.041	(0.061)
# Observations	78		83		732		1,549		782		682	

Notes: This table reports means of key demographics for the voting age population, and for politicians at each level of Nepal's local government separately by party. Ability is the z-score of the residual from the regression $Income_i = f(Education_i, Age_i) + \gamma_w + \varepsilon_i$, where $Education_i$ is a dummy variable equal to one for having above median education, Age_i is a categorical variable with five year age bins, and γ_w are ward fixed effecs. Function f represents the fact that this specificaton includes a dummy for each subgroup and for every possible double and triple interaction. Standard errors are reported in parentheses. We are able to estimate means for included castes in the Dalit Female Member seat as our data indicate that 14 of the 682 Dalit Female Members are from included castes.

Table A6: Elite Status and Becoming a Politician

Panel A - Candidates						
Dependent variable:	Candidate in Ward Race (=1) x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.010***	0.003	0.020***	0.011***	0.017***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female (=1)	-0.055***	-0.051***	-0.057***	-0.053***	-0.054***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Education (z-score)		0.013***		0.013***		0.013***
		(0.001)		(0.001)		(0.001)
Income (z-score)		0.005***		0.013***		0.012***
		(0.001)		(0.001)		(0.002)
Asset Index (z-score)		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Party	Maoist	Maoist	UML	UML	NPC	NPC
# Observations	2540433	2540433	2540433	2540433	2540433	2540433
R-Squared	0.000	0.001	0.000	0.001	0.000	0.001
Mean in Population	0.028	0.028	0.030	0.030	0.028	0.028
Panel B - Representatives						
Dependent variable:	Wins Seat in Ward Race (=1) x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.002*	0.000	0.010***	0.006***	0.005***	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Female (=1)	-0.012***	-0.011***	-0.025***	-0.022***	-0.019***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education (z-score)		0.003***		0.006***		0.004***
		(0.001)		(0.001)		(0.001)
Income (z-score)		0.001**		0.007***		0.006***
		(0.001)		(0.001)		(0.001)
Asset Index (z-score)		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Party	Maoist	Maoist	UML	UML	NPC	NPC
# Observations	2540433	2540433	2540433	2540433	2540433	2540433
R-Squared	0.001	0.001	0.000	0.001	0.000	0.001
Mean in Population	0.006	0.006	0.012	0.012	0.010	0.010

Notes: This table reports on the predictors of receiving a party ticket (panel A) and of winning office (Panel B) separately for each party. UML corresponds to the United Marxist Lenininst and NPC to the Nepali Congress Party. All regressions include constituency fixed effects.
Levels of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A7: Elite Status and Candidacy by Party

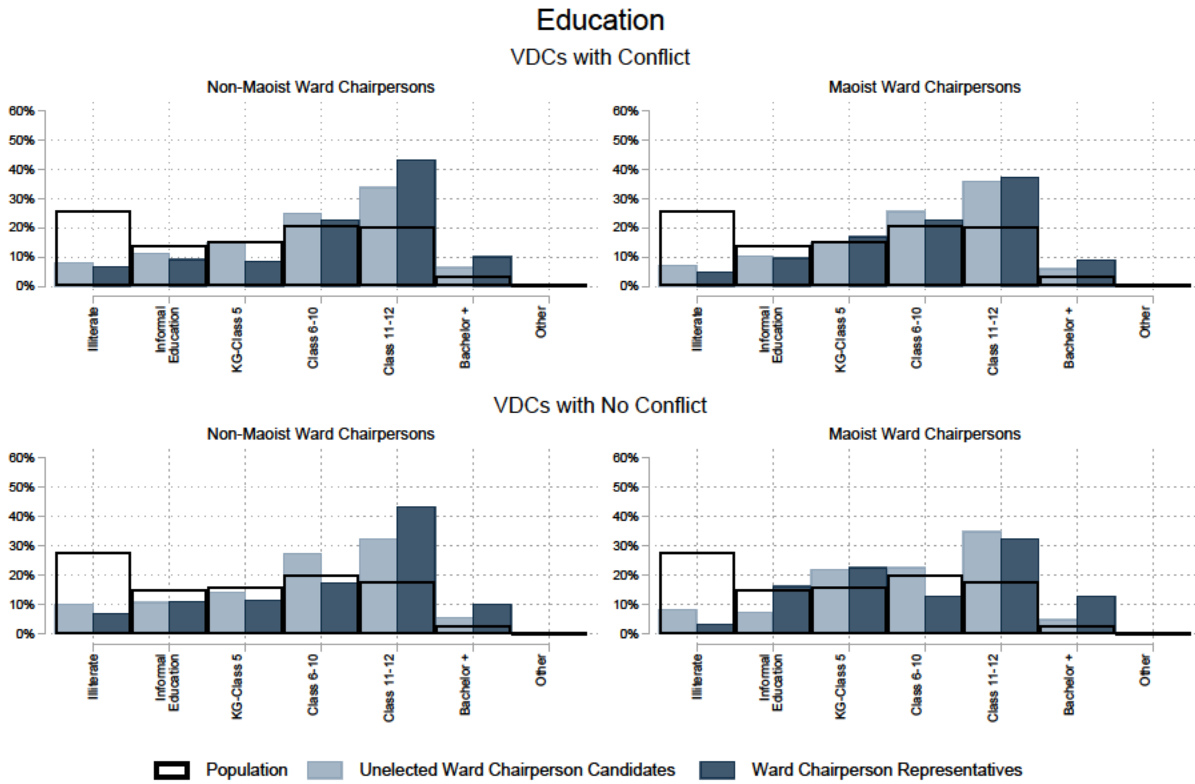
Panel A - Candidates						
Dependent variable:	Candidate in Municipal Race (=1) x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.004***	0.001	0.004***	0.001	0.005***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female (=1)	-0.001	0.001	0.000	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education (z-score)		0.004***		0.006***		0.005***
		(0.001)		(0.001)		(0.001)
Income (z-score)		0.002***		0.002***		0.003***
		(0.001)		(0.001)		(0.001)
Asset Index (z-score)		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Party	Maoist	Maoist	UML	UML	NPC	NPC
# Observations	2540433	2540433	2540433	2540433	2540433	2540433
R-Squared	0.000	0.000	0.000	0.000	0.000	0.000
Mean in Population	0.005	0.005	0.006	0.006	0.005	0.005
Panel B - Representatives						
Dependent variable:	Wins Seat in Municipal Race (=1) x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Elite Caste (=1)	0.001*	0.000	0.003***	0.001	0.003***	0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Female (=1)	-0.000	-0.000	-0.000	0.001	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Education (z-score)		0.001***		0.003***		0.002***
		(0.000)		(0.001)		(0.000)
Income (z-score)		0.001**		0.001***		0.001***
		(0.000)		(0.001)		(0.000)
Asset Index (z-score)		-0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Party	Maoist	Maoist	UML	UML	NPC	NPC
# Observations	2540433	2540433	2540433	2540433	2540433	2540433
R-Squared	0.000	0.000	0.000	0.000	0.000	0.000
Mean in Population	0.001	0.001	0.003	0.003	0.002	0.002

