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Labor market changes and human capital investment: Evidence from migration boom in Nepal

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Abstract

Economic theory suggests that schooling decisions are motivated by returns to education and opportunity cost. In a rapidly changing economic context, changes in returns to education can significantly influence schooling decisions. Migrating to the resource-abundant Gulf countries in short-term contracts represent an additional, and often the most lucrative, labor market option for many young individuals in South Asian developing countries. However, most of these jobs do not tend to demand high education qualifications. This paper studies whether access to low-skilled jobs in construction and service sector led to a reduction in schooling investment. Utilizing the Nepal Census data and instrumental variables method to account for endogeneity of migration, I estimate the impact of migration boom by comparing average education across cohorts and across areas with different rates of migration. The study finds that increase in low-skilled migration possibilities reduced educational investment in Nepal by 3%. Given the importance of human capital accumulation in long-term development, providing additional incentives to keep individuals longer in school would help maximize the benefits from migration.

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1 Introduction

Do individuals respond to greater availability of low-skilled jobs by reducing educational attainment? Low-skilled jobs become more abundant when an economy specializes in low-skilled sector or when there is growth in external labor demand for low-skilled workers. Both of these phenomena are quite common in many developing countries. For an individual facing these circumstances, opportunity cost of staying in school rises; even more so when jobs require temporary or permanent relocation. In addition, effective rate of return on schooling investments falls. This is because an individual is more likely to be employed in one of these jobs in the future. A theory of human capital investment suggests that schooling investments should fall as a result of decrease in returns to education.

In this paper, I examine whether a rapid boom in low-skilled, temporary, international labor migration reduced schooling in Nepal. An increasing number of Nepalese have found contractual employment in the countries of Gulf Cooperation Council (GCC)[1] and Malaysia. Studying the consequences of low-skilled job growth using this particular context of temporary labor migration (TLM) boom is appealing for two reasons. First, demand for labor is exogenous to domestic economic conditions. The migration boom in Nepal and other South Asian countries resulted from oil wealth accumulated by the Gulf nations, which in turn expanded construction and other service sectors requiring large amounts of low-skilled labor (Ewers 2014). Second, TLM in Nepal is a highly centralized system requiring migrants to use formal channels to migrate. This makes obtaining migration data easier than seasonal migration, which remains largely undocumented.

The boom studied in this paper is a five-fold increase in migration from Nepal to the Gulf and Malaysia after 2000. The number of individuals seeking permits to travel abroad for work increased from 28,000 in 1999 to more than 550,000 in 2014 (see Figure 1). As a consequence, remittance inflows into Nepal amounted to 29% of GDP in 2014 (World Bank 2014) and contributed to reductions in poverty (Lokshin et al. 2010). TLM has been beneficial to the Nepalese economy over the past fifteen years. However, it is also important to carefully analyze the long-term consequence of this phenomenon.

One reason TLM could impact long-term growth is due to the types of jobs available. TLM migrants are mostly employed in low-skilled services and construction sectors that do not require much schooling. If exposure to greater migration possibility leads to lower schooling attainment, long-term growth could be harmed. Human capital accumulation through schooling is considered to be a driver of long-term economic and social development. Many development policies focus on improving schooling attainment. In light of the impact of TLM on schooling, policy-makers in high migration sending countries should pay attention to provide schooling incentives to maximize long-term benefits of migration.

[1]The GCC includes Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates (UAE).

My empirical strategy is to compare schooling decisions of individuals who were 18-27 years old in 2011 between locations with different degrees of exposure to migration. Migration exposure is measured by location-specific TLM rate, defined as the percentage of households with at least one TLM migrant, at the time of schooling choice.[2] TLM rates vary between 0 to 74% in 2011, with an average of 16%. The spatial variation in migration boom, illustrated at the district level by Figure 2, allows me to study the responses of individuals in high and low boom locations. Larger migration boom in one's village creates stronger migration networks and reduces migration cost by increasing available information. As a result, the probability of entering the foreign labor market goes up. When returns to schooling are low in the foreign market, this reduces the optimal choice of schooling.

Although migration boom in one's location is exogenous from an individual's perspective, it could be correlated with unobserved location-specific factors that influence education decision. To address the resultant bias in Ordinary Least Squares (OLS) estimates, I use fraction of "early migration" castes who lived in neighboring locations in 2001 as an exogenous factor that influenced migration boom in a village. When the opportunity to migrate first arose in Nepal, members of Gurung, Limbu, Magar, Rai and Tamang castes migrated first due to their historical migration experience as soldiers in the Gurkha regiment of British and Indian Army; I refer to these caste groups collectively as the "Gurkha" caste. They are also actively engaged in recruiting activities- record from the Department of Foreign Employment (DoFE) reveals that a majority of migrant recruitment firms are operated by members of this caste group. Therefore, locations with greater abundance of these caste members were more likely to experience migration boom.

This study finds evidence of negative effect of migration on education in Nepal. In the baseline model, a 1 percentage point increase in 2011 migration rates reduced probability of continuing beyond secondary schooling[3] by 0.05 percentage point for 18-22 year old males and 0.1 percentage point for 23-27 year old males in rural areas. Given that the proportion of schooling is 0.13 and 0.15 respectively, this represents an impact of about 3.8% and 6.67%. I do not find a statistically significant impact on girl's education. The regression controls for baseline economic variables, village caste characteristics and district fixed effects.[4]

The results are robust to exclusion of districts where civil war between 1996 and 2006 could potentially confound the relationship between migration and education. Point estimates are larger (more negative) for subsample of individuals who come from households with higher average education. These individuals are less credit-constraint and have greater access to skilled jobs domestically; thus, they are most likely to obtain more schooling in absence of migration boom. Furthermore, limiting the analysis to members of Brahman,

[2]Since migration data is only available for 2001 and 2011, I interpolate migration rates for years when the each cohort made their schooling decision.

[3]Education in Nepal is divided into Primary (grades 1-5), lower secondary (6-8), secondary (8-10), higher secondary (11-12) and post-secondary.

[4]Nepal's 3982 villages and municipalities are divided into 75 districts.

Chhetri and Newar caste, who were disproportionately more likely achieve high education, I find that point estimates almost doubled compared to the baseline estimates. However, after taking into account the higher rates of post-secondary schooling in these groups, I find that the impacts are proportional to initial rates of dependent variable.

The estimates measure net effect of various mechanisms through which migration might impact education. Besides decreasing rate of return, labor migration prospects could increase local wages and raise opportunity cost of schooling for younger cohorts. Or, remittances could relieve liquidity constraint and allow individuals stay in school longer. Further, changes in family structure, for instance an absent parent, could also have direct impact. The results of this study reveals that rate of return and opportunity cost dominate any positive impact through increased income. This is not surprising given that the Nepal Living Standards Survey 2010 found less than 5% of remittances were spent on educational expenditure (Central Bureau of Statistics 2011).

This study contributes to the literature on the impact of emigration on sending regions in two ways. First, it focuses on the understudied topic of South-South migration. Most existing studies focus on permanent migration from developing to developed countries examining the brain drain issue (Djajic 2014). The unique aspect of South-South migration is that returns to skills could be low and thus knowledge from the brain drain literature cannot be directly applied. Second, this paper provides evidence of spillover effects of migration on non-migrant households. The focus of current work has been on the impact of migration on remaining members of the household. We know much less about broader effects of migration on other households in the area. Incentive effects of community migration on schooling choices have been speculated by McKenzie and Rapoport (2011) in the case of Mexico, although they consider them to be "second order effects" (pg. 1339). Given the magnitude of the impact, I show that such incentive effects can be large. Since non-migrant households are less likely to reap benefits of remittances received by migrant households, studying the impact on these households becomes all the more important.

On the policy front, this paper draws attention to possible trade-off between short-term poverty alleviation and long-term impacts of migration. Most developing countries with TLM have focused on harnessing its poverty-reducing impacts (McKenzie et al. 2014). Indeed, migration can help many individuals in developing countries come out of poverty (Clemens 2011) However, policy-makers should also pay greater attention to long-term impacts of migration boom and devise appropriate policies to maximize the benefits of such migration. Since schooling is considered a driver of long-term growth, providing incentives for students to stay in school longer would maximize the benefits of migration.

The long-term dynamics is crucial because fortune of migrant labor depends heavily on economic conditions in destination countries (McKenzie et al. 2014). It would wise to not rely too heavily on migration for long-term development, and focus on strategies that foster economic development domestically. The diverse experiences of labor exporting economies is relevant to this point. Figure 3 shows historical trajectory of contract employment in selected Asian countries. As demonstrated in figure, South Korea and Philippines, while initially following similar paths, diverged considerably in their dependence on contract migration similar to TLM. The latest available data, shown in table 1, shows continued reliance of the Philippines on migration. This poses an important question: will developing countries ultimately grow out of their dependency on labor export and remittance, or will they gravitate towards an equilibrium characterized by a large stock of outbound workers with limited opportunities for productive employment at home? Much depends on how migration effects drivers of long-term economic growth.

2 Background

2.1 Temporary labor migration in Nepal

Temporary labor migration in Nepal started in the 1990s after a series of liberalization policies that made it easier for Nepalese to obtain travel documents. On the other hand, seasonal migration to India for work and as soldiers in the British Gurkha regiment was historically important among certain groups within the country. Stagnant manufacturing, political conflict and lack of domestic opportunities led to its rapid growth after 1999 (Sapkota 2013). The ensuing remittance has made substantial contributions to poverty reduction (Lokshin et al. 2010) and forms essential part of rural Nepals livelihood strategy (Seddon et al. 2002). Although there is a fair amount of domestic migration, foreign migration is much more valuable for Nepalese households. According to statistics from the Nepal Living Standards Surveys (NLSS), larger number of households have migrants in TLM, and the remittances from these sources are more important in terms of value than those from domestic and India migration. Average remittances from the Gulf States and Malaysia are almost five times larger than remittances from India (Central Bureau of Statistics 2011, p. 83)

Temporary labor migration is promoted and regulated by the Nepalese government, similar to many other developing countries such as Philippines (see McKenzie et al. 2014). The Government has signed multiple bilateral agreements with labor importing nations to help formalize the emigration process (Department of Foreign Employment 2014). The government has also designed regulations to protect rights of the migrants. Licensed private recruitment agencies (locally known as "manpower companies") receive demand from foreign firms, advertise the jobs in local dailies and select migrants. The migrants receive information about foreign jobs from newspaper advertisements and from agents who inform them of job availability. The Nepal Migration Survey (NMS) conducted by the World Bank in 2009 revealed that 41% of migrants to the

Gulf were approached by a recruitment agent, while 17% sought services of a manpower company (World Bank 2011, p. 51). In contrast, almost all jobs in India were found through personal contacts. The final selection of the migrants is done either by a representative of the foreign firm or the manpower company on its behalf. Each migrant obtains a labor permit from the DoFE before they can leave the country. Although it is possible for migrants to directly apply for permits, it is much more common for migrants to go through the recruitment agency. Out of the 550,000 permits acquired during the 2013/14 season, 78500 were obtained directly by individuals and the remaining through recruitment agencies (DoFE 2014, p. 60). Figure 4 summarizes the flow of information between various stakeholders.

2.2 Characteristics of early migrants

Since historical context of migration contributes to empirical strategy of this study, I will briefly discuss trends in early TLM in Nepal. What are the characteristics of early migrants and the areas from which they arise? Using the 2001 census micro-sample data, I study some of these characteristics. The 2001 census asked about absent[5] household member's age at the time of departure, duration of absence, destination country and reason for leaving. Additionally, some individuals found in the household listed TLM destinations as their place of residence 5 years prior to the census. To study early TLM from Nepal, I classify as early migrants absentees whose duration of absence is greater than 5 years or household members who reported living in one of the TLM destinations 5 years prior. I report their individual and household characteristics in Table 2.

Out of the 12834 TLM absentees in the 2001 Census micro-sample, 1682 or 13.1% had left 5 or more years ago. 98% of these were males, with average age at departure 27. This contrasts with average age at departure of early twenties for India migrants and mid-twenties for other migrants. Unfortunately, the 2001 Census did not ask about the education of these absentees. So, I report the maximum adult educational attainment in the household of the migrant, along with information on caste composition.

A total of 1708 households had early TLM migrants. Migrant households tend to be slightly less educated than non-migrant households, but early TLM households had slightly higher education than later TLM households. This is most likely because education helped get through the formal process of recruitment for early migrants. Proportionately higher fraction of Muslim and Gurkha households took up TLM early. This caste-wise variation in migration has been maintained until today. In 2001 census data, among the top 15 major castes (by population), Limbu (7.4% of households), Gurung (6.7%), Rai (4.2%), Magar (4.3%) and Muslim (4.1%) sent the most migrants. Other caste members had TLM rate of less than 2.5%. In 2011, 21.6% of Gurkha households had TLM migrants. While aforementioned castes have maintained the lead,

[5]Only household members who were not in Nepal at the time of the survey were included in the module

other castes have also started sending migrants at a high rate of 12%.

2.3 Distribution of migrant jobs

What kind of jobs can Nepalese migrants expect to obtain in destination countries? Statistical information on the types of jobs available to migrants comes from governments of destination countries, which makes comparisons difficult. I present evidence from a variety of sources, all of which point towards low-skilled bias of the jobs available to migrants. Results from the 2012 labor force survey of Qatar shows that out of 1.24 million non-Qatari economically active population, 0.1 million worked in manufacturing and 0.5 million worked in construction (Ministry of Development Planning and Statistics 2012). Similarly, the Saudi Arabia Manpower Survey of 2013 revealed that of the 6 million non-Saudi population, 1.5 and 1.3 million were engaged in construction and trade respectively. The proportion of Saudi males employed in these sectors with secondary education or below is 72% and 82% respectively (Central Department of Statistics & Information 2013, Table 13). These statistics suggest that most of jobs available to migrants are in sectors that do not have high education requirements.

2.4 Education in Nepal

Formal education in Nepal comprises of primary (grade 1-5), lower secondary (6-8), secondary (9-10), School Leaving Certificate (SLC), Higher Secondary (11-12), Bachelors and Post-Graduate. According to Department of Education (2013), net enrollment ratio (NER) is 95.3% at primary level, 72.2% at lower secondary level, 54.3% at secondary level, and 10.4% at higher secondary level in 2012. The NER saw an almost 20 percentage point increase between 2008 and 2013 (Department of Education 2013, p. 30). The SLC, the national exam taken after grade 10 and which determines eligibility to enter higher secondary education, had success rate of 43.3% in 2014. Most of the students who fail the exam come from government-run schools.

In table 3, I report the distribution of years of schooling, divided into categories (cannot write, primary, lower secondary, secondary, SLC, and above SLC), for males aged 18-37 who already left school, according to their migration status in 2011 (non-migrant, TLM, India migrant and other migrant). TLM migrants have a lower rate of post-SLC education than non-migrants and foreign migrants to destinations other than India. The table also reveals that a large fraction of migrants do not have education information, which plays an important role in comparing educational achievement of migrants vis-a-vi TLM migrants. The missing education is definitely non-random. Since the migrant questions were answered by the household head, its more likely that household heads with lower education would be unable to answer the question. This means that migrants themselves are less likely to have high education.

Table 4 shows suggestive evidence of lower returns to schooling in TLM. The log difference in monthly earnings between lowest and highest education category is 0.47 for current and return migrants, and more than 0.7 for domestic workers. This implies that the wage premium of post SLC education is roughly 47% for migrants and 70% for domestic workers. However, these numbers do not take into account selection issues, and the entire difference cannot be attributed to differences in return to schooling in the two labor markets.

It is also important to note that access to education varies significantly by caste. Members of the Brahman, Chhetri and Newar caste groups tend to have the greatest access to education and lucrative employment opportunities. Study by Tiwari (2010) shows that 73% of those with high education (SLC and above) came from Brahman, Chhetri and Newar community, even though they comprise of 38.3% of population. I analyze these groups separately.

3 Literature Review

A large number of studies have looked at the consequences of migration on education in sending regions. One strand of this literature focuses on the impact of remittances, demonstrating that remittances relieve credit constraints and allow greater investment in all forms of human capital, including health and education. In El Salvador, remittances increase the likelihood of school attendance among migrant households (Edwards and Ureta 2003, Acosta 2006). However, variations have been noted along the urban-rural divide and among different age groups. Edwards and Ureta (2003) find that a $100 increase in remittance lowers the likelihood of leaving school before 7th grade by 54%, thus allowing children to stay longer is school in rural areas, while finding no impact in urban areas. Acosta (2006) finds increased school attendance for boys aged 11-14 years and girls aged 11-17 years, although there is no significant impact on older boys (15-17 years old). Yang (2008) finds positive effect of remittances on schooling in the case of Philippines. The study uses variation in the exchange rate shocks experienced by households that send migrants to different destinations. The results show households with relatively favorable exchange rate shock (which increased value of the remittances) keep children longer is school and increase educational expenditure.

However, remittance is only one consequence of migration of a household member; there exists other channels through which household migration might impact schooling. Migration of a household member increases future migration possibilities, reduces parental supervision of young children, and decreases available labor in the household (Borjas 1987; Gitter et al. 2011; McKenzie and Rapoport 2011). All these could have negative impact on educational attainment. For instance, the prospect of foreign migration, particularly easy availability of low-skilled foreign jobs, might induce migrant households to avoid investing in education of their children (Gibson et al., 2011). Migration can also have general equilibrium effects on domestic wages, further reducing schooling incentives. Large-scale migration could lead to shortages of adult males, therefore increasing wages and employment opportunities for younger males domestically. Mishra (2007) found that out-migration from a particular skill category increased wages in that category in Mexico. The implication for TLM is that low-skilled wages could rise in sending regions and further reduce rate of return and increase opportunity cost of schooling. This effect could be more relevant in Nepal, where government rules prohibit individuals younger than 18 year old from obtaining permits to participate in TLM. But they could still drop out and be employed domestically.

The theoretical model developed by Azarnet (2012) lays out the following mechanism: "the process of human capital accumulation in the source country slows down because the possibility of a higher-wage low-skilled guest-worker employment abroad lowers the relative attractiveness of the skilled employment in the home country" (p. 328). Furthermore, even when there are returns to skills in foreign employment, skills that are rewarded in the foreign market may not be transferable to domestic conditions, encouraging repeat migration (Constant et al. 2013). Although studies have found that emigrants to developed countries have enhanced earning potential once they return (Dustmann et al. 2011), this is unlikely to be true for TLM. This is because of demand side constraints salaries offered in destination countries is much higher than those offered domestically for similar or sometimes higher skilled work. Still, education might impact a potential migrant's ability to navigate the application process, adjust to new culture and avoid fraud in the recruitment process, a channel that has remained unexplored.

There is some empirical evidence of this channel dominating. McKenzie and Rapoport (2011) find that living in migrant households reduces probability of completing high school by 13% for males and 14% for females in Mexico. In rural China, high school enrollment is negatively related to opportunities for migration to urban areas (de Brauw and Giles, 2008). Gitter et al. (2011) could not find any impact of increased migration opportunities on male education in Mexico. They speculate that possibility of migration at a younger age could directly lead to lower schooling outcomes for males.

Existing studies highlight the multiple channels through which remittances might impact educational choices. But all these papers focus on what happens when a member of the household migrates. Given sufficiently strong migration networks, this channel could also be important for households *without* current or past migrants. Household decisions may be influenced not only by migrants within the household, but also by migration in their communities, particularly when migration is large-scale. Even for non-migrant households, community-level migration provides them with new information about foreign labor markets, which might be taken into account while making education decisions. There is a much richer literature on how demand for education depends on incentives.

A large literature on demand for schooling finds important role played by rate of return. Willis and Rosen

(1979) made one of the first attempts to study the response of education to expected returns. Using sample of US individuals, they find that decision to attend college strongly depends on expected lifetime earnings gains. More recently, Abramitzky and Lavy (2014) study the impact of a change in payment system that effectively raised returns to education on schooling decisions of individuals in Israel. The redistribution policy, that made renumeration more responsive to human capital, increased student's investment in schooling. Similarly, studies have found impact of (low) skill-biased technological change and resource boom to have negative impact on drop out rates in the US (Cascio and Narayan 2015). Both of these strands of literature suggest a negative impact of a low-skilled migration boom.

That perceived returns to education impact actual educational outcomes is found by Jensen (2010) for Dominican Republic as well as Kaufman (2008) and Attanasio and Kaufman (2008) for Mexico. Attanasio and Kaufman (2008) elicit risk perceptions and perceived returns to education from junior and senior high school graduates and their parents. They conclude that both risk perceptions and perceived returns are important factors influencing schooling decisions, but returns are more important in decisions to enter college.

Nguyen (2008) and Jensen (2010) conduct experimental study where households are provided information about returns to education. Both studies find that schooling investment is higher when households were provided with labor market return. Nguyen (2008), set in Madagascar, focused on short-term behavior and found increased performance and attendance in the first few months. Jensen (2010) studied long-term impacts of the intervention in Dominican Republic. Providing estimates of returns increased perceived returns relative to baseline in the treatment group, and students in this group completed 0.2 more years of schooling over four years (Jensen 2010, p.518). The author emphasizes that it is the perceived return to education that matters. Furthermore, in rural areas, information about domestic returns to education might be lacking due to lack of sources of such information (Jensen 2010, p. 517). In the case of Nepal, information on foreign labor markets is readily available from recruitment agents.

Jayachandran and Lleras-Muney (2009) study the impact of reduction in maternal mortality in educational investment of girls in Sri Lanka. The idea is that greater life expectancy increases life-time earnings potential, which acts as a positive incentive to acquire more education. In this paper, men serve as comparison group. The authors use a triple difference strategy to identify the impact. They find that each additional year of life-expectancy increases literacy by 2% and years of schooling by 3% (0.11 years). The small impact of both Jayachandran and Llera-Muney (2009) and Jensen (2010), could point to the relatively greater importance of schooling cost in these settings.

Munshi and Rosenzweig (2006) study how men and women in belonging to different castes made schooling choices in response to globalization-related changes returns to occupation. Schooling choices respond to expectations about returns to different occupation. The key variable of interest is the language of instruction (English v/s Marathi) chosen by different caste-members. The assumption is that globalization improved returns to English-language by making white-collar jobs more attractive.

Coxhead and Phan (2013) study how households with connections to the state sector, where returns to education are significantly higher, invest more in education of their children. In this case, probability of employment in the state sector drives investment in education. These studies, taken together, point to returns to education as being an important factor in education decision.

4 Empirical Strategy

In this paper, I use a instrumental variables strategy to take into account possible endogeneity of migration rate. Migration boom could be endogenously related to education outcomes for two reasons. First, individuals in high migration areas could share characteristics that make them different from individuals in low migration areas (hence the difference in their rate of migration). Their unobserved factors that lead them to prefer migration at a greater rate might also have a direct impact on their educational choices. Alternatively, there might be something inherent in the location of high migration that could also influence education of all cohorts. Not accounting for all of unobserved locational heterogeneity will lead to biased estimates. In order to minimize bias in the estimates, I use instrumental variable (IV) to account for endogeneity of migration boom.

Instrumental variables strategy is common in the study of the impact of migration. For example, McKenzie and Rapoport (2011) and Woodruff and Zenteno (2001) use historical migration rates as instruments for probability of migration from Mexico to the US. Testing the predictions of the brain drain literature, Batista et. al (2012) use local migration rate as an instrument for individual migration probability. They argue that since local migration rates in their context were determined by historical economic conditions, which are very different from current economic situation, local migration rates can serve as a valid instrument. This is less obvious in the case of Nepal, since TLM is a recent phenomenon.

In Nepal's context, Gurkha caste members were more likely to engage in TLM; the presence of these caste-members around the village could be used to instrument for migration boom. The 1991 census available at the district level shows that the top 10 districts sending migrants to Gulf countries comprised 36.5% Gurkha population, compared to 17.65% Gurkha in the rest of the country. Looking at census data from 2001, the first year for which household data is available, 3.48% of Gurkha households had migrant members, as compared to 1.27% of other caste groups. The reason could be that these caste groups had a history of sending migrants as soldiers in the British army (see Shrestha 2015 and references there in for details). As a result of this migration history, Gurkha caste members were more likely to seek migration opportunities, and members of this caste are more likely to have information about opportunities in the Gulf. Thus other individuals living amongst these members are also likely to gain information about migration and therefore lead to migration boom.

Caste characteristics of the village cannot directly be used as an instrument since it is unlikely to satisfy the exclusion criterion. For instance, different castes might have different cultural preference to education, which has a direct impact on schooling. In fact, Shrestha (2015) finds that Gurkha caste members, because of their desire to join the British Army, increased their educational attainment in response to higher educational requirements by the British Army. Therefore, presence of Gurkha caste members could directly influence educational attainment in a location. However, having early migrant caste members in the neighborhood is positively correlated with migration. So, I use proportion of Gurkha caste members in a village's neighborhood as the instrument. As we will see in the results section below, the proposed instrument does a good job of explaining migration rates in a village.

The correlation between neighborhood caste characteristic and migration could arise for two reasons. First, through the process of *social learning*: "a process by which an individual learns from his neighbors experiences (their previous decisions and outcomes)" (Munshi 2004, 185), but applied in the case of migration decisions rather than technology adoption, and across spatial units rather than individuals. Initial migration decisions of individuals were (partly) exogenously determined by caste membership. Proximity to these early caste provided information about TLM, leading to further migration. Second, return migrants tend to work as recruiters for manpower companies. Anecdotal evidence gathered during interviews with managers of manpower companies revealed that they tend to recruit mostly from the proprietor's home district. It is conceivable that neighboring villages would be the most likely place for recruiters.

The identifying assumption is that, after controlling for own-village caste characteristic, neighborhood caste characteristic does not impact education attainment in the village. One concern is that existence of caste-based discrimination might have led to policies that address outcomes for specific caste group, including schooling. While there have been multiple calls for such policies, there is little evidence that effective policies have been instituted. There is no specific data on government investments in education disaggregated by region. However, government reports suggest that most of the investment has been targeted towards primary education. Therefore, existence of such differential investment should not impact average education at higher level.

4.1 Other econometric issues

As discussed above, a problem arises due to non-linearity in education cost. In Nepal, and possibly in other developing countries, education cost are non-linear due to lack of infrastructure. While it is easier to gain access up to SLC education, education costs rise discontinuously for higher-secondary education (grade 11 and 12). This is primarily due to lack of infrastructure. Estimates from the Nepal Living Standards Survey 2010 reveal that distance to closest upper secondary school (that provide post SLC education) is 6 kilometers (3.8 miles) in rural areas, more than four times the distance to closest primary school. Due to lack of access, detecting any impact on post SLC education will be difficult as any change is going to be at a very small margin and will require a large dataset. The Census micro-sample data provides a good sample size for these calculations. However, the design of the census survey leads to another issue of sample selection.

Sample selection problem arises since the dataset only tracks foreign migrants while ignoring domestic migrants. This poses sample selection problem if domestic migrants are more educated than individuals in the sample and domestic migration is correlated with foreign migration. In the census, it is only possible to track domestic migrants to their district, not village. This can also be seen by directly comparing education of domestic migrants, TLM migrants, India migrants and other migrants from the Nepal Labor Force Survey 2008, which tracked both domestic and international migrants. As can bee seen in Table 5, domestic migrants had almost one grade higher education than TLM migrants in the rural areas. The main reason is that 36% of domestic migrants in the sample were students.

Existing dataset does not allow me to address this issue adequately. This sample selection could bias the results against finding a significant relationship if domestic migration is a substitute for TLM. We can analyze the situation in the setting of measurement error. Let s^* be the true average education in a village. Since we do not observe the upper tail of the schooling distribution, the observed measure of average education s is an underestimate. So, we can write

$$s^* = s + u,$$

where $u > 0$. Running a regression of s on migration rate M to estimate the true parameter β gives us

$$\begin{aligned} \hat{\beta} &= \frac{Cov(s, M)}{Var(M)} \\ &= \frac{Cov(s^*, M)}{Var(M)} - \frac{Cov(u, M)}{Var(M)} \\ &= \beta - \frac{Cov(u, M)}{Var(M)} \end{aligned} \tag{1}$$

The bias is zero only if the measurement error is uncorrelated with migration rate. However, TLM and domestic migration are likely to be negatively correlated. This is because access to better jobs domestically will obviate the need for foreign migration. As a result, the estimated coefficient will be larger than the true population value. Since I expect the true relationship between schooling and TLM to be negative, the results in the paper are likely to be underestimates of true relationship.

Domestic migration could also pose a problem if the location of enumeration is not the same village an individual was living in when they were making schooling choices. If current location had different TLM rate than location at the time of schooling decision, this could bias the results. In the sample used for this study, 14% of males 18-27 were born in different district. If we focus on the rural sample, this proportion is 8%. The 17760 males aged 18-27 whose district of residence is different from district of birth, the correlation between TLM rates in the respective district is 0.49. Since this correlation is high, I expect the bias to be small.

5 Empirical estimation

The following econometric model is used to estimate the impact of TLM on schooling outcomes:

$$Y_{ij} = \beta_0 + \alpha_0' X_{ij} + \alpha_M M_j + \gamma' W_j + e_{ij}. \tag{2}$$

where Y_{ij} is schooling variable for individual i in location j, β_0 is the constant term, α_0 is the vector of coefficient associated with individual-level variables X_{ij}, α_M is the coefficient on migration rate M_j in location j at the time of schooling decision, γ' is the vector of coefficient on location-specific characteristics W_j, and e_{ij} is the error term.

5.1 Data

The analysis in this study is based on 18-27 year old males from 15% public use sample of Nepal Census 2011. A useful feature of the 2011 census is that, unlike previous censuses, education information of absentee population was also recorded. Basic information such as age, caste, gender, education, migration status and location are also reported. The census used systematic sampling technique. From each enumeration area (EA), 1 in 8 households were randomly selected to be part of the sample household and information was collected from all members present in the household. The household head also answered questions related to age, education, age at departure, destination and reason for absence for usual members of the household who were abroad at the time of the survey.

The dependent variable is a dummy indicating whether an individual has completed more than SLC education. I use this variable as measure of education to reduce measurement error. Education of individuals is usually reported by the household head, who may not always have an accurate information, particularly about migrant's education. Further, education is more likely to be missing for low-education households. Since SLC is a standardized national exam that serves as a pre-requisite for many jobs, information on whether the schooling achieved is below or above SLC is much more accurate.

The main explanatory variable of interest is the migration rate in a location at a time when schooling decision is made. I only have data on migration rate in 2001 and 2011, which is measured as percentage of households in the location with at least one migrant to the Gulf or ASEAN countries.[6] These are computed using the micro-sample of 2001 and 2011 census.[7] I take a weighted average of the 2001 and 2011 migration in order to get a measure of migration rate in the middle of the decade. Specifically, for individuals 18-22 year old in 2011, I compute migration rate in 2008 by placing weight of 0.7 on the 2011 variable and 0.3 on 2001 variable. Similarly I place 0.3 weight on the 2011 variable and 2001 on the 2001 variable to get migration rate in 2004, which is relevant to those 23-27 in 2011.

The estimates of migration rate for years between 2001 and 2011 assumes a linear trend in migration over time. Figure 5 shows correlation between 2001 and 2011 migration rates. The trends show strong positive relationship between migration rates over time. Figure 6 shows the relationship between change in post-SLC schooling rate between 2001 and 2011 and TLM rate at the village-level, separately for the younger and older cohort. There is suggestive evidence of negative relationship, with high migration villages experiencing smallest increase.

The variable used to instrument for migration rate is the concentration of Gurkha caste in neighborhood locations in 2001. In order to compute this variable for a village, I add the number of Gurkha caste members in 10 closest villages (based on latitude and longitude) and divide by the total population in those villages. The caste characteristic of individuals and village is controlled separately in the regressions.[8] The caste-wise population of each location comes from full enumeration tables of Census 2001.

Household education variable is defined as the maximum educational attainment of a residing household member older than 39 in 2011. Some younger households do not have any member meeting this requirement. A separate variable indicates such households. The reason for excluding younger household members is to ensure that this measure is unaffected by migration boom. In one specification, I interact the instrument with this variable. Those households meeting the requirement are classified as having low (0-5), medium (6-SLC), and high.

Locations are rural villages. I exclude urban areas from the sample since they tend to be outliers with

[6]This is the level of aggregation used for migration destination in the 2011 census.

[7]In order to get an accurate estimate of location-specific migration rate, locations with less than 50 households are dropped.

[8]There are over a 100 recognized caste in Nepal. Caste-related studies in Nepal usually group them into eleven categories. This study uses dummies for the eight major caste based on population, aggregating the five Gurkha caste.

respect to post-SLC education. I also control for baseline economic differences in locations by including the following variables measured in 2001: distance to closest urban area, average education of 15-17 year olds, percent of population born in different district and percentage of males older than 29 in skilled occupation. I also include a district dummy to control for unobserved district-level effects. The complete list of variables and basic summary statistics is provided in Tables 6 and 7.

I divide the sample into two age groups- 18-22 years, and 23-27 years. Due to the rapid boom in TLM after 2000, the two cohorts would have different levels of exposure to migration possibility and thus make different educational choice. The same estimation is run separately on males and females to study different effects on the two groups.

5.2 Standard errors

Bertrand et al. (2004) discuss how ignoring senior autocorrelation while conducting difference-in-difference analysis leads to underestimate of standard errors. In the case of geographic variables, spatial correlation of unobservables could also lead to underestimate of standard errors. Clustered standard errors provides better estimates. The choice of clusters in this paper is difficult as it uses neighbor's characteristics in the estimation. In principle, villages that share neighbors should be included in the same cluster as their errors could be correlated if there is measurement error in the data. But one village could belong to multiple clusters. Since the variable that is averaged over the neighbors is the full count census data, measurement error should be minimum and classical. Therefore, all standard errors are clustered at the village level. Clustering at the district level increases the standard errors but does not change the statistical significance of the result.

6 Empirical Results

Ordinary Least Squares regressions, reported in Table 8 demonstrate a negative effect of temporary labor migration. For males aged 18-22 in 2011, a one percentage-point increase in TLM rate is associated with a 0.1 percentage point decrease in the likelihood of continuing beyond SLC. The estimated impact is 0.25 for 23-27 year olds. For females, the corresponding estimates are 0.11 and 0.13 respectively.

Accounting for the endogeneity of migration increases the estimated impact. Table 9 shows the predictive power of proposed instrument. After controlling for own early migration caste, early migration activity in the village and neighborhood, and other village characteristics, having early migrant caste members in the neighborhood is strongly related to migration boom. A percentage point increase in Gurkha caste members in the neighborhood is associated with 0.07 percentage point increase in 2011 migration rate for the 18-22 year old cohort and 0.05 percentage point for the 23-27 year old cohort. The F-statistics on the hypothesis that the coefficient on the instrument variable is zero is more than 10, which surpasses the rule of thumb threshold for strong instrument.

Instrumental variables estimates are reported in Table 10.[9] The results suggest that a one percentage point increase in TLM rate caused a 0.5 percentage point decrease in probability of males 18-22 continuing beyond SLC. The impact is double for the 23-27 cohort. IV estimates show very small and statistically insignificant impacts on female education of migration boom. Comparing these estimates at the average rate of above SLC education of 12 percent, the estimated effect is a 3.6% impact at the mean.

The results agree with the findings of McKenzie and Rapoport (2011) on two aspects. First estimates of impact increase when IV estimation is used. Second, the direction of impact is negative. However, the magnitude of impact is order of magnitude lower in my case. In a comparable estimate, McKenzie and Rapoport (2011) find that living in a migration household has a 9 percentage point lower chance of completion 10 to 11 years of schooling. This could be because McKenzie and Rapoport (2011) assess impact of living in a migrant household, where as this paper is interested looks at average effect on all households, regardless of their migration status. Another reason could be due to difference in the way of handling individuals enrolled in school at the time of the survey. McKenzie et al. (2011) argue, correctly, that we haven't observed the desired level of schooling for these individuals, and thus assume that the schooling data for these individuals are right-censored. I don't correct for this fact, and thus could be underestimating the true impact, particularly for the 18-22 cohort.

The control variables have intuitive signs. Likelihood of continuing education above SLC increases with household education. Average village-level educational accomplishment of 15-17 year olds in 2001 is a strong predictor of schooling attainment in 2011. Individuals further away from urban areas have lower likelihood of continuing schooling beyond SLC. Village-level caste variables are significant for Gurkha, Muslim, Yadav, and Brahman.

6.1 Late migration districts

The above estimates show a net effect of migration boom, which includes negative affect of rate of return and positive impact of remittance inflows. Isolating the impact of labor market return from other impact is difficult. We could focus on households with no migration history, as they are only affected by migration through its labor market consequence. However, households' migration decisions are endogenous and I do not have accurate measure of household migration history. Therefore, I focus on locations which started the

[9] The IV results in the paper is based on a linear second stage. Marginal effects from a probit second stage regression give similar estimates.

migration boom later. The 1991 census shows that some districts had already begun sending migrants to the Gulf before 1991. Official records also show that in 1994, the first year for which such records in available, about 3500 individuals applied for labor permits. In 2011, the average of rate of migration in villages in districts that sent migrants early is much higher, as shown in Table 11.

Therefore, I exclude the 11 districts who had more than 0.5 percentage "Arab" migrants in 1991 census.[10] I report the results in Table 12, columns 1 and 2. The results show a much larger impact on the 18-22 cohort of 0.62 percentage point reduction in education for a percentage point increase in migration rate. This result provides suggestive evidence that the negative impact of migration on education is highest in the middle of migration rates. Low rates of migration in a village do not change individual incentives. In villages with high rates of migration, on the other hand, most households enjoy remittance inflows. So, the positive impact of remittance income on schooling counteracts the negative incentive effect.

The estimates on the 23-27 year old sample is not statistically different from the full sample. This group of individuals were less likely to benefit from the remittance inflows resulting from TLM, but were still influenced by the incentive affect.

6.2 Impact of conflict

The rise in temporary labor migration in Nepal also coincided with intensified conflict waged by the Maoist insurgency. The effect of this decade-long conflict, which beginning in 1996 and intensified after 2001, was quite large (Macours 2011, Tiwari 2010). Since conflict induces migration and also reduces educational investment by destroying infrastructure, the estimates could be picking up some of these effects. Existing research on conflict in Nepal has pointed towards economic and social inequalities across various caste groups (Tiwari 2010). Different factors have been thought to explain Nepal's conflict, including poverty (Do and Iyer 2007, Hatlebakk 2009), inequality (Macours 2011, Tiwari 2010), and landlessness (Murshed and Gates 2005). Some of these factors, such as proportion of household with land, included in the analysis in this paper. In order to ensure that the results are robust, I exclude districts with the highest intensity of conflict.[11] The intensity of conflict is measured by number of displacements per ten thousand people, with data compiled by a Nepali human rights organization Informal Sector Service Centre (INSEC).[12] The excluded districts had more than 100 conflict-induced displacements per 10000 people and are located in Mid- and Far-Western regions of Nepal.

The results after excluding high-conflict districts are shown in Table 12, columns 3 and 4. The results are

[10] The excluded districts, in order of their Arab migrant rate are: Myagdi, Kaski, Morang, Sankhuwasabha, Baglung, Syangja, Terhathum, Tanahu, Parbat, Khotang and Dhankuta. The migration rates in these districts ranged from 2.41 per 100 households in Myagdi to 0.5 per 100 households in Dhankuta.

[11] The districts excluded are: Bajura, Dailekh, Dolpa, Jajarkot, Jumla, Kalikot, Mugu, Rolpa, Salyan, and Surkhet.

[12] http://www.inseconline.org/.

quite similar to the baseline regression. Overall, the results indicate small bias due to impact of conflict. This could be because the intensity of conflict was highest on the Mid-West and Far-West part of the country (Murshed and Gates 2005, Tiwari 2010), where was TLM boom took place in the Eastern and Central regions. It is also possible that conflict-induced displacement encouraged temporary migration domestically or to India. The fixed cost of TLM could have been prohibitively high in a conflict-related situation, where access to credit could also be minimum.

6.3 Brahman, Chhetri and Newar castes

Given the high degree of inter-caste inequality in Nepal, the average effect of migration could mask high degree of heterogeneity across castes. I focus my attention to the castes with the highest access to education - Brahman, Chhetri and Newar. Tiwari (2010) shows that Brahman, Chhetri and Newar comprised 75% of all individuals with post-SLC education in Nepal, even though they account for only 33% of the total population. Columns 5 and 6 of Table 12 report the results.

I find that an one percentage point increase in TLM rate reduced likelihood of post-SLC education by 1 percentage point for the 18-22 cohort and by 1.9 percentage point for the 23-27 cohort. These estimates are twice that of the baseline regression. However, these groups also have much higher rates of post-SLC education - 30% for the 18-22 cohort and 38% for 23-27 cohort. As fraction of education rate, the estimates impact is 3.3% and 6.3% respectively.

6.4 Heterogeneity by household education

I also explore if the impact of migration is different for individuals with different household-level education. The response of individuals' schooling to new employment opportunities depends on how much schooling they would have gained in absence of any change in labor market characteristics. Individuals who live in households with higher education are more likely to have more education in absence of migration boom.

The results show large impact on individuals of 23-27 year old cohort coming from highly educated households. An individual from high education household is almost 1.8 percentage point less likely to obtain post-SLC education as a result of a percentage point increase in migration rate. I find no evidence of heterogeneous impact on 18-22 year old cohort. Similar regressions on females also do not show any impact.

7 Discussion and conclusion

In this paper, I have examined the impact of a large increase in low-skilled migration opportunities on schooling outcomes in Nepal. The results show that low-skilled migration discourages educational investment due to low returns to education and higher opportunity cost. Further, I find that the impact is proportional to the baseline level of education; groups with higher level of education in the baseline have proportionally larger negative impact. The results confirm findings from earlier studies that expected rate of return and opportunity cost are important determinants of schooling.

This study draws attention to possible long-term impacts of low-skilled migration. TLM confers obvious benefits to households in the short-run through remittances. Greater income and reduced poverty can also benefit the next generation by allowing investment in health, improving childhood nutrition, and possibly reducing need for child labor. All of these factors can contribute to improved schooling. However, during periods of booming migration opportunities, this type of migration can also reduce schooling of young adults. In light of possible negative consequence of low-skilled migration on schooling, policy-makers need to think carefully about how to maximize benefits of such migration.

The need for careful consideration of all aspects of low-skilled migration also arises from diverse historical experiences of other countries. In some cases, TLM had an inverse-U shape pattern over time; as sending regions developed, domestic income-generating opportunities improved and obviated the need for migration. Such a pattern is observed in South Korea. On the other hand, negative impact on long-term drivers of domestic economic growth might lead to continued reliance on migration. Philippines, whose initial pattern of TLM was similar to that of South Korea, continues to send large fractions of its population abroad as low-skilled migrants. Some of this could be due to lack of industrialization due to the Dutch Disease effect of remittance inflows (De Dios and Williamson 2014). The role played by the impact of TLM on long-term drivers of growth needs to be explored further. A high level of TLM could lead to a low equilibrium level of schooling investment, possibly reducing future growth potential.

The results from this study also suggest that any policy designed to improve schooling outcomes in countries with TLM needs to keep in mind the variation in rate of return across different regions. Individuals who are more likely to migrate would require larger incentives due to their lower rate of return. Therefore, incentive programs, such as conditional cash transfer, will have to incorporate these variations across high and low migration areas.

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A Figures and Tables

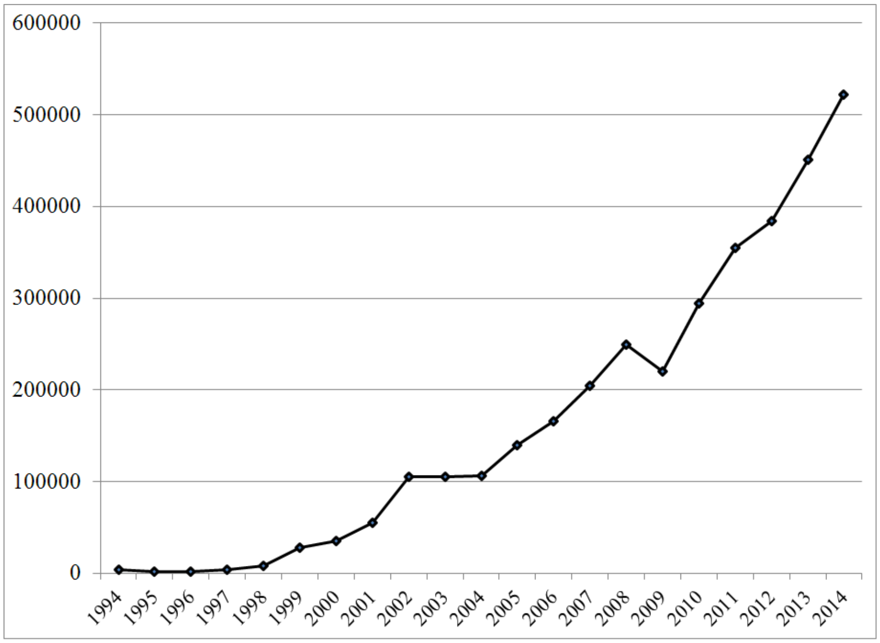

Figure 1: Labor migration boom in Nepal. Figure shows number of application for work permits recorded by the Department of Foreign Employment, Nepal, the government agency that regulates labor migration.
Source: Based on data published by Department of Foreign Employment, Nepal

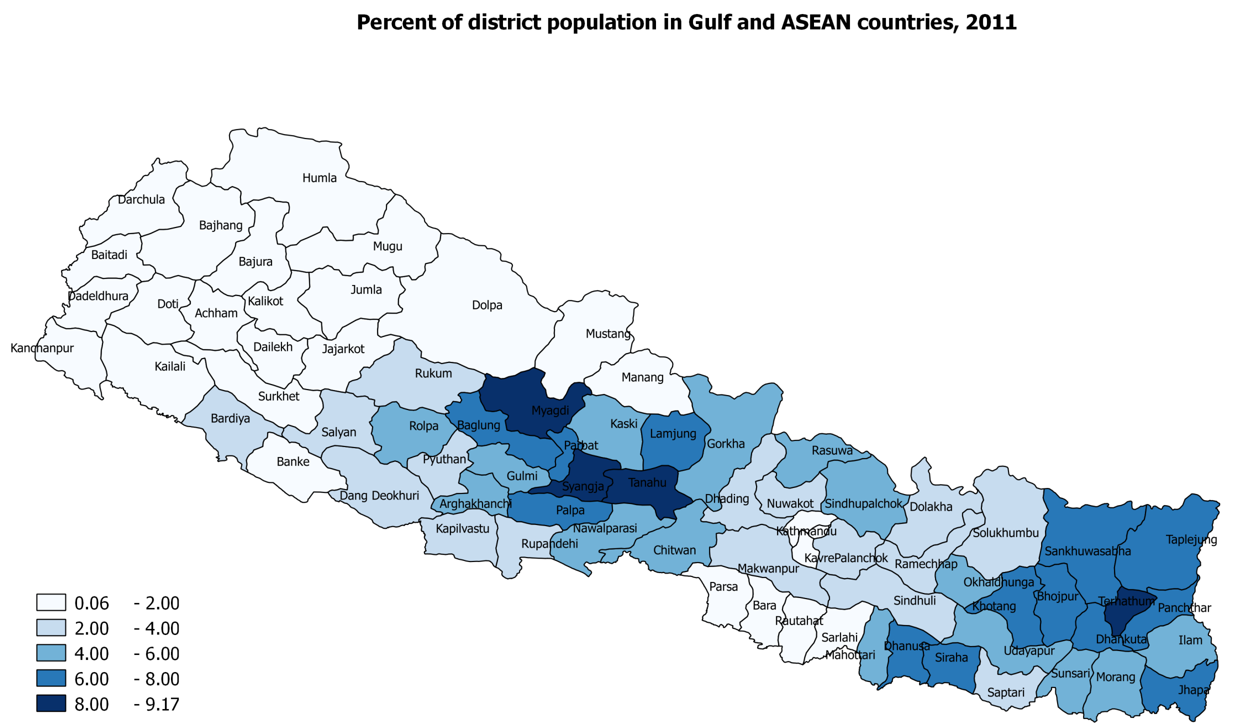

Figure 2: Spatial variation in migration rates across Nepal. The figure shows district-wise percentage of households with migrants to ASEAN and Gulf countries in 2011.
Source: Based on data from 2011 Nepal Census

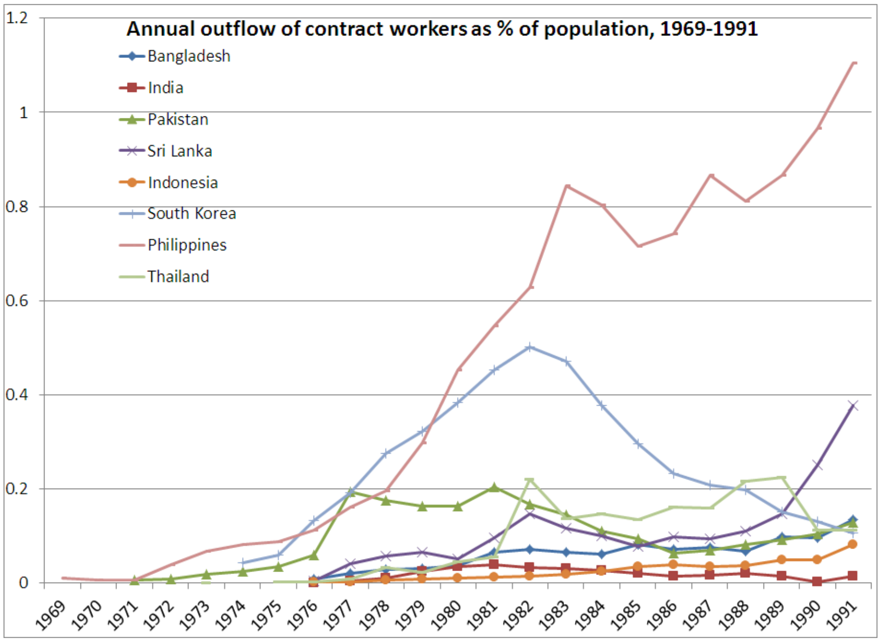

FIGURE 3: Temporary labor migration from selected countries. The figure shows historical trends in contract migration from selected countries.
Source: Based on ILO data reported in Skeldon (1997)

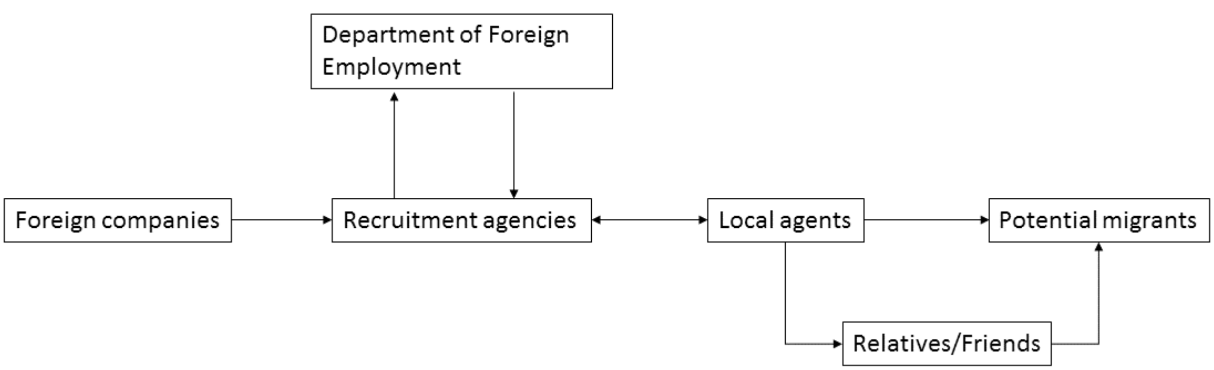

FIGURE 4: Information flow in temporary labor migration. The direction of arrows show flow of information.

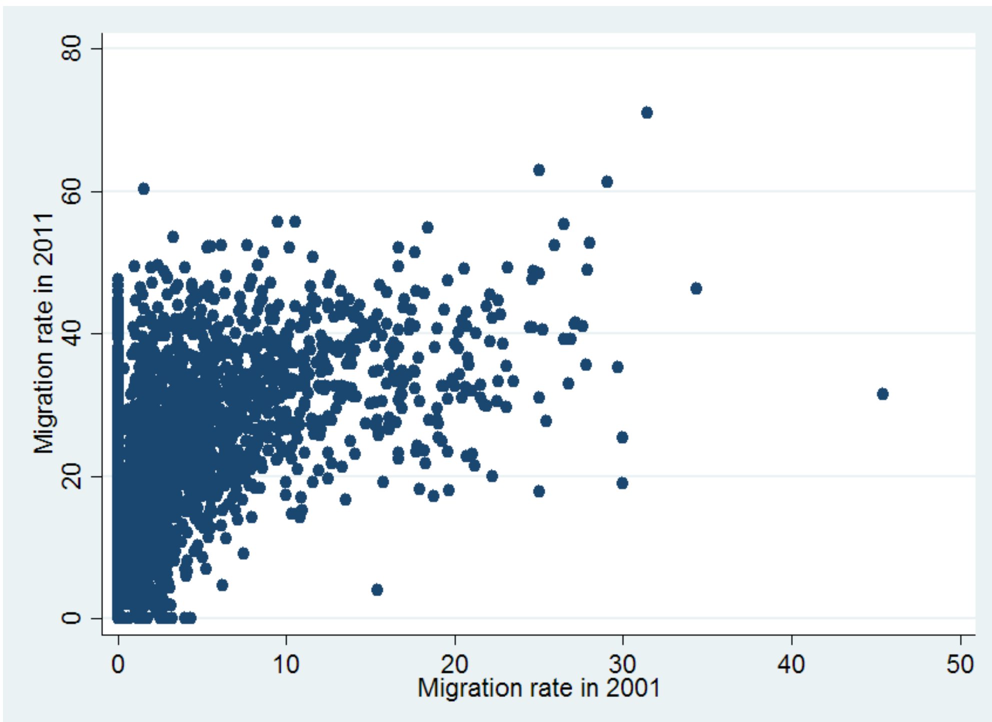

FIGURE 5: Migration rate of villages in 2001 and 2011

(A) Age 18-22

(B) Age 23-27

FIGURE 6: Correlation between change in SLC rate and TLM rate.
The vertical axis is the difference between village-level post-SLC education rate for age group 18-22 and 23-27 in 2011 and 2001.

Table 1: Estimates of migrant stocks from selected Asian countries

Country	Year	Migrant Workers (mn)	Work age Population (15-64) (mn)	Percent of working age population
Myanmar	2006	1.84	32.34	5.69
Thailand	2002	0.34	44.6	0.76
Laos	2004	0.17	3.13	5.43
Cambodia	2006	0.18	8.16	2.21
Vietnam	2005	0.4	54.38	0.74
Philippines	2006	8.2	51.48	15.93
Malaysia	1995	0.25	12.42	2.01
Singapore	2002	0.15	2.98	5.03
Indonesia	2007	2.7	149.6	1.8
China	2004	0.53	920.6	0.06
Nepal	2011	1.9	15.1	12.58

Source: For countries other than Nepal, Hugo (2008, pg. 15), for Nepal, Nepal Census 2011

TABLE 2: Characteristics of absentees pre-2001 by destination

	TLM migrants		India migrants		Other migrants		Non-migrant households
	Early	Late	Early	Late	Early	Late	
Individual characteristics							
Male	.99	.98	.9	.87	.83	.76	
	(.12)	(.14)	(.31)	(.34)	(.37)	(.43)	
Age	26.99	27.36	20.6	23.15	24.28	26.5	
	(7.35)	(6.99)	(8.21)	(10.81)	(8.24)	(9.73)	
Total individuals	1682	11152	25085	39429	2528	4485	
Household characteristics							
Highest adult education	2.45	2.14	2.15	1.34	5.35	5.32	2.97
	(3.99)	(3.81)	(3.89)	(3.03)	(5.5)	(5.47)	(4.54)
Prop. of Muslim	.08	.05	.03	.01	.01	0	.03
	(.27)	(.23)	(.17)	(.11)	(.09)	(.06)	(.17)
Prop. of Gurkha	.37	.37	.22	.2	.47	.44	.18
	(.48)	(.48)	(.42)	(.4)	(.5)	(.5)	(.38)
Prop. of Yadav	.02	.01	.01	.01	0	.01	.03
	(.15)	(.12)	(.1)	(.1)	(.07)	(.08)	(.17)
Prop. of Other caste	.53	.56	.73	.78	.52	.55	.76
	(.5)	(.5)	(.44)	(.41)	(.5)	(.5)	(.43)
Number of households	1708	10386	24739	29155	2308	3475	455953

Source: Calculation from Census 2001 micro-sample.

The table shows mean and standard deviation (in parenthesis) of early TLM migrants (those absent for 5 years or longer) relative to late migrants and non-TLM migrants. Number of household includes those with at least one migrant of relevant category.

Table 3: Cumulative distribution of educational attainment for males 18-37 by migration status

	Non-migrants	TLM	India	Other dest.
Cannot write	0.226	0.032	0.042	0.005
Primary	0.444	0.265	0.383	0.064
Lower Secondary	0.629	0.502	0.621	0.133
Secondary	0.752	0.67	0.747	0.215
SLC	0.874	0.835	0.843	0.373
Above SLC	0.999	0.91	0.896	0.962
Missing	0.999	1	0.998	0.999

Source: Nepal Census 2011
Cumulation distribution of education by migration status.

Table 4: Mean log monthly income by education of migrants and domestic workers

	Current migrants		Return migrants		Domestic workers	
	Non TLM	TLM	Non TLM	TLM	Urban	Rural
Primary or less	8.494	9.46	8.413	9.365	8.382	8.087
Secondary	8.642	9.524	8.783	9.403	8.539	8.227
SLC	9.125	9.587	8.779	9.604	8.686	8.507
Post SLC	10.002	9.932	8.932	9.836	9.094	8.868

Table shows sample means of log monthly earnings for each group. Estimates for current and return migrants computed from Nepal Migration Survey 2009. Estimates for domestic workers computed from Nepal Labor Force Survey 2008. The domestic sample includes males 15-60 with non-zero earnings. The migrant sample includes all males. Corresponding survey weights are used in computing the means.

Table 5: Comparison of education by migration status

	Urban	Rural
Domestic migrants	10.23	9.33
TLM	8.9	8.13
India migrants	8.56	7.66
Other migrants	11.47	10.04
Non migrants	9.24	6.94

Source: Nepal Labor Force Survey 2008
Table shows average education by migration status for males 18-27 year old.

Table 6: Summary statistics: Individual and household variables

	Age 18-22 N=148476		Age 23-27 N=128821		Age 28-32 N=117227		Age 33-37 N=81935	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Above SLC	0.127	0.333	0.147	0.355	0.113	0.317	0.091	0.288
Age	19.92	1.474	24.977	1.34	29.905	1.409	34.678	0.993
Caste								
Chhetri	0.165	0.371	0.161	0.368	0.162	0.368	0.164	0.37
Brahman	0.102	0.303	0.112	0.315	0.116	0.32	0.115	0.32
Tharu	0.071	0.256	0.068	0.252	0.069	0.253	0.072	0.259
Newar	0.03	0.17	0.031	0.174	0.032	0.177	0.034	0.18
Gurkha	0.208	0.406	0.21	0.407	0.2	0.4	0.191	0.393
Muslim	0.045	0.208	0.043	0.203	0.043	0.202	0.039	0.195
Yadav	0.042	0.201	0.042	0.2	0.045	0.208	0.044	0.206
Household education								
None[a]	0.132	0.339	0.213	0.41	0.385	0.487	0.521	0.5
Low	0.518	0.5	0.484	0.5	0.399	0.49	0.33	0.47
Medium	0.23	0.421	0.201	0.401	0.143	0.35	0.097	0.296
High	0.12	0.325	0.102	0.303	0.074	0.261	0.052	0.222

Source: Computed from Nepal Census 2011 micro-data
[a] Household education is based on maximum education of those 40 years and older. Households classified as "none" do not have any members older than 40.

Table 7: Summary statistics: village-level variables

	N	Mean	Std. Dev.	Min	Max
Caste characteristics					
Percentage of Gurkha	3617	23.035	27.131	0	99.731
Percentage of Yadav	3617	4.229	10.171	0	71.72
Percentage of Muslim	3617	3.894	9.762	0	81.745
Percentage of Chhetri	3617	17.476	20.715	0	99.795
Percentage of Brahman	3617	11.076	13.953	0	78.566
Percentage of Newar	3617	3.344	8.277	0	97.24
Percentage of Tharu	3617	4.406	13.228	0	94.86
Economic characteristics					
Distance to nearest urban (in km.)	3617	22.614	18.084	1.923	142.037
Average education of 15-17 year olds	3617	4.521	1.739	0	10
Percentage of domestic immigrants	3617	5.328	8.361	0	76.555
Percentage individuals in skilled occupation	3617	5.696	5.721	0	59.109
TLM rate 2011	3617	16.75	12.896	0	70.97
TLM rate 2001	3617	2.459	4.524	0	45.45
Percentage Gurkha in neighborhood	3617	20.352	17.51	0	74.40

Source: Computed from Nepal Census 2001.
Caste data comes from full enumeration tables. Economic variables are village-level averages computed from 15% micro-sample. Villages with less than 50 households, and 58 urban municipalities are excluded. Domestic immigrants is defined as those born in different location.

Table 8: OLS results

	Males		Females	
	Age 18-22	Age 23-27	Age 18-22	Age 23-27
	(1)	(2)	(3)	(4)
Migration rate	-0.00118***	-0.00252***	-0.00109***	-0.00133***
	(0.000211)	(0.000376)	(0.000219)	(0.000322)
Household education				
Low	-0.0323***	-0.00198	-0.000302	0.0170***
	(0.00354)	(0.00302)	(0.00282)	(0.00216)
Medium	0.0187***	0.0687***	0.0433***	0.0781***
	(0.00401)	(0.00418)	(0.00351)	(0.00354)
High	0.186***	0.270***	0.183***	0.235***
	(0.00555)	(0.00570)	(0.00496)	(0.00593)
Baseline econonmic characteristics of village				
Distance to urban	-0.00966***	-0.00209	-0.00948***	-0.00380
	(0.00264)	(0.00310)	(0.00262)	(0.00253)
Average education 15-17 yo	0.00504***	0.00957***	0.00617***	0.00676***
	(0.00118)	(0.00132)	(0.00102)	(0.00107)
Domestic migrants	0.000859***	0.00105***	0.00118***	0.00117***
	(0.000171)	(0.000198)	(0.000153)	(0.000185)
Skilled occupation	0.00272***	0.00438***	0.00235***	0.00337***
	(0.000322)	(0.000434)	(0.000339)	(0.000311)
Observations	117,548	101,780	116,057	101,073
R-squared	0.156	0.187	0.172	0.191

Robust standard errors clustered at village level in parentheses. The regression also includes district dummies.*** p<0.01, ** p<0.05, * p<0.1

Table shows instrumental variables regression of above SLC education on village migration rate. Other control variables not reported include: age, age-squared, individual caste dummies (Chhetri, Brahman, Tharu, Newar, Muslim, Yadav), village proportions of castes and district dummies.

Table 9: First stage OLS regression explaining migration rate in 2011

Dep. var. TLM rate	Males		Females	
	Age 18-22	Age 23-27	Age 18-22	Age 23-27
Percent Gurkha in neighborhood	0.0742***	0.0505***	0.0703***	0.0481***
	(0.0210)	(0.0130)	(0.0218)	(0.0132)
Percent Gurkha	0.113***	0.0722***	0.115***	0.0729***
	(0.0384)	(0.0263)	(0.0372)	(0.0265)
Percent Yadav	0.00589	0.00429	0.00474	0.00188
	(0.0246)	(0.0183)	(0.0275)	(0.0186)
Percent Muslim	0.109***	0.0720***	0.105***	0.0683***
	(0.0304)	(0.0185)	(0.0302)	(0.0178)
Percent Chhetri	0.0568*	0.0312*	0.0545*	0.0322*
	(0.0301)	(0.0187)	(0.0291)	(0.0184)
Percent Brahman	0.0162	0.0105	0.0154	0.0128
	(0.0305)	(0.0188)	(0.0298)	(0.0186)
Percent Newar	0.0151	0.0174	0.0154	0.0221
	(0.0320)	(0.0208)	(0.0316)	(0.0204)
Percent Tharu	0.0158	0.00766	0.0103	0.00656
	(0.0203)	(0.0109)	(0.0201)	(0.0101)
Avg. education of 15-17 yo	0.633***	0.379***	0.626***	0.377***
	(0.145)	(0.114)	(0.149)	(0.103)
Domestic in-migration	0.0445**	0.0302**	0.0408**	0.0296***
	(0.0172)	(0.0121)	(0.0187)	(0.0112)
Skilled occupation	-0.146***	-0.0825***	-0.136***	-0.0805***
	(0.0265)	(0.0167)	(0.0259)	(0.0160)
Distance to urban	-0.948**	-0.655**	-0.775*	-0.600**
	(0.433)	(0.302)	(0.421)	(0.264)
Observations	117,548	101,780	116,057	101,073
R-squared	0.677	0.638	0.681	0.640
F-stat 1st stage	12.54	14.99	10.38	13.21

Standard errors in parentheses clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

TLM rate for cohorts is computed as a weighted average of 2001 and 2011 TLM rates, with 30% and 70% weights placed on the 2011 TLM rate for cohorts 18-22 and 23-27 respectively. All explanatory variables are measured in 2001. Regression also controls for 75 district dummies.

Table 10: IV results

	Males		Females	
	Age 18-22	Age 23-27	Age 18-22	Age 23-27
	(1)	(2)	(3)	(4)
Migration rate	-0.00518**	-0.0101**	-0.00306	-0.00573
	(0.00241)	(0.00422)	(0.00262)	(0.00378)
Household education				
Low	-0.0316***	-0.000190	0.000507	0.0182***
	(0.00354)	(0.00318)	(0.00285)	(0.00232)
Medium	0.0196***	0.0711***	0.0442***	0.0795***
	(0.00400)	(0.00438)	(0.00354)	(0.00361)
High	0.185***	0.271***	0.184***	0.235***
	(0.00554)	(0.00571)	(0.00493)	(0.00592)
Baseline economic characteristics of villages				
Average education 15-17 yo	0.00768***	0.0125***	0.00747***	0.00849***
	(0.00196)	(0.00221)	(0.00197)	(0.00181)
Domestic migrants	0.00104***	0.00128***	0.00126***	0.00130***
	(0.000206)	(0.000244)	(0.000196)	(0.000219)
Skilled occpuation	0.00215***	0.00377***	0.00209***	0.00303***
	(0.000449)	(0.000563)	(0.000462)	(0.000421)
Distance to urban	-0.0128***	-0.00613	-0.0107***	-0.00592*
	(0.00342)	(0.00385)	(0.00306)	(0.00305)

Robust standard errors clustered at village level in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table shows instrumental variables regression of above SLC education on village migration rate. Other control variables not reported include: age, age-squared, individual caste dummies (Chhetri, Brahman, Tharu, Newar, Muslim, Yadav), village proportions of castes and district dummies.

Table 11: Migration rate in villages belonging to districts with different migration rate in 1991

Migration in 1991	Avg. TLM in 2001	Avg. TLM in 2011	Number of villages
Highest 11 districts	8.186	29.423	433
Remaining districts	1.68	15.027	3184

Source: Nepal Census 1991, 2001 and 2011

Table 12: Impact of migration rate estimated in subsamples

	Late boom	Late boom	Low conflict	Low conflict	BCN	BCN
	18-22	23-27	18-22	23-27	18-22	23-27
	(1)	(2)	(3)	(4)	(5)	(6)
TLM rate	-0.00615**	-0.00952*	-0.00540*	-0.0103**	-0.0104**	-0.0191**
	(0.00304)	(0.00492)	(0.00282)	(0.00477)	(0.00517)	(0.00864)
Observations	109,737	94,794	108,396	94,412	44,088	39,188
R-squared	0.153	0.187	0.156	0.187	0.165	0.158
F-stat 1st stage	8.397	11.52	9.533	11.81	6.935	8.040

The table shows the marginal impact of village TLM rate in 2011 on probability of above-SLC schooling on subsamples. "Late boom" excludes districts with TLM rates more than 0.5% in 1991. "Low conflict" means excluding districts with higher impact of conflict. "BCN" means samples comprising of Brahman, Chhetri and Newar caste only. Robust standard errors clustered at village level reported in parenthesis.

Table 13: Heterogenous impact by household education

	Males Age 18-22	Males Age 23-27	Females Age 18-22	Females Age 23-27
TLM rate	-0.00621*	-0.00988*	-0.00407	-0.00577
	(0.00329)	(0.00509)	(0.00315)	(0.00436)
Interaction with household education				
Low*TLM rate	0.00423*	0.00475	0.00305	0.000639
	(0.00242)	(0.00345)	(0.00187)	(0.00254)
Medium*TLM rate	0.000784	0.000678	0.00240	-0.000944
	(0.00243)	(0.00406)	(0.00201)	(0.00308)
High*TLM rate	-0.00112	-0.0181***	-0.00206	-0.00263
	(0.00328)	(0.00542)	(0.00259)	(0.00544)
Low HH educ	0.0219	0.0550**	0.0329	0.00624
	(0.0311)	(0.0222)	(0.0205)	(0.0160)
Medium HH educ	0.107***	0.0968***	0.0658***	0.0503**
	(0.0325)	(0.0304)	(0.0240)	(0.0240)
High HH educ	0.398***	0.511***	0.362***	0.261***
	(0.0458)	(0.0470)	(0.0357)	(0.0420)
Observations	117,548	101,780	116,057	101,073
R-squared	0.156	0.181	0.173	0.193

Table shows IV estimates of the impact of migration boom on post-SLC schooling. Robust standard errors clustered at village level in parentheses. Other control variables not reported include: age, age-squared, individual caste dummies (Chhetri, Brahman, Tharu, Newar, Muslim, Yadav), village proportions of castes, village economic variables and district dummies.

*** p<0.01, ** p<0.05, * p<0.1

Table 14: Above SLC rate by baseline SLC and TLM rate for males and females 23-27

		TLM rate							
		0-25%	25-50%	50-75%	75-100%	0-25%	25-50%	50-75%	75-100%
		Females				Males			
Baseline SLC rate	0-25%	0.04	0.06	0.06	0.06	0.1	0.09	0.08	0.08
	25-5%	0.04	0.07	0.07	0.07	0.11	0.12	0.1	0.09
	50-75%	0.07	0.09	0.1	0.08	0.15	0.15	0.13	0.11
	75-100%	0.14	0.24	0.15	0.13	0.24	0.3	0.2	0.17