Civil conflict and international migration in Nepal

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Economics

at

The University of Waikato

by

Hari Prasad Sharma

THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

2020

Abstract

A growing literature studies the causes and consequences of civil conflict. Several of these studies are of Nepal's civil conflict that lasted for a decade from 1996. Coincident with this conflict was a surge in work-related emigration, affecting education and human capital investments, labour supply, and local economic activity. While a few prior studies look at the effects of Nepal's conflict on emigration, many key features of the conflict are ignored. In particular, heterogeneity due to the highly localized nature of the conflict tends to be ignored by the type of data and research designs used in prior studies. In this thesis, I contribute to the literature on the causes and consequences of civil conflict by constructing and using very local indicators of driving forces and intensity of Nepal's civil conflict.

Contrary to prior literature that suggests there is more conflict in poorer regions, I find poverty is associated with less conflict risk and conflict intensity, partly due to a change in strategy by the rebels in Nepal to target richer middle class and urban areas to win the war. At the same time, inequality and caste-based polarisation at local levels were major contributors that escalated the civil conflict. In order to study conflict escalation and also to study the impact of conflict intensity on migration, I construct a database of conflict deaths, and of poverty, inequality and caste polarization for almost 4000 localities. In contrast, most previous research on Nepal relies on data aggregated to the district level, suppressing detail as there are only 75 districts and there was far more variation in conflict intensity within districts than between districts. Estimated impacts of conflict on emigration are substantially distorted by using district-level conflict data.

The growth in emigration that sees over two million Nepalese working abroad has also given a great boost to remittances, which are now equivalent to about one-third of GDP. The effects of emigration and remittances on human capital investment – particularly child schooling and child labour – remain debated in the literature. I construct a two-wave panel at the locality level to study these issues, with careful attention paid to the endogeneity of emigration and to spatial spillover

effects. In localities with a greater increase in emigration, the net enrolment rate in secondary education rises and child labour for older children decreases. A possible channel for this effect is that migration and remittances help credit constrained households to cover extra schooling costs and compensate for the foregone earnings from child labour. In addition to finding an overall positive effect of emigration, I find that the direct (own) effect of emigration increases labour supply of the female labour force but decreases the labour supply in the agriculture sector. There are also positive spatial spillover effects for rural localities, that likely occur through rising local wage rates.

Given these generally positive effects of emigration, the fact that local conflict intensity suppressed the growth in emigration suggests that there is a lasting negative effect of the civil conflict in particular parts of Nepal. These effects would not be apparent in the overly aggregated data on conflict that has been used to date. Thus, one contribution of this thesis is to show the benefit of a very local focus on the causes and consequences of civil conflict.

Note on Publication

Several working papers have been produced from this thesis and some are currently submitted for journal publication and are under review. The list of papers is as follows;

Working papers:

Sharma, H., & Gibson, J. (2020). *Escalation of civil war in Nepal: The role of poverty, inequality and caste polarisation.* (MPRA Paper No. 101450). Munich, Germany: Munich University Library (Chapter Two)

Sharma, H., & Gibson, J. (2019). *Civil war and international migration from Nepal: Evidence from a Spatial Durbin Model* (Working Paper in Economics 19/06). Hamilton, New Zealand: University of Waikato. (Chapter Three)

Sharma, H., & Gibson, J. (2020). *Effects of international migration on child schooling and child labour: Evidence from Nepal* (Working Paper in Economics 20/067). Hamilton, New Zealand: University of Waikato. (Chapter Four)

Sharma, H. (2020). *The effect of emigration and remittances on labour supply of the left-behind: Evidence from Nepal.* (MPRA paper No. 102091). Munich, Germany: Munich University Library. (Chapter Five)

Acknowledgements

First of all, I would like to express my sincere thanks to my chief supervisor Professor John Gibson for his guidance and input throughout my PhD journey. His immense knowledge, expertise and patience boosted my confidence to go deeper into the analysis in order to excel in research. My research data is from Nepal's Civil war; conducting a rigorous academic study on such a sensitive topic and connecting it with socio-economic perspectives has been a tough job, but under his supervision and guidance I left no stone unturned. Additionally, I would like to thank Prof. David Fielding from Otago University and Associate Professor Liang Choon Wang from Monash University for their comments and valuable input in my Thesis that have helped me to improve my work.

I would also like to express my gratitude to Dr. Susan Olivia and Ms. Maria Neal for their unending support and encouragement that has helped so much in my research. I would also like to acknowledge the amazing support of the University and the Department of Economics by providing a Doctoral Fellowship and study award to fund my entire PhD research, and for giving me an opportunity to test my teaching skills.

I am thankful to the Central Bureau of Statistics-Nepal for their support and for providing access to various databases such as National Population and Housing data, the Nepal Living Standards Survey and the Labour Force Survey. I am extremely thankful to INSEC (Informal Sector Service Center) Nepal for making the raw conflict data available.

I am thankful to Geua Boe-Gibson for helping me to draw maps and to learn ArcGIS. I would also like to thank PhD fellows from the Department of Economics, who helped me to lighten my days with fun and humour. My special thanks to department seminar participants, and PhD students from other universities who I have met in various conferences for their constructive feedback and ideas that helped me to enhance the quality of my research. I would like to express my gratitude to every

individual who became a part of my journey and provided the support and motivation that sustained me throughout the rigorous four years of my research.

Finally, I am grateful to my parents, my siblings, and my friends for their love and prayers throughout my journey. I am also privileged to have had my wife (Jinita) by my side in this journey; her knowledge and constructive feedback certainly added value to my research. Without the emotional and moral support from my family and friends, I could not have accomplished my academic goal so smoothly.

Table of Contents

Abstract ii
Acknowledgements v
Table of Contents vii
List of Tables ix
List of Figures x
Chapter One: Introduction 1
1.1 Motivation and contribution of the study 1
1.2 Research Questions 5
1.3 Escalation of civil conflict in Nepal 5
1.4 A brief history of migration from Nepal 7
1.5 Introduction to the data and sources 9
1.6 Main Results 11
1.7 Organisation of the thesis 12
References 13
Chapter Two: Escalation of civil war in Nepal- The role of poverty, inequality and caste polarisation 15
2.1 Introduction 16
2.2 Nepal's civil conflict (1996-2006) 21
2.3 Data and Empirical Methods 25
2.3.1 Survey to census imputation of small area poverty 26
2.3.2 Household Assets indictor for inequality: 29
2.3.3 Ethnic polarisation index 30
2.3.4 Econometric Model 31
2.4 Results and discussion 33
2.5 Conclusion 45
2.6 Reflection on this chapter 46
References 48
Appendix 52
Chapter Three: Mean-Reverting Errors and Spatially Aggregated Conflict Data- Impacts of Civil War on International Migration from Nepal 55
3.1 Introduction 56
3.2 Context 61
3.2.1 Emigration from Nepal 61
3.2.2 Nepal's Civil War 66
3.3 Data and Methods 71
3.3.1 The Econometric Model 72
3.4 Results 75

3.4.1 Sensitivity Analysis 84
3.5 Conclusions 87
3.6 Reflection on this chapter 88
References 90
Appendix 93
Chapter Four: Effects of international migration on child schooling and child labour: Evidence from Nepal 97
4.1 Introduction 98
4.2 Context 103
4.2.1 School education in Nepal 103
4.2.2 Migration from Nepal 106
4.3 Data and Methods 107
4.3.1 The Econometric Model 109
4.4 Results and discussion 116
4.5 Conclusions 127
4.6 Reflection on this chapter 129
References 130
Appendix 133
Chapter Five: The effect of emigration and remittances on labour supply of the left-behind: Evidence from Nepal 135
5.1 Introduction 136
5.2 Context: Migration from Nepal 139
5.3 Data and Methods 141
5.3.1 Interconnected matrix: 145
5.3.2 The Econometric Model 147
5.4 Results and discussion 151
5.5 Conclusions 167
5.6 Reflection on this chapter 168
References 170
Appendix 174
Chapter Six: Conclusion and implications 175
Conclusion 175
Implications 178
Appendix: Co-Authorship forms 180

List of Tables

Table 2.1. Variable definitions and descriptive statistics 34
Table 2.2. Estimated effects on conflict probability and conflict intensity using logit and negative binomial models 36
Table 2.3. Cross-sectional analyses of effects of poverty, inequality and polarisation on conflict.....41
Table 2.4. The estimated direct, indirect and total impacts from Spatial Autoregressive models 44
Table 3.1. Variable definition and descriptive Statistics 92
Table 3.2. Spatial Durbin models for change in the VDC emigration rate between 2001 and 2011, with different spatial granularity of conflict data 78
Table 3.3. Estimated direct, indirect, and total impacts, averaging over all 3982 VDCs 83
Table 4.1. Descriptive statistics.....105
Table 4.2. The first stage migration and remittance model estimating the effect of instrument 117
Table 4.3. The effect of migration on net enrolment rate at Basic and Secondary education for children aged 5-12 and 13-16.....120
Table 4.4. The effect of migration on child labour force participation and no of hour worked in labour market 123
Table 4.5. The effect of migration on school attendance and dropout rate of children aged 5-16, 5-12 and 13-16 125
Table 5.1. Descriptive statistics.....144
Table 5.2. The first stage model for locality emigration rate.....152
Table 5.3. Second stage regression model for labour force participation (LFP) rates 155
Table 5.4. Spillover effects on labour force participation rate: neighbours based on closest geographical proximity.....157
Table 5.5. Spillover effects on labour force participation rates in urban and rural localities: neighbours based on geographical proximity 160
Table 5.6. Spillover effects on labour force participation rate: neighbours based on road network 162
Table 5.7. Spillover effects on labour force participation rate: neighbours based on shortest geographical distance to the market.....166

List of Figures

Figure 2.1. (a) Conflict affected villages (b) Conflict related deaths, each year 17
Figure 2.2. Nepal's conflict (1996-2000) (a) Conflict affected villages,
(b) Number of deaths 22
Figure 2.3. Nepal's conflict (2001-2005) (a) Conflict affected villages,
(b) Number of deaths.....24
Figure 2.4. Spatial variation in poverty rate in all 75 districts of Nepal 29
Figure 3.1. Average emigration rates from Nepal, 2001and 2011 62
Figure 3.2. Emigration rate to (a) all countries, (b) India (c) other Asia and
Middle East at VDC level, 2001 Census.....63
Figure 3.3. Change in emigration rate at VDC level between 2001 and
2011 to (a) all countries, (b) India (c) other Asia and Middle East 65
Figure 3.4. Annual conflict-related deaths during civil war in Nepal 67
Figure 3.5. Spatial variation in conflict intensity: (a) deaths, (b) death rates,
(c) smoothed by District 69
Figure 3.6. Main results are robust to inclusion or exclusion of control variables:
Estimated direct, indirect and total impacts of conflict intensity.....85
Figure 4.1. (a) Migrants share in India and MEOA (b) Mean of migration rate 114
Figure 4.2. The migrants share and migration rate in 2001 and 2011 115
Figure 5.1. a) Spatial distribution of PSUs, b) PSU and Road network 145
Figure 5.2. Spatial distribution of PSU and local market 164

Chapter One: Introduction

1.1 Motivation and contribution of the study

A growing literature studies the causes and consequences of civil war. The identification of the short- and long-term impacts of civil conflict is crucial to guide post conflict policy. More generally, understanding why conflict escalates and persists and what are the underlying mechanisms that prolong conflict are important to the design of adequate policies and institutions. Recently, Nepal's civil conflict, which lasted for about ten years (1996-2006), has received attention in the literature, especially in terms of impacts on migration, human capital, women's empowerment, local economic activities, and so on. The rise in civil conflict was accompanied by growth in work related international migration from Nepal. Specifically, the growth in emigration from Nepal is such that over two million Nepalese people are now working abroad. This rise in work related migration reduced poverty considerably. Yet, the issue of how emigration and remittances affect human capital and domestic labour supply are important policy concerns since the country is expected to have a 17% emigrant population by 2025 (Sijapati et al., 2015).

In light of the existing state of knowledge, this thesis is intended to make several contributions to the literature. First, I aim to identify the role of poverty, inequality and caste polarisation in escalating civil conflict, and subsequently estimate the impact of civil conflict on international migration. Second, in contrast to previous literature, I develop conflict intensity measures and associated factors at the local level (third sub-national level or village) for almost 4000 localities. Most previous research in Nepal has focussed on more aggregated units of just 75 Districts. Third, I highlight key a aggregation issue in civil conflict related literature that may have distorted the estimated impact of civil war. Fourth, I explore the impacts of emigration on human capital and labour supply to highlight possible long term effects of civil conflict. More precisely, if civil conflict has an impact on emigration, which is a major income generating activity in Nepal, then long term impacts of conflict crucially depend on how emigration affects human capital, local

markets, and so on. Fifth, I examine spatial spillover effects of emigration and remittances on labour supply.

In the last ten years, there has been a surge in literature exploring the causes of civil conflict and its consequences for migration, education, women's empowerment and so on in Nepal. For example, major studies are conducted by Adhikari (2012), Bohara et al. (2006), Do and Iyer (2010), Murshed and Gates (2005), Nepal et al. (2011), Pivovarova and Swee (2015) and Shrestha (2017). Apart from Nepal et al. (2011), these prior studies have ignored a key feature of Nepal's civil conflict, which is that it was very localised and heterogeneous. While conflict spread from west to east of the country over ten years, it was not evenly spread across the country and localities were not all affected to the same extent.

The common problem with these studies is that they typically rely on spatially aggregated conflict data that are easily available at the district level (second subnational level) and ignore the local variation. In fact, there was far more variation in conflict intensity within districts than between districts. Nepal's civil conflict was very localized, and almost 45% of localities (also known as Village Development Committees or VDCs and sometimes just villages) had no deaths recorded. In contrast, when data are aggregated to the district level just two of 75 districts (that is, 3% of the total) had no conflict-related deaths. Thus, the spatially aggregated data make the conflict appear more widespread, and this may distort estimated impacts on migration, human capital and other outcomes of research interest. Over aggregation of conflict data is inappropriate if there is lot of heterogeneity in conflict at local level (Sambanis, 2002; Taydas & Peksen, 2012). In particular, this can create mean reverting measurement error that will distort the estimated impact of conflict. This bias matters because researchers need to correctly identify the local consequences of conflict in order to design appropriate post conflict policy.

Similarly, when studies look at determinants of civil conflict, they often use survey estimates like poverty and inequality, which are traditionally available only at the first or second

sub-national level (such as province and district). However, the administrative level for which survey data are easily available is not necessarily the right aggregation level, especially in countries like Nepal with a lot of local heterogeneity (Cederman & Gleditsch, 2009). Studying civil conflict at overly-aggregated levels like the district level may distort our understanding of how conflict escalates and persists. This may be a major issue in conflict-related studies in other countries where researchers appear to have assumed that civil war is a fairly aggregated outcome and the factors that affect conflict are homogeneous across the country or across larger spatial units. Instead of designing an analysis based on the availability of aggregated poverty and inequality estimates, a better solution is to use modern small-area estimation techniques to get welfare estimates at the very local level to reflect local heterogeneity (Elbers et al., 2003).

Another key trend that my research exploits is that Nepal has also witnessed a significant rise in work related migration along with the rise in civil conflict. Consequently, emigration for work emerged as a major source of livelihoods and subsequent inflows of remittances led to a significant reduction in national poverty. Yet, there are limits on our understanding of how emigration is translating into better child school performance and labour supply of non-migrants, both in Nepal and more generally (Davis & Brazil, 2016; McKenzie & Rapoport, 2011). Relatedly, there is also rising policy concern in Nepal regarding falling labour supply in agriculture and the manufacturing sector. Indeed, the manufacturing sector partly relies on labour coming from India, while agricultural households either have to rely on family exchange labour or leave the land barren due to the labour shortages.

Previous studies in Nepal including Acharya & Leon-Gonzalez (2014), Shrestha (2017), and Karki Nepal (2016) and studies from elsewhere that explore the impact of emigration and conflict on human capital tend to focus on simple indicators, such as the school attendance rate. This is a relatively crude measure because most school-age children are in school and it doesn't capture the impact on quality of schooling. Indeed, in Nepal, most of the school-age children are in school and

it is over-age enrolment, slow progression, and grade repetition rather than non-attendance are the major problems.

Similarly, while a rise in outflow of labour has increased household disposable income, it has reduced the supply of labour in the domestic labour market, either due to migrants leaving the country or non-migrant members withdrawing from the labour market. There are some studies like Lokshin et al. (2009), Phadera (2016), and Shrestha (2017) that explore the effect of emigration on the labour force participation (LFP) of non-migrants. Yet, these studies only explore the direct (own) impacts of emigration and ignore spatial spillovers where not only the sending locality but also neighbouring localities are affected if the labour markets are spatially interconnected. These spatial spillover effects may have important policy implications in a country like Nepal where villages are often closely linked.

This thesis contributes to the peace and conflict literature by constructing indicators of conflict intensity and its driving forces like poverty and inequality at the local level (at the third sub-national level or village) for almost 4000 localities. I use modern small-area estimation techniques linking census data to surveys to derive precisely estimated welfare estimates for 3862 localities. Likewise, I use census data to estimate wealth inequality, which is based on a household assets indicator (McKenzie, 2005), and caste (ethnic) polarization index for each of the 3862 localities. To measure the impacts of emigration on child schooling and the labour supply of non-migrants, I use a two-wave panel at locality level (for almost 500 sampling units) paying careful attention to the endogeneity of emigration and to spatial spillover effects. I use the predicted migration rate as an instrument variable to overcome endogeneity concerns. I develop age-specific schooling outcomes such as net enrolment rates and child labour indicators. Considering the important role of emigration and remittances in the local economy, I measure direct and spatial spillover effects on labour force participation rates. Specially, I develop a geographic proximity and road network based interconnectedness matrix to capture potential spillover effects.

1.2 Research Questions

In light of the existing state of knowledge, this study aims to address the following research questions:

i) What is the effect of poverty, inequality and caste polarisation on the escalation of civil conflict at local level in Nepal?

ii) What is the impact of civil conflict on international migration from Nepal and does the answer to this question depends on how data on conflict are aggregated?

iii) How does international migration and subsequent remittances affect child schooling and child labour?

iv) How does international migration affect the labour supply of left behind members? Does international migration also have a spillover effect on interconnected localities?

1.3 Escalation of civil conflict in Nepal

Nepal's civil war, which erupted in 1996, was a direct outcome of failed development policies, regional inequality, social and economic injustice, rising poverty and inequality (urban and rural inequality, caste based inequality, elite and non-elite inequality) and continued domination by the ruling class. The armed movement of Maoists (a rebel group) aimed to transform the country from a constitutional monarchy to communist rule and establish the principle of equality. The demand for greater equality, women's inheritance rights, an end to racial and caste-based discriminatory practices, and autonomy for local indigenous groups drew major support, especially from the relatively poor and underprivileged western regions of the country. At the beginning, the Maoist campaign to punish the perpetrators of caste- and gender-based discrimination and sexual abuse drew greater support from women, and the *Dalit* and *Janjaties* caste groups.[1]

[1] *Janjaties* are indigenous communities, they were landless and worked as slaves for the dominant castes for many years. *Dalits* are considered as untouchable and historically they were slaves and constitutionally not free to own physical assets.

Once the Maoists had gained popular support from rural and underrepresented communities, they began their political campaign by targeting police installations to confiscate supplies of weapons and ammunition. The lack of resistance from the police force in the western region meant that by 2001 the Maoists had quietly taken control of twenty major districts (of 75) (Libois, 2016; Pivovarova & Swee, 2015). Overall, in the first five years (1996-2000) of the civil war, conflict was low in intensity; less than 1700 people were killed and only around 500 villages (out of a total of 3982 villages), mostly from western Nepal, had experienced some form of conflict. The Maoists began the war as a weak rebel group, and in the first five years, they consolidated their organisational and military capacities, and this enabled them subsequently to pose a considerable challenge to the government forces.

Until 2000, only the police force was deployed to control these Maoist influences in the countryside. After the Royal Massacre in 2001, which occurred independent of the Maoist conflict, the conflict intensified and engulfed more than 55% (2280 out of 3982) of the localities in Nepal. The Maoists sensed an opportunity in the weakening political situation and falling public confidence in the government, especially because many people blamed the new king, Gyanendra, for the Royal Massacre. As the Maoists' popularity extended in the west of the country, they strategized to gain control over the central and eastern part of the country and ultimately to capture the capital city, Kathmandu. They also realised that winning over the middle class was the only way to capture strategically important urban areas and cities, and was an important source of income, which would help win the war for them. This strategic shift is known as the "*Prachanda Path*".

The year 2001 was a major milestone in the history of the armed conflict, witnessing the extension and intensification of the conflict from both sides. The increase in conflict intensification was led by the government's first state of emergency declaration and subsequent deployment of 54,000 Royal Nepalese Army soldiers throughout the country in 2001 to back up the police force as a part of the Global War on Terror (Sharma, 2006). From the rebels' side, initial weapon raids that

were limited to remote and abandoned posts in the countryside were transformed into more organised large- scale attacks on government strongholds and urban areas. The rise and spillover of armed conflict (from west to east) and ongoing political instability also destabilized the economy and increased unemployment, which further fuelled the intensity of the conflict. The civil conflict took a very ugly turn and many civilians and members of the middle class lost their lives in the crossfire.

The Maoists progressively expanded their armed struggle across the country, eventually controlling 35 of the 75 districts (Pivovarova & Swee, 2015), and repeatedly challenged the Nepalese Army and police force. As a result, the conflict reached its peak in 2001-2004 before beginning to subside in 2005 and afterwards. In 2005, the Maoists called for a unilateral ceasefire to participate in peace talks with seven major political parties. Later in 2006, a popular uprising and demonstration by the Nepali people against the King brought the end of the Monarchy. A peace agreement signed with the political parties led to the end of the decade-long conflict.

1.4 A brief history of migration from Nepal

Nepal has been sending labourers to the Indian subcontinent as far back as the 19th century when Nepalese used to migrate to Lahore within Punjab. Therefore, those working abroad are often known as "*lahures"*. Over time, the migration to the Indian subcontinent rose substantially, and it was augmented by the territorial expansion of Nepal and the "*Sagauli"* Peace treaty with the British East India Company. Later, the 1950 open border treaty with India and free labour mobility between India and Nepal made India an attractive and low-cost destination for migrants. Nepalese men were mainly employed in the Indian army, Indian police force and other public sector jobs. Until 1980, India was the only destination for work related migration due to restricted international mobility and a low capacity to finance migration to other destinations. After 1981, Nepal witnessed a decline in the share of migrants working in India. This share declined to 77% in 2001 from a little over 90% in 1981 and further dropped to 38% in 2011 (CBS, 2001, 2011). Yet India is still a

primary destination for people from relatively poor regions, and seasonal migration to India from the far west and mid-west regions is still very high. The pre-existing migrant networks in major Indian cities that help with job search make this an attractive destination for the poor.

Over the last two decades, foreign labour migration beyond India has become a major source of income for Nepalese households and the overall economy. The adoption of a free market economy and democracy in 1990 increased mobility and freedom of the labour force. After 1995, there was a remarkable increase in international migration due to the oil boom in the Gulf countries and economic growth in the ASEAN region. Migration for work to another dozen destinations, especially in the Middle East, is a new phenomenon in Nepal, which was facilitated by the Labour Act 1985. This act has allowed private recruiters to directly recruit Nepalese workers for foreign employment (Government of Nepal, 2014). This new opportunity to migrate to high-income destinations has become a boom for the Nepali workforce, especially from the central and eastern regions, because their close proximity to the capital city facilitates recruitment and they have greater access to finance to pay upfront migration-related costs. In 2002, two-thirds of people migrating abroad (other than to India) were employed in Gulf countries, which was a ten-fold increase from the 1997 figure. In the last decade, the outflow of migrants has extended from the Middle-East and North African countries to other Asian countries, such as Hong Kong and Korea. Between 2001 and 2011, there was a more than 200% increase in labour emigration, and if this trend continues, by 2025 Nepal is expected to have an oversees migrant population of 4.4 million (around 17% of the total population) (Sijapati et al., 2015).

The rise in migration was followed by a surge in remittance inflow, which has become an important pillar of Nepal's national and household economy to finance imports and consumption. From a meagre USD 55 million in 1993, the remittance inflow increased to USD 147 million in 2001. As a result of the continued outflow of the labour force after the decade-long civil conflict and political instability, the remittance inflow jumped to USD 3.3 billion in 2011 and USD 6.3

billion in 2017. With the increase in the size of remittances, their share and role in bringing stability to the national economy have also increased. In 2001, the contribution of remittances to GDP was only 2.4%, but this figure increased to 21.6% in 2010 and 31% in 2017. However, the actual size of remittances is likely much greater, given that the majority of migrants in India send remittances via informal channels, which are undocumented. The massive surge in remittance inflow has increased household disposable income, fuelled household consumption and led to a decline in the poverty rate, which fell from 42% in 1996 to 25% in 2010.

1.5 Introduction to the data and sources

In this thesis, I use the INSEC (Informal Sector Service Centre) database to measure the risk of and intensity of local conflict. INSEC is an independent NGO in Nepal and is the most reliable source, which closely monitored human rights violations during the civil war and collected and stored detailed information on approximately 15,000 conflict victims (Libois, 2016; Valente, 2016). While the database has detailed information about conflict victims, year of death, perpetrators, place of death, residence of the victim and so forth, it was stored as raw data and aggregated and published at the district level only. Earlier studies use this district level aggregated data that are easily available for all 75 districts of Nepal. As opposed to these studies, I use the raw data to identify the locality of victimisation for each of the almost 4000 VDCs in Nepal, successfully geocoding a little over 97% of the conflict cases. In my thesis, every death and every disappearance that was never relocated is counted as a death.

The second way that I utilise much more finely grained local information is in terms of some of the drivers of conflict. Typically, survey estimates from national sample surveys are available at the first or second subnational level, and total observations are insufficient to yield welfare estimates for lower administrative levels. While other major studies for Nepal rely on national sample surveys for welfare estimates, typically available at the district or higher level, I link the Nepal Living Standard Survey (NLSS) 1996, a nationally representative dataset, with Census 2001

extract data to get welfare estimates for all these census households.[2] I use these household welfare estimates to derive poverty estimates for almost 4000 localities. Additionally, I also use extract data with a approximately one-in-seven subset of the tenth and eleventh national population and housing censuses in 2001 and 2011. Both censuses provide information about age, education, literacy, international migrants, and household assets for each observation. Previous studies mostly rely on consumption to measure inequality among households, instead, I use a household assets indicator (as a wealth inequality measure) from census 2001 given that assets are a long term indicator of household wealth. Using the 2001 and 2011 censuses, I derive emigration rates, literacy, working-age population indicators and so on at the locality level. Similarly, local level information on village level forest cover and elevation is extracted from Goodman et al. (2019). I use night time light satellite observation data (from the Defence Meteorological Satellite Program) to measure local economic activity.

A further innovation of my research in that while previous studies in Nepal rely on cross-sectional data to estimate the impacts of emigration, I use the 2008 Nepal Labour Force Survey (NLFS II) and 2010 Nepal Living Standard Survey (NLSS III) 2010 data to construct a two-wave panel. These two surveys have the same sampling frame so I can develop a two-period panel of almost 500 primary sampling units that are common to the both surveys (CBS, 2010). With this dataset, I am able to examine impacts of migration that should not be affected by time-invariant unobservables. Additionally, one of the major contributions of this thesis is that I identify GPS coordinates of these 500 local units (using Google maps and Municipality and Village maps) and use national road network data from the World Food Programme (WFP) to measure spatial spillover effects. This is a type of impact that is ignored so far in previous studies.

[2] CBS provides access to census extract data only which has unit record data for around 11% of the national population for census 2000 and 15% for census 2010.

1.6 Main Results

In this sub-national level study, I find that the wealthier villages in Nepal experienced more conflict because the rebels targeted the middle class to gain resources and as an entry point into strategically important cities or urban areas. While poverty may be a cause of civil war at the national level, the same relationship need not exist at the local level because rebels target specific areas that align with their strategic interests. In contrast to poverty, conflict is likely to occur and persist in those areas that have high relative inequality. This result supports the fact that people weigh relative wellbeing more heavily than absolute wellbeing, and inequality plays a major role in creating social tension and breaking harmony. Similarly, localities with greater polarisation in terms of caste had higher risk of conflict as the minority group in these localities harbours grievances and seeks vengeance.

The effect of civil conflict on migration is negative, and it primarily reduces the emigration to high-income destinations because conflict affected the incomes of the residents and their financing capacity. Conflict can also interfere with travel to Kathmandu city that was needed for recruitment and visa processing (in contrast to emigration to India that proceeds informally). Consequently, the conflict-affected localities experienced lower growth in emigration and so may still suffer from after effect as these localities are likely to have less access to remittances. To estimate the distortion that may have been caused by over aggregation of conflict data, I also compare district vs village level aggregation of conflict. I find that district-level aggregation tends to overstate the impact of conflict, by up to four-fold. While measurement error usually attenuates econometrics estimates, for mean-reverting error that results from over-aggregation, exaggeration of impacts is possible. Thus, using more aggregated conflict data, such as district-level death rates, may bias microeconomic effects of the war.

Moreover, I also find that migration increases the net enrolment in secondary education, and this positive effect on human capital occurs through reduced child labour. Migration helps households to overcome liquidity constraints, which lessens the need for children to be in the labour

market, and increases education outcomes. Similarly, the direct effect of emigration is increasing labour force participation, but this positive effect is limited to the female labour force. Emigration is also associated with a fall in labour force participation in the agriculture sector as farm work is less preferred in remittance receiving households. Additionally, the spillover effect of emigration on labour supply is positive and its magnitude is as large as the direct effect, but this type of spillover is limited to the rural localities. The positive effect of emigration on labour supply occurs through the rise in local wage rates and in local economic activities that create an incentive to participate in the labour market.

1.7 Organisation of the thesis

This thesis contains six chapters. In the introduction (Chapter One), I present the motivation for this research and briefly discuss the major literature gaps, the data used and the major findings. Chapters Two to Five are the major body of this thesis. In the next two chapters, I discuss the determinants of civil conflict and the effect of conflict on international migration. Chapter three also presents an analysis of the aggregation issue in conflict data that may have affected previous research. In these chapters, I use disaggregated conflict data at the village level and explore the causes and consequences of civil conflict. Chapters Four and Five examine the effect of migration on child schooling, child labour and labour supply of non-migrants. In Chapter Four, I discuss the instrumental variables strategy and show how age-specific enrolment rates could better capture the effect of emigration compared to the traditionally used school attendance rate. Chapter Five focuses on the effects of migration on labour supply, and explores direct and spatial spillover effects that may have important policy implications. Chapter Six presents the conclusions and implications for future research and policy.

References

Acharya, C., and Leon-Gonzalez, R. (2014). How do migration and remittances affect human capital investment? The effects of relaxing information and liquidity constraints. *Journal of Development Studies, 50*(3), 1-17.

Adhikari, P. (2012). The plight of the forgotten ones: Civil war and forced migration. *International Studies Quarterly, 56*(3), 590-606.

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

Cederman, L., & Gleditsch, K. (2009). Introduction to Special Issue on "Disaggregating Civil War". *Journal of Conflict Resolution, 53*(4), 487-495.

Central Bureau of Statistics [CBS] (2001). *National Population Census 2001, Report on Nepal's Tenth Census*. Kathmandu, Nepal: His Majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2010). *Nepal Living Standard Survey III 2010: Statistical Report, Vol 1 and 2*. Kathmandu, Nepal: Government of Nepal.

Central Bureau of Statistics [CBS] (2011). *National Population and Housing Census 2011, National Report*. Kathmandu, Nepal: Government of Nepal.

Davis, J., & Brazil, N. (2016). Disentangling fathers' absences from household remittances in international migration: The case of educational attainment in Guatemala. *International Journal of Educational Development, 50*, 1-11.

Do, Q. T., & Iyer, L. (2010). Geography, poverty and conflict in Nepal. *Journal of Peace Research, 47*(6), 735-748.

Elbers, C., Lanjouw, J. O., & Lanjouw, P. (2003). Micro–level estimation of poverty and inequality. *Econometrica, 71*(1), 355-364.

Goodman, S., BenYishay, A., Lv, Z., & Runfola, D. (2019). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & Geosciences, 122*, 103-112.

Government of Nepal [GON] (2014). *Labour migration for employment. A Status Report for Nepal 2013/2014.* Kathmandu, Nepal: Author.

Karki Nepal, A. (2016). The impact of international remittances on child outcomes and household expenditures in Nepal. *Journal of Development Studies, 52*(6), 838-853.

Libois, F. (2016). *Households in times of war: Adaptation strategies during the Nepal Civil War* (Working Paper No. 1603). Namur, Belgium: University of Namur, Department of Economics.

Lokshin, M., & Glinskaya, E. (2009). The effect of male migration on employment patterns of women in Nepal. *The World Bank Economic Review, 23*(3), 481-507.

McKenzie, D. J. (2005). Measuring inequality with asset indicators. *Journal of Population Economics, 18*(2), 229-260.

McKenzie, D., & Rapoport, H. (2011). Can migration reduce educational attainment? Evidence from Mexico. *Journal of Population Economics, 24*(4), 1331-1358.

Murshed, S. M., & Gates, S. (2005). Spatial–horizontal inequality and the Maoist insurgency in Nepal. *Review of Development Economics, 9*(1), 121-134.

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

Phadera, L. (2016). *International migration and its effect on labor supply of the left-behind household members: Evidence from Nepal*. Conference paper presented in Agriculture and Applied Economics Association Annual Meeting.

Pivovarova, M., & Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from Nepal. *World Development*, *66*(1), 308-321.

Sambanis, N. (2002). A review of recent advances and future directions in the quantitative literature on civil war. *Defence and Peace Economics*, *13*(3), 215-243.

Sharma, K. (2006). The political economy of civil war in Nepal. *World Development*, *34*(7), 1237-1253.

Shrestha, M. (2017). *Push and pull: A study of international migration from Nepal* (Policy Research Working Paper No. 7965). Washington, DC: World Bank.

Sijapati, B., Bhattarai, A., & Pathak, D. (2015). *Analysis of labour market and migration trends in Nepal*. Kathmandu, Nepal: GDC Country Office Nepal, GIZ.

Taydas, Z., & Peksen, D. (2012). Can states buy peace? Social welfare spending and civil conflicts. *Journal of Peace Research*, *49*(2), 273-287.

Valente, C. (2013). Education and civil conflict in Nepal. *The World Bank Economic Review*, *28*(2), 354-383.

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

Hari Sharma & John Gibson

Abstract

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

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

JEL codes: D74, I32, O53

2.1 Introduction

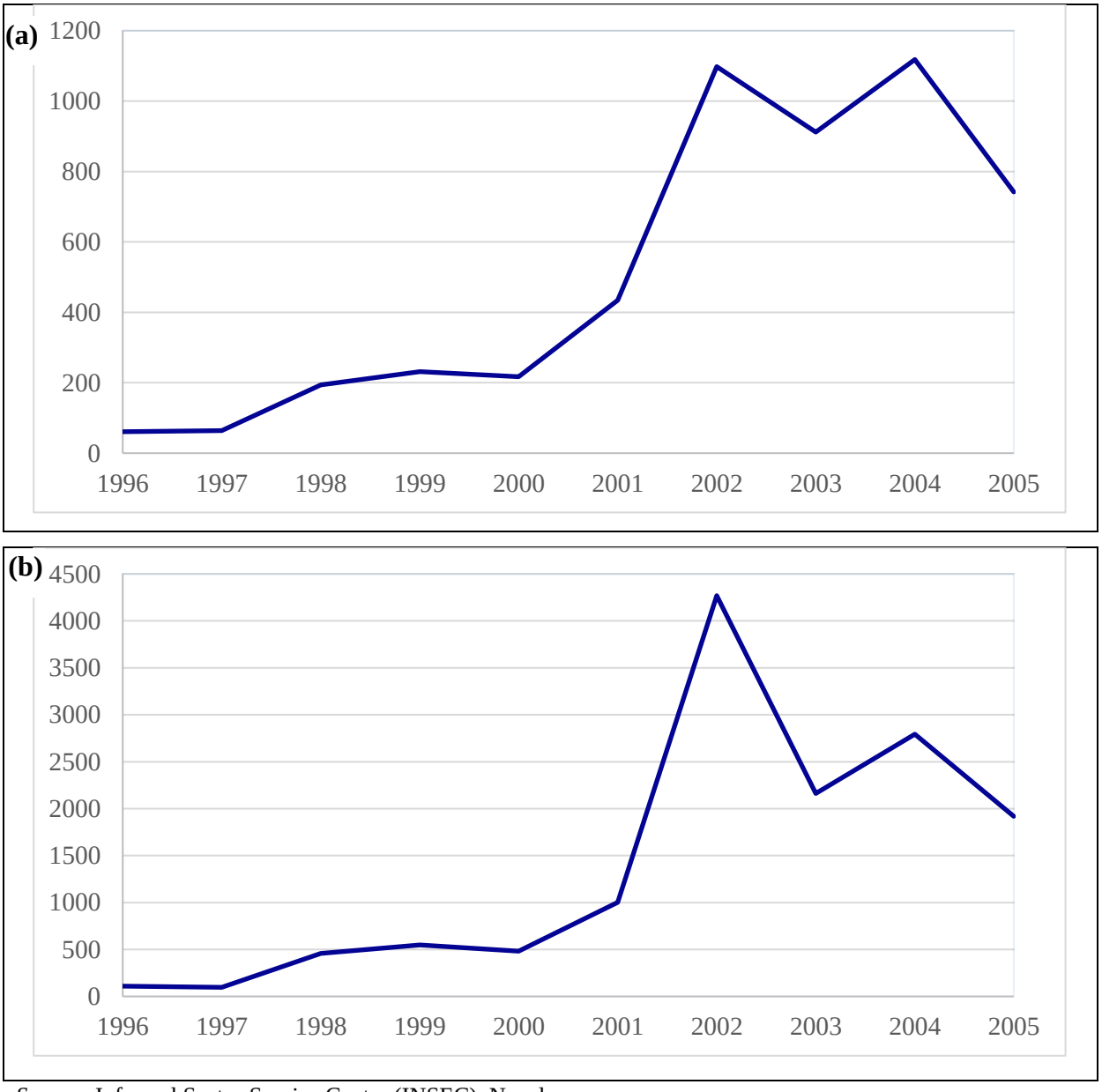
Civil war is detrimental to development of a country. Understanding why conflict escalates and the propagation mechanisms that prolong conflict are important concerns for designing policies and institutions that can further the peaceful coexistence of people. Many studies explore causes of civil war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

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

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

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

Figure 2.1: (a) Conflict affected villages (b) Conflict related deaths, each year



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

An important issue for researchers studying heterogeneous conflicts is the appropriate level of spatial aggregation. If raw data on conflict deaths can be geo-coded, researchers can aggregate to any level. Survey estimates used in conflict models, such as for inequality and poverty, were traditionally available only at the first or second sub-national level (such as provinces and districts) but modern small-area estimation techniques linking census data to surveys give welfare estimates at the very local, village level (Elbers et al., 2003). Therefore, the administrative level for which data are easily available matters less now for choosing the right aggregation level (Cederman & Gleditsch, 2009). The prior studies of Nepal's civil war mostly use district level data. Sharma & Gibson (2019) note this may not be desirable as death rates varied far more within districts than between districts. Moreover, a district covers 2000 km^2, on average, which is 55-times larger than the average locality, so a lot of fine detail may be lost in district data. Poverty and related characteristics such as caste and the local environment also can vary significantly within districts (Central Bureau of Statistics, 1996). Likewise, spatial factors such as forest cover and elevation are heterogeneous within districts, and these factors may make some localities more vulnerable to conflict than others (Braithwaite, 2006, 2010). For these reasons we model the escalation of Nepal's civil war at the locality level, using both cross-sectional and panel analyses for almost 4000 localities.

In contrast, prior studies of causes and effects of the civil conflict in Nepal mostly use district-level data. Do & Iyer (2010) explored effects of district-level poverty on the conflict. Related studies examine effects of horizontal inequality, relative deprivation, polarisation, civic participation and social capital (Bohara et al., 2006; Deraniyagala, 2005; Murshed & Gates, 2005; and Sharma, 2006b). Holtermann (2016) considers the relative capacity of rebels to escalate conflict. The data used in these studies is district level or even more aggregated. In terms of consequences of the conflict, Adhikari (2012), Pivovarova & Swee (2015), De Juan & Pierskalla (2016), and Shrestha (2017) examine effects on internal displacement, on schooling, on political

trust and on emigration. While outcome measures in these studies are often at a more disaggregated level, such as from household survey data, the conflict rates are calculated at the district level and so smooth over much of the heterogeneity in the conflict.

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

We find a negative effect of local poverty rates on the risk of conflict and the number of deaths. The poverty rates are for each locality, from small-area estimates linking detailed welfare indicators from the National Living Standards Survey to spatial coverage of the 2001 National Population Census. Other studies for Nepal, like Do & Iyer (2010), Sharma (2006a), and Hatlebakk (2010) find district-level poverty rates are positively related to conflict but this may be from overly-aggregated data disguising patterns seen at more local levels. Our results are consistent with what is proposed by Boulding (1962) and found (for Liberia) by Hegre et al. (2009), that rebel groups protect zones of influence and take conflict to the government strongholds as the rebels get stronger. In Nepal the Maoist rebels made a major strategic shift in 2001, to target urban areas and the middle class, so as to access resources and to garner greater support as a way to win the war. More

generally, our results support the agnostic view that, notwithstanding the fact that internal conflict is more likely in poor countries (Theisen, 2008, Braithwaite et al., 2016), poverty is neither a necessary nor a sufficient condition for the escalation of internal conflict (Tollefsen, 2017; Verwimp et al., 2019).

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

Overall, the data, method and range of covariates in this paper go well beyond prior papers relating to Nepal. While other studies use cross-sectional analysis, we use time and spatial fixed effects to account for heterogeneity over time and space. We model conflict and conflict intensity in two ways; whether a death(s) occurred in a locality in a given year (using a logit model), and how many deaths per locality each year (using a negative binomial model). The rest of the paper is as follows: section 2.2 provides background on Nepal's civil war, and the data collection and empirical strategy are discussed in section 2.3. The findings are reported in section 2.4 and the conclusions are presented in section 2.5.

2.2 Nepal's civil conflict (1996-2006)

In the lead-up to the civil war, 1990 was an important milestone in the social and political transformation of modern Nepal, with steps to restore democracy, and increase political freedom, social mobility and economic advancement. Yet, the transition to democracy was marked by corruption and weak institutions, and increased power of traditional elite dominant groups. Social and economic transformations gave greater freedom to middle class and "dominant caste" populations but marginalized, indigenous and socially excluded communities were side-lined from this improvement.[3] In fact, political participation and access to employment, healthcare and education for these communities failed to take off. Thus, while the national poverty rate was 42% in 1996 (CBS, 1996), it was far higher in the marginalized far-west and mid-west regions, at 58% and 62%, and also much higher for *Dalit* communities and for the class known as *Janjaties*.[4] Elite capture of the centre and rising poverty in rural areas created grievances and resentment towards the state.

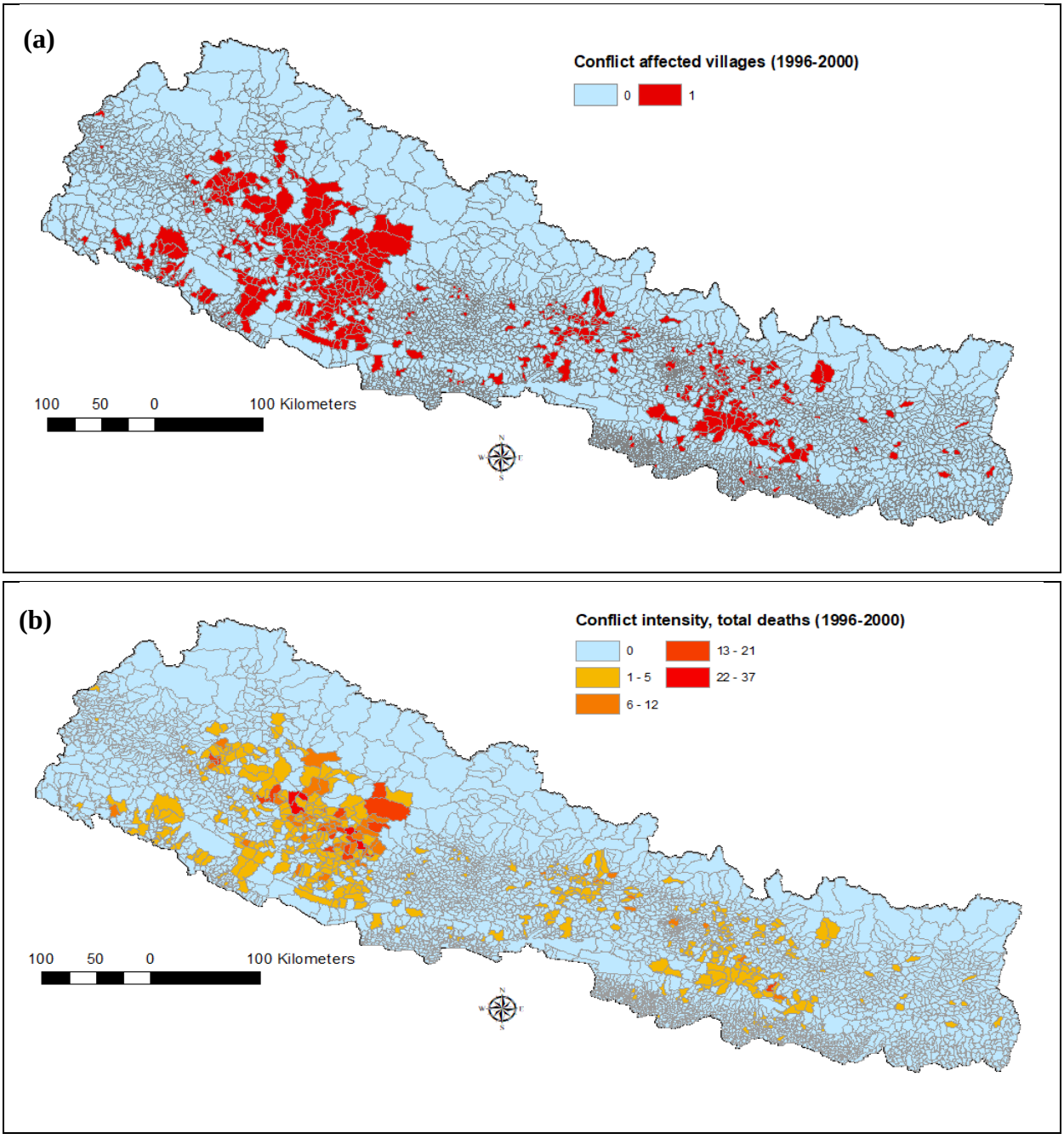
In 1996, the Communist Party of Nepal (CPM-Maoist) formally declared war against the state so as to replace the constitutional monarchy with rules enforcing equality (Gobyn, 2009). The Maoist movement benefitted from the resentments created by rising social and political inequality and by poverty, and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

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

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

underdeveloped regions of the mid-west and far-western parts of Nepal (Figure 2.2). Indeed, until 2000, conflict was largely limited to western Nepal, with only 493 villages having conflict-related deaths and 1693 people killed.

Figure 2.2: Nepal's conflict (1996-2000) (a) Conflict affected villages, (b) Number of deaths



Source: INSEC, Nepal.

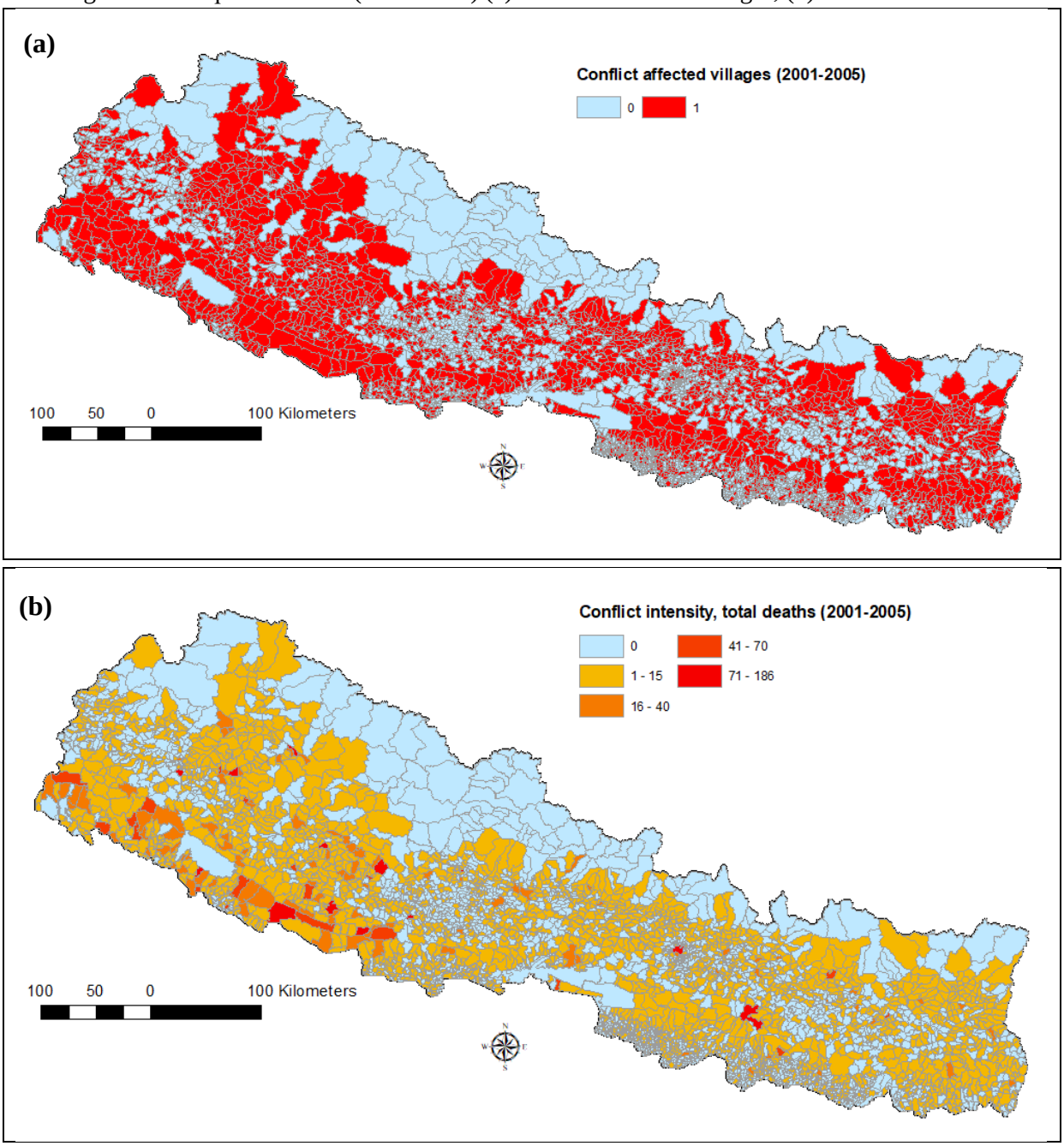
In 2001, it became clear to the rebels that a struggle against the state that was limited to poor and remote regions was unlikely to succeed. Instead, they needed to capture urban areas and gain middle class support, both as a source of resources to fund rebellion and as a gateway to seizing the

cities as a way to win the war (Gobyn, 2009). Rapid expansion of Maoist cadres and increased activities in new areas also precipitated this need to form a new war strategy. The second national Maoist convention in February 2001 adopted a new approach and decided to wage large-scale war to win over the middle class and gain access to urban areas (Davis et al., 2012; Gates & Miklian, 2010; Gobyn, 2009; Nayak, 2007). This strategic shift is also known as the "*Prachanda Path"* (Ogura, 2008). This reformulation of the Maoist war strategy aimed to destabilise the central power of the state, instigate revolt within the security forces, and garner support of mainstream political forces such as civil society and the urban population in order to win the war (Nayak, 2007).

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

The spread in conflict from 2001 is shown in Figure 2.3, with almost 60% of localities (specifically, 2280 out of 3982) experiencing conflict-related deaths between 2001 and 2005. Thus, 2001 is seen as a major milestone in the history of Nepal's armed conflict, with a rapid spread out from rural western regions to begin challenging the government in the urban areas and cities in the richer central and eastern parts of the country (Holtermann, 2016; Nayak, 2007). Yet even with this spread there was a lot of heterogeneity in conflict intensity, as most conflict-affected localities had fewer than 15 deaths over this five year period (three per year, on average) with more localized hotspots in areas that had more than 40 people killed per locality over the five-year period (Figure 2.3b).

Figure 2.3: Nepal's conflict (2001-2005) (a) Conflict affected villages, (b) Number of deaths



Source: INSEC, Nepal.

At least some of this heterogeneity in deaths was due to the hit-and-run war tactics of the rebels, that killed many civilians and led to increasing human rights abuse from both sides (Nayak, 2007). The escalation of armed conflict also destabilized the economy and increased unemployment, which further fuelled the intensity of the conflict as rebels gained popularity and support from the unemployed. The extent of escalation is shown by the fact that the Maoist rebels eventually controlled half of all districts (Pivovarova & Swee, 2015), and repeatedly challenged the

Nepalese Army and police force. From this greater position of strength, the rebels called for a ceasefire in 2005 to enable their participation in peace talks with seven major political parties. These peace talks marked the beginning of a new chapter in Nepal's politics as the popular uprising and demonstrations by the Nepali population against the King in 2006 brought an end to both the civil conflict and the Monarchy. The peace agreement formally ended a decade-long civil war that cost over 15,000 lives.

2.3 Data and Empirical Methods

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

The shift in the rebels' strategy from early 2001 and the militarization after the Royal Massacre in June 2001 created a sharp change in the extent and location of the conflict. This is seen in the comparison of Figures 2.2 and 2.3 and in the far greater number of conflict-affected villages and conflict deaths from 2001 onwards seen in Figure 2.1. Given this dramatic shift, we argue that conflict from 2001 was substantially different to what had occurred in the five years prior, and indeed was a shift that changed the structure of Nepal's politics. Thus, our models focus on this new phase of conflict, by considering the changing risk of a locality being conflict-affected and the changing number of conflict deaths in each year from 2001 to 2005. We allow an impact from the past by using conflict data from 1996 to 2000 as one of several explanatory factors for the location and intensity of conflict in the 2001-05 period.

Our other sources of data include an extract from the tenth national population and housing census in 2001. Microdata are provided for what is roughly a one-in-ten sample on age, education, literacy, international migration, household assets and so on (Central Bureau of Statistics, 2001), and we use these data to construct control variables. Our forest cover and elevation data are locality-level averages from *AidData* (Goodman et al., 2019). Night time lights, from satellite observation, are used to measure local economic activity (Gibson et al., 2020). The variables of main interest are poverty rates, a caste-based polarisation index, and inequality (overall, in terms of assets, and also looking at relative inequality amongst the poor), all measured at the local level. The computation of these variables is discussed in the following sub-sections.

2.3.1 Survey to census imputation of small area poverty

Poverty and inequality may be important drivers of conflict escalation. The maps in Figures 2.2 and 2.3 highlight the heterogeneous nature of the conflict, and suggest the need for local measures of poverty. Previous conflict-related research on Nepal uses district level poverty estimates, from the 1996 Nepal Living Standards Survey (NLSS). However, this survey has limited spatial coverage because the sample of just over 3300 households is from only 275 localities, less than seven percent of the total. So using these data directly makes researchers choose either to focus on a small subset of localities or to use poverty rates calculated at a spatially aggregated level that may disguise much of the heterogeneity. Also, the NLSS sample is designed to be representative at the ecological zone level (five zones) and not at the district level where the sample is too small (often just 12 or 24 households drawn from one or two villages in a district).

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

calculate poverty rates for every locality. Consider the following linear model of per capita consumption:

$$Y_{ch} = \beta X_{ch} + u_{ch} \quad (2.1)$$

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

$$u_{ch} = \eta_c + e_{ch} \quad (2.2)$$

where η_c is the cluster effect and e_{ch} is a household-specific random error term. The cluster effect captures the unobserved similarities in consumption for households surveyed in the same locality, which if unaccounted for would lead to distorted measures of uncertainty when the predicted consumption for each census household is used to calculate local poverty rates. The ELL method involves estimating a "beta model" of consumption and an "alpha model" of the household-specific random error (details are reported in Appendix A.2.1 and A.2.2).

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

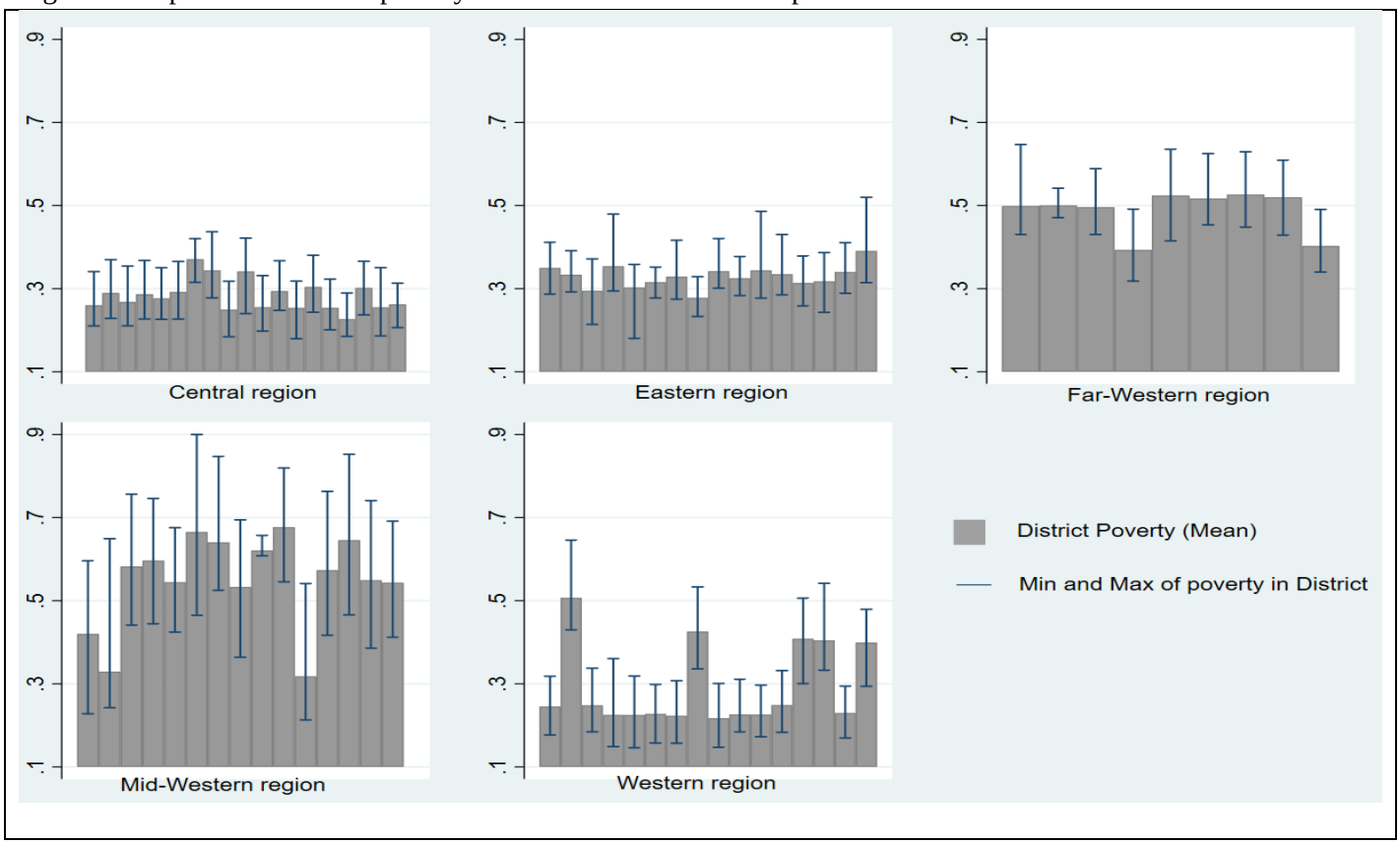
$$\tilde{Y}_{ch} = X_{ch}\tilde{\beta}_{GLS} + \tilde{\eta}_c + \tilde{e}_{ch} \quad (2.3)$$

By repeating the simulation 200 times we create a new set of coefficients and disturbance terms each time. The mean value of all 200 simulated consumption values is calculated for each census

household and is used to calculate locality-level poverty rates, while the standard deviation for the 200 simulations provides an estimate of the standard error. Generally, ELL estimates at locality level have similar precision to that of survey estimates at district level.

The average poverty rate from the ELL simulations is 35.0%. This is midway between survey estimates of 41.8% in 1996 and 30.8% in 2004 (Central Bureau of Statistics, 2004). Our estimate matches these, as it relates to 2001 (we use census data from that year); a linear decline in poverty between 1996 and 2004 would give a rate of 35% for 2001. Of note is that the poverty rate varies greatly over space, with a lot of within-district heterogeneity. Figure 2.4 shows this heterogeneity, contrasting the mean poverty rate in the district with the lowest and highest rates. For instance, *Dhading* district in central Nepal has a mean poverty rate of 31.8 % with a lowest poverty rate of 21.3% and a highest rate of 54.0%. This variation in poverty rates is seen in all regions. The fact that some localities may be more vulnerable to conflict than others, due to differences in their poverty rates, would be obscured if the more aggregated poverty rates, such as from the district level, were used.

Figure 2.4: Spatial variation in poverty rate in all 75 districts of Nepal



Source: Authors calculation from Small Area Estimation

2.3.2 Household Assets indictor for inequality:

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

$$Y_i = a_1\left(\frac{x_1 - \bar{x}_1}{s_1}\right) + a_2\left(\frac{x_2 - \bar{x}_2}{s_2}\right) + \cdots + a_k\left(\frac{x_k - \bar{x}_k}{s_k}\right) \qquad (2.4)$$

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

Given that Y_i can take negative values (as the mean is zero across all households), we cannot use measures of inequality like the Gini coefficient that are only defined for positive values. Instead, our measure of relative inequality for locality l is estimated as:

$$IN_l = \frac{\sigma_l}{\sqrt{\lambda}} \qquad (2.5)$$

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

2.3.3 Ethnic polarisation index

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

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

$$RQ = 1 - \sum_{i=1}^{N} \left[\frac{0.5 - \pi_i}{0.5}\right]^2 \pi_i \qquad (2.6)$$

where π_i is the share of each caste group (for *N* groups) in a locality. The RQ index captures distance of a group from a (1/2,0,…..0,1/2) bipolar distribution. For example, a locality with two individuals has distance zero if both belong to the same group, and is otherwise one. To construct an RQ index we identify six different groups, following the caste classification of Nepal's 2006 DHS survey (Bennett et al., 2008). Those of *Brahmin*, *Chhetri* and *Newars* caste are one group, and are considered the dominant group. *Dalits* are one group. The *Janjaties* from the hills ecological zone are one group and from the *terai* (lowlands) are another. The *Dalits* and *Janjaties* groups are considered the dominated group. We put other castes from the *terai* ecological zone into one group, and all other remaining castes that do not belong to any of the above classifications into one group. Our polarisation index is motivated by the fact that conflict is more likely to occur if a large minority group faces a large majority group. Therefore, the RQ Index is able to capture conflict effects when there are two major contesting groups in a society (Montalvo & Reynal-Querol, 2005).

2.3.4 Econometric Model

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

$$Conflict_{it} = X_i\beta_n + V_i b_n + M_{it}\theta_n + conflict_{96-00} + \alpha_z + \delta_t + e_{it} \qquad (2.7)$$

The binary conflict outcome and intensity of conflict are denoted by $Conflict_{it}$. We use X_i to represent variables of interest, such as the poverty rate[5], inequality and polarisation, which are

[5] A concern with interpreting results for equation 2.7 is the independence assumption embedded in equation 2.1. The small area estimate of poverty could be the outcome of conflict rather than a cause. For example, conflict may affect local economic activities if people in a conflict affected locality are reluctant to go out for work, and then the error term in equation 2.1 may correlate with the right-hand side variable, so beta (β) is no longer an estimator of causal effects. There are two main reasons why this is unlikely and why the independence assumption should hold. First, one of the benefits of survey to census imputation in this setting is that the imputed poverty rates are due to chronic poverty. The census attributes (like assets, age, gender, education and so on) used in the imputation do not fluctuate much in the short

measured at one point in time. The time-invariant control variables are denoted by V_i, while time-variant controls are denoted by M_{it}. The coefficient vectors to estimate are β, θ and b, while e_{it} is an error term that we initially treat as independent and identically distributed (iid) across panels and time with variance (σ^2). We later use a spatial autoregressive model as a robustness check, relaxing these error assumptions. We also use time fixed effects for each year and 15 zonal (or 75 district) fixed effects for variation over space, denoted by δ_t and α_z. We use a logistic regression model for the binary conflict outcome, and a negative binomial regression model for the count data to deal with the over-dispersion in conflict deaths.

Control variables:

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

The risk of conflict often increases with distance from the capital city as the state may particularly fortify their headquarters. Another spatial effect is that rebels often concentrate near

run and so this approach is unlikely to capture any transitory increase in poverty that is caused by conflict. Second, while Nepal's civil conflict lasted for ten years it started to escalate only after 2001. Specifically, after the Royal massacre, the new King Gyanendra mobilised the Nepalese Army in November 2001 and civil conflict escalated after this. In contrast, the poverty estimates from census 2001 are unlikely to be affected by conflict because census fieldwork was conducted in July 2001 while before the Army was mobilised.

international borders (Buhaug et al., 2009; Cederman et al., 2009). To control for these effects, we include distance to the capital city (*Kathmandu*) and to the Indian border (which has free movement unlike Nepal's other borders) calculated using *ArcGIS* software.

Some studies highlight the role of geographic attributes like forest cover and elevation in influencing conflict (Buhaug et al., 2009; Cederman et al., 2009). In guerrilla war, rebels may shelter in forests and high elevation areas, that are strongholds for them, to plan timely attacks on government forces. Considering this, we include forest cover and elevation in our model. In Nepal, villages located in very high elevations have only small populations and so may have experienced less conflict. We include a mountainous region dummy variable for localities above 2800 metres elevation. Urbanization, industrialization and socioeconomic development also influence conflict but data on these factors at subnational level are sparse so we use locality-level satellite-detected night time light data as a proxy, as lights provide a reasonable measure of local economic activity (Henderson et al., 2012).

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

2.4 Results and discussion

The definitions and summary statistics for all variables are reported in Table 2.1. Our main results are reported in Table 2.2, using six models – three for the risk of conflict (logit models) and three for the number of deaths (negative binomial models). The models differ by type of fixed effects (for

15 regional zones or for 75 districts) and whether the caste polarisation rate is interacted with the local population share of the dominant caste groups. Two further tables are presented after the main results, to show the robustness of the main findings to replacing the panel specification with either cross-sectional models or with spatial spillover models.

Table 2.1: Variable definitions and descriptive statistics (N=3982)

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

Source: Author's calculation from NLSS-1996, Census 2001 and INSEC and other sources documented in text.
Note: Whether conflict-affected, number of victims, share of forest cover and local urban activity are time-varying, with averages over T=5 shown, other variables are measured in a pre-conflict year (2001 or earlier).

Effects of poverty and inequality

Poverty is often considered as a major driver of conflict, as poor people may harbour grievances against the state and may have less to lose from involvement with rebels. Yet it is unclear whether relationships that seem to hold in aggregate data also hold at the very local level (Tollefsen, 2017). At least for Nepal, conflict seems higher in localities with a lower poverty rate, contrary to what prior studies based on district level data have suggested. Using the results in column 1 of Table 2.2, where unobserved factors are controlled for at the zonal level, for every ten percentage point

increase in the locality poverty rate (just under a one standard deviation change) within same Zone, the risk of conflict would decrease by 4.2 percentage points (the effect is statistically significant at the $p < 0.01$ level). In terms of the expected number of conflict deaths, the results in column 2 suggest there would be 0.2 fewer deaths per locality with a ten percentage point higher poverty rate within same Zone. These results suggest that during the escalation of the conflict, wealthier areas had more risk than did poorer areas, as their families and assets were the direct targets of some of the violence[6].

[6] To overcome endogeneity concerns about equation 2.1, the 2001 conflict period was dropped from the model as a robustness test. After restricting the conflict period studied to 2002 to 2005, the impacts of poverty appear to be similar to what is reported in the main results, and so the conclusions continue to hold.

Table 2.2: Estimated effects on conflict probability and conflict intensity using logit and negative binomial models

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

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

These results are consistent with the concept of support and target value proposed by Boulding (1962).[7] Rebel groups first protect their primary zone of influence and then take the conflict to the government's stronghold areas, which has strategic importance to the rebels in terms of what they need in order to win the war (Hegre et al., 2009). At the beginning of the civil conflict in Nepal (1996-2000), the Maoist armed movement was restricted to the poor and underdeveloped region of the country, where they have gained the people's support and strengthened their rebel forces. After transforming into a formidable fighting force (year 2000 onwards), the Maoists shifted the war strategy and targeted areas in order to win middle class support, both as a source of resources and as a gateway to the cities or urban areas (Gobyn, 2009; Holtermann, 2016). The Maoists realised that their traditional way of struggle was unlikely to win a war if they lacked middle-class support (Nayak, 2007).

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

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

a lower position than others, even amongst the poor, it may lead to a sense of unfairness that plays a role in heightening social tensions.

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

Effect of caste polarisation

In localities with greater polarisation in terms of caste, there was more risk of conflict and greater intensity of conflict. According to the results in column 2 of Table 2.2, a standard deviation increase in local caste polarisation within same zone would increase the expected number of conflict deaths by 0.1 per locality per year. Although effects of caste are rarely examined our result is consistent with other findings that diversity based on race, identity, ethnicity, and linguistics plays a key role in escalating civil war (Bosker & de Ree, 2014; Cederman et al., 2009; Nepal et al., 2011; Janus & Riera-Crichton, 2015). In Nepalese society, identity of an individual and alliances they form are defined by the pre-existing caste system, which is still prevalent in almost every part of the country.

To further explore effects of caste-based polarisation and the influence of dominant castes (*Brahmin*, *Chhetri* and *Newars*), we interact these two variables, with the results in the last two columns of Table 2.2. The larger the share of the dominant group (the ones doing the caste-based discriminatory practices) and the greater the polarisation, the higher the odds of conflict and the intensity of conflict. This result is consistent with the idea that discriminatory practices carried out by the dominant caste against minority groups contributed to the escalation of conflict. If membership growth for the Maoists and increased Maoist rebel activities were partly due to the

exclusionary, caste-based discriminatory practices against *Dalits* and *Janjaties* it suggests that the rebels benefitted from local grievances in polarised villages. In particular, the rebels may have gathered support from the two dominated groups to make common-cause in their fight against the caste-based discriminatory practices.

The coefficient on the emigration rate is worth discussing here. In table 2.2, the effect of emigration (a control variable) is very large, in that it suggests that a one standard deviation increase in the emigration rate within the same zone reduces the conflict risk by 9 percent and the conflict intensity by 0.03 deaths. The outflow of the labour force to foreign employment reduces the risk of conflict for two major reasons. First, emigration reduces the number of people that can otherwise be recruited by rebels and mobilised to fight against the state. Second, the subsequent inflow of remittances serves as additional household income and helps to reduce grievances against the state. Therefore, households that have emigrants are less likely to participate in conflict or support rebels' activities.

Robustness check

We use two different approaches to check whether our main findings are robust. The first is to recast the model as cross-sectional, by collapsing the annual variation from 2001 to 2005. In other words, our first dependent variable is redefined as a dummy for whether a locality had any conflict deaths from 2001 to 2005, and the second dependent variable is the total number of those deaths. For time-varying controls (forest cover and night lights) we use the average of their values from 2001 to 2005. In Table 2.3, Model 1 presents the results where the polarisation index, the poverty rate and the inequality indicators are all directly included, and in Model 2 the polarisation index is interacted with the dominant caste population share.

The main finding that the risk of conflict and the number of conflict deaths is lower in localities with a higher poverty rate persists when the temporal variation has been suppressed. For example, a locality with a ten percentage point higher poverty rate (slightly less than one standard

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

Table 2.3: Cross-sectional analyses of effects of poverty, inequality and polarisation on conflict

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

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

Our second sensitivity analysis relaxes an assumption that is inherent when using typical regression approaches, that the conflict events in one locality are independent in space from events in other (neighbouring) localities. The diffusion aspect of conflict over space and time, either at national or local level, receives little attention (Schutte & Weidmann, 2011). There are a range of spatial spillover models available (LeSage & Pace, 2009; Fischer & Getis, 2009) but they are only

rarely used to study conflict (Anselin & O'Loughlin, 1992; Ayana et al., 2016). If spillovers are ignored it may lead to estimation bias, and also to incorrect inferences if errors are wrongly treated as independent. These issues likely matter to the escalation of conflict in Nepal because there was considerable clustering in the conflict deaths, with a statistically significant global Moran statistic (*I= 159.6*) for the relationship between deaths in a locality and deaths in neighbouring localities.

To allow for spatial spillovers we use a spatial autoregressive model (SAR), where the spatial lag of the dependent variable (the average in neighbouring localities) is included as an additional regressor.[8] This lag structure allows for spatial spillovers because if a change in covariate *X* causes a local change in the outcome, that may affect outcomes of neighbours; in turn, the change in the outcome for the neighbours affects the outcomes of their neighbours, including the original area. For both the risk of conflict and conflict intensity (which is measured as number of deaths per thousand of population), the coefficient on the spatially lagged dependent variable is 0.26 and is statistically significant at the $p<0.01$ level. Thus there is strong evidence of spatial spillovers in conflict.

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

- *Direct effect*: the effect of a change in a covariate in locality *i* on the dependent variable in locality *i*, averaged over all 3982 localities
- *Total effect*: the effect of the same change in the covariate in all localities on the dependent variable in locality *i*, averaged over all localities
- *Indirect effect*: the difference between the total effect and direct effect.[9]

Table 2.4 presents the result for this decomposition, which shows similar patterns to the main

[8] Due to the simultaneity, this model is estimated with generalized spatial two-stage least squares (GS2SLS), using the estimator developed by Drukker et al. (2013). If we include a spatial lag of the error term this variable is statistically insignificant ($p < 0.22$) and other coefficients are similar to those that contribute to Table 2.4.
[9] An intuitive discussion and example of these direct, indirect and total effects is provided in Gibson (2019).

results in Table 2.2. In particular, poverty still has a negative effect on the risk of conflict and the intensity of the conflict while local inequality (of assets) has positive effects on conflict, especially though the direct channel. While caste polarisation is still associated with a greater risk of conflict, it has a weakly negative effect on conflict intensity (deaths), in contrast to the results that did not allow for spillovers. Another change from the earlier results is that the inequality amongst the poor has no impact on conflict intensity, but still makes the risk of conflict higher. The patterns of impacts from the control variables are largely as they were from the models that did not account for spillovers. The results in Table 2.4 suggest most of our findings are robust to using a more general spatial model and so our conclusion about the conflict escalating into non-poor areas from 2001 onwards continues to hold.

Table 2.4: The estimated direct, indirect and total impacts from Spatial Autoregressive models (SAR)

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

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

2.5 Conclusion

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

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

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

and Iyer (2010) that found a positive association between poverty and conflict; spatial aggregation may have contributed to this result.

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

2.6 Reflection on this chapter

As discussed in section 3, one of the major concerns with the evidence reported here is that poverty may be the outcome of civil war so the coefficient on the imputed poverty rate may be biased. The treatment effects reported in this chapter are estimated in a different way from the treatment effects reported in chapter 4 and 5 in the sense that formal modelling of endogeneity is not considered here. In contrast, instrument variables (using historical migration rates) are used in chapter 4 and 5 to overcome endogeneity concerns. A key difference is that the imputed poverty rate used in this chapter is based on census attributes that should not reflect transitory change in poverty due to conflict (if there is any such reverse effect). Therefore, even in the absence of instrument variables like those used in chapter 4 and 5, the poverty estimates used here are less likely to be affected by civil conflict and so the regression coefficients should still be valid

estimates of treatment effects. Nevertheless, in other settings where the timing of conflict and the timing of measurement of poverty (either directly through survey or indirectly through census-to-survey imputation) differ from the current situation, researchers may be advised to use valid instrumental variables for poverty when analyzing the impact of poverty on civil conflict.

Additionally, the predicted poverty rate is considered as data in the main conflict model without considering the errors that may surround our poverty estimates. This happens because the poverty estimates of some villages are more accurately estimated than others, but all are equally weightage in the main model. The one approach to deal with this challenge is to use standard error of prediction as a weighting variable so that villages with the most precise estimates of imputed poverty will get higher weights than others. The implementation this weighting approach is outside the scope of this study.

References

Adhikari, P. (2012). The plight of the forgotten ones: Civil war and forced migration. *International Studies Quarterly*, *56*(3), 590-606.

Anselin, L., & O'Loughlin, J. (1992). Geography of international conflict and cooperation: Spatial dependence and regional context in Africa. In M. D. Michael (Eds.), *The new geopolitics,* (pp. 39-75). Gordon and Breach Science.

Ayana, E. K., Ceccato, P., Fisher, J. R., & DeFries, R. (2016). Examining the relationship between environmental factors and conflict in pastoralist areas of East Africa. *Science of The Total Environment*, *557*, 601-611.

Bennett, L., Dahal, D. R., & Govindasamy, P. (2008). *Caste, ethnic and regional identity in Nepal: Further analysis of the 2006 Nepal Demographic and Health Survey.* Calverton, MD: Macro International.

Bleaney, M., & Dimico, A. (2011). How different are the correlates of onset and continuation of civil wars? *Journal of Peace Research*, *48*(2), 145-155.

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

Bosker, M., & de Ree, J. (2014). Ethnicity and the spread of civil war. *Journal of Development Economics*, *108*, 206-221.

Boulding, Kenneth. 1962. *Conflict and defense: A general theory.* New York, NY: Harper.

Bownas, R. A. (2015). Dalits and Maoists in Nepal's civil war: Between synergy and co-optation. *Contemporary South Asia*, *23*(4), 409-425.

Braithwaite, A., Dasandi, N., & Hudson, D. (2016). Does poverty cause conflict? Isolating the causal origins of the conflict trap. *Conflict Management and Peace Science*, *33*(1), 45-66.

Braithwaite, A. (2006). The geographic spread of militarized disputes. *Journal of Peace Research, 43*(5), 507-522.

Braithwaite, A. (2010). Resisting infection: How state capacity conditions conflict contagion. *Journal of Peace Research, 47*(3), 311-319.

Buhaug, H., & Gleditsch, K. S. (2008). Contagion or confusion? Why conflicts cluster in space. *International Studies Quarterly*, *52*(2), 215-233.

Buhaug, H., Gates, S., & Lujala, P. (2009). Geography, rebel capability, and the duration of civil conflict. *Journal of Conflict Resolution, 53*(4), 544-569.

Central Bureau of Statistics [CBS] (1996). *Nepal Living Standard Survey I 1996: Statistical Report, Vol 1 and 2.* Kathmandu, Nepal: His Majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2004). *Nepal Living Standard Survey II 2004: Statistical Report, Vol 1 and 2.* Kathmandu, Nepal: His Majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2001). *National Population Census 2001, Report on Nepal's Tenth Census.* Kathmandu, Nepal: His Majesty Government of Nepal.

Cederman, L. E., Buhaug, H., & Rød, J. K. (2009). Ethno-nationalist dyads and civil war: A GIS-based analysis. *Journal of Conflict Resolution, 53*(4), 496-525.

Cederman, L., & Gleditsch, K. (2009). Introduction to Special Issue on "Disaggregating civil war". *Journal of Conflict Resolution, 53*(4), 487-495.

Davis, P K., Larson E.V., Haldeman Z, Oguz, M., and Yashodhara Rana, Y. (2012). Public support for the Maoists in Nepal. In *Understanding and influencing public support for insurgency and terrorism* (pp. 119-150). Santa Monica, CA: Rand National Defense Research Institute.

De Juan, A., & Pierskalla, J. H. (2016). Civil war violence and political trust: Micro level evidence from Nepal. *Conflict Management and Peace Science*, *33*(1), 67-88.

Denny, E. K., & Walter, B. F. (2014). Ethnicity and civil war. *Journal of Peace Research, 51*(2), 199-212.

Deraniyagala, S. (2005). The political economy of civil conflict in Nepal. *Oxford Development Studies*, *33*(1), 47-62.

Do, Q. T., & Iyer, L. (2010). Geography, poverty and conflict in Nepal. *Journal of Peace Research, 47*(6), 735-748.

Drukker, D. M., Prucha, I. R., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal, 13*(2), 221-241.

Eastin, J. (2018). Hell and high water: Precipitation shocks and conflict violence in the Philippines. *Political Geography, 63*, 116-134.

Elbers, C., Lanjouw, J. O., & Lanjouw, P. (2003). Micro–level estimation of poverty and inequality. *Econometrica, 71*(1), 355-364.

Esteban, J., Mayoral, L., & Ray, D. (2012). Ethnicity and conflict: An empirical study. *American Economic Review, 102*(4), 1310-42.

Esteban, J. M., & Ray, D. (1994). On the measurement of polarisation. *Econometrica*, *62*(4), 819-851.

Fischer, M., & Getis, A. (Eds.). (2009). *Handbook of applied spatial analysis: Software tools, methods and applications*. Berlin, Germany: Springer Science & Business Media.

Gates, S., & Miklian, J. (2010). *Strategic revolutionary phases of the Maoist insurgency in Nepal.* Unpublished manuscript.

Gibson, J. (2019). Are you estimating the right thing? An editor reflects. *Applied Economic Perspectives and Policy*, *41*(3), 329-350.

Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). *Night lights in economics: Sources and uses* (Working Paper 2020-01). Oxford, England: Centre for the Study of African Economies, University of Oxford.

Gobyn, W. (2009). From war to peace: The Nepalese Maoists's strategic and ideological thinking. *Studies in Conflict & Terrorism*, *32*(5), 420-438.

Gomes, J. F. (2015). The political economy of the Maoist conflict in India: An empirical analysis. *World Development*, *68*, 96-123.

Goodman, S., BenYishay, A., Lv, Z., & Runfola, D. (2019). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & Geosciences*, *122*, 103-112.

Goyal, R., Dhawan, P., and Narula, S. (2005). *The missing piece of the Puzzle: Caste discrimination and the conflict in Nepal.* New York, NY: Center for Human Rights and Global Justice, NYU Law School.

Hegre, H., Østby, G., & Raleigh, C. (2009). Poverty and civil war events: A disaggregated study of Liberia. *Journal of Conflict Resolution*, *53*(4), 598-623.

Hatlebakk, M. (2010). Maoist control and level of civil conflict in Nepal. *South Asia Economic Journal*, *11*(1), 99-110.

Henderson, J. V., Storeygard, A., and Weil, D. (2012). Measuring economic growth from outer space. *American Economic Review 102*(2), 994-1028.

Hoelscher, K., Miklian, J., & Vadlamannati, K. C. (2012). Hearts and mines: A district-level analysis of the Maoist conflict in India. *International Area Studies Review*, *15*(2), 141-160.

Holtermann, H. (2016). Relative capacity and the spread of rebellion: Insights from Nepal. *Journal of Conflict Resolution*, *60*(3), 501-529.

Janus, T., & Riera-Crichton, D. (2015). Economic shocks, civil war and ethnicity. *Journal of Development Economics*, *115*, 32-44.

Joshi, M., & Pyakurel, S. R. (2015). Individual-level data on the victims of Nepal's Civil War, 1996–2006: A new dataset. *International Interactions*, *41*(3), 601-619.

Khanna, G., & Zimmermann, L. (2017). Guns and butter? Fighting violence with the promise of development. *Journal of Development Economics*, *124*, 120-141.

Koubi, V., & Böhmelt, T. (2014). Grievances, economic wealth, and civil conflict. *Journal of Peace Research*, *51*(1), 19-33.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton, FL: CRC Press.

Macours, K. (2010). Increasing inequality and civil conflict in Nepal. *Oxford Economic Papers*, *63*(1), 1-26.

McKenzie, D. J. (2005). Measuring inequality with asset indicators. *Journal of Population Economics*, *18*(2), 229-260.

Miller, G. L., & Ritter, E. H. (2014). Emigrants and the onset of civil war. *Journal of Peace Research*, *51*(1), 51-64.

Montalvo, J. G., & Reynal-Querol, M. (2005). Ethnic polarisation, potential conflict, and civil wars. *American Economic Review*, *95*(3), 796-816.

Murshed, S. M., & Gates, S. (2005). Spatial–horizontal inequality and the Maoist insurgency in Nepal. *Review of Development Economics*, *9*(1), 121-134.

Nayak, N. (2007). The Maoist movement in Nepal and its tactical digressions: A study of strategic revolutionary phases, and future implications. *Strategic Analysis*, *31*(6), 915-942.

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

Ogura, K (2008). *Seeking state power: The communist party of Nepal (Maoist).* Berlin, Germany: Berghof Foundation.

Pivovarova, M., & Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from Nepal. *World Development*, *66*, 308-321.

Regan, P. M., & Frank, R. W. (2014). Migrant remittances and the onset of civil war. *Conflict Management and Peace Science*, *31*(5), 502-520.

Reynal-Querol, M. (2002). Ethnicity, political systems, and civil wars. *Journal of Conflict Resolution*, *46*(1), 29-54.

Sambanis, N. (2002). A review of recent advances and future directions in the quantitative literature on civil war. *Defence and Peace Economics*, *13*(3), 215-243.

Schutte, S., & Weidmann, N. B. (2011). Diffusion patterns of violence in civil wars. *Political Geography*, *30*(3), 143-152.

Sharma, H., & Gibson, J. (2019). *Civil War and International Migration from Nepal: Evidence from a Spatial Durbin Model* (Working Paper in Economics 19/06). Hamilton, New Zealand: University of Waikato.

Sharma, K. (2006a). The political economy of civil war in Nepal. *World Development*, *34*(7), 1237-1253.

Sharma, K. (2006b). Development policy, inequity and civil war in Nepal. *Journal of International Development*, *18*(4), 553-569.

Shrestha, M. (2017). *Push and pull: A study of international migration from Nepal* (Policy Research Working Paper No. 7965). Washington, DC: World Bank.

Taydas, Z., & Peksen, D. (2012). Can states buy peace? Social welfare spending and civil conflicts. *Journal of Peace Research*, *49*(2), 273-287.

Theisen, O. M. (2008). Blood and soil? Resource scarcity and internal armed conflict revisited. *Journal of Peace Research, 45*(6), 801–818.

Tollefsen, A. F. (2017). Experienced poverty and local conflict violence. *Conflict Management and Peace Science*, 37(3), 323-349.

Verwimp, P., Justino, P., & Brück, T. (2019). The microeconomics of violent conflict. *Journal of Development Economics, 141*, 1-6.

Ware, H. (2005). Demography, migration and conflict in the Pacific. *Journal of Peace Research*, *42*(4), 435-454.

Wolfson, M. C. (1994). When inequalities diverge. *The American Economic Review*, *84*(2), 353-358.

Appendix

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

Table A.2.1: Beta Model estimates, Covariates Selected from Backward Stepwise Regression (with removal at $p>0.1$)

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

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

Table A.2.2: Alpha Model estimates, Covariates Selected from Backward Stepwise Regression (with removal at $p>0.1$)

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

					(4.1)***
Members attending school*yhat*yhat	0.000				
	(3.31)***				
HH head religion*yhat*yhat	0.000		0.000		
	(2.87)***		(2.26)**		
Literate members in HH*yhat*yhat	0.000				0.000
	(2.46)**				(2.13)**
HH head "Upper caste" *yhat*yhat	0.000				
	(4.0)***				
Intercept	-5.654	-7.932	-10.486	-8.412	1.330
	(7.39)***	(23.76)***	(34.2)***	(52.63)***	0.520
R-squared	0.1455	0.0762	0.0643	0.0558	0.1850

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

Chapter Three: Mean-Reverting Errors and Spatially Aggregated Conflict

Data- Impacts of Civil War on International Migration from Nepal

Hari Sharma & John Gibson

Abstract

A growing literature studies microeconomic effects of war on human capital formation and labour market activity. A common research design is to relate spatially aggregated data on conflict rates at the first or second sub-national level to more spatially disaggregated survey data on outcomes of interest. Several studies focus on Nepal's civil war, that ran for a decade from 1996, and use conflict-related deaths in Nepal's 75 districts (the second sub-national level). Variation in the conflict-related death rate within Nepal's districts is more than three times higher than the variation between districts. Consequently, using district-level conflict data creates a mean-reverting measurement error on the right-hand side of regression models, makes the conflict seem more widespread, and biases econometric estimates of conflict impacts. Prior studies also ignore spatial spillovers, where conflict may affect outcomes not only locally but also in surrounding areas. To deal with these biases, we use measures of conflict intensity for Nepal's 3982 localities in a spatial Durbin model of the change in emigration rates between the 2001 and 2011. We distinguish emigration to India, which is informal and long-standing, from emigration to other countries that is a recent development for Nepal and requires formal recruitment and visa processes. Higher conflict intensity is associated with slower growth in the emigration rate between 2001 and 2011. It is mainly indirect impacts, based on the spatial lags, which matter and it is emigration to destinations other than India most deterred by the conflict. The estimated impacts would be substantially distorted if conflict intensity was aggregated at the district level, as in much of the literature.

Keywords: Civil war, emigration, mean-reverting measurement error, Spatial Durbin model, Nepal

JEL Codes: C21, D74, F22, O15

3.1 Introduction

A growing literature studies microeconomic effects of war on human capital formation and labour market activity. A recent review by Verwimp et al. (2019) notes that an objective of this literature is to study 'ways in which individuals, households, and communities, behave, adapt, make decisions and live in conflict-affected contexts' (p.1). A typical research design is to relate spatially aggregated data on conflict rates at the first or second sub-national level to more spatially disaggregated survey data on outcomes of interest. For example, studies of Nepal's civil war, that ran for a decade from 1996, use conflict-related deaths in 75 districts (the second sub-national level) as predictors of internal displacement rates (Adhikari, 2012), and of survey measures of female employment (Menon and Van der Meulen Rodgers, 2015), schooling attainment (Pivovarova and Swee, 2015), and international migration (Shrestha, 2017).[10] Elsewhere, Chamarbagwala and Morán (2011) use civil war victimization data for Guatemala's 22 *departamentos* (the first sub-national level) to predict individual-level human capital formation, while Kountchou et al. (2019) use conflict data for 53 districts in Chad in a model of child health and nutrition for 20,000 children in 650 DHS survey clusters.[11]

A problem with this research design is that the vector of data on conflict indicators is implicitly 'stretched' to line it up with the more disaggregated outcome measures, and this is likely to cause a bias in econometric estimates of the impact of the conflict. The local conflict rate is likely to influence individual decisions about labour market activity and human capital investments and will vary from the district-level conflict rate. Specifically, using district-level rates creates a mean-reverting measurement error; the fatality rate in areas with no (or few) fatalities is overstated by

[10] Do and Iyer (2010) use district-level data to study geographic and poverty-related causes of the conflict.

[11] There are examples of using more finely-grained conflict data, including Fergusson et al. (2019) who use municipality level conflict rates for Colombia, Guariso and Verpoorten (2014) who use sub-district conflict rates for Rwanda, and Libois (2016) who counts deaths in a 20 km buffer around surveyed villages in the 12 months prior to the 2004 Nepal Living Standard Survey. Simpler indicators used in Nepal include a dummy variable for DHS villages that reported any conflict deaths between 1996 and 2004 (Nepal et al., 2018) and the number of months that a village (for the 380 villages in the 2016 DHS) was exposed to conflict (Phadera, 2019). Yet the issues associated with the optimal level of spatial aggregation of conflict data are not discussed in these studies.

using fatality rates for more aggregated areas, while it is understated for localities with higher fatality rates than the district average. If errors are mean-reverting, regression coefficients may be exaggerated, rather than attenuated as happens with random measurement error, with exaggerated impacts seen in the results we report below for Nepal. Also, the instrumental variables (IV) estimator may be biased and inconsistent (Black et al., 2000). Thus, even if a researcher has a plausible instrumental variable, used because of concerns about the endogeneity of local conflict rates, if there is mean-reverting measurement error then the IV estimates of conflict impacts are still likely to be biased.

A key issue when aggregating conflict data is what aggregation level best preserves information. A desirable property for forming groups is that knowing that an observation is in a particular group tells us, by itself, a lot about the observation. Hence, within-group variation should be low and between-group variation high if the group indicator is to be informative. The spatial heterogeneity in intensity of Nepal's civil war means a lot of information is lost if conflict data are aggregated to district level. For example, variation in total deaths and in the death rate within districts was more than three times higher than variation between districts. This within-district heterogeneity also shows up as a low intra-district correlation coefficient (ρ=0.08), which can be interpreted as a measure of the reliability of the district-level mean. Knowing that a household comes from a particular district is not very informative about the conflict experienced by that household because the district mean has such low reliability. At district level the conflict also seems more widespread; while all but two (of 75) districts had some fatalities, only about half of the 3982 localities had any conflict-related fatalities. This pattern is also likely to occur elsewhere because civil wars in developing countries are often spatially concentrated conflicts (Verwimp et al., 2019).

While maximizing between-group variation would seem to suggest using conflict data for the finest possible spatial unit (e.g. an individual street), two other considerations come into play. A very small area, like a street, is unlikely to correspond to the spatial range of the daily activities

carried out by people living in conflict-affected contexts, and so bigger spatial units may be more relevant. Offsetting that, there are often restrictions on media during wars, limiting access to information about how intense or widespread is the conflict. For example, press freedom was suspended after Nepal's army mobilized to fight the Maoist insurgents in 2001, and targeting of journalists by both the army and the Maoists led to some media self-censorship (Hutt, 2006). Under these conditions, news of local outbreaks of conflict may not spread across a district via media and may instead be by word of mouth. Districts in Nepal have average area of 2000 km^2 (similar to the UK county of Warwickshire or to Mauritius) while the average locality is just 36 km^2. With fairly big districts and small localities, and restricted media, it is likely that one would know the local conflict rate rather than the district conflict rate, because parts of a district may be up to 50 km away. So a second consideration is: for what level of spatial aggregation is it likely that individuals knew the conflict rate?

In order to study these issues more formally, we measure conflict intensity for Nepal's 3982 localities (VDCs or Village Development Committees, once known as *panchayats*). We use conflict death rates from 2002 to 2004, when fighting was heaviest, with two-thirds of the total 15,000 deaths occurring in those three years. Our results would be largely the same if we used data on the full decade of conflict-related deaths. We find a strong mean-reversion if district conflict rates are used to proxy for VDC conflict rates, which exceeds the degree of mean reversion found in several other variables in development economics (as tabulated by Abay et al. (2019)). This matters because strong mean reversion for right-hand side variables causes regression coefficients to be exaggerated, overstating the impacts of the conflict.

The particular outcome we focus on is emigration, because labour export is a key feature of Nepal's economy, with two million Nepalese working abroad sending almost US$7 billion in annual remittances (equivalent to 29% of GDP, the third highest rate in the world). The existing literature suggests conflict increased emigration from Nepal (Shrestha, 2017). More generally, the

idea that conflict is an important push factor in international migration is widespread in the literature (e.g. Naude, 2008). Yet conflict can also increase the costs of migration, by making travel for documentation (passports and visas) and recruitment more hazardous and also by lowering the ability to finance migration if conflict negatively affects incomes or access to lenders. Given these potentially offsetting effects, we test if the local intensity of Nepal's civil war, measured at the VDC level, affected the growth in emigration rates, both in the same localities and elsewhere. We separate emigration to India, which is low-cost, informal, and has occurred for decades, from emigration to other countries, where formal (and costly) recruitment and visa processing (in Kathmandu) is required, and which has been a recent large-scale development for Nepal.

Our migration data are from Nepal's 2001 and 2011 census of population, which asks about members of households who are overseas. The peak conflict period occurred between the two censuses, which limits use of panel data methods to relate contemporaneous conflict to contemporaneous emigration, where VDC-level fixed effects could be used to deal with omitted heterogeneity. Instead, we use long differences, with our outcome measures the change in the emigration rates for each VDC between 2001 and 2011. With differencing we remove the influence of time-invariant factors, such as geography, that may affect conflict and the propensity to emigrate. Control variables from the census are also in long differences, while our main variable of interest is the conflict intensity at the peak of the fighting, from 2002-04. We use a spatial Durbin model that allows indirect effects of the conflict in one locality to affect outcomes in (all) other localities. This deals with another problem in the existing literature, of not allowing for spatial spillovers, where local conflict may affect outcomes not only in that particular area but also in surrounding areas.

We find that an increase in conflict intensity, by one death per thousand population at the peak of the conflict (2002-04), is associated with slower growth in the emigration rate between 2001 and 2011. Specifically, the emigration rate rose by 3.9 persons per thousand fewer (equivalent to ten percent of the mean increase) than it would have in the absence of the conflict. This effect is

predominantly though the indirect channels that operate via the spatial lags in the conflict rate and in the emigration rate. When we disaggregate by destination, it is emigration to non-India destinations that is most depressed by conflict. This likely reflects the greater cost (and hence, sensitivity to conflict-induced income losses) of this emigration channel and the need to travel to Kathmandu for visa and recruitment purposes, while travel to India for work could use multiple routes to avoid conflict hot spots.

A different picture emerges if we measure conflict intensity at the district level. Using more spatially aggregated conflict data suggests there is a large and statistically significant direct effect of higher conflict intensity (of one death per thousand) *increasing* the VDC-level emigration rate by eight persons per thousand overall and by eleven persons per thousand to India. These direct effects are offset by even larger negative indirect effects, so that the total effect of one more death per thousand appears as a suppression of the 2001 to 2011 increase in the emigration rate by about eight persons per thousand (with similar magnitudes, but not precision, of the effects for India and for the other destinations). These total effects are up to four times larger than when the conflict intensity is measured at the VDC level. These results suggest that using more aggregated conflict data, such as district level death rates, may bias estimates of the micro economic effects of the war because of mean-reverting errors.

Our findings also imply that people in VDCs that experienced the highest intensity of localized conflict may still be suffering at least one after-effect of the war. It is likely that remittance income in these areas is lower than it is elsewhere, since they did not participate as much in the huge growth in work-related emigration that the rest of Nepal experienced between 2001 and 2011. If this is the case, it is even more important to correctly diagnose the local consequences of the conflict. Expecting positive effects of local conflict intensity on emigration could lead one to predict that conflict-affected areas will have a higher expected remittance income (from their expected higher emigration rate), which might help offset some of the conflict-related losses. In

fact, it is likely that remittance income grew less in these conflict-affected areas than elsewhere because the conflict had a mildly suppressing effect on their participation in the growing rate of emigration.

The remainder of the paper is structured as follows: Section 3.2 provides the context for our study; Section 3.3 discusses the data and our econometric model; Section 3.4 contains the results, and Section 3.5 concludes.

3.2 Context

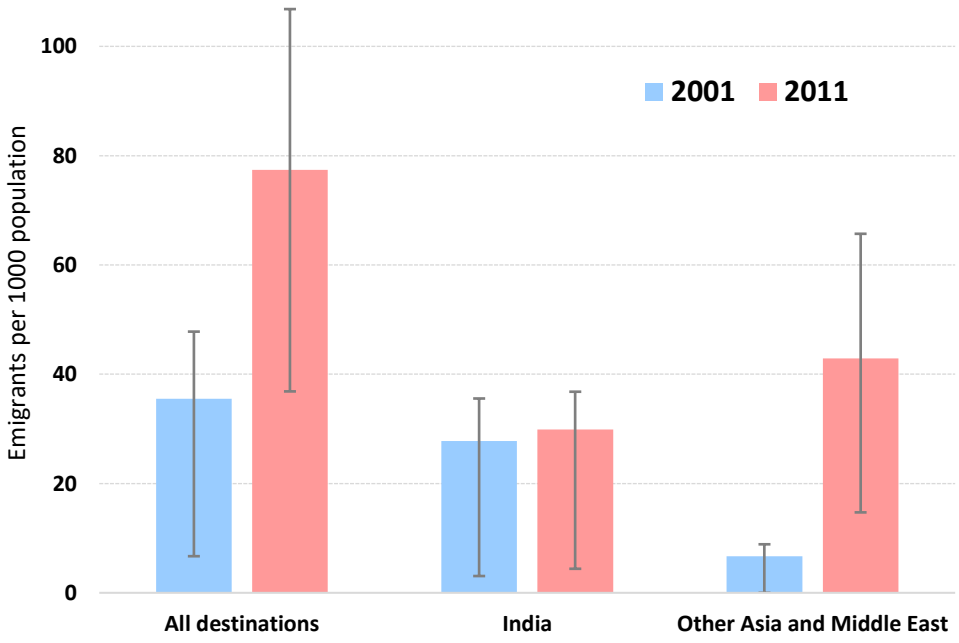
3.2.1 Emigration from Nepal

Nepal has a long history of work-related migration, especially to its southern neighbour. This includes British Army recruitment of hill Nepali during World War II and recruitment of Gurkha regiments by India to fight in the Indo-China and Indo-Pakistan wars. An open border treaty in 1950 made India an attractive and low-cost destination to escape domestic unemployment. Thus, emigration for employment emerged as a major household activity (Sapkota, 2013). For example, the third Nepal Living Standards Survey showed that one-third of households in 2010 had at least one member working abroad; mostly amongst the 15 to 59 age group. This emigration opportunity was especially used by households in the western and mid-western regions of Nepal, which have poor land productivity, high poverty and food insecurity, and poor infrastructure. These two regions accounted for 36% and 48% of the emigrants in India according to the censuses in 2001 and 2011 (Central Bureau of Statistics, 2001, 2011).

In recent years the demand for workers in the Middle East created a new opportunity for emigrants from Nepal. Beginning in 1993/94, when 3,605 people obtained a permit to move for foreign employment in the Middle East, demand for this type of permit-based emigration (as opposed to the informal migration to India) rose strongly, such that there was a seven-fold increase (to annual recruitment of 28,000 workers) in just six years. However, the major period of increase, which also saw a spreading out to ASEAN countries like Malaysia, and to richer labour-scarce

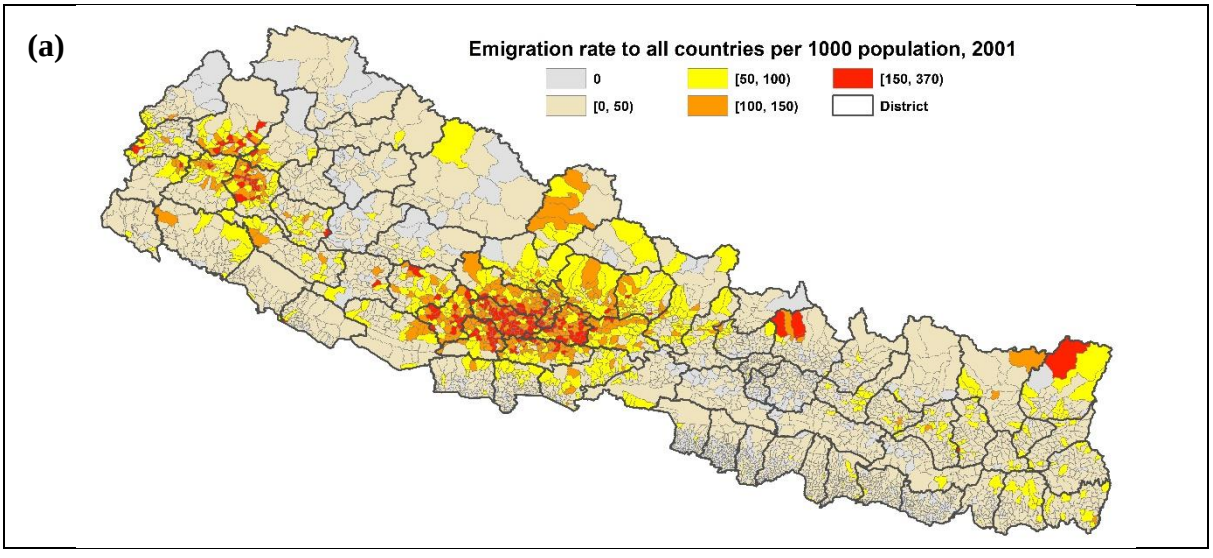
countries like Korea, came in the decade from 2001. Between the population censuses in 2001 and 2011 Nepal's emigration rate more than doubled, to be over seven percent in 2011. This was due almost entirely to emigration to destinations other than India, as seen in Figure 3.1 which shows the mean and the 25th and 75th percentiles of the VDC-level emigration rate in each census. The mean emigration rate to India hardly changed, going from 28 to 30 per thousand from 2001 to 2011; for destinations elsewhere it rose from 7 to 43 per thousand. This sharp rise in emigration to places other than India more than doubled Nepal's overall emigration rate. In over one-quarter of localities the emigration rate now exceeds ten percent (shown by the grey capped bar). Emigrants provide at least US$7 billion in annual remittances (equivalent to 29% of GDP, the third highest rate in the world) and probably more, since most remittances from India are undocumented.

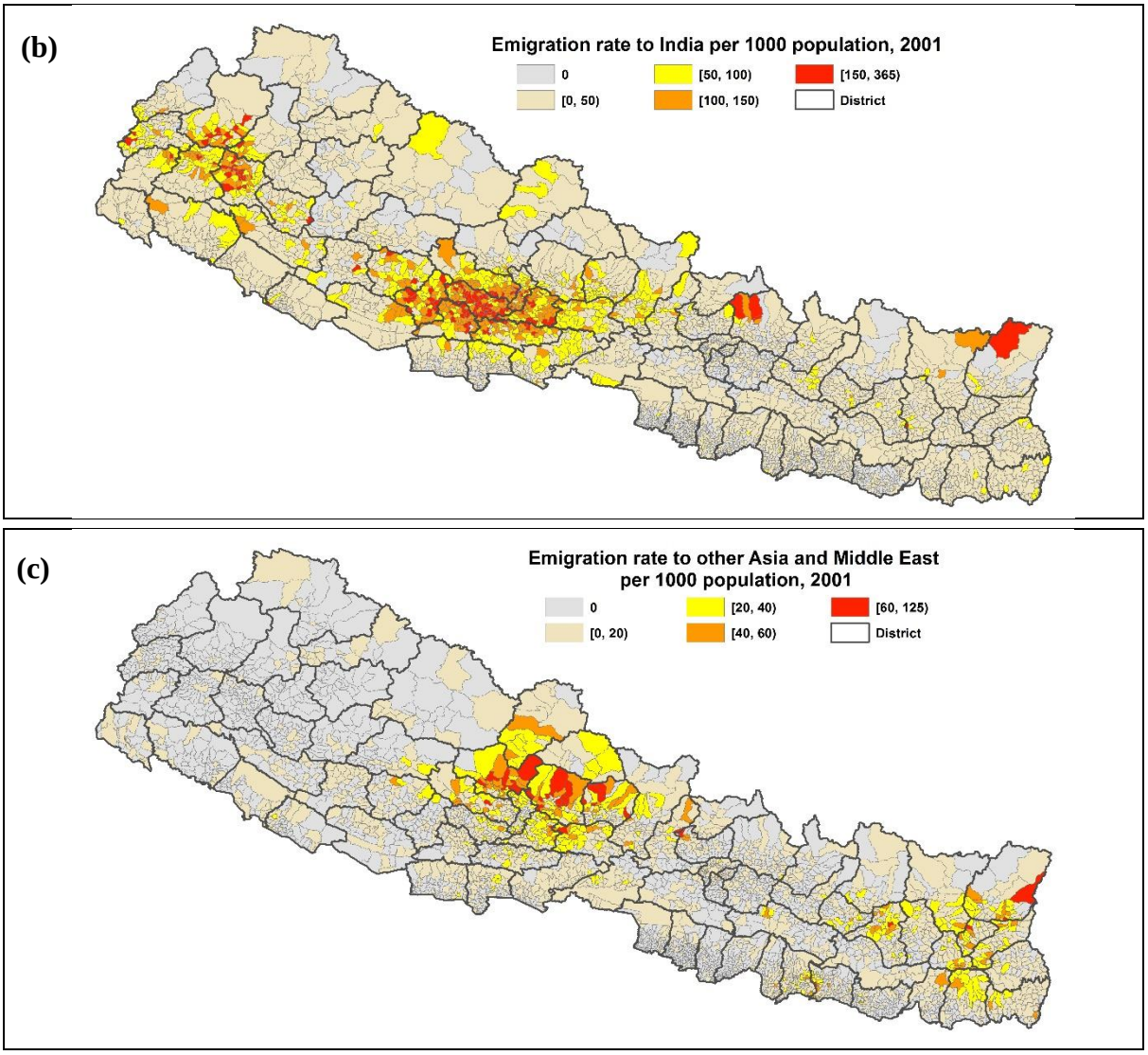
Figure 3.1: Average emigration rates from Nepal, 2001 and 2011
(bars show inter-quartile range)



In terms of where these emigrants came from, Figure 3.2 maps the emigration rates in 2001. Given that three-quarters of all emigrants were in India in that year, the map for all destinations (panel a) is much like the map for where emigrants to India came from (panel b). The concentration of emigrant-source areas in the western and mid-western regions is apparent. In contrast, even though they were numerically far fewer in 2001, the emigrants going to locations other than India (shown in panel c of Figure 3.2) were predominantly from the central and eastern regions of Nepal. One cause of these spatial patterns is that people from relatively poor areas tend to emigrate to India as a low cost option due to their lack of wherewithal to finance emigration to elsewhere, like the Middle East, that offers higher returns. Roughly speaking, it takes from US$2,000-US$10,000 to emigrate to a non-India destination, in addition to the commuting cost to Kathmandu in order to obtain a passport and get a permit from the Ministry of Labour and Employment. The nearby central region is more developed, so people from there have many advantages in partaking in non-India emigration, including lower commuting cost for getting the needed documents, high literacy rates, and access to financial institutions to help fund the up-front costs of recruitment and visa charges.

Figure 3.2: Emigration rate to (a) all countries, (b) India (c) other Asia and Middle East at VDC level, 2001 Census



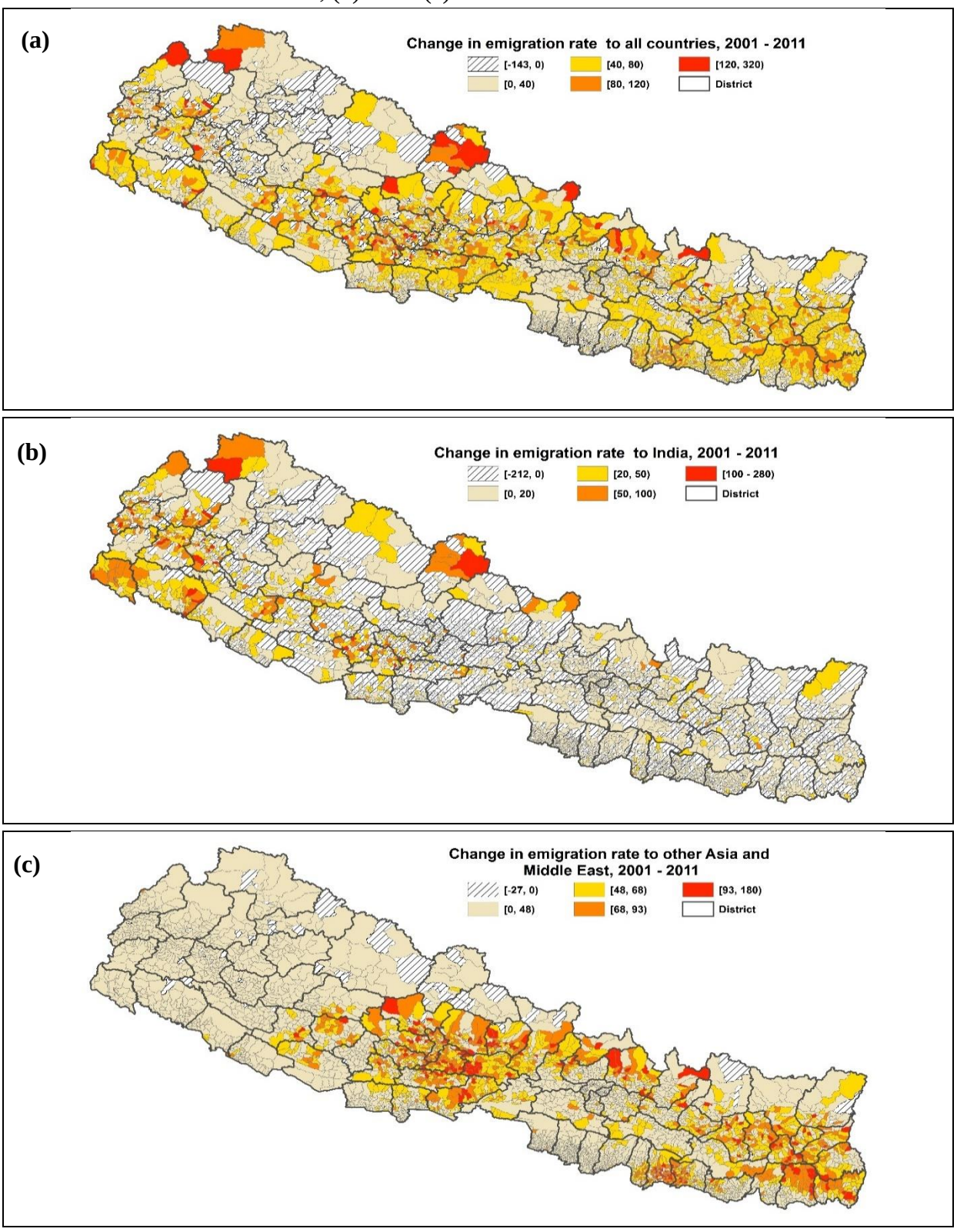


Source: Author's calculations from Census extract data

The change in emigration rates between 2001 and 2011, at the VDC-level, is shown in Figure 3.3. The first panel shows emigration to all countries, the second panel is for emigration to India, and the third is for other Asian destinations and the Middle East. These maps show the spatial distribution of the outcome variables that our econometric models focus on. One feature that is apparent from panel (a) is that almost all parts of Nepal experienced higher emigration rates over this decade; less than ten percent of VDCs had no rise in emigration rates (shown by the hatched areas in the map). It is also clear that there is a lot of variation within districts; the standard deviation for within-district variation is twice as large as for between-district variation and the intra-

district correlation in the change in emigration rates is only 0.21. This suggests that it is important to conduct analyses at a disaggregated level.

Figure 3.3: Change in emigration rate at VDC level between 2001 and 2011 to (a) all countries, (b) India (c) other Asia and Middle East



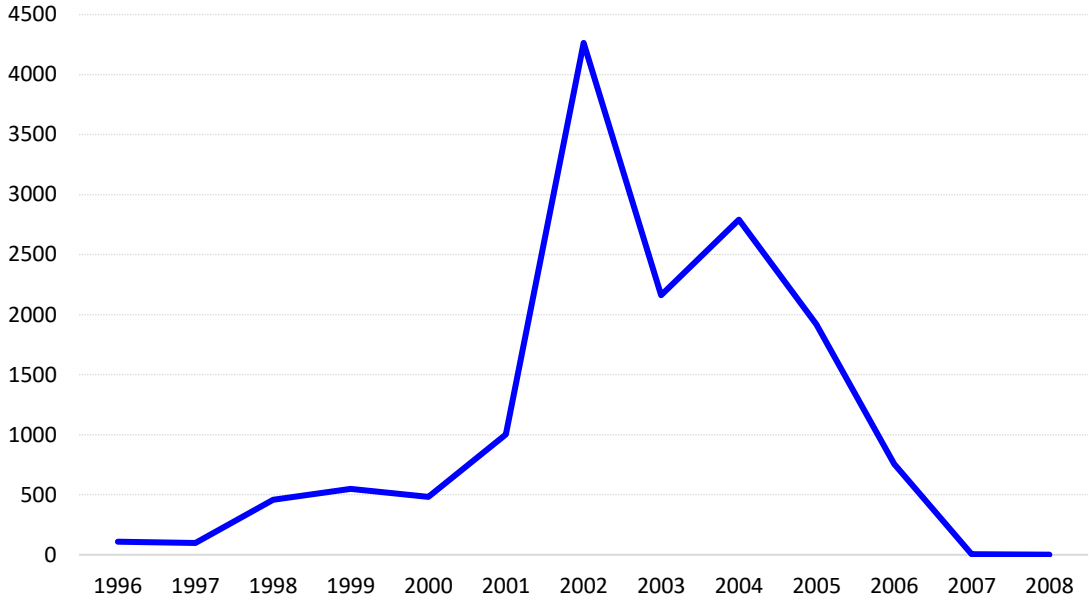
Source: Author's calculations from Census extract data

The second panel in Figure 3.3 shows the change in the emigration rate to India. Almost one-half of all VDCs, which cover more than half of Nepal's area, had a fall in the rate of emigration to India. Conversely, the areas of increased emigration to India were along the northern border, in the very far west and a scattering of VDCs in the mid-western regions. When we consider the emigration to other Asian and Middle Eastern destinations (panel c), western areas of Nepal are some of the lowest participants, being in the lowest category of increase (shown by the tan colour) or even having decreasing rates. In contrast, the richer central and eastern areas were the major source of increase in emigration rates to non-India destinations, although with considerable heterogeneity within districts.

3.2.2 Nepal's Civil War

In 1996, the Communist Party of Nepal (CPM-Maoist) formally declared war against the state with the aim of abolishing the constitutional monarchy and establishing communist rule. Initially, the conflict was restricted to the poorest and underdeveloped regions in the far west and mid-western regions of Nepal. The Maoists benefited from the remoteness, and the dense forest and mountains, which favoured guerrilla tactics for their occasional attacks on police posts and on private firms and banks. Chronic poverty in these regions also helped to draw in support of some locals because the Maoists seized land from high caste landlords and let the poor and low caste *Dalit* people use it (Bownas, 2015). While the police retaliated against these attacks (including claims of torturing people they believed were militants), there was no involvement by the army. Over five years of mainly localized fighting, which slowly grew in intensity, approximately 2000 people had been killed in total (Figure 3.4).

Figure 3.4: Annual conflict-related deaths during civil war in Nepal



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

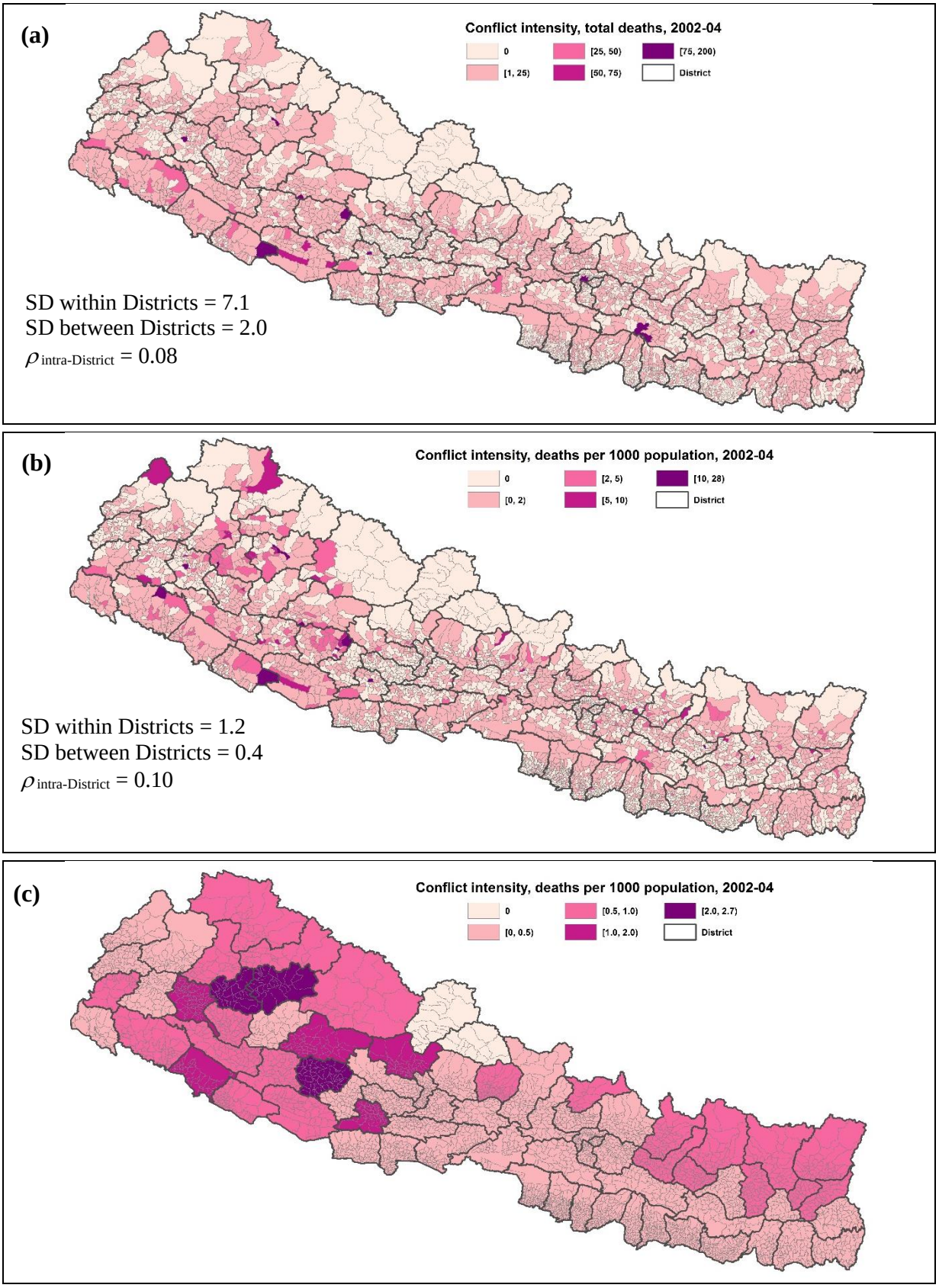
The war took an unexpected turn to more generalized and intensive conflict, after the killing in June 2001 of King Birendra and his family, murdered by the then crown prince, who subsequently committed suicide. The new King, Gyanendra Shah mobilised the army to deal with the insurgents, after on-going peace talks broke down in late 2001. Consequently, the conflict spread rapidly and became more intense, with over 4000 deaths in 2002, and more than 2000 deaths per year in 2003 and 2004 (Figure 3.4). In total, two-thirds of all conflict deaths occurred in this three year period. During this period the Maoists had some control in at least 35 of the 75 districts (Pivovarova & Swee, 2015), with a parallel government (Libois, 2016). In 2005, the Maoists called for a unilateral ceasefire so as to join peace talks with other major political parties. Later in 2006, an uprising of the Nepali population against the King brought an end to the monarchy. By then, a peace agreement signed with all political parties led to the end of the decade-long conflict and by the time of elections in 2008 the political party based on the Maoists won close to half of the seats.

The data in Figure 3.4 are from the Informal Sector Service Centre (INSEC), a NGO that monitored human rights violations by both Maoist and government forces. Their data are considered the most reliable source on the conflict intensity during the civil war (Libois, 2016; Valente, 2013).

For each death and disappearance (equated to death if they were never located) in INSEC's district-level dataset we disaggregated to VDC level by using the report of where the victimization event occurred. These data cover the army, police, insurgents, and civilians who may be killed in cross-fire, by landmines, and so on. Of the 15,021 deaths covered in the INSEC data (Joshi & Pyakurel, 2015), we could identify the VDC where the death occurred in over 97 percent of cases, for 14,595 victims.

The location of deaths during the 2002-04 peak in the conflict is mapped in Figure 3.5a. The conflict was often very localized, and almost half of all VDCs (*n*=1954) had no deaths recorded. In contrast, just two of 75 districts (that is, 3% of the total) had no conflict-related deaths. Thus, the spatially aggregated data make the conflict appear more widespread. At the other end of the distribution, just 13 VDCs had 50 or more deaths and 29 had 30 or more deaths (that is, averaging ten deaths per year). Variance decompositions also show that district-level analysis may mislead; the standard deviation (SD) in the number of deaths is 7.1 within districts and only 2.0 between districts. In other words, there is more than three times as much variability within a district as between districts. This also shows up in the low value (0.08) of the intra-district correlation in deaths (Figure 3.5a).

Figure 3.5: Spatial variation in conflict intensity: (a) deaths, (b) death rates, (c) smoothed by District



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

In Figure 3.5b we consider death rates rather than deaths, since Nepal's population is unequally distributed over space (and the Maoists initially established in low density areas). Using death rates tilts conflict intensity slightly to the west, but it remains the case that the standard deviation in death rates within districts is three times as large as between districts so a district level analysis understates the spatial heterogeneity and exhibits mean reversion. We illustrate this effect in Figure 3.5c, which takes the same death rate data as in Figure 3.5b but averages it to district level before mapping; the conflict appears to be far more widespread, both in the west and also in the north east. Our econometric analysis in Section IV shows that this spreading effect causes bias in models that estimate impacts of the conflict.

This bias occurs because using district level death rates create a mean-reverting error. If we consider the VDC level death rate as the correct variable for explaining outcomes at VDC level – such as the change in VDC-level emigration rates – the difference between the district level death rate and the VDC level death rate is the measurement error. On average, this error is roughly zero, because the same data are just being aggregated and averaged in different ways, but it is non-random. In particular, this measurement error negatively correlates with the correct variable; regressing the measurement error on the VDC level death rate yields a coefficient of -0.89 (standard error of 0.005). Abay et al (2019) recently collated estimates of the mean reversion parameter from various contexts, with values that range from -0.3 to -0.8, where the more negative the value, the stronger the mean reversion. Unlike the standard random measurement error, that attenuates regression coefficients when the mis-measured variable is on the right-hand side, with a strong enough mean reversion the regression coefficients can be exaggerated. Such exaggeration is likely in the current context because the magnitude of the mean reverting parameter for conflict rates (-0.89) exceeds the values of the mean reversion parameters reported in other contexts where regression coefficients are found to be exaggerated (Gibson et al, 2015).

3.3 Data and Methods

In addition to conflict data from INSEC described above, our main data sources are the tenth and eleventh national population and housing censuses from 2001 and 2011. Nepal does not give microdata access to the full census but the Central Bureau of Statistics (CBS) provided extracts with complete records for over one-tenth of households, covering all VDCs. Census questions on household members working abroad provide our measures of emigration, and we express these as rates using the extract-level population for each VDC in each census.[12] We also use census data on literacy rates and educational attainment, and on age structure.

The census lacks measure of local urban growth, the absence of which may be a push factor for emigration. We therefore measured disaggregated urban growth using night time lights as detected by satellite, taking a three year average for 1999-2001 and for 2009-11 to smooth short-term fluctuations. These lights data are best thought of as measuring urban growth because it takes 800-times more light than a typical incandescent bulb in order to be detected from space with the sensors on the Defence Meteorological Satellite Program (DMSP) satellites (Gibson et al., 2020). We further rule out measuring rural economic activity by setting luminosity thresholds to distinguish urban and rural areas, where these thresholds match those recently used for a study of how urban development in India affects rural areas (Gibson, et al., 2017). Thus, changes in night time lights between 2001 and 2011 are more likely to be a proxy cause of emigration, rather than a result (e.g. as might occur if subsequent remittances enabled rural dwellers to electrify their dwelling).

Table 1 has complete definitions and descriptive statistics for all of the variables that we use. The analysis is mostly cast in terms of long differences between 2001 and 2011 and so some of the environmental and infrastructural factors that may affect emigration rates and conflict intensity can

[12] For expressing the conflict intensity as rates per thousand population we use the full population counts for each VDC from the 2001 census, since we do not need household-level data for that purpose.

be ignored if they are fixed in the medium term. However, we do include a dummy variable for whether a VDC borders India (which is true for 7.6% of them) based on a GIS analysis. We also use the baseline emigration rates from the 2001 census which should capture other (relatively time-invariant) factors that make particular localities more or less prone to having high emigration. Our objective in using these various control variables is so that the intensity of the conflict (which, recall, took an unexpected turn after the death of the King in 2001) is not acting as a proxy for some omitted local factors.

3.3.1 The Econometric Model

The *N*-vector of long differences in VDC-level emigration rates is denoted ΔM_i, the conflict intensity variables are denoted C_i, there are five control variables in the matrix X_i (the change in the working age population share, the change in the literacy rate and in the share of working age individuals with grade 8 schooling or above, the change in local urban activity as proxied by night lights, and a dummy for whether the VDC borders India), and the lagged VDC-level emigration rate from 2001 is $M_i^{t=2001}$. Our spatial Durbin model (SDM) is:[13]

$$\Delta M_i = \delta W \Delta M_i + \beta_1 C_i + \beta_2 W C_i + \beta_3 X_{1i} + \beta_4 W X_{1i} + \cdots + \beta_{11} X_{5i} + \beta_{12} W X_{5i} + \beta_{13} M_i^{t=2001} + \beta_{14} W M_i^{t=2001} + v_i \quad (3.1)$$

Here the spatial weighting matrix *W* describes the structure of spatial relationships between each VDC. The *W* matrix has zeros along the main diagonal, given that no VDC is its own neighbor, while the off diagonals are set to unity for immediate neighbors (using Queen contiguity weights) and zero otherwise. This model allows for changes in an explanatory variable in a particular VDC to not only affect the change in the emigration rate in that VDC, but also in the surrounding areas. The parameters to estimate are δ and $\beta_1, \ldots, \beta_{14}$, while v_i is a random error term

[13] For an excellent overview of the spatial Durbin model see Elhorst (2012).

which the generalized spatial two-stage least squares estimator (Kelejian and Prucha, 1999; Drukker et al., 2013) that we use allows to be heteroscedastic.

The spatial Durbin model is a general model that nests several alternatives, such as the spatial autoregressive model, where only the dependent variable is spatially lagged, the spatial error model, where only the errors are spatially lagged, and aspatial models such as OLS, where there are no spatial lags for any variables.[14] The SDM gives unbiased coefficient estimates even if the true data-generation process is a spatial autoregressive model or a spatial error model, but the reverse is not true given that it involves omitting relevant variables. Thus, the SDM provides a good general basis for testing the effects of conflict on emigration.

A feature of the SDM is that the total effect of changes in an independent variable—such as in conflict intensity—may be quite different to what is shown by $\hat{\beta}_1$ since a local change in the emigration rate may affect the emigration rates of neighbours, which, in turn, affects the emigration rate of their neighbours, including the original locality. In addition to these effects that operate through the spatial lag of the dependent variable, the lags on the independent variables also mean that local changes can affect outcomes elsewhere. These spillover and feedback effects let us decompose effects of conflict on emigration into direct and indirect components. To see how, note first that equation (3.1) can also be written in matrix notation (where the five control variables in the *X* matrix, and all of the subscripts, are suppressed for reasons of expositional simplicity, and *I* is the identity matrix) as:

$$\Delta M = (I - \delta W)^{-1}(\beta_1 C + \beta_2 WC) + (I - \delta W)^{-1} v \tag{3.2}$$

Following Elhorst (2012), the partial derivatives can then be written as:

[14] For example, the spatial autoregressive model can be derived from our SDM by imposing the restrictions that $\beta_2 = \beta_4 = \beta_6 = \beta_8 = \beta_{10} = \beta_{12} = \beta_{14} = 0$. The spatial error model can be derived by imposing a common factor (COMFAC) restriction.

$$\frac{\partial \Delta M}{\partial C} = (I - \delta W)^{-1}(\beta_1 I_N + \beta_2 W) \quad (3.3)$$

The total marginal effect of conflict intensity on the inter-censual change in the emigration rate, ΔM includes both direct and indirect effects, and these will vary across VDCs as a result of spatial feedbacks. The estimator that we use follows LeSage and Pace (2009) in reporting a single direct effect, that averages the diagonal elements of the $N \times N$ matrix in (3.3), and a single indirect effect, that averages the row sums of the non-diagonal elements of that matrix. Note that indirect effects of conflict arise not only from the neighbours of a VDC, when $\beta_2 \neq 0$ but also from (potentially) all VDCs through spatial autocorrelation when $\delta \neq 0$. In other words, there can be both local and global spillovers, depending on the magnitude of the estimated β_2 and δ coefficients.

The indirect effects are important for two reasons. First, while the conflict was highly localized, as the maps in panel A and B of Figure 3.5 show, the impact on emigration may be felt more widely, depending on the strength of the δ and β_2 coefficients. Seen in this light, one problem with previous research using district-level conflict rates, effectively spreading the conflict over space (as seen in panel C of Figure 3.5), is that it lacks an explicit framework like the SDM that lets the data dictate the degree of spreading. In our estimates, the marginal effects (direct, indirect, and total) are computed for each of the 3982 VDCs, allowing for the possibility that in some cases there will be a lot of spreading of the effects and in others there will be little. This variation may depend on geography, population density, infrastructure, the size of spatial units, and so forth. The second reason that these indirect effects may matter is that the two different emigration channels available to Nepalese – informal to India and formal to elsewhere – have quite different spatial transactions costs. A person could go to India from the VDC where they live, and the free border lets them choose amongst a multitude of routes, so that their journey was not disrupted by conflict (or the risk, thereof). However, to emigrate elsewhere an aspiring migrant first had to go to Kathmandu to get a passport and to be recruited and undergo formal visa processing. This requirement to reach a

particular place, rather than to simply cross anywhere along a border, limits the set of routes available. Moreover, there were often lengthy delays in this process, so repeated trips to Kathmandu may have been necessary, and this extra travel meant that there was more potential to be disrupted (or to be deterred) by outbreaks of conflict along the way than was the case for emigration to India. In other words, outbreaks of conflict can act to raise the cost of emigration, and so, all else the same, lower the emigration rate.

Notwithstanding the generality of the SDM, the coefficient estimates are vulnerable to potential endogeneity of conflict intensity to VDC-level changes in emigration. One difficulty in the current context is that a possibly plausible instrumental variable for conflict intensity – distance from the capital city, if it is expected that government forces are strongest there so insurgency is more likely further away – would fail the exclusion restriction because travel to Kathmandu was needed for recruitment for migration to non-India destinations. We rely on the fact that the conflict took an unexpected turn after the 2001 killing of the royal family; only about 400 VDCs had been affected by conflict by then, but over 2200 were affected by conflict after then (Nepal et al, 2018). This sudden change, plus the fact that we model *changes* in emigration rates (effectively giving us village-level fixed effects) should weaken the threat of either reverse causation – requiring the change in emigration rates between 2011 and 2001 to affect the conflict rate in 2002-04 – or of omitted factors like geography and poverty that correlate with both conflict and emigration. Moreover, even without a plausible instrumental variable, studying the mean-reversion in conflict data at different levels of spatial aggregation is useful because with mean-reverting errors in right-hand side variables the IV estimates of conflict impacts are still likely to be biased.

3.4 Results

The results of estimating equation (3.1) are reported in Table 3.2. There are six sets of results, with separate equations for the change in the emigration rate to all countries, to India, and to other Asian and Middle East destinations (corresponding to the maps of the dependent variables in panels (a),

(b), and (c) of Figure 3.3).[15] The last three columns of results in Table 3.2 show what happens when the VDC-level death rate variable is replaced with a district-level death rate (which is mapped in Figure 3.5c) while the rest of the model stays the same as the corresponding model whose results are reported in columns 1-3. The comparison between the results in the first three and last three columns in Table 3.2 illustrates the bias due to mean-reverting errors that come from overly-aggregated conflict measures.

The results show that higher VDC-level conflict intensity, by one death per thousand, directly reduce growth in the emigration rate for non-India destinations by -0.45 persons per thousand (statistically significant at $p<0.06$). The same effect, for all-destinations emigration, is almost the same but is imprecisely estimated, while conflict intensity appears to have no direct effect on the VDC-level change in the emigration rate to India. This variation supports the disaggregation of the emigration outflows into the low-cost, informal, channel to India, and the higher cost, more formal and more recent channel to other destinations.

The coefficients with respect to the spatially weighted average of the conflict intensity in neighbouring VDCs are larger, at between –0.6 and –3.6. For example, for a VDC where the weighted average death rate amongst its neighbours was one person per thousand higher, the 2001 to 2011 increase in the all-destination emigration rate from the surrounded VDC would be 3.6 persons per thousand lower, and this effect is statistically significant at the $p<0.01$ level. The spatial lag of the change in the emigration rate is always statistically significant at $p<0.01$ for all three outcomes. Given that the δ and β_2 coefficients are statistically significant, local conflict will have spatial spillover effects on the change in emigration rates, and these are calculated using equation

[15] The models reported in the table also allow tests of the nesting restrictions to derive some of the other models from the SDM. For example, for the all-destinations model, the restrictions to derive the spatial autoregressive model are rejected with a chi-squared test statistic of 320, those to derive the spatial error model are likewise rejected (chi-squared=305) and those to nest an OLS model are even more strongly rejected (chi-squared=332).

(3.3) and presented later.[16] The spatial lags indicate that conflict in neighbouring localities matters, and this may be thought of as raising the cost of emigration; for example, by making journeys for recruitment and documentation (passports and visas) more hazardous.

[16] Elhorst (2012) distinguishes local indirect effects as those associated with $\beta_2 \neq 0$ and global indirect effects as those associated with $\delta \neq 0$. As noted earlier, we follow LeSage and Pace (2009) in defining direct effects as "own region effects", i.e. the effect of a change in a covariate *in VDC i* on the dependent variable in *i* averaged over all VDCs, whereas the total effect is the effect of the same change in the covariate in all VDCs on the dependent variable in VDC *i* averaged over all VDCs. The indirect effect is then simply the difference between the total and direct effect.

Table 3.2: Spatial Durbin models for change in the VDC emigration rate between 2001 and 2011, with different spatial granularity of conflict Data

	Conflict Intensity Measured At VDC Level			Conflict Intensity Measured at District Level		
Emigration to:	*All Countries*	*India*	*Other*[a]	*All Countries*	*India*	*Other*[a]
Conflict intensity (Death rate at peak (2002-04)	-0.483	-0.011	-0.445	8.643	11.510	4.877
	(0.91)	(0.03)	(1.90)*	(2.58)***	(4.67)***	(2.48)**
Δ share of working age (15-59)	-31.834	-38.119	-13.709	-33.117	-36.533	-13.771
	(2.29)**	(3.91)***	(1.47)	(2.39)**	(3.80)***	(1.49)
Δ literacy rate	-9.488	3.453	7.929	-11.315	-0.054	7.414
	(1.29)	(0.67)	(1.90)*	(1.54)	(0.01)	(1.78)*
Δ share of 15-59 schooled to grade ≥ 8	-0.985	1.296	7.095	-1.393	-0.253	7.024
	(0.20)	(0.36)	(2.21)**	(0.28)	(0.07)	(2.17)**
Δ local urban activity (night lights DN)	-0.584	-0.266	-0.142	-0.610	-0.287	-0.160
	(1.73)*	(1.48)	(0.66)	(1.84)*	(1.61)	(0.74)
VDC borders India	-3.029	3.558	-2.012	-2.974	3.418	-2.011
	(1.20)	(2.17)**	(1.32)	(1.19)	(2.10)**	(1.33)
VDC level emigration rate, 2001	-0.370	-0.499	-0.086	-0.374	-0.505	-0.090
	(12.41)***	(16.09)***	(1.51)	(12.48)***	(16.49)***	(1.60)*
$W \times$ Conflict intensity	-3.563	-1.259	-0.637	-18.419	-15.400	-11.237
	(3.14)***	(1.39)	(1.01)	(4.48)***	(4.70)***	(4.42)***
$W \times \Delta$ share of working age (15-59)	190.341	-14.093	129.084	170.322	-12.648	113.444
	(7.08)***	(0.58)	(6.72)***	(6.17)***	(0.51)	(5.94)***
$W \times \Delta$ literacy rate	-114.502	-60.024	-87.956	-95.099	-42.828	-71.005
	(8.96)***	(6.71)***	(11.26)***	(7.09)***	(4.58)***	(8.19)***
$W \times \Delta$ share of 15-59 schooled to grade ≥ 8	-58.544	-19.489	-36.554	-47.084	-12.842	-27.397
	(4.81)***	(2.19)**	(5.09)***	(3.73)***	(1.35)	(3.70)***
$W \times \Delta$ local urban activity (night lights DN)	-0.088	0.497	-0.681	0.300	0.519	-0.544
	(0.12)	(1.35)	(1.33)	(0.41)	(1.39)	(1.05)
$W \times$ VDC borders India	-17.668	-3.760	-13.639	-18.341	-3.263	-14.644
	(3.10)***	(1.04)	(3.58)***	(3.24)***	(0.90)	(3.85)***
$W \times$ VDC level emigration rate, 2001	0.558	0.600	0.801	0.570	0.611	0.851
	(13.75)***	(14.72)***	(7.70)***	(13.96)***	(15.11)***	(8.07)***
Spatial lag of change in emigration rate (δ)	0.183	0.911	0.588	0.195	0.932	0.581
	(2.84)***	(9.76)***	(11.54)***	(2.84)***	(10.08)***	(10.80)***
Pseudo-R^2	0.1513	0.1211	0.2935	0.1542	0.1247	0.303
Wald test for model (Chi-squared, 13 df)	422.79	487.63	2065.32	452.00	516.13	2147.66

Notes: Estimates are from generalized spatial two-stage least squares with heteroscedastic errors. *N*=3982 VDCs. Variables measured in changes (shown by Δ) are for the change from 2001 to 2011. [a]*Other* is other Asia and Middle East.

Before turning to the estimates of direct, indirect, and total effects, we comment on two other aspects of the results in Table 3.2. First, several control variables show significant effects, particularly the change in the working age share of the total population (which rose on average by 1.4 percentage points but with a wide range across VDCs). Improvements in the level of human capital, in terms of the change in the literacy rate (which rose 17 points over the decade) and in the share of working age individuals with at least eight years of schooling (a share which rose by one-tenth over the decade) generally depress the rate of increase in the emigration rate, especially with the spatially lagged terms. This suggests that emigration is especially a vent for surplus unskilled labour from Nepal. There is less rise in the emigration rate in VDCs that had faster urban economic growth (as proxied by night lights) but with imprecisely estimated coefficients. For a VDC on the border with India there was a bigger rise in the emigration rate to India, by almost four persons per thousand, but the spatial lag of the same effect is negative and so it is only after the equation (3.3) estimates are computed that a clear picture of the total effect will be available.

The temporal lag of the emigration rate for a VDC has significant negative effects on the growth in emigration from that VDC, for emigration to India and to all destinations, but this effect is not apparent for the more formal emigration to other Asian and Middle East destinations. The negative coefficients could suggest a convergence process, with VDCs that had historically low emigration rates having a faster rate of change, to catch up to the leaders. It is also the case that regressions without the temporal lag of the emigration rate, which are reported in Appendix Tables 3.1a, 3.1b, and 3.1c, show generally similar patterns for coefficients to what is seen in Table 3.2. These appendix tables also show what the results are like if the total conflict rate, based on deaths per thousand from 1996 to 2006, is used instead of the death rate at the peak of the conflict, and these sensitivity analysis results also are similar to the main results. The appendix tables also report a parallel set of aspatial OLS results that omit the spatial lags, although the data are not consistent with the parametric restrictions that OLS models need.

The last thing to note in the Table 3.2 results is what the last three columns show, using district-level conflict rates. Comparing with the first three columns, it seems that aggregating conflict data makes a big difference, due to the mean-reverting measurement error on the right-hand side. An increase by one death per thousand in a district would seem to directly increase the emigration rate by between five and 12 persons per thousand, being larger for emigration to India than to elsewhere and all of these effects are statistically significant at the $p<0.01$ level. The direction of the effect is the opposite of what the VDC-level conflict data show, although the interpretation is complicated because the spatial lags of the district-level conflict rates are all significantly negative and so the total effects will reflect this offsetting influence. It is clear, however, that smoothing the conflict data (as seen in comparing Figures 3.5b and 3.5c) has a potentially large effect on econometric estimates. This effect of aggregation could skew the interpretations of how Nepal's civil conflict affected the change in emigration (and perhaps skew the interpretation for impacts on other microeconomic outcomes).[17]

The direct, indirect and total impacts of changes in the independent variables on the outcomes are reported in Table 3.3, where these are calculated from the models reported in Table 3.2. As noted above, we report the average impacts; the extent to which conflict intensity in a particular VDC impacts on the change in the emigration rate in another VDC depends partly on how many degrees of separation there are, in terms of the number of neighbours of neighbours needed to transmit the spillover effects over space and so the averages are a convenient way to deal with the multitude of marginal effects that could be presented. When we use the VDC-level conflict rate, we find that an increase in conflict intensity, by one death per thousand population at the peak of the

[17] This conclusion also holds if we control for travel time or travel distance from each VDC to Kathmandu, either directly or interacted with the conflict variables. Such estimates are only approximate, because some VDCs lack road access, so we had to calculate travel time and distance (using *Google Maps*) to the nearest point on the road network. The effect of conflict intensity, when measured at the district level, is still much larger than the effect when measured at the VDC level, even with these additional control variables. Likewise, if we were to just use OLS, despite the restrictions to derive OLS from the SDM being strongly rejected, we would find that apparent conflict impacts on VDC-level emigration were overstated almost ten-fold if conflict intensity is measured at the district level (with a coefficient on conflict intensity of -5.3, compared to -0.56 using VDC-level conflict rates).

conflict (2002-04), is associated with slower growth in the emigration rate between 2001 and 2011. The impacts for direct, indirect, and total effects are always negatively signed, for all three outcome variables, although they are never statistically significant for the change in emigration to India. Once again, it appears that the constraints on growth of the informal and low-cost emigration to India differ from the constraints on growth of emigration to other destinations. These effects in Table 3.3 are statistically significant for two out of three of the direct, indirect, and total impacts for both all-destinations emigration and for the other Asia and Middle East emigration.

In terms of the magnitudes of these impacts, for all-destination emigration a death rate of one per thousand at the peak of the conflict (2002-04) suppresses the rise in the emigration rate between 2001 and 2011 (which rose 40 per thousand on average) by 3.9 persons per thousand. In percentage terms, this is a ten percent smaller rise than would be predicted in the absence of the conflict-related deaths. This effect operates predominantly though the indirect channels, reflecting the fact that decisions to emigrate can depend on outbreaks of conflict in neighbours as well as in the home area, most likely due to these outbreaks raising the costs of emigration (e.g. by making travel to Kathmandu more dangerous and so less likely, thereby lowering the chance to be recruited). When we disaggregate the change in emigration rates into emigration to India and emigration to other Asia and the Middle East, it is only for the non-India destinations that the conflict intensity has a statistically significant effect in depressing the rate of increase in emigration.

To compare how the total impacts of conflict on emigration appear when conflict is estimated at two different aggregation levels, a model with both the VDC level and District level conflict conflict data on the right-hand side (with VDC level emigration as the outcome variable) was estimated. The direct, indirect, and total impact of conflict rates at district level aggregation are as large as ten times the impact of conflict rates at the VDC level aggregation (refer to Appendix Table 3.2). This pattern is consistent with the exaggeration that is caused by mean reverting measurement error if we aggregate conflict data at an inappropriate level. More broadly, this issue

of over-aggregation of conflict rates may eventually distort our understanding of how civil war affects emigration, human capital, labour market activities and so on.

Table 3.3: Estimated direct, indirect, and total impacts, averaging over all 3982 VDCs

	Change in Emigration Rate to All Countries				Change in Emigration rate to India				Change in Emigration rate to other[a]			
	VDC Conflict		District Conflict		VDC Conflict		District Conflict		VDC Conflict		District Conflict	
Direct Effect	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat
Conflict Intensity	-0.557	1.07	8.282	2.55**	-0.221	0.48	10.581	4.51***	-0.519	2.23**	4.199	2.25**
Δ Share of Working age (15-59)	-28.055	2.06**	-29.508	2.17**	-47.193	4.64***	-45.818	4.43***	-3.746	0.42	-5.258	0.58
Δ literacy rate	-11.868	1..66*	-13.458	1.88*	-7.119	0.96	-8.451	1.17	1.072	0.25	2.030	0.47
Δ Share of 15-59 schooled to grade ≥8	-2.187	0.44	-2.436	0.49	-2.107	0.47	-2.853	0.62	4.429	1.33	5.142	1.54
Δ local urban activity (night lights DN)	-0.584	1.79*	-0.606	1.89*	-0.219	1.38	-0.237	1.50	-0.205	1.03	-0.211	1.06
VDC borders India	-3.402	1.38	-3.391	1.39	3.462	2.02**	3.403	1.99**	-3.232	2.26**	-3.287	2.31**
VDC level emigration rate, 2001	-0.360	12.33***	-0.363	12.46***	-0.472	15.65***	-0.477	16.03***	-0.024	0.44	-0.026	0.48
Indirect Effect												
Conflict Intensity	-3.348	3.33***	-15.879	4.61***	-4.483	1.29	-18.765	2.22**	-1.350	1.53	-12.538	5.18***
Δ Share of Working age (15-59)	169.234	7.79***	152.036	6.69***	-175.254	1.84*	-187.620	1.58	182.940	9.00***	157.302	7.55***
Δ literacy rate	-106.600	6.84***	-90.294	5.74***	-204.200	1.87*	-171.850	1.51	-125.910	6.80***	-99.500	5.56***
Δ Share of 15-59 schooled to grade ≥8	-53.857	4.80***	-43.942	3.75***	-65.733	1.58	-52.536	1.15	-48.947	4.57***	-34.784	3.18***
Δ local urban activity (night lights DN)	-0.017	0.03	0.167	0.26	0.914	0.99	1.012	0.94	-1.156	1.77*	-0.951	1.45
VDC borders India	-16.711	3.30***	-17.558	3.46***	-1.862	0.16	0.311	0.03	-22.408	4.37***	-23.587	4.71***
VDC level emigration rate, 2001	0.449	13.86***	0.461	14.05***	0.521	4.59***	0.564	3.57***	1.135	11.02***	1.191	11.73***
Total Effect												
Conflict Intensity	-3.906	3.93***	-7.600	4.55***	-4.704	1.28	-8.185	0.99	-1.877	2.02**	-8.339	4.87***
Δ Share of Working age (15-59)	141.179	6.55***	122.528	5.37***	-222.454	2.26**	-233.440	1.90*	179.193	8.51***	152.044	6.99***
Δ literacy rate	-118.470	7.19***	-103.752	6.24***	-211.329	1.84*	-180.299	1.52	-124.837	6.22***	-97.470	5.03***
Δ Share of 15-59 schooled to grade ≥8	-56.044	4.54***	-46.378	3.58***	-67.841	1.53	-55.389	1.13	-44.518	3.69***	-29.643	2.41**
Δ local urban activity (night lights DN)	-0.601	1.26	-0.440	0.91	0.695	0.78	0.775	0.74	-1.361	2.22**	-1.162	1.90*
VDC borders India	-20.113	4.63***	-20.949	4.79***	1.600	0.13	3.091	0.24	-25.641	5.15***	-26.874	5.53***
VDC level emigration rate, 2001	0.089	4.89***	0.099	5.26***	0.049	0.46	0.086	0.58	1.111	11.38***	1.165	12.23***

Notes: dy/dx denotes marginal effect, which is derived from SDM. t-statistics with heteroscedastic errors, ***, **, * denote statistical significance at 1%, 5%, or 10%. *N*=3982 VDCs. [a] *Other* is other Asia and Middle East

In contrast, if the district-level conflict rates are used, a direct effect of conflict in seeming to increase emigration appears. Specifically, higher conflict intensity (of one death per thousand) would seem to directly increase the VDC-level emigration rate by eight persons per thousand for all-destinations emigration, and by eleven persons per thousand to India. However, these direct effects are offset by even larger negative indirect effects, so that the total effect of one more death per thousand appears as a suppression of the 2001 to 2011 increase in the emigration rate of between 4.6 persons per thousand for emigration to India and 8.2 persons per thousand for emigration to other Asia and the Middle East. These total effects are up to four times larger than those that are estimated when the conflict intensity is measured at the VDC level. This overstatement is most likely due to the mean-reverting measurement error that results from using conflict data that are too spatially aggregated, compared to using the VDC-level conflict data.

3.4.1 Sensitivity Analysis

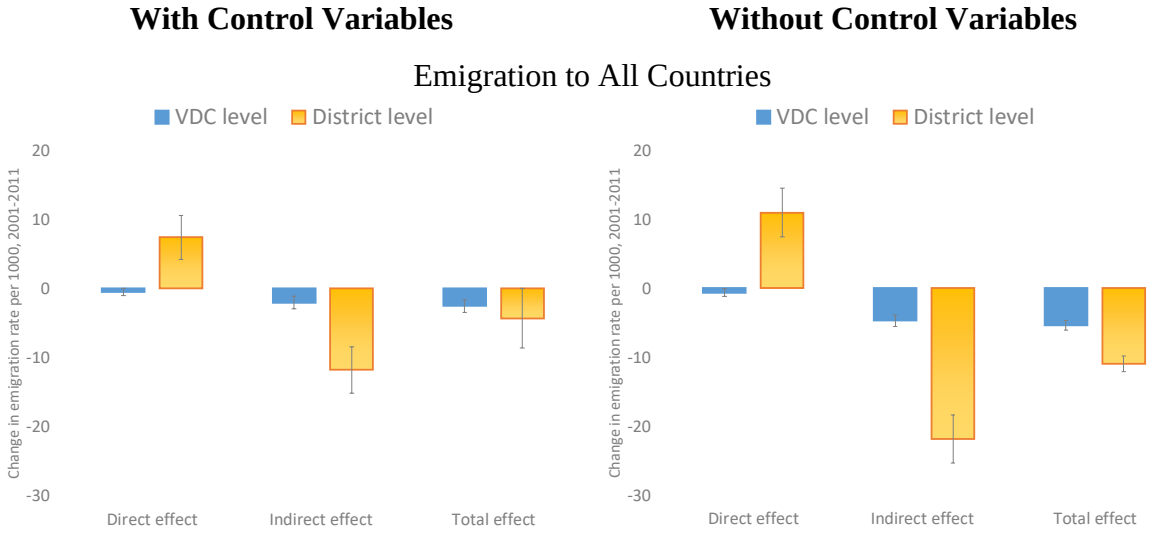
The results presented in Table 3.2 have several control variables included to ensure regression coefficients on conflict rates are not capturing effects of omitted relevant variables. Yet there may be concerns that some of these controls could be endogenous, if changes in emigration affect, say, the measured change in VDC-level literacy rates (as may happen if emigration is skill-selective).[18] In order to allay these concerns, we also estimated models without control variables from the census (working age share, literacy rate and share of the working age with Grade 8 or higher schooling). We report results from this sensitivity analysis in Figure 3.6, with the first column showing the direct, indirect, and total effects for emigration to all countries, to India, and to non-India destinations, with conflict measured either at the VDC level or the district level. These results correspond to those in Table 3.3, and are the baseline specification for the sensitivity analysis. The charts in the second column show the results without control variables. The patterns are exactly the

[18] The format of the Nepal census questions allows us to construct controls that should not be (mechanically) endogenous to village-level emigration rates, because we have proxy information on characteristics of emigrants so we can calculate changes with and without the emigrants included. For the change in the village level literacy rates the two ways of calculating the variable are highly correlated (r=0.97).

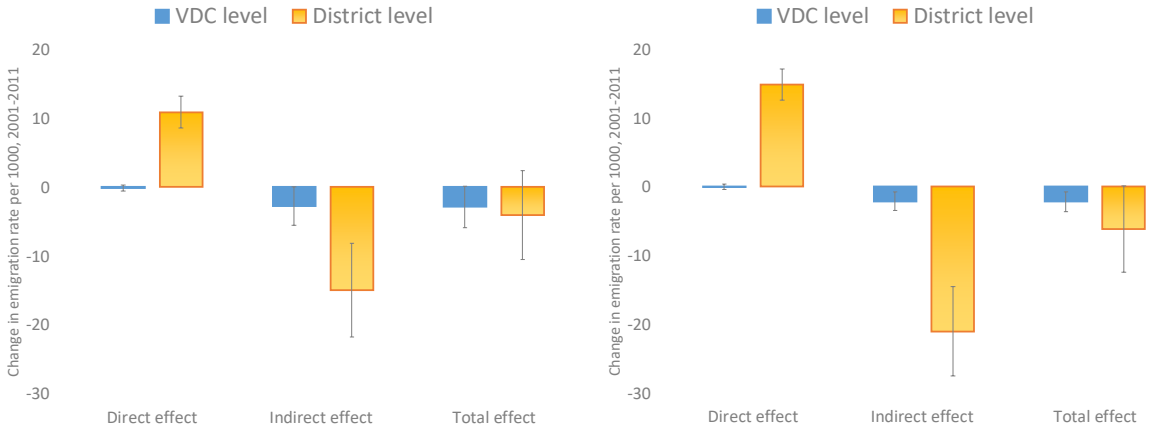
same as with control variables but the magnitudes are larger. Hence, our findings that using district level death rates leads to exaggerated impacts, that conflict had less effect on emigration to India, and that the indirect effects exceed direct effects are all repeated. Therefore, our main results in Table 3.3 can be thought of as a lower bound estimate of how much bias comes from using overly-aggregated conflict data, as we could have gotten larger effects by excluding control variables from the main specification.

In addition, if the studied conflict period is expanded to 2001-2004 from 2002-2004, in order to see if using 2001 conflict as baseline makes any difference to the estimates, the estimated effect of conflict on emigration is still very similar to what is reported when the focus is on the 2002-2004 conflict. The primary reason for this is that the government mobilised Nepalese Army only in November 2001 and it is after this that the conflict was escalated. Thus, the data on conflict for periods from 2001 is similar to the data on conflict for periods from 2002, given that it was only very late in 2001 that escalation occurred. Indeed, until 2001 less than 600 villages have experienced some form of conflict and only 20 percent of deaths occurred up to this point in time.

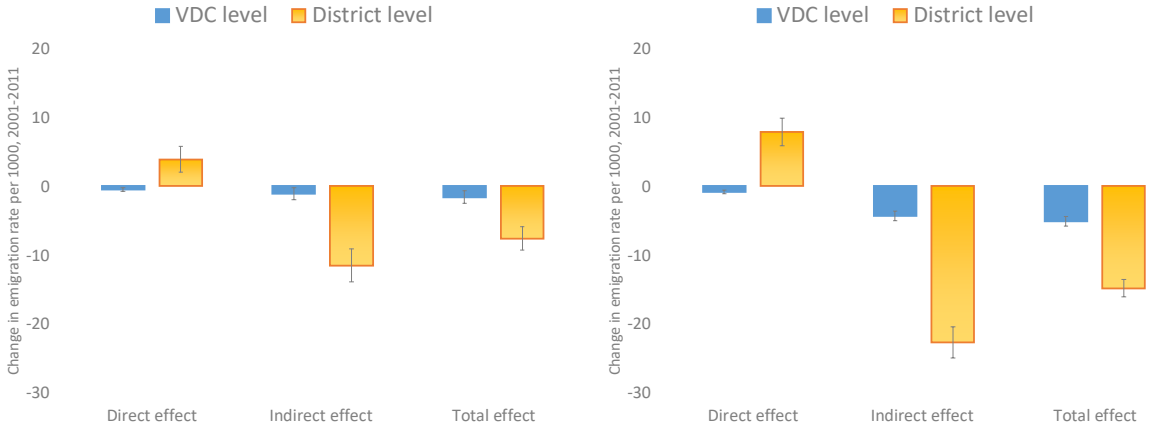
Figure 3.6: Main results are robust to inclusion or exclusion of control variables: Estimated direct, indirect and total impacts of conflict intensity



Emigration to India



Emigration to Other Asia and the Middle East



Notes: Direct, indirect, and total effects average over all 3982 VDCs, as in Table 3. Results in the first column are for models with working age share, literacy rate and grade 8 or above education rate included in regression models, while these control variables are excluded for results in the second column. Bars show standard errors.

3.5 Conclusions

In this paper, we show that research into the microeconomic effects of civil conflict may be distorted if conflict data are overly aggregated. A common research design in this literature is to match census or survey data on microeconomic outcomes (especially for human capital indicators) to data on conflict intensity that is reported at a more spatially aggregated level. Typically the conflict data is reported for the first or second sub-national level even though there may be more finely-grained locations listed in the original field reports on instances of conflict-related deaths.

In the civil war in Nepal, the conflict was mostly very localized, with almost half of localities suffering no conflict-related deaths and with much greater variation in death rates within districts than between districts. Yet if district-level conflict data are used, the conflict appears much more generalized, with only three percent of districts not affected. Spatially aggregated death rates have a mean-reverting measurement error, to the extent that the behaviour of individuals living in conflict is most affected by their local conflict rate. When we use the finely grained data, a greater intensity of conflict during Nepal's civil war is associated with a slight depressing effect on the growth in emigration, equivalent to about ten percent of the growth that occurred from 2001 to 2011. However, if we use more aggregated conflict data, the conflict appears to have far larger effects – both indirectly and directly. This exaggeration of estimated impacts is to be expected when there is a strong mean-reverting error in right-hand side variables of regression models. This problem of using conflict data that are reported at an overly-aggregated spatial level, which makes the conflict appear much more widespread than it truly is and creates a mean-reverting error, may undermine the contribution that empirical studies of conflict can make.

In the specific context of Nepal, the importance of distinguishing between low-cost, informal, and higher cost, formal, emigration is also highlighted. The growth in informal emigration to India appears less deterred by conflict. Given the free mobility across the India-Nepal border, a migrant could leave their home area and travel to an employment destination in India via multiple

routes in order to avoid conflict hotspots. The same flexibility was not available for accessing migration to the Middle East and other destinations that required an expensive (and sometimes lengthy) process of obtaining a passport, a visa, and being recruited. This process may have entailed repeated trips to Kathmandu and conflict either in the home locality or in localities on the way to Kathmandu could deter some potential emigrants, which is why the indirect effects from spatial spillovers also matter. More generally, the idea that conflict can increase costs of migration and interfere with the ability to finance migration may matter to post-war reconstruction policy that may assume that conflict is mainly a push factor for migration. It is possible that people in conflict-affected areas need additional support to access migration opportunities that can help in rebuilding livelihoods.

3.6 Reflection on this chapter

The results in this chapter suggest that the indirect impact of civil conflict on emigration appears to be very large and dominates the direct impact, which is a finding that requires further discussion. There are multiple channels through which indirect effects of civil conflict can transmit from one locality to another, and disrupt the economic opportunity, mobility, and livelihoods of people in other areas. First, the higher conflict in one village not only affects the household's income generating capacity in the same village but also on its neighbours, because villages in Nepal are interconnected and interdependent. People move from one village to another for livelihood opportunities. A second reason is that emigration to the Middle East and high-income Asian countries requires travel to Kathmandu for visa and recruitment (and often multiple trips are needed for these purposes). So, conflict in neighbouring villages or in the neighbours of neighbours can interfere with these types of journeys. In contrast, one can select multiple routes to avoid conflict hotspots if one wanted to emigrate to India, given the long open border between Nepal and India. Furthermore, the conflict in neighbouring villages increased the risk and restricted the mobility to work or participate in any income generating activities. Villages are linked by labour markets, marriage markets and informal

finance markets, so disruptions in neighbouring villages may affect the ability to pay the upfront costs of emigration to non-India destinations, for example, by lowering labour demand, or by reducing the ability to take informal loans. The conflict and destruction of local market in neighbouring villages also would have negative consequences in income by preventing households from participating in market-oriented activities.

Additionally, the inclusion in the models of the temporal emigration rate in 2001 requires further discussion. The temporal lag of the emigration rate is used as an additional control variable to allow for the fact that there may be some villages that exhibit convergence or that neighbouring villages may have a network effect that operates over time. For example, a higher emigration rate in 2001 may leave less scope for the emigration rate to grow over the 2001 to 2011 period or alternatively the network between people in neighbouring villages that helps in job search and recruitment may encourage more emigration. This additional control essentially isolates the impact of the emigration rate on growth of emigration over 2001 to 2011 if baseline emigration correlates with conflict over the 2002 to 2004 period.

References

Abay, K., Abate, G., Barrett, C., & Bernard, T. (2019). Correlated non-classical measurement errors, 'second best' policy inference, and the inverse size-productivity relationship in agriculture. *Journal of Development Economics, 139*(1), 171-184.

Adhikari, P. (2012). The plight of the forgotten ones: Civil war and forced migration. *International Studies Quarterly*, *56*(3), 590-606.

Black, D., Berger, M., & Scott, F. (2000). Bounding parameter estimates with non-classical measurement error. *Journal of the American Statistical Association, 95*(451), 739-748.

Bownas, R. (2015). Dalits and Maoists in Nepal's civil war: Between synergy and co-optation. *Contemporary South Asia*, *23*(4), 409-425.

Central Bureau of Statistics [CBS] (2001). *National Population Census 2001, Report on Nepal's Tenth Census*. Kathmandu, Nepal: His majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2011). *National Population and Housing Census 2011, National Report*. Kathmandu, Nepal: Government of Nepal.

Chamarbagwala, R., & Morán, H. E. (2011). The human capital consequences of civil war: Evidence from Guatemala. *Journal of Development Economics*, *94*(1), 41-61.

Do, Q. T., & Iyer, L. (2010). Geography, poverty and conflict in Nepal. *Journal of Peace Research, 47*(6), 735-748.

Drukker, D. M., Prucha, I. R., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*, *13*(2), 221-241.

Elhorst, J. P. (2012). Dynamic spatial panels: Models, methods, and inferences. *Journal of Geographic Systems 14*(1), 5–28.

Fergusson, L., Ibáñez, A., & Riaño, J. (2019). Conflict, educational attainment and structural transformation: La Violencia in Colombia. *Economic Development and Cultural Change* (forthcoming).

Guariso, A., & Verpoorten, M. (2014). Armed conflict and schooling in Rwanda: Digging deeper. *Peace Economics, Peace Science and Public Policy*, *25*(1), 1-40.

Gibson, J., Beegle, K., De Weerdt, J., & Friedman, J. (2015). What does variation in survey design reveal about the nature of measurement errors in household consumption? *Oxford Bulletin of Economics and Statistics*, *77*(3), 466-474.

Gibson, J., Datt, G., Murgai, R., & Ravallion, M. (2017). For India's rural poor, growing towns matter more than growing cities. *World Development, 98*(1), 413-429.

Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). *Night lights in economics: Sources and uses* (Working Paper No. 2020-01). Oxford, England: Centre for the Study of African Economies, University of Oxford.

Hutt, M. (2006). Things that should not be said: Censorship and self-censorship in the Nepali press media, 2002-02. *The Journal of Asian Studies, 65*(2), 361-392.

Joshi, M., & Pyakurel, S. R. (2015). Individual-level data on the victims of Nepal's Civil War, 1996–2006: A new dataset. *International Interactions, 41*(3), 601-619.

Kelejian, H. H., & Prucha, I. R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, *40*(2), 509-533.

Kountchou, A., Sonne, S., & Gadom, G. (2019). *The local impact of armed conflict on children's nutrition and health outcomes: Evidence from Chad.* Paper presented at the CSAE Conference, University of Oxford.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton, FL: CRC Press.

Libois, F. (2016). *Households in times of war: Adaptation strategies during the Nepal Civil War* (Working Paper No. 1603). Namur, Belgium: University of Namur, Department of Economics.

Menon, N., & Van der Meulen Rodgers, Y. (2015). War and women's work: Evidence from the conflict in Nepal. *Journal of Conflict Resolution*, *59*(1), 51-73.

Naudé, W. (2008). *Conflict, disasters, and no jobs: Reasons for international migration from Sub-Saharan Africa* (Research Paper No. 2008/85). Helsinki, Finland: *UNU-WIDER.*

Nepal, A., Halla, M., & Stillman, S. (2018). *Violent conflict and the child quantity-quality tradeoff. IZA Discussion Paper* No. 11690.

Phadera, L. (2019). *Unfortunate moms and unfortunate children: Impact of the Nepali civil war on women's stature and intergenerational health.* Washington, DC: World Bank.

Pivovarova, M., & Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from Nepal. *World Development, 66*(1), 308-321.

Sapkota, C. (2013). Remittances in Nepal: boon or bane? *The Journal of Development Studies, 49*(10), 1316-1331.

Shrestha, M. (2017). *Push and pull: A study of international migration from Nepal* (Policy Research Working Paper No. 7965). Washington, DC: World Bank, Washington DC.

Valente, C. (2013). Education and civil conflict in Nepal. *The World Bank Economic Review, 28*(2), 354-383.

Verwimp, P., Justino, P., & Brück, T. (2019). The microeconomics of violent conflict. *Journal of Development Economics, 141*, 1-6.

Table 3.1: Variable definition and descriptive statistics (*N*=3982)

	Mean	Std Dev	Minimum	Maximum
Δ VDC level emigration rate to all countries (emigrants per 1000 population)	39.351	37.589	-143.128	318.253
Δ VDC level emigration rate to India (emigrants per 1000 population)	0.289	29.365	-212.253	280.411
Δ VDC level emigration rate to other Asia and Middle East (per 1000 population)	37.01	30.184	-26.805	180.328
VDC conflict Intensity (Deaths per 1000 population at peak period (2002-2004) of conflict)	0.446	1.267	0	27.746
District conflict Intensity (Deaths per 1000 population at peak period (2002-2004) of conflict)	0.463	0.442	0	2.706
Δ share of working age (15-59) population to total population	0.014	0.0475	-0.304	0.215
Δ literacy rate (share of individuals in the VDC who are literate)	0.173	0.086	-0.37	0.551
Δ share of individuals aged 15-59 with schooling to grade ≥ 8	0.102	0.12	-0.611	0.717
Δ local urban activity (proxied by night light digital number (DN) | luminosity >20%)	-0.001	1.648	-17.913	19.25
VDC borders India (=1, otherwise zero)	0.076	0.265	0	1
VDC level emigration rate to all countries, 2001 (emigrants per 1000 population)	41.539	49.12	0	370.69
VDC level emigration rate to India, 2001 (emigrants per 1000 population)	34.01	45.949	0	362.069
VDC level emigration rate to other Asia and Middle East, 2001 (per 1000 population)	6.893	12.623	0	121.827

Source: Author's calculations from census extracts, from INSEC data on the conflict, and from DMSP night lights.
Note: All variables that are measured as change (denoted by Δ) are for the change from 2001 to 2011.

Appendix

Appendix Table 3.1a: Regression models for the change in the emigration rate (to All Countries) between 2001 and 2011, at VDC level, Nepal

	Spatial Durbin Models				Ordinary Least Squares Models			
	During Peak (2002-04)		Entire War (1996-08)		During Peak (2002-04)		Entire War (1996-08)	
Conflict intensity (at VDC level)	-0.483	0.369	-0.194	0.295	-0.796	-0.754	-0.757	-0.728
	(0.91)	(0.80)	(0.52)	(0.91)	(1.70)*	(1.61)*	(2.34)**	(2.24)**
Δ share of working age (15-59)	-31.834	-47.665	-32.689	-49.074	34.678	33.372	33.561	32.264
	(2.29)**	(3.25)***	(2.35)**	(3.35)***	(2.74)***	(2.64)***	(2.65)***	(2.55)**
Δ literacy rate	-9.488	-9.687	-9.447	-9.524	-37.527	-37.034	-37.132	-36.643
	(1.29)	(1.27)	(1.29)	(1.25)	(5.40)***	(5.33)***	(5.34)***	(5.27)***
Δ share of 15-59 schooled to grade ≥ 8	-0.985	-6.163	-0.979	-6.100	-15.376	-16.601	-15.067	-16.31
	(0.20)	(1.21)	(0.20)	(1.19)	(3.03)***	(3.29)***	(2.97)***	(3.23)***
Δ local urban activity (night lights DN)	-0.584	-0.609	-0.58	-0.606	-0.803	-0.786	-0.803	-0.786
	(1.73)*	(1.82)*	(1.73)*	(1.82)*	(2.24)**	(2.19)**	(2.24)**	(2.19)**
VDC borders India	-3.029	-2.208	-3.002	-2.159	-9.74	-9.094	-9.84	-9.186
	(1.20)	(0.89)	(1.19)	(0.87)	(4.43)***	(4.07)***	(4.37)***	(4.11)***
Emigration rate to all countries, 2001	-0.370		-0.370		-0.031		-0.031	
	(12.41)***		(12.42)***		(2.56)**		(2.59)***	
$W \times$ Conflict intensity	-3.563	-3.749	-2.020	-2.205				
	(3.14)***	(3.32)***	(2.64)***	(2.93)***				
$W \times$ Δ share of working age (15-59)	190.341	171.657	188.364	170.182				
	(7.08)***	(6.58)***	(6.99)***	(6.53)***				
$W \times$ Δ literacy rate	-114.502	-80.003	-115.147	-80.723				
	(8.96)***	(6.30)***	(8.98)***	(6.32)***				
$W \times$ Δ share of 15-59 schooled to grade ≥ 8	-58.544	-23.829	-58.57	-23.964				
	(4.81)***	(2.03)**	(4.78)***	(2.03)**				
$W \times$ Δ local urban activity (night lights DN)	-0.088	0.010	-0.059	0.080				
	(0.12)	(0.13)	(0.08)	(0.11)				
$W \times$ VDC borders India	-17.668	-17.653	-17.935	-17.905				
	(3.10)***	(3.25)***	(3.16)***	(3.29)***				
$W \times$ Emigration rate to all countries, 2001	0.558		0.556					
	(13.75)***		(13.69)***					
Spatial lag of change in emigration rate (δ)	0.183	0.433	0.183	0.434				
	(2.84)***	(6.87)***	(2.82)***	(6.85)***				
(Pseudo-)R2	0.1513	0.053	0.150	0.052	0.017	0.016	0.018	0.016
Wald test for model (Chi-squared)	422.79	299.80	418.46	299.46	69.90	63.18	72.45	65.70

Notes: t-statistics from heteroscedasticity-robust standard errors in ( ), ***, **, * denote statistical significance at 1%, 5%, or 10%. *N*=3982. Wald-tests have 13[12] degrees of freedom for SDM and 7[6] for OLS, with smaller value in [ ] for models without the temporal lag of the emigration rate. The spatial weights matrix, *W* uses first-order Queen contiguity.

Appendix Table 3.1b: Regression models for the change in the emigration rate to India between 2001 and 2011, at VDC level, Nepal

	Spatial Durbin Models				Ordinary Least Squares Models			
	During Peak (2002-04)		Entire War (1996-08)		During Peak (2002-04)		Entire War (1996-08)	
Conflict intensity (at VDC level)	-0.011	1.022	0.062	0.662	0.173	0.387	0.075	0.058
	(0.03)	(2.84)***	(0.23)	(2.73)***	(0.49)	(1.06)	(0.31)	(0.23)
Δ share of working age (15-59)	-38.119	-41.341	-38.323	-42.524	-80.257	-81.97	-80.916	-82.191
	(3.91)***	(3.68)***	(3.95)***	(3.80)***	(8.42)***	(8.30)***	(8.47)***	(8.35)***
Δ literacy rate	3.453	-3.832	3.414	-3.76	9.885	8.932	10.068	9.084
	(0.67)	(0.64)	(0.66)	(0.63)	(1.89)*	(1.65)*	(1.92)*	(1.68)
Δ share of 15-59 schooled to grade ≥ 8	1.296	-8.876	1.310	-8.852	-1.970	-7.987	-1.793	-7.834
	(0.36)	(2.21)**	(0.36)	(2.20)**	(0.51)	(2.03)**	(0.47)	(1.99)**
Δ local urban activity (night lights DN)	-0.266	-0.315	-0.264	-0.314	-0.138	-0.069	-0.137	-0.068
	(1.48)	(1.41)	(1.47)	(1.41)	(0.51)	(0.25)	(0.51)	(0.24)
VDC borders India	3.558	2.25	3.572	2.28	3.906	6.285	3.856	6.246
	(2.17)**	(1.23)	(2.18)**	(1.24)	(2.31)**	(3.61)***	(2.28)**	(3.59)***
Emigration rate to India, 2001	-0.499		0.500		-0.156		-0.157	
	(16.09)***		(16.19)***		(15.96)***		(15.99)***	
$W \times$ Conflict intensity	-1.259	-2.287	-0.777	-1.317				
	(1.39)	(2.28)**	(1.36)	(2.02)**				
$W \times$ Δ share of working age (15-59)	-14.093	32.075	-12.646	33.262				
	(0.58)	(1.34)	(0.52)	(1.39)				
$W \times$ Δ literacy rate	-60.024	-9.455	-60.861	-10.065				
	(6.71)***	(0.95)	(6.74)***	(1.00)				
$W \times$ Δ share of 15-59 schooled to grade ≥ 8	-19.489	7.268	-19.309	6.977				
	(2.19)**	(0.72)	(2.14)**	(0.68)				
$W \times$ Δ local urban activity (night lights DN)	0.497	0.376	0.482	0.369				
	(1.35)	(0.75)	(1.30)	(0.73)				
$W \times$ VDC borders India	-3.76	-2.021	-4.087	-2.081				
	(1.04)	(0.47)	(1.14)	(0.49)				
$W \times$ Emigration rate to India, 2001	0.600		0.601					
	(14.72)***		(14.72)***					
Spatial lag of change in emigration rate (δ)	0.911	1.131	0.927	1.130				
	(9.76)***	(10.06)***	(10.10)***	(10.14)***				
(Pseudo-)R2	0.1211	0.0047	0.1163	0.0017	0.084	0.025	0.084	0.025
Wald test for model (Chi-squared)	487.63	253.16	494.55	255.94	363.23	101.88	363.02	100.80

Notes: t-statistics from heteroscedasticity-robust standard errors in ( ), ***, **, * denote statistical significance at 1%, 5%, or 10%. *N*=3982. Wald-tests have 13[12] degrees of freedom for SDM and 7[6] for OLS, with smaller value in [ ] for models without the temporal lag of the emigration rate. The spatial weights matrix, *W* uses first-order Queen contiguity.

Appendix Table 3.1c: Regression models for change in the emigration rate to Other Asia and the Middle East between 2001 and 2011, at VDC level, Nepal

	Spatial Durbin Models				Ordinary Least Squares Models			
	During Peak (2002-04)		Entire War (1996-08)		During Peak (2002-04)		Entire War (1996-08)	
Conflict intensity (at VDC level)	-0.445	-0.443	-0.227	-0.248	-1.189	-1.212	-0.731	-0.82
	(1.90)*	(1.96)*	(1.33)	(1.50)	(3.40)***	(3.28)***	(3.02)***	(3.21)***
Δ share of working age (15-59)	-13.709	-17.930	-13.461	-17.799	76.269	97.844	76.136	97.385
	(1.47)	(1.90)*	(1.45)	(1.89)*	(8.04)***	(9.82)***	(8.02)***	(9.76)***
Δ literacy rate	7.929	4.155	7.584	4.033	-19.85	-34.386	-19.728	-34.15
	(1.90)*	(0.98)	(1.81)*	(0.96)	(3.80)***	(6.28)***	(3.77)***	(6.63)***
Δ share of 15-59 schooled to grade ≥ 8	7.095	7.020	6.929	6.952	-6.978	-5.923	-6.917	-5.791
	(2.21)**	(2.23)**	(2.15)**	(2.21)**	(1.85)*	(1.49)	(1.83)*	(1.45)
Δ local urban activity (night lights DN)	-0.142	-0.166	-0.139	-0.165	-0.732	-0.785	-0.734	-0.786
	(0.66)	(0.79)	(0.65)	(0.79)	(2.74)***	(2.78)***	(2.74)***	(2.78)***
VDC borders India	-2.012	-2.164	-2.032	-2.154	-9.890	-13.675	-9.927	-13.709
	(1.32)	(1.43)	(1.33)	(1.42)	(5.90)***	(7.76)***	(5.91)***	(7.78)***
Emigration rate to India, 2001	-0.086		-0.086		0.768		0.767	
	(1.51)		(1.53)		(21.55)***		(21.50)***	
$W \times$ Conflict intensity	-0.637	-0.206	0.176	0.264				
	(1.01)	(0.34)	(0.44)	(0.68)				
$W \times$ Δ share of working age (15-59)	129.084	125.221	130.965	125.076				
	(6.72)***	(7.05)***	(6.76)***	(7.02)***				
$W \times$ Δ literacy rate	-87.956	-103.633	-90.166	-105.305				
	(11.26)***	(14.60)***	(11.60)***	(14.86)***				
$W \times$ Δ share of 15-59 schooled to grade ≥ 8	-36.554	-26.346	-37.751	-27.236				
	(5.09)***	(3.78)***	(5.24)***	(3.91)***				
$W \times$ Δ local urban activity (night lights DN)	-0.681	-0.509	-0.698	-0.513				
	(1.33)	(1.01)	(1.37)	(1.03)				
$W \times$ VDC borders India	-13.639	-16.297	-13.286	-15.962				
	(3.58)***	(4.25)***	(3.47)***	(4.15)***				
$W \times$ Emigration rate to India, 2001	(0.801)		0.799					
	(7.70)***		(7.67)***					
Spatial lag of change in emigration rate (δ)	0.588	0.738	0.590	0.743				
	(11.54)***	(22.77)***	(11.50)***	(22.98)***				
(Pseudo-)R2	0.2935	0.1476	0.2922	0.1465	0.1515	0.0524	0.1510	0.0522
Wald test for model (Chi-squared)	2065.32	2084.4	2044.17	2084.52	709.80	219.60	706.93	219.12

Notes: t-statistics from heteroscedasticity-robust standard errors in ( ), ***, **, * denote statistical significance at 1%, 5%, or 10%. *N*=3982. Wald-tests have 13[12] degrees of freedom for SDM and 7[6] for OLS, with smaller value in [ ] for models without the temporal lag of the emigration rate. The spatial weights matrix, *W* uses first-order Queen contiguity.

Appendix Table 3.2: Estimated direct, indirect, and total impacts after including VDC and District conflict in one model

Change in emigration rate to	All countries		India		Other	
Direct Effect	dy/dx	t-stat	dy/dx	t-stat	dy/dx	t-stat
Village Conflict Intensity	-0.474	(0.89)	-0.50	(1.00)	-0.25	0.98
District Conflict Intensity	8.720	(2.65)***	11.05	(4.59)***	4.41	(2.35)**
Δ Share of Working age (15-59)	-29.257	(2.15)**	-45.27	(4.34)***	-6.38	(0.71)
Δ literacy rate	-13.241	(1.85)*	-8.19	(1.14)	1.71	(0.40)
Δ Share of 15-59 schooled to grade ≥8	-2.391	(0.48)	-2.90	(0.63)	5.20	(1.56)
Δ local urban activity (night lights DN)	-0.608	(1.89)*	-0.24	(1.53)	-0.21	(1.06)
VDC borders India	-3.367	(1.38)	3.41	(1.99)**	-3.24	(2.28)**
VDC level emigration rate, 2001	-0.364	(12.46)***	-0.48	(16.01)***	-0.03	(0.47)
Indirect Effect						
Village Conflict Intensity	-1.608	(1.31)	-5.76	(1.15)	1.50	(1.32)
District Conflict Intensity	-14.271	(3.98)***	-13.20	(1.67)*	-13.97	(5.17)***
Δ Share of Working age (15-59)	153.740	(6.74)***	-183.44	(1.55)	156.84	(7.46)***
Δ literacy rate	-89.871	(5.72)***	-170.53	(1.51)	-101.56	(5.64)***
Δ Share of 15-59 schooled to grade ≥8	-44.386	(3.78)***	-54.06	(1.16)	-34.89	(3.16)***
Δ local urban activity (night lights DN)	0.139	(0.22)	0.94	(0.87)	-0.94	(1.42)
VDC borders India	-17.646	(3.47)***	-0.36	(0.03)	-23.84	(4.71)***
VDC level emigration rate, 2001	0.460	(14.02)***	0.56	(3.53)***	1.19	(11.68)***
Total Effect						
Village Conflict Intensity	-2.082	(1.60)	-6.25	(1.18)	1.24	(1.01)
District Conflict Intensity	-5.551	(2.58)***	-2.15	(0.27)	-9.56	(4.26)***
Δ Share of Working age (15-59)	124.484	(5.43)***	-228.71	(1.87)*	150.46	(6.84)***
Δ literacy rate	-103.111	(6.21)***	-178.72	(1.52)	-99.86	(5.13)***
Δ Share of 15-59 schooled to grade ≥8	-46.777	(3.60)***	-56.96	(1.14)	-29.68	(2.39)**
Δ local urban activity (night lights DN)	-0.469	(0.97)	0.69	(0.66)	-1.15	(1.86)*
VDC borders India	-21.013	(4.78)***	3.05	(0.23)	-27.08	(5.50)***
VDC level emigration rate, 2001	0.097	(5.14)***	0.08	(0.56)	1.17	(12.17)***

Notes: dy/dx denotes marginal effect, which is derived from SDM. t-statistics with heteroscedastic errors, ***, **, * denote statistical significance at 1%, 5%, or 10%. N=3982 VDCs. a Other is other Asia and Middle East

Chapter Four: Effects of international migration on child schooling and child labour: Evidence from Nepal

Hari Sharma and John Gibson

Abstract

In the last two decades, Nepal experienced a significant rise in work-related migration and subsequent remittance inflows. We examine the impacts on child education and child labour in a two-wave panel constructed from the 2008 Nepal Labour Force Survey and the 2010 Nepal Living Standards Survey. We use grade-specific net enrolment rates rather than the more commonly studied attendance rate, and exploit variation in destination-driven predicted migration as an instrumental variable. Migration and remittances appear to raise net enrolment of children in secondary education. The positive effect on school outcomes is complemented by a fall in child labour force participation. The effects appear larger for children aged ten and above, and seem to predominantly operate through remittances.

Keywords: Human capital, child labour, migration, school enrolment, Nepal

JEL Codes: I20, J22, F22, I21, O15

4.1 Introduction

Labour migration from developing to developed countries has recently increased and is now an important livelihood strategy for many people in poor countries. The impact of this mobility on the welfare of the left-behind population, and especially on child labour and school outcomes, is of great interest (McKenzie & Rapoport, 2011; Davis & Brazil, 2016). The education of left-behind children is of particular interest to policymakers, given that human capital helps the escape from poverty by raising future earnings. In light of this interest, the current study identifies the impact of migration and remittances on child labour force participation and schooling in Nepal, which is a major supplier of work-related emigrants.

Theoretical studies emphasize positive effects of migration options on child human capital. Higher expected earnings from the prospect of migration raise expected returns to education; the higher returns to skill in the future induces human capital formation today (Batista et al., 2012; Beine et al., 2011; Beine et al., 2008; Beine et al., 2001; Fan & Stark, 2007; Gibson & McKenzie, 2010). Yet effects of migration on child schooling are not straightforward. Some theoretical and empirical studies find either no effects or even negative effects of migration on schooling (Acharya & Leon-Gonzalez, 2014, 2019; Acosta, 2011; Amuedo-Dorantes & Pozo, 2010; Bucheli et al., 2018; Cellini, (2007); Davis & Brazil, 2016; Di Maria & Lazarova, 2012; Koska et al., 2013; McKenzie & Rapoport, 2011; Nguyen & Nguyen, 2015; Shrestha, 2017). Suggested reasons for a lack of positive impact include: parental absence and family disruption; the need for extra workers due to household labour shortages; and, increased opportunity cost of participating in higher education if local wages rise.[19] Having a migrant family member in a foreign country may also dis-incentivize children from pursuing education if they perceive that less-skilled jobs in the destination can fetch them higher income from migrating rather than staying in school (Bredl, 2011; Salas, 2014).

[19] Migration may force children to skip school and to participate in the labour market to help make up for the monetary loss faced when economically productive co-residents leave the household to go abroad.

A typical outcome of migration is subsequent remittances. Many studies from developing countries like Egypt, Mexico, Nepal, El Salvador, Sri Lanka, Ecuador, Peru, and Haiti find positive effects of remittances on schooling (Acharya & Leon-Gonzalez, 2014, 2018; Acosta, 2011; Alcaraz et al., 2010; Amuedo-Dorantes & Pozo, 2010; Azizi, 2018; Bredl, 2011; Bucheli et al., 2018; Calero et al., 2009; De & Ratha, 2012; Koska et al, 2013; Ngoma & Ismail, 2013; Salas, 2014; Shrestha, 2017) although Karki Nepal (2016) finds no significant impact on enrolment and child labour. The effects may also differ between boys and girls, and between quantity (enrolments) and quality (such as sending children to private schools).

The empirical ambiguity of remittance effects reflects the fact that, theoretically, there can be offsetting effects. In one direction, remittances help households to overcome borrowing constraints and smooth consumption, which matters because many people in developing countries lack access to credit (Bredl, 2011; Gyimah-Brempong & Asiedu, 2015; Köllner, 2013; Kugler, 2006; Mansuri, 2006; McKenzie & Rapoport, 2011; Melkonyan & Grigorian, 2008). These borrowing constraints may limit human capital investment, which translates into lower secondary school enrolment rates (given that this level of schooling is more costly than primary schooling), high dropout rates and low college enrolment rates (De Gregorio, 1996; Melguizo et al., 1996; Sun & Yannelis, 2016). Partly due to borrowing constraints, school children may do economic work, adversely affecting school performance, so a big income boost (e.g. scholarships) may be needed to reduce child labour (Datt & Uhe, 2019). Thus remittances may alleviate the need for child labour, and by releasing children from working may improve their schooling (Calero et al., 2009; Nguyen & Nguyen, 2015). On the other hand, if remittances fund migration and if the return to migration exceeds the returns to schooling, then remittances may have an indirect negative effect by raising the opportunity costs of staying in school (Köllner, 2013).

Previous studies on effects of migration on left-behind children tend to focus on simple indicators, such as whether a child is in school (for Nepal this includes Acharya & Leon-Gonzalez,

2014 and Shrestha, 2017). This is a relatively crude measure because most school-age children are in school and it does not capture any impact on the quality of schooling. For instance, after the introduction of Nepal's Education for All (EFA) program (2001-08) and School Sector Reform Program (SSRP) (2009-2015), school attendance is already above 90 percent (CBS, 2008, 2010). However, children may not be in the age-appropriate grade. For example, in 2009/10 Nepal's Gross Enrolment Rate (GER) at Primary and Lower Secondary level was above 120%, due to over-age enrolments (DOE, 2015). If we only study school attendance, rather than age-appropriate enrolment, the impacts of migration and remittances on the timely transition through schooling will be obscurred.

Therefore, in contrast to prior studies, we consider the effect of migration and remittances on age-specific schooling outcomes and child labour indicators. Our age specific schooling measures are net enrolment rates at Basic (grade 1 to 8 for children aged 5 to 12) and Secondary education level (grade 9 to 12 for children aged 13 to 16), which is the new education structure in Nepal. We consider age-specific attendance rates of children aged 5-16, 5-12, and 13-16, and dropout rates for the same age ranges.

Only a few studies, such as Karki Nepal (2016) and Datt et al. (2019), have constructed age related schooling outcomes similar to ours. Karki Nepal (2016) developed age specific grades for children aged 5-17 and assigns a value of one if the child is currently enrolled in their age specific grade (and zero otherwise). Datt et al. (2019) restrict their whole sample to 6-14 years old children, and separate outcomes by gender but not by age group. While these two studies analyse the impacts on the whole sample, we separate the impact of emigration on child education for two different age groups, children aged 5-12 and 13-16. The impact of emigration may not be apparent on younger children who are of an age when school education in free and the opportunity cost of going to school is very low, but emigration may certainly affect the educational outcomes of older children. The primary reason for this is that the cost of schooling increases with the age. Higher levels of

schooling require higher monetary commitment from parents, and also their family must forego the additional income from child labour of older children. To allow for this pathway, and compared to these two prior studies, we additionally constructed a child labour indicator to help isolate the particular pathways through which emigration can affect the child schooling. We develop child labour force participation rates, on the extensive and intensive margins, for those children aged 8-10 and aged 11-16.

A further difference from most studies is that we allow for local spillovers. Typically, studies just compare households with and without a migrant(s) abroad; this may understate the impacts if migration affects households without migrants through local multiplier and general equilibrium effects (Theoharides, 2018). For example, if migration changes the return to education the decisions of both migrant and non-migrant households about the optimal level of educational investment may be affected. Similarly, if migration affects local wages, then the opportunity cost of going to school changes as well. Therefore, we conduct our analysis at the PSU level (Primary Sampling Unit which we denote as village in this paper). The advantage of using village level data is that the local spillover effects will show up at village level but may be missed at household level. These spillover effects should matter in Nepal, where households living in the same village are closely interconnected and interdependent.

The decision to migrate is endogenous (Gibson et al., 2011) and so instrumental variables (IV) may be used to mitigate bias in econometric estimates of migration impacts. A related source of bias is that cross-sectional data are often used to estimate emigration impacts, even though such data have a risk of bias due to omitted variables. Instead, we use panel data with village fixed effects to deal with time-invariant omitted factors at the village level (and time dummies to deal with spatially-invariant time effects). We also utilise the strength of the 2001 Census data (compared to Datt et al. (2019) who rely on survey data) to construct an instrumental variable, following the commonly used shift share approach in the literature (Christian & Barrett, 2017;

Jaeger et al., 2018). Specifically, we identify a plausibly exogenous instrument for the migration rate using village-level variation in predicted migration (derived from the destination country demand for migrants). This is based on a trend migration rate which depends on the baseline (in 2001) village share of migrants in each destination. We assume that a demand shock (change in demand for migrants) in the destination would primarily affect villages with stronger pre-existing migrant networks to that destination. The variation in predicted migration rates is determined by the factors outside of Nepal, and so such factors should only affect child schooling and child labour in Nepal through the migration and remittances channel.

We use two nationally representative household surveys - National Labour Force Survey 2008 and National Living Standard Survey 2010 – to construct a two-period village-level panel. We find that migration increases net enrolment rate in secondary education, and this positive effect occurs through reduced child labour for those aged 11-16. One pathway through which this effect could occur is that migration and remittances help credit constrained households to cover schooling costs and compensate for the foregone earnings from child labour. Yet the opposite picture would emerge if we were to just estimate effects on attendance and dropouts, as in some previous studies; specifically, migration seems to decrease attendance and increase dropouts. However, because of Nepal's universal free education program, the dropout rate is very low (especially in the 2010 survey) and so the estimated effect is for a rare outcome. Plausibly, there is more to be learned from examining the net enrolment rates in order to see overall schooling impacts that account for timely progress through the various school grades.

The rest of the paper is as follows: Section II briefly describes education and migration in Nepal and Section III discuss the data, methodology and empirical strategy. Section IV presents the results, while Section V has the conclusions and policy discussion.

4.2 Context

4.2.1 School education in Nepal

Nepal has three schooling systems- public (community-based), institutional (private) and religious (*Madrasas*). Of the 36,016 schools nationwide, 30,034 are public, 5087 are private and the other 895 are religious schools. Community schools are funded by the government and managed by the school management committee (SMC). Institutional schools are privately owned and managed, are fully funded by fees paid by parents for school-related activities, and have become more widespread (especially in urban areas) after the education sector was opened for private investment. The institutional schools are considered to be quality education providers and they charge high fees. The religious schools are *Madarasha, Gumba,* and *Gurukul,* they are few in number and are operated and funded by the religious organizations.

For a long time (1850-1950) under the rule of *Rana*, education in Nepal was centralized and limited to the ruling and *high caste* elites. The end of *Rana* period brought the provision of the decentralized education system in Nepal, and during the *Panchayat* system, the 1971 Education Act was introduced along with the national education plan to nationalize school education. These schools were managed at the local level with centralized control. Later, in an effort to decentralise management of public schools, the EASA 2001 (Education Act Seventh Amendment) has aided establishing school management committees (SMC) with full representation of parents.

More recently, universal free education is seen as a way to address poverty and to achieve high economic growth. To boost the universal access to quality education, Ministry of Education (MOE) has initiated a number of strategies and reform programs including BPEP I (1992-1998), BPEP-II (1998-2003), EFA program (2001-08), and SSRP (2009-2015). Through these programs, MOE has introduced and developed planning and strategies to transform school education and increase access to quality education. The Education for All (EFA) program has focused on improving access and quality of primary education and supported the tradition of community

management in school. Under EFA, the government has supported free compulsory primary education to increase the participation from disadvantaged and marginalized groups. To further increase access and complete educational sector reform, the government has introduced SSRP (2009-2015). The main goal of SSRP was to meet Millennium Development Goals in education, and it was also aimed to expand equitable access to education, improve quality and relevance, and strengthen the institutional capacity of the entire school education system.

Previously, Nepal's education system had primary level (grade 1 to 5), lower secondary level (grade 6-8), secondary level (grade 9-10) and higher secondary level (grade 11-12) that should correspond to ages 5-9, 10-12, 13-14 and 15-16. The 8th Amendment to the Education Act, in 2016, reclassified school education in two broad categories- Basic Education (1-8 grade) and Secondary Education (9-12 grade) that should be for children aged 5-12 and 13-16.[20] In 2011, while the gross enrolment rate at basic and secondary education was as high as 124.4% and 86%, net enrolment rates were just 46.2% and 27.1% (Ministry of Education, 2016). The high gross enrolments at primary level and very low net enrolments at secondary and higher secondary level (see Table 4.1 for details) indicates that the school progression rate is very poor and over-aged children are enrolled. The universal free education and partial scholarship program, especially for girls, is mandated by the constitution of Nepal. This has increased access to education, yet school progression at secondary education level remains low. Moreover, given that child labour coexists with schooling, any small value of scholarships may not be sufficient to reduce child labour (Datt & Uhe, 2019) and raise school retention. Therefore, other factors like family income, including from remittances, are also important to improve children's access to education.

[20] Education Act 8th Amendment has categorised school education into Basic and secondary education. Basic education (until 8 schooling year) includes Early Childhood Development (ECD) to Lower secondary level while secondary education (9-12 schooling year) includes Secondary (9-10) and Higher secondary (11-12) level (MOE, 2016).

Table 4.1: Descriptive statistics (N=499)

	NLFS 2008		NLSS 2010	
	Mean	Std Dev	Mean	Std Dev
Basic Education (grade 1-8) enrolment rate for child aged 5 -12	0.705	0.148	0.813	0.031
Secondary Education (grade 9-12) enrolment rate for child aged 13 -16	0.176	0.178	0.361	0.288
Primary level (grade 1-5) Gross Enrolment Rate for children of all age	1.397	0.626	1.358	0.609
Primary level (grade 1-5) Net Enrolment Rate for children of aged 5-9	0.552	0.194	0.718	0.235
Lower secondary level (grade 6-8) Gross Enrolment Rate for children of all age	0.854	0.63	0.984	0.662
Lower secondary level (grade 6-8) Net Enrolment Rate for child aged 10-12	0.137	0.171	0.326	0.306
Secondary level (grade 9-10) Gross Enrolment Rate for children of all age	0.591	0.66	0.929	0.867
Secondary level (grade 9-10) Net Enrolment Rate for child aged 13-14	0.061	0.129	0.191	0.277
Higher Secondary level (grade 11-12) Gross Enrolment Rate for children of all age	1.307	1.874	0.935	1.038
Higher Secondary level (grade 11-12) Net Enrolment Rate for child aged 15-16	0.078	0.17	0.137	0.252
Attendance rate for children of all age	0.903	0.114	0.919	0.115
Dropout rate for children of all age	0.129	0.028	0.011	0.031
Child labour force participation (child labour) for child aged 11-16	0.495	0.322	0.588	0.332
Child labour force participation (child labour) for child aged 8-10	0.232	0.273	0.324	0.342
Hours spend in labour market by child aged 11-16	21.928	15.20	16.909	13.988
Hours spend in labour market by child aged 8-10	8.678	10.212	6.208	8.234
Migration rate (in 1,000 ppln)	71.525	50.584	85.738	59.196
Average remittance received by Household in PSU (In NPR)	3705	5993	4471	6703

Note: Above figure are rates which ranges from 0 to 1. The quantity of child labour participation is reported in average number of hours spend in last seven days. Migration rate is measured as number of migrants in per thousand of population. The average remittance includes remittance from all the sources which is divided by no of household in PSU. Basic education includes primary and lower secondary level, and secondary education combines secondary and high-secondary level. NPR is Nepalese rupees.

4.2.2 Migration from Nepal

Nepal has a long history of work-related migration. After conquest of the Kathmandu valley by the King *Prithivinayaran Shah*, migration to India rose substantially, and was further augmented by territorial expansion of Nepal and the *Sagauli* peace treaty with the British government.[21] The 1950 open border treaty with India, which allowed free labour mobility, made India an attractive and low-cost destination to escape domestic unemployment, especially for households in the far-west and mid-west regions of Nepal that have high unemployment, poverty, and food insecurity. India is the first choice for people from relatively poor regions since well-established migrant's network helps new migrants to find a job in Indian cities and there are no recruitment and visa costs. For instance, migrants from the far-west and mid-west regions of Nepal accounted for 48% and 36% of total work-related Nepalese migrants to India in 2001 and 2011 (CBS, 2001, 2011).

The migration for work to other destinations, especially the Middle East, is a fairly new phenomenon in Nepal. The restoration of democracy in 1990 and the official move to embrace the market economy has facilitated and encouraged migration by allowing private recruiters to recruit Nepalese workers for foreign employment (GON, 2014). This new opportunity to migrate to high wage destinations has become a boom for the Nepali migrants, especially from central and eastern regions whose close proximity to the capital city aids recruitment and visa processes. People in these regions also have more access to finance for upfront migration-related costs. In the last decade, the outflow of migrants extended from Middle-East and North African countries to ASEAN, Hong Kong and Korea. Recently, skilled migration to OECD countries is also rising. For instance, one-fifth of migrants are in developed countries like USA, Canada, Europe, Japan and Australia (CBS, 2008, 2010). Migration to high wage destinations has become an alternative income-generating activity to escape high unemployment and low quality of life in Nepal. Consequently, the out-migration continues to rise and one-third of households have at least one

[21] After this treaty, the British army was permitted to recruit three Gurkha regiments from Nepalese hill people.

migrant member working abroad, mostly in the 15-59 age group (CBS, 2010).

The rise in migration has led to a massive surge in remittances, rising from US$0.9 billion in 2004/05 to US$6 billion in 2016/17. Nepal is now the sixth-highest remittance-receiving country, in terms of remittances as a share in national GDP. This share reached 31.3% in 2016, up from 10.7% in 2001. Yet actual remittance inflows are likely much higher because the informal channel remittances, especially from India, are difficult to track. According to CBS (2010), around 55% of households receive remittances each year and the average size of remittances sent per migrant is around US$730 a year. Of that, the average household spends around 87% on daily consumption and loan repayment, and just six percent is used for education and capital formation.

4.3 Data and Methods

We use data from the 2008 Nepal Labour Force Survey (NLFS II) and the 2010 Nepal Living Standard Survey (NLSS III). The primary sampling units for NLSS III are a subset of those used for the NLFS II, where this design was to take advantage of the cartographic segmentation and household listing already carried out in 2008 (CBS, 2010)[22]. Out of 799 PSU in NLFS II (399 Urban and 400 Rural PSU), 174 urban and 325 rural PSU were randomly selected to provide a sample of 499 PSU used for NLSS III. Thus, we can average over the surveyed households in each PSU to construct a two-wave village-level panel to study impacts of migration and remittances, allowing for inter-household spillovers within villages.

Both surveys have information on household members working abroad, and age, gender, ethnicity, literacy, education and employment status of household members, remittance income and household land ownership. We develop basic and secondary level net enrolment rates and four indicators for child labour force participation for school-aged (5-16) children. Our unit of observation is a village, and we measure migration as a rate; in terms of migrants per thousand

[22] In NLFS II, PSU's are either individual wards, sub-wards, or groups of neighboring wards of a village (CBS, 2010). In NLSS III, 12 households are randomly selected for interview within each PSU, while 20 household are interviewed per PSU in NLFS II.

population. We calculate the average remittances per household in each village (in terms of 1000s of Nepalese rupees, NPR).

We use the above information to construct as control variables, the quantity of land owned (a proxy for wealth), the average members per household, the share of migrants whose education is grade 8 or above, the share of the working-age population (15-60) in total populaton, the share of the working-age population with grade 8 or above education, the literacy rate, and the unemployment rate.[23] The surveys did not have relationship matrixes to enable us to directly identify the parents of each child. Therefore we developed a proxy, that assumes that household residents aged 30 and above are likely to have a school aged children in the household. For this 30 and above age group we calculate the proportion who have high school education or higher, and use this as a proxy for parental education, which is usually relevant to children's schooling outcomes. We also use data from the 2001 population census, to calculate for each village the international destinations of migrants. We separate migration to India from MEOA (Middle-East and Other Asia) since these are two different migration channels – informal and low-cost to India, and formal and high-cost to the Middle East and Other Asian countries (MEOA) (Sharma & Gibson, 2019). We create measures of historical migration networks separately for these two main migration channels.

We assume that the effect of migration is mainly channeled through remittances, given that identifying separate effects can be difficult because migration and remittances are highly correlated. Also, remittances depend upon migrants becoming established in the destination, so it may take some time to compensate their left-behind family members for the initial loss of local income that the migrant would have earned if they had not emigrated. Of the total migrants from Nepal, 76% of them are living abroad for more than a year (CBS, 2008, 2010), and these are the ones most likely to send remittances. Thus, households with longer duration emigrants may see more pronounced

[23] We apply the definition of unemployment from NLFS II to both surveys, which is that someone did not have a job or business but either looked for work in the last 30 days or did not look for work but was available for work.

effects than do households sending new migrants. With our village-level data we are implicitly averaging over these differences.[24]

4.3.1 The Econometric Model

We assume that altruistic parents get utility from additional human capital of household members. They send children to school if they expect the discounted value of future returns from the additional year of schooling to outweigh the current costs. We consider that migration can have two opposing effects. It may decrease child human capital if parental absence, household labour shortages, and family disruption effects dominate. Conversely, if a household is credit constrained then migration-induced remittances will increase household consumption and may release the children from labour market activity, allowing them to spend more time in school education.

We use a fixed-effect panel model to reduce endogeneity bias, due to unobserved village characteristics that are correlated with schooling and migration. Our use of village-level averages also helps mitigate effects of measurement error in the household-level data. Various advantages of panel data fixed-effect models are discussed in Hsiao (2007) and Adams Jr (2011). Our panel fixed effect model is as follows:

$$Y_{it} = \mu_i + \lambda_t + \beta X_{itmig} + \theta X_{it} + u_{it} \quad (4.1)$$

$$u_{it} \sim N(0, \sigma^2 l_N) \quad (4.2)$$

In equation (4.1), the NT × 1 vector of dependent variables, denoted by Y_{it}, is modelled as depending on μ_i and λ_t village and time fixed effects, the variables of main interest, migration and remittances, are denoted as a matrix of X_{itmig} and other control variables (like size of land owned, parents education, share of working age population) are denoted by matrix X_{it}. The β and θ are

[24] Initially, the increase in income and the relaxation of credit constraints from receipt of remittances would primarily help a household with debt repayment, but as the duration of migration rises the effects on human capital may appear.

vectors of coefficients for X_{it} and u_t is a NT × 1 vector of error terms which is clustered at the district level for the 71 districts in the survey.

Villages may differ in terms of their population composition, school access and quality, market access, labour market conditions and so on. The village and time fixed effects allow us to control for time-invariant village effects, and for space-invariant time effects but time-variant unobserved characteristics that may correlate with migration and schooling still pose a problem. Specifically, the endogeneity of migration may bias the estimate of β because it is likely that households are not randomly participating in migration and instead there may be a simultaneity of migration decisions and human capital decisions, so there is threat of reverse causality. For example, a village with high illiteracy and poverty, low education and high rates of child labour may only be able to send migrants to a low-cost destination like India. So schooling, migration, and subsequent remittances may be affected by factors that are unobservable, but correlated with outcomes and with the treatment variables.

To address potential endogeneity from migrant self-selection, a shift-share instrumental variables (IV) strategy is often used (Acharya & Leon-Gonzalez, 2014; Acosta, 2011; Adams Jr, 2011; Calero et al., 2009; Datt et al., 2019; Koska et al., 2013). We use a similar Bartik-style shift share instrument and follow the Theoharides (2018) strategy to develop a potential instrumental variable for emigration. We use locality-level historical emigration to destination country shares from census data (from 2001) to construct this IV. Nepal has been sending migrants overseas, especially to India, and recently emigration for work to high-income destinations like the Middle East, North Africa and Malaysia has also increased. There are two potential impacts of historical emigration patterns on the sending locality. First, previous emigration plays the role of a network for new migrants and thus it increases the labour outflow by reducing the cost of emigration through lowering job search costs and increasing information flows. Second, the inflow of remittances helps households to overcome borrowing constraints and increases the financing capacity of households

for subsequent migration to the same destination or to other high-income destinations (noting that these destinations tend to be costly in terms of recruitment and visas, unlike the low cost, low return work-based emigration to India). The previous literature heavily relies on this IV considering that previous migration to a destination is a good predictor of subsequent migration, due to network effects (Amuedo-Dorantes & Pozo, 2010; Acosta, 2011; Acharya & Leon-Gonzalez, 2014). This relationship is shown in Figure 4.2, for migration from Nepal to either India or MEOA where the emigration rates in 2001 and 2011 are strongly correlated. Therefore, to construct our IV we follow the following process:

Consider the migration network in terms of the share of labour that migrated from village i to destination country k in year 2001 (out of the total number of people who migrated to k from Nepal). We then sum the total number who migrated to destination k in each year t (2008 and 2010 given the timing of our panel). To predict the total number of migrants from the village in each survey year (that is, in 2008 and 2010) we weight the total migrants to destination k by the 2001 village i migrants share to destination k. Our predicted migrant flows, which reflect destination-driven demand for migrants, for each village are:

$$M_{ikt}^{p} = \sum_{i}^{n} M_{kt} \frac{M_{ik}^{2001}}{M_{k}^{2001}} \tag{4.3}$$

Where M_{ikt}^{p} is the predicted number of people migrating to destination k from village i in year t, M_{kt} is the total number of people who migrated from Nepal to destination k in year t (2008 or 2010), and $\frac{M_{ik}^{2001}}{M_{k}^{2001}}$ is the share that migrants from village i have in the total national migrants to destination k in the past (in 2001 in our case). First, we estimate the predicted migration rate to India and MEOA separately considering that these two are the major migrants' destinations. Second, we sum predicted migration rate to India and MEOA to estimate total predicted migrants from that locality. Our predicted migration rate is a single instrumental variable which is a

combination of emigration to India and MEOA. Later, we normalize the total predicted migrants by dividing the sum by the total village population, which is essentially our instrument for migration.

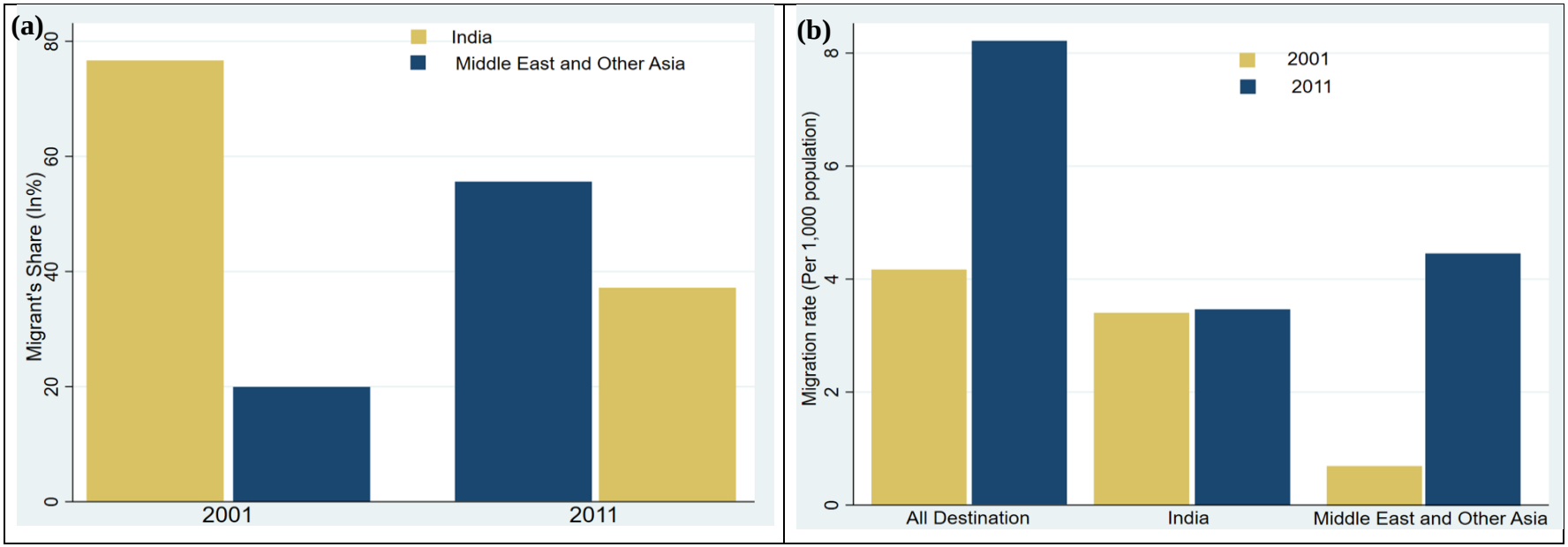
Our instrument can be interpreted as time trend migration flow as it reflects current emigration flow based on historical emigration rate. We expect that our predicted migration rate is a strong predictor of the current migration rate in each locality. Villages that have sent migrants previously to India or MOEA are expected to send migrants in similar manner. The existing migrant's network in destination and inflow of remittances encourages further migration as the network helps new migrants to find jobs and the inflow of remittances helps to finance the cost of migration. For Nepal's five development regions, in census 2001 to 2011 the migrants' distribution across destinations is quite stable, for example, India is still a favourite destination for people from mid-west and far-west regions while relatively developed regions like central and eastern regions prefer sending migrants to MEOA. The relationship between 2001 and 2011 migrants share (refer to Figure 4.1 and 4.2) is quite strong, as villages continue to send migrants to destination countries at a similar rate, with just a small fall for India and a rise for MEOA. The local migration pattern over 2001 and 2011 strongly suggest that early migration patterns influence outflow of migration and their destination choice.

Our identification strategy will be invalid only if 2001 emigration rate correlates with the current child schooling outcome. In contrast, we argue that the historical emigration rate is not correlated with current child schooling outcomes, and any time invariant unobserved village characteristics that may correlate with the 2001 emigration rate is controlled for by village level fixed effects. Our use of the above instrumental variable along with village and time fixed effect should be a valid identification strategy. We estimate equation (4.1) using our village predicted migration rate (as derived from equation (4.3)) as instrumental variable for the actual village migration rate in our migration model. The resulting estimates should show the effect of migration on schooling and child labour and we can rule out reverse causation that would occur if the current

schooling conditions and child labour rates affect migration. The reason we can rule out this channel is that our predicted migration variable depends on the migration network from a decade before, yet current school enrolment and child labour rates should not matter to historical migration.

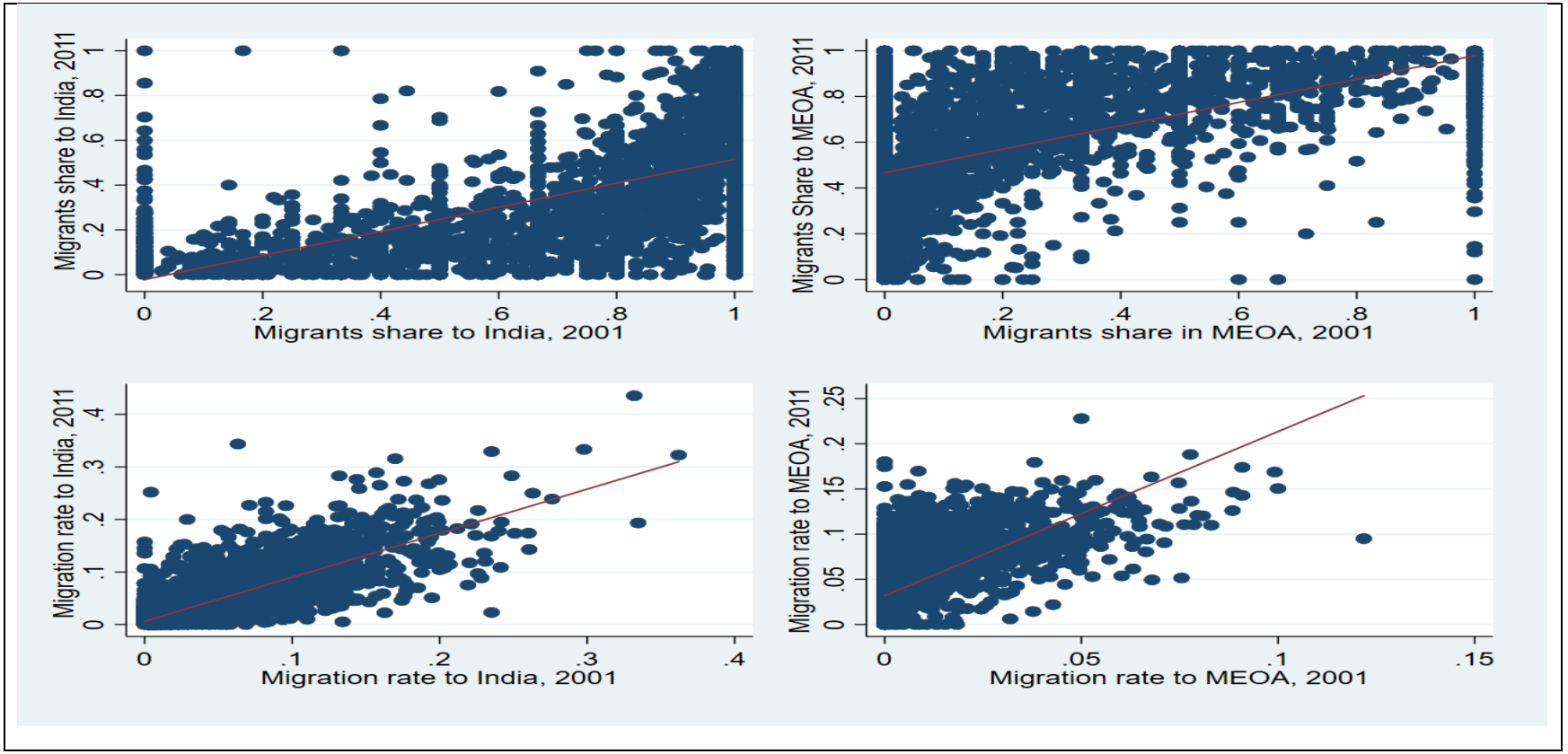
Separately, we also estimate additional remittance models, and we use the same IV (equation 4.3) and replace X_{itmig} in equation (4.1) with X_{itrem}, where X_{itrem} stands for remittances. We consider that the impact of emigration channeled through remittances, and that a locality that had a higher emigration rate in 2001 is likely to receive more remittances today because the past migration network influences current emigration and that will lead to higher remittances. For instance, emigration and remittances are highly correlated since the primary motivation behind migration is getting higher earnings and sending remittances back home to improve household welfare. Therefore, we expect that past emigration will affect remittance inflows today through higher emigration, and that may affect the child schooling outcome. The validity of this IV for remittance model has the same reasoning as for the migration model since the impact of past migration affects current remittances through the channel of current emigration.

Figure 4.1: (a) Migrants share in India and MEOA **(b)** Mean of migration rate



Source: CBS (2001), (2011). *Note*: MEOA is Middle-East and Other Asia

Figure 4.2: The migrants share and migration rate in 2001 and 2011



Source: CBS (2001), (2011)

4.4 Results and discussion

The results of the first stage equations, for the migration rate and the value of remittances received, are reported in Table 4.2. The instrumental variable that is derived from equation (4.3) has a strong first-stage effect on the migration rate (the *F*-test for excluding the instruments is 18.72 and 26.55 and so it easily exceeds the usual threshold of 10 for not having weak instruments) after controlling for village and time fixed effects. The first stage equations closely reflect recent migration trends for Nepal (these trends are seen in Figure 4.1). For example, in census 2001 and 2011, overall there is a two-fold increase in mean migration rate, and this increase is contributed by nearly four times increase in the share of migrants going to MEOA (CBS, 2001, 2011).

Table 4.2: The first stage migration and remittance model estimating the effect of instrument

	Migration	Remittance
Predicted migration rate	0.175	0.184
	(4.698)***	(4.481)***
Agriculture land owned	1.132	-4.448
	(0.560)	(1.636)
No. of Household member	4.376	3.015
	(1.981)*	(1.791)*
Parents education (with high school or above)	61.410	67.564
	(2.140)**	(0.950)
Share of working age (15-60)	-203.554	-30.482
	(6.412)***	(0.953)
Share of Migrants with grade ≥ 8	5.940	14.445
	(1.360)	(1.374)
Share of 15-60 with grade ≥ 8	3.661	0.276
	(0.159)	(0.020)
Literacy rate aged ≥ 17	0.098	0.1315
	(0.400)	(0.648)
Unemployment rate	47.717	80.876
	(1.376)	(0.846)
R-Squared	0.181	0.159
F-Statistics	18.72	26.55
Observation	998	998

This table shows first-stage results for migration rate instrumented with predicted migration to India and MEOA also including unreported time and village fixed effects. Both columns show the results from both IVs. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 71 Districts), ***, **, * denote 1%, 5%, 10% statistically significance.

Given the validity of the instrumental variables, we proceed with the main analyses, which are laid out as follows (with fuller details given below). Table 4.3 contains results for the impacts of migration and remittances on Basic and Secondary education net enrolment rates. Table 4.4 has the results for the effects of migration and remittances on child labour force participation, in terms of the extensive margin (whether working or not) and the intensive margin (how many hours worked). Finally, the impacts of migration and remittances on the more typically studied indicators, of school attendance and the dropout rate, are reported in Table 4.5, where the purpose of these additional results is to contrast with the more nuanced results shown in Tables 4.3 and 4.4.

Effect of migration on school performance

The effect of migration on child schooling depends, in part, on how the remittances that migration enables help households to overcome liquidity constraints. To the extent that extra income from

remittances reduces the need for child labour, and provides more funds for schooling related expenses, it can be expected to improve indicators of school performance, such as the net enrolment rate. There will also be other changes due to migration, to the extent that migration opportunities change the decision-making of parents and children about the optimal investment in their human capital. The results in Table 4.3 shows that both migration and remittances have positive and significant effects on the net enrolment rate in secondary education for children aged from 13 to 16. Specifically, a rise in the migration rate by one person per thousand of population would raise the mean net enrolment rate at secondary school by 0.46% ($p < 0.05$). A similar pattern is observed for the net enrolment rate in lower secondary, senior secondary, and higher secondary level in Table A.4.2. Similarly, the remittance model shows an impact on secondary school mean net enrolment of around 0.44% ($p < 0.01$) for an increase of NPR 1,000 in the average value of remittances received. Another way to see the magnitude of these effects is in terms of standard deviation changes, where a one standard deviation increase in the migration rate and in the value of remittances received would result in 0.92 and 0.76 standard deviation increases in the secondary school net enrolment rate. While there is an overall positive effect on secondary school net enrolment rate, result in Table 4.3 weakly indicates that the migration and remittances reduce Basic education net enrolment rate. The effect is significant (at $p < 0.10$) in migration model only.

There are two other notable features about the results in Table 4.3. First, the effects on net enrolment at the Basic education level, for children aged 5-12, precisely estimated only for migration. There are several possible reasons for this pattern; first, there may be parental absence or family disruption effect of migration on the younger children that may impair their school performance. Second, the enrolment rates at the Basic level are universally much higher, and so there is less scope for between-village variation than is possible at the secondary school level and the estimated effect may for the rare outcome. Third, the Basic education level is far cheaper (see Table A.4.1 for details) and so borrowing constraints may be less binding on enrolment decisions at

this level. In that case, migration and the resulting receipt of remittances are less needed to overcome these less binding constraints.

The second feature of Table 4.3 is that coefficient estimates are larger (and consequently more statistically significant) when the instrumental variables approach is used. For the fixed effects models without instrumental variables, even with control variables and time and village fixed effects, there is still the threat of reverse causality that would bias the coefficient estimates. The difference between the FE and FE-IV specifications reinforces the importance of having plausibly exogenous sources of variation when studying the impacts of migration and remittances.

Table 4.3: The effect of migration on net enrolment rate at Basic and Secondary education for children aged 5-12 and 13-16

	Basic education (aged 5-12)				Secondary education (aged13-16)			
	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
Migration Model	-0.016	-0.250			0.023	0.460		
	(0.853)	(1.956)*			(1.141)	(2.426)**		
Remittance Model			-0.006	-0.244			0.041	0.441
			(0.412)	(1.639)			(1.62)	(3.299)***
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared (within)	0.26		0.26		0.35		0.357	
Wald test (Chi-squared)		787.06		3693.66		299.41		1273.83
Observation	997	997	997	977	992	992	992	992

This table shows the second-stage results for educational outcome for children aged 5-12 and 13-16. Table presents both migration and remittance models. The OLS FE and FE-IV are also presented in the table to show the difference in the coefficients if migration is not instrumented. In FE-IV we have instrumented migration with predicted migration to India and MEOA. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 71 Districts), ***, **, * denote 1%, 5%, 10% statistically significance. *Note:* Basic education aged 5-12 indicates the enrolment of child aged 5 to 12 in primary and lower secondary level. Secondary education aged 13-16 indicates the enrolment of child aged 13 to 16 in secondary and higher secondary level. Migration and remittance estimates are in percentage. Full results are available from authors.

An important feature of the Table 4.3 results is that the positive impact of migration only comes into play for the children aged 13 and above in secondary school. This age-specificity is likely due to several factors. First, the secondary school cost is much higher for households, with the figures in Appendix A.4.1 showing costs are up to four times as high as the cost of school at the Basic level. Second, in addition to the out of pocket cost of secondary education, parents also have to consider the opportunity cost of sending children in this age group to school. For instance, child labour force participation rates (for ages 10-14) in rual and urban areas are 37% and 15%, respectively and, around 55% of children aged 10-14 attend school while also working in the labour market (CBS, 2008). Thus, if remittances help households to overcome liquidity constraints, which lessens the need for children to be the labour market, then this effect should show up especially for older children at the secondary school level. Third, at the secondary level there are more private school options, and enrolment in these schools can be thought of as a quality response rather than a quantity response. This response on the quality margin may be another pathway through which migration and remittances help in achieving a timely completion of secondary education (Acharya & Leon-Gonzalez, 2014).

Effect of migration on child labour force participation

The migration of parents or other economically productive household members may mean that left-behind children have to undertake additional household work or participate in the labour market to compensate for the foregone inputs of time and money. This may especially matter early in the duration of the migration tenure, because it takes time for migrants to become established and to save some money and send it back home (McKenzie & Rapoport, 2011). Eventually, remittances may rise to compensate for the income loss and the household may rearrange activities to require less labour or use some remittance income to hire in labour, and so when that stage is reached the time demands on children may fall. Consequently, at the household level there is a duration-dependent heterogeneity in the impact of emigration and remittances on the left-behind (Gibson et

al., 2013) and averaging across households in a village will yield a net effect of the offsetting positive and negative impacts on the demand for child labour.

It appears that for Nepal in the 2008-10 period that we study the net effect of migration and remittances is to reduce the risk of child labour (Table 4.4). This result is in line with previous studies like Calero at al. (2009), Gyimah-Brempong et al. (2015), and Koska et al. (2013). The reduction in the child labour force participation rate as migration rises and as remittances increase is apparent both for younger children (age 8-10) and for older children (age 11-16). Specifically, the impact for the younger children is that a one percentage point increase in the migration rate would result in a 0.61% ($p<0.01$) fall in the labour force participation rate while for older children the impact is a 0.40% fall ($p<0.05$). We also observe a similar pattern in results from the remittance model; if the village average of remittance receipts rises by NPR 1000 then it would reduce the child labour force participation rate by 0.59% for the younger children and by 0.39% for the older children (both effects are statistically significant at the $p<0.01$ level).

Table 4.4: The effect of migration on child labour force participation and no of hour worked in labour market

	Labour force participation rate				No's of hour worked			
	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
Panel A: For children aged 8 to 10								
Migration Model	0.007	-0.609			0.003	-0.038		
	(0.210)	(2.837)***			(0.303)	(0.600)		
Remittance Model			-0.019	-0.588			-0.002	-0.037
			(1.03)	(3.645)***			(0.462)	(0.648)
R-Squared (within)	0.099		0.100		0.080		0.080	
Walt test (Chi-squared)		34.57		265.23		195.37		65.57
Panel B: For children aged 11 to 16								
Migration Model	0.019	-0.403			-0.031	-0.595		
	(0.963)	(2.395)**			(1.647)	(3.781)***		
Remittance Model			-0.003	-0.3892			-0.063	-0.575
			(0.160)	(3.162)***			(4.88)***	(5.472)***
R-Squared (within)	0.237		0.236		0.099		0.122	
Walt test (Chi-squared)		165.91		1798.43		118.13		68.24
Control Variables	Yes	Yes		Yes	Yes	Yes		Yes
Time and Village Fixed Effects	Yes	Yes		Yes	Yes	Yes		Yes
Observation	998	998		998	998	998		998

This table shows the second-stage results for Child labour force participation for children aged 8-10 and 11-16 at extensive and intensve margin. Table has two different panel (A and B) for two different age group of children. Table presents both migration and remittance models. The OLS FE and FE-IV are also presented in the table to show the difference in the coefficients if migration is not instrumented. In FE-IV we have instrumented migration with predicted migration to India and MEOA. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 71 Districts), ***, **, * denote 1%, 5%, 10% statistically significance. *Note:* Migration and remittance estimates are in percentage. Full results are available from authors.

In addition to the effects of migration and remittances on the probability that a child is in the labour force, there is also an effect on the number of hours that they work. These effects are predominantly negative, and especially for the older children. For example, if the village average remittance receipts rise by NPR 1000 then average hours worked by 11-16 year olds would decline by 0.58 hours, according to the IV results. There is a very small and imprecisely estimated negative effect of migration on hours worked by 8-10 year old children (an average fall of less than three minutes per week) while there is a much larger negative effect on the hours worked by older children.

Effect of migration on school attendance and dropout rates

In order to examine the effects of migration and remittances on commonly used schooling measures in previous studies, we also developed attendance and dropout rate estimates. These only consider whether a child is currently enrolled, irrespective of whether they are in the appropriate grade for their age. Results are shown in Table 4.5 (Panel A and B). From the IV estimates it seems that migration and remittances reduce the likelihood of a child being enrolled in school. For example, the results suggest that an increase in migration rate reduces the attendance rate for a child aged 5-16 by 0.07% ($p < 0.10$). For the sub-group of older children (aged 13-16) the estimated fall in the attendance rate is by 0.38% ($p < 0.01$). We observe similar pattern in dropout rates, in that migration and remittances appear to increase the number of children out of school who have previously enrolled. For instance, effects on dropout are 0.07% and 0.27% (at $p < 0.01$) for the children aged 5-12 and 13-16. The remittances model shows similar results. The apparently negative effect of migration on school attendance that can be inferred from the results in Table 4.5 (and is contrary to the results in Table 4.3) does align with some earlier findings for Nepal, such as Acharya & Leon-Gonzalez (2014), and also some findings from elsewhere.

Table 4.5: The effect of migration on school attendance and dropout rate of children aged 5-16, 5-12 and 13-16

	Child aged 5-16				Child aged 5-12				Child aged 13-16			
	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
Panel A: Attendance rate												
Migration Model	-0.002	-0.067			0.005	0.028			-0.007	-0.384		
	(0.266)	(1.654)*			(0.634)	(0.383)			(0.404)	(3.086)***		
Remittance Model			0.013	-0.063			0.015	0.027			0.002	-0.369
			(2.02)**	(1.397)			(1.88)*	(0.392)			(0.19)	(2.655)**
R-Squared (within)	0.056		0.061		0.041		0.047		0.077		0.077	
Wald test		9505.29		22771.96		4222.42		16912.4		854.43		2430.66
Panel B: Dropout rate												
Migration Model	0.000	0.0799			0.002	0.070			-0.004	0.268		
	(0.026)	(5.131)***			(0.347)	(3.990)***			(0.302)	(2.701)***		
Remittance Model			0.001	0.076			0.001	0.069			-0.006	0.257
			(0.867)	(2.948)***			(0.76)	(2.42)**			(0.642)	(2.379)**
R-Squared (within)	0.005		0.006		0.013		0.013		0.043		0.043	
Wald test		34.04		80.83		24.11		84.03		34.71		79.74
Control Variables	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes
Time and Village FE	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes
Observation	998	998	998	998	997	997	997	997	992	992	992	992

This table shows the second-stage results for Child school attendance and dropout rate for children aged 5-16, 5-12 and 13-16. Table has two different panels (A and B) for attendance and dropout rate. Table presents both migration and remittance models. The OLS FE and FE-IV are also presented in the table to show the difference in the coefficients if migration is not instrumented. In FE-IV we have instrumented migration with predicted migration to India and MEOA. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 71 Districts), ***, **, * denote 1%, 5%, 10% statistically significance. *Note:* Migration and remittance estimates are in percentage. Full results are available from authors.

It is important to emphasize the contrast between the Table 4.3 and Table 4.5 results. In Table 4.3, it is seen that migration and remittances improve age-appropriate enrolment rates in secondary education (for 13-16 year olds) yet in Table 4.5 it appears that school attendance (at any schooling level) for this age group is depressed by migration and remittances, while the dropout rate is increased. Adding interest to this contrast is the fact that the outcome variables in Table 4.5 – attendance rates and dropout rates – are more like the outcome variables that previous studies for Nepal have used, while an innovation of the current study is to calculate and the age-appropriate net enrolment rate as the preferred outcome measure. One motivation for doing this is that the simple attendance rate is a crude measure of schooling outcomes as it do not capture the quality dimension, such as the timely transition through the various levels of schooling. This is especially in settings such as Nepal where over 90% of school-age children are in some sort of school, albeit with considerable over-age enrolment (as seen from gross enrolment rates of almost 1.4, meaning that there are 40% more children in primary grades 1-5 than would be expected from the age structure of children).

The second implication of the contrast between the Table 4.3 and Table 4.5 results is that the effects of migration and remittances on human capital of the left behind may operate in fairly subtle ways; for example, by improving age-specific enrolment of older children but not of younger children, with the most likely explanation for this pattern due to the differing costs of the various levels of schooling (including the opportunity cost of labour market work). Given that many previous studies have used simple enrolment and dropout indicators, like those in Table 4.5, we suggest that it is important to construct other measures of schooling outcomes such as age-specific net enrolment rates, schooling deprivation indices, schooling inequality indices, and scores in national assessment of student achievement, in order to better understand the actual situation in terms of the school performance of children (Datt et al., 2020). This is especially because, for

policymakers, school performance may be more important than school attendance because better school performance can translate into a productive workforce and break the cycle of poverty.

4.5 Conclusions

Work-related international migration from Nepal has become a major income generating activity for households. From the period 2001 to 2010, Nepal experienced a significant rise in emigration rates and in remittance inflows, and in the same period the country has managed to reduce the poverty rate by half. While prior studies have linked this increase in migration and in remittances to the poverty reduction that occurred, concerns have remained about the impacts on child human capital (and relatedly on child labour), as it is the quality of human capital that will be important to ongoing poverty reduction in the future. Even though the beneficial effects of remittance on the macroeconomic indicators like GDP, the current account, and trade have been studied (e.g. Sapkota, 2018) the potential long term impact on human capital is still not very clear. In part, this uncertainty reflects the offsetting pathways that, theoretically, can come into play – overcoming borrowing constraints and reducing the need for child labour on the one hand, but also possibly reducing the opportunity cost of staying in school, on the other.

In order to inform understanding of the impacts of migration and remittances on human capital in Nepal we have constructed a two-wave panel of 499 villages, from the Nepal Labour Force Survey 2008 and the Nepal Living Standard Survey 2010. Our research design exploits the variation in village-level predicted migration rate, which is driven by destination countries and so should have impacts on these villages that only operate through migration and remittances. In contrast to prior studies, we focus on net enrolment rates as our main outcome variables. The advantage of studying net, rather than gross, enrolment rates is that it recognizes that over-age enrolment, slow progression, and grade repetition are common problems that plague schooling in many developing countries.

Our results show that the rise in migration and remittances increased the net enrolment in Secondary education (for older children aged 13-16) even while it was having a weakly negative effect on enrolment in Basic education. The several possible reasons are; first, for younger children, there may be a parental absence or family disruption effect that outweighs the positive effect of remittance. Second, Basic education is much cheaper for parents, with a schooling cost that is about four times lower than at the secondary level. Thus, borrowing constraints may matter less for enrolment at Basic level, whereas migration and remittances come to matter for the higher cost of Secondary level education – both public and private. There is suggestive evidence that the positive effect on Secondary education is channeled through reduced child labour. The rise in remittance receipts helps households to compensate for the initial income loss from having productive members abroad, so this reduces the need for children to be in the labour market. In turn, with reduced need for child labour it may free the child to participate in secondary education.

In contrast to these findings, if we use a cruder indicator such as the school attendance rate, which does not distinguish between age-appropriate and over-age enrolments, it appears that the effect of migration and remittances is to reduce the number of children attending school. We believe that when a country has universal free education (at the Basic level) and when the majority of children are in school (as is the case for over 90% of Nepali children), the simple measure of whether a child is in school or not may provide misleading inferences. In particular, such a simple indicator fails to show impacts on the quality of schooling outcomes and on the timely progression through the schooling system. Hence, one take-away from the current study is the need to develop other measures of schooling outcomes, which can also help to measure some of the more subtle impacts of migration and remittances. Moreover, given the positive impact that remittances are shown to have, from a policy perspective it is important to increase remittance receipts. One way to do this, independent of increasing the number of emigrants, is to decrease the cost of remitting to, especially, rural areas. This reduction in costs could come from increasing the number of financial

institutions operating in rural areas, as a policy intervention to help achieve greater impacts of migration and remittances on human capital.

4.6 Reflection on this chapter

In this study we rather focus on within variation than between variation. The within variation provides more degrees of freedom and more variability in the data compared to between variation which would be single cross section in our case. In fact, it improves our econometrics estimates (by reducing the impacts of measurement error in data) and allows us to control impacts of omitted variable in our model by using time and spatial fixed effect.

There is an important (albeit technical) estimation challenge posed by working with village level averages in each survey year. The dependent variables are bounded from below by zero and from above by one. If there is a non-linear relationship between the explanatory variables and the outcome variables then this bounding may lead to model misspecification, particularly when the outcome variable is near either zero or one. In this case, the fractional response model may be more appropriate because it restricts E(Y/X) within the [0,1] interval. However, the application of fractional response models is outside the scope of this study, as it requires the application of a two-stage residual inclusion approach to overcome endogeneity concerns.

We have also not included conflict intensity in our model even though that may have some effect on local labour market activities. We consider that the impact of conflict on our estimates is minimal because the conflict ended in 2006 and the survey data we use are for 2008 and 2010. Moreover, the village and time fixed effects should control for any lingering influence on our outcome variable.

References

Acharya, C., and Leon-Gonzalez, R. (2014). How do migration and remittances affect human capital investment? The effects of relaxing information and liquidity constraints. *Journal of Development Studies, 50*(3), 1-17.

Acharya, C., and Leon-Gonzalez, R. (2019). The quest for quality education: International remittances and rural–urban migration in Nepal. *Migration and Development, 8*(2), 119-154.

Acosta, P. (2011). School attendance, child labour, and remittances from international migration in El Salvador. *Journal of Development Studies, 47*(6), 913-936.

Adams Jr, R. H. (2011). Evaluating the economic impact of international remittances on developing countries using household surveys: A literature review. *Journal of Development Studies, 47*(6), 809-828.

Alcaraz, C., Chiquiar, D., & Salcedo, A. (2012). Remittances, schooling, and child labor in Mexico. *Journal of Development Economics, 97*(1), 156-165.

Amuedo-Dorantes, C., & Pozo, S. (2010). Accounting for remittance and migration effects on children's schooling. *World Development, 38*(12), 1747-1759.

Azizi, S. (2018). The impacts of workers' remittances on human capital and labor supply in developing countries. *Economic Modelling, 75*, 377-396.

Batista, C., Lacuesta, A., & Vicente, P. C. (2012). Testing the 'brain gain' hypothesis: Micro evidence from Cape Verde. *Journal of Development Economics, 97*(1), 32-45.

Beine, M., Docquier, F., & Oden-Defoort, C. (2011). A panel data analysis of the brain gain. *World Development, 39*(4), 523-532.

Beine, M., Docquier, F., & Rapoport, H. (2008). Brain drain and human capital formation in developing countries: Winners and losers. *The Economic Journal, 118*(528), 631-652.

Beine, M., Docquier, F., & Rapoport, H. (2001). Brain drain and economic growth: Theory and evidence. *Journal of Development Economics, 64*(1), 275-289.

Bredl, S. (2011). Migration, remittances and educational outcomes: The case of Haiti. *International Journal of Educational Development, 31*(2), 162-168.

Bucheli, J., Bohara, A., & Fontenla, M. (2018). Mixed effects of remittances on child education. *IZA Journal of Development and Migration, 8*(1), 1-18.

Calero, C., Bedi, A. S., & Sparrow, R. (2009). Remittances, liquidity constraints and human capital investments in Ecuador. *World Development, 37*(6), 1143-1154.

Cellini, R. (2007). Migration and welfare: A very simple model. *Journal of International Development, 19*(7), 885-894.

Central Bureau of Statistics [CBS] (2001). *National Population Census 2001, Report on Nepal's Tenth Census*. Kathmandu, Nepal: His Majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2008). *Nepal Labour Force Survey-II 2008: Statistical Report.* Kathmandu, Nepal: Government of Nepal.

Central Bureau of Statistics [CBS] (2010). *Nepal Living Standard Survey III 2010: Statistical Report, Vol 1 and 2*. Kathmandu, Nepal: Government of Nepal.

Central Bureau of Statistics [CBS] (2011). *National Population and Housing Census 2011, National Report*. Kathmandu, Nepal: Government of Nepal.

Christian, P., & Barrett, C. B. (2017). *Revisiting the effect of food aid on conflict: A methodological caution* (Policy Research Working Paper, No. 8171). Washington, DC: World Bank.

Datt, G., & Uhe, L. (2019). A little help may be no help at all: Size of scholarships and child labour in Nepal. *The Journal of Development Studies*, *55*(6), 1158-1181.

Datt, G., Wang, L. C., & Badji, S. (2020). Is emigration of workers contributing to better schooling outcomes in Nepal? *Review of International Economics*, *28*(4), 1046-1075.

Davis, J., & Brazil, N. (2016). Disentangling fathers' absences from household remittances in international migration: The case of educational attainment in Guatemala. *International Journal of Educational Development, 50*, 1-11.

De Gregorio, J. (1996). Borrowing constraints, human capital accumulation, and growth. *Journal of Monetary Economics*, *37*(1), 49-71.

De, P. K., & Ratha, D. (2012). Impact of remittances on household income, asset and human capital: Evidence from Sri Lanka. *Migration and Development*, *1*(1), 163-179.

Di Maria, C., & Lazarova, E. A. (2012). Migration, human capital formation, and growth: An empirical investigation. *World Development*, *40*(5), 938-955.

Department of Education [DOE] (2015). *The Flash Report I 2014-15.* Kathmandu, Nepal: Government of Nepal.

Fan, C. S., & Stark, O. (2007). International migration and "educated unemployment". *Journal of Development Economics*, *83*(1), 76-87.

Gibson, J., & McKenzie, D. (2010). How does high-skilled emigration affect small countries? Microeconomic evidence from Tonga. *Annals of Economics and Statistics / Annales D'Économie Et De Statistique*, (97/98), 167-185.

Gibson, J., McKenzie, D., & Stillman, S. (2011). The impacts of international migration on remaining household members: Omnibus results from a migration lottery program. *Review of Economics and Statistics*, *93*(4), 1297-1318.

Gibson, J., McKenzie, D., & Stillman, S. (2013). Accounting for selectivity and duration-dependent heterogeneity when estimating the impact of emigration on incomes and poverty in sending areas. *Economic Development and Cultural Change*, *61*(2), 247-280.

Government of Nepal [GON] (2014). *Labour migration for employment. A Status Report for Nepal 2013/2014.* Kathmandu, Nepal: Author.

Gyimah-Brempong, K., & Asiedu, E. (2015). Remittances and investment in education: Evidence from Ghana. *The Journal of International Trade & Economic Development*, *24*(2), 173-200.

Hsiao, C. (2007). Panel data analysis: Advantages and challenges. *TEST*, *16*(1), 1-22.

Jaeger, D. A., Ruist, J., & Stuhler, J. (2018). *Shift-share instruments and the impact of immigration* (No. w24285). Cambridge, MA: National Bureau of Economic Research.

Karki Nepal, A. (2016). The impact of international remittances on child outcomes and household expenditures in Nepal. *Journal of Development Studies*, *52*(6), 838-853.

Köllner, S. (2013). *Remittances and educational attainment: Evidence from Tajikistan* (Wirtschaftswissenschaftliche Beiträge, No. 124). Würzburg, Germany: Julius Maximilian University of Würzburg.

Koska, O. A., Saygin, P. T., Artal-Tur, A., & Çağatay, S. (2013). International migration, remittances, and the human capital formation of Egyptian children. *International Review of Economics and Finance, 28*, 38-50.

Kugler, M. (2006). Migrant remittances, human capital formation and job creation externalities in Colombia. *Coyuntura Social, 34*, 45-74.

Mansuri, G. (2006). *Migration, school attainment, and child labor: Evidence from rural Pakistan.* Washington, DC: World Bank.

McKenzie, D., & Rapoport, H. (2011). Can migration reduce educational attainment? Evidence from Mexico. *Journal of Population Economics, 24*(4), 1331-1358.

Melguizo, T., Sanchez, F., & Velasco, T. (2016). Credit for low-income students and access to and academic performance in higher education in Colombia: A regression discontinuity approach. *World Development, 80*, 61-77.

Melkonyan, T. A., & Grigorian, M. D. A. (2008). *Microeconomic implications of remittances in an overlapping generations model with altruism and self-interest* (WP/08/19). Washington, DC: International Monetary Fund.

Ministry of Education [MOE]. (2016). *School Sector Development Program (2016-2023).* Kathmandu, Nepal: Government of Nepal.

National Education Account in Nepal [NEAN]. (2016). *National Education Account Nepal 2016: Expenditure for Education 2009-2015.* Kathmandu, Nepal: Ministry of Education, Government of Nepal.

Nguyen, C.V., & Nguyen, H.Q. (2015). Do internal and international remittances matter to health, education and labor of children and adolescents? The case of Vietnam. *Children and Youth Services Review, 58*, 28-34.

Ngoma, A. L., & Ismail, N. W. (2013). Do migrant remittances promote human capital formation? Evidence from 89 developing countries. *Migration and Development, 2*(1), 106-116.

Salas, V. (2014). International remittances and human capital formation. *World Development, 59*(C), 224 237.

Sapkota, C. (2013). Remittances in Nepal: Boon or Bane? *The Journal of Development Studies, 49*(10), 1-16.

Sharma, H., & Gibson, J. (2019). *Civil War and International Migration from Nepal: Evidence from a Spatial Durbin Model* (Working Paper in Economics 19/06). Hamilton, New Zealand: University of Waikato.

Shrestha, M. (2017). *The impact of large-scale migration on poverty, expenditures, and labor market outcomes in Nepal.* Washington, DC: World Bank.

Sun, S. T., & Yannelis, C. (2016). Credit constraints and demand for higher education: Evidence from financial deregulation. *Review of Economics and Statistics, 98*(1), 12-24.

Theoharides, C. (2018). Manila to Malaysia, Quezon to Qatar international migration and its effects on origin-Country human capital

Appendix

A.4.1: Per capita expenditure by household, activity cost and total cost (In NPR) at each level

Education level	Total Household cost	Total cost by activities[25]	Total cost
Primary level	**5,417**	**14,832**	**15,459**
Community school[26]	1888	13,092	13,092
Institutional school	25,576	27,546	27,116
Lower secondary	**7,410**	**15,905**	**16,482**
Community school	3525	13,419	12,419
Institutional school	28,307	29,668	29,668
Secondary	**14,298**	**26,468**	**27,083**
Community school	7,589	22,236	22,236
Institutional school	42,973	45,138	45,138
Higher secondary	**24,978**	**34,963**	**35,528**
Community school	16,359	29,334	29,334
Institutional school	46,203	48,823	48,823

Source: Nepal Education Account in Nepal [NEAN] (2016)

[25] Activity cost includes teaching, uniform, text book, transport, private tuition etc.
[26] Community schools are owned and managed by government, and institutional schools are privately managed.

A 4.2: The effect of migration on lower secondary, secondary and higher secondary net enrolment rate school aged children 10-16

	Lower-Secondary				Secondary				Higher Secondary			
	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
Migration Model	-0.003	0.575			-0.012	1.155			0.036	0.173		
	(0.116)	(3.62)***			(0.466)	(2.055)**			(1.525)	(0.476)		
Remittance Model			0.019	0.546			0.039	1.097			0.062	0.1644
			(0.96)	(2.887)***			(1.847)*	(1.506)			(1.911)*	(0.452)
R-Squared (within)	0.265		0.266		0.18		0.184		0.073		0.083	
Wald test		118.52		340.84		25.40		58.10		27.52		115.44
Control Variables	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes
Time and Village FEs	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes

This table shows the second-stage results for net enrolment rate for child aged 10 to 16. Lower-Secondary NER indicates enrolment of child aged 10-12 in lower secondary level, Secondary NER indicates the enrolment of child aged 13-14 in secondary level and Higher-Secondary NER indicates the enrolment of child aged 15-16 in higher secondary level. Table presents both migration and remittance models. The OLS FE and FE-IV are also presented in the table to show the difference in the coefficients if migration is not instrumented. In FE-IV we have instrumented migration with predicted migration to India and MEOA. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 71 Districts), ***, **, * denote 1%, 5%, 10% statistically significance. *Note:* Migration and remittance estimates are in percentage. Full results are available from authors. *N = 998*

Chapter Five: The effect of emigration and remittances on labour supply of the left-behind: Evidence from Nepal

Hari Sharma

Abstract

The growth in work-related emigration and subsequent inflows of remittances have raised policy concerns about its impacts on labour supply in emigration-source countries. The growing literature in this area ignores spillover effects from emigration and remittances in one locality affecting outcomes in nearby localities. A two-period panel of 500 localities in Nepal is used, along with exogenous changes in predicted emigration rates, to identify impacts of emigration and remittances on labour supply. There is a positive impact on labour supply, but just for females. Also, emigration and remittances are associated with labour shifting out of agriculture as farm work is less preferred in remittance receiving households. While the spillover effect of emigration is as large as the direct effect, spillovers are limited to rural localities. Given the typical nature of rural labour markets, emigration-driven remittances help to overcome borrowing constraints and boost local activity that increases local wage rates and creates additional employment opportunities for the non-emigrants.

Keywords: labour supply, emigration, spillovers, remittances, Nepal

JEL Codes: D1, J22, O13, O15

5.1 Introduction

Labour export to countries like India and MENA (Middle East and North Africa) region is an important source of livelihood in Nepal. A growing literature in Nepal and other countries often links emigration and remittances with the poverty reduction (Acharya & Leon-Gonzalez, 2012; Acosta et al., 2008; Adams Jr & Page, 2005; Gupta et al., 2009; Lokshin et al., 2010). Yet little is known about how these changes affect the labour force participation of the left-behind. Similarly, while there is a literature on general equilibrium and spillover effects of emigration (Marchiori et al., 2013; Weyerbrock, 1995), effects on labour supply are largely ignored. It is likely that emigration and the resulting non-labour income in the form of remittances not only affect the sending locality but also neighbouring localities if the labour markets or other markets are spatially interconnected (e.g. being either adjacent or connected by road networks). These spatial linkages can significantly shape livelihoods (Abbay & Rutten, 2016; Banerjee et al., 2020; Dillon et al., 2011; Gibson & Rozelle, 2003; Jacoby & Minten, 2009; Shrestha, 2020). Given this potential importance, this paper aims to identify the direct and spatial spillover effect of emigration on the labour supply of non-migrants.

While there has been recent attention to this question, the extant studies are based on direct effects, often within the same household. For example, negative effects of emigration on labour supply of remaining male or female household members are found in Tajikistan (Justino & Shemyakina, 2012), Jamaica (Kim, 2007), Nicaragua (Funkhouser, 2006), Pakistan (Mughal & Makhlouf, 2013) and rural Mexico (López-Feldman & Escalona, 2017). These effects also show up in cross country studies (Chami et al., 2018). Similarly, Cabegin (2006), Funkhouser (2006) and Melkonyan and Grigorian (2012) have found upward shifts in reservation wages and change in occupation choice of the left-behind non-migrants. Similar studies in Nepal by Lokshin and Glinskaya (2009), Phadera (2016), and Shrestha (2017) all explore the effects of emigration on labour supply without considering any spatial spillovers.

Spillover effects are commonly studied in other areas, including the impacts of information flows, innovation and foreign direct investment (FDI) on firms' productivity growth and domestic industrial growth (Cainelli & Lupi, 2010; De Lucio et al., 2002; Henderson, 2003; Song & Son, 2019). While remittances are also a source of external finance for development, similar studies to identify spillover effects of emigration and remittances hardly exist. In order to fill this gap, this paper also examines spatial spillover effects of emigration, using different methods to consider 'nearby' localities, in terms of both straight-line and road distance. There is a need for such an analysis because if emigration-driven development in one locality affects the outcomes in other locality, then by ignoring spillover effect the total impact of emigration would be understated.

The main results in this study use geographic proximity based interconnectedness matrix (to capture the potential spillover effects), which is also most commonly used in the literature to show interconnectedness between localities or firms (Cainelli & Lupi, 2010; Song & Son, 2019).[27] However, the interconnectedness among localities is often not limited to geographic proximity but it also depends on the spatial pattern of roads or other transportation networks, the pattern of markets and so forth (Abbay & Rutten, 2016; Boussauw et al., 2012; Gibson et al., 2017). Given this limitation of geographical proximity measures, this study also uses a road network based measure for interconnectedness. This would reflect the critical impact of roads on livelihoods (Gibson & Rozelle, 2003; Shrestha, 2020). Additionally, there is also a within-locality local multiplier effect, especially emigration has a cross-household effect in which emigration from one household may affect the labour supply decision of other households in the same locality (Posso, 2012). Ignoring this effect may understate the impacts of emigration on non-migrant households.

In order to study these issues, I use the 2008 National Labour Force Survey (NLFS-II) and the 2010 National Living Standard Survey (NLSS-III) 2010 to construct a two-period panel of 499

[27] Typically, geographic coordinates (latitude and longitude) of localities are used to draw a straight line distance, and localities that fall within some preset distance are defined as interconnected neighbours.

localities based on village average. The advantage of taking village averages is that it captures within-village spillovers, which may be missed in household level data. This within village spillover is important in Nepal because households living in the same village are often interdependent. For instance, (non-monetary) family labour exchange is very common in the rural agriculture sector, where members of two households jointly work in their farmland in rotation to avoid using paid labour. Therefore, from both national surveys, I develop labour force participation (LFP) rate for each village for age group 17 to 65. A disaggregated analysis further considers participation in agriculture and non-agriculture separately and participation of males and females separately.

The endogenous nature of migration poses a major challenge to identifying impacts of emigration and remittances on the left-behind (Gibson et al., 2011). The two-wave panel that I construct allows for both time fixed effects and village fixed effects where the effect of time-invariant unobservable factors on outcome variable and migration is ruled out. Nevertheless, if time-varying village characteristics correlate with both village-level emigration and domestic labour market trends, the empirical results could be biased. In order to deal with this threat to the validity of the analysis, I use an instrumental variables approach that exploits village-level variation in predicted emigration rates. These predictions use the destination country-specific demand for migrants, and so are plausibly exogenous at the village level. The predicted emigration rate is based on a time trend emigration rate which depends on the baseline (in 2001) village share of migrants in each destination. I assume that a demand shock (change in demand for migrants) in the destination would primarily affect villages that have stronger pre-existing migrant networks to that destination. The variation in predicted emigration rates is determined by factors outside of Nepal, and so it should only affect labour supply decisions in Nepal through the channel of emigration and remittances.

The results show that, after accounting for endogeneity, the direct effect of emigration increases the labour force participation rate of the left-behind; a pattern that would not be apparent if endogeneity was ignored. However, this positive effect is limited to the female workforce with no significant effect on males. There is also a fall in the labour force participation rate in agriculture sector as farm work is less preferred in households that receive remittance income. In addition to finding an overall increase in labour supply, I find that the spillover effect of emigration also increases labour supply and it is as large as the direct effect. The overall increase in labour supply is linked with the rise in local wage rate and economic activities (through general equilibrium effect) that incentivises non-migrants from interconnected localities to participate in the labour market. However, these spillover effects occur primarily for rural localities. One likely reason is that the rural labour market is financially constrained and has limited in-migration, so emigration plays a greater role to overcome borrowing constraints and reinvigorate the local economy that creates employment opportunities for non-migrants. Whereas the urban labour market has a large formal or semi-formal credit institution and a repository of the reserve labour force due to rural-urban migration (Harris & Todaro, 1970), so financial constraints are less binding and the boost provided by emigration and remittances may be less needed to stimulate the local economy.

The outline of this paper is as follows. Section two briefly discusses emigration and remittances in Nepal, followed by the discussion of data and econometric model in section three. The estimated results are broadly discussed in section four, and the final section has conclusions.

5.2 Context: Migration from Nepal

Nepal has a long history of work-related migration. As far back as the 19th century, Nepalese used to migrate to Lahore city in Punjab. The long open border and visa-free mobility have traditionally made India the most attractive and lowest-cost destination to escape domestic unemployment. Since 1981 the share of migrants working in India has declined sharply; census data show the share was over 90% in 1981, then 77% in 2001 and just 38% in 2011. However, for poor regions in Nepal like

the Far-western and Mid-western region, India continues to be an important destination, with these two regions accounting for 36% and 48% of total Nepalese migrants in India in 2011 and 2001 (CBS, 2001, 2011). This outflow of labour force to India is sustained by the well-established migrants' network which helps new migrants to find jobs in Indian cities, often on a seasonal basis.

A more recent development for Nepal since 1990 is the rising share of migrants going to high-income destinations after the government allowed private recruiters to recruit Nepali labour force to Gulf countries and Malaysia. After 2001 (when the intensity of Nepal's civil conflict was high), the number of people migrating to high-income destinations has increased substantially. The rise in civil conflict, stagnant economic growth, political instability, high unemployment and rise in demand for the Nepali worker in MENA and Malaysia has further fuelled outflow of labour force. For instance, in 1994/95, around 3600 people have secured a work permit, and this number has increased by more than 100,000 work permits in a single year from 2001 onwards.

Lately, the skill-related migration to developed countries like North America, Europe and South Korea has also increased and people from a relatively developed region like central and eastern Nepal are migrating to high-income destinations. The better income-generating prospect, a better quality of education and life and strong social capital are some of the important drivers of diversification in international migration. Overall, the number of people who have emigrated has increased to 1.9 Million (7.7 % of the total population) in 2011 from 0.76 Million (3.3% of the population) in 2001 (CBS, 2001, 2011). As a result, one-third of households have at least one migrant member abroad mostly in the 15-59 age group (CBS, 2008, 2010).

Subsequently, the inflow of remittances has also increased and now it plays an important part in the stability of the economy. Nepalese households and economy are heavily reliant on remittances to finance imports and consumption and to maintain the balance of payments. The total value of remittances from formal sources increased from USD 55 Million in 1993 to USD 147 million in 2001. Thereafter, with a decade-long civil conflict and with political instability,

remittances are ever more important, increasing from USD 3.3 billion in 2011 to USD 6.3 billion in 2017. The value of remittances relative to national GDP was only 2.4% until 2001 but increased to 21.6% in 2010 and 31% in 2016 which has placed Nepal as a sixth ranked country in the world in terms of remittances relative to GDP. In addition to the formal channel, Nepal also receives a large amount of undocumented remittances from the informal channel, especially from India. About 55% of households receive remittances, with an average value per household is around USD 730 per annum (CBS, 2010). The massive surge in remittance inflows has increased household disposable income and led to a massive decline in poverty, which fell from 42% in 1996 to 25% in 2010.

In the last two decades, Nepal has also experienced a structural transformation but triggered by foreign employment rather than job creation in the manufacturing sector that would occur in a Lewis-type model. The outflow of labour to foreign employment deprived both agriculture and manufacturing sector of a cheap local labour supply. These two sectors are facing labour shortages, and often agricultural households either have to rely on the family exchange labour or leave arable land barren (Jaquet et al., 2019; Kharel et al., 2019). Meanwhile, even as Nepal exports labour the manufacturing sector is partly relying on labour coming from India, and in the absence of a cheap local labour force, some factories are forced to shut down. Therefore, understanding the impacts of emigration and remittances on labour supply in Nepal is a major policy issue which this study aims to address.

5.3 Data and Methods

This paper relies on the 2008 Nepal Labour Force Survey (NLFS II) and the 2010 Nepal Living Standard Survey (NLSS III). The commonality between these two surveys is that the primary sampling units (which I also refer to as villages or localities) for NLSS III are a subset of those used for the NLFS II. This design was to take advantage of the cartographic segmentation and household listing already carried out in 2008 (CBS, 2010). From 799 PSU in NLFS II (half urban and half rural), 174 urban and 325 rural PSU were randomly selected to provide a sample of 499 PSUs for

the NLSS III (CBS, 2010). In both surveys the selection of households within PSUs is random, so it is possible to construct village averages from the household data.[28] Using these two surveys I construct two-period panel of 499 villages. The use of village averages allow for inter-household spillovers to take place and mitigate the effects of measurement error in the household-level data.

These two surveys have information about international migration and remittances, domestic migration and remittances, age, gender, literacy, education and employment status of the household members, household land ownership and so on. This study includes 41,693 (56% of the total population in the survey from NLFS II) and 15,505 (54% of the surveyed population from NLSS III) non-migrating workforce aged 17 to 65. The total number of migrants (in the same age range) in NLFS II and NLSS III are 18,418 and 8,438 respectively, which is equivalent to 25% and 30% of the surveyed population.[29]

The detailed data on wage and non-wage employment, agriculture and non-agriculture employment and self-employment activities allow me to calculate Labour Force Participation (LFP) rates for each locality.[30] The LFP rate is further disaggregated into a male rate and a female rate and rates for the agriculture and non-agriculture sectors. The LFP rates are the outcome measures in the empirical results section below. In the data set, one important point to note that an individual can engage in more than one job (maybe in agriculture and non-agriculture sector), and agriculture and non-agriculture work can be self-employment activity. Therefore, with multiple sources of livelihood, we may observe an increase in labour supply with unchanged or reduction in LFP in one of these sectors (agriculture or non-agriculture sector).

[28] In NLFS II, 20 households are surveyed per PSU (which are either individual wards or sub-wards or groups of neighboring wards (CBS, 2010)). In NLSS III, 12 households were randomly selected per PSU.
[29] A migrant is defined as a member of a household currently away from home (residing in foreign destination) for at least six consecutive months at the time of the survey.
[30] I followed NLFS II definition to construct LFP rate as the ratio of economically active population (employed and unemployed) to total population aged 17 to 65. Someone managing his/her own business in agriculture or non-agriculture sector or both is considered as self-employed.

The variable of main interest is the locality emigration rate per 1,000 population.[31] The other covariates are average household size, average quantity of land owned per household (a proxy for wealth), the gross enrolment rate at the higher secondary level (level 12), the share of the working-age (age 15-60) in total population, the share of the working-age population with at least basic level education (grade ≥ 8), average literacy rate and the share of emigrants with at least basic level education (grade ≥ 8). International emigration may be a two-step process, where someone first migrates domestically and then moves to a foreign country once they accumulate sufficient resources. Therefore, I also include the domestic migration rate and the average remittances received from domestic migrants as additional controls. The definitions and summary statistics of all variables that are used in the main results are presented in Table 5.1.

[31] I derive emigration rate by dividing the number of emigrants from the village by the village total population.

Table 5.1: Descriptive statistics (N=499)

	NLFS 2008		NLSS 2010	
	Mean	Std. Dev	Mean	Std. Dev
Labour force participation rate (In percentage)	83.90	14.68	85.96	12.29
Labour force participation rate-Male (In percentage)	89.96	10.29	89.72	10.63
Labour force participation rate-Female (In percentage)	78.29	21.49	82.73	17.20
Labour force participation rate-Agriculture sector (In percentage)	55.57	35.07	58.80	34.83
Labour force participation rate-Non agriculture sector (In percentage)	58.63	17.73	62.72	16.43
Emigration rate to India (number of emigrants per 1,000 population)	32.68	43.11	33.09	46.46
Emigration rate to MEOA (number of emigrants per 1,000 population)	24.56	25.95	29.01	30.69
Average remittance received per household (In NPR)	3705	5993	4471	6703
Agriculture land owned by households (in Acres)	1.075	0.828	1.171	0.894
Average number of members per household	5.124	0.96	5.209	1.084
Share of working age (15-60) in the population	0.537	0.091	0.529	0.098
Share of emigrants with schooling to grade ≥ 8	0.556	0.317	0.628	0.322
Share population aged 15-60 with schooling to grade ≥ 8	0.381	0.227	0.402	0.219
Literacy rate (share of individual in locality who are literate)	0.690	0.158	0.657	0.18
Unemployment rate for adult aged 17-65	0.024	0.037	0.019	0.031
Higher Secondary level (grade 11-12) Gross Enrolment Rate for children of all age	1.307	1.874	0.935	1.038
Domestic migration rate (local migrants per 1,000 population)	61.76	59.72	93.05	85.21
Average remittance received from domestic migrants (In 1,000 NPR)	2.54	3.72	0.06	0.12

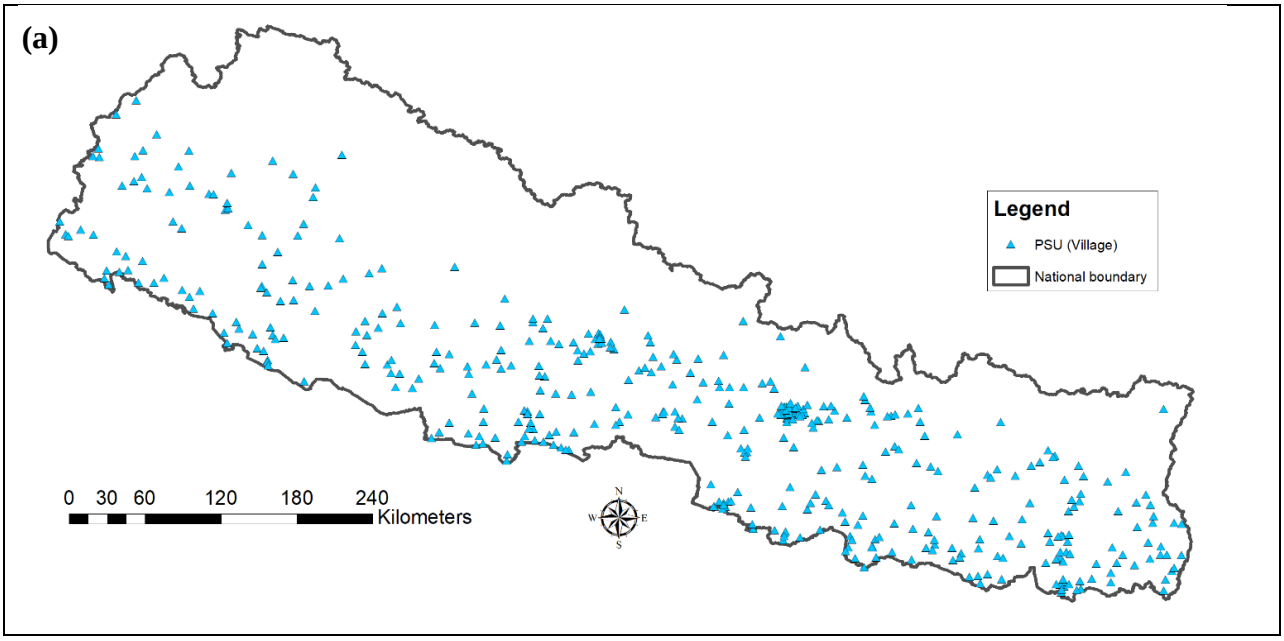
Source: Authors own calculation from NLFS 2008 and NLSS 2010. *Note:* MEOA is a MENA (Middle East and North Africa) and Other Asia

5.3.1 Interconnected matrix:

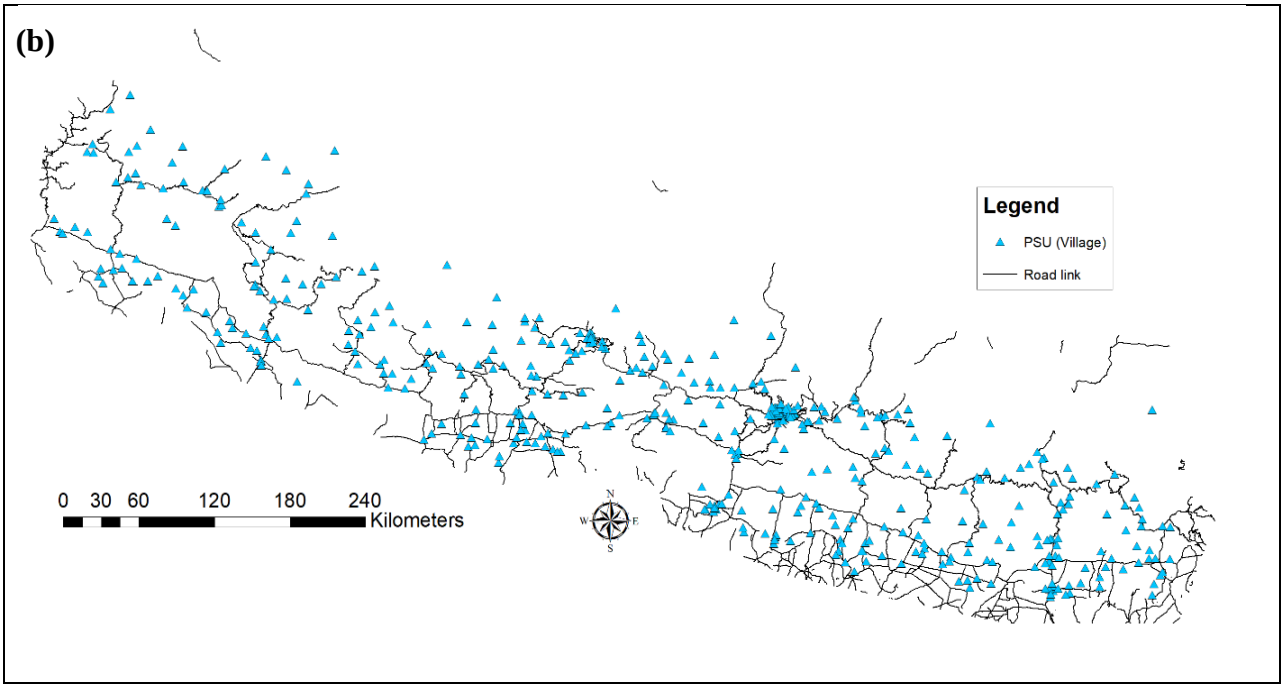
Understanding spillover effects of emigration and remittances has an important policy implication in a country like Nepal, where emigration is a major income generating household activity. It is important because impacts of emigration and remittances often spill from one locality to another when they are interconnected, by affecting the local wage rate, economic activities and so on.[32] Additionally, there is also a general equilibrium effect of remittance, especially this additional source of income is spent in locally produced goods which helps to reinvigorate the local economy.

The estimation of spillover effect crucially depends on the interconnected locality matrix which is often derived from locality specific GPS (global positioning system) coordinates. But, neither the NLFS II nor the NLSS III survey gathered GPS (global positioning system) coordinates during their fieldwork. Therefore I have retrospectively geo-coded each village, based on Village and Municipality administrative data and using G*oogle Maps*. The locations of all 499 localities (PSUs) are shown in Figure 5.1(a).

Figure 5.1: a) Spatial Distribution of PSUs, b) PSUs and Road network



[32] The direct effect of emigration may reduce the total labour supply from the sending locality which may affect the local wage rate in the same locality and its neighbours. Similarly, the inflow of remittances may help to reinvigorate the local economy and increase economic activities in the surrounding locality.



I allow for two types of interconnectedness when estimating spillover effects. The first uses geographic proximity-based interconnection matrix where I identify the closest five interconnected localities, based on straight-line distance between the GPS coordinates of each locality. As discussed earlier, geographic proximity may be less appropriate if heterogeneity in geographic characteristics like elevation and topography interferes with straightline travel. In the context of Nepal with the mountainous topography, where average elevation can range from anywhere between 700 to 6000 meters, the geographic distance between two localities may not always be an appropriate measure of interconnectedness. The travel time and travel cost to go from one 'nearby' locality to another vary considerably across the country and this variation may affect their interconnectedness. As highlighted by Shrestha (2020), there are several reasons for this heterogeneity in interconnectedness. First, localities on a North-South axis are more connected via road than are localities that lie on an East-West axis. Second, the barriers to commute between geographically nearby localities are much higher and costlier in the hills and mountains than is the case in Nepal's low land regions. Thus, even if two localities are close or interconnected by

geographic proximity, spillover may not take place between them if they are not connected by the road network.

To overcome this limitation I develop a second interconnected matrix where I use road network data to identify neighbours (see figure 5.1(b)).[33] I use recent data on Nepal's road network, which is extracted from the World Food Programme (WFP). The road network data cover every road at the village level, even walking trails. However, I limit attention to highways and primary and secondary roads as these are the main medium for transportation. For this study, I consider localities interconnected if they are joined by a road link, with the nearest neighbour estimation approach used. I define interconnectedness based on two conditions: the geographic proximity of two localities must be the shortest, and the two localities must be within five kilometres (km) of the closest point on the road network.[34] If two shortest distance localities are outside a five km radius of the closest road network, they will be considered as non-neighbours. Based on these criteria I identify 349 (168 Urban and 181 Rural) localities and 334 (161 Urban and 173 Rural) localities as the first and second shortest distance neighbouring localities with road connectivity within a five km radius.

5.3.2 The Econometric Model

There can be two offsetting effects of emigration and remittances on the labour supply of the left behind. They may decrease their labour supply if reservation wages rise as remittances (non-labour income) increase the demand for leisure. Conversely, emigration may increase local wages due to former workers going abroad and also if remittances are invested in businesses so that local labour demand rises, and with higher local wages the substitution effect would outweigh the income effect,

[33] This is the same road network data used in Shrestha (2020). The survey data are from 2008 and 2010, if new road networks have developed recently then this may affect definition of interconnectedness between localities.
[34] The GPS coordinates of a village are the points which represent the center point of the locality based on its geographic size. Road networks often pass through the population settlement area which is not necessarily the centroid of the village. To allow for this, I have kept a margin of 5 km which will essentially help to determine if a village is connected with the road link or not.

so labour supply should rise. Given this ambiguity, empirical estimates are needed. Initially, spillovers are not considered, so the model is:

$$Y_{it} = \mu_i + \lambda_t + \beta X_{itmig} + \theta X_{it} + u_{it} \quad (5.1)$$

$$u_{it} \sim N(0, \sigma^2 l_N) \quad (5.2)$$

In equation (5.1), the NT × 1 vector of dependent variables (labour force participation rates) are denoted by Y_{it}, and these are modelled as depending on μ_i and λ_t village and time fixed effects, on the variable of main interest – the locality emigration rate – as denoted by matrix X_{itmig} and other control variables (such as average holdings, the working age population share and so forth) in matrix X_{it}. The β and θ are vectors of coefficients for X_{itmig} and X_{it}, and u_{it} is a NT × 1 vector of error terms which is clustered at the village level.

To examine the spillover effect on labour supply, the interconnectedness matrix based on geographic proximity and the road network is used, following the identification strategy applied by Brinkman and Mok-Lamme (2019). The models are as follows;

$$Y_{it} = \mu_i + \lambda_t + \delta X_{jtmig} + \theta X_{it} + u_{it} \quad (5.3)$$

$$u_{it} \sim N(0, \sigma^2 l_N) \quad (5.4)$$

Equation (5.3) is similar to Eq. (1), but this time X_{jtmig} is the emigration rate of interconnected locality j and δ is the response coefficient.

The two models discussed thus far, for direct effects (or own-estimation) and for the spillover effects, include village and time fixed-effects to reduce endogeneity bias, which may arise from unobserved village characteristics that correlate with labour supply and emigration. To the extent that these unobserved characteristics are time-varying, the fixed effects strategy will not remove all endogeneity bias. It is quite likely that village characteristics like labour market condition and access to credit vary over time and are correlated with both emigration and labour supply (Adams Jr, 2011). Moreover, in both the 2008 and 2010 datasets, I observe strong regional heterogeneity in emigration rates. Therefore, the spatial variation to identify the own-effect (and

spillover effects) is not necessarily random, and if time-varying village characteristics are correlated with both village-level emigration and domestic labour market trends, the empirical results are likely to be biased.

Therefore, this study uses instrumental variable estimation approach for both Eq. (1) and (3) to overcome endogeneity bias (Acosta, 2011; Acharya & Leon-Gonzalez, 2014; Calero et al., 2009; Koska et al., 2013). Specifically, I follow the strategy of Theoharides (2018) to predict the locality level emigration rate to various destinations using historical (baseline) emigration patterns (from the 2001 census data). We use locality-level historical emigration to destination country shares from census data (from 2001) to construct this IV. Nepal has been sending migrants overseas, especially to India, and recently emigration for work to high-income destinations like the Middle East, North Africa and Malaysia has also increased. The historical emigration affects current migrants' outflow for two important reasons. First, previous emigration plays the role of a network for new migrants and thus it increases the labour outflow by reducing the cost of emigration through lowering job search costs and increasing information flows. Second, the inflow of remittances helps households to overcome borrowing constraints and increases the financing capacity of households for subsequent migration to the same destination or to other high-income destinations. Therefore, this study relies on the fact that historical emigration to a destination is a good predictor of subsequent emigration. I use destination-specific time trend instruments in a standard two-stage least squares estimation approach for Eq. (5.1) and (5.3).

Consider the migration network in terms of the share of people who had migrated from village i to destination country k by 2001 (out of the total number of people who had migrated to k from Nepal). The total number of migrants who migrated to destination k in each year t (2008 or 2010 given the timing of panel) is then summed. To predict the total number of migrants from the village in each survey year (that is, in 2008 and 2010), I weight the total migrants to destination k

by the 2001 village i migrants share to destination k. The predicted migrant flows (demand for migration) from each village then is:

$$M_{ikt}^{p} = \sum_{i}^{n} M_{kt} \frac{M_{ik}^{2001}}{M_{k}^{2001}} \tag{5.5}$$

Where M_{ikt}^{p} is the predicted number of people migrating to destination k from village i in year t (2008 or 2010), M_{kt} is the total number of people who had migrated from Nepal to destination k by year t (2008 or 2010), and $\frac{M_{ik}^{2001}}{M_{k}^{2001}}$ is the village i migrants share in total national migrants to destination k in the past (in 2001 in this case, which is when the baseline migration network is measured). The predicted number of migrants is normalized by dividing M_{ikt}^{p} by the total village population each year. Our IV has two parts, one is predicted emigration rate to India and second is predicted emigration rate to MEOA. We consider that these two are major destinations for migration given that 35% migrants in 2011 are in India and 55% are in MEOA (CBS, 2011).

The performance of this IV depends on stability of the distribution of migrants across destinations over time (Theoharides, 2018). For Nepal's five development regions, these distributions across destinations are quite stable. For example, India remains a favourite destination for people from the mid-west and far-west regions while relatively developed regions like central and eastern regions prefer sending migrants to MEOA (Middle East and Other Asia). The relationship between 2001 and 2011 migrants share is also quite strong, as villages continue to send migrants to destination countries at a similar rate, with just a small fall for India and a rise for MEOA. Therefore, these instruments should be reasonably good predictors of the actual migration rate. A distinction is made between the predicted migration rate to India and the predicted migration rate to MEOA, considering that these two are the major migrants' destinations, and one is a lower-cost and lower-return destination (India).

While the migration trends from different parts of the country are quite uniform and stable over time, the shares of the two major destinations have shifted. According to CBS (2001, 2010),

emigration to India has a falling share, whereas the share of migrants going to MOEA has increased from 20% in 2001 to a little over 55% in 2011. Given that emigration to MOEA is more expensive, these changing shares may imply that regions or villages are continuously sending migrants for foreign employment, and the remittances are helping households to improve welfare and to finance further emigration to higher cost destinations. So, the two predicted migration variables derived from Eq. (5.5) are a good predictor of current emigration rates. The estimated result should show the effect of emigration on labour supply while ruling out reverse causation that would occur if the current labour supply affects migration. These two predicted emigration rates are derived from the migration network from a decade before, and so labour supply in 2008 or 2010 should not affect historical migration. In other words, given that the IVs are external to the local labour supply, they are unlikely to be correlated with unobservable characteristics.

5.4 Results and discussion

In this section, I outline the first stage and main results. The OLS and IV estimates of direct and spillover effects of emigration on labour supply are then reported. The first stage result for the IV regression is in Table 5.2 using two instruments, the predicted emigration rate to India and to MEOA. As expected, the coefficient on instrumental variables that are derived from Eq. (5.5) have strong first-stage effects on the emigration rate after controlling for village and time fixed effects. Results are closely associated with the recent migration trends in Nepal; the share of migrants in India has decreased to 37% in 2011 (from 75% in 2001), the share in MEOA has increased to 56% in 2011 (from 20% in 2001) (CBS, 2001, 2011). The localities have also altered the destination; those sending migrants to India earlier are now sending to MEOA. This shift in the destination is also evident from the sign of coefficients of the instrumental variables, which is negative for India and positive for MEOA. The *F*-test for excluding the instruments is 13.77 which easily exceeds the usual threshold of ten needed for not having weak instruments. The weak instrument test statistics are also presented in the second-stage results tables.

Table 5.2: The first stage model for locality emigration rate

	Emigration Rate
Predicted migration to India	-1.017 (3.311)***
Predicted migration to MEOA	0.825 (5.054)***
Agriculture land owned	2.838 (1.185)
Average household size	2.144 (0.958)
Share of working age (15-60)	-2.870 (8.696)***
Share of Migrants with grade ≥ 8	6.831 (1.426)
Share of 15-60 with grade ≥ 8	-19.027 (0.886)
Literacy rate aged ≥ 17	42.416 (1.917)*
Higher secondary Gross Enrolment Rate	3.002 (2.551)**
Internal migration rate	-0.180 (5.950)***
Average size of domestic remittance	-0.425 (0.694)
F-Statistic (for excluding the two instruments)	13.77
R-Squared	0.263
Observations	998

This table shows first-stage results for migration rate instrumented with predicted migration to India and to MEOA using time and village fixed effects. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 499 villages), ***, **, * denote 1%, 5%, 10% statistically significance.

The main results are reported in Table 5.3 to 5.6, first for the direct effects and then the spillover effects. Sub-sample results are given for male and female labour force participation rates, for agriculture and non-agriculture, and for urban and rural localities. An alternative specification to test for spillover effect using market-based interconnectedness and a Spatial Durbin Model (SDM) is presented in Table 5.7. One additional table, with estimates of the impact of emigration on the local agriculture wage rate, is presented in A.5.1 (this is a cross-sectional IV model designed to

illustrate a causal pathway that lies behind the main results for the impact of emigration and remittances on labour supply).

Direct effect of emigration on Labour force participation rate[35]

First, I look at the direct effect of emigration on the labour force participation rate. Table 5.3 column 1 presents results from an OLS model for the full sample. The corresponding instrumental variable results are in column 2, while columns 3-6 presents sub-sample results using instrumental variables. It is to note that all of the instrumental variable results rely on the destination-driven predicted migration model reported in Table 5.2, and the F-tests for excluding the instruments give values of at least 14.5.

The first thing to note from Table 5.3 is the contrast between the OLS and IV results, which suggests that time-varying factors correlated with emigration and labour supply will bias OLS results, even with village fixed effects and a rich set of control variables. All of the subsequent results reported, therefore, use the instrumental variables approach. According to the IV results in column 2, a rise in the emigration rate by ten persons per 1,000 population would increase the labour force participation rate of the left-behind by 1.3 percentage points ($p < 0.05$). Thus, it appears that the income effect from remittances increasing the demand for leisure is outweighed by a substitution effect that induces more labour supply. Indeed, there is evidence that higher local emigration rates increase the local wage rate (see Table A.5.1) which induces this substitution effect of greater labour supply.

The results in columns 3 and 4 of Table 5.3 show that the higher LFP rate is entirely due to female labour supply. While there is no change in the male LFP rate, the female LFP rate would rise by 2.7 percentage points for every 10 more emigrants per 1000 population from a locality (significant at $p<0.01$). There are several reasons for this gendered pattern. First, emigration has

[35] In addition to the emigration model, I also run a separate model for remittance using same instruments. Results and conclusions for direct and spillover effect continue to hold in both emigration and remittance models. The result from remittance model is available from the author.

contributed significantly to empowering women in Nepal (Gartaula et al., 2010; Maharjan et al., 2012) which has increased their mobility and participation in the labour market, especially in the agriculture sector. Second, other members of households may have to participate in the labour market to replace the initial income loss as a worker leaves local employment due to emigration (Posso, 2012), especially as it takes time for emigrants to get established and begin sending remittances (Gibson et al., 2013; McKenzie & Rapoport, 2011). Also, remittances may increase investment in self-employment/small enterprises, and this boost in local economic activities may increase demand for female-specific tasks.

Table 5.3: Second stage regression model for labour force participation (LFP) rates

	OLS	IV model				
	1	2	3	4	5	6
	LFP	LFP	LFP-Male	LFP-Female	LFP-Agri	LFP-NonAgri
Emigration	-0.003	0.128	0.011	0.265	-0.110	0.011
	(0.342)	(1.970)**	(0.188)	(2.820)***	(2.444)**	(0.162)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time and Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared (within)	0.154					
Wald test		34919	29948	13443	8482	4707
Hansen statistics (Over identification test)		0.009	0.286	0.057	0.789	0.228

These outcome variables are labour force participation rates for adult aged 17-65. The IV results have locality emigration rates instrumented with (destination-trend-based) predicted migration to India and to MEOA. The t-statistics in ( ) are derived from cluster-robust standard errors (clustered at 499 villages), ***, **, * denote 1%, 5%, 10% statistically significance. Emigration impacts are in percentage form. Agri stands for agriculture and NonAgri stands for non-agriculture. *N=998*. Full results are available from the author.

Table 5.3 column 5-6 shows the impact of emigration on labour force participation in agriculture and non-agriculture sector. This is of particular interest here as the agriculture sector in Nepal is facing labour shortages, and over time there has been a notable increase in cultivable lands that are left barren. The result from this study is consistent with previous studies which have found that the left-behind shift out of agriculture, either increases leisure or move to non-farm employment. For instance, every ten person per 1,000 population increase in emigration would reduce labour force participation rate in agriculture sector by 1.1 percentage point ($p < 0.05$). In the case of non-agriculture sector, the effect is positive but very small and imprecisely estimated. The plausible reason for this is that, in Nepal, the agriculture sector is less attractive due to its low productivity and farm wages or agricultural self-employment hardly generates sufficient income for the household to achieve a high standard of living. Therefore, for households that have alternative sources of income in the form of remittances, farm work is less preferred. Also, the left-behind often change the sector of employment and shift to self-employment activities because remittances help them to overcome borrowing constraints and start a new enterprise (Sousa & García-Suaza, 2018). This result is also comparable to the recent studies like Acosta (2007), Amuedo-Dorantes and Pozo (2006), and López-Feldman and Escalona (2017) which highlighted the role of emigration in the reallocation of the labour force.

Spillover effect of emigration on Labour force participation

In this section, I examine the spillover effect of emigration on neighbouring interconnected localities. I look at the spillover effects in the first five nearest neighbours, initially based on geographic proximity. Later, I also compare the spillover effect in rural and urban localities separately because these localities have quite different labour markets and in-migration trends.

Table 5.4: Spillover effects on labour force participation rate: neighbours based on closest geographical proximity

	Labour Force Participation Rate				
	1st Neighbour	2nd Neighbour	3rd Neighbour	4th Neighbour	5th Neighbour
Emigration	0.1208 (2.481)**	0.1113 (2.824)***	0.0223 (0.541)	0.0828 (1.770)*	0.1010 (2.400)**
Control Variables	Yes	Yes	Yes	Yes	Yes
Time and Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
Wald test	46454	42348	53153	42435	39402
Weak IV test statistics	18.14	27.41	21.66	20.26	25.43
Hansen statistics (Over identification test)	0.415	1.092	4.175**	0.493	0.854

Notes; The columns correspond to models where the definition of an interconnected village extends from the closest nearest neighbour up to fifth neighbour. Other notes, see Table 5.3.

Each column of Table 5.4 presents the results of Eq. (5.3), for each of the five nearest neighbour interconnected localities. There is strong evidence of spillover effects on the labour supply of non-migrants. A rise in emigration from a locality by ten persons per 1,000 population would increase labour force participation rates in neighbouring localities by 0.2 to 1.2 percentage points (estimates are statistically significant for four out of five columns). For the first two neighbours, the effects are similar to the direct (own-) effect in Table 5.3 (column 2), so it is likely that the combined effect (direct and spillover effect) of emigration would be at least twice the size of direct effect. The extant literature tends to ignore this spillover effect, which may operate through the increase in local wage rates and economic activities in the same and surrounding localities that are important sources of labour market adjustment (Brandsma et al., 2014; Shrestha, 2017). For instance, remittances sent home by emigrants are generally spent on locally produced goods that not only affect the economic activities of the sending locality but also of the interconnected localities. The rise in economic activities in neighbouring locality creates incentives for non-migrants to participate in the labour market.

Next, it is useful to think about how this spillover effect operates in rural and urban localities separately. This comparison is important because urban labour markets are more integrated than rural ones. Also, rural-to-urban migration due to the wage differential is very common and an important source that sustains equilibrium in the urban labour market (Harris & Todaro, 1970), but the same is not so for the rural labour market (i.e. urban-to-rural migration is rare). In Table 5.5, I examine the spillover effect for the first three nearest neighbours for both Urban and Rural localities. I limit the interconnected neighbours to the three nearest localities. The first three and last three columns report the results for urban localities and rural localities respectively. The notable feature of Table 5.5 is that the coefficients are precisely estimated only for the rural locality, and spillover occurs only between the first two nearest neighbours. The magnitude of spillover effect in first two nearest neighbours in the rural locality is 0.9 and 1.3 percentage

points (significant for both at $p< 0.05$), which is similar to the results in Table 5.3 and 5.4, for every ten person per 1,000 population increase in emigration.

There are several reasons for this effect on the rural locality. Rural labour markets are less integrated and are financially constrained due to the lack of formal financial institutions. The remittance sent by emigrants helps to boost the rural local economy by overcoming financial constraints in the absence of formal credit. Similarly, remittances are generally spent in locally produced goods in the rural locality, which increases the local economic activities and affects the surrounding localities. Additionally, the urban labour market has a reserve labour force and has a large formal or semi-formal credit institution, therefore, emigration has limited impact, especially urban labour markets rely less on remittance to boost economic activities.

Table 5.5: Spillover effects on labour force participation rates in urban and rural localities: neighbours based on geographical proximity

	Labour Force Participation Rate					
	Urban localities			Rural localities		
	1st Neighbour	2nd Neighbour	3rd Neighbour	1st Neighbour	2nd Neighbour	3rd Neighbour
Emigration	0.0511 (0.723)	0.0641 (1.084)	-0.0221 (0.392)	0.1278 (2.412)**	0.0925 (2.081)**	-0.0589 (1.049)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time and Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	583	1041	1017	34494	38471	34926
Weak IV test statistics	8.33	17.22	15.30	4.40	8.28	6.21
Hansen statistics (Over identification test)	0.123	0.864	1.199	0.229	0.024	3.620*
Observations	348	348	348	650	650	650

Notes: See Table 5.4

As discussed earlier, given the heterogeneity in spatial features of Nepal, the localities separated by the shortest geographic distance are not necessarily interconnected. So, in addition to geographical distance interconnectedness, I introduce a road network among localities. In this case, two shortest distance localities would be defined as interconnected localities or neighbours if they have access to the road network in their vicinity. This time, I limit interconnected locality only for the first two neighbours. Similar to the above results, Table 5.6 (columns 1 and 2) shows that the spillover effect of emigration is still positive and significant on the labour supply. The effect on labour force participation rate is as large as 1.1 percentage points ($p < 0.05$) for an additional ten person per 1,000 population increase in emigration. From this result, it implies that the spillover effect continues to operate and matters to the locality irrespective of how we define interconnectedness.

Table 5.6: Spillover effects on labour force participation rate: neighbours based on road network

	1st Neighbour	2nd Neighbour
Emigration	0.1161 (2.66)***	0.112 (2.94)***
Control Variables	Yes	Yes
Time and Village Fixed Effects	Yes	Yes
Wald test	51688	51664
Weak IV test statistics	30.21	46.56
Hansen statistics (Over identification test)	0.066	1.195

Notes: The closest neighbours are based on geographic proximity and road links, as explained in the text. Other notes, see Table 5.4.

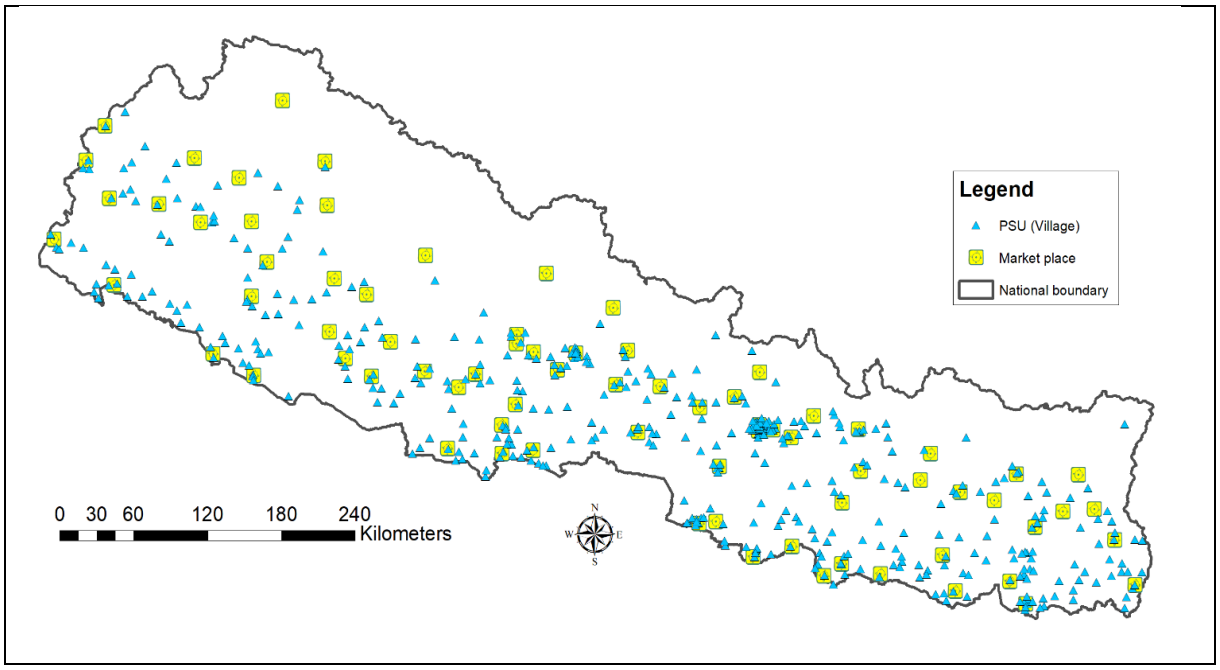
The strong spillover effect is consistent with the fact that emigration and remittances have unintended consequences on interconnected localities. The results also show that the change in local wage rates and the boost in economic activities (that occurs through general equilibrium effects) are the important mechanisms that create employment opportunities in surrounding localities and incentivise non-migrants to engage in economic activities.

Robustness test

I use two different approaches to check the robustness of spillover effect. First I redefined the interconnected matrix based on geographic proximity to the common market which plays a greater role to connect two localities. More specifically, neighbours are interconnected via the common market for employment, trade and so on rather than just the physical distance or road link. Therefore, with this specification emigration from one locality affects outcomes in the interconnected locality through the market. To redefine interconnectedness, I include the coordinates of 77 major markets across the country and linked them with the PSU coordinates (see Figure 5.2). The neighbouring matrix is now a combination of the shortest geographic distance between localities as well as the access to a common marketplace.[36]

[36] The major challenge in developing market based interconnectedness is that locality can have access to more than one local market at a time and people do not necessarily stick to one closest local market, they commute to multiple markets. Also, it is not necessary that two shortest distance neighbours also have the shortest distance to the same common market. Given this challenge, I use a loose definition of local market interconnectedness and limit interconnectedness to the first closest neighbour only. In this case, two shortest geographic distance localities are considered as interconnected if they are also within the 15 km radius from the point of any common market. If first shortest distance localities are outside the 15 KM radius from any of the common market then it is treated as non-neighbours and I assume there is no spillover between these localities. This has yielded 320 (172 rural and 148 urban) first shortest distance localities connected via local market.

Figure 5.2: Spatial Distribution of PSU and local market



Second, I use Spatial Durbin Model which by design addresses spatial heterogeneity issues when labour force participation in one locality is not independent in space from other (neighbouring) localities. Spatial model corrects the estimation bias that may arise from the spatial heterogeneity and autocorrelation of labour force participation over space (LeSage & Pace, 2009, 2010). In SDM, spatial lag of labour force participation and emigration (the average in neighbouring localities) are included as an additional regressor.[37] The coefficient on the spatially lagged of labour force participation rate is 0.21 and is statistically significant at the $p<0.01$ level. Thus, there is strong evidence of spatial spillover of labour force participation.

The results from the common market neighbouring matrix (second stage regression) and SDM are reported in Table 5.7. Even after restricting the interconnectedness to the closest market place (in column 1), the main conclusion continues to hold. The result illustrates that the increase in emigration by ten person per 1,000 population would increase the labour force participation rate by

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

1.1 percentage points, which is similar to the result in table 5.4. Similarly, in SDM (in Table 5.7), the indirect impact, which includes both local and global spillover effect, of an increase in emigration by ten person per 1,000 population would increase the labour force participation rate by 0.59 percentage points at $p < 0.05$. These results illustrate that the main results are robust to a different definition of interconnectedness and spatial heterogeneity and autocorrelation of emigration and labour supply.

Table 5.7: Spillover effects on labour force participation rate: neighbours based on shortest geographical distance to the market

	IV regression	Spatial Durbin Model (Impacts)		
	Model 1	Direct	Indirect	Total
Emigration	0.1182	-0.008	0.059	0.0513
	(2.478)**	(0.83)	(2.22)**	(1.61)
Control Variables	Yes		Yes	
Time and Village Fixed Effects	Yes		Yes	
R-Squared (within)			0.1671	
Wald test	47327			
Weak IV test statistics	26.76			
Hansen statistics (Over identification test)	0.066			

Notes: Model 1 is a FE-IV model, similar to those in Table 5.6 but using the closest neighbour that has access to a market (as close as 15 km from the locality). The Spatial Durbin Model (SDM) provides local and global spillover estimates of emigration with a weight matrix constructed from the five nearest neighbours (KNN5). In SDM, emigration estimate is weighted average of first five neighbours. Other notes, see Table 5.3.

5.5 Conclusions

The growth in emigration and remittance in Nepal has raised policy concerns about its impacts on falling labour supply for domestic industries and agriculture sector. The extant literature that looked into this issue has only analysed the direct (own-) effect of emigration on the labour supply. Yet spillover effect that may have important policy implications in sending countries is so far overlooked. Typically, emigration and subsequent remittances inflow not only affect the sending locality but also the nearby interconnected localities. Therefore, I developed a locality interconnection matrix based on the geographic distance and the road network to measure these spillover effects. For this study, I develop a two-period panel of 499 localities in Nepal and use variation in the predicted emigration rate as a plausible instrument variable to overcome endogeneity concerns.

After accounting for endogeneity, I find that the direct (own) effect of an increase in emigration rate by ten person per 1,000 population is associated with an increase in the labour force participation rate by around 1.3 percentage points. The positive effect of emigration is limited to the female labour force, and there is 2.6 percentage points increase in female labour force participation for every ten person per 1,000 population increase in emigration. The positive effect occurs through the rise in local wage rates that outweigh income effects from remittances increasing the demand for leisure and induce substitution effect of greater labour supply. The other possible channels are an increase in women economic empowerment and mobility (especially in the agriculture sector) and a boost in local economic activities. In contrary, emigration is reducing labour force participation in agriculture sector, either left-behind members increase leisure or move to non-farm employment. Especially, this sector is considered as low productive and working on the farm is less preferred in remittance receiving households.

Moreover, the spillover effect of emigration is increasing labour supply and this positive effect is as large as the direct effect. However, given the distinct nature of labour markets in rural

and urban localities, the spillover effect is limited to the rural areas (without any significant impact on urban locality). There are several possible reasons for this pattern; first rural labour markets are less integrated and financially constrained, so emigration and remittances help to overcome borrowing constraints and boost the local economy in the absence of formal credit. Additionally, remittances are generally spent in locally produced goods that create demand, generate employment and boost rural local economy. Second, the urban labour markets have a large formal or semi-formal credit institution, therefore they depend less on remittances to overcome borrowing constraints.

Overall, this paper provides insights into the multiple channels that emigration and remittances can affect the local labour market activities. One major takeaway from this study is that to improve the overall welfare of the region, each household doesn't need to send a member for foreign employment, instead, policymakers can focus on increasing the value of remittance, either by sending skilled migrants or reducing the remitting cost. The higher remittance will have a multiplier effect on the local economy and the reduced number of emigrants would help to overcome labour shortage problems.

5.6 Reflection on this chapter

The results in Chapter 3 showed the impact of the civil war on emigration and other research has shown impacts on labour force participation. The conflict affected the ability to travel outside the village for emigration and for local employment. If civil war correlates with the past emigration (as shown above) and if past emigration, in turn, affects current labour force participation (as shown in this chapter), then there may be some doubt on our estimates in terms of an omitted relevant variable (the risk of conflict or the conflict intensity). However, the use of historical (2001) emigration as a driver of our instrumental variable strategy is from a time when the civil war was still at an early stage. Furthermore, our use of time and village fixed effects should control any lingering influence of the civil war on our estimates. in particular, since the civil war ended in 2006

and our survey data are from 2008 and 2010, the direct impacts of the civil war on labour force participation can be ruled out. Whether indirect effects, operating through the impact on historical emigration and net of any time and village fixed effects, are important enough to cause bias is something that may be examined with future research.

References

Abbay, A. G., & Rutten, R. (2016). Does spatial proximity to small towns matter for rural livelihoods? A propensity score matching analysis in Ethiopia. *Letters in Spatial and Resource Sciences*, *9*(3), 287-307.

Acharya, C. P., & Leon-Gonzalez, R. (2012). *The impact of remittance on poverty and inequality: A micro-simulation study for Nepal* (GRIPS Discussion Paper 11-26). Tokyo, Japan: National Graduate Institute for Policy Studies.

Acharya, C., and Leon-Gonzalez, R. (2014). How do migration and remittances affect human capital investment? The effects of relaxing information and liquidity constraints. *Journal of Development Studies*, *50*(3), 1-17.

Acosta, P. (2007). Entrepreneurship, labor markets and international remittances: Evidence from El Salvador, In: C. Ozden and M. Schiff (Eds.), *International migration, economic development and policy (*pp. 141–160*).* Washington, DC: World Bank.

Acosta, P., Calderon, C., Fajnzylber, P., & Lopez, H. (2008). What is the impact of international remittances on poverty and inequality in Latin America? *World Development*, *36*(1), 89-114.

Acosta, P. (2011). School attendance, child labour, and remittances from international migration in El Salvador. *Journal of Development Studies*, *47*(6), 913-936.

Adams Jr, R. H., & Page, J. (2005). Do international migration and remittances reduce poverty in developing countries? *World Development*, *33*(10), 1645-1669.

Adams Jr, R. H. (2011). Evaluating the economic impact of international remittances on developing countries using household surveys: A literature review. *Journal of Development Studies*, *47*(6), 809-828.

Amuedo-Dorantes, C., & Pozo, S. (2006). Migration, remittances, and male and female employment patterns. *American Economic Review*, *96*(2), 222-226.

Banerjee, A., Duflo, E., & Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, 102442.

Boussauw, K., Neutens, T., & Witlox, F. (2012). Relationship between spatial proximity and travel-to-work distance: The effect of the compact city. *Regional Studies*, *46*(6), 687-706.

Brandsma, A., Kancs, D. A., & Persyn, D. (2014). Modelling migration and regional labour markets: An application of the new economic geography model RHOMOLO. *Journal of Economic Integration*, *29*(2), 372-406.

Brinkman, J., & Mok-Lamme, D. (2019). Not in my backyard? Not so fast. The effect of marijuana legalization on neighborhood crime. *Regional Science and Urban Economics, 78*, 103460.

Cabegin, E. (2006). *The effect of Filipino overseas migration on the non-migrant spouse's market participation and labor supply behavior* (Discussion Paper 2240). Bonn, Germany: Institute for Study of Labor (IZA).

Cainelli, G., & Lupi, C. (2010). Does spatial proximity matter? Micro-evidence from Italy. In N. De Liso and R. Leoncini (Eds.), *Internationalization, technological change and the theory of the firm* (pp 163-186). London, England: Routledge.

Calero, C., Bedi, A. S., & Sparrow, R. (2009). Remittances, liquidity constraints and human capital investments in Ecuador. *World Development*, *37*(6), 1143-1154.

Central Bureau of Statistics [CBS] (2001). *National Population Census 2001, Report on Nepal's Tenth Census*. Kathmandu, Nepal: His Majesty Government of Nepal.

Central Bureau of Statistics [CBS] (2008). *Nepal Labour Force Survey-II 2008: Statistical Report.* Kathmandu, Nepal: Government of Nepal.

Central Bureau of Statistics [CBS] (2010). *Nepal Living Standard Survey III 2010: Statistical Report, Vol 1 and 2*. Kathmandu, Nepal: Government of Nepal.

Central Bureau of Statistics [CBS] (2011). *National Population and Housing Census 2011, National Report*. Kathmandu, Nepal: Government of Nepal.

Chami, R., Ernst, E., Fullenkamp, C., & Oeking, A. (2018). *Are remittances good for labor markets in LICs, MICs and fragile States? Evidence from cross-country data* (WP/18/102). Washington, DC: International Monetary Fund.

De Lucio, J. J., Herce, J. A., & Goicolea, A. (2002). The effects of externalities on productivity growth in Spanish industry. *Regional Science and Urban Economics*, *32*(2), 241-258.

Dillon, A., Sharma, M., & Zhang, X. (2011). Estimating the impact of rural investments in Nepal. *Food Policy*, *36*(2), 250-258.

Funkhouser, E. (2006). The effect of emigration on the labor market outcomes of sender households: A longitudinal approach using data from Nicaragua. *Well-Being and Social Policy, 2*(2), 5–25.

Gartaula, H. N., Niehof, A., & Visser, L. (2010). Feminisation of agriculture as an effect of male out-migration: Unexpected outcomes from Jhapa District, Eastern Nepal. *International Journal of Interdisciplinary Social Sciences*, *5*(2). 565-578.

Gibson, J. (2019). Are you estimating the right thing? An editor reflects. *Applied Economic Perspectives and Policy*, *41*(3), 329-350.

Gibson, J., Datt, G., Murgai, R., & Ravallion, M. (2017). For India's rural poor, growing towns matter more than growing cities. *World Development*, *98*(1), 413-429.

Gibson, J., McKenzie, D., & Stillman, S. (2013). Accounting for selectivity and duration-dependent heterogeneity when estimating the impact of emigration on incomes and poverty in sending areas. *Economic Development and Cultural Change*, *61*(2), 247-280.

Gibson, J., McKenzie, D., & Stillman, S. (2011). The impacts of international migration on remaining household members: Omnibus results from a migration lottery program. *Review of Economics and Statistics*, *93*(4), 1297-1318.

Gibson, J., & Rozelle, S. (2003). Poverty and access to roads in Papua New Guinea. *Economic Development and Cultural Change*, *52*(1), 159-185.

Gupta, S., Pattillo, C. A., & Wagh, S. (2009). Effect of remittances on poverty and financial development in Sub-Saharan Africa. *World Development*, *37*(1), 104-115.

Henderson, V.J (2003). Marshalls Scale Economies. *Journal of Urban Economics*, *53*(1), 1–28.

Harris, J. R., & Todaro, M. P. (1970). Migration, unemployment and development: A two-sector analysis. *The American Economic Review*, *60*(1), 126-142.

Jacoby, H., & Minten, B. (2009). On measuring the benefits of lower transport costs. *Journal of Development Economics*, *89*(1), 28-38.

Jaquet, S., Kohler, T., & Schwilch, G. (2019). Labour migration in the middle hills of Nepal: Consequences on land management strategies. *Sustainability*, *11*(5), 1349.

Justino, P., & Shemyakina, O. (2012). Remittances and labor supply in post-conflict Tajikistan. *IZA Journal of Labor & Development*, *1*(1), 1-28.

Kharel, P., Dahal, K., Davalos J., Singh D., (2019). *Can remittances support development in Nepal?* (Policy brief No.203). Kathmandu, Nepal: South Asian Watch on Trade Economics and Environment (SAWTEE).

Kim, N. (2007). *The impact of remittances on labor supply: The case of Jamaica* (Policy Research Working Paper 4120). Washington, DC: World Bank.

Koska, O. A., Saygin, P. T., Artal-Tur, A., & Çağatay, S. (2013). International migration, remittances, and the human capital formation of Egyptian children. *International Review of Economics and Finance, 28*, 38-50.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton, FL: CRC Press.

LeSage, J., & Pace, R. K. (2010). Spatial econometric models. In: M. Fischer and A. Getis (Eds.), *Handbook of applied spatial analysis: Software tools, methods and applications* (pp. 355-376). Berlin, Germany: Springer Science & Business Media.

Lokshin, M., Bontch-Osmolovski, M., & Glinskaya, E. (2010). Work-related migration and poverty reduction in Nepal. *Review of Development Economics, 14*(2), 323-332.

Lokshin, M., & Glinskaya, E. (2009). The effect of male migration on employment patterns of women in Nepal. *The World Bank Economic Review*, *23*(3), 481-507.

López-Feldman, A., & Escalona, D. (2017). Remittances and labour allocation decisions at communities of origin: The case of rural Mexico. *Applied Economics Letters*, *24*(4), 238-242.

Maharjan, A., Bauer, S., & Knerr, B. (2012). Do rural women who stay behind benefit from male out-migration? A case study in the hills of Nepal. *Gender, Technology and Development, 16*(1), 95-123.

McKenzie, D., & Rapoport, H. (2011). Can migration reduce educational attainment? Evidence from Mexico. *Journal of Population Economics, 24*(4), 1331-1358.

Marchiori, L., Shen, I., & Docquier, F. (2013). Brain drain in globalization: A general equilibrium analysis from the sending countries' prospective. *Economic Inquiry, 51*(2), 1582-1602.

Melkonyan, T. A., & Grigorian, D. A. (2012). Microeconomic implications of remittances in an overlapping generations model with altruism and a motive to receive inheritance. *Journal of Development Studies*, *48*(8), 1026-1044.

Mughal, M., & Makhlouf, F. (2013). Labour effects of foreign and domestic remittances: Evidence from Pakistan. *International Review of Applied Economics, 27*(6), 798-821.

Phadera, L. (2016). *International migration and its effect on labor supply of the left-behind household members: Evidence from Nepal*. Conference paper presented in Agriculture and Applied Economics Association Annual Meeting.

Posso, A. (2012). Remittances and aggregate labor supply: Evidence from sixty-six developing nations. *The Developing Economies, 50*(1), 25-39.

Shrestha, M. (2017). *Push and pull: A study of international migration from Nepal* (Policy Research Working Paper No. 7965). Washington, DC: World Bank.

Shrestha, S. A. (2020). Roads, participation in markets, and benefits to agricultural households: Evidence from the topography-based highway network in Nepal. *Economic Development and Cultural Change, 68*(3), 839-864.

Song, Y., & Son, S. (2019). Identifying the impact of geographical proximity on spillover effect of FDI: The evidence from Indian local firms' performance gains. *The North American Journal of Economics and Finance*, *52*, 1-20.

Sousa, L. D., & García-Suaza, A. (2018). *Remittances and labor supply in the northern triangle* (Policy Research Working Paper 8597). Washington, DC: World Bank.

Theoharides, C. (2018). Manila to Malaysia, Quezon to Qatar international migration and its effects on origin-country human capital. *Journal of Human Resources*, *53*(4), 1022-1049.

Weyerbrock, S. (1995). Can the European community absorb more immigrants? A general equilibrium analysis of the labor market and macroeconomic effects of east-west migration in Europe. *Journal of Policy Modeling*, *17*(2), 85-120.

Appendix

Table A.5.1: Effects of emigration on male and female rural agriculture wages (Instrumental variables estimates)[38]

	Male log wage	Female log wage		
	Task-1	Task-2	Task-3	Task-4
Emigration	0.0037	0.0022	0.0028	0.0029
	(3.943)***	(1.625)	(2.449)**	(2.415)**
Agriculture land owned	-0.0262	-0.0404	-0.0362	0.0167
	(0.642)	(1.152)	(1.169)	(0.580)
Share of working age (15-60)	0.0281	0.0196	0.0227	0.0223
	(5.080)***	(2.853)***	(3.722)***	(3.695)***
Internal migration rate	0.0019	0.0005	0.0009	0.0010
	(4.865)***	(0.954)	(1.894)*	(2.207)**
Average domestic remittance	-0.2008	0.2962	0.2093	0.1063
	(0.724)	(1.146)	(1.037)	(0.502)
Higher secondary GER	0.0837	0.0593	0.0529	0.0703
	(2.748)***	(1.850)*	(1.992)**	(2.485)**
R-Squared	0.046	0.075	0.070	0.056
Observation	277	288	265	259

Estimates are from a cross sectional instrumental variable model (for 2010), with emigration rate at locality level instrumented with predicted migration to India and MEOA. Wages are in logs. The t-statistics in ( ) are derived from robust standard errors. Task 1-4 are agriculture related tasks, Task-1 is for males and Tasks 2-4 are female specific.

[38] Wage rates are taken from NLSS 2010 community questionnaire, which provides information about the agricultural wage rate in the community for different agricultural tasks. Thus, the wage rates are only available from agriculture sector from rural locality.

Chapter Six: Conclusion and implications

Conclusion

Considerable attention has been paid to Nepal in academic literature in the last two decades. There are at least two reasons for this. Firstly, there is interest to learn a lesson from its decade-long civil war that killed over 15,000 people. Secondly, because of the growing export of Nepal's labour to international destinations. Yet despite the literature on the causes and consequences of the civil war in Nepal, key features have remained largely unexamined. The major issue with the prior studies is that they have used overly aggregated conflict data. These data are easily available for the 75 districts of Nepal but they ignore the local level heterogeneity in conflict. For example, by looking at more finely-grained data at the locality level, for almost 4000 localities, it is apparent that the within-district variation in conflict deaths, which is ignored in earlier studies, was at least three times higher than the variation between districts. The loss of information from the over aggregation of conflict data to the district level may distort our understanding of how conflict escalates and, in turn, distort understanding of impacts of the conflict on migration, education, health and so on.

The rise in conflict was also accompanied by increased international migration from Nepal. By 2011 the share of the population working abroad had increased to 7% from 3.3% in 2001. The opening of new economic opportunities for migrants and a rise in demand for Nepali workers from regions like the Middle East, North Africa and Malaysia increased the labour force outflow. This labour migration raises important issues because even though the positive role of emigration on poverty reduction in developing countries is widely accepted, impacts on human capital formation and on the labour supply of non-migrants remained uncertain. Improved understanding of these issues matters especially in conflict-affected countries. For instance, if emigration has any positive effect on human capital and labour supply then the long term effect of Nepal's civil conflict crucially depends on the impact of conflict on emigration. In other words, understanding the impacts of emigration and remittances on human capital and labour supply of the left behind are

vital to the design of adequate policies for the rehabilitation of conflict affected localities. So that they can better participate in the opportunities that emigration provides.

Even though Nepal's civil war lasted for almost ten years from 1996 to 2006, conflict intensity increased only after 2001, with more than 85% of the total deaths in the 2001-2006 period, and with lot of heterogeneity in local level death rates. Therefore, in contrast to previous studies, I focus on the conflict after 2000 in order to understand why conflict escalates and persists over time. I geocode 15,000 conflict-related deaths to the locality level for almost 4000 localities. My second departure from the previous literature, which uses welfare estimates from national sample surveys for more aggregated areas like districts, is to use small area estimation and household assets and caste indicators from census to estimate poverty, inequality and caste polarisation for almost 4000 localities. I use locally disaggregated conflict data to measure impacts on international migration, and I show that the estimated impacts of conflict crucially depends on the spatial level that the researcher chooses to aggregate conflict data.

Additionally, this thesis contributes to the migration literature by investigating the effects of emigration on child schooling and labour supply of non-migrants. While previous literature uses simple schooling indicators, I use age-specific schooling outcomes like the net enrolment rate for children aged 5-16. In contrast to prior studies that only focus on direct (own) effects of emigration on labour supply, I estimate direct and spatial spillover effects. I use a two-period panel data for almost 500 sampling units and use village GPS coordinates of each sampling unit and the national road network to develop an interconnected locality matrix so as to estimate spatial spillover effects. I use historical migration rates to develop the predicted migration rate as an instrument variable in order to overcome endogeneity concerns.

With these new finely grained data and using econometric models that allow for spillovers I find the following:

A higher poverty rate decreased the risk and intensity of the civil conflict because the rebel groups targeted wealthier villages to gain resources, which aligned with their strategic interests. In contrast to poverty, higher wealth inequality, greater relative deprivation and caste polarisation were major causes for escalation of the civil war in Nepal. It seems that inequality and identity-based discrimination increases the risk of conflict as it creates a sense of injustice.

In terms of its impacts, I find that conflict has reduced emigration to high-income destinations such as the Middle East, North Africa and Malaysia because it directly affected the income of the residents and interrupted journeys to Kathmandu city, which were required for recruitment and visa processing. In district versus village comparison of conflict data aggregation, I find that district-level aggregation overstates the impacts of conflict due to mean-reverting measurement errors and produces apparent impacts that are up to four times larger than when the conflict is measured at the locality level.

Moreover, I find that emigration increases the net enrolment rate in secondary education, and this positive effect on human capital occurs through reduced child labour. Emigration primarily helps credit-constrained households to cover schooling costs and compensates for foregone earnings from child labour. Similarly, while I find that emigration is associated with the rise in labour supply, especially for females, there is reduced labour supply in the agriculture sector because remittance receiving households prefer non agriculture work or leisure over the farm employment. Additionally, the spatial spillover effect of emigration increases the labour supply and its magnitude is as large as the direct effect. The positive effect on labour supply occurs through an increase in local wage rates and in local economic activities.

Putting these new findings together, I find that conflict affected localities are still suffering from the after effect of conflict. These localities have not participated to the same extent in the huge growth in emigration compared to the other villages, as a result of this, these localities will have lower remittance inflows and will have lower human capital investment. Additionally, these

findings have important implications for future research and policy, considering the impact of aggregation bias on estimated outcomes and the role of spillover effects in labour supply.

Implications

Lessons for future research

This subnational level study reinforces the importance of identifying an appropriate aggregation level for conflict data in order to correctly estimate the causes and consequences of civil conflict. Based on my findings, in the future, researchers should choose the aggregation level that best preserves local information rather than choosing an aggregation level based on the easily available data. My result shows that over aggregation of conflict data may result in loss of local information and distort findings. Additionally, survey estimates in conflict models, such as poverty and inequality, which are generally available at first or second sub-national need not provide a reason for the aggregation of conflict data. Instead, researchers could use small area estimation techniques to derive welfare estimates for any subnational level in order to preserve the local information. This is important because research needs to identify the true effect of civil conflict in order to guide post-conflict rehabilitation.

Moreover, for future research, my study also suggests that there is a need to develop other measures of schooling outcomes like schooling deprivation indices, schooling inequality indices, and scores in national assessment of student achievement, and so forth, in order to estimate the effect of emigration on quality of schooling outcome. In a country like Nepal where school education is universally free and over 90% of school-age children are enrolled in school, attendance and dropout rates may not correctly capture the effects of emigration on quality of schooling. This study also highlights the greater role of the spatial spillover effect of emigration on labour supply, and given this, in future research, researchers should consider this additional channel to measure the total effect of emigration.

Policy implications

Based on the above findings, a major takeaway of this study is that reducing inequality and discriminatory practices are important policy interventions that can further the peaceful coexistence of people. One way of doing this is introducing measures such as land redistribution or targeted transfer of resources from high income to low income populations to reduce poverty and gap between rich and poor, which will lessen the risk of conflict in the future. Similarly, in Nepalese society, caste-based unequal and discriminatory practices are still widely in practice, therefore a policy to transform society to remove such practices would help to reduce social tension. The changes in constitutional laws that ensure equal rights for all citizens are not sufficient, the government should ensure that constitutional changes are put into action. Such changes will transform society and reduce grievances toward the state, which is crucial to eliminate large-scale conflict in the future.

My study noted the positive impacts of emigration on human capital and labour supply. Considering the negative impact of conflict on emigration to high income destinations, policymakers must keep conflict affected villages in their development agenda as these villages are likely to have low human capital formation and low economic activities. They have not been able to participate in emigration to high income destinations to the same extent as have less conflict affected areas. Additionally, increasing remittances can be important policy intervention to help achieve greater impacts on the local economy. Policymakers can provide skill related training to migrants and encourage more skilled migration that will increase the total value of remittances that workers receive. Another way of doing this is decreasing the cost of remitting to, especially, rural areas by increasing the number of financial institutions operating in rural areas.

Appendix: Co-Authorship forms

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Student and Academic Services Division
Wahanga Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

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

Nature of contribution by PhD candidate	Conceptualising and designing the study, designing the empirical strategy, data cleaning, empirical analysis and writing of initial draft.
Extent of contribution by PhD candidate (%)	85

CO-AUTHORS

Name	Nature of Contribution
John Gibson	Guidance, critical feedback and editing the draft

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
John Gibson	John Gibson	10/9/20

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Co-Authorship Form

Student and Academic Services Division
Waharoa Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter Three: Mean-Reverting Errors and Spatially Aggregated Conflict Data: Impacts of Civil War on International Migration from Nepal

Nature of contribution by PhD candidate	Conceptualising and designing the study, designing the empirical strategy, data cleaning, and empirical analysis.
Extent of contribution by PhD candidate (%)	70

CO-AUTHORS

Name	Nature of Contribution
John Gibson	Guidance, research design, editing the draft and assisting with the journal submission

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
John Gibson	John Gibson	10/9/20

THE UNIVERSITY OF WAIKATO

Co-Authorship Form

Student and Academic Services Division
Waharoa Ratonga Matauranga Akonga
The University of Waikato
Private Bag 3105
Hamilton 3240, New Zealand
Phone +64 7 838 4439
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in your appendices for all the copies of your thesis submitted for examination and library deposit (including digital deposit).

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter Four: Effects of international migration on child schooling and child labour: Evidence from Nepal

Nature of contribution by PhD candidate	Conceptualising and designing the study, designing the empirical strategy, data cleaning, empirical analysis and writing of initial draft.
Extent of contribution by PhD candidate (%)	85

CO-AUTHORS

Name	Nature of Contribution
John Gibson	Guidance, critical feedback and editing the draft

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and

Name	Signature	Date
John Gibson	John Gibson	10/9/20