Notes: This table reports on the predictors of receiving a party ticket (panel A) and of winning office (Panel B) separately for each party. UML corresponds to the United Marxist Lenininst and NPC to the Nepali Congress Party. All regressions include constituency fixed effects.
Levels of significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A8: Frequency of stated reasons for differences in conflict areas by political party leaders

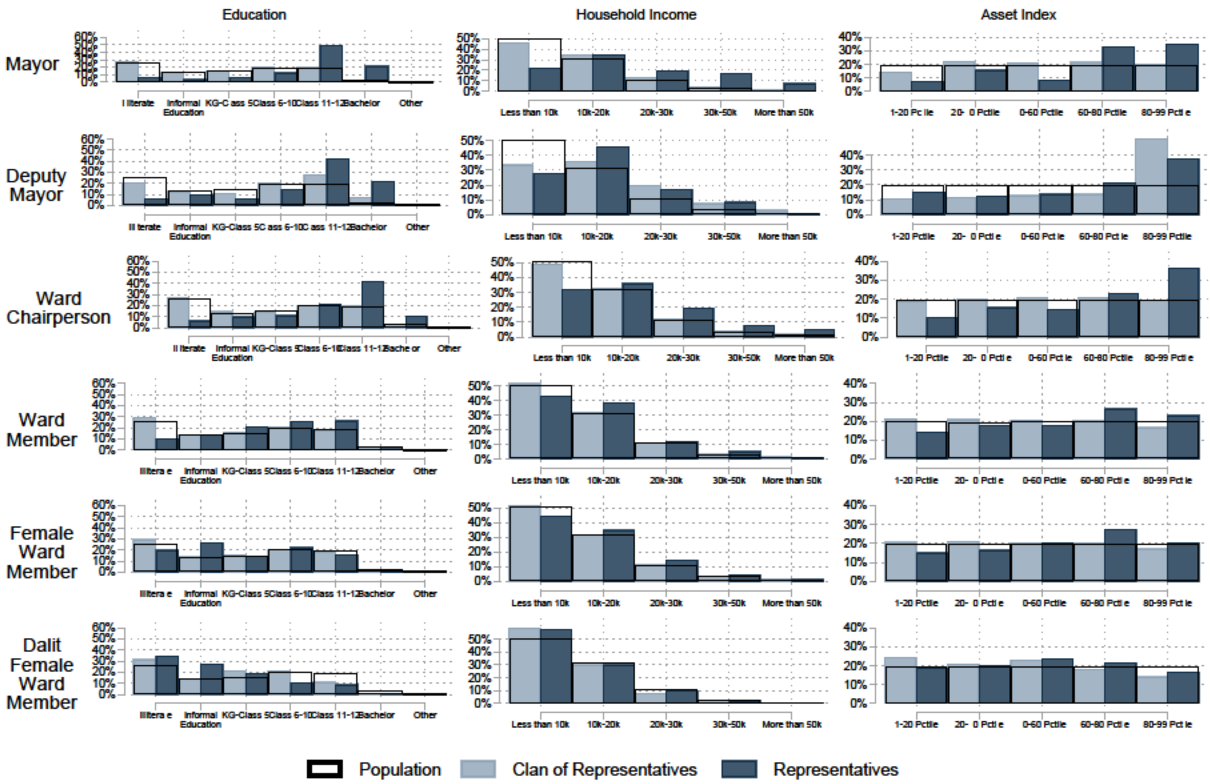
Sample	Total	UML	Maoist	Nepali Congress
Greater political participation by non-elite castes	13	6	5	2
Greater political consciousness	13	6	5	2
Maoist coercion	12	2	0	10
Stronger norms of inclusion	5	2	3	0
Stronger norms of democratic engagement	4	2	0	2
Altered perceptions of marginalized groups	4	1	2	1
Direct effect of Maoist presence during revolution	4	2	1	1
Displacement of population	4	2	1	1
Marginalized groups were most populous	3	0	0	3

Figure A2: Conflict and Education across Parties



Notes: The figure shows the distribution of education for the adult population in 11 districts in Nepal as well as for unelected candidates and elected representatives for ward chair positions. The distributions are further shown across VDCs that did and did not experience conflict during the Maoist Revolution, as measured by whether a death occurred in the VDC from the Insec data. Additionally, these distributions are separated for Maoist politicians and politicians from the UML and Nepali Congress.

Figure A3: Political Selection by Position



Notes: