Essays on the Determinants of International Migration

by

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Abstract

This thesis explores the determinants of international migration of low-skilled workers, in particular, from Nepal to Malaysia and the Persian Gulf countries. The first chapter explores how potential migrants trade the risks (of mortality) with (financial) rewards of migrating abroad. The second chapter investigates how potential migrants learn about mortality rates abroad from the incidents of migrant deaths. The third chapter investigates how various 'push' and 'pull' shocks affect international migration when a low-cost low-return destination like India is also available for the migrants.

Do potential migrants have accurate information about the risks and returns of migrating abroad? And, given the information they have, what is their revealed willingness to trade risks for higher earnings? To answer these questions, the first chapter sets up and analyzes a randomized field experiment among 3,319 potential work migrants from Nepal to Malaysia and the Persian Gulf countries. The experiment provides them with information on wages and mortality incidences in their choice destination and tracks their migration decision three months later. I find that potential migrants severely overestimate their mortality rate abroad, and that information on mortality incidences lowers this expectation. Potential migrants without prior foreign migration experience also overestimate their earnings potential abroad, and information on earnings lowers this expectation. Using exogenous variation in expectations for the inexperienced potential migrants generated by the experiment, I estimate migration elasticities of 0.7 in expected earnings and 0.5 in expected mortality. The experiment allows me to calculate the trade-off the inexperienced potential migrants make between earnings and mortality risk, and hence their value of a statistical life (VSL). The estimates range from \$0.28 million to \$0.54 million (\$0.97m - \$1.85m in PPP), which is a reasonable range for a poor population. At this revealed willingness to trade earnings for mortality risk, misinformation lowers migration.

In the second chapter, I study how potential work migrants infer mortality rates from incidents of migrant deaths. Using administrative databases on deaths and outflows of work-migrants from Nepal to Malaysia and the Persian Gulf countries, I investigate how death of a migrant from a district affects subsequent migration from the district. After controlling for confounds using district-month, destination-month and district-destination fixed effects, I find two key features of the migration response. First, migrant death lowers migration from the district in the subsequent 12 months. There is limited substitution across destinations as well as spillovers to neighboring districts. Second, the migration response to a migrant death is stronger when there are more migrant deaths in the recent past. This indicates that the potential migrants over-weight recent deaths in forming their beliefs on mortality rates abroad. I then convert the migration response to change in perceived mortality rate abroad using the earnings elasticity of migration and the value of statistical life from the first chapter. I find that one migrant death increases the perceived mortality rate by 6.7 per

thousand for a two-year migration episode. This response is too large to be explained by a model of rational Bayesian learning. Models of learning fallacy, such as belief in the law of 'small' numbers, in conjunction with other heuristic decision making rules, can explain high response to death as well as large observed overestimation of mortality rate.

In the third chapter, I study migration choices in the presence of liquidity constraints and varying costs of migration. I present a simple theoretical framework that analyzes migration response to both push and pull factors in such settings. This framework implies that a shock to the push factors in the origin leads to differential observed response to migration to various destinations, as they affect different parts of the wealth distribution. I test the implications of this framework in context of international migration from Nepal using a panel of 452 villages observed at three points in the 2000s. I use rainfall shocks and deaths due to conflict as 'push' shocks and growth in manufacturing and construction in destination countries as the 'pull' shocks. I find that a rainfall shock that increases household income by US$ 100 increases migration to India by 54 percent but has no effect on migration elsewhere. Increase in conflict, which reduces consumption and amenity of the wealthier more, increases migration abroad, particularly from the urban areas. Increase in demand from the destination countries, particularly the Gulf countries and Malaysia has strong effects on migration to those destinations. These findings are consistent with the theoretical framework, and suggest presence of large liquidity constraints. Increase in income can boost migration to India whereas a reduction in cost of migration might increase profitable migration elsewhere. The responsiveness to 'pull' shocks suggests that households are willing to take advantage of these opportunities.

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For Buba and Mummy,

who made numerous difficult sacrifices,

chose what they thought was right, over what they desired the most.

This is but a small tribute for all you have done for me, for your countless blessings,

and your unflinching support towards whatever I choose to do.

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Contents

Chapter 1

Get rich or die tryin': Perceived earnings, perceived mortality rate and the value of a statistical life of potential work-migrants from Nepal

1.1 Introduction

The number of workers moving across international borders for work is increasing. By 2013, international migrants accounted for over 12 percent of the total population in the global North, over six times the share in 1990 (UNDESA, 2015). The 2011 Gallup poll estimates that more than 1 billion people want to migrate abroad for temporary work (Esipova, Ray, and Publiese, 2011). Anecdotes and media reports abound on the risks these migrants are undertaking in search of a better life for themselves or their families. For example, more than 3,770 migrants died in the Mediterranean Sea in 2015 on their way to Europe (International Organization for Migration, 2015). In 2014, about 445 people died while trying to cross the US-Mexico border (Carroll, 2015). A high death toll is not the plight only of those who try to migrate illegally or who are forced to move. *The Guardian* reports that almost 1,000 workers, all of whom were legal migrants from Nepal, India and Bangladesh, died in Qatar in 2012 and 2013 (Gibson, 2014).

The intense desire to migrate despite the risks has led policymakers to be concerned that potential migrants may have unrealistic expectations about migration. In countries like Nepal, where more than 7 percent of adult, working-age males leave the country for work abroad in a given year, there is great concern that they make the decision recklessly.[1]

Policymakers and academics often have contradictory views on whether the level of observed migration is higher or lower than optimal. Policymakers believe that most potential migrants are misinformed – in particular, that they expect to earn more than they actually do upon migration and underestimate the risks of working abroad. Many policymakers also believe that potential migrants, knowingly or unknowingly, are trading off risks at unreasonably low prices to the extent that their experience is often termed exploitative.[2] Put together, these notions suggest that the observed rate of migration is higher than is optimal and that accurate information would lower the level.

Academic studies, on the other hand, find migration to be profitable and hugely beneficial for the marginal migrant and his or her family (see Bryan, Chowdhury, and Mobarak, 2014; McKenzie, Stillman, and Gibson, 2010, for a few examples). These studies suggest that the level of migration is suboptimal and that increased migration would be welfare improving. If anything, potential migrants' beliefs about earnings and risks are pessimistic, which suppresses migration (as briefly suggested in Bryan, Chowdhury, and Mobarak, 2014). Alternatively, many academic studies assume that individuals are fully informed and have rational expectations about the conditions at their destinations, and attribute low levels of migration to high costs, monetary and otherwise (see Kennan and Walker, 2011; Morten and Oliveira, 2014; Morten, 2013; Shenoy, 2015, for example). This literature argues that the costs, most of which are fixed, keep migration sub-optimally low and give rise to a large spatial disparity in earnings.

In this paper, I investigate whether misinformation causes suboptimal levels of migration in the context of the migration of Nepali workers to Malaysia and the Persian Gulf countries. Given the concerns on the part of policymakers, I focus on how potential migrants' beliefs on earnings and the mortality rate abroad, and the tradeoff between these two factors – the value of a statistical life (VSL) – affect migration.

Using data collected for this study, I find that potential migrants are indeed misinformed about potential earnings and mortality risk, but not always in a way that policymakers expect. Consistent

[1] An extreme example of the opinion of many policymakers is the following quote from an expert on Nepali migration: "They go without asking questions. They are not ready to listen. They just want to go. They never even bother to ask how much they will earn." (Pattisson, 2013a). Though this statement may be an exaggeration, the view that potential migrants lack information or are misinformed is widely held.

[2] Migrants working at high-risk jobs for low wages has been dubbed a form of modern-day slavery. Several newspaper articles and commissioned research reports express this view (see Deen, 2013; The Asia Foundation, 2013, and other news articles quoted elsewhere in the paper).

with widely held notions described above, inexperienced potential migrants, meaning those who have never before migrated abroad for work, overestimate their earning potential. Compared to experienced migrants – those who are better informed as they have migrated abroad for work before – they expect to earn 26 percent more. I argue that this estimate is a lower bound on the extent of misinformation as the pool of experienced migrants in my sample is likely to be selected from the higher end of the actual earnings distribution. This suggests that, even in a context where 15 percent of the households have a current migrant in one of these destinations, potential migrants can still be misinformed about their earning potential abroad. However, contrary to popular belief, potential migrants also overestimate their mortality risk abroad. The median inexperienced potential migrant expects the mortality rate to be 7 times the actual mortality rate they face, and the median experienced potential migrant expects the mortality rate to be 4 times the actual average rate. Misinformation at the mean is even larger at 13 and 21 times the actual rate for the experienced and inexperienced potential migrants, respectively.

This two-sided misinformation implies that migration decisions are being made inefficiently, and that potential migrants would make different choices with accurate information. Whether these inefficiencies cause the aggregate migration level to be too high or too low depends upon two things: the elasticity of migration with respect to expected earnings abroad and the elasticity of migration with respect to expected mortality rate abroad. These two elasticities will also pin down the VSL, which will elucidate whether potential work migrants are making reasonable trade-off with the information that they have.

To estimate these elasticities and the VSL, I conducted a randomized controlled trial that provides information and observes changes in expectations and subsequent migration decisions. Among 3,319 potential migrants who came to Kathmandu to apply for a passport in January 2015, I randomly provided information on earnings and/or mortality incidences of Nepali workers in their destination of choice. The earnings information treatments provided information on the average contractual wages reported to the official authority of Nepal by two cohorts of migrants. The mortality incidence information treatments consisted of death tolls of Nepali migrants from some pre-determined districts in Nepal. To avoid deception, I gave individuals information from different districts with high and low numbers of deaths. Death information was cross-randomized with wage information.

The informational interventions changed the earnings and mortality rate expectations of potential migrants, particularly of those who were likely to be misinformed. To measure the effect of information on their expectations, I elicited their beliefs on earnings upon migration and on the mortality risk to be faced while abroad. The information treatment on deaths, particularly the 'low' death information, lowered their expected mortality rate by 20 percent relative to the expectation of those who did not receive any information (control group). The effect was larger for inexperienced potential migrants, at 30 percent relative to the expectation of the control group. Information on earnings also lowered earnings expectations for the inexperienced potential migrants: compared to the control group, those who received earnings information expected to earn 8 percent less. However, for the experienced, providing wage information had no effect. This is not surprising, as the experienced migrants had better information about their earning potential abroad.

Moreover, these changes in expectations led to changes in migration decisions. Three months after the interventions, inexperienced potential migrants provided with 'low' death information were 7 percentage points more likely to have migrated, and those provided with wage information were 6 percentage points less likely to have migrated. The effects are about 30 percent of the migration rates observed in the group that did not receive any information. This finding has the clear policy implication that a simple and well-targeted informational intervention can change perceptions as well as the actual migration decisions of potential migrants.

Using the experimental setup, I estimate a binary choice model of the migration decisions of inexperienced potential migrants with randomized information assignments as instruments for mortality risks and earnings from migration.[3] Under the assumption that the information treatments did not change unobserved amenities associated with migration (which I discuss in the main text), the estimated coefficients imply an earnings elasticity of migration of 0.7 and an elasticity of migration with respect to expected mortality rate of 0.5. The (negative) ratio of coefficients on mortality rate and earnings gives the implicit value of a statistical life (VSL) as revealed by their decision to migrate. These coefficients imply a VSL of \$0.28 million to \$0.54 million (\$0.97m - \$1.85m in PPP). These estimates are lower compared to the estimates for the US (Viscusi and Aldy, 2003), but these differences can be accounted for by differences in earnings. In both cases, the estimates of VSL are 100 to 300 times the median household income.[4] This suggests that, given the level of information that potential migrants have, the tradeoff they are willing to make does not appear to be unreasonably low. Furthermore, this level of VSL and the estimated earnings and mortality elasticities of migration suggest that misinformation along these two dimensions has indeed lowered

[3]Since the information treatments did not change earnings expectations of experienced potential migrants, this strategy would not work for this group.

[4]In per-capita terms, the estimate for Nepal would be higher given the larger household sizes.

migration overall. This result is driven by the fact that misinformation on mortality rate dwarfs misinformation on earnings, whereas the migration response to changes in these expectations are roughly the same.

These findings raise the question of how such a large level of misinformation on mortality rate can persist despite high migration flows. To investigate this, I infer the change in the perceived mortality rate for potential migrants following an actual death of a migrant. I take the migration response to an actual migrant death from Chapter 2, and use the estimated earnings elasticity and the VSL to translate the migration response into an induced change in beliefs on mortality rate. This exercise suggests that potential migrants update their beliefs on mortality rate by a considerable amount following death events. Additionally, the response is greater when there have been more migrant deaths in the recent past. As explored in Chapter 2, these patterns are inconsistent with models of rational learning. Models of learnings fallacy, such as the law of 'small' numbers, combined with some heuristic decision rules may explain the observed high levels of overestimation as well as the sensitivity to recent information about migrant deaths (see Rabin, 2002; Tversky and Kahneman, 1971, 1973; Kahneman and Tversky, 1974, for related literature). Therefore, a fallacious belief-formation process, which leads to high overestimation of mortality rate abroad among potential migrants, has kept migration levels lower than optimal in this context.

Apart from providing an important insight into how beliefs can affect migration, this paper makes a methodological contribution to the literature estimating the VSL from revealed preferences. Thus far, much of the empirical literature has taken the route of estimating the wage hedonic regression (see Thaler and Rosen (1976) for a theoretical foundation, and Viscusi and Aldy, 2003 and Cropper, Hammitt, and Robinson, 2011 for reviews). One key issue with this literature is that in many settings, mortality risks are correlated with unobserved determinants of wages confounding identification (see Ashenfelter, 2006; Ashenfelter and Greenstone, 2004a, for critiques). In this study, the use of randomized treatments as instruments effectively solves the omitted variables and endogeneity problem. Further, by directly measuring individual perceptions on earnings and mortality risk, I overcome the bias resulting from measurement error of the risks or the issue of decision-makers being unaware of the true risks (see Black and Kniesner, 2003, for effects of biases from measurement errors).[5] To the best of my knowledge, this is the first study to estimate the VSL

[5]Though I elicit subjective perceptions on earnings and wages, it is different from the strand of literature that estimates VSL by eliciting subjective willingness to pay directly. See Cropper, Hammitt, and Robinson (2011) for a review of this literature.

using exogenous variations in perceived risks and rewards generated from a randomized experiment.[6]

This paper also contributes to the relatively scant literature seeking to quantify the extent of misinformation on earnings in context of international migration. McKenzie, Gibson, and Stillman (2013) and Seshan and Zubrickas (2015) find that those who do not migrate, including family members, have different expectations about earnings abroad. However, contrary to the current study, these studies find that potential migrants and their family members underestimate the potential earnings from migration. In a context similar to these studies, Beam (2015) finds that attending a job fair increases expectations of earnings abroad, but does not induce them to take any actions towards migrating abroad. This study also adds to the literature on the effectiveness of providing information on improving outcomes for migrants. Shrestha and Yang (2015) find that informing Filipino maids working in Singapore about the legal processes for changing jobs improves their working conditions and, for those with worse job characteristics, facilitates job transition. On the other hand, Bryan, Chowdhury, and Mobarak (2014) find that providing job related information in the context of seasonal migration within Bangladesh has absolutely no effect on migration or other outcomes. To the best of my knowledge, there are no other rigorous studies that quantify the extent of misinformation on risks associated with migration.

This paper builds on and adapts the literature on eliciting probabilistic expectations in developing countries to the current context. Many studies in developing countries have used some variant of the elicitation methodology developed in Manski (2004) and Dominitz and Manski (1997) and have adapted it to diverse contexts (see Attanasio, 2009; Delavande, Giné, and McKenzie, 2011, for recent reviews). Specifically, this study adapts the approach used in Attanasio and Kaufmann (2009) to elicit the range of subject beliefs, and the approaches used in Dizon-Ross (2014) and Delavande and Kohler (2009) to elicit a coarse measure of the entire probability distribution of the subjects' beliefs. While the latter studies elicit probability density function (pdf) of beliefs within a pre-determined and wide range of values, I allow for the range of values to be determined by the range of beliefs of the respondents themselves. This allows for a more precise estimate of the p.d.f. of their beliefs. As far as I know, in a developing country context, McKenzie, Gibson, and Stillman (2013) remains the only other study to elicit subjective expectations of potential earnings from migration abroad, and Delavande and Kohler (2009) is the only other study to elicit subjective

[6]This paper is closest in approach to Greenstone, Ryan, and Yankovich (2014) and León and Miguel (2013) who use a discrete-choice framework to study re-enlistment decisions of US soldiers and transportation choices of travelers to the Sierra Leone airport, respectively. While the institutional settings in their respective contexts drive identification in these studies, the identification of this study comes from the randomized assignment of information treatments. See Section 1.6 for a detailed discussion.

expectations on mortality rate.

Finally, this paper relates to a growing literature on the effectiveness of targeted information in ameliorating information failure. Some examples of studies where information interventions have proven to be quite successful include Jensen (2010), Nguyen (2008), and Dinkelman and Martínez A (2014) on improving schooling; Dizon-Ross (2014) on parental investment in the schooling of their children; Duflo and Saez (2003) on better planning for retirement; De Mel, McKenzie, and Woodruff (2011) on better access to credit; Dupas (2011a) and Godlonton, Munthali, and Thornton (2015) on safer sexual behaviors; Madajewicz, Pfaff, Van Geen, Graziano, Hussein, Momotaj, Sylvi, and Ahsan (2007) on choices of safe drinking water; and Shrestha and Yang (2015) on improving job satisfaction among migrant workers. This study shows another context where providing credible information can be a powerful policy tool to enable potential migrants to make informed decisions.[7]

The rest of the paper is organized as follows: Section 1.2 describes the context and the study setting, Section 1.3 outlines the intervention design and empirical strategy, Section 1.4 discusses the effect of the interventions on perceptions, Section 1.5 describes the follow-up survey and presents the effect of the interventions on migration and other outcomes, Section 1.6 outlines the methodology for VSL estimation and presents the results, Section 1.7 uses the VSL and the elasticity estimates to understand the large extent of misinformation on mortality risks, and Section 1.8 concludes.

1.2 Context and study setting

With remittances from abroad comprising almost a third of the national GDP, international migration for work is tremendously important for Nepal. In this section, I first describe the national context of migration to Malaysia and the Persian Gulf countries. I then describe the context specific to this study and compare the study sample with the population of migrants in the country along a few observable characteristics.

1.2.1 Context

In recent years, Nepal has been one of the biggest suppliers of low-skill labor to Malaysia and the Persian Gulf countries. This phenomenon, however, is quite recent. As Appendix Table 1.B.1 shows

[7]Providing information may not be sufficient to change behaviors in other contexts (see Bryan, Chowdhury, and Mobarak, 2014, for instance), especially when other constraints are more binding. In addition, the content of the information, its manner of presentation, the identity of the information provider, and the identity of the recipient may matter in determining the effectiveness of providing information (see Dupas, 2011b, for a review of the role of information in the context of health).

that historically migrant-to-population ratio hovered slightly above 3 percent and was driven mostly by migration to India, with which Nepal maintains an open border. However, between 2001 and 2011, the share of non-India migrants exploded six-fold with only a small change in the share of India migrants. The rising Maoist conflict in the early 2000s and the economic instability during the conflict and in years following the end of that conflict are often cited as key reasons behind this surge. However, in Chapter 3, I find that migration flows to non-India destinations are more responsive to shocks in the destination economies than to incomes at the origin. This suggests that the booming demand for low-skill labor in Malaysia and the Persian Gulf countries in the 2000s is key in attracting many Nepali workers.

By 2011, one out of every four households had an international work migrant and almost a fifth (18 percent) had a migrant in destinations outside India. More than a fifth (22 percent) of Nepal's male working-age population (15-45) is abroad, mostly for work. This surge has been driven by work-related migration to these primary destinations: Malaysia, Qatar, Saudi Arabia, and the United Arab Emirates. This type of migration is typically temporary with each episode lasting 2-3 years.[8] In many of the countries, especially in the Persian Gulf, a work visa is tied to specific employment with a specific employer.[9] It is rare that such migrants eventually end up permanently residing in the destination countries.

The outflow of Nepali workers to these countries has continued to increase in recent years. Appendix Figure 1.B.1 shows the numbers of work permits granted by the Department of Foreign Employment (DoFE) for Nepali workers seeking employment abroad.[10] In 2013 alone, the share of males acquiring work permits was about 7 percent of the adult working-age population in the country. As a result, remittance income as a share of national GDP increased from a mere 2.4 percent in 2001 to about 29 percent in 2013 (The World Bank).

The process of finding jobs in these destination countries is heavily intermediated. Potential migrants typically contact (or are contacted by) independent local agents who link them to recruitment firms, popularly known as "manpower companies", in Kathmandu. These local agents are typically fellow villagers with good contacts in the manpower companies who recruit people for foreign employment from their own or neighboring villages. In addition, most local agents also help

[8]The modal migration duration to the Persian Gulf countries is 2 years and to Malaysia is 3 years.

[9]Naidu, Nyarko, and Wang (2014) study the impact of relaxing such a constraint in Saudi Arabia.

[10]The Government of Nepal has allowed private recruitment of workers to certain countries since the mid 90s upon clearance from the Ministry of Labor. The Department of Foreign Employment was established in December 2008 to handle the increased flow of migrant workers to these destinations. The DoFE numbers presented here exclude work migrants to India and to other developed countries.

potential migrants obtain passports and other related travel documents. The manpower companies receive job vacancies from firms (or employment agencies) abroad. They are responsible for screening (if at all) and matching individuals with job openings, processing contracts, obtaining necessary clearances from the DoFE, obtaining medical clearances, arranging for travel, visa and other related tasks. Both local agents and the manpower companies receive a commission, which potential workers pay prior to departure. It is unclear what fraction of the total costs of intermediation is borne by the employer, the employee, and what portions of the service charge go to the local agents and the manpower companies.[11]

With a large share of the adult male population working mostly in a handful of destination countries, one might expect that information about the risks and rewards of migration would flow back home. Information, especially about earnings abroad, would be expected to flow well among potential work migrants though information about mortality rate, due to its rare occurrence, may be harder to learn. The potential migrants could even use the social network of current migrants to find work abroad (as in Munshi, 2003).

However, there is a growing sense among policymakers that potential migrants do not have proper information about the rewards of migration. Anecdotes abound on how migrants discover the true nature of their jobs to their frustration and dissatisfaction only upon arrival at their destination. Since the intermediaries are paid only when people migrate, they have financial incentives to distort the information they provide, drawing potential migrants abroad. Though migrants need contracts from employers to receive clearances prior to migration, recruitment agents and agencies commonly acknowledge that many of these contracts are not honored (the potential migrants may or may not be aware of this). Further, a large share of the potential migrant earnings comes from over-time compensation, which may not be explicitly mentioned in the contracts that workers receive. Because of these varied and biased sources of information, and because of somewhat fraudulent paperwork practices, potential migrants are often misinformed about their potential earnings.

Similarly, policymakers and journalists alike are of the opinion that potential migrants are submitting themselves to high risk of mortality by migrating to these countries. In recent years, national and international media have given considerable attention to the numbers of Nepali workers who die abroad, and to the exploitative conditions they work under. (see Pattisson, 2013b, and several

[11]Though the Government of Nepal has agreements with some countries that employers, not potential workers, must pay the cost of migration (including travel costs and intermediation fees), the agreements do not seem to hold in practice. The amounts potential work migrants expect to pay is, in reality, higher than the cost of travel and reasonable levels of intermediation fees.

ensuing articles in *The Guardian*, for instance). With a distinctly humanitarian perspective,they portray the system, as a 'modern-day slavery'. This focus could give potential migrants a misleading impression of mortality rates, as the stocks of Nepali migrants in these countries are rarely included in these reports. Further, deaths of men of the same age group in Nepal rarely receive media or policy attention unless they are a result of some horrific accident. Such biases in reporting could make it much harder for potential migrants to be accurately informed about the underlying death rates from migration abroad.

All of this culminates in a belief among policymakers that potential migrants, knowingly or unknowingly, are trading high risks at unreasonably low prices. However, policymakers' beliefs are, after all, beliefs – not often fully guided by rigorous evidence. For instance, there is no evidence on potential migrants' actual beliefs on mortality rate and whether they actually respond to media coverage of deaths. The higher death tolls could, in fact, simply reflect increased migration to those destinations as a result of increased opportunities abroad.

1.2.2 Study setting and sample

The baseline survey for this study and the experiment was conducted at the Department of Passport (DoP) in Kathmandu in January, 2015. Though Nepali citizens can obtain a new passport from the office of the Chief District Officer in their respective district headquarters at a cost of US $50, it takes almost 3 months to receive a passport. On the other hand, if they apply for their passports at the DoP in Kathmandu, they can opt for the 'fast-track' option and obtain their passport within a week at a cost of US $100. Many potential migrants, who are often guided by local agents, use this expedited service to obtain their passports. DoP officials estimated that during the period of the study, an average of 2,500 individuals applied for passports every day. However, not everyone who has a passport will eventually migrate.[12] In fact, many of the study subjects mentioned that they were not sure whether they would eventually go for foreign employment and were applying for passports just to have the option of going abroad.

For this study, passport applicants who just finished submitting their applications were approached and screened for eligibility for the study. Any male applicant who expressed an intention of working in Malaysia or the Persian Gulf countries was eligible. Enumerators explained the purpose of this study, and those who consented to be interviewed were taken to a designated section on

[12] The estimates of the number of Nepali leaving the country hovers around 1,000 to 2,000 per day, many of whom may have old passports.

the premises of DoP for the full interview.[13] At this stage, the passport applicants were told that the purpose of the study was to find out how well informed potential migrants were about work migration abroad, and to see how information affected their migration decision. They were not told the exact nature of the information treatment.

The DoP office is a busy environment, yet the study was conducted in an area reserved exclusively for the study, free from outside interference. The DoP restricts non-applicants from entering the premises of the office, due to the volume of applicants, so no family members, friends, or local recruitment agents interfered with the interviews.[14] Figure 1.1 shows the setting, with individuals queuing at the application counters, and the designated area in the foreground, where enumerators are interviewing the respondents and entering their responses in electronic data collection devices.

Between January 4, 2015 and February 3, 2015, we interviewed 3,319 eligible potential migrants. Though the study was conducted in the DoP in Kathmandu, it appears to be representative of the population of current migrants in the country (Appendix Table 1.B.2). The average potential migrant in the study sample is 27.6 years of age and has 7.5 years of schooling, quite similar to the age and schooling of current migrants in the 2011 census (top panel, columns 1 and 2). It is important to note that the study sample is predominantly low-skilled. Only 15 percent of the sample had completed more than 10 years of schooling, and only 2 percent had any college education. The study sample is predominantly rural and participants are equally likely to be from the southern plains (Terai) as from the hills and mountains – again, similar to the distribution of migrants in the census (second panel, columns 1 and 2). Compared to the migrants in the census, the study sample is slightly more likely to be from the mid-western and far-western regions. However, this difference could reflect a change in the actual trend as migration has become more ubiquitous in 2014 than it was in 2011. Similarly, the distribution of migrants looks similar across Malaysia and the Gulf countries in both the samples (third panel, columns 1 and 2).

There are three distinct groups of potential migrants in the study sample. There are 1,411 "inexperienced" potential migrants who have not yet migrated abroad for foreign employment. Of the remainder, 1,341 are "experienced" potential migrants, those who have migrated abroad for work abroad, but do not have an existing employment contract abroad. That is, these individuals have

[13]Due to the large volume of people submitting their applications, the enumerators could not systematically keep a record of how many people they approached in a day. Though the office accepted applications from 8:00 AM until 4:00 PM, most eligible applicants chose the morning hours. On most days, the eligible applicants stopped coming in by 2:00 PM.

[14]The DoP made an exception for this study by letting the enumerators inside the premises and allowing them to conduct the interviews.

to search for employment again. The remaining 567 potential migrants are "on leave" from their work abroad. That is, they have an existing employment contract abroad and do not have to look for work. They are back in Nepal on a holiday and must renew their passports. For the remainder of the paper, I will use this classification unless explicitly noted otherwise.

The average inexperienced potential migrant is younger and slightly more educated than the experienced one, is 6.4 years younger and has 0.7 more years of schooling (Appendix Table 1.B.2, columns 3 and 4). The difference in schooling is likely to represent the national cohort trend in schooling more than anything else. The geographic distribution of these two groups is quite similar, except that the inexperienced are more likely to be from mid-western and far-western regions than are the experienced ones – again possibly reflecting a geographic trend as migration became more ubiquitous over the years. In terms of destination choices, the inexperienced are more likely to want to go to Malaysia than the experienced.

1.3 Survey design and empirical strategy

The first part of this section describes the nature of the information provided, along with the experimental design. I then describe the process by which expectations on earnings and mortality were measured. The second part of this section discusses balance checks, and the third part presents the empirical specification.

1.3.1 Design of the informational intervention

Each of the eligible male subjects who consented to be interviewed was asked questions on basic demographics, location and previous migration experience. They were also asked to name the destination country they were most likely to go to. They were given some information relevant to their chosen destination. The information was provided verbally by the enumerators as well as in the form of a card that the respondents could keep for the duration of the interview. The precise content of the information depended upon a random number generator built into the data-collection devices.

There were three types of information that could be provided to the individuals: basic information, wage information, and death information. When individuals were selected to receive either the wage or the death information, they could get either the 'high' variant of the information or the 'low' variant. I picked two different information treatment arms because there were no pre-existing information on the beliefs of potential migrants. Providing two different information treatments would ensure that at least one of them would serve as new information to the potential migrants. Since deliberate misinformation was already a concern in this context, I chose not to deceive them. For the wage information, the only source of information available was the wage reports made by previous cohorts of migrants to the DoFE in their application to receive the permit for employment abroad. Therefore, two different years were chosen to generate the 'high' and the 'low' variant of the wage information, and the year the information was pertinent to was stated clearly when providing the information. For the death information treatment arms, I provided information on the death toll from a reference district. I varied the reference district to generate the 'high' and 'low' variants. Death toll was provided instead of death rates to emulate the kind of information they would see in reality. Further, providing respondents with numbers prevents them from repeating the same rates when they were asked about their mortality beliefs later in the survey.

The following lays out the precise wording and the content of the information treatments:

1. Basic information: This information was provided to everybody. This contained information on the number of people leaving Nepal for work in the subject's destination of choice. For example:

   Every month, XXXX people from Nepal leave for work in DEST

2. Wage information: A randomly chosen third of the respondents did not receive any information on wages. Another third received the 'high' variant with information for 2013, net earnings of $5,700, whereas the remainder received the 'low' variant with information for 2010, net earnings of $3,000, using the exchange rate at the time of the survey. However, simply adjusting the 'low' 2010 numbers for the observed exchange rate increase of 30 percent and yearly inflation rate of 10 percent, would bring the estimate quite close to the 'high' 2013 numbers. As the year of the statistic was clearly mentioned in the information provided to them, many seemed to have accounted for the changes themselves. Therefore, the manipulation within the two groups is not too large. In any case, the exact wording of the information was:

   In YYYY, migrants to DEST earned NRs. EEEE only in a month

3. Death information: As with the wage information treatment, a randomly chosen third of the respondents received no information on deaths, another third received the 'high' variant and

the remainder received the 'low' variant. The information provided was the number of deaths of Nepali migrants in their chosen destination from some pre-determined district. For the 'high' variant, the district was chosen from the top 25^{th} percentile of the mortality distribution in the country, whereas for the 'low' variant, the district was chosen from the bottom 25^{th} percentile.[15] If the national migrant stock in the destination countries was evenly distributed throughout all the districts, the 'high' death information translated to an annual mortality rate of 1.9 per 1000 migrants and the 'low' death information translated to a mortality rate of 0.5 per 1000 migrants. The exact wording of the information was:

> **Last year, NN individuals from DIST, one of Nepal's 75 districts, died in DEST**

A built-in random number generator determined what wage and death information (if any) would be provided to each of the respondents. The assignment of wage information treatments was independent of the assignment of death information treatments. Figure 1.2 shows two examples of the cards shown to respondents. On the left is an example of the card shown to a respondent intending to migrate to Malaysia for work and who is chosen to receive a 'high' wage information and a 'low' death information. On the right is an example of the card shown to a respondent intending to migrate to Qatar for work and who is chosen to receive the 'high' death information and no wage information. The full set of information provided is shown in Appendix Table 1.B.3. Table 1.1 shows the breakdown of the sample by randomization group.

1.3.2 Eliciting beliefs on earnings and mortality rate

After the cards were shown to the respondents, they were asked questions designed to elicit their beliefs on earnings and mortality upon migration.[16] As discussed in the Introduction, the approach and questions derive from the probabilistic expectations elicitation method of Manski (2004) and Dominitz and Manski (1997) adapted to eliciting subjective probability with visual aids in developing countries. At first, the respondents were asked to mention a range of possible monthly earnings from migration:

[15] Only 1.4 percent of the candidates that received any death information were from the same district as the reference district. 6.8 percent were from a neighboring district of the reference district.

[16] During the pilot, I tried a variant of the questionnaire that elicited expectations both before and after the information intervention. The elicitation of expectations constituted the bulk of the questionnaire, and therefore respondents resorted to anchoring their answers when the same question was asked after the information intervention. Hence, I decided to elicit expectation only once in the survey after the information intervention. Consequently, I compare expectations across people of different groups.

> If you worked in this job, what is the min/max earnings that you will make in a month?

When enumerators entered the range in their data-collection devices, the software uniformly divided the range into five categories. Enumerators then asked a more detailed question to elicit the entire probability distribution of their beliefs across the five categories spanning the range of their expected earnings. The script for the question to elicit the probability density function was:

> Now I will give you 10 tokens to allocate to the 5 categories in the range that you mentioned. You should allocate more tokens to categories that you think are more likely and fewer tokens to categories that you think are less likely. That is, if you think that a particular category is extremely unlikely, you should put zero tokens. Similarly, if you think that a particular category is certain, you should put all the tokens in that category. If you think all of the categories are equally likely, you should put equal number of tokens in all of them. There are no right and wrong answers here, so you should place tokens according to your expectation about your earnings abroad. Note that each token represents a 1 in 10 chance of that category being likely.

This process of using tokens is similar to that of using beans by Delavande and Kohler (2009) to elicit subjective probability distribution on mortality.

To elicit the range of their beliefs on mortality rates abroad, the following leading question was asked:

> Suppose that 1000 people just like you went to [DEST] for foreign employment for 2 years. Remember that these individuals are of the same age, health status, education, work experience and have all other characteristics as you do. Suppose all of them work in the same job. Now think about the working conditions and various risks they would face during their foreign employment. Many people will be fine but some get unlucky and get into accidents, get sick or even die. You may have heard about such deaths yourself. Taking all this into account, of the 1000 people that migrate for foreign employment, at least (most) how many will die within 2 years upon migrating to [DEST]?

The data-collection devices again automatically divided the range uniformly into five categories based on the range of expected mortality.[17] Enumerators then asked the subjects to distribute the

[17] In cases where respondents gave a range less than 5, they were asked to place tokens in the integer values that they mention. For instance, if they mentioned 1 and 4 as their range, they were asked to place token in categories: 1, 2, 3, and 4.

ten tokens across the five categories based on their beliefs, using a script very similar to the one described above. Enumerators were trained extensively on the scripts and were instructed to be patient with the respondents. They were instructed to repeat the script as well as give additional explanations if the respondents seemed unclear on what was being asked.

To minimize any confusion among respondents, a few confirmatory follow-up questions were added to ensure that the question captured their true beliefs. For instance, if someone answered "50" to the first question, a follow-up question would confirm whether they mean 1 out of 20 individuals would die. If, in response to the follow-up question, the respondent felt that his initial answer was not in line with his beliefs, he would reconcile his estimate.

1.3.3 Balance

Individuals in the initial survey were randomly assigned to various treatment groups based on a random number generator built into the software of the data-collection devices. Based on the random number, an appropriate intervention message would appear on the screens, which the enumerators would read out to the subjects after giving them the corresponding information cards. A few characteristics of the respondents were collected prior to randomization: their age, years of schooling, prior migration experience, location and their intended destination. I check for balance by comparing means for each of these characteristics between any two arms of each type of intervention. For the death interventions, I compare average characteristics in the control group with the 'high' treatment group, the control group with the 'low' treatment group and finally the 'high' treatment group with the 'low' treatment group. Appendix Tables 1.B.4- 1.B.9 show the detailed comparisons.

The overall sample looks well balanced with only 2 out of 48 comparisons significantly different for death groups at 95 and 90 percent significance levels. Similarly, 3 out of 48 comparisons in the wage groups are significant at the 95 percent significance level and 4 at the 90 percent level. These results are what one would expect purely from random chance. The joint tests across all comparisons have a p-value of 0.65 for comparisons within death information treatment arms and 0.48 for comparisons within wage information treatment arms, which affirms that randomization was balanced across these observable characteristics.

Since most of my analysis focuses on subgroups of inexperienced and experienced migrants, I present balance checks for these subgroups as well.[18] For the sample of inexperienced potential

[18]Since the survey did not have a pre-existing pool of potential candidates, randomization was done in-field in real time without the possibility of a stratification by prior experience.

migrants, only 1 out of 39 comparisons is significantly different at the 5 and 10 percent significance levels for both types of interventions. This is lower than what one would expect from random chance. Consequently, for the sample of experienced migrants, of the 42 comparisons, 3 appear significant at the 95 percent significance level and 7 at the 90 percent level. This is slightly higher than what one would expect by random chance alone (2 and 4 at the 95 and 90 percent significance levels). However, the joint test across all outcomes fails to reject equality across the treatment arms at conventional levels. Furthermore, in all of the empirical specifications to follow, the point estimates are similar and the substantive results the same with the inclusion or exclusion of these variables as controls.

1.3.4 Empirical specification

The randomized nature of the intervention implies that the basic empirical specification to estimate the effect of the programs is quite straightforward. I estimate

$$y_i = \delta_1 DeathLo_i + \delta_2 DeathHi_i + \alpha_1 WageLo_i + \alpha_2 WageHi_i + X_i\beta + \varepsilon_i \tag{1.1}$$

where y_i is the outcome for individual i, $DeathLo_i$, $DeathHi_i$, $WageLo_i$ and $WageHi_i$ are indicators of whether individual i receives any of these treatments. X_i are a set of controls which includes full set of interactions between education categories, age categories and location, indicators for the chosen destination, and enumerator fixed effects. ε_i represents the error term, and I allow arbitrary correlation across individuals at the date of initial survey $\times$ enumerators level. The standard errors remain quantitatively similar with alternative clustering specifications.

1.4 Does providing information affect perceptions?

Using data from the control group (which does not receive any information on wages or deaths), the first part of this section establishes that potential migrants are indeed misinformed about earnings and mortality risks of migration. To do so, I only use the data on the subjects that did not receive any informational intervention. In the second part of this section, I estimate the impact of the informational treatment on perceptions about mortality and earnings.

1.4.1 Descriptive evidence on the extent of misinformation

Misinformation in expected earnings

Misinformation about earnings abroad may persist even in cases where a large share of the population is a migrant. As discussed earlier, local agents and recruitment companies have an incentive to exaggerate earnings information to induce potential migrants to go. Moreover, previous migrants may also provide biased information. They may lie about their earnings to their social network if they fear social taxation, or feel pressure to maintain any social prestige they gain from having migrated abroad (as in McKenzie, Gibson, and Stillman, 2013, Seshan and Zubrickas, 2015, and Sayad, Macey, and Bourdieu, 2004). This has fueled concern among policymakers that potential migrants may overestimate their earning potential abroad.

However, systematic evidence on the degree of such misinformation is rare. To date, there are no credible surveys of migrants in the destination countries to determine the actual earnings of Nepali migrants.[19] Further, the government does not have a way to track actual earnings abroad. The Department of Foreign Employment only receives reports of contractual earnings from potential migrants when they apply for permits to work abroad, and even this data is not publicly available. In this section, I use the survey data I collected to compare potential migrants' expectations with a few benchmarks to establish that potential migrants are misinformed on their earning potential.

An inexperienced potential migrant expects to earn more than the experienced ones (those who have migrated before).[20] On average, an inexperienced potential migrant expects to earn $12,300 (net) from one migration episode, which is 26 percent more than the expectation of those who have migrated before (Figure 1.3). This pattern holds for most of the distributions of earnings expectations. Above the 20th percentile, each quantile of expected earnings of inexperienced potential migrants is higher than the corresponding quantile for those who have migrated before. For instance, the median inexperienced potential migrant expects to earn 23 percent more compared to the median migrant with prior migration experience, and the extent of the discrepancy remains about the same even at the 95th percentile.

It is quite striking that the inexperienced migrants expect to earn more than those with greater

[19]The closest to this approach is the Nepal Migration Survey of 2009 conducted by the The World Bank (2011), which asked household members about the earnings of the foreign migrants. It also asked the returnees the actual earnings they made during their migration episode. Other than the fact that this data was collected almost six years ago, it also suffers from reporting biases of the household members, and reflects the misinformation within the household as highlighted in Seshan and Zubrickas (2015).

[20]Note the change in definition of experienced migrants for this part. For this part, experienced also includes those who are back on vacation and have an existing employment contract abroad.

experience and arguably better training. However, the sample of experienced migrants in this study is non-random: it only includes those who want to migrate again. If good experience in migration makes them more likely to migrate again (as in Bryan, Chowdhury, and Mobarak, 2014), then the extent of misinformation presented here is likely to be a lower-bound estimate of the actual gap in information. If experienced migrants migrate for lower earnings abroad because their outside option of staying home is much worse, then the extent of misinformation here is likely to be an upper bound. In the current context, however, the former channel is more likely to be predominant.[21]

The expectations of potential migrants are also much higher compared to the information provided to them. As Figure 1.3 shows, only 15 percent of the inexperienced potential migrants and 10 percent of those who have migrated before expect to earn less than the 'high' information provided of $5,700. Virtually no one expects to make less than the 'low' information provided of $3,000. However, the official figures may not reflect the actual earnings of migrants abroad as it does not include over-time pay, which is often a large share of a migrant worker's compensation abroad.

In any case, these comparisons, though not perfect, are suggestive of large information gaps between the earnings expectations of the inexperienced potential migrants and the actual earnings they are likely to accrue once abroad. The actual extent of misinformation for inexperienced potential work migrants is likely to be bigger than 26 percent but smaller than that suggested by the comparison with the official figure.

Misinformation on expected mortality rate

Contrary to the popular notion, potential migrants seem to overestimate their mortality rate abroad by a large factor. The average expected two-year mortality rate of inexperienced migrant is 28 per 1000, which is 68 percent higher than the expectations of those who have migrated before. Figure 1.4 shows that not just the mean, but every quantile of expected mortality rate of inexperienced potential migrants is higher than the corresponding quantile for those who have prior migration experience. For instance, the median expected mortality rate for the experienced is 10 per thousand, whereas it is 5.8 for those who have migrated before. However, these expectations are much higher compared to the actual mortality rate faced by the migrants once abroad. The deaths data from the Foreign Employment Promotion Board, the authoritative data source for mortality of Nepali workers abroad, and migration data from the Census and the Department of Foreign Employment

[21] In the data collected by The World Bank (2011), returnees who earned more are more likely to express a desire to migrate again in the near future. Those who earned above the median during their foreign-migration experience are 18 percent more likely to express a desire to migrate again.

show that the two-year mortality rate of Nepali workers in these destination countries is 1.3 per thousand.[22] Only 3 percent of inexperienced potential migrants and 11 percent of those who have migrated before expect the mortality rate to be lower than what it actually is. The overestimation at the mean is 21 times the actual figure for the inexperienced ones and 13 times for those who have migrated previously. The extent of overestimation is smaller at the median, but still 8 and 4 times the actual rate for both inexperienced and experienced (those who have migrated before), respectively.[23]

The difference between the actual and reported mortality rates raises the question of whether the reports are errors in the reporting of their underlying beliefs or a truthful reporting of their mistaken beliefs. Reporting of the beliefs could be wrong because, despite measures taken during the interview process, subjects may not be able to articulate very small probabilities well (though they say the risk is 5 per 1000, it may be the same for them as 5 per 900, for instance). On the other hand, beliefs could be inaccurate because of biases in information sources as discussed above or because of the way potential migrants form beliefs. For most of the paper, I treat the reported beliefs as a true reporting of their (biased) beliefs, and I return to address this issue in Section 1.7 with evidence which is consistent with this.

1.4.2 Impact of information on beliefs

To guide the empirical analysis of the impact of information treatments on respondents' beliefs, 1.C outlines a simple learning model. In this model, individuals have normally distributed priors and believe that the information I provided is a random draw from another normal distribution. Individuals use Bayes' rule to form their posterior beliefs, which results in a few testable predictions about the effect of informational interventions. First, individuals update in the direction of the information. To the extent that potential migrants (especially the inexperienced ones) overestimate their mortality risks and earning potential, information, when effective, would lower their perceived mortality risks and earning potential. Second, information lowers the individual variance of posterior belief, and third, the effect of the information is increasing with the quantile of individual belief

[22]To put this number in perspective, the mortality rate of average Nepali men with the same age distribution as the sample is 4.7 per 1000 for a two-year period. The mortality rate of average US men with the same age distribution as the sample is 2.85 per 1000 for a two-year period. Note that this information on relative risks was not provided to the potential migrants.

[23]The finding that (young) adults overestimate their mortality expectation is not uncommon. Delavande and Kohler (2009) find that males aged under 40 in rural Malawi have median mortality expectations that are over 6 times the true mortality rate with higher bias for younger cohorts. Similarly, Fischhoff, Parker, de Bruin, Downs, Palmgren, Dawes, and Manski (2000) find that adolescents aged 15-16 in the US overestimate their mortality rate by a factor of 33 even after excluding the "50 percent" responses.

distribution. In the rest of this section, I discuss the effect of information on the beliefs about earnings and mortality risk in light of this framework.

Effect on perception of mortality risks

Consistent with the framework, Table 1.2 shows that the 'low' death information lowers potential migrants' perceived mortality risk of migration by 4 per thousand which is 20 percent of the control group mean (column 1). The effect with the controls (column 2) is only slightly larger. Other information treatments do not seem to alter the perceived mortality rate of migration by a substantive amount. For inexperienced potential migrants, providing the 'low' death information lowers their perceived mortality risk of migration by 7.4 per thousand, which is 27 percent of the control group mean (column 3). Adding controls (column 4) slightly increases this point estimate. The 'high' death information lowers expected mortality rate by 1.8 per thousand (3.9 with control), but the effect is not very precise (columns 3 and 4). These effects are consistent with the learning framework described in 1.C and the fact that potential migrants, especially the inexperienced, overestimate their expected mortality rate relative to the truth as well as relative to the information provided to them.[24] In terms of its effectiveness in filling the knowledge gap, the 'low' death information reduces perceived misinformation by 50 percent, and the 'high' death information reduces the perceived misinformation by 15 percent.[25]

Furthermore, the 'low' death information treatment also lowers the perceived mortality risk of the experienced by 2.2 per thousand (3 with controls), which are 13 percent (17 with controls), but are estimated imprecisely (columns 5 and 6). Even though the effect is insignificant, it is quite large and reduces misinformation by almost a third.[26] The 'high' death information treatment has an imprecisely estimated positive effect on expected mortality rate for this group. In terms of the learning framework, this would mean the signal was interpreted as being noisy. Furthermore, the prior of the experienced group is much higher compared to the inexperienced group, which explains

[24] I also find that the inexperienced potential migrants update more drastically when the reference district happens to be their own or a neighboring one, suggesting that potential migrants consider signals from their own or neighboring districts as more precise. In fact, among those provided 'low' death information from a reference district that happens to be their own or a neighboring district, the average expected mortality rate for those is only 15 per 1000, almost half of the control group mean. But since there are only 30 individuals in this group, I do not conduct further analysis using this variation.

[25] I define reduction in perceived misinformation as $\frac{\hat{\delta}}{\hat{\theta_0}-\hat{s}}$, where $\hat{\delta}$ is the effect of the intervention, $\hat{\theta_0}$ is the prior mean estimated from the control group, which receives no information, and $\hat{s}$ is the perceived mean of the signal distribution as calculated in 1.C. If $\hat{s}$ is taken to be the actual value of the information provided to them, the extent of reduction in misinformation is 28 and 8 percent for the 'low' and 'high' death information, respectively.

[26] If $\hat{s}$ is taken to be the actual value of the information provided, then the reduction in misinformation is 14 percent.

why the effect of information is opposite for this group.

As I have the entire probability distribution about beliefs of mortality risks, I show the results on various quantiles of an individual's belief about the mortality risks in Appendix Table 1.B.10. Consistent with the framework in 1.C, the result suggests that the information affected the entire distribution of the individual belief with larger effects in higher quantiles of their belief distribution. For the inexperienced, the 'low' death information lowered the average of the 10th percentile of their beliefs by 6.5 deaths per thousand, which translates to 27 percent of the control group mean. Similarly, the information treatment lowered the average of the 90th percentile of their belief by 8.4.

Furthermore, for the inexperienced group, the effect of the information treatment seem to be coming from higher end of the distribution of expected mortality rate. As Appendix Figure 1.B.2 shows, the effect of the 'low' death information is higher at higher deciles of the expected mortality rate distribution (bottom right plot). As the figure shows, other information treatments do not have statistically significant effects at any point of the distribution, except that the effect at the largest deciles are estimated more imprecisely than others. This suggests that the 'low' death information corrects expectations on mortality rates and does so from the individuals who are more likely to have much higher expectations about mortality rate, and are therefore, more likely to be misinformed.

These effects suggest that for the inexperienced potential migrants, the 'low' death information treatment lowered their entire distribution of beliefs on mortality rates consistent with simple Bayesian model of learning described in 1.C. Further, it lowered the expected mortality rate from those who would have otherwise had higher expected mortality rates. Consequently, the group receiving this treatment had lower variance of the expected mortality rate than the control group.[27]

Effect on perceptions of earnings

Consistent with the framework, Table 1.3 shows that the information interventions reduced the expected net earnings for the inexperienced potential migrants.[28] The 'high' wage information reduced the expected net earnings by $1,100, which is 8 percent of the control group mean (column

[27] I can reject equality of variance between the 'low' death information group and the control group using the robust Levene (1961) as well as Brown and Forsythe (1974) tests. I cannot reject equality of variance in expected mortality rate for any other pairwise comparison.

[28] The net earnings from migration is their expected monthly earnings multiplied by the modal duration of a migration episode to their chosen destination after subtracting the expected fees of migrating abroad to that destination. All the effects of the interventions are concentrated in expected monthly earnings with no effect in expected fees (monetary costs) to migrate. The results are almost identical if the analysis is repeated on the (gross) earnings from migration. I use net earnings simply for ease of interpretation.

3). The 'low' wage information reduced expected earnings by \$860, only slightly smaller than the effect of the 'high' wage information treatment. As discussed in Section 1.3.1, the information treatments differed in terms of the year of the statistic, but were similar after the numbers were adjusted for the inflation and the increase in exchange rate of the destination countries. Therefore, it is not surprising that the effects of these information treatments are also quite similar. In fact, this suggests that inexperienced potential migrants are quite sophisticated in the way they treat the wage information treatment.

The calculations in 1.C provides some support for the inexperienced potential migrants interpreting the 'high' and the 'low' wage information in a similar way. Imposing a Bayesian learning model on the average inexperienced potential migrant's beliefs in the control and treatment groups, one can infer the signal mean and variance without using information on the provided signal. The 'high' wage information was inferred as a signal drawn from a distribution with mean \$6,700 and standard deviation of \$1,200. Similarly, the 'low' wage information was inferred as a signal drawn from a distribution with mean \$6,200 and a standard deviation of \$1,600. The fact that these two distributions are quite similar is suggestive that the inexperienced potential migrants actually treated the 'high' and the 'low' wage information in a similar way.

Neither of the wage information treatments had any effect on the earnings expectation of the experienced potential migrants (Table 1.3, columns 5 and 6). The estimated effects are both small and statistically indistinguishable from zero. The lack of effect for the experienced potential migrants is expected as they have better source of information about their earnings potential.

Appendix Table 1.B.11 shows the effect of the interventions on various quantiles of the individual's probability distribution of their beliefs on earnings. For the inexperienced potential migrants, the 'high' wage intervention lowers the 10th percentile of their belief on earnings by about \$800 (8 percent) and the 'low' wage intervention lowers it by \$600 (6 percent). As predicted by the simple learning framework, the magnitudes of these effects become larger for higher quantiles of their beliefs.

Furthermore, for the inexperienced group, the effect of the information treatment seem to be coming from higher end of the distribution of expected net earnings. As Appendix Figure 1.B.3 shows, the 'high' wage information appears to have lowered the earnings expectation more from the higher end of the expected earnings distribution whereas the 'low' wage information treatment seems to have lowered perceptions throughout the distribution without a higher effect at the higher end of the distribution. This suggests that individuals who did not completely believe the 'low' wage information provided are likely to have been at the higher end of the expected earnings distribution. Because of the larger effect of the 'high' wage information on higher end of the expected earnings distribution, this group has lower variance than the control group.[29] Here too, the 'high' wage information managed to squeeze the distribution of expected earnings for the treatment group but the 'low' wage failed to do so.

1.5 Does information affect migration and other outcomes?

The initial survey in January 2015 collected phone numbers for the respondent, his wife and a family member (when available). These subjects were contacted again in April 2015 through a telephone survey. The primary purpose of the telephone survey was to determine the migration status of the initial respondent. Upon contact and consent, enumerators administered a short survey, collecting information on migration-related details, job search efforts, and debt and asset positions. The first part of this section describes the follow-up survey protocols and discusses attrition. The second part discusses the effect of information on migration choices and robustness to various definitions of migration. The last part of this section describes the impact of informational interventions on other outcomes measured during the follow-up survey.

1.5.1 Follow-up survey and attrition

Follow-up survey and protocol

These April 2015 follow-up telephone surveys were conducted from the data collection firm's office under close supervision of two supervisors. Enumerators were given specific SIM cards to be used during the office hours for the purposes of the follow-up survey. A protocol was developed to reach out to as many initial respondents (or their family members) as possible. Enumerators would first call the initial respondent's phone number followed by the wife's and the family member's phone number if the former could not be contacted. If anyone picked up the phone, enumerators confirmed the identity of the initial respondent or their family members and made sure that they were talking about the correct initial respondent. Then enumerators noted the migration status of the initial respondent: if he was available, they administered the follow-up survey to him; if he had already migrated, they administered it to the telephone respondent (usually the wife, siblings or parents). In

[29] I reject equality of variance using the Levene (1961) and Brown and Forsythe (1974) tests only for the comparison between the control group and the 'high' wage information group and not for other pairs.

case the initial respondent was known to be in the country, enumerators made up to three attempts to administer the follow-up survey to him, before resorting to the telephone respondent.

If no one could be contacted on any of the phone numbers, then the enumerators would try the set of phone numbers again at another time or day. Enumerators attempted to call each set of numbers for six days with at least one attempt every day before giving up on contacting the subjects. If the telephone respondents were busy at the time of the call, enumerators made an appointment with them and contacted them at a time of their choosing. This protocol was designed to ensure that the subjects, or their family members, were contacted whenever possible and the failure to contact them either meant that the telephone numbers provided were either wrong or that the subjects had already migrated.

Attrition

Following this protocol, the enumerators were able to conduct detailed follow-up survey with 2,799 initial respondents (or their family members) between March 26 and April 24, 2015.[30] This represents 84 percent of the overall sample, 85 percent of the inexperienced potential migrants, 86 percent of the experienced potential migrants, and only 78 percent for those who had an existing contract abroad and were back only on a leave. Since the main outcome of interest of the study is migration, attrition from the survey is also potentially an outcome to the extent that I am less likely to obtain information about a migrant.

I consider three separate measures of attrition. The first, Attrition-F, considers whether the full follow-up survey was conducted or not. The second, Attrition-M, considers whether it was possible to determine the migration status of the initial respondent. This measure differs from the first measure when enumerators were able to determine the migration status of the individuals but were not able to conduct the full follow-up interview. The attrition rate, according to this measure, is 13 percent for the overall sample, 12 percent each for the samples of inexperienced and experienced potential migrants. Among the 13 percent of the subjects with unknown migration status, it is possible to know about the attempted calls to the numbers provided by them. The phones of many in this group were switched off or not in operation, but for a few, the numbers provided were wrong (confirmed either by the telephone operator or by the person who answered the phone). In very

[30]Follow-up surveys ended after a 7.8 magnitude earthquake struck Kathmandu on April 25, 2015, one day ahead of the planned end date. In the last working day (April 24), only 26 interviews (0.9 percent of total successful follow-up interviews) were conducted. When the follow-up interviews were in full swing, about 120 successful follow-up interviews were conducted in a day.

few cases, the respondents refused to identify themselves or provide any information on the study subjects. Hence, my third measure of attrition (Attrition-W) indicates confirmed wrong numbers or refusal to interview. According to this measure, the attrition rate is about 3 percent in the overall sample as well as the subgroups.

The first measure of attrition, Attrition-F, is correlated with the information treatments. As the top panel of Table 1.4 shows, this measure of attrition is higher for death information treatments (marginally significant) and lower for wage information treatments (columns 1 and 2). For the inexperienced potential migrants, the 'high' wage information reduces this measure of attrition by 4 percentage points, significant at 10 percent level (columns 3 and 4). For the experienced potential migrants, the 'low' death information increases attrition by 6 percentage points (column 5).

The second measure of attrition, Attrition-M, is also correlated with information treatments. As the second panel of Table 1.4 shows, this measure of attrition matches the correlation pattern observed for Attrition-F. For the overall sample, death information treatments increase attrition whereas wage information treatment reduce it (columns 1 and 2). For the inexperienced potential migrants, in particular, the 'high' wage information treatment lowers this measure of attrition by 4 percentage points (columns 3 and 4). Whereas, for the experienced potential migrants, the 'low' death information treatment increases attrition by 6 percentage points (column 5).

The third measure of attrition, Attrition-W, is not correlated with any of the information treatments (bottom panel, Table 1.4). This measure of attrition is low and, more importantly, not correlated with the treatment status. Particularly for the inexperienced migrants, even the direction of the effects does not match the pattern observed for other measures of attrition.

Attriters look broadly similar to non-attriters except for a few characteristics. As Appendix Table 1.B.12 shows, attriters, by all three measures, have similar characteristics as non-attriters in except for completed years of schooling (first and second panels). For both the subgroups, I cannot reject the joint null that attriters and non-attriters have the same age, geography and locations. However, attriters have lower completed schooling by more than 1 year compared to non-attriters (first panel, row 2). This also makes some intuitive sense as those who have fewer years of schooling are likely to have fewer cellphones in the family or could be more likely to misreport phone numbers. However, as seen in Table 1.4, correlation patterns between treatments and attrition measures remain the same despite adding controls, including schooling. [31]

[31] I also estimate selection on observables correction proposed by Fitzgerald, Gottschalk, and Moffitt (1998) to adjust for the fact that attriters are different from non-attriters. The key results are qualitative and quantitatively the same. All results presented in the paper are without the correction.

More importantly, attriters, as classified by the first measures, Attrited-F and Attrited-M, had anticipated earlier migration even during the initial survey in January. In the initial survey, respondents were asked to assign 10 tokens to five bins representing their likely time of migration: 0-3 months, 4-6 months, 8-9 months, 10-12 months, and 12+ months. Compared to non-attriters, attriters by those first two measures were more likely to indicate certainty of migrating within three months or a much quicker expected migration time (third panel, Appendix Table 1.B.12). However, attriters by the third measure, Attrited-W, did not have different expectations than non-attriters.

This suggests that attriters by the first two measure attrited precisely because they have migrated. To incorporate, I define my migration outcome based on different assumptions on the attriters. In measures of migration and other outcome that suffer from missing variables problem, I also estimate the Lee (2009) bounds of effects.

Since the two wage information treatments seem to have similar effects on the expected mortality and earnings as well as attrition, I pool the two treatments into a single wage information treatment group from this point forward. The results remain essentially the same with the more disaggregated specification as well.

1.5.2 Effect on migration

As discussed above, I have various measures of migration status based on various assumptions that I make about the attriters. For those whose migration status is observed, I treat them as migrants if they have already left or are confirmed to leave within two weeks of the follow-up survey.[32] For my preferred measure of migration (Migrated-P), I assume all attriters are migrants except those subjects who provided wrong phone numbers or refused to provide any information to the enumerators. That is, this measure of migration treats Attrition-W as missing and considers those with switched off or unavailable phones as migrants. With this measure, as shown above, missing data is uncorrelated with information treatment and hence the estimates of equation 1.1 are unbiased. Furthermore, those with phones switched off or unavailable during the follow-up had expected to migrate earlier and are indeed more likely to be actual migrants.

For the inexperienced potential migrants, migration decision is consistent with the change in expectations about earnings and mortality rate. As Table 1.5 shows, 'low' death information increased migration by 7 percentage points whereas the wage information treatments lowered migration by 6 percentage points (top panel, columns 3 and 4). These effects are over 20 percent of the migration

[32]The results are essentially the same if the confirmed departure time is changed to 1 week or 0 week instead of 2.

rate observed in the control group. The effects are also what one would expect, given the change in expectations that the treatments induced. The 'low' death information lowered the expected mortality rate abroad, making the destinations more appealing and inducing more them to migrate. On the other hand, the wage information treatments lowered the expected earnings abroad, making destinations less attractive and inducing fewer of them to migrate.

The effect on expectations also resonate on migration decision of the experienced potential migrants. As Table 1.5 shows, the 'low' death information, which lowered expected mortality rates abroad increased migration by 9 percentage points (top panel, columns 5 and 6). On the other hand, the wage information treatments, which failed to induce a change in expectations, also failed to induce a migration response.

The effect of information treatments remain qualitatively and quantitatively similar for the second measure of migration (Migrated-A). This measure of migration treats all attriters as having migrated. As the second panel of Table 1.5 shows, the effect of information treatments on this measure of migration is quite similar to the effect on the preferred measure (Migrated-P).

Because of the missing variables problem, the effect of the information treatments on the basic measure of migration (Migrated-B) is biased. This measure treats all those individuals with unconfirmed migration status (Attrited-M) as missing. For the inexperienced potential migrants, 'low' death information is not correlated with Attrited-M, and hence, as Table 1.5 shows, the effect on this measure of migration is almost the same as for the previous two measures of migration (bottom panel, columns 3 and 4). However, the effect of wage information treatment is two thirds the size of the effect for other measure of migration. This is precisely what one would expect if wage interventions led the potential migrants to not migrate and therefore more likely to be found during the follow-up survey.

The third panel of Table 1.5 shows the results for this measure of migration (Migrated-B). For the inexperienced potential migrants, 'low' death information treatment increased migration by 7 percentage points. This effect, significant at 5 percent level, is almost 30 percent of the migration rate in the control group. For this group, death 'high' information also increases migration slightly (9 percent) but the effect is insignificant. Note that since missing data (Attrition-M) is not correlated with death interventions, these points estimates similar to the preferred measure of migration. However, since missing data (Attrition-M) is correlated with wage information treatments, the point estimate for wage information treatments is lower and not significantly different from zero at conventional levels. This is precisely what one would expect if wage interventions led the inexperienced potential migrants to not migrate and therefore more likely to be found during the follow-up survey. Similarly, for the experienced migrants, 'low' death information, which increased attrition, has a smaller effect than for other measures. Again, this is what one would expect if 'low' death information led the experienced potential migrants to migrate more and therefore less likely to be found during the follow-up survey.

Lee (2009) bounds on effect of the information treatments on the basic measure of migration (Migrated-B), also supports that attrition (Attrited-M) captures unobserved migration. As Table 1.6 shows, the bounds on the effects of the death information treatments for inexperienced potential migrants are tight and similar in magnitude as the effect on the preferred measure of migration (second panel, columns 1 and 2). However, the lower bound on the effect of wage information on migration is similar to the effect on the preferred measure (Migrated-P) whereas the upper bound on the effect is similar to the effect on the basic measure (Migrated-B). That is, selectively dropping a random subset of those who migrated and are from the wage information treatment group, in order to balance attrition, produces an estimate not too different from the effect on the basic measure (Migrated-B). However, selectively dropping a random subset of those who did not migrate and are from the wage information treatment group to balance attrition produces an estimate different from the effect on the basic measure and very similar to the effect on the preferred measure (Migrated-P). This also suggests that attrition is likely to be more among migrants than non-migrants.

1.5.3 Effect on other outcomes

In this section, I investigate the effect of the information treatments in other outcomes that were collected using the full follow-up survey. This would shed light on other effects of the intervention or the mechanism of the migration effect. Since these measures were collected through the full follow-up survey, these measures suffer from attrition (Attrition-F).

Appendix Table 1.B.13 shows that the information treatments did not affect whether the potential migrants choose the same country or region (Persian Gulf versus others) as they did during the initial survey. Between the initial survey and the follow-up, about 40 percent of the inexperienced and 28 percent of experienced potential migrants changed their destination country. The information treatments barely changed this – the effects are not just statistically insignificant, but also numerically small. The same holds true for potential migrants changing their intended (or chosen) destination region.

The wage information increases the chance that inexperienced potential migrants seek new manpower companies, but has no effect on seeking consultations from other source. As Appendix Table 1.B.14 shows, inexperienced migrants receiving wage information are 6 percentage points more likely to consult different manpower companies after the initial survey (top panel, columns 3 and 4). This effect is 26 percent of the likelihood in the control group. The Lee (2009) bounds on this estimate are positive and large, suggesting that the effect is large despite the missing variables concern (Appendix Table 1.B.15, middle panel, column 3). This probably reflects an action that inexperienced potential migrants can take upon realizing that they had been misinformed. However, none of the information treatments affect whether they consult with family members or friends (mid and bottom panel, Appendix Table 1.B.14). Similarly, none of the information treatments affects any of these outcomes for the experienced potential migrants.

As Appendix Table 1.B.16 shows, none of the information treatments changed whether households took out new loans (top panel), paid back old loans (mid panel), or bought new assets (bottom panel). However, for the experienced potential migrants, the 'low' death information increases the probability that they bought new assets between the two rounds of the survey and wage information reduces the likelihood of buying new assets. The wage result is particularly inconsistent with the rest of the results as it did not affect perceptions or expectation or any other outcome, hence I attribute this odd result to random chance.

1.6 Estimates of VSL

Since the information treatments are effective in changing the expectations of inexperienced potential migrants concerning both earnings and mortality rate associated with migration, I estimate the value of a statistical life (VSL) for this group by using the information treatments as instruments. The first part of this section describes the methodology and the contribution of this paper in estimating VSL, the second presents the estimates for the pool of inexperienced potential migrants, and the third explores robustness. The final part estimates the VSL for various subgroups.

1.6.1 Methodology and contribution

Schelling (1968) shaped the way economists think about VSL as the willingness to trade-off wealth W for a marginal change in the probability of death d holding everything else constant. That is,

$$VSL = \frac{dW}{dd}$$

holding everything else, including utility, constant.

The empirical approach to estimating VSL in this context can be motivated by a simple binary choice framework. The utility that a potential migrant i receives from migrating can be written as

$$U_i^M = \alpha + \beta d_i + \gamma W_i + \varepsilon_i$$

where W_i is the expected earnings from migration, d_i is the expected mortality risk from migration, and ε_i represents the unobserved individual specific factors that influence the utility from migration. The utility that the potential migrant i receives from not migrating is unobserved and can simply be written as $U_i^H = \alpha' + u_i$. Then the migration decision M_i of potential migrant i is given by

$$\begin{aligned} M_i =& \mathbf{1}\left(U_i^M > U_i^H\right) \\ =& \mathbf{1}\left(u_i - \varepsilon_i < \alpha - \alpha' + \beta d_i + \gamma W_i\right) \end{aligned}$$

with

$$E_i\left[M_i\right] = Pr\left(u_i - \varepsilon_i < \alpha - \alpha' + \beta d_i + \gamma W_i\right)$$

By making assumptions on the distribution of $\epsilon_i \equiv u_i - \varepsilon_i$, $\hat{\beta}$ and $\hat{\gamma}$ could be consistently estimated if d_i and W_i are not correlated with ϵ_i. But because of omitted variables (such as inherent ability or carefulness), W_i and p_i are likely to be correlated with ϵ_i (which includes, among other things, earning option and mortality risks of not migrating). To solve this problem, I use the exogenous variation in d_i and W_i generated by the informational interventions as instruments for d_i and W_i for the pool of inexperienced migrants.

Hence, I estimate the following system of equations

$$\begin{aligned} E_i\left[M_i\right] = & Pr\left(\epsilon_i < \alpha - \alpha' + \beta d_i + \gamma W_i\right) \\ d_i =& \mu_1 DeathLo_i + \mu_2 DeathHi_i + \mu_3 WageInfo_i + \eta_i \\ W_i =& \delta_1 DeathLo_i + \delta_2 DeathHi_i + \delta_3 WageInfo_i + \nu_i \end{aligned} \quad (1.2)$$

where $DeathLo_i$, $DeathHi_i$ and $WageInfo_i$ indicate whether potential migrant i receives the 'low' death information or the 'high' death information or any of the wage information.

To make progress in estimation, I assume that $(\epsilon_i, \eta_i, \nu_i)$ are individually and jointly normally distributed. Randomization guarantees that (η_i, ν_i) is independent of the informational treatments. Furthermore, with the assumption that the treatments did not change unobserved amenities associated with migration, the information treatment is also uncorrelated with ϵ.[33] Given the random assignment of treatment and the assumption on error terms, maximum likelihood estimation of equation (1.2) yields the most efficient estimator of β and γ up to scale. Given this setup, VSL is simply the ratio of two estimates

$$VSL = \frac{dW}{dd} = -\frac{\frac{\partial E[M]}{\partial d}}{\frac{\partial E[M]}{\partial W}} = -\frac{\beta}{\gamma}$$

and can be estimated by $\widehat{VSL} = -\frac{\hat{\beta}}{\hat{\gamma}}$.

I estimate this equation using both the levels and logarithm of expectations to allow η and ν to be log-normally distributed. I also estimate the model with 2SLS assuming linear probability model and find that the point estimates for the VSL are similar. The advantage of estimating equation (1.2) over estimating 2SLS is that it gives the ratio of coefficients an utility constant interpretation as the definition of the VSL implies. The results with 2SLS estimates are presented in the appendix.

This method of estimating VSL by observing choices of individuals is quite novel in the rich literature on the subject. Most estimates follow the wage hedonic approach following seminal work by Thaler and Rosen (1976) (see Viscusi and Aldy, 2003; Cropper, Hammitt, and Robinson, 2011, for review of empirical estimates). Thaler and Rosen (1976) show that the slope of the observed market locus in the wage-mortality risk plane gives the willingness to pay of the workers to avoid marginal increments in mortality risks (i.e. the VSL). But getting consistent estimate of the market locus (or its slope) has been difficult because of two key problems.

First, in most estimations using the wage hedonic approach, mortality risk is correlated with unobserved determinants of wages (see Ashenfelter, 2006, for a critique). This introduces a selection bias in the estimates with an unknown direction and magnitude of the bias. The current study overcomes this problem by using exogenous variation in (expected) earnings and (expected) mortality risks generated by randomly provided information.[34]

The second issue with the wage hedonic approach is that mortality risks are measured with errors and maybe known imperfectly to agents. Black and Kniesner (2003) emphasize that the

[33]One way to check this assumption is to see whether the information treatments changed their occupation choices, and it does not. Furthermore, for the inexperienced potential migrants the wage information treatments do not change mortality rate expectations and the death information treatments do not change earnings expectations (columns 3 and 4 of Table 1.2 and Table 1.3). These results suggest that the exclusion assumption is likely to hold in this context.

[34]Lee and Taylor (2014) is one of the rare studies to estimate VSL using an exogenous variation in plant level risk. They exploit the random assignment of federal safety inspection to instrument for plant level risk to estimate the equilibrium relationship between wages and risks.

measurement errors are non-classical in nature and leads to large biases in either direction.[35] In this study, I directly measure expectations on earnings and mortality risks without the need to worry about whether they (as well as the econometrician) know the actual mortality rate and the earnings involved.[36] Rather than the actual risks involved with the occupation, it is the perceived risks that is actually relevant in the decision-making process.

The second, and somewhat new, approach to estimating VSL is by modeling the choices made by individuals or populations. In this vein, Ashenfelter and Greenstone (2004b) model the decision of states to adopt a higher speed limit to compute VSL. In their setting, states choose to adopt higher speed limit if the monetary value of times saved per marginal fatality is higher than the VSL. The authors estimate the monetary value of times saved per marginal fatality by instrumenting fatalities with a plausibly exogenous increase in speed limits in rural interstate roads in the US from 55 mph to 65 mph in 1987. Though this gives them a well identified upper bound estimate of the VSL, their estimates of actual VSL suffers from lack of exogenous variation in modeling the decision of the states to adopt the speed limit. Furthermore, this VSL is the tradeoff by the state (or the median voter if the preference of the states represent the policy choices of the median voter) and could be different from the tradeoff made by individuals.

In a more refined modeling of individual choices, Greenstone, Ryan, and Yankovich (2014) study the reenlistment decision (and occupation choices within the military) of US soldiers when faced with varying monetary incentives and mortality risks. In a methodology similar to this paper, the authors infer the VSL of US soldiers by looking at the ratio of coefficients on mortality risk and monetary incentives of a discrete choice model of occupation choice. The identifying variation in their study comes from the institutional process that determines compensation for reenlistment and variety of occupations undergoing different mortality risks as the US engages in various military actions. Another study that employs the discrete choice framework to estimate the VSL is León and Miguel (2013), which examines the transportation choices made by travelers to the international airport in Sierra Leone. The identifying variation in this study comes from the availability of different options at different periods over which the data was collected.

This study is methodologically similar to Greenstone, Ryan, and Yankovich (2014) and León and Miguel (2013), as it infers VSL from the ratio of coefficients in a model of migration choices of potential migrants, but it extends the approach with a randomized information experiment that

[35] In fact, they estimate VSL to be negative in half their specifications.

[36] This, of course, is assuming that the respondents are able to articulate the risks accurately during the survey.

introduces exogenous variation in perceptions of earnings and mortality risks. To the best of my knowledge, this is the first study to employ randomized controlled trial in estimating the VSL.

1.6.2 Estimates of VSL for inexperienced potential migrants

Both the logarithmic and the levels specifications estimate migration elasticities that are quite similar across specifications. As Table 1.7 shows, across all three measures of migration, an increase in (logarithm of) expected mortality rate lowers probability of migration and an increase in (logarithm of) expected earnings increases migration probability as expected (top panel). For the preferred measure of migration (Migrated-P), an increase in one percent in expected mortality rate reduces migration by 0.16 percentage points (column 1). This translates to an elasticity of migration to expected mortality risk of 0.5. Similarly, an increase in one percent in expected earnings increases migration by 0.22 percentage points, which translates to an elasticity of migration to expected earnings of 0.7. The bottom panel of the table estimates similar elasticities with the levels specification. An increase in expected mortality rate by 1 percentage points reduces migration rate by 6 percentage points (column 1). This point estimate translates to an elasticity of 0.5, which is exactly the same elasticity from the logarithmic specification. An increase in expected earnings by $1000 increases migration rate by 1.1 percentage points which implies an elasticity of 0.5 which is only slightly smaller compared to the elasticity estimated using the logarithmic specification. Since expected mortality and expected earnings are more likely to follow a log-normal distribution than a normal distribution, I prefer the estimates with logarithms rather than levels.[37]

These estimates suggest that misinformation has actually lowered the migration rate because potential migrants overestimate mortality more than they overestimate earnings. If inexperienced potential migrants had true information on the mortality risk (1.3 per 1000 for two-year period instead of 27.57), migration would increase by 47 percentage points from its current level (assuming the effect are the same for large changes in perceptions). Similarly, if inexperienced potential migrants had the same net earnings expectations as the experienced ones ($9,660 instead of $12,270), migration would decrease by 5 percentage points. The net effect on migration would therefore be an increase of 42 percentage points – a remarkable 140 percent. Even assuming a much lower actual earnings of $6,000 for the inexperienced (since the expectations of the experienced are likely to be an upper bound on the counterfactual earnings), migration would still go up by by 31 percentage

[37] I cannot reject the null of normality for the log of both expectations in the untreated group using a Kolmogorov-Smirnov test. However, the more stringent forms of the test reject normality.

points (102 percent from the current level).

The VSL implied by this choice is the ratio of the marginal effect of the expectations on migration decision. For the logarithmic specifications, the estimates of VSL range from \$0.28 million to \$0.63 million, depending upon the different measures of migration used (top panel, Table 1.7). The VSL using the preferred measure of migration (Migrated-P) is estimated more precisely than others but the estimated magnitudes are quite similar. For the levels specification, the estimates of the VSL range from \$0.43 million to \$2.35 million for various measures of migration (bottom panel). The levels specification yields larger and noisier estimates than the logarithmic specifications. Except for the measure of migration with attrition problem (Migrated-B), all the estimates are statistically different from zero and qualitatively similar to their logarithmic counterparts. The VSL from the preferred measure with the levels specification is \$0.54 million and its logarithmic counterpart is within one standard error from this estimate. [38]

Comparison with estimates in the literature

It is hard to compare these estimates of VSL, estimated for the pool of potential international migrants from Nepal, to most estimates in the literature, which apply to the US labor market. As reviewed in Viscusi and Aldy (2003) and Cropper, Hammitt, and Robinson (2011), typical US estimates range from \$5.5 million to \$12.4 million (in 2014 US\$).[39] The preferred estimates in this study ranges from \$0.28 million to \$0.54 million (\$0.97 million to \$1.85 million in PPP\$).[40] It is reasonable to expect a lower VSL in the context of Nepal compared to the US as the average Nepali potential migrant has a much lower income: US GDP per capita is 23 times the GDP per capita of Nepal in PPP terms. In fact, several studies find the developing country estimates of the VSL are in general lower than the estimates from the US (in Viscusi and Aldy, 2003, for example).[41] Nevertheless, the VSL estimates in this paper are a comparable proportions of the median household income in Nepal as the estimates in the US: 150 to 300 times the median household income in Nepal versus 100 to 250 times that in the US.

Estimates for populations outside the US, especially for developing countries, is quite rate and

[38]The 2-SLS estimation of equation (1.2) produces very similar point estimates for VSL but are estimated with larger standard errors (results in Appendix Table 1.B.17).

[39]Deflated using Urban CPI series.

[40]Using PPP conversion factor (US\$ to PPP\$ for Nepal) of 3.45 from The World Bank.

[41]Interestingly, the estimates of VSL from Greenstone, Ryan, and Yankovich (2014) (\$0.18 million to \$0.83 million in 2014 US\$) are more in line with those from this study. However the VSL is expected to be much lower among US soldiers, who probably have higher preference for risky activities, than the average American. In fact, even within the soldiers, the authors find a lower VSL for those taking risky jobs.

vary widely. For instance Kremer, Leino, Miguel, and Zwane (2011) estimate the VSL of less than \$1000 based on the revealed willingness of Kenyan households to travel further for cleaner water. León and Miguel (2013) estimate a VSL of \$0.6m to \$0.9m from the revealed choices on transportation options while traveling to the international airport in Sierra Leone. Greenstone and Jack (2015) highlight the paucity of VSL estimates in developing countries and call for more research in developing revealed preference measures of the willingness to pay for lower mortality (through improving environment quality).

1.6.3 Robustness to various points on the belief distribution

If potential migrants have uncertain priors about earnings and mortality rate while abroad, then they may not act as expected utility maximizers who maximize the probability weighted average of utilities in various states of the world. In such cases, the expected value of their beliefs may not be the right measure that influences their migration decision. It could be possible that people behave in an uncertainty-averse manner and use a different utility maximization rule. For instance, Gilboa and Schmeidler (1989) propose a max-min rule where agents maximize utility assuming the worst possible state. In this part, I explore robustness of the VSL estimates to using alternative points in their belief distribution.

Table 1.8 shows that the estimates in Section (1.6.2) are robust to a few alternative decision-making rules. In column 1, I assume that individuals are extremely cautious about migrating and assume the worst. That is, they assume that the actual mortality risk is the highest end of their belief distribution and the actual earnings, at the lowest. With this assumption, the estimated VSL is \$0.16 million using the logarithmic specification and \$0.37 million using the levels specification. These estimates are smaller than those in Table 1.7 but are unlikely to be statistically different. Similarly, column 3 assumes the opposite of column 2: that the individuals take the most optimistic view in making their migration decision. They assume that earnings are the highest end of the belief distribution and mortality is the lowest end of their belief distribution. With this assumption, the estimated VSL is slightly higher but statistically similar to the corresponding estimates in Table 1.7. Column 2 performs this exercise assuming that the midpoint of their belief distribution are the relevant parameters and column 5 does the same assuming that their most strongly held beliefs are the relevant parameters. Both of these exercises produce slightly lower estimates than Table 1.7, but well within a margin of statistical errors. This table suggests that the estimates of VSL are quite robust to alternative decision-making rules on migration with the estimates ranging between

$0.16 million to $0.32 million with the logarithmic specification and $0.35 million to $0.61 million with the levels specifications.

1.6.4 Estimates of VSL for subgroups of inexperienced potential migrants

In this part, I present VSL estimates of equation (1.2) for various subgroups of the inexperienced potential migrants. Table 1.9 presents results of these estimates.

As Table 1.9 shows, the older half of the inexperienced potential migrants seem to have higher but less precisely estimated VSL than the younger ones (columns 1 and 2). The difference is driven by the differences in elasticities with which migration responds to changes in expectations. The implied elasticities of migration with respect to expected mortality and earnings are 0.4 and 0.2 respectively for the old whereas they are 0.6 and 1.1 for the young.

Columns (3) and (4) show the results bifurcated by education level. The low group refers to those with at most 8 years of schooling (below median) and the high group refers to the rest. Even the high education group is low-skill with average schooling of 10 years. The low education group has an average schooling of 5 years (median of 6 years). The low educated group is quite sensitive to changes in expected mortality (elasticity of 0.6) but extremely insensitive to changes in expected earnings (elasticity of 0.05). Hence, this group has extremely large but imprecisely estimated VSL. Similarly, the more educated groups are also less sensitive to changes in expected earnings with an elasticity of 0.16. However, the earnings estimates are quite noisy. This subgroup analysis is less informative than the previous one as the responsiveness to changes in expected earnings is estimated with large standard errors. A change in specification (for example, using the levels instead of logarithms) or estimating the equation using 2SLS (as in Appendix Table 1.B.19) does not improve precision of this estimate. It is possible that the responsiveness to expected earnings does not vary much by education (at least in this range of low schooling in the data) and hence, splitting the sample this way leads to nothing but a loss in statistical power.

Inexperienced workers who choose manual work have lower estimated VSL than those who pick non-manual work (column 5 and 6). It is important to note that even the jobs classified as non-manual are low-skilled, labor-intensive work as drivers, guards, security personnel, domestic workers, and hotel and restaurant workers. The difference between these two subgroups arises, again, from the difference in responsiveness to changes in expected earnings. The manual laborers are more than twice as responsive as the non-manual workers to changes in expected earnings with an elasticity of 1.0. Hence, this group has a lower VSL of $0.14 million compared to the workers in non-manual group with a (imprecisely estimated) VSL of \$0.41 million.

1.7 Why is expected mortality rate so high?

Section 1.6.2 establishes that the estimated VSL are reasonable and that misinformation actually has led to lower migration in this context. At the implied willingness to trade off earnings for mortality rate, migration is suppressed because of extremely high expectations of mortality rate relative to the truth. .In this section, I show that the high mortality rate expectation is a consequence of over-inference by potential migrants in response to actual migrant deaths rather than misreporting or an artifact of data collection method.

The instrumental variables estimate of the VSL and the migration elasticities are consistent even though the expectations are measured with error. The instrumental variables estimate also solves any measurement issue that can be modeled as an additive component (either in logarithmic or in levels of the expectations). Hence, I use the VSL and the elasticity estimates, along with my estimates from Chapter 2 to infer the change in perceived mortality rate for potential migrants in response to a single migrant death.

In Chapter 2, I find that, after controlling for an array of confounding fixed effects, one migrant death in a district reduces monthly migrant flow from that district by 0.9 percent for 12 months. This represents a total of 11 percent reduction of monthly migrant flow (albeit over a year) in response to a single death. I then calculate a one-time increase in migrant earnings necessary to induce the same number of potential migrants to migrate so that the net effect on migration is zero. Using the earnings elasticity of migration estimate of 0.7 from Section 1.6.2, I find that migrant earnings need to increase by 15 percent. That is, a one-time increase in migrant earnings of 15 percent will offset the reduction in migrant flows caused by a single migrant death.

Finally, I use the estimate of VSL from Section 1.6.2, to translate the change in earnings to change in perceived mortality rate. I use the following discretized formulation of the VSL and the elasticities to do so,

$$\Delta d = \frac{\Delta W}{VSL} = \frac{1}{VSL} \cdot \beta \cdot \frac{1}{\varepsilon} \cdot W \tag{1.3}$$

where d represents the perceived probability of death and W is the average potential earnings from migration, β is the migration effect of the death, and ε is the earnings elasticity of migration. Using the preferred estimate of VSL and $\frac{\beta}{\varepsilon} = 0.15$ from above, I find that the change in perceived probability following a single death in the district is 6.7 per thousand.[42]

The high perceived mortality rates expressed by the potential migrants are consistent with the effect on perceptions generated by a single death and their exposure to migrant deaths. The inexperienced potential migrants expect the mortality rate to be 27.6 per thousand per migration episode. From the estimates above, they only need 4.1 deaths in their district to generate this level of expected mortality rate starting form a prior of zero. In 2013, an average district experienced 4.3 deaths in five months, suggesting that such high level of mortality perception can be generated even if potential migrants are making decisions about mortality risks only based on past five months of migrant mortality incidences in their districts.

In Chapter 2, I also find evidence that potential migrants react more adversely when there have been more migrant deaths in the recent past. Subsequent migrant flow falls more drastically in response to a migrant death in districts which have experienced many migrant deaths in the recent past compared to the response in districts which have experienced few migrant deaths in the recent past. That is, potential migrants seem to be over-weighting recent deaths in forming their priors on mortality rate. In Chapter 2, I show that the amount of updating following a migrant death, and the responsiveness of updating recent deaths cannot be generated by a rational Bayesian learnings model. A model of a learning fallacy, the law of 'small' numbers, correctly predicts the over-inference result as well as the dependence on the number of deaths in the recent past (see Rabin, 2002, for mathematical formulation). Belief in the law of 'small' numbers, in conjunction with availability or other heuristic decision rule could also explain the high observed overestimation of mortality rate (as in Tversky and Kahneman, 1971, 1973; Kahneman and Tversky, 1974). One such heuristic explanation could be that potential migrants do not pay attention to migrant deaths unless they are actively thinking about migrating abroad, in which case they form their priors by observing migrant deaths in their districts in the past few months. Since they also commit the fallacy of believing in the law of 'small' numbers which makes them over-infer from recent information such as actual migrant deaths in the district or even the information provided in this study.

Hence, the high expectation of mortality rate among potential migrants is consistent with the experience potential migrants probably have and the way they appear to process it. The large extent of misinformation seems to be driven by the fallacious way they form their priors on mortality rate

[42] Assuming that each component of equation (1.3) is normally distributed with the estimated mean and variance, and also that these components are uncorrelated with each other, the standard error for the change in perceived mortality rate is 3.72. The calculation is robust to using VSL and elasticity estimate from the levels specification, which results in a change in perceived mortality rate of 5.8 per thousand.

abroad.

1.8 Conclusion

The gain from international migration is expected to be huge, but there could still be important non-institutional barriers to migration. I show that misinformation about both the rewards and risk associated with migration could be important deterrent, even in a context where a large share of population migrates for work. I find that potential work migrants from Nepal to Malaysia and the Persian Gulf countries overestimate their earnings potential as well as the mortality rate abroad. Contrary to the prevalent belief among policymakers , the extent of overestimation of mortality rate far outweighs the extent of overestimation of earnings. Individuals are not migrating recklessly by trading off high mortality risk for small increase in earnings: the estimated VSL of \$0.28 million to \$0.63 million, revealed from their decision to migrate, is quite reasonable for a poor population. Therefore, at their current willingness to trade off mortality risk with earnings, they would be more willing to migrate abroad if they had accurate information about the earnings and mortality risk abroad.

However, the reason for low migration in this study is distinct from those seen in the literature. Though misinformation on earnings has been documented previously in other contexts, most notably in McKenzie, Gibson, and Stillman (2013), misinformation on the risks of migration has not. This finding suggests that information frictions, particularly about risks that workers face abroad, could suppress migration substantially. Failing to take these into account could lead researchers to estimate high (fixed) costs of migration. In this regard, the estimated costs of migration have to be interpreted not just as monetary and psychic, but also as perceived cost, stemming from misinformation on earnings and, more importantly, risks.

Furthermore, in conjunction with my findings in Chapter 2, I show that such misinformation on mortality rate may arise because of fallacious inference by potential migrants. I find they seem to drastically update their beliefs about the mortality rate in response to an actual death of a migrant. Furthermore, the response to a migrant death is larger when potential migrants have seen more migrant deaths in recent months. While models of rational Bayesian learning fail to generate the magnitude of updating or the dependence on recent migrant deaths, models of learning fallacy, such as the law of 'small' numbers, combined with some heuristic decision rules can explain the large observed overestimation.

Finally, this paper presents a novel and credible way to estimate the VSL of inexperienced potential work migrants from Nepal. I estimate the VSL by exploiting the exogenous variation in expectation of earnings and mortality risks generated by randomly provided information in a model of migration decision. Two features of this setting make this approach to estimating the trade-off between earnings and mortality rate feasible. First, inexperienced potential migrants are misinformed about the mortality rate as well as earnings they could make abroad. Second, they are responsive to information provided to them and their migration choices reflect the changed perceptions induced by the information treatments. This approach could potentially be applied to other settings that meet the two criteria.

1.A Figures and Tables

1.A.I Figures

Figure 1.1: Study setting in Department of Passport

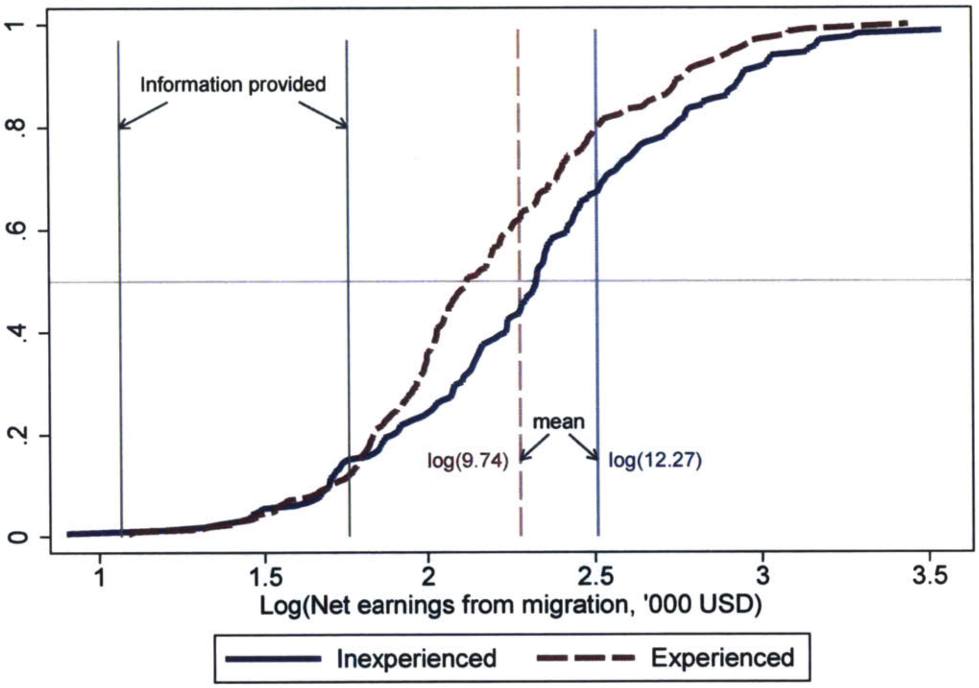
Note: This picture shows the study setting at the Department of Passport in Kathmandu during January 2015. The people waiting to submit their passport applications are standing in line in front of several counters along the wall to the right. To the top left is the waiting area for applicants before they stand up in line in front of the counters. The foreground shows the area reserved exclusively for this study. People who finished submitting their application were approached and screened for feasibility for the study. Once they consent, they would be brought to this area for interviews.

Figure 1.2: Sample information cards shown to respondents

Note: This figure shows samples of two cards shown to the respondents. The person receiving the card to the left wants to go to Malaysia. He got the general information on national flow of workers to Malaysia, the wage information of 2013 ('high' wage), and ('low') death information indicating the number of migrants who died in Malaysia and were from a pre-determined district.

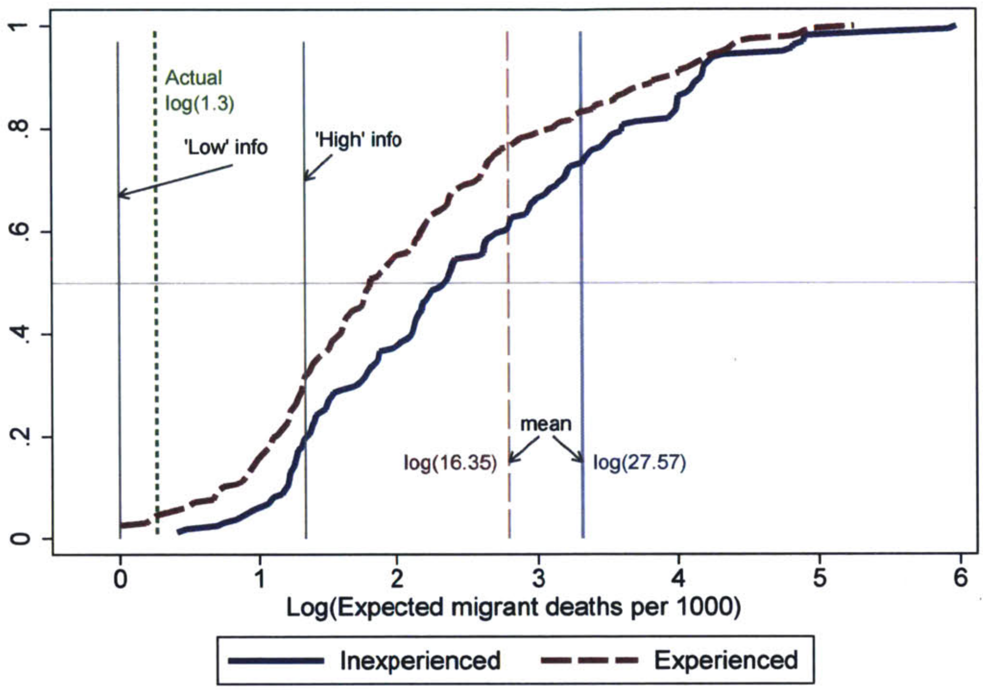
The person receiving the card to the right wants to go to Qatar. He got the general information on national flow of workers to Qatar, and ('high') death information indicating the number of migrants who died in Qatar and were from a pre-determined district. This individual did not get any wage information.

Figure 1.3: Earnings expectations of potential migrants



Source: Author's calculations on the survey data collected for this project.
Note: This figure shows the cumulative distribution function (cdf) of expected net earnings from migration for potential migrants in the control group (they do not receive any information on wages or deaths). The solid blue line plots the cdf for the inexperienced ones whereas the dashed red line plots the cdf for the experienced potential migrants.
"Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past for foreign employment.
The means for these two groups are indicated in the figure by vertical lines and are labeled accordingly. The black vertical lines to the left show the level of information that was provided to the 'high' and 'low' wage treatment groups.

Figure 1.4: Misinformation on expected mortality rate among potential migrants



Source: Author's calculations on the survey data collected for this project
Note: The figure shows the cumulative distribution function (cdf) of expected mortality rate abroad for potential migrants in the control group (they do not receive any information on wages or deaths). The solid blue line plots the cdf for the inexperienced ones whereas the dashed red line plots the cdf for the experienced potential migrants.
"Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past for foreign employment.
The means for these two groups are indicated in the figure by vertical lines and are labeled accordingly. The short-dashed green verticle line represents the true mortality rate faced by the migrants. True mortality rate is computed using deaths data from the Foreign Employment Promotion Board and the migrant stock data from Census 2011. The black vertical lines to the left show the level of information that was provided to the 'high' and 'low' wage treatment groups and are labeled accordingly.

1.A.II Tables

Table 1.1: Sample size by randomization groups

		Death Information treatment			
		None	'Low'	'High'	Total
Wage	None	376	354	384	1,114
information	'Low'	339	359	352	1,050
treatment	'High'	382	410	363	1,155
	Total	1,097	1,123	1,099	3,319

Note: This table shows the sample size in each of the information treatment cells. Within each of death and wage information, respondents were equally likely to receive no information, 'low' information, and 'high' information with equal probability. Death information was cross-randomized with wage information.

Table 1.2: Effects of information treatments on expected mortality rate (per 1000 migrants)

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
Death info: 'high'	0.221	-0.743	-1.849	-3.889	1.598	1.150
	(1.587)	(1.644)	(3.047)	(3.013)	(2.124)	(2.146)
Death info: 'low'	-4.327**	-4.843***	-7.413**	-8.081**	-2.250	-3.020
	(1.733)	(1.708)	(3.247)	(3.221)	(2.071)	(2.344)
Wage info: 'high'	-0.843	-1.218	2.098	1.781	-2.899	-4.198
	(1.678)	(1.680)	(2.931)	(3.179)	(2.586)	(2.812)
Wage info: 'low'	-0.626	-0.699	2.209	2.580	-3.125	-2.817
	(1.843)	(1.846)	(2.991)	(3.028)	(2.889)	(2.955)
Controls	NO	YES	NO	YES	NO	YES
Observations	3319	3319	1411	1411	1341	1341
R-squared	0.003	0.087	0.005	0.112	0.004	0.118
Control group mean	21.276		27.570		17.417	
SD	(39.973)		(51.029)		(28.786)	

Source: Author's calculations on the survey data collected for this project
Note: This table shows the impact of information treatments on expected mortality rate (per 1000 migrants) estimated using equation (1.1). Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, and surveyor fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor × date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.3: Effects of information treatments on expected net earnings (in USD '000)

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
Death info: 'high'	-0.498*	-0.461*	-0.647	-0.357	-0.500	-0.339
	(0.279)	(0.263)	(0.432)	(0.393)	(0.342)	(0.288)
Death info: 'low'	-0.160	-0.069	-0.604	-0.193	0.157	0.118
	(0.243)	(0.229)	(0.433)	(0.333)	(0.327)	(0.299)
Wage info: 'high'	-0.280	-0.459**	-1.071**	-0.988***	0.238	-0.034
	(0.260)	(0.211)	(0.426)	(0.339)	(0.297)	(0.251)
Wage info: 'low'	0.072	0.007	-0.858**	-0.402	0.557	0.241
	(0.270)	(0.213)	(0.416)	(0.328)	(0.342)	(0.312)
Controls	NO	YES	NO	YES	NO	YES
Observations	3319	3319	1411	1411	1341	1341
R-squared	0.002	0.251	0.008	0.333	0.005	0.335
Control group mean	10.851		12.268		9.656	
SD	(8.183)		(11.122)		(4.396)	

Source: Author's calculations on the survey data collected for this project
Note: This table shows the impact of information treatments on expected net earnings from migration (in USD '000) estimated using equation (1.1). The net earnings from migration is their expected monthly earnings multiplied by the modal duration of a migration episode to their chosen destnation after subtracting the expected fees of migrating to that destination.
Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, and surveyor fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor × date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.4: Correlation between information treatments and various attrition measures

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
	Attrition F - did not conduct full follow-up survey					
Death info: 'high'	0.006	0.004	-0.001	0.010	0.016	0.011
	(0.016)	(0.015)	(0.023)	(0.025)	(0.023)	(0.023)
Death info: 'low'	0.031*	0.024	0.013	0.010	0.063***	0.048**
	(0.016)	(0.016)	(0.025)	(0.026)	(0.021)	(0.022)
Wage info: 'high'	-0.031**	-0.030**	-0.040*	-0.039*	-0.021	-0.011
	(0.015)	(0.015)	(0.023)	(0.023)	(0.023)	(0.023)
Wage info: 'low'	0.003	-0.002	0.008	-0.002	0.011	0.000
	(0.017)	(0.017)	(0.025)	(0.025)	(0.024)	(0.024)
Controls	NO	YES	NO	YES	NO	YES
Control group mean	0.162		0.152		0.149	
SD	(0.369)		(0.360)		(0.357)	
	Attrition M - do not know migration status					
Death info: 'high'	0.018	0.016	0.005	0.017	0.025	0.020
	(0.015)	(0.015)	(0.022)	(0.023)	(0.020)	(0.021)
Death info: 'low'	0.037**	0.029**	0.013	0.009	0.068***	0.056***
	(0.015)	(0.014)	(0.023)	(0.023)	(0.020)	(0.020)
Wage info: 'high'	-0.031**	-0.030**	-0.044**	-0.042**	-0.015	-0.012
	(0.014)	(0.014)	(0.021)	(0.021)	(0.021)	(0.021)
Wage info: 'low'	-0.003	-0.005	-0.013	-0.024	0.015	0.004
	(0.015)	(0.015)	(0.023)	(0.023)	(0.022)	(0.023)
Controls	NO	YES	NO	YES	NO	YES
Control group mean	0.130		0.127		0.112	
SD	(0.337)		(0.334)		(0.316)	
	Attrition W - Wrong numbers or refused to interview					
Death info: 'high'	0.002	0.001	-0.002	0.001	-0.003	-0.000
	(0.008)	(0.008)	(0.012)	(0.012)	(0.013)	(0.013)
Death info: 'low'	0.004	0.002	-0.003	-0.003	0.014	0.013
	(0.009)	(0.009)	(0.013)	(0.013)	(0.014)	(0.013)
Wage info: 'high'	-0.001	0.000	-0.011	-0.005	-0.001	0.005
	(0.007)	(0.008)	(0.011)	(0.011)	(0.012)	(0.013)
Wage info: 'low'	0.003	0.004	0.009	0.014	-0.006	-0.010
	(0.007)	(0.007)	(0.013)	(0.013)	(0.011)	(0.011)
Controls	NO	YES	NO	YES	NO	YES
Control group mean	0.040		0.036		0.043	
SD	(0.196)		(0.188)		(0.205)	

Source: Author's calculations on the survey data collected for this project

Note: This table checks whether the three measures of attrition are correlated with information treatments using equation (1.1). The heading of each panel indicates and defines the measure of migration. Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, and surveyor fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor $\times$ date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$

Table 1.5: Effects of information treatments on actual migration

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
Effect on preferred measure of migration, Migrated-P						
Migrated or will do so in 2 weeks, or reasonable attriters, excludes Attrited-W						
Death info: 'high'	**0.036***	**0.040****	**0.019**	**0.034**	**0.056**	**0.044**
	(0.020)	**(0.019)**	**(0.029)**	**(0.030)**	**(0.034)**	**(0.038)**
Death info: 'low'	**0.062*****	**0.071*****	**0.069****	**0.072****	**0.095*****	**0.088*****
	(0.021)	**(0.020)**	**(0.031)**	**(0.031)**	**(0.030)**	**(0.032)**
Wage info: any	**-0.008**	**-0.015**	**-0.057****	**-0.067****	**0.022**	**0.018**
	(0.019)	**(0.018)**	**(0.027)**	**(0.029)**	**(0.029)**	**(0.031)**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Observations	**3210**	**3210**	**1364**	**1364**	**1297**	**1297**
R-squared	**0.003**	**0.240**	**0.007**	**0.136**	**0.007**	**0.168**
Control group mean	**0.410**		**0.308**		**0.370**	
SD	**(0.493)**		**(0.463)**		**(0.484)**	
Effect on alternative measure of migration, Migrated-A						
Migrated or will do so in 2 weeks, or all attriters						
Death info: 'high'	0.036*	0.040**	0.017	0.033	0.052	0.043
	(0.019)	(0.018)	(0.029)	(0.030)	(0.034)	(0.037)
Death info: 'low'	0.062***	0.071***	0.064**	0.068**	0.100***	0.094***
	(0.020)	(0.019)	(0.031)	(0.031)	(0.030)	(0.031)
Wage info: any	-0.008	-0.015	-0.056**	-0.062**	0.019	0.016
	(0.019)	(0.018)	(0.027)	(0.029)	(0.028)	(0.030)
Controls	NO	YES	NO	YES	NO	YES
Observations	3319	3319	1411	1411	1341	1341
R-squared	0.003	0.226	0.006	0.138	0.007	0.163
Control group mean	0.434		0.333		0.398	
SD	(0.496)		(0.473)		(0.491)	
Effect on basic measure of migration, Migrated-B						
Migrated or will do so in 2 weeks, excludes Attrited-M						
Death info: 'high'	0.028	0.032*	0.016	0.023	0.039	0.026
	(0.020)	(0.019)	(0.028)	(0.030)	(0.034)	(0.038)
Death info: 'low'	0.045**	0.060***	0.063**	0.069**	0.063**	0.068*
	(0.021)	(0.020)	(0.030)	(0.030)	(0.032)	(0.035)
Wage info: any	0.004	-0.004	-0.039	-0.044	0.023	0.020
	(0.019)	(0.018)	(0.025)	(0.028)	(0.030)	(0.031)
Controls	NO	YES	NO	YES	NO	YES
Observations	2877	2877	1242	1242	1181	1181
R-squared	0.002	0.264	0.006	0.132	0.004	0.177
Control group mean	0.349		0.236		0.322	
SD	(0.477)		(0.426)		(0.469)	

Source: Author's calculations on the survey data collected for this project

Note: This table shows the impact of information treatments on various measures of migration, estimated using equation (1.1). The heading of each panel indicates and defines the measure of migration. Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, and surveyor fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor × date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.6: Lee (2009) bounds of treatment effect on basic migration (Migrated-B)

	Death Info		*Wage info*
	High	Low	Any
	(1)	(2)	(3)
Sample: All			
Lower bound	0.021	0.030	-0.006
	(0.024)	(0.024)	(0.022)
Upper bound	0.043*	0.073***	0.013
	(0.025)	(0.025)	(0.021)
95 % CI	[-0.019 0.085]	[-0.010 0.115]	[-0.043 0.048]
Sample: Inexperienced			
Lower bound	0.015	0.063**	-0.063**
	(0.030)	(0.031)	(0.032)
Upper bound	0.022	0.077**	-0.031
	(0.035)	(0.036)	(0.028)
95 % CI	[-0.041 0.088]	[0.006 0.143]	[-0.117 0.016]
Sample: Experienced			
Lower bound	0.027	0.040	0.023
	(0.036)	(0.037)	(0.031)
Upper bound	0.056	0.121***	0.029
	(0.039)	(0.041)	(0.033)
95 % CI	[-0.035 0.122]	[-0.022 0.189]	[-0.035 0.092]

Source: Author's calculations on the survey data collected for this project
Note: This table shows the estimated Lee (2009) bounds for the basic definition of migration (Migrated-B). See Table 1.5 and the text for the definition of Migrated-B. Each column in each panel represents a separate estimation of the bounds. Each estimation is performed on the sample of the treatment group indicated by the column heading and the control group. For each estimation a lower bound, an upper bound is reported with standard errors in parentheses. The 95% confidence interval on the bounds is reported in brackets. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.7: Binary choice instrumental variable estimates of VSL for inexperienced potential migrants

	Migrated - P	Migrated - A	Migrated - B
	Preferred	Alternative	Basic
	(1)	(2)	(3)
	Logarithmic specification		
	Coefficients		
Log(expected mortality per 1000)	**-0.485*****	-0.460***	-0.513***
	(0.040)	(0.068)	(0.043)
Log(expected net earnings, USD '000)	**0.699*****	0.768***	0.332***
	(0.099)	(0.137)	(0.087)
	Marginal Effects		
Log(expected mortality per 1000)	**-0.155*****	-0.149***	-0.160***
	(0.011)	(0.020)	(0.012)
Log(expected net earnings, USD '000)	**0.224*****	0.248***	0.103***
	(0.031)	(0.046)	(0.027)
VSL (in '000 USD)	**282.412*****	245.497***	632.501***
	(50.938)	(75.040)	(188.667)
	Levels specification		
	Coefficients		
Expected mortality (per 1000)	**-0.017*****	-0.016***	-0.017***
	(0.002)	(0.001)	(0.002)
Expected net earnings (USD '000)	**0.031****	0.038***	0.007
	(0.013)	(0.007)	(0.013)
	Marginal Effects		
Expected mortality (per 1000)	**-0.006*****	-0.006***	-0.006***
	(0.001)	(0.000)	(0.001)
Expected net earnings (USD '000)	**0.011****	0.013***	0.003
	(0.005)	(0.003)	(0.005)
VSL (in '000 USD)	**538.220****	430.156***	2354.663
	(264.302)	(94.444)	(4471.196)

Source: Author's calculations on the survey data collected for this project

Note: This table shows instrumented probit estimates of the effect of expected earnings and expected mortality rate on migration choices of inexperienced potential migrants, estimated using equation (1.2). Information treatments are used as instruments for expected earnings and expected mortality. The heading of each column indicates the measure of migration used as the outcome variable. See text and Table 1.5 for the definition of these measures. The heading of each panel indicates whether the logarithm or levels of expectations is used in the estimation. Coefficients of estimations as well as marginal effects are reported with standard errors in parentheses. Standard errors are clustered at the surveyor $\times$ date of interview level. The bottom of each panel presents the VSL, which is estimated as the ratio of two marginal effects. Standard errors for the VSL are computed using the delta method. $***: p < 0.01$; $**: p < 0.05$; $*: p < 0.1$

Table 1.8: Robustness in estimates of VSL under some alternative utility maximization rule

	Least optimistic	Median	Most optimistic	Most likely (modal)
	(1)	(2)	(3)	(4)
		Logarithmic specification		
		Coefficients		
Beliefs on mortality risk	-0.484***	-0.477***	-0.431***	-0.438***
per 1000	(0.113)	(0.028)	(0.053)	(0.047)
Beliefs on net earnings,	0.767***	0.807***	0.781***	0.824***
USD '000	(0.166)	(0.107)	(0.071)	(0.113)
		Marginal Effects		
Beliefs on mortality risk	-0.155***	-0.152***	-0.139***	-0.139***
per 1000	(0.033)	(0.008)	(0.015)	(0.013)
Beliefs on net earnings,	0.246***	0.257***	0.251***	0.262***
USD '000	(0.057)	(0.032)	(0.022)	(0.035)
VSL (in '000 USD)	157.360**	238.197***	322.092***	215.996***
	(68.405)	(36.457)	(54.377)	(46.097)
		Levels specification		
		Coefficients		
Beliefs on mortality risk	-0.013***	-0.017***	-0.021***	-0.016***
per 1000	(0.001)	(0.003)	(0.002)	(0.001)
Beliefs on net earnings,	0.034**	0.048***	0.034***	0.051***
USD '000	(0.014)	(0.015)	(0.010)	(0.006)
		Marginal Effects		
Beliefs on mortality risk	-0.005***	-0.006***	-0.007***	-0.006***
per 1000	(0.000)	(0.001)	(0.001)	(0.000)
Beliefs on net earnings,	0.012***	0.017***	0.012***	0.018***
USD '000	(0.005)	(0.005)	(0.003)	(0.002)
VSL (in '000 USD)	368.865**	353.220**	613.984***	320.578***
	(158.346)	(154.951)	(196.121)	(35.699)

Source: Author's calculations on the survey data collected for this project

Note: This table shows instrumented probit estimates of the effect of beliefs on earnings and mortality rate on migration choices of inexperienced potential migrants, estimated using equation (1.2). The preferred measure of migration (Migrated-P) is used as the dependent variable. Information treatments are used as instruments for beliefs on earnings and mortality rate. Instead of using the expected value of their beliefs as the variables of interset, this table takes different points in these belief distributions based on assumptions on the relevant decision-making parameters.

The first column assumes that potential migrants are least optimistic about migration while making their migration decision. They take the maximum of their belief distribution on mortality rate and the minimum of their belief distribution on net earning as the relevant parameter in their migration decision.

The second column assumes that potential migrants make migration choices by taking the median of their belief distributions.

The third column assumes that potential migrants are most optimistic about migration while making their migration decision. They take the minimum of their belief distribution on mortality rate and the maximum of their belief distribution on net earnings as the relevant parameter in their migration decision.

The fourth column assumes that potential migrants take the most likely points in their belief distribution as the relevant parameters for their migration decision.

The heading of each panel indicates whether the logarithm or levels of expectations is used in the estimation. Coefficients of estimations as well as marginal effects are reported with standard errors in parentheses. Standard errors are clustered at the surveyor $\times$ date of interview level. VSL is estimated as the ratio of two marginal effects and its standard error computed using the delta method. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.9: Binary choice instrumental variable estimates of VSL for subgroups

	Old	Young	Low educ	High educ	Manual	Non-manual
	(1)	(2)	(3)	(4)	(5)	(6)
			Logarithmic specification			
			Coefficients			
Log(expected	-0.334***	-0.607***	-0.716***	-0.287***	-0.540***	-0.428***
mortality per 1000)	(0.106)	(0.020)	(0.032)	(0.041)	(0.025)	(0.059)
Log(expected net	0.232	1.135***	0.063	0.127	1.201***	0.492
earnings, USD '000)	(0.295)	(0.173)	(0.092)	(0.110)	(0.123)	(0.508)
			Marginal Effects			
Log(expected	-0.115***	-0.180***	-0.216***	-0.093***	-0.163***	-0.139***
mortality per 1000)	(0.034)	(0.005)	(0.006)	(0.013)	(0.006)	(0.017)
Log(expected net	0.080	0.336***	0.019	0.041	0.362***	0.160
earnings, USD '000)	(0.102)	(0.043)	(0.028)	(0.035)	(0.032)	(0.161)
VSL (in '000 USD)	691.685	176.361***	3784.212	1098.457	142.562***	411.008
	(989.257)	(25.987)	(5476.132)	(931.811)	(16.757)	(411.136)
			Levels specification			
			Coefficients			
Expected mortality	-0.015	-0.016***	-0.020***	-0.011***	-0.007***	-0.012**
(per 1000)	(0.010)	(0.001)	(0.000)	(0.003)	(0.000)	(0.006)
Expected net earnings	0.011	0.077***	0.010	-0.034*	0.209***	0.014
(USD '000)	(0.015)	(0.015)	(0.011)	(0.018)	(0.001)	(0.021)
			Marginal Effects			
Expected mortality	-0.006	-0.005***	-0.007***	-0.004***	-0.002***	-0.004**
(per 1000)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
Expected net earnings	0.004	0.026***	0.004	-0.011**	0.063***	0.005
(USD '000)	(0.005)	(0.005)	(0.004)	(0.006)	(0.000)	(0.007)
VSL (in '000 USD)	1400.798	206.146***	1900.729	-313.326**	34.569***	912.446
	(2511.384)	(39.629)	(2045.586)	(159.151)	(0.178)	(1597.543)

Source: Author's calculations on the survey data collected for this project

Note: This table shows instrumented probit estimates of the effect of expected earnings and expected mortality rate on migration choices for various subgroups of inexperienced potential migrants, estimated using equation (1.2). The preferred measure of migration (Migrated-P) is used as the dependent variable. Information treatments are used as instruments for beliefs on earnings and mortality rate in all cases.

"Old" refers to those who are 21 years or higher, and "Young" refers to the rest. 58 percent of the sample is old.

"Low educ" refers to those who have 8 or fewer years of schooling, and "High educ" refers to the rest. 50 percent of the sample has low education.

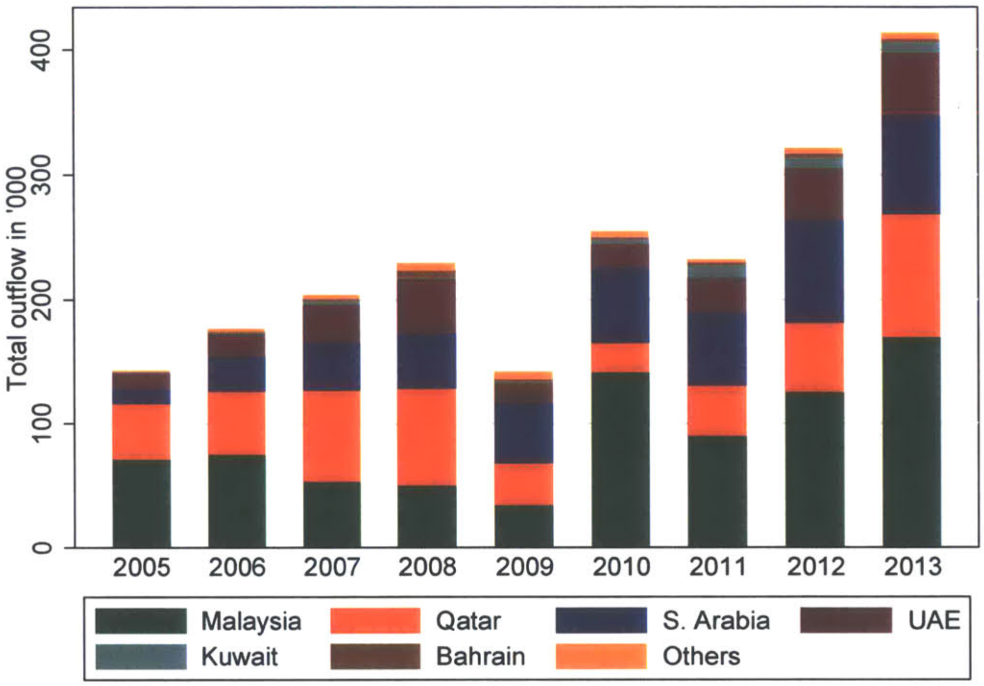
"Manual" refers to those who want to migrate as construction or other manual labor work, and "Non-manual" refers to the rest who migrate for other low-skill work. 38 percent of sample wants to migrate for manual work.

The heading of each panel indicates whether the logarithm or levels of expectations is used in the estimation. Coefficients of estimations as well as marginal effects are reported with standard errors in parentheses. Standard errors are clustered at the surveyor $\times$ date of interview level. VSL is estimated as the ratio of two marginal effects and its standard error computed using the delta method. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

1.B Appendix Figures and Tables

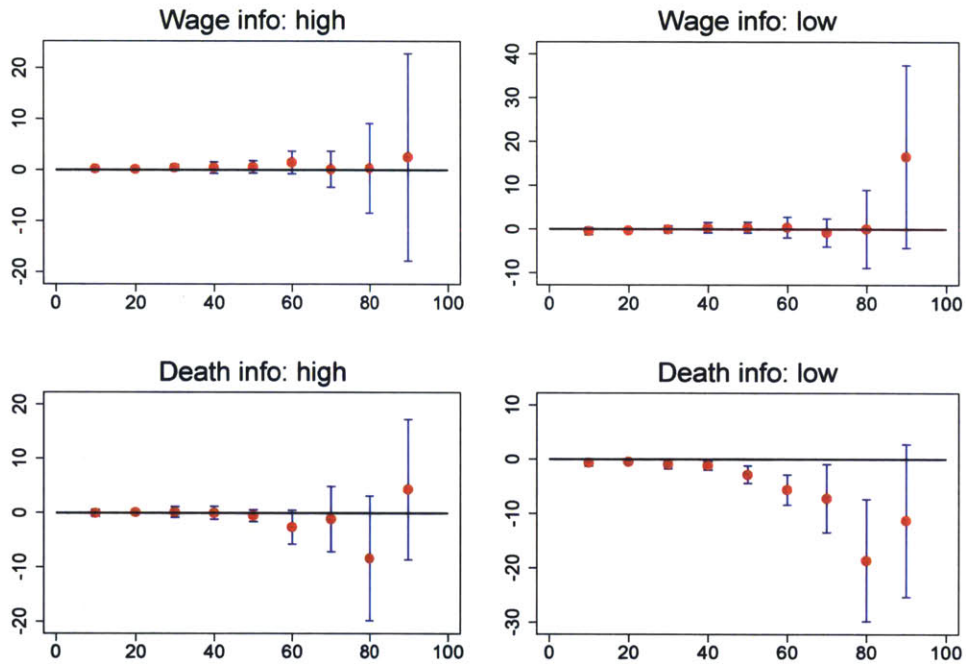
1.B.I Figures

Figure 1.B.1: Permits granted by DoFE for work abroad



Source: Author's calculation on the data provided by Department of Foreign Employment (DoFE).
Note: This figure shows the number of work-permits issued by DoFE for work abroad by year and destination country.

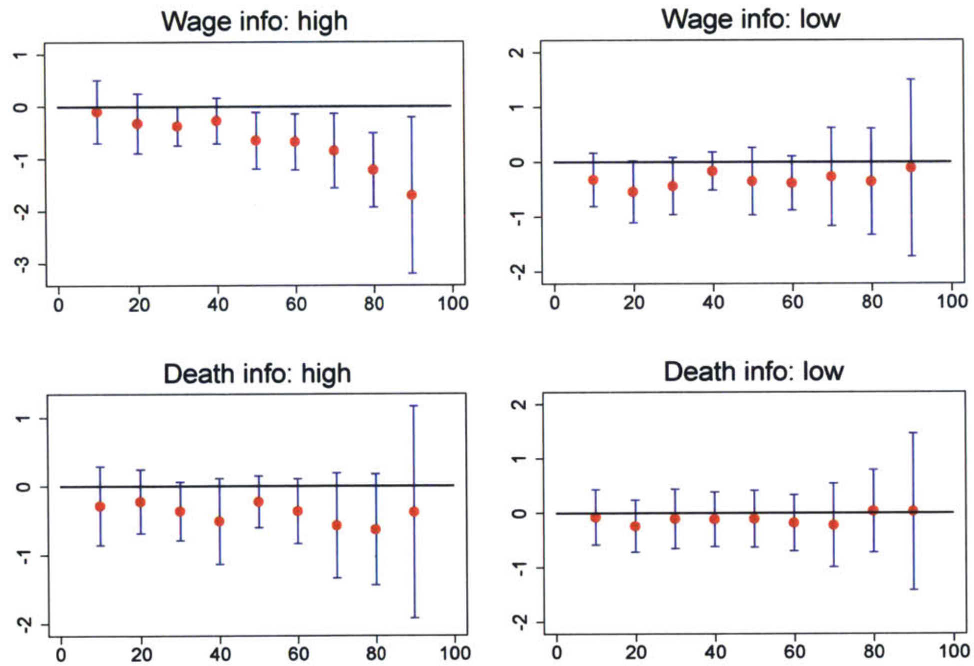
Figure 1.B.2: Quantile treatment effects of information treatments on expected mortality for inexperienced potential migrants



Source: Author's calculations on the survey data collected for this project

Note: Figure shows the Least Absolute Deviation estimates of equation (1.1) on expected mortality rate at each decile for the group of inexperienced potential migrants. Point estimates are shown as red dots with 95% confidence bands in blue. The estimates control for destination fixed effects, fixed effects for schooling categories, age categories, location and geography. The figure consolidates estimates from 9 different estimates at each decile.

Figure 1.B.3: Quantile treatment effects of information treatment on expected net earnings for inexperienced potential migrants



Source: Author's calculations on the survey data collected for this project
Note: Figure shows the Least Absolute Deviation estimates of equation (1.1) on expected net earnings at each decile for the group of inexperienced potential migrants. Point estimates are shown as red dots with 95% confidence bands in blue. The estimates control for destination fixed effects, fixed effects for schooling categories, age categories, location and geography. The figure consolidates estimates from 9 different estimates at each decile.

1.B.II Tables

Table 1.B.1: International migration from Nepal and remittance income

	Migrant/Population share			Remittance Income
Year	All	India	Non-India	% of GDP
1961	3.49			
1981	2.68	2.48	0.19	
1991	3.56	3.17	0.37	1.5
2001	3.41	2.61	0.78	2.4
2011	7.43	2.80	4.63	22.4

Source: Migrant/Population share from the Census reports for respective years, Remittance as a share of GDP from the World Development Indicator database (The World Bank)
Note: This table shows the migrant to population share for each of the census years since 1961. It also shows the share broken down by destination. The last column shows the personal remittance income as a share of national GDP for the years available.

Table 1.B.2: Population comparison between absentees in Census 2011 and survey sample

	Census (2011) mean/(SD) (1)	Survey Data: All mean/(SD) (2)	Inexperienced mean/(SD) (3)	Experienced mean/(SD) (4)	On leave mean/(SD) (5)
Demographics					
Age	27.171	27.573	23.502	29.966	32.040
	(6.944)	(7.148)	(5.883)	(6.402)	(6.433)
Completed Education	7.189	7.469	7.777	7.046	7.706
	(3.418)	(3.532)	(3.409)	(3.582)	(3.618)
Geography and Location					
Hills and Mountain	0.495	0.501	0.517	0.472	0.530
	(0.500)	(0.500)	(0.500)	(0.499)	(0.500)
Southern Plain (Terai)	0.505	0.499	0.483	0.528	0.470
	(0.500)	(0.500)	(0.500)	(0.499)	(0.500)
Urban	0.113	0.083	0.073	0.088	0.093
	(0.317)	(0.275)	(0.260)	(0.283)	(0.291)
Eastern Region	0.333	0.276	0.245	0.293	0.315
	(0.471)	(0.447)	(0.430)	(0.455)	(0.465)
Central Region	0.281	0.373	0.413	0.366	0.287
	(0.450)	(0.484)	(0.493)	(0.482)	(0.453)
Western Region	0.292	0.159	0.074	0.180	0.324
	(0.455)	(0.366)	(0.261)	(0.384)	(0.468)
Mid/Far Western Region	0.094	0.192	0.269	0.160	0.074
	(0.291)	(0.394)	(0.443)	(0.367)	(0.262)
Destination Country					
Malaysia	0.264	0.255	0.359	0.204	0.118
	(0.441)	(0.436)	(0.480)	(0.403)	(0.323)
Qatar	0.296	0.232	0.201	0.231	0.310
	(0.457)	(0.422)	(0.401)	(0.421)	(0.463)
Saudi Arabia	0.245	0.198	0.135	0.212	0.319
	(0.430)	(0.398)	(0.342)	(0.409)	(0.466)
U.A.E.	0.138	0.230	0.232	0.239	0.208
	(0.345)	(0.421)	(0.422)	(0.427)	(0.406)
Other destinations	0.056	0.085	0.073	0.115	0.046
	(0.231)	(0.279)	(0.260)	(0.319)	(0.209)

Source: Author's calculations using 2011 Housing and Population Census Public Use Microdata Sample and the survey data collected for this project

Note: This table presents the descriptive statistics of the absentee population in the 2011 Housing and Population Census (column 1) and the study sample (columns 2 - 5). The Housing and Population Census of Nepal defines absentee population as "persons away or absent from birth place or usual place [of residence] for employment or study or business purpose [abroad]". Columns 3-5 presents the descriptive statistics by subgroups of the study sample. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad. "On leave" refers to potential migrants who are back home on leave from their work abroad.

Table 1.B.3: Description of information provided to the subjects

	Destination Countries				
	Malaysia	Qatar	Saudi Arabia	U.A.E	Kuwait
Monthly flow	14,100	8,300	6,500	4,200	700
Wage 'High' (NPR)	24,500	25,000	23,000	26,000	26,500
Wage 'Low' (NPR)	12,500	15,500	13,500	19,000	15,000
Death 'High'	9	8	9	3	2
Death 'Low'	2	1	2	1	1

Note: This table presents the exact nature of information provided to the participants. Each row lists the information provided in each of the treatment groups for potential migrants to the Destination countries listed in the columns. Monthly flow is the average number of work-reated migrants leaving Nepal every month in 2013. Wage information is provided as monthly wages in Nepali Rupees (exchange rate US$ 1= NPR 100). Death information provided indicates the number of deaths that occured in a pre-determined district in 2013.

Table 1.B.4: Randomization balance table: Death

	Death information			'Low' - None	'High' - None	'High' - 'Low'	Joint test
	None	'Low'	'High'				
	mean/(sd)	mean/(sd)	mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Demographics				
Age	27.919	27.585	27.216	−0.334	−0.703**	−0.369	2.662
	(7.264)	(7.059)	(7.111)	(0.304)	(0.307)	(0.301)	(0.070)
Completed education	7.462	7.498	7.448	0.036	−0.014	−0.050	0.059
	(3.533)	(3.516)	(3.550)	(0.150)	(0.151)	(0.150)	(0.942)
Migrated before	0.590	0.576	0.559	−0.014	−0.031	−0.017	1.092
	(0.492)	(0.494)	(0.497)	(0.021)	(0.021)	(0.021)	(0.336)
Heard of deaths	0.213	0.260	0.244	0.046**	0.031	−0.015	1.983
	(0.410)	(0.439)	(0.430)	(0.024)	(0.024)	(0.024)	(0.138)
On leave	0.308	0.277	0.309	−0.031	0.002	0.033	1.038
	(0.462)	(0.448)	(0.463)	(0.025)	(0.026)	(0.026)	(0.354)
			Geography and location				
Eastern	0.285	0.267	0.277	−0.018	−0.009	0.009	0.459
	(0.452)	(0.443)	(0.448)	(0.019)	(0.019)	(0.019)	(0.632)
Central	0.366	0.382	0.369	0.016	0.003	−0.013	0.325
	(0.482)	(0.486)	(0.483)	(0.021)	(0.021)	(0.021)	(0.723)
Western	0.167	0.159	0.152	−0.007	−0.015	−0.007	0.452
	(0.373)	(0.366)	(0.359)	(0.016)	(0.016)	(0.015)	(0.636)
Mid/Far Western	0.181	0.191	0.202	0.010	0.021	0.011	0.752
	(0.386)	(0.394)	(0.402)	(0.017)	(0.017)	(0.017)	(0.472)
Southern plain (Terai)	0.489	0.492	0.517	0.004	0.028	0.024	1.032
	(0.500)	(0.500)	(0.500)	(0.021)	(0.021)	(0.021)	(0.356)
Urban	0.074	0.092	0.082	0.018	0.008	−0.010	1.176
	(0.262)	(0.289)	(0.274)	(0.012)	(0.011)	(0.012)	(0.309)
			Chosen destination				
Malaysia	0.256	0.246	0.263	−0.010	0.007	0.017	0.439
	(0.437)	(0.431)	(0.440)	(0.018)	(0.019)	(0.018)	(0.645)
Qatar	0.218	0.231	0.247	0.013	0.029	0.016	1.277
	(0.413)	(0.421)	(0.431)	(0.018)	(0.018)	(0.018)	(0.279)
Saudi Arabia	0.201	0.198	0.194	−0.004	−0.008	−0.004	0.101
	(0.401)	(0.398)	(0.395)	(0.017)	(0.017)	(0.017)	(0.904)
U.A.E	0.242	0.231	0.218	−0.012	−0.024	−0.012	0.899
	(0.429)	(0.421)	(0.413)	(0.018)	(0.018)	(0.018)	(0.407)
Other	0.082	0.095	0.078	0.013	−0.004	−0.017	1.141
	(0.275)	(0.294)	(0.269)	(0.012)	(0.012)	(0.012)	(0.320)
Joint test across all regressions: F-stat							0.878
p-value							0.650

Source: Author's calculations on the survey data collected for this project

Note: This table checks whether death information treatments are correlated with characteristics collected prior to the treatment. The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.5: Randomization balance table: Wage

	Wage information			'Low' -	'High' -	'High' -	Joint
	None	'Low'	'High'	None	None	'Low'	test
	mean/(sd)	mean/(sd)	mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Demographics				
Age	27.747	27.138	27.801	−0.609**	0.054	0.663**	2.863
	(7.126)	(6.998)	(7.292)	(0.304)	(0.303)	(0.305)	(0.057)
Completed education	7.327	7.542	7.541	0.215	0.214	−0.001	1.368
	(3.551)	(3.482)	(3.557)	(0.151)	(0.149)	(0.150)	(0.255)
Migrated before	0.578	0.562	0.584	−0.016	0.005	0.022	0.563
	(0.494)	(0.496)	(0.493)	(0.021)	(0.021)	(0.021)	(0.570)
Heard of deaths	0.244	0.239	0.234	−0.005	−0.009	−0.005	0.079
	(0.430)	(0.427)	(0.424)	(0.024)	(0.024)	(0.024)	(0.924)
On leave	0.278	0.303	0.312	0.025	0.034	0.008	0.956
	(0.448)	(0.460)	(0.463)	(0.026)	(0.025)	(0.026)	(0.385)
			Geography and location				
Eastern	0.276	0.275	0.278	−0.000	0.002	0.003	0.012
	(0.447)	(0.447)	(0.448)	(0.019)	(0.019)	(0.019)	(0.988)
Central	0.359	0.389	0.371	0.030	0.012	−0.017	1.012
	(0.480)	(0.488)	(0.483)	(0.021)	(0.020)	(0.021)	(0.364)
Western	0.162	0.150	0.165	−0.011	0.004	0.015	0.485
	(0.368)	(0.358)	(0.372)	(0.016)	(0.016)	(0.016)	(0.616)
Mid/Far Western	0.204	0.186	0.185	−0.018	−0.018	−0.000	0.798
	(0.403)	(0.389)	(0.389)	(0.017)	(0.017)	(0.017)	(0.450)
Southern plain (Terai)	0.525	0.497	0.476	−0.028	−0.049**	−0.021	2.732
	(0.500)	(0.500)	(0.500)	(0.022)	(0.021)	(0.021)	(0.065)
Urban	0.075	0.090	0.082	0.015	0.007	−0.008	0.811
	(0.264)	(0.287)	(0.275)	(0.012)	(0.011)	(0.012)	(0.444)
			Chosen destination				
Malaysia	0.247	0.256	0.261	0.009	0.015	0.005	0.325
	(0.431)	(0.437)	(0.440)	(0.019)	(0.018)	(0.019)	(0.722)
Qatar	0.240	0.229	0.227	−0.011	−0.013	−0.002	0.304
	(0.427)	(0.420)	(0.419)	(0.018)	(0.018)	(0.018)	(0.738)
Saudi Arabia	0.194	0.188	0.210	−0.006	0.016	0.023	0.973
	(0.396)	(0.391)	(0.408)	(0.017)	(0.017)	(0.017)	(0.378)
U.A.E	0.225	0.240	0.227	0.015	0.002	−0.013	0.395
	(0.418)	(0.427)	(0.419)	(0.018)	(0.018)	(0.018)	(0.674)
Other	0.094	0.088	0.074	−0.007	−0.020*	−0.013	1.479
	(0.292)	(0.283)	(0.263)	(0.012)	(0.012)	(0.012)	(0.228)
Joint test across all regressions: F-stat							0.990
p-value							0.480

Source: Author's calculations on the survey data collected for this project
Note: This table checks whether wage information treatments are correlated with characteristics collected prior to the treatment. The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.6: Randomization balance table for inexperienced potential migrants: Death

	Death information			'Low' -	'High' -	'High' -	Joint
	None	'Low'	'High'	None	None	'Low'	test
	mean/(sd)	mean/(sd)	mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Demographics				
Age	23.969	23.532	23.041	−0.437	−0.928**	−0.490	2.918
	(6.318)	(5.805)	(5.506)	(0.398)	(0.387)	(0.365)	(0.054)
Completed education	7.733	7.704	7.889	−0.030	0.155	0.185	0.407
	(3.397)	(3.427)	(3.405)	(0.224)	(0.223)	(0.220)	(0.666)
			Geography and location				
Eastern	0.242	0.227	0.264	−0.015	0.022	0.037	0.900
	(0.429)	(0.419)	(0.441)	(0.028)	(0.028)	(0.028)	(0.407)
Central	0.411	0.426	0.402	0.015	−0.009	−0.024	0.300
	(0.493)	(0.495)	(0.491)	(0.032)	(0.032)	(0.032)	(0.741)
Western	0.080	0.076	0.066	−0.004	−0.014	−0.010	0.355
	(0.272)	(0.265)	(0.249)	(0.018)	(0.017)	(0.017)	(0.701)
Mid/Far Western	0.267	0.271	0.268	0.004	0.001	−0.003	0.012
	(0.443)	(0.445)	(0.443)	(0.029)	(0.029)	(0.029)	(0.988)
Southern plain (Terai)	0.484	0.479	0.487	−0.005	0.002	0.008	0.029
	(0.500)	(0.500)	(0.500)	(0.033)	(0.033)	(0.032)	(0.971)
Urban	0.076	0.074	0.070	−0.002	−0.005	−0.003	0.053
	(0.265)	(0.261)	(0.256)	(0.017)	(0.017)	(0.017)	(0.949)
			Chosen destination				
Malaysia	0.376	0.338	0.363	−0.037	−0.013	0.025	0.729
	(0.485)	(0.474)	(0.481)	(0.031)	(0.032)	(0.031)	(0.483)
Qatar	0.187	0.197	0.219	0.011	0.032	0.021	0.770
	(0.390)	(0.399)	(0.414)	(0.026)	(0.026)	(0.026)	(0.463)
Saudi Arabia	0.136	0.139	0.132	0.003	−0.004	−0.007	0.046
	(0.343)	(0.346)	(0.339)	(0.023)	(0.022)	(0.022)	(0.955)
U.A.E	0.238	0.239	0.219	0.002	−0.019	−0.021	0.363
	(0.426)	(0.427)	(0.414)	(0.028)	(0.027)	(0.027)	(0.696)
Other	0.064	0.086	0.068	0.022	0.004	−0.018	0.938
	(0.246)	(0.281)	(0.252)	(0.017)	(0.016)	(0.017)	(0.392)
Joint test across all regressions: F-stat							0.625
p-value							0.909

Source: Author's calculations on the survey data collected for this project

Note: This table checks whether death information treatments are correlated with characteristics collected prior to the treatment for inexperienced potential migrants (those who have never migrated before for foreign employment). The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.7: Randomization balance table for inexperienced potential migrants: Wage

	Wage information			'Low' -	'High' -	'High' -	Joint
	None	'Low'	'High'	None	None	'Low'	test
	mean/(sd)	mean/(sd)	mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Demographics					
Age	23.740	23.237	23.524	−0.503	−0.217	0.287	0.856
	(6.001)	(5.749)	(5.896)	(0.385)	(0.386)	(0.380)	(0.425)
Completed education	7.864	7.670	7.794	−0.194	−0.070	0.125	0.387
	(3.357)	(3.415)	(3.457)	(0.222)	(0.221)	(0.224)	(0.679)
		Geography and location					
Eastern	0.264	0.230	0.239	−0.033	−0.025	0.009	0.759
	(0.441)	(0.422)	(0.427)	(0.028)	(0.028)	(0.028)	(0.468)
Central	0.372	0.443	0.424	0.071**	0.052	−0.019	2.610
	(0.484)	(0.497)	(0.495)	(0.032)	(0.032)	(0.032)	(0.074)
Western	0.087	0.070	0.064	−0.018	−0.023	−0.005	0.989
	(0.282)	(0.255)	(0.246)	(0.018)	(0.017)	(0.016)	(0.372)
Mid/Far Western	0.277	0.257	0.272	−0.020	−0.004	0.016	0.264
	(0.448)	(0.437)	(0.446)	(0.029)	(0.029)	(0.029)	(0.768)
Southern plain (Terai)	0.496	0.465	0.489	−0.031	−0.007	0.023	0.473
	(0.501)	(0.499)	(0.500)	(0.033)	(0.032)	(0.033)	(0.623)
Urban	0.066	0.087	0.067	0.021	0.001	−0.020	0.982
	(0.248)	(0.282)	(0.249)	(0.017)	(0.016)	(0.017)	(0.375)
		Chosen destination					
Malaysia	0.366	0.335	0.374	−0.031	0.008	0.039	0.877
	(0.482)	(0.472)	(0.484)	(0.031)	(0.031)	(0.031)	(0.416)
Qatar	0.194	0.211	0.200	0.017	0.006	−0.011	0.221
	(0.396)	(0.408)	(0.400)	(0.026)	(0.026)	(0.026)	(0.802)
Saudi Arabia	0.132	0.124	0.150	−0.008	0.018	0.026	0.702
	(0.339)	(0.330)	(0.357)	(0.022)	(0.023)	(0.022)	(0.496)
U.A.E	0.226	0.257	0.214	0.031	−0.011	−0.042	1.262
	(0.418)	(0.437)	(0.411)	(0.028)	(0.027)	(0.028)	(0.283)
Other	0.083	0.074	0.062	−0.009	−0.021	−0.012	0.749
	(0.276)	(0.262)	(0.242)	(0.018)	(0.017)	(0.016)	(0.473)
Joint test across all regressions: F-stat							0.914
p-value							0.576

Source: Author's calculations on the survey data collected for this project
Note: This table checks whether wage information treatments are correlated with characteristics collected prior to the treatment for inexperienced potential migrants (those who have never migrated before for foreign employment). The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.8: Randomization balance table for experienced migrants: Death

	Death information			'Low' - None	'High' - None	'High' - 'Low'	Joint test
	None	'Low'	'High'				
	mean/(sd)	mean/(sd)	mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demographics							
Age	29.953	30.143	29.783	0.190	−0.170	−0.360	0.353
	(6.377)	(6.426)	(6.412)	(0.423)	(0.433)	(0.430)	(0.703)
Completed education	7.199	7.092	6.833	−0.107	−0.366	−0.259	1.199
	(3.612)	(3.531)	(3.604)	(0.236)	(0.244)	(0.239)	(0.302)
Heard of deaths	0.208	0.261	0.262	0.053*	0.054*	0.001	2.332
	(0.406)	(0.439)	(0.440)	(0.028)	(0.029)	(0.029)	(0.097)
Geography and location							
Eastern	0.306	0.297	0.276	−0.009	−0.030	−0.021	0.492
	(0.461)	(0.457)	(0.448)	(0.030)	(0.031)	(0.030)	(0.612)
Central	0.362	0.355	0.384	−0.007	0.023	0.030	0.456
	(0.481)	(0.479)	(0.487)	(0.032)	(0.033)	(0.032)	(0.634)
Western	0.183	0.192	0.163	0.009	−0.020	−0.030	0.682
	(0.387)	(0.395)	(0.370)	(0.026)	(0.026)	(0.026)	(0.506)
Mid/Far Western	0.150	0.156	0.177	0.006	0.027	0.021	0.656
	(0.357)	(0.363)	(0.382)	(0.024)	(0.025)	(0.025)	(0.519)
Southern plain (Terai)	0.509	0.498	0.583	−0.011	0.074**	0.085**	3.723
	(0.500)	(0.501)	(0.494)	(0.033)	(0.034)	(0.033)	(0.024)
Urban	0.074	0.100	0.090	0.027	0.016	−0.011	1.030
	(0.262)	(0.301)	(0.286)	(0.019)	(0.019)	(0.020)	(0.357)
Chosen destination							
Malaysia	0.190	0.212	0.210	0.022	0.020	−0.002	0.408
	(0.393)	(0.409)	(0.408)	(0.027)	(0.027)	(0.027)	(0.665)
Qatar	0.208	0.259	0.224	0.051*	0.016	−0.034	1.750
	(0.406)	(0.438)	(0.417)	(0.028)	(0.028)	(0.029)	(0.174)
Saudi Arabia	0.210	0.188	0.241	−0.022	0.031	0.053*	1.848
	(0.408)	(0.391)	(0.428)	(0.026)	(0.028)	(0.027)	(0.158)
U.A.E	0.275	0.214	0.229	−0.061**	−0.046	0.015	2.509
	(0.447)	(0.410)	(0.421)	(0.028)	(0.029)	(0.028)	(0.082)
Other	0.118	0.128	0.097	0.010	−0.022	−0.032	1.123
	(0.323)	(0.335)	(0.296)	(0.022)	(0.021)	(0.021)	(0.326)
Joint test across all regressions: F-stat							1.339
p-value							0.126

Source: Author's calculations on the survey data collected for this project

Note: This table checks whether death information treatments are correlated with characteristics collected prior to the treatment for experienced potential migrants (those who have migrated before for foreign employment but do not have an existing job contract abroad). The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.9: Randomization balance table for experienced migrants: Wage

	Wage information			'Low' - None	'High' - None	'High' - 'Low'	Joint test
	None mean/(sd)	'Low' mean/(sd)	'High' mean/(sd)	b/(se)	b/(se)	b/(se)	F/(p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Demographics				
Age	30.101	29.491	30.250	−0.610	0.149	0.759*	1.691
	(6.376)	(6.103)	(6.672)	(0.423)	(0.428)	(0.434)	(0.185)
Completed education	6.815	7.236	7.108	0.421*	0.293	−0.128	1.615
	(3.599)	(3.507)	(3.625)	(0.241)	(0.237)	(0.242)	(0.199)
Heard of deaths	0.241	0.243	0.246	0.002	0.005	0.002	0.015
	(0.428)	(0.430)	(0.431)	(0.029)	(0.028)	(0.029)	(0.985)
			Geography and location				
Eastern	0.258	0.311	0.313	0.053*	0.054*	0.001	2.133
	(0.438)	(0.464)	(0.464)	(0.030)	(0.030)	(0.031)	(0.119)
Central	0.378	0.365	0.356	−0.014	−0.023	−0.009	0.264
	(0.486)	(0.482)	(0.479)	(0.033)	(0.032)	(0.033)	(0.768)
Western	0.176	0.165	0.196	−0.011	0.020	0.031	0.724
	(0.382)	(0.372)	(0.397)	(0.026)	(0.026)	(0.026)	(0.485)
Mid/Far Western	0.187	0.158	0.136	−0.029	−0.051**	−0.022	2.285
	(0.390)	(0.365)	(0.343)	(0.026)	(0.024)	(0.024)	(0.102)
Southern plain (Terai)	0.568	0.547	0.472	−0.020	−0.096***	−0.075**	4.729
	(0.496)	(0.498)	(0.500)	(0.034)	(0.033)	(0.034)	(0.009)
Urban	0.086	0.095	0.084	0.009	−0.002	−0.011	0.177
	(0.281)	(0.293)	(0.278)	(0.019)	(0.018)	(0.019)	(0.837)
			Chosen destination				
Malaysia	0.194	0.217	0.203	0.023	0.009	−0.014	0.358
	(0.396)	(0.412)	(0.402)	(0.027)	(0.026)	(0.028)	(0.699)
Qatar	0.239	0.219	0.233	−0.020	−0.006	0.014	0.248
	(0.427)	(0.414)	(0.423)	(0.028)	(0.028)	(0.028)	(0.780)
Saudi Arabia	0.204	0.219	0.213	0.015	0.009	−0.006	0.145
	(0.404)	(0.414)	(0.410)	(0.028)	(0.027)	(0.028)	(0.865)
U.A.E	0.237	0.229	0.250	−0.008	0.013	0.021	0.281
	(0.425)	(0.421)	(0.433)	(0.029)	(0.028)	(0.029)	(0.755)
Other	0.127	0.117	0.101	−0.010	−0.026	−0.015	0.757
	(0.333)	(0.322)	(0.302)	(0.022)	(0.021)	(0.021)	(0.469)
Joint test across all regressions: F-stat							1.165
p-value							0.264

Source: Author's calculations on the survey data collected for this project
Note: This table checks whether wage information treatments are correlated with characteristics collected prior to the treatment for experienced potential migrants (those who have migrated before for foreign employment but do not have an existing job contract abroad). The first three columns show the mean and standard deviations of the variables for each treatment arm. The next three columns show the difference between the two groups and the standard errors of the difference. The column heading indicates which groups are being compared. Column 7 tests whether the three arms have the same mean. The bottom of the panel presents the F-statistic and the associated p-value for a joint test of equality of all outcomes across all treatment arms.
$^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$

Table 1.B.10: Estimates of treatment effects at various quantiles of beliefs on mortality rate

Quantiles:	p = min	p=10	p=30	p=50	p=70	p=90	p=max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Sample: All				
Death info: 'high'	0.019	0.020	0.010	0.190	0.821	0.803	0.710
	(1.242)	(1.359)	(1.445)	(1.550)	(1.695)	(1.803)	(1.986)
Death info: 'low'	-3.417**	-3.745**	-4.002**	-4.263**	-4.415**	-4.880**	-5.627***
	(1.319)	(1.445)	(1.569)	(1.689)	(1.838)	(1.958)	(2.154)
Wage info: 'high'	-0.766	-0.768	-0.858	-0.746	-0.870	-0.774	-0.951
	(1.281)	(1.382)	(1.498)	(1.631)	(1.797)	(1.915)	(2.136)
Wage info: 'low'	-0.433	-0.431	-0.664	-0.564	-0.702	-0.114	-0.297
	(1.381)	(1.518)	(1.631)	(1.771)	(1.960)	(2.105)	(2.361)
Observations	3319	3319	3319	3319	3319	3319	3319
R-squared	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Control group mean	16.798	18.797	20.239	22.028	24.011	26.188	29.846
SD	(27.790)	(30.547)	(34.915)	(37.849)	(41.906)	(46.580)	(55.176)
			Sample: Inexperienced				
Death info: 'high'	-1.924	-1.780	-1.728	-1.623	-1.640	-1.834	-2.459
	(2.421)	(2.617)	(2.775)	(2.950)	(3.226)	(3.462)	(3.819)
Death info: 'low'	-6.211**	-6.494**	-6.771**	-6.993**	-7.559**	-8.443**	-10.048**
	(2.480)	(2.682)	(2.897)	(3.085)	(3.438)	(3.701)	(4.081)
Wage info: 'high'	1.336	1.535	1.313	1.776	2.242	2.664	2.609
	(2.206)	(2.392)	(2.600)	(2.803)	(3.125)	(3.366)	(3.658)
Wage info: 'low'	1.823	2.058	1.491	1.806	2.290	3.357	3.538
	(2.315)	(2.513)	(2.686)	(2.847)	(3.158)	(3.378)	(3.735)
Observations	1411	1411	1411	1411	1411	1411	1411
R-squared	0.006	0.005	0.005	0.005	0.005	0.005	0.006
Control group mean	21.933	24.042	25.991	28.000	31.179	34.097	39.412
SD	(34.748)	(37.808)	(43.960)	(47.232)	(53.928)	(60.295)	(70.535)
			Sample: Experienced				
Death info: 'high'	1.217	1.050	0.970	1.251	2.622	2.889	3.381
	(1.537)	(1.706)	(1.837)	(2.020)	(2.380)	(2.521)	(2.818)
Death info: 'low'	-1.310	-1.823	-2.144	-2.474	-2.329	-2.399	-2.451
	(1.661)	(1.802)	(1.925)	(2.080)	(2.148)	(2.267)	(2.591)
Wage info: 'high'	-2.110	-2.293	-2.262	-2.392	-3.080	-3.080	-3.275
	(1.857)	(2.052)	(2.254)	(2.508)	(2.823)	(2.973)	(3.395)
Wage info: 'low'	-2.262	-2.481	-2.441	-2.516	-3.388	-3.020	-3.385
	(2.131)	(2.350)	(2.536)	(2.809)	(3.121)	(3.335)	(3.816)
Observations	1341	1341	1341	1341	1341	1341	1341
R-squared	0.003	0.003	0.003	0.004	0.005	0.005	0.004
Control group mean	13.609	15.643	16.745	18.469	19.565	21.034	23.155
SD	(20.826)	(23.696)	(26.048)	(28.955)	(29.430)	(31.750)	(36.517)

Source: Author's calculations on the survey data collected for this project

Note: This table shows the effect of the information treatments on various $p-$quantiles of individual belief about mortality rate abroad, estimated using equation (1.1). The p in the column headings indicates the quantile of the beliefs used as the outcome. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.11: Estimates of effects at various quantiles of beliefs on net earnings

Quantiles:	p=min	p=10	p=30	p=50	p=70	p=90	p=max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Sample: All				
Death info: 'high'	-0.424*	-0.369	-0.341	-0.421	-0.426	-0.458	-0.573*
	(0.243)	(0.234)	(0.242)	(0.261)	(0.271)	(0.286)	(0.322)
Death info: 'low'	-0.208	-0.104	-0.026	-0.087	-0.069	-0.085	-0.112
	(0.213)	(0.204)	(0.207)	(0.222)	(0.229)	(0.244)	(0.297)
Wage info: 'high'	-0.176	-0.136	-0.123	-0.189	-0.210	-0.232	-0.386
	(0.236)	(0.221)	(0.225)	(0.237)	(0.246)	(0.261)	(0.297)
Wage info: 'low'	0.084	0.200	0.187	0.151	0.127	0.136	0.130
	(0.248)	(0.236)	(0.241)	(0.249)	(0.259)	(0.270)	(0.316)
Observations	3319	3319	3319	3319	3319	3319	3319
R-squared	0.001	0.001	0.001	0.002	0.001	0.001	0.002
Control group mean	9.326	9.583	9.916	10.527	10.968	11.442	12.455
SD	(7.560)	(5.330)	(5.109)	(5.870)	(6.199)	(6.476)	(9.005)
			Sample: Inexperienced				
Death info: 'high'	-0.536	-0.378	-0.305	-0.446	-0.491	-0.521	-0.669
	(0.376)	(0.322)	(0.329)	(0.370)	(0.384)	(0.409)	(0.482)
Death info: 'low'	-0.492	-0.327	-0.253	-0.400	-0.425	-0.487	-0.696
	(0.374)	(0.322)	(0.324)	(0.362)	(0.381)	(0.402)	(0.492)
Wage info: 'high'	-0.917**	-0.803**	-0.718**	-0.862**	-0.921**	-0.948**	-1.312***
	(0.379)	(0.328)	(0.337)	(0.366)	(0.386)	(0.408)	(0.484)
Wage info: 'low'	-0.796**	-0.594*	-0.581*	-0.660*	-0.708*	-0.710*	-0.972**
	(0.377)	(0.325)	(0.329)	(0.353)	(0.369)	(0.386)	(0.467)
Observations	1411	1411	1411	1411	1411	1411	1411
R-squared	0.008	0.006	0.005	0.006	0.006	0.006	0.008
Control group mean	10.297	10.339	10.688	11.597	12.221	12.803	14.268
SD	(10.402)	(6.480)	(5.871)	(7.163)	(7.575)	(7.864)	(11.930)
			Sample: Experienced				
Death info: 'high'	-0.429	-0.471	-0.489	-0.536	-0.508	-0.535	-0.593
	(0.296)	(0.308)	(0.326)	(0.339)	(0.357)	(0.372)	(0.410)
Death info: 'low'	0.057	0.081	0.157	0.134	0.170	0.155	0.095
	(0.280)	(0.297)	(0.314)	(0.327)	(0.336)	(0.355)	(0.391)
Wage info: 'high'	0.312	0.300	0.262	0.239	0.240	0.196	0.218
	(0.269)	(0.275)	(0.287)	(0.296)	(0.307)	(0.319)	(0.344)
Wage info: 'low'	0.564*	0.595*	0.563*	0.545	0.537	0.536	0.661
	(0.299)	(0.314)	(0.328)	(0.331)	(0.358)	(0.373)	(0.410)
Observations	1341	1341	1341	1341	1341	1341	1341
R-squared	0.005	0.005	0.005	0.005	0.004	0.004	0.004
Control group mean	8.385	8.848	9.197	9.616	9.923	10.341	11.036
SD	(3.800)	(3.967)	(4.214)	(4.380)	(4.594)	(4.869)	(5.421)

Source: Author's calculations on the survey data collected for this project

Note: This table shows the effect of the information treatments on various p–quantiles of individual belief about earnings abroad, estimated using equation (1.1). The p in the column headings indicates the quantile of the beliefs used as the outcome. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.12: Characteristics of the attriters

Attrition measure	All F (1)	All M (2)	All W (3)	Inexperienced F (4)	Inexperienced M (5)	Inexperienced W (6)	Experienced F (7)	Experienced M (8)	Experienced W (9)
Demographics									
Age	0.417	0.797**	1.005	0.080	0.343	0.756	-0.535	-0.413	0.296
	(0.351)	(0.380)	(0.825)	(0.434)	(0.490)	(1.015)	(0.502)	(0.543)	(1.007)
Completed years	-1.158***	-1.128***	-1.670***	-1.313***	-1.297***	-1.836***	-1.161***	-1.061***	-1.811***
of schooling	(0.178)	(0.188)	(0.344)	(0.271)	(0.291)	(0.508)	(0.301)	(0.315)	(0.555)
Geography and location									
Eastern	-0.004	-0.003	0.056	-0.013	0.005	0.143**	-0.005	-0.006	0.073
	(0.021)	(0.023)	(0.046)	(0.032)	(0.035)	(0.072)	(0.036)	(0.038)	(0.074)
Central	0.019	0.009	0.061	-0.020	-0.038	-0.031	0.065*	0.053	0.044
	(0.023)	(0.025)	(0.048)	(0.037)	(0.040)	(0.072)	(0.039)	(0.041)	(0.075)
Western	-0.038**	-0.030*	-0.079***	-0.014	-0.023	-0.010	-0.072***	-0.062**	-0.092**
	(0.016)	(0.018)	(0.027)	(0.018)	(0.019)	(0.036)	(0.026)	(0.029)	(0.045)
Mid/Far Western	0.023	0.024	-0.037	0.047	0.057	-0.103*	0.012	0.016	-0.026
	(0.019)	(0.021)	(0.035)	(0.034)	(0.038)	(0.056)	(0.030)	(0.032)	(0.053)
Southern Plain	0.035	0.045*	0.129***	-0.020	0.021	0.160**	0.101***	0.082**	0.136*
(Terai)	(0.024)	(0.025)	(0.047)	(0.037)	(0.041)	(0.071)	(0.039)	(0.041)	(0.073)
Urban	0.000	0.007	0.000	-0.007	-0.002	-0.009	0.022	0.028	0.027
	(0.013)	(0.014)	(0.027)	(0.019)	(0.021)	(0.036)	(0.024)	(0.026)	(0.049)
Expected time of migration									
Within 2 months	0.109***	0.131***	0.058	0.068**	0.062*	0.033	0.098**	0.112***	0.111
	(0.024)	(0.025)	(0.049)	(0.033)	(0.036)	(0.065)	(0.039)	(0.042)	(0.077)
Certainly in 3	0.113***	0.135***	0.064	0.066**	0.062*	0.029	0.102***	0.114***	0.126
months	(0.024)	(0.025)	(0.048)	(0.032)	(0.036)	(0.063)	(0.039)	(0.042)	(0.077)

Source: Author's calculations on the survey data collected for this project

Note: This table tests whether attriters are different from non-attriters on the characteristics shown in the left side of the table. The measure of attrition being tested is indicated by its corresponding letter in the second row of the table headings. The measures of attrition are defined in Table 1.4. Each cell is a separate regression. The estimated regression is $y_i = \alpha + \beta ATTRIT_i + \varepsilon_i$ where y_i are the characteristics reported in the leftmost column and $ATTRIT_i$ is the measure of attrition indicated by the column heading (second row of the table). The first row of the table headings indicate the sample for which the tested is being performed. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. Coefficients (β) are reported along with robust standard errors in parentheses. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.13: Effects of information treatments on chosen destination

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
	Destination country changed					
Death info: 'high'	-0.005	0.001	-0.034	-0.035	0.032	0.044
	(0.023)	(0.022)	(0.035)	(0.036)	(0.035)	(0.037)
Death info: 'low'	-0.004	-0.003	-0.021	-0.021	0.006	0.017
	(0.022)	(0.022)	(0.039)	(0.040)	(0.033)	(0.036)
Wage info: any	-0.007	0.003	-0.028	-0.021	0.030	0.027
	(0.020)	(0.019)	(0.032)	(0.033)	(0.029)	(0.029)
Controls	NO	YES	NO	YES	NO	YES
Observations	2687	2687	1140	1140	1107	1107
R-squared	0.000	0.157	0.002	0.153	0.002	0.170
Control group mean	0.308		0.396		0.277	
SD	(0.462)		(0.491)		(0.449)	
	Destination region changed					
Death info: 'high'	-0.007	-0.003	-0.020	-0.008	-0.001	0.017
	(0.016)	(0.016)	(0.028)	(0.028)	(0.024)	(0.024)
Death info: 'low'	-0.004	-0.002	-0.012	-0.003	-0.004	-0.002
	(0.017)	(0.017)	(0.032)	(0.033)	(0.025)	(0.025)
Wage info: any	-0.010	-0.005	-0.016	-0.008	-0.002	0.005
	(0.014)	(0.014)	(0.025)	(0.027)	(0.022)	(0.021)
Controls	NO	YES	NO	YES	NO	YES
Observations	2687	2687	1140	1140	1107	1107
R-squared	0.000	0.103	0.001	0.110	0.000	0.170
Control group mean	0.146		0.209		0.115	
SD	(0.353)		(0.408)		(0.321)	

Source: Author's calculations on the survey data collected for this project

Note: This table shows the impact of information treatments on changes in destination choices between treatment and follow-up, estimated using equation (1.1). The heading of each panel indicates the specific measure of destination choice. Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, surveyor fixed effects, and respondent fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor $\times$ date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$.

Table 1.B.14: Effects of information treatments on seeking consultations

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
	Consulted new manpower company					
Death info: 'high'	-0.027	-0.012	-0.004	-0.004	-0.053	-0.008
	(0.020)	(0.019)	(0.034)	(0.033)	(0.035)	(0.035)
Death info: 'low'	-0.014	-0.009	0.008	0.018	-0.051	-0.031
	(0.022)	(0.021)	(0.035)	(0.035)	(0.032)	(0.031)
Wage info: any	0.023	0.019	0.065**	0.064**	0.003	-0.015
	(0.018)	(0.017)	(0.027)	(0.027)	(0.030)	(0.028)
Controls	NO	YES	NO	YES	NO	YES
Observations	2714	2714	1171	1171	1120	1120
R-squared	0.001	0.231	0.004	0.245	0.003	0.266
Control group mean	0.269		0.241		0.343	
SD	(0.444)		(0.429)		(0.477)	
	Consulted with family members					
Death info: 'high'	-0.024	-0.018	-0.029	-0.025	-0.040	-0.032
	(0.021)	(0.019)	(0.030)	(0.028)	(0.033)	(0.031)
Death info: 'low'	-0.002	-0.008	0.029	0.015	0.004	0.013
	(0.022)	(0.019)	(0.033)	(0.031)	(0.030)	(0.030)
Wage info: any	0.010	0.005	0.045	0.028	-0.022	-0.021
	(0.018)	(0.018)	(0.029)	(0.028)	(0.028)	(0.027)
Controls	NO	YES	NO	YES	NO	YES
Observations	2748	2748	1178	1178	1136	1136
R-squared	0.001	0.237	0.005	0.267	0.002	0.254
Control group mean	0.693		0.688		0.737	
sd	(0.462)		(0.465)		(0.442)	
	Consulted with friends					
Death info: 'high'	-0.009	-0.007	-0.030	-0.027	-0.020	-0.009
	(0.022)	(0.020)	(0.034)	(0.033)	(0.035)	(0.033)
Death info: 'low'	0.036*	0.034*	0.058*	0.051*	0.018	0.027
	(0.021)	(0.020)	(0.031)	(0.030)	(0.033)	(0.035)
Wage info: any	-0.006	-0.010	-0.006	-0.017	0.002	0.010
	(0.017)	(0.015)	(0.026)	(0.025)	(0.029)	(0.029)
Controls	NO	YES	NO	YES	NO	YES
Observations	2748	2748	1181	1181	1136	1136
R-squared	0.002	0.205	0.007	0.215	0.001	0.222
Control group mean	0.689		0.741		0.682	
SD	(0.464)		(0.440)		(0.468)	

Source: Author's calculations on the survey data collected for this project

Note: This table shows the impact of information treatments on seeking consulations during follow-up, estimated using equation (1.1). The heading of each panel indicates the specific measure of seeking consultations. Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, surveyor fixed effects, and respondent fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor × date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$.

Table 1.B.15: Lee (2009) bounds of treatment effect on changing manpower companies

	Death Info		*Wage info*
	High	Low	Any
	(1)	(2)	(3)
	Sample: All		
Lower bound	-0.032	-0.029	0.015
	(0.022)	(0.023)	(0.022)
Upper bound	-0.016	0.023	0.027
	(0.025)	(0.026)	(0.019)
95 % CI	[-0.070 0.028]	[-0.067 0.066]	[-0.024 0.060]
	Sample: Inexperienced		
Lower bound	-0.002	0.005	0.051
	(0.035)	(0.035)	(0.034)
Upper bound	0.006	0.024	0.071**
	(0.039)	(0.040)	(0.030)
95 % CI	[-0.067 0.079]	[-0.058 0.095]	[-0.008 0.124]
	Sample: Experienced		
Lower bound	-0.063*	-0.082**	-0.000
	(0.036)	(0.038)	(0.034)
Upper bound	-0.037	0.004	0.005
	(0.039)	(0.041)	(0.031)
95 % CI	[-0.126 0.031]	[-0.144 0.072]	[-0.065 0.063]

Source: Author's calculations on the survey data collected for this project
Note: This table shows the estimated Lee (2009) bounds for the effect of information treatments on whether they consulted new manpower companies between the initial and final surveys. Each column in each panel represents a separate estimation of the bounds. Each estimation is performed on the sample of the treatment group indicated by the column heading and the control group. For each estimation a lower bound, an upper bound is reported with standard errors in parentheses. The 95% confidence interval on the bounds is reported in brackets. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.16: Effects of information treatments on credit and assets

	All		Inexperienced		Experienced	
	(1)	(2)	(3)	(4)	(5)	(6)
			Took out new loans			
Death info: 'high'	0.027	0.011	0.003	-0.021	0.036	0.003
	(0.021)	(0.021)	(0.031)	(0.033)	(0.032)	(0.034)
Death info: 'low'	0.023	0.009	0.005	-0.020	0.052	0.027
	(0.021)	(0.021)	(0.032)	(0.034)	(0.034)	(0.037)
Wage info: any	0.004	-0.000	-0.009	-0.009	0.013	0.010
	(0.018)	(0.018)	(0.027)	(0.028)	(0.028)	(0.026)
Controls	NO	YES	NO	YES	NO	YES
Observations	2739	2739	1178	1178	1133	1133
R-squared	0.001	0.092	0.000	0.184	0.003	0.132
Control group mean	0.293		0.314		0.286	
SD	(0.456)		(0.466)		(0.453)	
			Paid back old loans			
Death info: 'high'	-0.019	-0.026*	-0.041*	-0.020	-0.003	-0.010
	(0.015)	(0.015)	(0.024)	(0.025)	(0.022)	(0.023)
Death info: 'low'	-0.002	-0.007	-0.016	-0.003	0.014	-0.003
	(0.014)	(0.015)	(0.022)	(0.024)	(0.022)	(0.023)
Wage info: any	0.000	-0.004	0.020	0.026	-0.015	-0.007
	(0.013)	(0.013)	(0.019)	(0.021)	(0.020)	(0.019)
Controls	NO	YES	NO	YES	NO	YES
Observations	2739	2739	1177	1177	1134	1134
R-squared	0.001	0.081	0.003	0.156	0.001	0.146
Control group mean	0.119		0.129		0.120	
SD	(0.324)		(0.336)		(0.327)	
			Bought new assets			
Death info: 'high'	0.025	0.029	0.008	0.023	-0.011	-0.001
	(0.023)	(0.023)	(0.037)	(0.037)	(0.029)	(0.033)
Death info: 'low'	0.046**	0.043*	-0.033	-0.021	0.092***	0.090**
	(0.021)	(0.022)	(0.033)	(0.035)	(0.033)	(0.037)
Wage info: any	-0.005	-0.013	0.004	-0.008	-0.059**	-0.066**
	(0.020)	(0.020)	(0.032)	(0.034)	(0.029)	(0.028)
Controls	NO	YES	NO	YES	NO	YES
Observations	2799	2799	1201	1201	1154	1154
R-squared	0.002	0.085	0.001	0.129	0.014	0.135
Control group mean	0.305		0.321		0.321	
sd	(0.461)		(0.469)		(0.469)	

Source: Author's calculations on the survey data collected for this project

Note: This table shows the impact of information treatments on reported changes in debt and asset position between treatment and follow-up, estimated using equation (1.1). The heading of each panel indicates the specific measure of destination choice. Odd numbered columns do not have any controls, even numbered columns control for a full set of interaction of age categories, education categories, location and geography, full set of interaction of location, geography and administrative regions, destination fixed effects, surveyor fixed effects, and respondent fixed effects. Standard errors, reported in parentheses, are clustered at the surveyor $\times$ date of interview level. "Inexperienced" refers to potential migrants who have not yet migrated for foreign employment. "Experienced" refers to potential migrants who have migrated in the past, but do not have an existing job contract abroad; it excludes those who are back home on leave from their work abroad. $***: p < 0.01$; $**: p < 0.05$; $*: p < 0.1$.

Table 1.B.17: 2-SLS estimates of VSL for inexperienced potential migrants

	Migrated - P		Migrated - A		Migrated - B	
	Preferred		Alternative		Basic	
	(1)	(2)	(3)	(4)	(5)	(6)
			Logarithmic specification			
Log(expected mortality per 1000)	**-0.247****	**-0.246****	-0.240**	-0.246**	-0.221**	-0.243**
	(0.115)	**(0.104)**	(0.116)	(0.109)	(0.102)	(0.096)
Log(expected net earnings, USD '000)	**0.344**	**0.576**	0.386	0.494	0.148	0.290
	(0.350)	**(0.503)**	(0.385)	(0.516)	(0.286)	(0.468)
VSL (in '000 USD)	**292.658**	**173.893**	255.377	204.275	612.548	342.367
	(322.218)	**(161.486)**	(275.531)	(218.349)	(1210.549)	(573.157)
Controls	**NO**	**YES**	NO	YES	NO	YES
			Levels specification			
Expected mortality (per 1000)	**-0.011***	**-0.010****	-0.011*	-0.010*	-0.010*	-0.009*
	(0.006)	**(0.005)**	(0.006)	(0.005)	(0.006)	(0.005)
Expected net earnings (USD '000)	**0.024**	**0.050**	0.028	0.050	0.007	0.012
	(0.033)	**(0.050)**	(0.036)	(0.054)	(0.026)	(0.039)
VSL (in '000 USD)	**462.442**	**199.412**	383.485	195.258	1340.595	773.284
	(699.784)	**(217.430)**	(527.758)	(226.762)	(4917.707)	(2680.114)
Controls	**NO**	**YES**	NO	YES	NO	YES

Source: Author's calculations on the survey data collected for this project
Note: This table shows 2SLS estimates of the effect of expected earnings and expected mortality rate on migration choices of inexperienced potential migrants. Information treatments are used as instruments for expected earnings and expected mortality rate. The heading of each column indicates the measure of migration used. See Table 1.5 and the text for the definition of these measures. The heading of each panel indicates whether the logarithm or levels of expectations is used in the estimation. Standard errors, reported in parentheses, are clustered at the surveyor × date of interview level. VSL is estimated as the ratio of two marginal effects and its standard error computed using the delta method. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.18: 2-SLS estimates of VSL for inexperienced potential migrants

	Least optimistic	Median	Most optimistic	Most likely (modal)
	(1)	(2)	(3)	(4)
		Logarithmic specification		
Beliefs on mortality risk	-0.237**	-0.228*	-0.215**	-0.204*
per 1000	(0.115)	(0.123)	(0.105)	(0.116)
Beliefs on net earnings,	0.343	0.352	0.377	0.352
USD '000	(0.371)	(0.359)	(0.339)	(0.340)
VSL (in '000 USD)	172.549	261.089	332.398	236.049
	(206.176)	(303.309)	(339.636)	(263.643)
		Levels specification		
Beliefs on mortality risk	-0.008*	-0.011*	-0.014*	-0.012
per 1000	(0.004)	(0.006)	(0.008)	(0.007)
Beliefs on net earnings,	0.026	0.034	0.024	0.039
USD '000	(0.038)	(0.043)	(0.028)	(0.045)
VSL (in '000 USD)	303.364	331.859	560.740	303.301
	(476.418)	(460.645)	(687.942)	(374.685)

Source: Author's calculations on the survey data collected for this project

Note: This table shows 2SLS estimates of the effect of beliefs on earnings and mortality rate on migration chioces of inexperienced potential migrants. The preferred measure of migration (Migrated-P) is used as the dependent variable. Information treatments are used as instruments for beliefs on earnigns and mortality rate. Instead of using the expected value of their beliefs as the variables of interest, this table takes different points in these belief distribution based on assumptions on the revelant decision-making parameters.

See Table 1.8 for the various decision-making choices based on the column headings.

The heading of each panel indicates whether the logarithm or levels of beliefs is used in the estimation. Standard errors are reported in parentheses and are clustered at the surveyor $\times$ date of interview level. VSL is estimated as the ratio of two coefficients and its standard error computed using the delta method. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 1.B.19: 2-SLS estimates of VSL for subgroups of inexperienced potential migrants

	Old (1)	Young (2)	Low educ (3)	High educ (4)	Manual (5)	Non-manual (6)
			Logarithmic specification			
Log(expected mortality per 1000)	-0.112	-0.510*	-0.324*	-0.098	-0.422	-0.190*
	(0.116)	(0.273)	(0.172)	(0.103)	(0.397)	(0.107)
Log(expected net earnings, USD '000)	0.056	0.936	0.075	0.066	0.915	0.221
	(0.423)	(0.677)	(0.295)	(0.413)	(1.122)	(0.342)
VSL (in '000 USD)	952.133	179.565	1446.771	722.138	146.199	407.212
	(7377.217)	(115.255)	(5868.918)	(4711.036)	(191.642)	(658.415)
			Levels specification			
Expected mortality (per 1000)	-0.003	-0.016	-0.003	-0.004	0.035	-0.005*
	(0.005)	(0.010)	(0.007)	(0.003)	(0.069)	(0.003)
Expected net earnings (USD '000)	0.006	0.075	0.012	-0.008	-0.184	0.007
	(0.024)	(0.091)	(0.029)	(0.026)	(0.607)	(0.021)
VSL (in '000 USD)	508.188	212.716	271.592	-447.926	191.417	717.889
	(2158.376)	(214.322)	(828.787)	(1274.781)	(446.338)	(2143.472)

Source: Author's calculations on the survey data collected for this project

Note: This table shows 2SLS estimates of the effect of expected earnings and expected mortality on migration choices for various subgroups of inexperienced potential migrants. The preferred measure of migration (Migrated-P) is used as the dependent variable. Information treatments are used as instruments for beliefs on earnings and moratlity rate in all cases.

See Table 1.9 for the definitions of the subgroups listed in the column headings.

The heading of each column indicates whether logarithm or levels of expectations is used in the estimation. Standard errors are reported in parentheses and are clustered at the surveyor $\times$ date of interview level. VSL is estimated as the ratio of two coefficients and its standard error computed using the delta method. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

1.C Normal learning from information

Individuals have normally distributed priors over earnings (or mortality risks) with mean θ_0 and variance σ_θ^2. That is, priors $\theta \sim \mathcal{N}\left(\theta_0, \sigma_\theta^2\right)$. Individuals assume that the signal, s, they see is a random draw from the distribution $\mathcal{N}\left(\theta, \sigma_s^2\right)$. Upon receiving the signal, individuals update their prior according to Bayes' rule. Normality of the priors and the signals mean that the posterior is also normally distributed with mean and variance given by

$$\theta|s \sim \mathcal{N}\left(\theta_1, \sigma_{\theta_1}^2\right) = \mathcal{N}\left(\frac{\sigma_s^2 \cdot \theta_0 + \sigma_\theta^2 \cdot s}{\sigma_s^2 + \sigma_\theta^2}, \frac{\sigma_s^2 \sigma_\theta^2}{\sigma_s^2 + \sigma_\theta^2}\right)$$

This simple result has the following direct implications for the effect of the signal (assuming $s < \theta_0$ without loss of generality):

1. Individuals update towards the signal. That is $s < \theta_1 < \theta_0$. The extent of updating depends upon the variance of prior and the perceived variance of the signal.

2. Posterior is more precise than the prior or the signal. That is, $\sigma_{\theta_1}^2 < \min\left\{\sigma_\theta^2, \sigma_s^2\right\}$

3. The effect of the information in each quantile of the individual belief distribution is increasing (in magnitude) with the quantile. Denote $\theta_1(p) - \theta_0(p)$ as the effect of the information on the p^{th} quantile of the individual belief distribution. Then

$$D(p) \equiv \theta_1(p) - \theta_0(p) = (\theta_1 - \theta_0) + (\sigma_{\theta_1} - \sigma_\theta)\,\Phi^{-1}(p)$$

   with

$$D'(p) = \frac{1}{\phi(z)}(\sigma_{\theta_1} - \sigma_\theta) < 0$$

   where $\Phi(z)$ and $\phi(z)$ denote the standard normal distribution and density functions respectively. The inequality follows from 2.

These results are investigated systematically in Table 1.2 and Appendix Table 1.B.10 for updating in response to a death signal, in Table 1.3 and Appendix Table 1.B.11 for updating in response to an earnings signal. The results are discussed in Section 1.4.2.

Furthermore, this simple framework is useful to infer how the subjects perceive the noisiness of the information provided to them. The distribution of priors is given by the distribution of the beliefs of the average person in the control group and the distribution of the posterior is given by the distribution of the beliefs of the average person in each of the treatment groups. Using these moments from data and updating rule given above, I can recover the perceived distribution of signals from which the information provided to them is drawn. This exercise is useful because the exact nature of the information provided to them left enough room for them to perceive the signal in different ways. For instance, the wage information provided the earnings but clearly mentioned the year of information was either 2010 or 2013. Similarly, the death information only provided the number of migrant deaths from a district without giving any information on stock of the migrants from the reference district.

Based on their updating behavior of the inexperienced migrants, the implied distribution of the signal is consistent with the information provided to them.[43] The 'high' wage information provided to them translated to a signal with a mean of \$6,700 and a standard deviation of \$1,200. The actual information provided in this treatment translates to a net earnings of \$5,800 in 2013, which is about 0.75 standard deviation of the implied mean. It could also be that individuals updated the 2013 information to 2015, making it more relevant to them. The 'low' wage information provided to them translated to a signal with a mean of \$6,200 and a standard deviation of \$1,600. The actual information provided in this treatment translates to a net earnings of \$2,900 in 2010. This information is about 2 standard deviations away from the implied mean of the signal distribution. This suggests that individuals could indeed be re-interpreting the information provided to them to make it relevant to their decision. For instance, when they saw the information provided to them was of 2010, they factored in how wages could have evolved in the past five years and adjusted their beliefs accordingly.[44] Some respondents assigned to this treatment group even complained during the survey saying that information could not have been true or is irrelevant for now. Furthermore, the implied distribution of signal seem similar for the 'high' and 'low' wage treatments indicating that these two treatments affects the behavior in a similar way.

Similarly, the 'high' death information translated to a signal with a mean mortality rate of 15 per 1000 with a standard deviation of 8.7, and the 'low' death information translated to a signal with a mean mortality rate of 13 per 1000 with a standard deviation of 4.4. The actual death rates implied by the information were 0.9 and 3.7 per 1000 respectively for the 'low' and 'high' treatments. This discrepancy could simply reflect the lack of knowledge about the migrant stock abroad or other biases leading to interpreting the signal with an upward bias.

[43]The same exercise could not be done with the experienced migrants as the information was irrelevant to them. The average individual in the treatment group (posterior) did not have a lower variance of his beliefs than the average individual in the control group (prior).

[44]Between 2010 and 2013, exchange rates in destination countries appreciated relative to Nepali Rupees by about 30 percent, inflation in Nepal increased by about the same amount. Even with these two adjustments the information provided becomes similar to the one provided in the 'high' treatment.

Chapter 2

Death scares: How potential work-migrants infer mortality rates from migrant deaths

2.1 Introduction

Media reports abound on numbers of migrants dying on their way to the destination countries or during their stay abroad. Within the first eight months of 2015, over 2,600 migrants have died in the Mediterranean Sea while on their way to Europe (International Organization for Migration, 2015). In 2014, about 445 people died while trying to cross the US-Mexico border (Carroll, 2015). Large death toll is not just the plight of those who try to migrate illegally or those who are forced to move. The Guardian reports that almost 1,000 workers, all of whom were legal migrants from Nepal, India and Bangladesh, died in Qatar in 2012 and 2013 (Gibson, 2014). Do potential migrants know the mortality rate abroad and choose to migrate anyway? If not, how do they infer the mortality rate from incidences of migrant death that they observe around them?

Depending upon how they process the information, learning from observed deaths may lead to an overestimate or an underestimate of the actual mortality rate. In this paper, I study how migration decision is affected by death of migrants in context of Nepali work-migrants to Malaysia and the Persian Gulf countries. I combine these estimates of migration responsiveness to death events, along with the estimate of the value of statistical life (VSL) and elasticities from Chapter 1 to infer how much each death changes a potential migrant's perceived mortality rate abroad.

If potential migrants have full information about the risk of death, or if they believe so, then their decision to migrate will have already factored in the (perceived) probability of death during migration. They will take realizations of death as conveying zero information and will not change their migration decision in response to incidences of death.[1] This presents a simple test of whether potential migrants are fully informed about the risk of death upon migration: if migration decision responds to death incidents, then potential migrants are not fully informed about the risk of death from migration.

I find that death of a migrant worker significantly lowers migration. Specifically, I study the effect of a migrant death in a district-destination cell on migration flows from the district in the subsequent months. After controlling for potential confounds with district-destination fixed effects, district-month fixed effects and destination-month fixed effects, one migrant death reduces monthly migrant flow from that district to the same destination (as the deceased migrant) by 1.2 percent for up to a year after the death. This clearly indicates that potential migrants do not consider themselves fully informed (and rational) on the mortality risk abroad. I also find some increase in migrant flow from the district to other destination countries. However, the amount of substitution to other destination does fully offset the negative effect. Overall, one migrant death (in any destination) in a district reduces total monthly migration outflow from that district (to any destinations) by 0.9 percent for the subsequent year.

The size of the effect, even without considering the spillover effects on the neighboring districts, is notably large. During the period of this study, 550 work migrants died annually, which led a reduction in migrant flow of almost 18,000 individuals (from the districts of the deceased) over the period of a year. The forgone income of this reduction is at least $57 million, which translates to 0.3 percent of the average annual national GDP for that period.[2] The forgone income, accounting for spillover effects amounts to 2.7 percent of the national GDP.

The migration response to migrant death suggests that potential migrants update their beliefs on mortality rate abroad after they observe a migrant death in their district. A rational Bayesian, who believes that migrants deaths are generated by an i.i.d process, will also update their beliefs in response to migrant deaths. However, for such a rational Bayesian, the sequencing of migrant deaths in previous periods does not affect the extent of updating in response to a current signal. Contrary to this prediction, the migration response to a migrant death in a district-destination cell is much larger if there have been more deaths in the past 6 months in the cell. In fact, the migration response to deaths is almost completely driven by district-destination cells that have experienced more than one migrant death in the past 6 months. Interestingly, the migration response is not sensitive to changes in the actual underlying death rates in the destination

[1] with the obvious caveat that the deceased do not affect the ability of the potential migrants to undertake migration (that is, the deceased are not family or close relatives)

[2] The forgone income includes the monetary cost of migration, but does not include any non-monetary cost of migration. It also does not adjust for the cost of living abroad (which, in many cases, is already netted into the income).

countries. This indicates that the updating rule that potential migrants use to form their beliefs on mortality rate depends upon the sequencing of migrant deaths in the recent past.

This suggests that potential migrants are committing a fallacy in their updating behavior. One possibility is that potential migrants are using some heuristic rule to form their beliefs (ala Kahneman and Tversky, 1974; Tversky and Kahneman, 1973). It could be that they think recent deaths represent the scenario more accurately, or that past few months of migrant deaths is what is on the top of their mind while making their migration decision. Another possibility, not necessarily mutually exclusive, is that the potential migrants expect the probability rules to apply exactly even for the 'small' samples of migrants from a district (ala Tversky and Kahneman, 1971; Rabin, 2002). Indeed, in his mathematical formulation of this fallacy, Rabin (2002) shows that such individuals, even when they are Bayesian in updating their beliefs, tend to over-infer from short sequence of signals and conclude that the true rate generating the sequence of signals to be more extreme than the truth. The finding that the amount of updating, and hence the migration response, depends upon the number of recent migrant deaths is consistent with Rabin's prediction.

Furthermore, I compute the change in perceived mortality risk for potential migrants following a single death event to show that the amount of updating is, in fact, too high. Using the estimates of earnings elasticity of migration from Chapter 1, I find that earnings need to go up by 15 percent to offset the migration response of a single death event. Further, using the estimate of the VSL from the same study, I find that the change in earnings translate to an increase in perceived two-year mortality rate of migration by 6.7 per thousand. This amount of updating from a single migrant death in the district is too high relative to the true rate of 1.3 per thousand. It is also too high compared to the updating behavior of a rational Bayesian, who believes the migrant deaths are generated by an i.i.d binomial process.

This remainder of the paper is organized as follows: Section 2.2 describes the migration process in context of Nepal and the data sources, Section 2.3 outlines the empirical strategy, Section 2.4 discusses the effect of migrant deaths on subsequent migrant flow, Section 2.5 calculates the change in perceived mortality rate induced by the death and compares it with the updating behavior of a rational Bayesian, and Section 2.6 concludes.

2.2 Context and Data

2.2.1 Migration from Nepal

Historically, migration of Nepali workers outside the country was low and was limited mostly to India. As Appendix Table 2.B.1 shows, before 2001, migrant to population ratio hovered slightly above 3 percent.

This was driven mostly by migration to India with which Nepal maintains an open border. The open border between Nepal and India has historically allowed Nepali workers to migrate to Indian cities for work for all or most part of the year. Migrating to other destinations for work has been, however, quite restricted historically. Being recruited to Indian or British army was one of the very few options available to Nepali commoners to migrate abroad. Only since the mid 90s, Government of Nepal allowed private recruitment of workers to certain countries upon clearance from the Ministry of Labor.

Work-related migration to destinations outside India surged after 2001. Between 2001 and 2011, the share of non-India migrants exploded six-fold with only a small change in the share of India migrants. This surge was driven by migration of Nepali workers, almost all male, to Malaysia and the Persian Gulf countries, particularly Qatar, Saudi Arabia, United Arab Emirates, Bahrain, and Kuwait. By 2011, these six countries alone hosted 0.9 million male Nepali workers, which is 83 percent of all male migration from Nepal to destinations outside India.[3] The outflow of male Nepali workers had continued to increase in the recent years. Appendix Figure 2.B.1 shows that in 2013 alone, over 0.4 million Nepali worker received permits from the Government of Nepal to work in these destination countries. This number represents 7 percent of the adult working age (15-45) male population in the country.

Consequently, Nepali workers became one of the largest suppliers of low-skill labor to these destination countries.[4] In 2013, Nepali workers were 17 percent of the total population in Qatar, making it the second largest population group behind Indian workers.[5] Similarly, Nepali workers are expected to be one of the largest minorities in other destination countries as well. As a result, remittance income from abroad has become extremely important to the Nepali economy. Remittance income as a share of national GDP increased from a mere 2.4 percent in 2001 to an overwhelming 29 percent by 2013 (The World Bank).

Migration of Nepali workers to these destination countries is different from typical international migration. Almost all of the migration is meant to be temporary. Work migrants to Malaysia usually go with an employment contract for 3 years, and migrants to the Persian Gulf countries usually go with an employment contract for 2 years. Their visa is always tied to work, and in many cases to a specific employer. Family members do not accompany the migrants unless they have a work-visa of their own. It is rare for these migrants to settle permanently in the destination countries.

The process of finding jobs in these destination countries is heavily intermediated. Potential migrants typically contact (or are contacted by) independent local agents that link them to recruitment firms, popularly

[3]This figure includes those who migrated for non-work related reasons. The six countries account for over 90 percent of all male migrants to non-India destinations who migrate specifically for work.

[4]An average migrant to these destinations has 7 years of schooling, and are 27 years old. Only 1 percent of them are aged above 45.

[5]`http://www.bqdoha.com/2013/12/population-qatar`.

known as "manpower companies", in Kathmandu. These local agents are typically fellow villagers with good contacts to the manpower companies and gather people for foreign employment from their own or neighboring villages. In addition, most of them also help potential migrants obtain passports and other related travel documents. The manpower companies in Kathmandu receive job vacancies from firms (or employment agencies) abroad. The manpower companies are responsible for screening (if at all) and matching individuals with demands for workers from abroad, processing contracts, obtaining medical clearances, arranging for travel, visa and other paperworks including obtaining necessary clearances from the Department of Foreign Employment (DoFE) for employment abroad.

2.2.2 Data on migration flows

The data on migration outflow comes from the Department of Foreign Employment (DoFE) that keeps a record of permits issued for work abroad. DoFE, a department under the Ministry of Labor, was established in December 2008 specifically to handle the processing and issuing of labor permits for Nepali workers with an employment contract in these destination countries. As discussed above, obtaining labor permits are mandatory for every work migrant from Nepal to these destination countries. I have individual level data (without personal identifiers) on all these registered work-migrants from 2009 to 2013. I observe the date of permit, district of residence, destination country, age, gender, contracted wages, fees paid, and occupation for each permit issued. I restrict my analysis to top 6 countries (Malaysia, Qatar, Saudi Arabia, United Arab Emirates, Kuwait and Bahrain) that cover more than 98 percent of all the permits issued by DoFE.

The sample I use consists of 1.34 million permits issued from January 2009 to December 2013. These migrants are predominantly male (98 percent) and quite young. Almost all migrants are aged 18-45 with an average age of 27 years. During this period, Malaysia led other countries as the most popular destination choice with over 9,000 permits being issued every month. As Figure 2.1 shows, outflow of migrants is increasing in recent years for most destinations. By 2013, over 1100 migrants were leaving the country per day with 40 percent going to Malaysia, 25 percent to Qatar and 20 percent to Saudi Arabia.

I aggregate this data up to the level of district-destination-month cells by taking the counts of migrants (for total outflow), and means for wages, fees and occupation choices. As Table 2.1 shows, the average migrant outflow per district per month per destination is 50 (top panel, column 1). The average reported monthly wage in the data is \$230 with average fees paid to intermediaries of \$580. The average monthly wages rose from \$200 in 2009 to \$270 in 2013, which, combined with the rise in US dollar exchange rate, led to an increase of 60 percent over the period (middle panel, columns 3 and 5). Similarly, fees charged fell (in Nepali Rupee) by 18 percent over the duration (middle panel, columns 4 and 5). A large share (53 percent) of the migrants reported their occupation as 'labor' which probably refers to manual work possibly in construction sectors. Since it is not possible to classify these occupations properly, I define a category 'non-construction' that includes all jobs that are definitely not in construction sector. The remaining jobs are either in construction or in other sectors that are not classifiable. As Table 2.1 shows, only a third of the workers identified going to work that can be classified as not being in construction sector and there is a large variation across destinations (column 6).

Furthermore, the reported wages and fees from this source differ from the expectations of potential workers. In Chapter 1, I find that potential work migrants expect to earn much higher while abroad and pay much higher fees to migrate to these destinations. The discrepancy results from misinformation in part of the potential migrants as well as misreporting from migrants to DoFE. Migrants may misreport their wages and fees to DoFE as the government has regulations on minimum wage and maximum fees for workers seeking employment abroad. Furthermore, the wages reported to DoFE do not include overtime work, which can be a large part of migrant earnings abroad. In any case, the wages reported here *are* contractual wages and potential migrants have to submit a copy of the contract from the employer for their application to the DoFE.

2.2.3 Data on migrant death

The data on migrant deaths comes from the Foreign Employment Promotion Board (FEPB). FEPB is a government body established to make foreign migration safe and organized. One of its main tasks include providing financial support to the family of the deceased and helping them retrieve bodies of the deceased workers. When a registered (received labor permits from DoFE) migrant worker dies abroad, his family is eligible to receive a compensation (of over $1,500 for the study period) through the FEPB. The FEPB provides compensation for any kind of death as long as the migrant had obtained permits from DoFE, died within the duration of his contract, and the family files a claim within a year of the date of death with necessary documents. The necessary documents would typically be issued by local authorities after verifying that the claimant is indeed related to the deceased migrant worker. This verification process may also aid in the transmission of the news of a migrant death in addition to the word-of-mouth diffusion of news among potential migrants. The records at FEPB are considered quite comprehensive counts of the death of registered migrant workers abroad.[6]

The data used in this paper contains all such claims made with FEPB for deaths that occurred from January 2009 to December 2013. For each deceased (anonymized), I observe the date of death, the country

[6] Note that it is not the complete census of all deaths of Nepali workers abroad as it relies on the claims made by the family of the deceased.

of death, district of residence in Nepal and the cause of death reported in the death certificate. Figure 2.2 shows the total number of deaths for every month in each of the major destination countries. The figure shows an increase in the reported number of deaths in most destinations akin to the increase in migrant outflow. Because migrant deaths are rare events, the numbers look sporadic for countries with smaller migrant flows, and therefore a small migrant stock. I aggregate this data up to the district-destination-month cell for analysis. Each district-destination cell experienced 0.1 deaths in a month, with the variation across destinations resembling the migrant stocks in the destination countries (Column 2, Table 2.1).

Though considered accurate source of information on the number of migrant deaths, this data source is not suitable for analyzing effects by cause of death. The cause of death in the FEPB database is the official cause of death listed in their death certificate issued in the destination countries. The causes of death might have been tampered with to avoid insurance and other hassles (legal hassle for employers, detailed medical procedure to determine the exact causes, delays in dead body repatriation for the family of the deceased). The prevalence and variance of 'natural' cause of death of adult young male across different destinations is an evidence of the dubious quality of information on the cause of death of Nepali migrant workers (Figure 2.3). Hence, I do not pursue any analysis on the cause of death.

The data suggest very low and fairly constant mortality rate of Nepali workers abroad. I compute death rate by using the counts from the FEPB database and estimated migrant stock in each month in the destination countries. To estimate the migrant stock, I assume that migrants to the Persian Gulf countries return after 2 years and migrants to Malaysia return after 2.5 years. Using this rule in migrant outflow database from DoFE, I obtain net flow of migrants to each destination in each month. Census of 2011 provides a snapshot of the migrant stock for June of 2011 in each of these destinations. This, along with the net flow of migrants provides an estimate of the migrant stock in each destination for each month.[7] The estimated overall two-year mortality rate is 1.3 per thousand migrant workers in 2013, which is slightly higher than the rate of 1.16 per thousand worker in 2010.[8] Though the estimated magnitude of the rate is slightly higher in 2013 compared to 2010, the plot of smoothened death rates suggests that migrant death rates remained fairly constant throughout the study period (Figure 2.4). The figure also shows that death rates in Malaysia and Saudi Arabia are slightly higher than death rates in Qatar and the UAE.

[7]This estimation assumes that no workers return before the expiration of their contract, or over-stay their contract illegally. Since it is impossible to get the data on such incidences, I make no adjustments for them. The effect of such irregularities in the stock of migrants, and hence the death rates, are likely to be negligible.

[8]To keep this rate in perspective, the two-year mortality rate of Nepali men in Nepal with the same age distribution as this sample is 4.6 per thousand. The two-year mortality rate of US men with the same age distribution is 2.8 per thousand.

2.3 Empirical strategy

I use triple difference estimator to estimate the effect of death of a particular individual from origin district o in destination country d in month t in the outflow of migrants (and other outcomes) from the district to the same destination in the months following month t. In an event study framework, I estimate

$$y_{odt} = \alpha_{od} + \gamma_{ot} + \xi_{td} + \sum_{i=-12}^{12} \tau_i D_{od,t-i} + \varepsilon_{odt} \tag{2.1}$$

where y_{odt} is the outcome for origin (district)- destination (country) cell at time (in months) t measured in months. $D_{od,t-i}$ is a dummy variable which indicator whether anyone from the district o died in destination d at time $t-i$. The coefficients τ_is are normalized so that it is zero at time $t-1$. α_{od} captures origin-destination fixed effects, γ_{ot} captures time (monthly) fixed effects for each district, and ξ_{td} captures destination country specific time fixed effects. I cluster standard errors at the district level allowing for arbitrary correlation in errors terms across months and destinations for a district.

Note that this estimation only uses data for $o-d$ cells in month t if there has been at least one death in the $o-d$ cell in the 12 months surrounding time t. Further, if the $o-d$ cell in month t has multiple deaths in the 12 months surrounding month t, then each $o-d-t$ observation will appear multiple times. That is, this specification will over-weight the $o-d$ cells with larger number of migrants deaths.

Alternatively, I estimate

$$y_{odt,x} = \beta D_{odt} + \alpha_{od} + \gamma_{ot} + \xi_{dt} + \varepsilon_{odt} \tag{2.2}$$

which has identical sets of fixed effects and $y_{odt,x}$ captures the outcome y for origin district - destination country cell for the next x months after month t. D_{odt} indicates whether there was a death event in origin-destination cell in month t. Note that this specification uses all $o-d$ cells for each of month without over-weighting any particular cell.

Essentially, β from this specification averages the τ_i from Equation (2.1) for $i < 0$ for x periods in the populations. As there are no pre-trends in the outcome (which I show in the following section), this specification identifies the same effect as equation (2.1). However, since these specifications use slightly different transformation of the dataset, the estimated results are slightly different. I use the event study specification to describe the result in a figure, and use results from Equation (2.1) for further calculations and heterogeneity analysis. In both of these specifications, the identifying assumption is that the deaths are uncorrelated with other determinants of migration (or other outcomes) after controlling for all the two-way fixed effects.

Equation (2.2) allows a natural way to extend the specification to explore heterogeneity of the effects of migrant death. To explore the heterogeneity by a characteristic X, I simply estimate

$$y_{odt,x} = \beta D_{odt} + \delta \left(D_{odt} \times X_{odt}\right) + \zeta X_{odt} + \alpha_{od} + \gamma_{ot} + \xi_{dt} + \varepsilon_{odt} \tag{2.3}$$

Here, δ denotes the marginal increase in the effect of death on outcome y with an increase in characteristics X.

In all these specifications, the identifying variation is the same and comes from three sources. Within each origin-destination cell, the variation comes from different months having different number of migrant deaths. Within each origin-month cell, the variation comes from different destination countries having different number of deaths. Within each destination-month cell, the variation comes from different districts having different numbers of deaths. All other sources of variations are subsumed by the fixed effects.

Though Equation (2.2) can be used to estimate the effects of death on migration flows to the same destination, as well as other destinations, it is not straightforward to compute the net effect of deaths on migration. To directly estimate the overall effect of deaths on migration (irrespective of destination countries), I estimate

$$y_{ot,x} = \beta D_{ot} + \alpha_o + \gamma_t + \nu_{ot} \tag{2.4}$$

where $y_{ot,x}$ represents the migration flow measure from district o in the x months following month t, D_{ot} is the number of deaths of migrants from district o that occurred in month t, α_o and γ_t represent the district and month fixed effects and ν_{ot} represents the error term. I allow for arbitrary correlation in error terms between any two periods for a district. To explore heterogeneity, I estimate

$$y_{ot,x} = \beta D_{ot} + \delta \left(D_{ot} \times X_{ot}\right) + \zeta X_{ot} + \alpha_o + \gamma_t + \nu_{ot} \tag{2.5}$$

where X_{ot} represents the variable of interest.

2.4 Results and discussion

In this section, I present the results of estimating the equations on various measures of migration, prices and job composition. The first part of this section tests whether potential migrants are fully informed about migrant death rate by examining the impact of death incidences on subsequent migration flows. The second part of this section checks whether prices and job composition responds locally following a migrant death.

Note that these changes are local and will only capture changes in prices and job composition within origin district-destination cells. The third part of this section tests whether potential migrants understand that the migrant deaths are generated by an i.i.d process

recent migrant deaths in the origin district- destination cell matter in how responsive potential migrants are to a current migrant death. A change in responsiveness based on recent death rules out some hypotheses. In particular, it rules out that potential migrants are Bayesian who believe that migrant death are generated by an i.i.d process.

2.4.1 Does migrant death affect subsequent migration flows?

The event study specification shows that migrant death in an origin district - destination cell suppresses migration flow in the same cell in the subsequent months (Figure 2.5, top left plot). I cannot reject the null that migration flows in the cell do not exhibit a trend in the months preceding the death event. As the plot shows, migration flow starts to drop after the migrant death. In particular, the drop becomes large after 3 months and continues to stay low even after 12 months of the death. The lag could be a result of the delay it takes for the information about migrant death to spread, or because the news may not be effective in changing migration decision of those who have already made all the preparations and investments to migrate.

There is also an evidence of substitution to other destinations following migrant death in an origin district - destination cell (Figure 2.5, top right plot). Here as well, I cannot reject the null that migration flows to destinations other than that of migrant death do not exhibit a trend in months preceding the death. As the plot shows, migration flows to other destinations start to rise after the migrant death. The magnitude of these effects (expressed in logarithm of migration outflow per district per destination per month) in this case are, however, lower than the effect on the same destination.

Migrant death in a district has spillover effects to neighboring districts (Figure 2.5, bottom two plots). The migration flows in neighboring districts (expressed in logarithm of flow per district per destination per month) responds in similar way to a migrant death in an origin district - destination cell. That is, in response to a migrant death in an origin district - destination cell, migrant flows from neighboring district to the same destination falls and migration flows from neighboring district to other destinations slightly increases.

The estimates of these effects using Equation (2.2) show similar results. Consistent with the event study plots, Table 2.2 shows that in response to every migrant death, the average monthly migration outflow in the origin district- destination cell falls by 1.2 percent for the subsequent 6 to 12 months (top panel, columns 1, 2, and 3). Similarly, the average monthly migration outflows to other destinations increase by 0.2 to 0.3 percent for every migrant death in a cell for the subsequent 6 to 12 months (columns 4, 5, and 6). This indicates that, as corroborated by event study plots, potential migrants substitute to other destinations. The second and third panels of the table show smaller but significant spillover to neighboring districts as well. The spillovers are limited to districts close to the district of migrant death. Migrant deaths in an origin district - destination cell have no effects on migration outflows from districts that are far (bottom panel, Table 2.2).

However, the increase in migration flow to other destinations does not fully offset the negative effect in the same origin district - destination cell. Table 2.3 shows that total migration from the district falls by 0.9 to 1.2 percent in the subsequent 6 to 12 months for every migrant death in the district (top panel, columns 1, 2, and 3). There are large spillovers of migrant death to the neighboring district, but the spillover is limited to immediate neighbors only. Migrant death does not have significant impact on the migration outflows from districts that are further away (bottom two panels).

The estimated effects are quite large and of significant consequence to the nation. During the period of analysis, the total monthly outflow of migrants from each district was 300. The total effect of 0.9 percent reduction for 12 months means 32.4 fewer migrants migrate over a year after the death of a single migrant from this district. If these individuals had migrated, they would earn at least \$6,100 on the net from a migration episode that lasts 2.21 years.[9] I assume that if they stayed back, they would earn \$2,900 in 2.21 years, which is the average income per employed male.[10] With these assumptions, a single death represents a loss of \$0.1 million in forgone earnings over the 2.21 year long migration episode. Accounting for spillovers effects of the death to neighboring district makes this figure as large as \$0.8 million.During the period of the study, an average of 550 migrant workers died annually. This led to a total forgone income of \$57 million (\$460 million with spillover) which translates to 0.3 percent (2.7 percent with spillover) of the average annual GDP for this period.[11] Note that, however, these calculations do not adjust for cost of living without migration, or for other monetary and other costs associated with migration.

2.4.2 Effect of death on job composition and prices

If migrant death makes potential migrants believe that a particular job category is more risky than others, then they may respond by changing the jobs for which they migrate. Additionally, intermediaries may anticipate this and offer potential migrants less risky jobs in response to a migrant death. However, this

[9]This estimate is half of the net earnings (net of migration fees) inexperienced potential migrants expect to make from a migration episode lasting 2.21 years (Chapter 1). I take half of the earnings to account for two major effects: misinformation and cost of living abroad that is not factored into the net earnings. In Chapter 1, I show that misinformation is at least 26 percent. In The World Bank (2011), returnees from these destinations mentioned that they saved 75 percent of their earnings. Hence, half of the net earnings is a conservative estimate of migrant income.

[10]Author's calculations from the Nepal Living Standards Survey-III, of 2010.

[11]GDP figures taken from The World Bank.

does not seem to be the case. The event study plots in Figure 2.6 confirms this (top and bottom plots in third column). For both the plots, I cannot to reject the null that all effects before the death and after the deaths are zero. As Table 2.4 shows, the estimated magnitudes of the effects are very small (top panel). These are, indeed, precisely estimated zero effects.

Another way in which intermediaries could respond to a migrant death is by offering potential migrants higher wages (if they can) or lowering their recruitment fees. Note that any changes in wages or contracts offered by the employer abroad will not be captured by the specification. Since the employers leave it to the intermediaries to select the workers within the country, any wage response they make to the laborers in response to the death of their workers will be subsumed by the destination-month fixed effects. Hence, if this specification finds an effect, it will be capturing the the response by the intermediaries who may be able to vary the net benefit of migration locally in response to a migrant death. change the wages and recruitment fees to entice potential migrants.

There is no evidence of wages and fees changing in response to the migrant death. Figure 2.6 confirms this (top and bottom plots in the first two columns). For all the plots, I cannot to reject the null that all effects before the death and after the deaths are zero. As Table 2.4 shows, the estimated magnitudes of the effects are precisely estimated zero effects.[12]

This suggests that the migration response to migrant death is not mediated by compensating changes in wages and cost of migration. Therefore, the migration impact of migrant death is a result of a shift in the migrant supply at a constant price. The shift in migrant supply is caused by the changed perceptions among potential migrants about the mortality rate abroad.

2.4.3 Does recent history of migrant deaths matter?

The effect of a migrant death in changing migration decision in Section 2.4.1 shows that potential migrants are not fully aware of the mortality rate in the destination country. One class of explanations is that potential migrants are committing some sort of fallacy by responding to migrant deaths, another class of explanations is that potential migrants uninformed about the underlying death rates and are learning about about it from the realizations of migrant deaths in their districts. The latter explanation presumes that potential migrants understand the underlying data generation process and treat realized deaths as i.i.d signals from this process. If potential migrants believe that migrant deaths are i.i.d signals generated by an underlying data generation process, then their updating behavior would only depend upon the signal that they receive

[12]The small magnitude of the effect rules out some of the concerns on quality of data on wages and fees. If the discrepancy in reported wages and actual wages can be modeled by measurement error, then the misreporting only leads to increased imprecision of the estimates. The same applies for fees as well. The estimated coefficients have both small magnitude as well as small standard errors.

at every period and not on the distribution of signals in the recent past. That is, the migration response to migrant death should not depend upon the number of deaths that have happened in the district in the recent past.

However, I find evidence that migration response to a current death depends upon realizations of migrant deaths in the recent past. Table 2.5 shows that when there have been no deaths in the past six months in the origin district - destination cell, migration flows does not respond significantly to a current migrant death in the cell (top panel, columns 1, 3, and 5). If anything, the point estimate of the response is positive. But for every additional migrant death in the cell in the past six months, the effect of a current death in the cell on the migration flows falls by 0.5 to 0.6 percentage points. Put it differently, if there has been one or fewer deaths in the origin district - destination cell in the past six months, current death in the cell does not affect migration flow. But, if there have been more than one migrant deaths in the cell, death in current month reduces migration flows in the cell by about 3.2 to 3 percent for the subsequent 6 to 12 months (top panel, columns 2, 4, and 6). That is, the entire effect of migrant death on migrant flows are driven by origin district - destination cells which have experienced more than 1 migrant deaths in the past 6 months.

Note that these effects are observed even after controlling for the response to changes in actual death rates in the destinations. As Table 2.5 shows, change in actual underlying death rates in destination countries, however, does not affect how migration flow responds to current death (top panel, third interaction term).

The interaction of the effects with recent deaths persists for migration to other destinations, as well as to migration from neighboring districts, but are estimated less precisely (Table 2.5, middle and bottom panel). As the table shows, migration responses to deaths are larger when there have been more deaths in the recent six months although not all coefficients are statistically different from zero. Note that, in particular, the interaction coefficients for migration flows to other destinations are as large as the overall effects in Table 2.2.

Table 2.6 shows that the interactions with recent deaths are important for effects on migration from the district as a whole. The table shows that in districts where 3 or fewer deaths occurred in the past six months, a current death does not change migration outflows. But if there have been more than 3 migrants death in the districts, then the migration flow falls by an additional 2 to 2.2 percentage points (top panel). The interaction effect is, however, limited to the same district as the migrant death (middle and bottom panel).

The evidence presented here suggests that potential migrants do not respond to migrant death as if it was generated by an i.i.d process. Most importantly, the clustering of the deaths seem to matter in the way they respond to migrant death. They respond to a migrant death more strongly when there have been more recent deaths. This suggests that potential migrants are committing a fallacy in the way they update their beliefs about mortality rate abroad.

One fallacy that generates update rule that depends on the sequencing of signals is the law of 'small' numbers (as coined by Tversky and Kahneman, 1971). Here, individuals fallaciously update their beliefs because they expect the probability rules to hold exactly even in 'small' samples. The context of this study is aptly suited for individuals to commit this fallacy. Potential migrants do not know the underlying mortality rate and have to infer it from the migrant death that they observe. But since death rates are very small, the sample size needed to accurately estimate death rate from incidences is large. Potential migrants may not have access to large number of migrants to make this inference, or have the patience to observe the sample at their disposal for a long duration. Therefore, they are likely to make inference based on the sample at their disposal and the migrants death that they observe, and hence commit the fallacy of believing in the law of 'small' numbers.

In his mathematical formulation of this fallacy, Rabin (2002) shows that such individuals, even when they are Bayesian in their updating rule, tend to over-infer from short sequences of signals. Therefore, they tend to conclude that the true rate generating the sequence of signals is more extreme than it actually is. In the current context, when they observe many migrant deaths in the recent months, potential migrants are likely to believe that the underlying mortality rate is much larger it actually is. To check that potential migrants are indeed over-inferring from the sequences of migrant death, in the next section, I compute the change in perceived mortality rate implied by the migration effect and compare it with the change in mortality rate of a Bayesian who does not commit this fallacy.

2.5 Over-inference of mortality rate

In the first part of this section, I calculate the implied change in perceived mortality rate in response to a migrant death using estimates of earnings elasticity and the value of statistical life (VSL) from Chapter 1. In the second part, I present a simple learning model of a Bayesian who believes that migrant deaths every month are generated by i.i.d binomial process and compute his level of updating in response to migrant deaths. I compare these two estimates to show that potential migrants update a lot more in response to a death than the model.

2.5.1 Computing the implied change in perceived mortality rate caused by migrant death

In Section 2.4.1, I present the estimates of $\beta = \frac{\partial \log M}{\partial D}$, the effect of a migrant death D, on migration flows M. Each death reduces migrant flow from a district by 0.9 percent for 12 months. This represents a total of 11 percent reduction in monthly migrant flow (albeit over a year) in response to a single migrant death. I then calculate a one-time increase in migrant earnings necessary to induce the same number of potential migrants to migrate so that the net effect on migration is zero. Since the earnings elasticity of migration, $\varepsilon = \frac{\partial \log M}{\partial \log W}$, the earnings increase necessary to offset the migration effect is given by:

$$\Delta W = \frac{\beta}{\varepsilon} \cdot W$$

A simple thought experiment behind this calculation is as follows: First, shock a district with a death of a migrant in a particular month. This will lead to a reduction in migration flows from the district for the next 12 months. At the same time, shock the district with a one-time increase in expected migrant earnings for all those who migrate in that month in such a way that it induces the same number of migrants as had been dissuaded by the migrant death. The equation above provides with precisely the amount of such earnings shock necessary to compensate the district for the fall in migrant flow induced by the migrant death.

Finally, I use the estimate of the VSL to translate the earnings response to change in perceived mortality rate. I use the discretized definition of the VSL, $VSL = \frac{\Delta d}{\Delta W}$, and the formula above to do so.

$$\Delta d = \frac{\Delta W}{VSL} = \frac{1}{VSL} \cdot \beta \cdot \frac{1}{\varepsilon} \cdot W \tag{2.6}$$

where d represents the perceived probability of death and W will be the average potential earnings from migration.

I use the earnings elasticity and the VSL estimates from Chapter 1 for this calculation. In that study, I randomly assign information on earnings and mortality to potential migrants without prior migration experience and observe how they affect their expectations on earnings and mortality rate as well as their migration choices. I then use the information assignments as an instrument that moves these expectations on a binary choice model of migration decision. The estimated earnings elasticity of migration is 0.7 and the elasticity of migration with respect to expected mortality of 0.5. I calculate the VSL as the trade-off the inexperienced potential migrants are willing to make between expected earnings and expected mortality. The (preferred) estimate of the VSL from the study is \$0.28 million.

With these estimates, I find large increase in perceived mortality rate following a single migrant death.

The earnings elasticity of 0.7 implies that earnings need to go up by 15 percent to offset the reduction in migrant flow following a migrant death.[13] Using the \$0.28 million estimate of the VSL, I find that the change in perceived mortality rate following one migrant death in the district is 6.7 per thousand during a two-year migration episode.[14] This level of updating of beliefs in response to a single migrant death is quite large. In particular, the increase in perceived mortality rate is more than 5 times the actual mortality rate of 1.3 per thousand.

2.5.2 How much would a rational (i.i.d) Bayesian update?

In this part, I outline a simple model of learning from migrant death. In this model, individuals are Bayesian who believe that deaths are generated by an underlying i.i.d process. Specifically, they believe that the number of migrant death in their district every month is generated by a binomial distribution $B(N,p)$ where N is the stock of migrants abroad and p is the true but unknown mortality rate. For purposes of simplicity, I assume that N is fixed and remains the same every period. Individuals' priors follow a beta distribution, $\mathcal{B}(a_0, b_0)$ where a_0 and b_0 are the parameters of this distribution. Given the binomial signal generating process, the priors a_0 and b_0 have the interpretation of their prior exposure to migrant deaths, and migrant survivals respectively before the Bayesian learning begins. As I assume a fixed stock of migrants, this simplifies to $b_0 = N - a_0$ with the prior expectation of mortality rate of $\frac{a_0}{N}$.

In each period, indicated by t, individuals observe the number of migrant deaths in their district, s_t, which is drawn from the binomial distribution. In period 1, after they observe s_1, their posterior belief on the mortality rate follows a beta distribution given by $\mathcal{B}(a_0 + s_1, N - a_0 + N - s_1)$. In general, in period n, after observing $s_1, s_2, \cdots, s_n$, their posterior distribution follows a beta distribution given by

$$\mathcal{B}\left(a_0 + \sum_{t=1}^{n} s_t, (n+1)N - a_0 - \sum_{i=1}^{n} s_t\right)$$

with expected mortality rate of $\frac{a_0 + \sum_{t=1}^{n} s_t}{(n+1)N}$. Note that when the number of periods, n, is large, the expected mortality rate limits to the true mortality rate p.

[13] It is not clear that the earnings elasticity estimated in Chapter 1 would apply to this setting. In Chapter 1, the subjects were inexperienced potential migrants applying for passports whereas in this study, it could involve any individual thinking of migrating abroad. Specifically, the sample in Chapter 1 could be more responsive to changes in earnings expectations as they have already prepared themselves to go abroad. In 2.C, I estimate earnings elasticity of migration using the same data as this study on migrant flow and wages. I use the relative exchange rate between other destination countries and Malaysia as an instrument that changes relative wages between other destinations and Malaysia. As Appendix Table 2.C.1 shows, the point estimate of the elasticity in the top 6 destinations is 1.2, which is, in fact, slightly larger than the estimate from Chapter 1. I use the estimate from the experiment as it has better identification due to the experimental setup.

[14] Assuming that each component of equation (2.6) is normally distributed with the estimated mean and variances, and also that these components are uncorrelated with each other, the standard error for this estimate is 3.72.

The calculation using alternative estimates of VSL from Chapter 1 of \$0.538m and elasticities of 0.7 from Chapter 1 and 1.2 from 2.C produce estimates of Δd ranging from 2.1 to 6.7 per thousand, quite similar to each other.

This model gives a simple prediction on the relationship between the signal at time t, s_t, and their posterior belief after time t. A regression of their posterior beliefs and the signal in period t produces an estimated coefficient of $\hat{\beta}_t = \frac{1}{(t+1)N}$. The same relationship holds for all periods t from 1 through n. Therefore, a regression of their posterior beliefs and the signal in all periods produces an estimated coefficient given by

$$\hat{\beta} = \frac{1}{n}\sum_{t=1}^{n}\hat{\beta}_t = \frac{1}{n}\sum_{t=1}^{n}\frac{1}{(t+1)N} = \frac{H_{n+1}-1}{nN}$$

where H_k represents the k-th Harmonic number. Note that the estimated coefficient falls with the size of migrant stock N and the period of observation n (at large levels of n).[15]

The amount of updating under this model is small relative to the estimates of actual updating done by potential migrants. In the study, we observe the each district for 60 periods. A district had an average of 13,300 migrants during the period of this study. Plugging these numbers into the formula above yields a coefficient that translates to a two-year mortality rate of 0.111 per thousand migrants. The actual estimated updating of 6.7 per thousand is 60 times this number. Even when we allow individuals to update based on 6 months of data on migrant deaths, this model predicts a coefficient of 0.479 per thousand migrants, only seven percent of the actual updating. The largest amount of updating this model can generate is when individuals observe only one month of signal. Even this method only generates a coefficient of 0.9, which is only 13 percent of the actual updating observed in the data.

This exercise emphasizes a few features of the way in which potential migrants update their beliefs on mortality rate following a migrant death. First, potential migrants update too much. The amount of updating that they do is 60 times higher than what a rational Bayesian who assumes that deaths are generated by an i.i.d process does. Simple explanations along the lines of potential migrants only using few months of data to form their beliefs does not suffice on its own. The observed level of updating is much higher than a rational Bayesian using only one month of migrant deaths to form their posterior. Allowing potential migrants to be misinformed about the stock of migrants could generate such large response. But with $n = 60$, rational Bayesian must assume that the stock of migrants from their district is only 220 in order to generate the observed size of the effect. Even with $n = 6$, that the rational Bayesian only observes past 6 months of deaths in their district, they must assume that the stock of migrants from their district is only 950. Both these numbers seem too small given the prevalence of migration in the country.

Furthermore, the rational Bayesian model does not match another key aspect of the updating process: that the sequencing of migrant deaths matter in their inference. This feature rules out other explanations of

[15] At large values of x, $H_x = \gamma + \log(x)$ where γ is some constant (Euler-Mascheroni constant).

the over-inference that involves potential migrants simply assigning larger decision weights to small probabilities (as in Kahneman and Tversky, 1979). The law of 'small' numbers explanation qualitatively matches both aspects of the observed learnings process. As proposed by Rabin (2002), I find that potential migrants do over-infer from migrant deaths, and they update differently when there has been too many or too few deaths (a streak of similar signals) in the recent past. This, however, is not to claim that other channels are not at all at play. For instance, it could be possible that one or many of the channels discussed here are at play in conjunction with the belief in the law of 'small' numbers. For example, they only observe migrant deaths of the past few months to form their beliefs and also believe in the law of 'small' numbers. A combination such as this could explain the large sensitivity to migrant deaths that we observe in the data.

The expected mortality rate expressed by potential migrants in Chapter 1 is consistent with these explanations. The inexperienced potential migrants expect the mortality rate to be 27.6 per thousand for a two-year migration episode. From the estimates above, they only need 4.1 deaths in their district to generate this level of expected mortality rate starting form a prior of zero mortality rate. In 2013, an average district experienced 4.3 deaths in 5 months, suggesting that such high level of mortality perception can be generated even if potential migrants are making decisions about mortality risks only based on past five months of migrant mortality incidences in their districts. Hence, the belief held by inexperienced potential migrants is consistent with an updating behavior where they only look at a few months of migrant deaths and believe in the law of 'small' numbers to form their beliefs.

2.6 Conclusion

This paper demonstrates two key features of how potential migrants form their beliefs on mortality rate abroad from migrant deaths. First, their response is large. A single migrant death in a origin district - destination cell reduces migration flow by 1.2 percent for 12 subsequent months. After accounting for the substitution to other destination countries, a single migrant death in the district reduces migration flow from the district by 0.9 percent for 12 subsequent months. This translates to an increase in their perceived mortality rate of 6.7 per thousand for a two-year migration episode. The amount of updating alone is 5 times the actual mortality rate. In addition, the amount of updating is several times larger than the updating of a rational Bayesian who believes that migrant deaths are generated by an i.i.d binomial process. The second crucial feature is that the response depends upon the recent history of migrant deaths in the district. If there have been no (or very few) deaths in the recent past, migrant death in the current period has no effect on the subsequent migration. However, if there have been more deaths in the recent past, migrant death in the current period period has larger effect on the subsequent migration. In fact, the large response to migrant deaths is almost completely driven by cells in which there have been more deaths in the recent past.

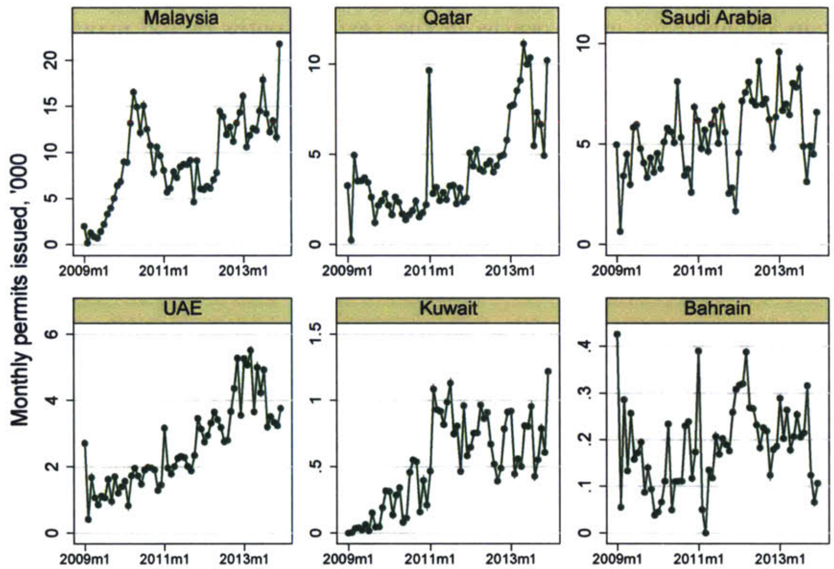
These two features are consistent with a model of belief updating where potential migrants commit a fallacy of believing in the law of 'small' numbers. As Rabin (2002) shows, such individuals, when they encounter a streak in signals, such as no deaths in the past 6 months or too many deaths in the past 6 months, erroneously believe that the deaths are generated by a more extreme underlying rate than the truth. As discussed above, the data matches both the over-inference result as well as the dependence of updating behavior on the sequence of signals.

Finally, this paper finds that the belief on mortality rate expressed by inexperienced potential migrants in Chapter 1 is consistent with their experience and their updating behavior. A suggested explanation for the high expected mortality is that the potential migrants observe migrant deaths in their own district for a few months to form their priors, but at the same time they commit the fallacy of the law of 'small' numbers which leads them to over-infer from the migrant deaths that they see.

2.A Figures and Tables

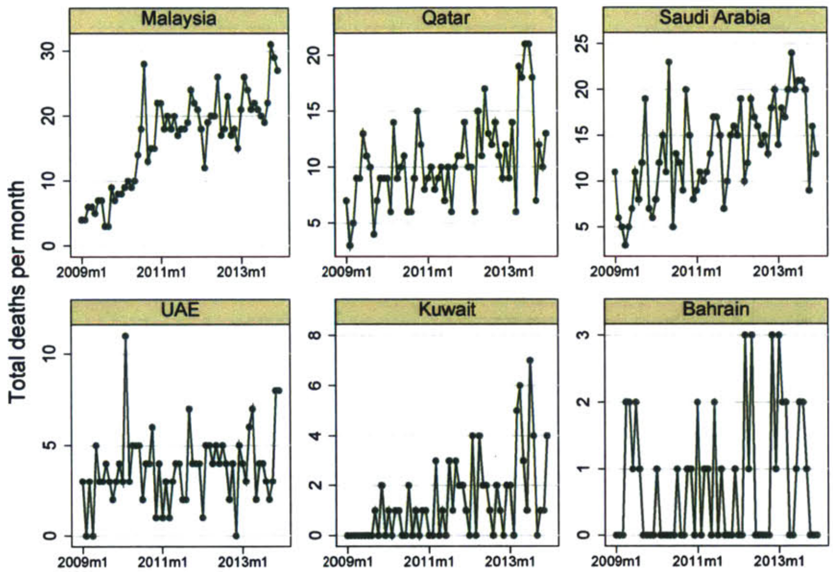
2.A.I Figures

Figure 2.1: Total permits issued by DoFE for top destination countries



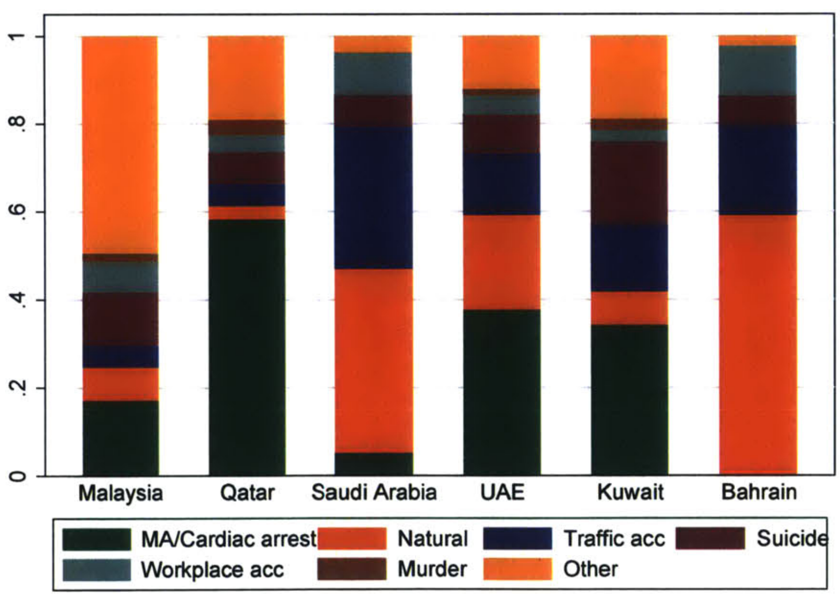
Source: Author's calculations from DoFE database
Note: This figure shows the number of work permits issued every month for the period of the study (2009-2013) to the top six destination countries. This does not include migration flows to India.

Figure 2.2: Monthly deaths in top destinations



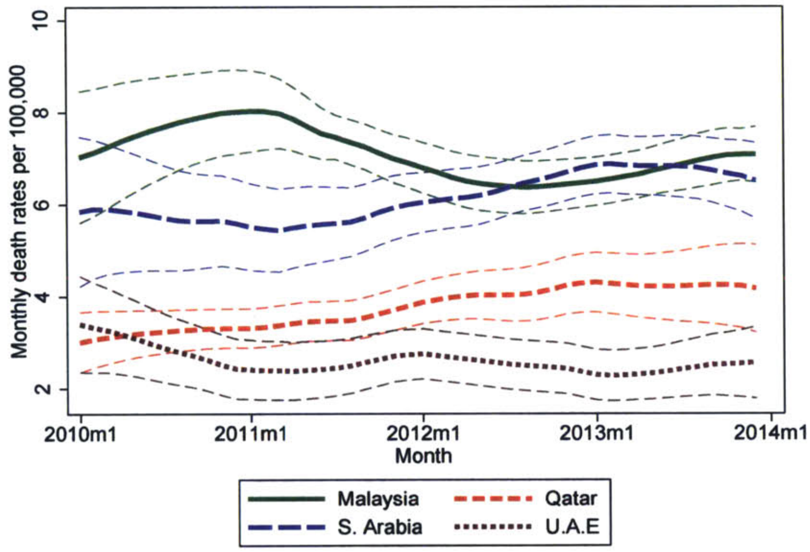
Source: Author's calculations from FEPB database
Note: This figure shows the number of deaths of registered Nepali migrants every month for the period of the study (2009-2013).

Figure 2.3: Official cause of migrant deaths by destination



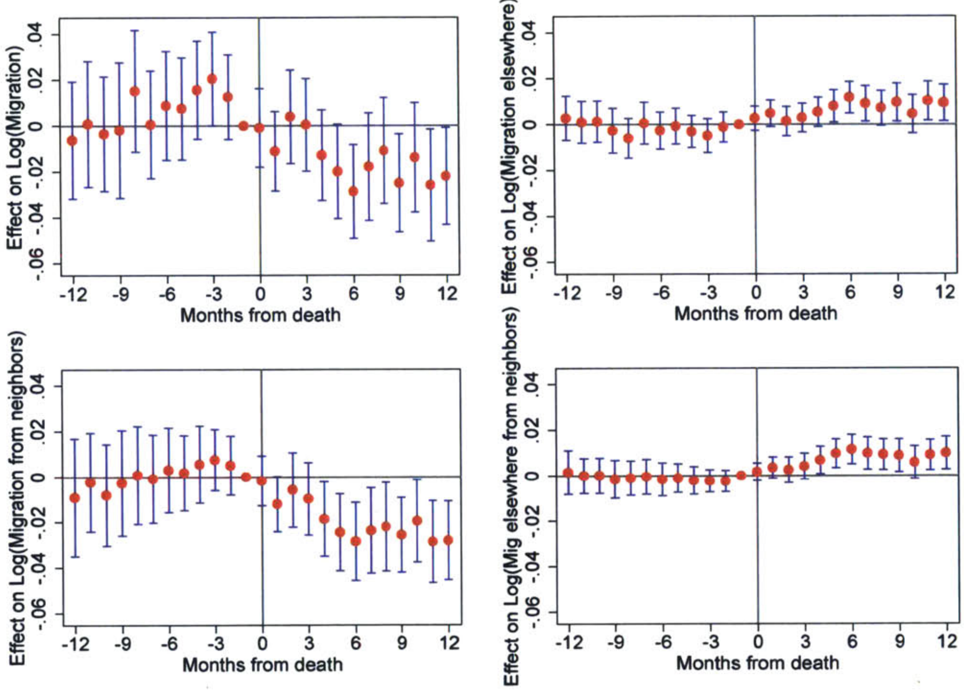
Source: Author's calculations from FEPB database
Note: This figure shows the official cause of deaths of Nepali migrants for each of the major destination countries

Figure 2.4: Deaths rates over time for top destination countries



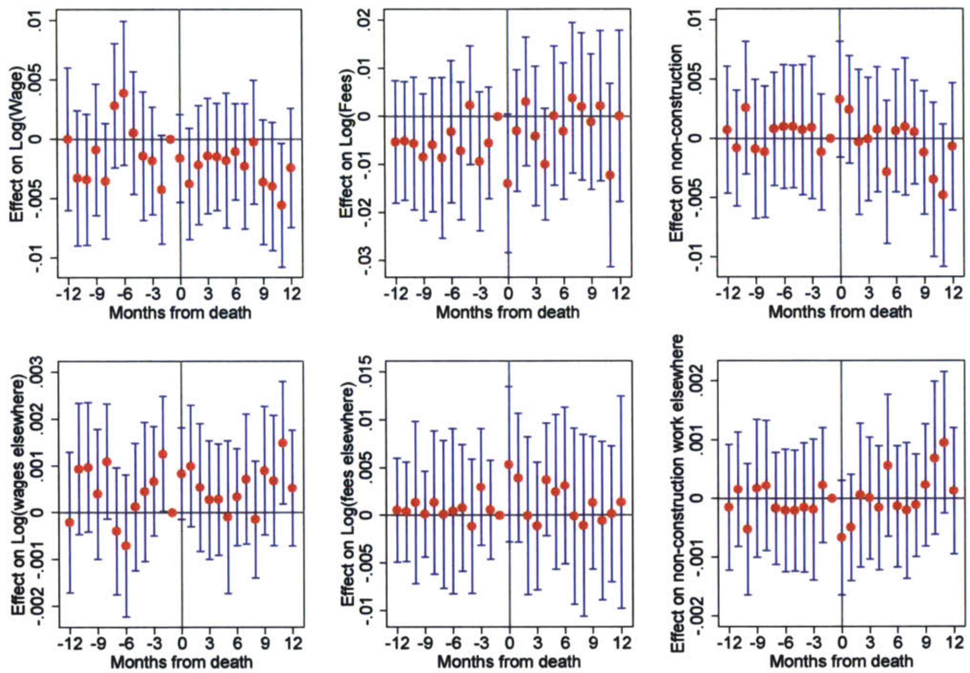
Source: Author's calculations from FEPB database and the 2011 Population and Housing Census Public Use Microdata Sample
Note: This figure shows the smoothened monthly death rates (per 100,000 migrants) of Nepali workers in the top destination countries. Locally linear regression with epanechnikov kernel and bandwidth of 4.5 used for smoothing. Thick lines show the point estimates whereas the light dashed lines around the thick lines show 95% confidence intervals.

Figure 2.5: Effect of a migrant death on migration flows: Event study plots



Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: This figure shows the relationship between migrant death and migrant flows in the months preceding and following a death event. The figures plot point estimates (in red) of τ_is from the event study specification, Equation (2.1), for 12 months before and after any death event.
The measure of migration flows are indicated on the y-axis of each plot. The plot on the top left shows the effect on the logarithm of migration flow from the same district to the same destination as the death event. The plot on the top right shows the effect on the logarithm of migration flow from the same district to other destinations as the death event. The plot on the bottom left shows the effect on the logarithm of migration flow from neighboring district to the same destination as the death event. The plot on the bottom right shows the effect on the logarithm of migration flow from neighboring district to other destinations as the death event.
The vertical line at 0 indicates the month of a migrant death.
In each plot, the blue lines denote the 95% confidence intervals. Robust standard errors are clustered at the district level.

Figure 2.6: Effect of a migrant death on wages, fees, and job composition: Event study plots



Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: This figure shows the relationship between migrant death and migrant wages, fees and job composition in the months preceding and following a death event. The figures plot point estimates (in red) of τ_is from the event study specification, Equation (2.1), for 12 months before and after any death event.
The y-axis of each plot denotes the dependent variable. The plots on the top row shows the effect on outcomes in the same destination as the death event. The plots on the bottom row shows the effect on outcomes in other destination as the death event. The outcome for the plots on the first column is the logarithm of monthly contractual wages. The outcome for the plots on the second column is the logarithm of fees paid by migrants to intermediaries. The outcome for the plots on the third column is the share of workers that migrate for jobs that are definitely not in construction industries.
The vertical line at 0 indicates the month of a migrant death.
In each plot, the blue lines denote the 95% confidence intervals. Robust standard errors are clustered at the district level.

2.A.II Tables

Table 2.1: Summary statistics

	Total Outflow mean/(sd) (1)	Number of Deaths mean/(sd) (2)	Wage (in US \$) mean/(sd) (3)	Fee (in US \$) mean/(sd) (4)	Echange rate NPR / US \$ mean/(sd) (5)	Share of non construction mean/(sd) (6)
	Overall means (means per district per destination per month)					
Mean	49.639	0.102	230.551	582.606		0.346
SD	(90.956)	(0.353)	(64.362)	(225.627)		(0.302)
	By year (means per district per destination country per month)					
2009	25.093	0.057	203.853	674.616	77.428	0.302
	(52.254)	(0.251)	(64.081)	(185.960)	(2.190)	(0.302)
2010	46.247	0.093	212.331	674.081	73.157	0.358
	(114.468)	(0.338)	(62.884)	(199.288)	(1.255)	(0.329)
2011	42.534	0.105	226.260	607.697	74.578	0.355
	(65.368)	(0.359)	(74.353)	(228.804)	(4.143)	(0.298)
2012	58.658	0.116	234.269	522.638	84.975	0.358
	(86.307)	(0.369)	(53.692)	(212.414)	(3.121)	(0.291)
2013	75.664	0.142	269.948	457.904	93.602	0.351
	(111.321)	(0.423)	(42.158)	(211.431)	(6.046)	(0.287)
	By Destination Country (means per district per month)					
Malaysia	124.452	0.218	192.791	766.250		0.057
	(152.036)	(0.508)	(38.771)	(94.362)		(0.089)
Qatar	56.187	0.141	226.671	365.417		0.228
	(79.923)	(0.402)	(40.218)	(222.834)		(0.165)
Saudi Arabia	72.869	0.178	206.008	530.926		0.251
	(88.556)	(0.458)	(33.528)	(155.410)		(0.159)
UAE	34.804	0.050	254.636	584.206		0.584
	(41.604)	(0.227)	(54.438)	(174.725)		(0.211)
Kuwait	7.037	0.018	264.430	666.013		0.571
	(10.687)	(0.136)	(70.982)	(213.247)		(0.308)
Bahrain	2.485	0.010	261.827	611.061		0.532
	(4.113)	(0.101)	(108.430)	(244.385)		(0.386)

Source: Author's calculations on migrant registration database of DoFE and migrant death database of FEPB.
Note: This table shows the means and standard deviations of the outcome variables. The column variables indicate the outcome variables. An observation in the dataset used to compute the summary statistics is a district-destination-month cell. Outcomes are first aggregated up to the cell level from the data provided by DoFE and FEPB.
Wages and fees are converted to USD using the monthly exchange rate between USD and Nepali Rupee.
The top panel shows the average of the outcome in a district-destination-month cell. The middle panel shows the average outcome in a district-destination-month cell in each year. The average is taken over all districts, destinations, and months in the year indicated in the corresponding row. The bottom panel shows the average outcome in a district-destination-month cell for each destination country. The average is taken over all districts and months.

Table 2.2: Effect of migrant deaths on district-destination level migration flows

	To same destination			**To other destinations**		
	6 months after death	9 months after death	12 months after death	6 months after death	9 months after death	12 months after death
	(1)	(2)	(3)	(4)	(5)	(6)
			log(*migration from district*)			
Deaths in month	-0.012**	-0.012***	-0.012***	0.002	0.003*	0.003**
	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Obs	27000	27000	27000	27000	27000	27000
Adj R2	0.979	0.984	0.987	0.998	0.998	0.998
			log(*migration from neighboring districts*)			
Deaths in month	-0.007***	-0.008***	-0.007**	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Obs	27000	27000	27000	27000	27000	27000
Adj R2	0.989	0.991	0.993	0.998	0.998	0.998
			log(*migration from* 2^{nd} *degree neighboring districts*)			
Deaths in month	-0.004**	-0.005**	-0.004**	0.001	0.001*	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Obs	27000	27000	27000	27000	27000	27000
Adj R2	0.993	0.995	0.996	0.999	0.999	0.999
			log(*migration from far neighboring districts*)			
Deaths in month	0.001	0.001	0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obs	27000	27000	27000	27000	27000	27000
Adj R2	0.999	0.999	0.999	0.999	0.999	0.999

Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: This table shows the effect of a death of a migrant in a district-destination cell on logarithm of migrant flows, estimated using Equation (2.2).
The first 3 columns show the effect on the logarithm of subsequent migration flows to the same destination as the deceased migrant. Columns (1), (2), and (3) show the estimates for subsequent flow in the 6, 9, and 12 months respectively.
The last 3 columns show the effect on the logarithm of subseqent migration flows to destinations other the country of migrant death. Columns (4), (5), and (6) show the estimates for subsequent flow in the 6, 9, and 12 months respectively.
The top panel shows the effect on migration flows from the same district as the migrant death. The second panel shows the effect on migration flows from neighboring districts. Neighboring districts share a border with the district of migrant death. The third panel shows the effect of a migrant death on migration flows from second degree neighboring districts. Second degree neighbors are separated from the district of migrant death by one district. The fourth panel presents the effects on migration flows from districts that are from the district of migrant death. These districts are separated from the district of migrant death by at least 3 districts in between.
Each column in each panel is a separate regression. For all specifications, standard errors are reported in parenthesis and are clustered at the district level. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 2.3: Effect of migrant deaths on district level migration outflow

	Flow in the next		
	6 months	9 months	12 months
	(1)	(2)	(3)
log(total migration from district)			
All deaths in month	-0.012**	-0.010**	-0.009**
	(0.005)	(0.005)	(0.005)
Obs	4499	4500	4500
Adj R2	0.967	0.973	0.976
log(total migration from neighboring district)			
All deaths in month	-0.015***	-0.013***	-0.013***
	(0.004)	(0.004)	(0.004)
Obs	4500	4500	4500
Adj R2	0.962	0.965	0.968
log(total migration from 2^{nd} degree neighbors)			
All deaths in month	-0.002	-0.001	-0.000
	(0.003)	(0.003)	(0.003)
Obs	4500	4500	4500
Adj R2	0.957	0.962	0.967
log(total migration from far neighbors)			
All deaths in month	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Obs	4500	4500	4500
Adj R2	0.991	0.992	0.992

Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: The table shows the effect of a death of a migrant from a district on the logarithm of migration flows, estimated using Equation (2.4)
Columns (1), (2), and (3) show the effect on flows in the subsequent 6, 9, and 12 months respectively.
The top panel shows the effect of a migrant death on flows from the same district. The second panel shows the effect on flows from neighboring districts. Neighboring districts share a border with the district of migrant death. The third panel shows the effect on flows from second degree neighboring districts. Second degree neighbors are separated from the district of migrant death by one district. The fourth panel shows the effect on flows from districts that are far from the district of migrant death. These districts are separated from the district of migrant death by at least 3 districts in between.
Each column in each panel is a separate regression. For all specifications, standard errors are reported in parenthesis and are clustered at the district level. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 2.4: Effect of migrant deaths on job-composition and prices

	To same destination			To other destinations		
	6 months after death	9 months after death	12 months after death	6 months after death	9 months after death	12 months after death
	(1)	(2)	(3)	(4)	(5)	(6)
			Share of jobs definitely non-noconstruction			
Deaths in month	-0.001	-0.001	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obs	25620	25987	26188	25620	25987	26188
Adj R2	0.711	0.776	0.816	0.920	0.934	0.944
			log(*contractual wages*)			
Deaths in month	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	25616	25987	26188	25526	25915	26126
Adj R2	0.852	0.885	0.908	0.954	0.963	0.966
			log(*fees paid for recruiting services*)			
Deaths in month	0.002	0.002	0.002	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	25579	25962	26176	25524	25911	26122
Adj R2	0.806	0.839	0.865	0.907	0.925	0.937

Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database

Note: This table shows the effect of a death of a migrant in a district-destination cell on job composition, logarithm of contracted wages, and logarithm of fees paid to intermediaries, estimated using Equation (2.2).

The first 3 columns show the effect on the outcomes for the same destination as the destination of the deceased migrant. Columns (1), (2), and (3) show the effect for the subsequent 6, 9, and 12 months respectively.

The last 3 columns show the effect on the outcomes for migrants going to destinations other the country of migrant death. Columns (4), (5), and (6) show the effect for subsequent the 6, 9, and 12 months respectively.

The top panel shows the effect on the share of migrants who go for a job that is definitely not in construction sector. The second panel shows the effect on the logarithm of average contractual wage of migrants. The bottom panle shows the effect on the logarithm of average fees paid by the migrants for recruitment services.

Each column in a panel represents a separate regression. In all cases, standard errors are reported in parenthesis and are clustered at the district-level. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Table 2.5: Heterogeneous effect of deaths on migration flows

Flow in the next	6 months		9 months		12 months	
	(1)	(2)	(3)	(4)	(5)	(6)
	log(migration to same destination)					
Deaths in month	0.006	0.010	-0.001	0.002	-0.003	0.000
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
x Deaths in past 6 months	-0.006***		-0.006***		-0.005**	
	(0.002)		(0.002)		(0.002)	
x $>$ 1 deaths in past 6 months		-0.022***		-0.019***		-0.016**
		(0.007)		(0.007)		(0.006)
x death rate in Destination	-0.001	-0.002	0.001	-0.000	0.001	-0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Deaths in past 6 months	-0.012***		-0.010**		-0.009**	
	(0.004)		(0.004)		(0.004)	
$>$ 1 deaths in past 6 months		-0.020*		-0.016		-0.014
		(0.011)		(0.010)		(0.010)
	log(migration to other destinations)					
Deaths in month	-0.006	-0.007*	-0.004	-0.005	-0.003	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
x Deaths in past 6 months	0.000		0.000		-0.000	
	(0.001)		(0.001)		(0.001)	
x $>$ 1 deaths in past 6 months		0.003		0.003		0.003
		(0.003)		(0.003)		(0.003)
x death rate in Destination	0.002*	0.001*	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Deaths in past 6 months	0.004**		0.004**		0.003**	
	(0.002)		(0.002)		(0.002)	
$>$ 1 deaths in past 6 months		0.010**		0.009**		0.007*
		(0.004)		(0.004)		(0.004)
	log(migration from neighbors to same destination)					
Deaths in month	-0.004	-0.002	-0.008	-0.007	-0.006	-0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
x Deaths in past 6 months	-0.001		-0.001		-0.001	
	(0.002)		(0.001)		(0.001)	
x $>$ 1 deaths in past 6 months		-0.014***		-0.013***		-0.012**
		(0.005)		(0.005)		(0.005)
x death rate in Destination	0.000	0.001	0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Deaths in past 6 months	-0.007**		-0.005*		-0.005*	
	(0.003)		(0.003)		(0.003)	
$>$ 1 deaths in past 6 months		-0.015**		-0.012*		-0.012*
		(0.007)		(0.007)		(0.007)

Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: The table shows how the migration effect of a death of a migrant in a district-destination cells changes with the number of deaths in the district-destination cell in the past six months. The estimates reported are β and δ coefficients from Equation (2.5). All specifications control for the effect of the interaction between current death and actual underlying death rates in the destination countries. The first two columns present the estimates for migrant outflow in the subsequent 6 months, columns (3) and (4) present the estimates for migrant outflow in the subsequent 9 months, and columns (5) and (6) present the estimates for migrant outflow in the subsequent 12 months. Odd numbered columns show the interaction with the number of deaths in the district-destination cell in the past 6 months. Even numbered columns show the interact with whether there has been more than one death in district-destination cell in the past 6 months.
The top panel shows the effect on migration outflow from in the same district-destination cells as the migrant death. The second panel shows the effect on migration outflow to destinations other than that of the migrant death. The third panel shows the effect on migration outflow from neighboring districts to the same destination as the migrant death.
For all panels, standard errors are reported in parenthesis and are clustered at the district level. $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$

Table 2.6: Effect of deaths in any destination on total migration outflow

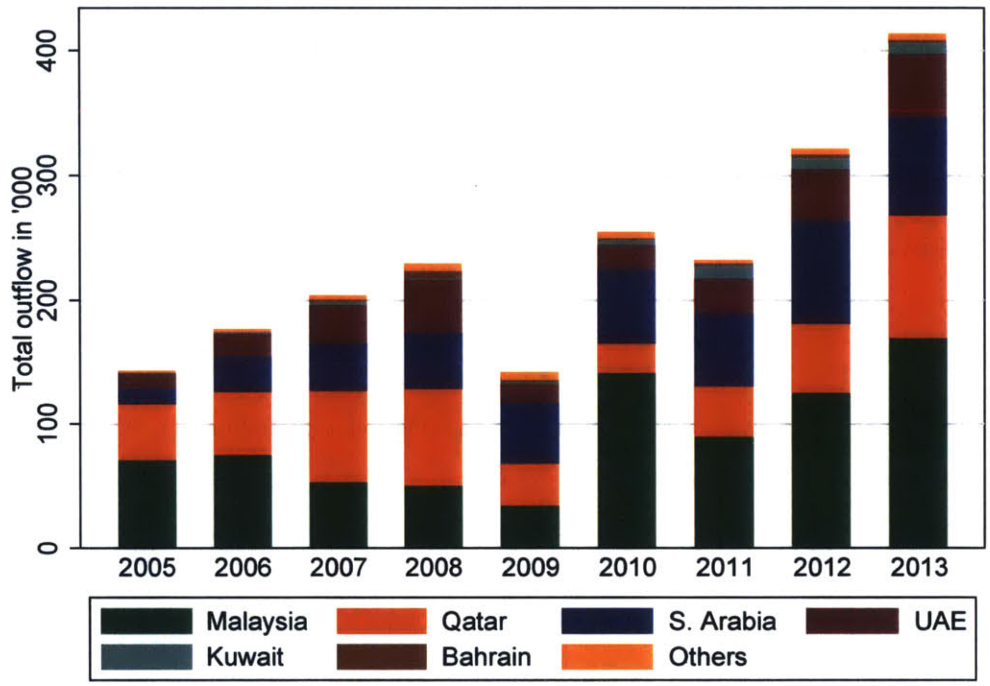
	Flow in the next		
	6 months	9 months	12 months
	(1)	(2)	(3)
log(total migration from district)			
All deaths in month	0.009	0.010	0.008
	(0.008)	(0.007)	(0.007)
x $>$ 3 deaths in past 6 months	-0.022**	-0.022**	-0.020**
	(0.010)	(0.010)	(0.009)
$>$ 3 deaths in past 6 months	0.016	0.015	0.006
	(0.020)	(0.021)	(0.020)
Obs	4049	4050	4050
Adj R2	0.972	0.976	0.978
log(total migration from neighboring district)			
All deaths in month	-0.014	-0.012	-0.012
	(0.011)	(0.011)	(0.011)
x $>$ 3 deaths in past 6 months	0.007	0.005	0.006
	(0.012)	(0.013)	(0.013)
$>$ 3 deaths in past 6 months	-0.028	-0.024	-0.025
	(0.021)	(0.021)	(0.020)
Obs	4050	4050	4050
Adj R2	0.964	0.967	0.968
log(total migration from 2^{nd} degree neighbors)			
All deaths in month	0.003	0.005	0.004
	(0.006)	(0.006)	(0.005)
x $>$ 3 deaths in past 6 months	0.000	-0.001	-0.001
	(0.007)	(0.007)	(0.006)
$>$ 3 deaths in past 6 months	0.013	0.018	0.018
	(0.015)	(0.014)	(0.013)
Obs	4050	4050	4050
Adj R2	0.958	0.964	0.967

Source: Author's calculations from the dataset constructed from the FEPB database and the DoFE database
Note: The table shows how the migration effect of a death of a migrant in district changes with whether there has been many ($>$ 3) migrant deaths in the district in the past six months. The estimates reported are β and δ coefficients from Equation (2.5).
Columns (1), (2), and (3) present the estimates for the migrant outflow in the subsequent 6, 9, and 12 months.
The top panel shows the effect on migration outflow from in the same district as the migrant death. The second panel shows the effect on migration outflow from neighboring districts. The third panel shows the effect on migration outflow from 2^{nd} degree neighboring districts.
For all panels, standard errors are reported in parenthesis and are clustered at the district level. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

2.B Appendix Figures and Tables

2.B.I Figures

Figure 2.B.1: Permits granted by DoFE for work abroad



Source: Author's calculation on the data provided by Department of Foreign Employment (DoFE).
Note: This figure shows the number of work-permits issued by DoFE for work abroad by year and destination country.

2.B.II Tables

Table 2.B.1: International migration from Nepal and remittance income

	Migrant/Population share			Remittance Income
Year	All	India	Non-India	% of GDP
1961	3.49			
1981	2.68	2.48	0.19	
1991	3.56	3.17	0.37	1.5
2001	3.41	2.61	0.78	2.4
2011	7.43	2.80	4.63	22.4

Source: Migrant/Population share from the Census reports for respective years, Remittance as a share of GDP from the World Development Indicator database (The World Bank)
Note: This table shows the migrant to population share for each of the census years since 1961. It also shows the share broken down by destination. The last column shows the personal remittance income as a share of national GDP for the years available.

2.C Exploiting exchange rate shocks to estimate wage elasticity of migration

In this section, I use the exchange rate shocks to wages to estimate the wage elasticity of migration. The first part outlines the methodology and the second part presents the estimates. The data used in this section is the reported wages and migration flows from the DoFE database described in Section 2.2.2. The monthly exchange rate data comes from the historic database of the online forex trading platform OANDA.[16]

2.C.I Empirical specification

The earnings elasticity of migration that I want to estimate is given by β in the following specification

$$\log\left(y_{dt}\right) = \alpha_d + \gamma_t + \beta \log\left(W_{dt}\right) + \varepsilon_{dt}$$

where y_{dt} represents the migrant flow from Nepal to destination country d in month t, W_{dt} is the contractual wage in Nepali Rupee for month t in destination country d. α_d and γ_t represent destination and time fixed effects. Estimating β from this specification will be biased as the unobserved determinants of migration flows is correlated with the wages offered to the migrants. Further, the relationship is an equilibrium relationship and suffers from reverse causality. That is, a change in wages leads to a change in migration flows, but at the same time a change in migration flows also leads to a change in equilibrium wages offered. Hence, an instrument for wages is needed to identify the elasticity.

One possibility is to use the exchange rate E_{dt} between Nepal and the destination country as an instrument. However, factors affecting exchange rate between Nepal and the destination country could directly affect migration flows in addition to its effect though migrant wages. Therefore, I estimate a slightly modified version of the equation:

$$\begin{aligned}\log\left(\frac{y_{dt}}{y_{Mt}}\right) &= \alpha_d + \gamma_t + \beta \log\left(\frac{W_{dt}}{W_{Mt}}\right) + \varepsilon_{dt} \\ \log\left(\frac{W_{dt}}{W_{Mt}}\right) &= \xi_d + \psi_t + \delta \log\left(\frac{E_{dt}}{E_{Mt}}\right) + \eta_{dt}\end{aligned} \tag{2.7}$$

where y_{Mt}, W_{Mt}, and E_{Mt} represents migration, contractual wages and exchange rates in Malaysia. By normalizing everything by Malaysian flows, wages and shocks, identification comes from the shocks to exchange rates between Malaysia and other destination countries. The exclusion restriction requires that the destination choice of potential migrants does not depend upon the relative exchange rates with Malaysia except through changes in relative wages. This is a more palatable assumption.

[16] `http://www.oanda.com/currency/average`.

The relative exchange rates and relative migrant flow appear to be strongly correlated. As shown in Figure2.C.1, between 2009 and mid-2011, relative exchange rate between the Persian Gulf countries and Malaysia fell drastically. Consequently, the relative flow of migrants from Nepal to Persian Gulf countries also fell. This figure essentially shows the reduced form relationship for estimating Equation (2.7).

Few issues arise in this estimation. For instance, shocks to exchange rates of a country are likely to be correlated over time and not correcting for this will lead to standard errors that are too small. Bertrand, Duflo, and Mullainathan (2004) show that with few groups, even clustering standard errors at the group level produces standard errors that too small. In this context, increasing group size by including other destination countries presents two main problems. First, migration to other destination countries is not as easy as migrating to the common destination countries. For example, European employers may not be as keen to sponsor the work visa of low-skilled Nepali workers as does Malaysia. Therefore, migration to Europe will responds less to increase in low-skill wages in Europe. The average elasticity estimated by including other countries will be lower than the elasticity for the most common destinations used in this analysis. Second, since migration to other destination is not as frequent, I do not observe wage information for the destinations in months in which there is no migration. The technique used to impute missing wage information affects the estimated elasticities. To impute wages for months in which there is no migration, I assume that the nominal wage in the destination country remains the same as the previous month and the variation is induced only by fluctuations in the exchange rates. This process describes the wage data quite well (with R-squared of 0.88) for countries where missing wage information is not a problem.

In addition to specifications with standard errors clustered at the country level, I also present specifications that cluster the standard error at country $\times$ period level. The period are defined such that exchange rates are unlikely to be serially correlated across periods. The first period between January 2009 and July 2011 is marked by steadily declining relative exchange rate, the second period between August 2011 and May 2013 is marked by fluctuating but relatively stable exchange rate, and the third period between June 2013 and December 2013 as the period of increasing relative exchange rate.

2.C.II Results

For the top 6 destinations, the relative exchange rates show strong first stages and reduced forms. As Table 2.C.1 shows, an increase in relative exchange rate of 1 percent increases relative migration to Malaysia by 6 percent (top panel, column 1). This comes at no surprise given the strong correlation between relative migration flows and relative exchange rates as seen in Figure 2.C.1. Similarly, an increase in relative exchange rate of 1 percent increases relative wages by 5 percent (middle panel, column 1). The 2SLS estimate of the wage elasticity of migration is 1.2. All of these estimates are statistically different from zero at conventional levels at both clustering specifications.

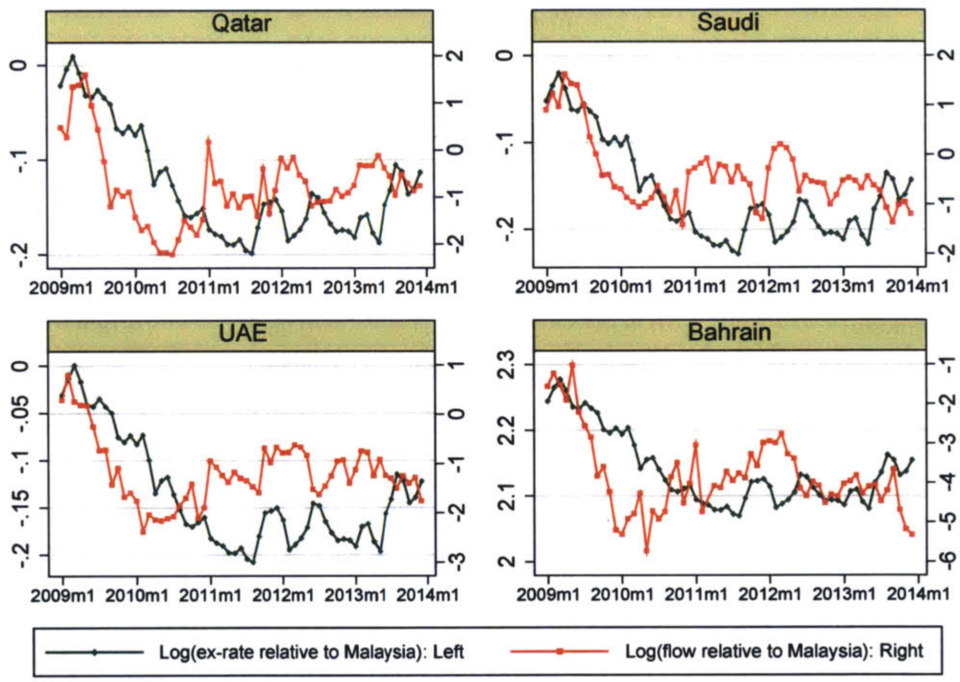
The point estimate of the elasticity is similar for the the top 10 destinations, but is estimated imprecisely (Table 2.C.1, column 2). As discussed earlier, due to institutional restriction in other countries, migration flows do not respond as strongly to changes in relative exchange rates. The wage effect of exchange rate shocks are also small and imprecisely estimated. Consequently, the estimated wage elasticity of migration is also imprecisely estimated. However, the point estimate of 1.4 is similar to the estimate for top 6 destinations.

Including more destination countries in the estimation simply exaggerates the problems discussed above (Table 2.C.1, columns 3 and 4). Due to institutional barriers, migration flow does not respond to exchange rate shocks. Since, missing wages are imputed from the changes in exchange rates, the first stage estimates are biased towards 1. As a result, the estimated wage elasticity of migration are much smaller and imprecisely estimated.

2.C.III Figures and Tables for 2.C

Figures

Figure 2.C.1: Relative exchange rates and relative migration



Source: Author's calculations from the dataset constructed from the DoFE database on migrant flow and historic exchange rate data from OANDA
Note: Green (dark) line represents logarithm of exchange rate of the country relative to Malaysia in left-axis. The red (light gray) line represents the logarithm of the ratio of migrant flow to the destination country relative to the flow to Malaysia (right-axis). The plot titles show the destination country.

Tables

Table 2.C.1: Effect of relative wage rate on relative migration

	Top 6 destinations (1)	Top 10 Destinations (2)	Top 15 Destinations (3)	Top 20 Destinations (4)
	Reduced form			
Log(Ex-rate relative to Malaysia)	6.211	0.554	0.451	0.258
	(1.583)**	(0.332)	(0.300)	(0.183)
	[1.915]***	[0.514]	[0.360]	[0.180]
	First stage			
Log(Ex-rate relative to Malaysia)	5.016	0.360	1.488	1.041
	(0.315)***	(0.866)	(1.214)	(1.067)
	[0.505]***	[5.318]	[3.652]	[1.026]
	2-SLS estimates			
Log(wage relative to Malaysia)	1.207	1.400	0.311	0.241
	(0.366)**	(2.744)	(0.269)	(0.180)
	[0.481]**	[21.783]	[0.907]	[0.254]
Observations	300	600	840	1140

Source: Author's calculations from the dataset constructed from the the DoFE database and the exchange rate data from OANDA

Note: This table shows the reduced form, first stages and the 2SLS estimates of the effect of logarithm of wages on logarithm of migrant flow using logarithm of exchange rate shocks as instruments, estimated using Equation (2.7). All variables: wages, migrant flow, and exchange rate are expressed relative to their values in Malaysia.

The column headings represents the sample of countries used for estimation. Except for the first column, wages are missing when there is no migration flow to that destination. Wages are imputed assuming that the nominal wage in destination currency remains the same as previous month. The only source of variation is through changes in the exchange rates.

Standard errors reported in parenthesis are clustered at the country level, whereas those reported in brackets are clustered at the country $\times$ period level. There are three periods: the first period defined as months between January 2009 and July 2011, the second period as months between August 2011 and May 2013, and the third period as months between June 2013 and December 2013. *** : $p < 0.01$; ** : $p < 0.05$; * : $p < 0.1$

Chapter 3

Push and pull: A study of international migration from Nepal

3.1 Introduction

International labor migration has surged in recent years with increasing number of workers moving across international borders for work. The stock of international migrants increased from 154 million in 1990 to 244 million in 2015 (UNDESA, 2015). Over 70 percent of international migrants are from developing countries. However, most of the migrants from developing countries migrate to other developing countries, though the returns to migration may be higher in the developed countries. Of the migrants that originate in the least developed countries, only 16 percent migrate to the global North. High costs of migration to and low demand for migrant workers in the developed countries potentially prevent migrants from migrating there.

In this paper, I investigate the migration response to the 'push' and 'pull' shocks, shocks that affect the origin and destination respectively, when destinations have varying costs of migration and individuals are liquidity constrained. For instance, a positive income shock in the origin may increase migration by making it more affordable or it may reduce migration by making it less desirable. The net effect on migration rates depends upon the distribution of households around the affordability and desirability margins. I outline a simple theoretical framework that captures these features and test its implications in the context of international migration from Nepal.

Several features make Nepal a good setting to study the effect of shocks on international migration. First, migration of workers from Nepal is large and crucial to the national economy. Though the historic migration rates are similar to the global average, by 2011 the migrant to population ratio increased to 7.4

percent, more than double the global average (Table 3.1). Consequently, foreign remittances became one of the largest source of national income, contributing over a fifth to the national GDP[1]. Second, most work migrants from Nepal choose between two distinct type of destinations that differ in terms of the costs and returns to migration. As seen in Table 3.1, India has been one of the key destinations for Nepali workers for the past several decades and continues to be the largest destination country. It serves as the low cost and low return destination for Nepali workers. However, the surge in migration in the 2000s was driven by migration to Malaysia and the Persian Gulf countries (especially Qatar, Saudi Arabia and the United Arab Emirates). Most of the migrants, about 90 percent of those who migrate for work, migrate to these destinations. These countries are the high-cost-high-return destinations for Nepali workers. Third, migration to these destination countries are facilitated institutionally. Nepal maintains an open border with India and workers can move across the border with extreme ease. In addition, agreements with Malaysia and the Persian Gulf countries make it relatively easy, though costly, for Nepali workers to migrate for (low-skilled) work in those destinations. Almost 500 thousand workers left Nepal in 2014 to work in these destination countries.

However, the destinations chosen by Nepali workers are not unique to migrants from Nepal. Nine Persian Gulf countries, which represent 1 percent of the global population, are destinations to 13 percent of the international migrants in the world (UNDESA, 2015)[2]. Along with India and Malaysia, these destinations account for over 16 percent of international migrants (21 percent of male migrants) in the world. These countries have become the workplace of low-skilled workers from the Philippines and South Asian countries who have been migrating to these countries for decades.

In the context of international migration from Nepal, I investigate the effect of three types of shocks using a panel of 452 villages across the country and observed in years 2001, 2008 and 2010. The first is the shock to farm income in the origin. Deviation of rainfall from its historic mean generates an exogenous variation in farm income both across the country for a given year and between different time periods for the same village. The second shock is a measure of conflict in origin which creates an income loss as well as an utility loss, more so for the richer households. The ten-year long Maoist insurgency, which killed over 13,000 people, generates a variation in conflict intensity experienced by different parts of the country. In addition, the dramatic change in the trajectory of the insurgency gives rise to inter-temporal variation in conflict intensity experienced by a given village. In addition to the two 'push' shock that affect the origin, I investigate the effect of an increase in the demand for low-skilled workers from abroad. I use the growth in

[1] In 2014, this share was 29 percent (The World Bank). Only two other countries – Tajikistan and Kyrgyz Republic – have a higher share of remittance to GDP.

[2] The nine countries are Bahrain, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. These are the largest destinations for international migrants in the Persian Gulf excluding Syria.

construction and manufacturing sector in various destination countries to proxy for these 'pull' shocks from the destination countries. Here as well, different destinations countries that are plausibly in quite different macroeconomic cycles generates the variation that identifies my estimates. Differential effects of the global recession of 2008, further generates variation in growth rates across different destination countries.

Consistent with the theoretical framework, I find that rainfall shocks increases migration to India, but has no effect on migration to non-India destinations. Increase in farm income of US$ 100 due to rainfall increases migration to India by 2.5 percentage points (54 percent increase from its 2010 level) but has no effect on migration elsewhere. Rainfall shocks increases the income of the poor, who rely on agriculture, and enables them to finance low-cost migration to India. However, since rainfall shocks generate income gain that are small in magnitude relative to the costs of migration to other destinations, they do not enable too many households to migrate outside India. Similarly, an increase in conflict intensity by one death per 1000 population increases international migration from urban areas by 3.1 percentage points which is equivalent to the effect of increasing household income by USD 420 in absence of conflict (after accounting for the average impact of conflict on urban consumption). Conflict reduces the consumption and amenity of the wealthier more, and therefore, induces a larger effect from richer (urban) areas. Lastly, I find that migration responds to increase in growth in construction and manufacturing sectors in the destination countries, particularly Malaysia and the Persian Gulf countries. These findings suggest that increase in income can boost migration to India whereas a reduction in cost of migration might increase profitable migration outside India as well. Furthermore, the responsiveness to 'pull' shocks suggests that households are willing to take advantage of the profitable opportunities abroad.

This paper contributes to the literature on the effect of income at origin on migration. The canonical model of Harris and Todaro (1970) suggests than an increase in income in the origin reduces migration. Abramitzky, Boustan, and Eriksson (2013) finds evidence consistent with this using historic migration from Norway. Studies in many other contexts, which use shocks to weather as a source of exogenous variation in income, also find evidence consistent with this[3]. Examples of these studies include Munshi (2003) for migration from Mexico to the US, Marchiori, Maystadt, and Schumacher (2012) for migration from Sub-Saharan Africa, and Gray and Mueller (2012) for migration from rural Ethiopia. However, several other studies find the opposite relationship between income shocks and aggregate level of migration and argue that liquidity constraints, particularly for poor households, prevent them from migrating. Examples include Angelucci (2015) for migration from Mexico to the US, Bazzi (2014) for migration from Indonesia, and

[3]The practice of using weather shocks as a source of exogenous variation in income is quite common throughout the literature (see Jacoby and Skoufias, 1998; Kazianga and Udry, 2006; Miguel, 2005; Paxson, 1992; Wolpin, 1982, among many others, for instance).

Halliday (2006) for migration from El Salvador. In a cross-country study, Clemens (2014) also finds the positive relationship between income and migration for very poor countries. My results for migration to India are consistent with the latter studies that find a positive relationship between income and migration. However, I also find that small income shocks are unlikely to affect migration to destinations with very large costs of migration.

This paper also contributes to the literature in the role of conflict on migration. Conflict could affect migration directly as people want to avoid it, or it could affect migration by lowering income at origin through its effect on the economy as a whole. Much of the literature on conflict-associated migration examines the direct channel and argues that the threat of violence is a key push factor behind such migration. Many studies have found empirical evidence for migration in response to such threats of violence (see Davenport, Moore, and Poe, 2003; Moore and Shellman, 2004; Melander and Öberg, 2007, for example). Similarly, Naudé (2008) finds an increase in international migration from Sub-Saharan Africa in response to armed conflict. In a context similar to this study, Williams and Pradhan (2009) find that conflict related events like violence and bomb blasts increased out-migration from the Chitwan valley of Nepal. However, these studies only focus on internally displaced people and refugees and do not consider the effect on broader set of households who might choose to migrate even though they are not directly forced to move.

Finally, this paper contributes to the relatively scant literature on the role of migrant demand from the destination on migration. Few examples include: Becker, Musabek, Seitenova, and Urzhumova (2005) that find sharp migration response from Kazakhstan to macroeconomic shocks in Russia, Yang (2008) that finds that migrants from the Philippines lengthen their stay when real wages in the destination increases unexpectedly, and McKenzie, Theoharides, and Yang (2014) that find more migrants leave the Philippines in response to positive shocks to the destination country's economy. Similar to these studies, I find that migration from Nepal responds positively to growth in the foreign labor intensive sectors in the destination country. Another, related and consistent evidence in the same context is in Chapter 2, where I find high wages due to exchange rate shocks in the destinations increases migration outflow from Nepal[4].

This paper stands out from the literature in two key ways. First, it looks at migration to multiple destinations as a response to the same 'push' shock. Most of the literature investigates migration response to all countries (Bazzi, 2014, for example) or to a specific destination country (Abramitzky, Boustan, and Eriksson, 2013; Angelucci, 2015, for example). This shortcoming exists in the literature because international migration is either dominated by migration to one particular country (for instance, from Mexico to the United States) or because the destinations are not too different in terms of the associated costs and returns

[4]Besides the actual shocks at destinations, expectations about wages and conditions in the destinations can also influence migration decision. This aspect of influencing perceived migrant demand is investigated in Chapter 1.

to migration. The context of Nepal makes it possible to investigate this because the two types of destinations are starkly different in terms of costs and return and the migration flows to these destinations are substantial. Second, this paper studies the effect of 'push' as well as the 'pull' factors in affecting migration decision, an addition to the literature that focuses on either one of the shocks as reviewed currently.

The remainder of the paper is organized as follows: Section 3.2 outlines a very simple theoretical framework, Section 3.3 describes the context and the data sources, Section 3.4 describes empirical strategy, Section 3.5 discusses the results, and Section 3.6 concludes.

3.2 Theoretical framework

In this section, I outline a very simple model of household migration decision to illustrate the key forces that drive my empirical results.

I assume that all households are farming households and their income depends upon the realized rainfall shock during plantation season. Total wealth of the household represented by $w + r$ where w is a measure of permanent wealth, and r represents income from farming. Households differ from each other only in terms of their permanent wealth which is distributed $F(\cdot)$ in the population.

In addition to total wealth, households value the peace p, of their place of residence. Conflict in the district of residence lowers p and households want to avoid conflict. Consistent with nature of conflict (as discussed below), I assume that p is valued more by the richer households. Formally, in absence of migration, households receive utility $V(w + r, p)$ increasing in both parameters and that marginal utility of wealth is increasing in peace. That is, $\frac{\partial^2 V}{\partial w \partial p} > 0$.

Households can choose to send some members outside the country. This type of migration serves two purposes: the migrating member can earn income while abroad, and if there is conflict in the origin, migration protects the member as well as the rest of the family from the brunt of conflict. This nature of avoiding conflict is slightly different from the usual conflict associated migration where entire households move, but is consistent with the nature of conflict in this context. By sending the productive members (usually the household 'head') abroad, households can stop them from being forcefully recruited to fight, or from them being used as a means to extort money from the households. If the key income earner migrates, then insurgents would have a harder time harassing the rest of the family and extorting money from them.

Migration is costly and the cost C of migration (and finding a job) depends upon the destination. As discussed in more detail later, there is a large variation in the cost of migration between different destinations with India being the cheap destination compared to the non-India destinations: Malaysia and the Persian

Gulf countries. This cost will determine where the migrant can and cannot go.

Once abroad, I assume that migrants always find work. This assumption is different from most studies in migration which focus on the risk associated with finding jobs in the destination (Bryan, Chowdhury, and Mobarak, 2014; Munshi, 2003, for example). This assumption is motivated by the fact that for migration outside India, one needs to have a job lined up before one can actually migrate abroad. For migration to India, I am assuming that, because of the historic nature of this migration, migrants will have sizable networks in India, which will help them find a job (more than 80 percent of migrants to India know someone in the destination city)[5]. Once the individuals migrate, their earning abroad, which depends upon the destination, is high enough to recuperate the cost of migration. The net gains from a migration episode increases with the cost of migration to that destination (as seen in Table 3.2). I assume a simple parametric form mC for the net income gain from migration with $m > 0$. Once a member migrates, the remainder of the household stay back but farm income suffers a loss. That is, the household will have αr of farming income where $\alpha < 1$. The case $\alpha = 1$ would represent the case where the migrant member was a surplus in farming. Formally, household that has a migrant abroad receives value $U\left(mC + w + \alpha r, p\right)$ which is increasing in both parameters. As discussed above, I also assume that households are better off with a migrant at time of conflict. That is, $\frac{\partial}{\partial p}V\left(\cdot\right) > \frac{\partial}{\partial p}U\left(\cdot\right)$.

Further, households are liquidity constrained and cannot borrow to finance migration. This assumption seems extreme as most of the migrants report that they borrowed money, typically from local moneylenders to finance their migration. However, as borrowers cannot credibly commit to repay after migration, lenders do not want to lend without a collateral. Borrowers usually post their house or land, worth more than the size of the loan, as collateral to get a loan. Hence only richer households with total wealth (liquid or illiquid) greater than the cost of migration can actually finance migration. That is, households can migrate only if $w + r > C$.

Hence, households migrate if and only if

$$U\left(mC + w + \alpha r, p\right) > V\left(w + r, p\right)$$

and

$$w + r > C$$

Households will choose the destination that has the highest return if they can afford it.

In this simple framework, increase in total wealth due to income shocks will have two opposing effects.

[5]Another interpretation is that the search cost of jobs abroad are borne before migration and is embeded in the cost of migration

On one hand, it will enable households to migrate by alleviating liquidity constraint. On the other hand, increased wealth make migration less desirable by increasing the utility of staying at home. Increasing conflict reduces the value of not migrating more than it reduces the value of migrating. Therefore, households choose to migrate, with richer households more likely to do so. Similarly, increasing the net benefit of migration mC increases migration. To obtain specific predictions about the sizes of the effects, I will make simplifying assumptions on the functional forms.

3.2.1 Linear functional form

To illustrate the key intuition and generate sharp testable predictions, I assume a linear functional form for the utilities. Specifically, $U(\cdot) = mC + w + \alpha r$, and $V(\cdot) = w + r + wp$. With these functional forms, households migrate if and only if

$$A \equiv C - r < w < \frac{mC - (1-\alpha) r}{p} \equiv D$$

The left end of the wealth distribution of migrants is bound by the affordability threshold. At this margin are very poor households that cannot afford the cost of migration due to liquidity constraints even though they may desire to migrate. The right end of the wealth distribution of migrants is bound by the desirability threshold (for a given level of conflict). At this margin are the wealthier households that choose not to migrate because migration the earnings gap between the destination and the origin is too low and, at peaceful times, they get additional premium of staying back. This simple framework predicts a stark inverted-U shape between household wealth and migration rate in the cross-section, a common feature of many models of migration (Bazzi, 2014; McKenzie and Rapoport, 2007, for instance).

Furthermore, this simple framework suggests that poorer households migrate to cheaper destinations (India) and richer household migrate to more expensive destinations. This pattern, in fact, is borne in the data. Figure 3.1 plots how the migration probability of households change with two measures of household wealth, w, separately for India and non-India destinations. The measures used are the highest level of education in the household (bottom figure) and the value of durables currently owned by the household that it had acquired it at least two years ago as the measure of wealth (top figure)[6]. Both plots in this figure shows that poor households are more likely to migrate to India than to other destinations. This figure, particularly the bottom plot, also shows the inverted U pattern as predicted by the framework. The extremely poor

[6]I choose these measure of wealth as the current consumption is endogenous to migration choice and as is durables recently acquired. Acquisition of durable assets (especially two years ago) and education can be considered to be pre-determined. I get the same pattern with alternative measures of pre-migration wealth such as the value of land owned by the household, and the imputed rental value of their houses.

cannot afford to migrate and the extremely rich do not desire to do so.

Given the cutoffs above, the total observed migration rate in an economy, or a village, denoted by M is

$$M = F(D) - F(A)$$

for each of the destination type[7].

The following comparative statics immediately follow:

$$\begin{aligned}
\frac{\partial M}{\partial p} &= -f(D)\frac{D}{p} < 0 \\
\frac{\partial M}{\partial r} &= -f(D)\frac{(1-\alpha)}{p} + f(A) \lesseqgtr 0 \\
\frac{\partial M}{\partial m} &= \frac{C}{p} f(D) > 0
\end{aligned}$$

which suggests that the magnitude of the effects depend crucially on the distribution of wealth and the thresholds.

The first comparative static suggests that increase in conflict increases migration. This is driven by the right (desirability) thresholds moving to the right. That is, richer households migrate because they experience a big negative shock to the peace premium. If the migration desirability threshold, D, is sufficiently high, then the effect is likely to be higher for the urban areas than for the rural areas as the proportion of households with wealth close to D will be higher.

The second comparative static suggests that increase in farm income has two counteracting effects. The first one is that the affordability threshold decreases. This effect is driven by liquidity-constrained households who are now able to finance migration due to increased income. Another effect is that the desirability threshold decreases as well. This effect is driven by households who now choose not to migrate because of increased total wealth without migration. The total effect depends, again, in the densities at the thresholds. If the distribution of wealth and the cutoffs for migration to India and non-India destinations are as depicted in Figure 3.2, then rainfall could have completely different effects on migration to India and migration to other destinations. For India, the fraction of households affected by relaxed liquidity constraints is much higher than the fraction of households for whom increased income makes migration less desirable. The liquidity effect is more likely to dominate, thereby increasing migration to India in response to a higher rainfall. On the other hand, for non-India migration, both thresholds have only smaller proportion of households around them and therefore the net effect is likely to be very small and of ambiguous sign. See Appendix 3.B for the

[7] M is zero if $D \leq A$. I assume that $D > A$, which, in the model, translates to an upper bound on the peace premium. That is, there is only so much utility you can get by staying back when it is peaceful.

details of how this figure is calibrated.

The third comparative static suggests that an increase in demand from abroad is likely to increase the number of households migrating to those destinations. This is also driven by increasing the desirability threshold: the households that chose not to migrate previously will migrate now, as the returns to migration are higher. Following Figure 3.2 again, the right cutoffs of migration to both destinations move further to the right, increasing migration in both places. For same unit change in migrant income, the effect for India migration is likely to be larger than the effect for non-India migration. However, same proportional change in migrant income, may induce larger response to non-India migration due to higher levels of migrant income.

3.3 Context and Data

3.3.1 International migration from Nepal

Historically, Nepal has seen reasonable rates of international migration, albeit mostly to India. Between 1961 and 2001, the migrant to population rate hovered around 3.4, and was almost entirely driven by migration to India (Table 3.1). This rate was slightly higher than the global international migration rate of 2.9 percent (UNDESA, 2015). The high rate can be attributed to the ethno-linguistic similarity between the two countries as well as the low cost of migration to India. Nepal maintains an open border with India, where citizens from one country are free to enter another at any time without any restrictions, paperwork or clearances. This allows workers of either country to take advantage of the economic opportunities in the other. Historically, workers, mostly from Far-western and Mid-western regions of Nepal, have been migrating to India to work as daily wage laborers or security guards or in restaurants in Indian cities. Because of frequent migration to India over a long period, there are well-established migration linkages between districts in Nepal and Indian cities that help newer migrants find work in India (Seddon, Adhikari, and Gurung, 2002).

Because of the open border and historical linkages, India serves as the low cost and low return destination for Nepali migrants. A typical migrant worker to India pays Rs. 6,250 (USD 83) to migrate and find a job in India (Table 3.2). This amount is roughly over two months of per-capita consumption in Nepal. They earn, on average, Rs. 6,400 (USD 85) a month, of which they save almost two-thirds. The median migrant spends about 9 months in India per migration episode. This is consistent with the view that migration to India is seasonal and workers stay home during planting and harvest season and migrate at other times of the year. Almost a third of these migrants finance migration through their own savings while 60 percent take out a loan, mostly from village lenders and then from friends and relatives[8].

[8]Author's calculations from Nepal Migration Survey 2009 and The World Bank (2011)

On the contrary, migration outside India is a relatively recent phenomenon. Historically, people migrated to non-India destinations mostly through recruitment in the British Army. The numbers were small and directed to destinations like the UK, Hong-Kong, Singapore and Brunei. It was only in the late 1980s that Nepalis have started to migrate to other destinations for work. Foreign migration became easier after democracy was introduced in the country in 1990 and international travel was made easier and more systematic. Only in the mid-90s, Government of Nepal allowed private recruitment agencies to recruit workers to a selected set of countries, mostly in the Persian Gulf and a few others like Malaysia, Japan and South Korea, upon obtaining clearance from the Ministry of Labor (Seddon, Adhikari, and Gurung, 2002). This has led way to the surge in migrant outflow form Nepal in the 2000s (see Table 3.1). This outflow has been dominated by the migration of low-skilled, mostly male, workers to Malaysia, and the Persian Gulf countries, especially, Qatar, Saudi Arabia, and the United Arab Emirates. By 2011, 15 percent of the households had a current migrant in these destination countries.

Most of the current migration to non-India destinations, especially to the Persian Gulf countries and Malaysia, happens through recruitment agents (The World Bank, 2011). Typically, potential migrants contact, or are contacted by, independent local agents that are connected to recruitment firms in Kathmandu. These recruitment firms receive demands for low-skilled workers from firms or agencies abroad and are fully responsible to fill the demands and arrange all necessary paperwork[9]. Migrants to these destinations pay the intermediaries more than Rs.100,000 (US$ 1333) for job-search, intermediation and other related costs (Table 3.2). This amounts to three years of per-capita consumption in Nepal.

Despite the higher costs, workers earn significantly more in Malaysia and the Persian Gulf countries once they are abroad. Most of these workers (65 percent) work in the booming construction and manufacturing industries. A typical worker in these destinations earns more than Rs.14,000 (US$ 187) in a month. They tend to save almost three quarters of this income (Table 3.2)[10]. The median migrant to the Gulf countries and Malaysia spends 2.3 years abroad per migration episode. More than 85 percent of them finance migration by borrowing, mostly from local loan merchants and from friends and relatives[11]. Borrowing from formal financial institutions is, however, quite infrequent with less than 5 percent of the migrants borrowing from banks. Of the remaining 15 percent too, most finance the migration through grants and help from family and friends.

Few key points of international migration from Nepal are worth highlighting, which ties the theoretical framework in the context. The cost of migrating to India and finding a job is much lower than the costs of

[9]For more details, see (Chapter 1, 2).

[10]Though the earnings in Malaysia seem to be lower than the earnings in the Gulf countries, it is believed that the wages are actually higher in Malaysia. Workers in the Gulf countries tend to work more hours.

[11]Author's calculations from Nepal Migration Survey 2009 and The World Bank (2011)

migrating elsewhere. Interestingly, these costs do not seem to vary by location of origin community or by the education level of the migrants[12]. The returns to migration also seem to follow the same pattern so that migration is quite profitable on average, given the typical duration of migration and the amount of savings while abroad. Jobs, particularly to non-India destinations, are prearranged so that there is no risk of not finding work conditional on migration. Vast majority of the migrants finance their migration by borrowing, but borrowing from formal financial institutions is quite low. Most migrants borrow from local moneylenders against a collateral.

Data on migration rates

The data on migration for this paper comes from three different surveys conducted by the Central Bureau of Statistics (CBS) of Nepal over 2001-2010 period. All three surveys have information on absentee members of the household and because of their unique and circumstantial survey design, forms a panel of nationally representative villages observed thrice during the decade.

In June 2001, CBS conducted the tenth national population census, which counted individuals and absentee members in the entire country. I use the sample census micro-data that which covers 95 percent of the villages in the country. Within each village, one-eighth of the households are interviewed.

The census of 2001 was used to develop a sampling frame for the Nepal Labor Force Survey-II (NLFS-II) of 2008. This survey selected 800 primary sampling units (PSUs), or village wards, through a stratified random sampling method. In each of these PSUs, they randomly selected and interviewed 20 households.

For the Nepal Living Standards Survey-III (NLSS-III) of 2010, the list of PSUs selected for NLFS-II was used as the sampling frame. Of the 800 PSUs, 500 were selected, again by stratified random sampling to be part of NLSS-III PSUs. This was done to save time in cartography and listing exercise by the CBS so that they could complete the survey before they began preparing the logistics for the census of 2011. In each of these PSUs, they randomly selected and interviewed 12 households each.

Though households cannot be tracked between these different surveys, 452 village wards are observed in all three datasets. Furthermore, these datasets also have information on the absentee members of the household: individuals that were considered member of the same household but had been absent at the time of enumeration. I use this information at the individual level to construct the migration rates at the village level. My measure of migration rate is the ratio of migrant to resident population in each village.

Additionally, I use district level migration rates from published census tables for years 1981 and 1991 to extend the panel back in time in some cases.

[12] Author's calculations from Nepal Migration Survey 2009 and The World Bank (2011)

Figure 3.3 shows the spatial distribution of these PSUs all over the country. There is at least one panel village in 70 of the 75 districts. In all of the estimations, I use the NLSS-III sampling weights of these PSUs to make my estimates nationally representative. The weighted migration rates in the panel are: 9.57 for year 2010, 8.06 for 2008, and 3.47 for year 2001, very close to rates reported in Table 3.1. A fuller set of descriptive statistics is presented in Table 3.3. Figure 3.4 shows the migration rates to India and non-India destinations for the 3 recent periods. As discussed above, migration to India tends to be more common from the mid and far-western regions of the country whereas migration elsewhere is increasing all over the country.

In the remainder of this section, I describe the context and relevance of the 'push' and 'pull' shocks in this context along with the source of the data.

3.3.2 Rainfall and income

Nepal is primarily an agricultural country with farm income heavily depending upon rainfall. During the 2001/2010 period, the share of agriculture in total GDP hovered between 35-38 percent (MoAD, 2013). In comparison, the total share of industry and manufacturing in GDP remained below 20 percent in the same period. In 2010, 80 percent of the households own agricultural land and the same proportion of the labor force is involved in agriculture[13]. Since the fraction of land that is irrigated remains low, agriculture depends heavily on rainfall. Rice and maize are the two major crops grown in the country, both of which are grown in the wet monsoon season. Rice is the key staple food and contributes to a fifth of the agricultural GDP (MoAC, 2008). In 2010, 74 percent of farming households grew rice and 61 percent of them grew maize[14]. Therefore, the amount of rainfall the country receives during the monsoon months is crucial for agricultural production. A one standard deviation increase in monsoon rainfall in a district improves the yield of rice by 2.7 percent, improving total production by 4.5 percent and total rice cultivated area by 1.8 percent. Similarly, maize production increases by 5.9 percent and area of cultivation by 6.8 percent in response to one standard deviation higher rainfall in monsoon[15].

Consequently, increased rainfall in the monsoon months increases farming income and consumption of farming households. I investigate the impact of rainfall directly on measures of income and consumption using three waves of cross-sectional surveys conducted between 1995 and 2010. I find that one standard deviation of rainfall increases farming income by Rs. 2,400 (about 16 percent of total farm income in 2010)

[13]Author's calculations from NLSS-III

[14]Author's calculations from NLSS-III

[15]Author's calculations from the historic rainfall data and historic production data for each of the districts for years 1975-2000. The estimated regression includes district fixed effects as well as year fixed effects. The identifying variation comes from geographic variation in rainfall measures within a given year and also inter-temporal variation in rainfall within a given district.

and increases consumption in subsequent year by almost the same amount (Rs. 2,300 or about 7 percent of total consumption in 2010) for households who do not receive any remittance income. Details of this exercise is described in Appendix 3.C.

Data on rainfall

The rainfall data that I use for this paper is provided by the Department of Hydrology and Meteorology (DHM) for years 1972 to 2010. The dataset contains average daily rainfall for each of the months from 1972-2010 collected from over 300 rainfall stations throughout the country. The distribution of these these stations is shown in Figure 3.3. I interpolate these rainfall measures to each of the 452 villages in my dataset using inverse of distance from the stations as weights. For each of the villages in my sample, I compute normalized monsoon rainfall in standard deviation units using historic (spanning 1972-2002) mean and standard deviation of monsoon rainfall in the village. The measure that I use for my analysis is the normalized monsoon rainfall in the year preceding the survey.

There is considerable variation in rainfall between years as well as within a given year. Figure 3.5 plots the histogram of normalized rainfall for the three survey years. Within each of the year, the range is well over 2 standard deviation and across the three years, the range is more than 4 standard deviations with considerable overlap between the years. From this graph alone, it looks like rainfall is trending down in the 2000s, but this is driven by exceptionally high rainfall around year 2000. The trend does not hold if rainfall distribution from earlier period (years, 1981 and 1991) is added.

3.3.3 Conflict: The Maoist insurgency

When international migration from Nepal began to increase drastically in late 90s and early 2000s, the ongoing Maoist insurgency took an unexpectedly sharp and violent turn. This led experts to believe that the conflict, which took over 13,000 lives and displaced many more, also pushed individuals outside the country (CBS, 2006; The World Bank, 2011, for instance). In this subsection, I discuss the context of the conflict and my data source.

The Maoist insurgency began, and gained momentum, as a anti-feudal and anti-elite movement. The insurgency, or the "People's War" as they call it, formally began on February 13, 1996 by a splinter faction of the leftist communist parties that was dissatisfied with the lack of progress since democracy was introduced in the country in 1990. As a sign of their movement, they attacked three police outposts and a few privately owned firms and banks located in remote parts of the country to symbolize their attack against the feudal government, the capitalists and the elites. Their movement spread gradually to other parts of the country with support from the rural and poor masses. Their expansion and operation included few key features: they seized land from the landlords and let poorer farmers cultivate under cooperative systems, they extorted money from the wealthy, attacked private firms and banks, and encouraged the poor and often marginalized people to join their movement by highlighting their pro-poor agenda(Macours, 2011). Their attacks on government police posts and subsequent retaliation by the police (which involved capturing and torturing people that they believed were militants) made the conflict increasingly violent. By 2001, 2000 people were killed, mostly in the mid and far-western regions of the country.

An unexpected incident changed the nature of the conflict and made it much more violent after 2001. Before 2001, King Birendra considered the Maoist insurgency to be an internal problem to be dealt by the government and the police force. He refrained from mobilizing the army against the insurgency even upon requests from the government to mobilize the army. On June 1, 2001, King Birendra and his entire family were massacred at a family dinner by the then crown prince, who subsequently turned the gun to himself. In a matter of days, Gyanendra, who was very far in the line of succession to the throne, and who survived as he was not present for the dinner, became the new monarch. King Gyanendra was less reluctant to use the army to suppress the insurgency. The ongoing peace talks with the government broke in late 2001 with the Maoists attacking an army barrack in one of the mid-Western district. The Nepal Army was deployed overnight and the conflict took a very violent turn. In 2002 alone, over 4600 people were killed. By 2006, when the insurgency eventually ended, over 13,000 people were killed and more than ten times as many displaced.

Another equally unexpected coalition emerged during the conflict that ended the insurgency in 2006. In a short duration, Gyanendra proved himself unpopular when he dismissed the elected parliament and started ruling the country through his handpick cabinet of ministers since 2005. This presented an unusual opportunity for the Maoists to become a mainstream political party by teaming up with the other political forces in a fight against the King. This movement led to the demise of the monarchy and an election was held in 2008 to write the constitution for the newly formed republic. The Maoists emerged as the largest party, confirming its transition to mainstream political force.

The geography and the trajectory of the insurgency produces spatial and inter-temporal variation in conflict intensity, which I exploit in my empirical study. Conflict intensity was lower before year 2001, when census data was collected. The conflict took an unexpectedly violent turn after 2001, until its end in 2006. The threat of violent Maoist conflict ended in 2008 when the constituent assembly elections were held, the year when the NLFS-II data was collected. The period between 2008 and 2010 represents a post-conflict peace period after the Maoists emerged as the largest party in the elections. Figure 3.6 shows the stark increase in conflict intensity before and after 2001. Conflict intensity increased from 0.1 deaths per 1000 population on average to 0.6 deaths per 1000 population in this period. The figure also shows large geographic variation in conflict intensity in both periods. Further, post-election peace ended violent conflict in all districts.

Conflict data

My measure of conflict intensity is based on data provided in the annual Human Rights Yearbooks published by the Informal Sector Service Center (INSEC), a Nepali non-governmental organization that monitors human rights issues in the country. INSEC reports the number of deaths due to Maoist conflict in each of the districts in the country. This dataset is identical to the one used by Do and Iyer (2010) in their study of the determinants of the conflict. I use conflict related deaths that occurred in the district between 1996 and 2001 as my measure of conflict intensity for year 2001. For year 2008, I use conflict related deaths that occurred in the district between 2001 and 2006. I set conflict intensity to zero for year 2010. I normalize the conflict deaths by dividing by the population of the district in 1991.

To convert conflict into monetary terms, I do an exercise similar to that with rainfall using three cross-sections of consumption surveys conducted between 1995 and 2010. I find that increase in conflict intensity of 1 deaths per 1000 population is correlated with a consumption loss of Rs. 3490 (10.6 percent of consumption in 2010). This correlation is much stronger for higher end of the wealth distribution, consistent with the nature of the conflict and the assumption in the theoretical framework (Appendix Table 3.C.1 and Appendix Figure 3.C.1)[16].

3.3.4 Demand of migrant workers

Demand data

Another shock that drives migration in the theoretical framework is the increased demand of workers in the destination countries, which increases migrant income. Since most migrant workers from Nepal work in construction and manufacturing industries, I use a measure of demand that reflects growth in construction and manufacturing industries in the key destination countries. Specifically, I use the growth rate in the levels of carbon dioxide emissions attributed to construction and manufacturing industries in India, Malaysia and the Gulf countries (Qater, Saudi Arabia, and United Arab Emirates). I get this measure from the World Development Indicators database (The World Bank) which reports carbon dioxide emissions calculated by U.S. Department of Energy's Carbon Dioxide Information Analysis Center (CDIAC) using data from the United Nations Statistics Division's (UNSTAT) World Energy Data Set and the U.S. Bureau of Mine's Cement

[16]See Appendix 3.C for details of this estimation.

Manufacturing data set. The UNSTAT collects this information from several countries using questionnaires designed to collect information on emissions from various sectors. Cement manufacturing data from the U.S. is used to estimate CO_2 emission from construction. Further, CDIAC continually maintains and updates this database based on supplemental information collected and upon availability of new information.

The variation in this dataset comes from the fact that the destination countries are in different cycles of construction and manufacturing. Further, the great recession of 2008 affected these destination countries quite differently, creating a useful variation in the data on the growth of migrant demand.

3.4 Empirical Strategy

Push shocks

Ordinary Least Squares estimates of the effect of shocks on migration in a cross-sectional data are fraught with problems. For instance, places with fertile land that is responsive to rainfall might also have more entrepreneurial people who are more likely to migrate. Similarly, places with extremely unequal land ownership might invite conflict as well as force people to migrate due to lack of economic opportunities. These characteristics, which are not always observable, will bias the OLS estimates obtained from cross-sectional data. A panel data solves this problem if such characteristics that time invariant by comparing changes in migration rates with changes in shocks within the same village over different period.

Given the structure of my migration data, I estimate the following model to study the impact of 'push' shocks on migration:

$$M_{it} = \beta X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{3.1}$$

where M_{it} is the migration rate in village i observed in time t, γ_t represents the survey year fixed effects which absorbs any national trends common to all villages, μ_i is the village fixed effect which absorbs all time invariant characteristics of the village, X_{it} is the shock that affects village i at time t and ε_{it} represents the error term. I allow the error term to be correlated between different villages within a district as well as over time. X_{it} are either conflict intensity in the district as defined above, or normalized rainfall in very recent past (one or two years ago). The identifying variation for this specification comes from variation within village over time as well as variation across villages in a given year.

Further, my measure of rainfall shock is in standard deviation units relative to the average historic rainfall in the village and is likely to be uncorrelated with any village specific trends in any of the related observed and unobserved variables. More importantly, individuals cannot predict rainfall shocks and engage in anticipatory migration. Hence, the variation in rainfall measure is likely to be uncorrelated with the error term.

Conflict intensity could, however, be driven by village .or region specific trends. This could bias the estimates of the effect of conflict intensity. However, the overall trajectory of this conflict, as discussed earlier, suggests that the two big factors that drove conflict intensity were quite unanticipated. The deployment of Nepali Army, which escalated the death toll stemmed from the massacre of the royal family and coronation of a new king who was not in the accession line. Similarly, the end of the conflict was brought together by an unlikely alliance between the mainstream political parties and the Maoists to overthrow the king.

Pull shocks

The regression model in Equation (3.1) cannot be used to estimate the effect of 'pull' shocks from the destination countries, as they will be completely subsumed by the year fixed effects. To look at whether migration responds to demand from the destination countries, I estimate a slightly different model:

$$M_{ijt} = \delta D_{jt} + \gamma_{ij} + \mu_{it} + \varepsilon_{ijt} \tag{3.2}$$

where M_{ijt} is the migration rate from village i to country j in time t, γ_{ij} is the destination-village fixed effect, μ_{it} is the village year fixed effect and D_{jt} is the recent growth rate in manufacturing and construction sector in country j (the Gulf countries, Malaysia, and India). As with equation (3.1), I allow the errors to be correlated across time and across different villages in the same district.

The identification of this specification comes from variation in demand from different destination countries within a village for a given year as well as from the variation in demand across time for a village-destination pair. The fixed effects remove all other sources of variation that might confound the estimation.

In the next section, I present results of estimating equations (3.1) and (3.2) and discuss how the results relate to the theoretical framework outlined in Section 3.2.

3.5 Results and discussion

3.5.1 A 'push': Rainfall shocks

As discussed in the previous section, income shocks due to rainfall could have an ambiguous effect on migration. It increases wealth, making migration less desirable, but also relaxes liquidity constraints, which makes migration affordable. As suggested by Figure 3.2, the fraction of households that are induced by the rainfall shock in overcoming the liquidity constraints might be very small relative to the fraction of household that now desire migration less when the cost of migration is very high. The former proportion is likely to be higher when the cost of migration is relatively low.

Consistent with this interpretation of the framework, I find that rainfall shocks increase migration to India whereas it has no effect on migration to non-India destinations. As Table 3.4 shows, a one standard deviation increase in rainfall increases migration to India by 0.8 percentage points. This amounts to 31 percent increase in migration rate from its 2001 level, 19 percent of 2008 level, and 17 percent of 2010 level. On the other hand, rainfall has no impact on migration to non-India destinations. The estimated effects are small and statistically insignificant.

Since I have only three periods, arbitrary trends in normalized rainfall could be driving the results. Indeed, Table 3.3 and Figure 3.5 shows that normalized rainfall in the past year has been falling between 2001 and 2010, whereas migration rates have been increasing over this period. To check that the trend in rainfall is not driving my results, I extend the panel further back in time using district level migration rates from the census of 1981 and 1991 to proxy for the migration rates in the village in 1981 and 1991. Table 3.5 shows the results for this extended panel. The same specification produces almost identical results except for effects on India migration from urban areas (columns 1, 3, and 5). The effect for the urban areas is about half the size of the effect for rural areas. This could be because urban areas are less reliant on rainfall for their income[17] or, according to the theoretical framework, because the fraction of households affected by the liquidity constraint is smaller in urban areas. Adding linear time trend only slightly reduces the point estimates. This indicates that time trends in rainfall are not driving the results.

In Table 3.6, I investigate whether rainfall shocks two years before the survey affects migration rates. I do this to capture the effect on migrants who left more than a year ago for whom it is not the last year's rainfall but the rainfall two years ago, that matters. Baseline estimation of Equation (3.1) shows that normalized rainfall two years ago matter almost as much as the normalized rainfall last year for migration to India (columns 1, 3, and 5). But this relationship is not robust to including region specific linear time trends (columns 2, 4, and 6). The magnitude of the effect of rainfall two years ago becomes much lower with the linear time trends. For non-India migration, the effects seem to be small and negative once I control for linear time trends. The results suggest that rainfall facilitates migration to India but not to other destinations and that, more recent rainfall matters more.

To further ensure that the trends in rainfall are not driving the results, I use a falsification test arising naturally in this setting. Though past rainfall may affect current migration rates, future rainfall should not affect it, as households cannot anticipate future rainfall shocks. A failure of this test would suggest

[17]only 45 percent of urban household owns agricultural land compared to 87 percent of rural households

that village specific trends, and not the increase in farm incomes are driving the migration results. Table 3.7 shows the results of this check. As expected, the coefficients are statistically insignificant with point estimates close to zero. This result is robust to including region specific linear time trends (columns 2, 4, and 6).

Since rainfall measure is essentially exogenous and affects migration only through farm income, I can interpret the rainfall shock as an instrument that shifts household income. Since I do not have income measures for the census data and the NLFS for years 2001 and 2008, I cannot use instrumental variable estimate directly. However, I do have income measures for three cross-sections of NLSS rounds conducted in 1995/96, 2003/04 and 2010. As described in detail in Appendix 3.C, I find that one standard deviation increase in rainfall increases farming income by Rs. 2,400 and, as seen from results in this section, increases migration to India by 0.008. Scaling the impact of rainfall on migration by the impact of rainfall on income, increase in farm income of Rs. 7,500 (USD 100) increases migration to India by 2.5 percentage points, a large 54 percent increase from its 2010 level. In terms of elasticities, the implied elasticity of migration to India with respect to farm income is 1.1. Similarly, the implied elasticity of India migration with respect to per-capita consumption is 2.5.

3.5.2 Another 'push': Conflict

As predicted by the theoretical framework, conflict increases international migration in general (Table 3.8). The increase in conflict intensity of one death per thousand population increases migration by 0.8 percentage points. This represents an increase of 11 percent in migration rates if conflict increased from its pre-2001 level to post-2001 level. Similar calculations suggest an increase of 9 percent in migration to India and 18 percent in migration to non-India destinations. Most of these results, though in the direction predicted by the framework, are estimated with large standard errors and are not significant at conventional levels.

The theoretical frameworks suggests that the migration response to conflict should be higher for the richer households. Consistent with this, I find that, for each type of destination, the migration response from the urban areas are about 6 times higher than the response in rural areas. An effect of 3.1 percentage points means that an increase in conflict from its pre-2001 level to post-2001 level in urban areas increases international migration by a large and significant 40 percent. This is a third of the observed increase in migration between 2001 and 2008. The corresponding increases are 62 percent for migration to India (two-thirds of the total increase) and 24 percent (one-sixth of the total increase) for migration to non-India destinations. These effects are large, and in case of urban migration to India, explain a large share of migration that happened between 2001 and 2008. These results suggests that the urban households respond more strongly to increased violence by migrating abroad.

As discussed earlier, conflict can affect migration in two broad ways. First, conflict causes a direct loss in income, which affects migration decision by affecting the desirability and affordability of migration. Second, people do not like conflict either because of the threat it poses to their safety or myriad of other reasons, which affects only the desirability of migration. The monetizing exercise, detailed in Appendix 3.C and tabulated in Table 3.C.1 suggests that increase in conflict intensity of 1 more death per 1000 population *lowers* consumption by Rs. 3,500. Using the results from rainfall shocks as the causal effect of income on migration, a fall in consumption of Rs. 3,500 predicts a *fall* of migration to India from urban areas of 0.65 percentage points [18]. But the observed *increase* in migration from urban areas to India in response to conflict is 1.98 percentage points (Table 3.8, column (3)). This suggests that the second channel must be more dominant to explain the opposite effect that we observe. The migration to India from urban areas in response to their dislike of conflict would then be 2.63 percentage points. This effect is the size of migration response to India from a rainfall shock that increases household income by Rs. 14,000 (USD 190).

Though useful, this exercise assumes a constant effect of conflict on wealth for everyone. This, however, is not true. As shown in Figure 3.C.1, the effect of conflict on consumption is much higher for the wealthier households. The estimate of US$ 190 is therefore a likely lower bound of the average valuation of conflict by urban households. Repeating the same exercise using the effect of conflict on consumption in urban areas (Rs 21,000 instead of Rs 3,500) suggests that the equivalent increase in household income of Rs 31,000 (US$ 420). That is, the increase in migration rates to India resulting from a unit increase in conflict would be offset by an increase in household income by US$ 420. The offsetting effect, however, comes from different part of the distribution: the liquidity constrained households being able to finance migration rather than the richer households who are affected more severely by conflict.

Furthermore, given the heterogeneous impact of conflict on consumption, the theoretical framework suggests that an increase in migration could be possible following an increase in conflict even through the consumption reduction channel. As Figure 3.C.1 suggests, the effect of conflict on consumption for the bottom 30 percentile is essentially zero. These are precisely the households that are near the affordability margin for migration to India (see Figure 3.2). An increase in conflict would not change the affordability status for liquidity constrained households, whereas for the slightly richer households around the desirability threshold, it would make migration more desirable and hence increase migration to India. Conflict has similar effects for non-India migration as well. For the households in the desirability threshold for non-India migration, conflict lowers income as well as amenity more than the poorer households, hence, pushing them

[18] The effect of rainfall on migration to India in urban areas is 0.005 (Table 3.5, column (6)), and the effect of rainfall on income is Rs 2,400 (Table 3.C.1, column (3)). Hence, the effect of Rs 3,500 is simply $\frac{0.005}{2400} \times 3500$

to migrate (particularly from the urban areas). However, because of the hight affordability threshold for non-India migrants, a negative income shock from conflict reduces their ability to finance migration, which creates a slightly more muted effect.

Hence, the observed effects are consistent with conflict having a direct effect as a reduction in amenity as well as an indirect and heterogeneous impact through income or consumption.

3.5.3 The 'pull': migrant demand

According to the theoretical framework, increase in demand for migrant workers, reflected by an increase in migrant income, increases migration by making it more desirable. Migrant demand from a particular destination country affects all of Nepal, which makes it impossible to separate the effect of migrant demand from within country trends in migration. Instead, what I can ask is whether migration responds to differential growths in various destinations. That is, whether migrants are more likely to go to Malaysia when migrant demand in Malaysia is growing faster relative to the Gulf countries.

The results show that migrant supply does respond to changes in migrant demand (Table 3.9). In particular, the most recent growth rates have the strongest impact in migration outflows. The coefficient of 0.015 in column 1 corresponds to an increase in migration of 3.7 percent (evaluated at the mean) in response to an increase in growth rate of 5 percentage points. The corresponding increase for non-India destinations implied by the coefficient of 0.033 is 14 percent.

The results get stronger when India is removed from the list of destinations. As the last three columns of Table 3.9 shows, the magnitude without India as a destination is almost twice as when India is included[19]. This suggests that migrant supply is less responsive to increased construction and manufacturing in India. This could be because the same percentage growth rate translates to a much bigger increase in migrant income in non-India destinations than in India. Consequently, in the language of the framework, the share of households that is induced to migrate to non-India destinations is much higher relative to India.

Pre-existing migrant networks does not seem to be the primary channel by which potential migrants learn about the rising migrant demand in the destination countries. To investigate this, I interact the growth rate in destination with the size of migrant network from the village to the destination in the previous period. I find, particularly in cases where India is excluded as a potential destination, that the size of the pre-existing migrant network does not affect the level of response to growth in destination countries. The estimated

[19]These results are consistent with what I find in Chapter 2 for migrant outflows from Nepal to Malaysia and the Persian Gulf countries. In an exercise in that study, I find that when relative exchange rates between destination changes, causing a shift in the wages that they earn, migrants respond by choosing the destination with a favorable exchange rate. I cannot use the same variation as a measure of a shock to destination wages in this study because Nepal has a fixed exchange rate with India.

regression coefficients are negative with p-values higher than 0.80 (results not shown). This suggests that potential migrants find information about migrant demand in Malaysia and the Persian Gulf countries from channels other than the existing local migrant network. The increased demand may be transmitted though recruitment companies and the local agents who seek workers more aggressively when migrant demand abroad is higher.

3.6 Conclusion

Workers want to move towards better economic opportunities and away from disamenities such as conflict. The 2011 Gallup polls estimates that over 1 billion individuals desire to migrate abroad, at least for temporary work (Esipova, Ray, and Publiese, 2011). But the fact that only 3 percent of the global population is an international migrant suggests that many who want to migrate do not, in fact, migrate. Lack of global mobility of workers has been suggested as one of the biggest distortion in the global economy (Clemens, 2011). Workers typically cannot migrate to places where the returns to their skills are highest for two key reasons. First, liquidity constraints may prevent them from being able to afford the costs of migration. And, second, the lack of demand for migrant workers, either economic or institutional, lowers the expected benefit from migration.

In this paper, I investigate how 'push' and 'pull' shocks affects the migration of Nepali workers to destinations that vary in their costs of, and returns to, migration. First, I find that income shocks, arising from positive rainfall shocks, increases migration to low-cost low-return destination (India), but these shocks do not affect the migration to high-cost high-return destinations such as Malaysia and countries in the Persian Gulf. Second, I find that negative shocks to amenity, measured by violent conflict, pushes people people abroad, particularly from wealthier urban areas. Third, I find that increase in migrant demand from the high-return destination, measured by growth in migrant-employing sectors, increases migration to those destinations.

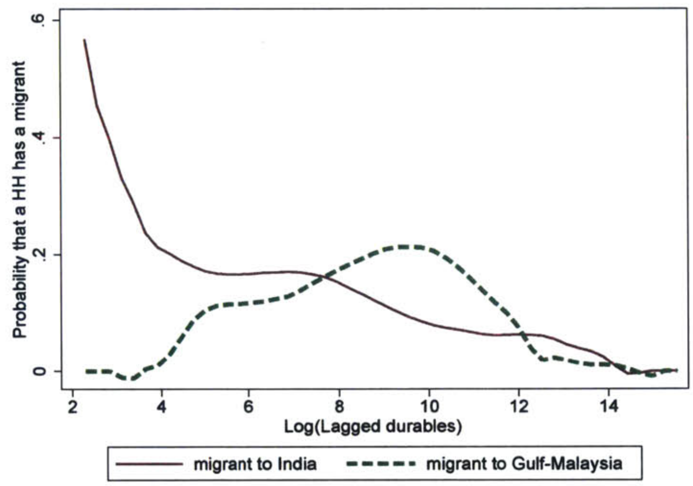
These patterns are consistent with a simple theoretical framework of migration choices with liquidity constraints and availability of destinations that differ in the costs of and returns to migration. It suggests that different types of households are liquidity constrained to migrate to India and to non-India destinations. Rainfall shocks, which increases the income of the poor farmers more, only allow the liquidity constrained households to afford migrating to India. These shocks, as they are small in size, are not able to push a sizable share of households above the affordability threshold for the expensive but lucrative non-India destinations. Similarly, conflict, which reduces the peace related amenity and the income of the richer more, makes migration more desirable for the wealthier households. Conflict pushes the wealthy households more as they are the ones taking a bigger hit in terms of income and amenity at the origin, and at the same time can also afford to migrate away to avoid conflict. Finally, growth in destinations in migrant-employing sectors translates to higher expected income from migration (either through higher wages, or through higher probability of finding a job) which makes migration more desirable.

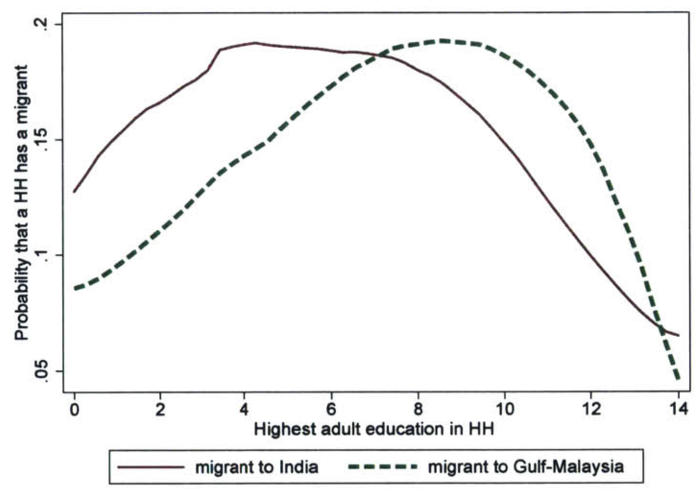
My results highlight several aspects of international migration. First, conflict – at least in the context of Nepal – selectively pushes wealthier households to migrate. Second, a large share of households are liquidity constrained and are not able to finance migration to destinations where the returns to their skills are the highest. Small increases in income may help them finance migration, but only to the low-cost and low return destinations. Large transfers might be needed to enable them to migrate to destinations that provide the highest return to their (low) skills. Third, a substantively large share of households are also constrained by the lack of demand from more lucrative destination countries. The large responsiveness to 'pull' shocks suggests that these households are willing to take advantage of the opportunities abroad should the demand increase. The rise in migrant labor demand from Malaysia and the Perisan Gulf countries is perhaps the biggest factor behind the over six-fold increase in migration from Nepal to these destination countries between 2001 and 2011.

3.A Tables and Figures

3.A.I Figures

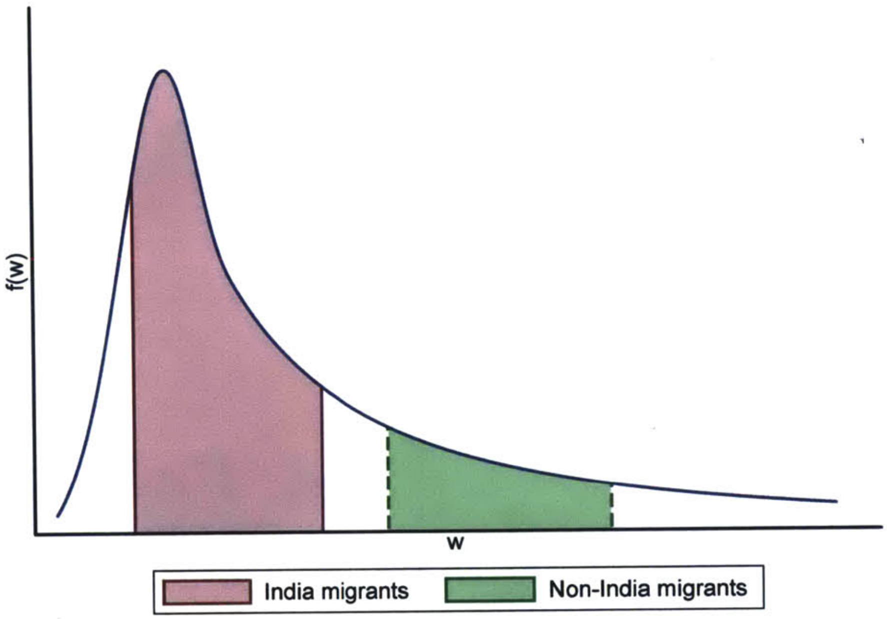
Figure 3.1: Migration probability and measures of household wealth





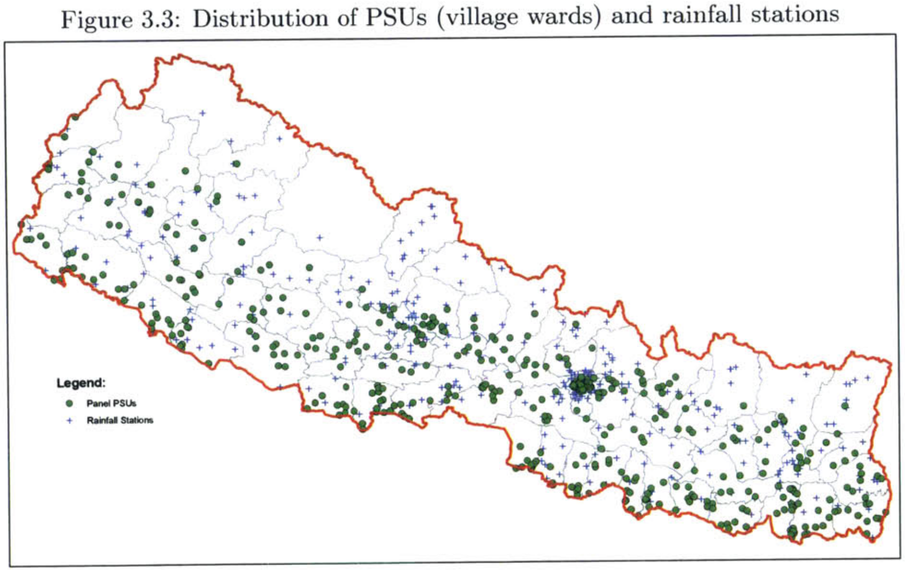
Source: Author's computation from the NLSS-III, 2010.
Note: The top plot shows the relationship between the probability of a household having a migrant and the value of durable assets acquired before the past two years. The bottom plot shows the relationship between the probability of a household having a migrant and the highest adult education level in the household. Both plots are estimated using locally linear regressions. In both plots, the solid (maroon) line shows the probability of a household having a migrant in India, and the dashed (green) line shows the probability of a household having a migrant in Malaysia and the Persian Gulf countries.

Figure 3.2: Model Illustration



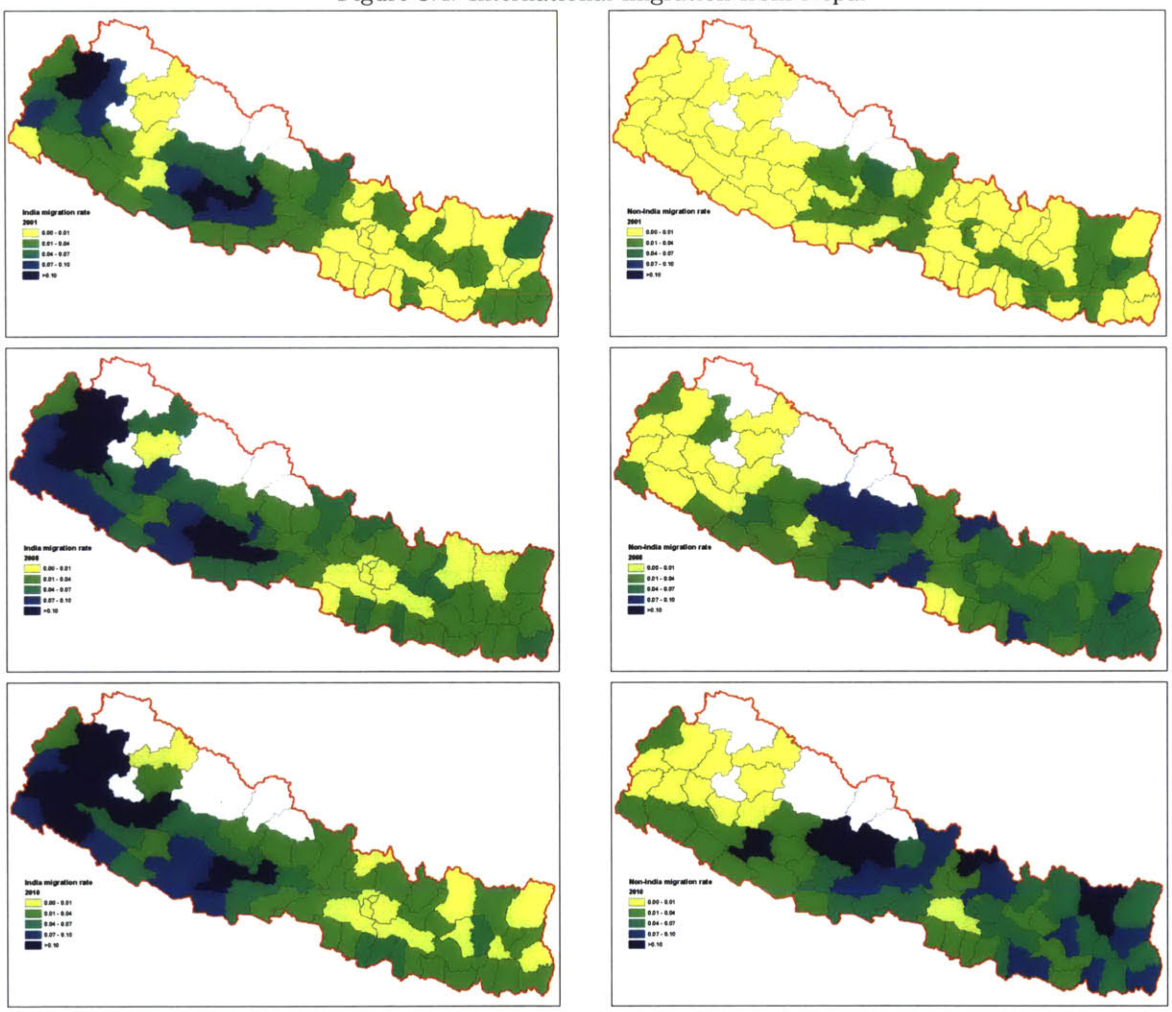
Note: This figures illustrates the plausible set of thresholds for migration to Indi and non-India destinations

Figure 3.3: Distribution of PSUs (village wards) and rainfall stations



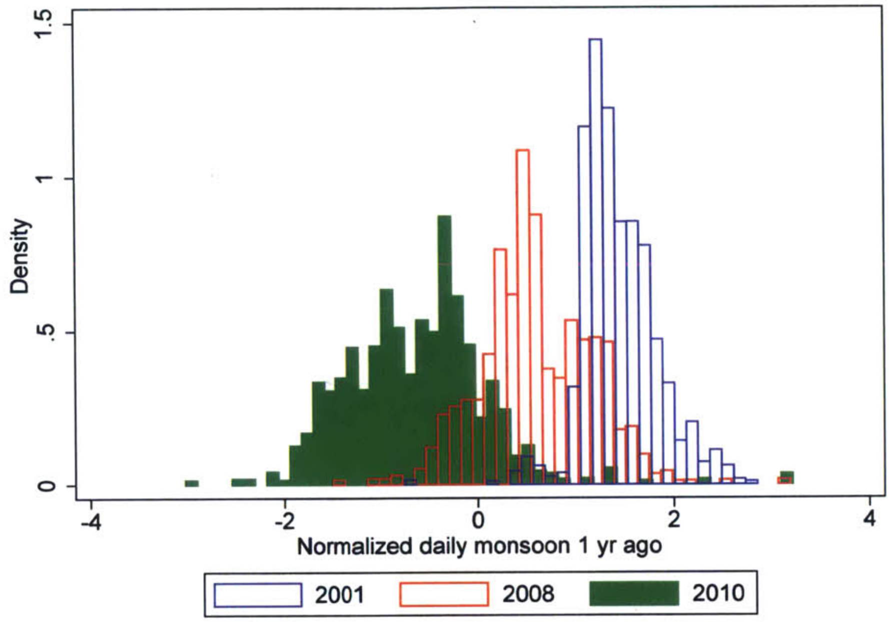
Note: This map plots the distribution of the panel of village wards (PSUs) and the rainfall stations throughout the country.

Figure 3.4: International migration from Nepal



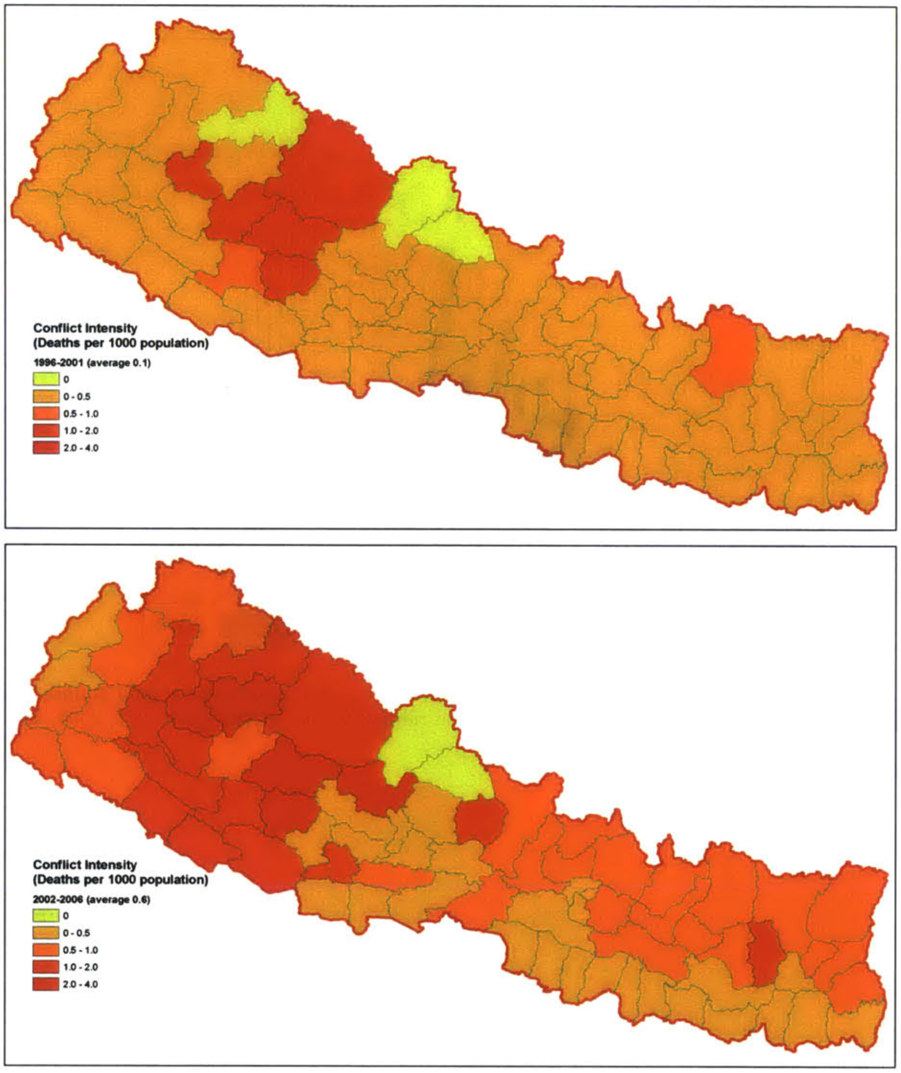
Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: These maps show the migration rates to India (Left panel) and non-India destinations (Right panel). The top row shows the rates for 2001, middle row for 2008, and bottom row for 2010.

Figure 3.5: Distribution of monsoon rainfall in 2001, 2008, 2010



Source: Author's calculation from the PSU level panel assembled from various surveys and the rainfall data. See text for details.
Note: This figures shows the distribution of past year's monsoon rainfall for the survey years 2001, 2008, and 2010.

Figure 3.6: Deaths from conflict in 1996-2001 and 2001-2006



Source: Author's calculations from the Conflict data from INSEC. See text for details.
Note: The top map shows the conflict intensity during 1996-2001. The bottom map shows the conflict intensity during 2002-2006 period. Conflict intensity measures the number of conflict related deaths normalized per 1000 population in 1991.

3.A.II Tables

Table 3.1: International migration and remittance

	Migrant/Population			Remittance income
Year	All	India	Non-India	% of GDP
1961	3.49			
1981	2.68	2.48	0.19	
1991	3.56	3.17	0.37	1.5*
2001	3.41	2.61	0.78	2.4
2011	7.43	2.80	4.63	22.4

Source: Migrant/Population shares from the Census reports for respective years; Remittance as a share of GDP from the World Development Indicator database (The World Bank).
Note: * Figure for 1993 (earlier figure not available)

Table 3.2: Migration costs and incomes

Destination	PC monthly cons (000 NPR)	Cost of migration (000 NPR)	Monthly income (000 NPR)	Monthly savings (000 NPR)
Nepal	2.90			
India		6.25	6.4	3.86
Gulf Countries		102.92	16.21	11.95
Malaysia		133.67	13.51	9.87

Source: Author's calculations from the Nepal Migration Survey, 2009.
Note: Self reported numbers by household members in Nepal. (These numbers are very similar to self-reports by returnees about their own income while abroad). Per-Capita (PC) consumption for Nepal from the Nepal Living Standards Survey-III, 2010

Table 3.3: Summary statistics

	All (1)	Rural (2)	Urban (3)
Year 2001			
Migration rate abroad	0.035	0.036	0.027
	(0.004)	(0.004)	(0.003)
Migration rate to India	0.026	0.030	0.011
	(0.003)	(0.004)	(0.002)
Migration rate to non-India	0.008	0.006	0.016
	(0.001)	(0.001)	(0.002)
Conflict related deaths per 1000	0.110	0.124	0.049
	(0.013)	(0.016)	(0.005)
Normalized daily monsoon 1 yr ago	1.441	1.472	1.301
	(0.018)	(0.021)	(0.032)
Normalized daily monsoon 2 yr ago	1.381	1.374	1.409
	(0.020)	(0.022)	(0.045)
Year 2008			
Migration rate abroad	0.081	0.085	0.063
	(0.003)	(0.004)	(0.004)
Migration rate to India	0.043	0.048	0.021
	(0.003)	(0.003)	(0.003)
Migration rate to non-India	0.037	0.036	0.042
	(0.002)	(0.002)	(0.003)
Conflict related deaths per 1000	0.592	0.638	0.392
	(0.028)	(0.034)	(0.029)
Normalized daily monsoon 1 yr ago	0.590	0.648	0.337
	(0.028)	(0.030)	(0.072)
Normalized daily monsoon 2 yr ago	-1.410	-1.401	-1.446
	(0.020)	(0.023)	(0.032)
Year 2010			
Migration rate abroad	0.096	0.098	0.086
	(0.004)	(0.004)	(0.006)
Migration rate to India	0.046	0.051	0.023
	(0.003)	(0.004)	(0.003)
Migration rate to non-India	0.050	0.047	0.063
	(0.003)	(0.003)	(0.005)
Conflict related deaths per 1000	0.000	0.000	0.000
	(.)	(.)	(.)
Normalized daily monsoon 1 yr ago	-0.639	-0.587	-0.865
	(0.036)	(0.042)	(0.059)
Normalized daily monsoon 2 yr ago	0.559	0.627	0.257
	(0.025)	(0.029)	(0.045)

Source: Author's calculation from the village level panel assembled from Census 2001, NLFS 2008, and NLSS-III 2010.
Note: Means are weighted by the NLSS-III sampling weights.

Table 3.4: Previous year's rainfall and International migration (2001-2010)

	All (1)	Rural (2)	Urban (3)
All International Migration			
Normalized daily monsoon 1 yr ago	0.007*	0.007	0.005
	(0.004)	(0.005)	(0.005)
Observations	1356	936	420
Adj R-squared	0.276	0.269	0.326
Migration to India			
Normalized daily monsoon 1 yr ago	0.008**	0.008**	0.008*
	(0.003)	(0.004)	(0.004)
Observations	1356	936	420
Adj R-squared	0.052	0.050	0.081
Migration to non-India			
Normalized daily monsoon 1 yr ago	-0.001	-0.001	-0.002
	(0.002)	(0.003)	(0.004)
Observations	1356	936	420
Adj R-squared	0.350	0.364	0.313

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of past year's monsoon on migration rates using Equation (3.1). The first column shows the effect for all the PSUs. The second and third columns split the sample into rural and urban areas respectively. The top panel shows the effect on all international migration. The second panel shows the effect on migration rates to India. The third panel shows the effect on migration rates to non-India destinations. All regressions are weighted by NLSS-III sampling weights. The explanatory variable measures previous year's average daily rainfall in the village during the monsoon months normalized by the historic rainfall in the village. Only recent years (2001, 2008, 2010) data used. Standard errors, reported in parenthesis, are clustered at the district level. $*: p < 0.1; ^{**}: p < 0.05; ^{***}: p < 0.01$.

Table 3.5: Previous year's rainfall and International migration (1981-2010)

	All		Rural		Urban	
	(1)	(2)	(3)	(4)	(5)	(6)
All International Migration						
Normalized daily monsoon	0.007**	0.005	0.008*	0.006	0.003	0.002
1 yr ago	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.355	0.359	0.346	0.350	0.414	0.414
Migration to India						
Normalized daily monsoon	0.009***	0.007***	0.009***	0.008***	0.006**	0.005**
1 yr ago	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.071	0.119	0.076	0.117	0.060	0.185
Migration to non-India						
Normalized daily monsoon	-0.002	-0.002	-0.001	-0.001	-0.003	-0.002
1 yr ago	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.415	0.466	0.417	0.474	0.426	0.465

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of past year's monsoon on migration rates using Equation (3.1). The first pair of columns show the effect for all the PSUs. The second and third pairs of columns split the sample into rural and urban areas respectively. The even numbered columns add linear time trends for each region. The top panel shows the effect on all international migration. The second panel shows the effect on migration rates to India. The third panel shows the effect on migration rates to non-India destinations. All regressions are weighted by NLSS-III sampling weights. The explanatory variable measures previous year's average daily rainfall in the village during the monsoon months normalized by the historic rainfall in the village. Data for all years (1981, 1991, 2001, 2008, 2010) are used with district level rates for 1981 and 1991. Standard errors, reported in parenthesis, are clustered at the district level. $*: p < 0.1; ^{**}: p < 0.05; ^{***}: p < 0.01$.

Table 3.6: Previous rainfall and International migration (1981-2010)

	All		Rural		Urban	
	(1)	(2)	(3)	(4)	(5)	(6)
All International Migration						
Normalized daily monsoon	0.006*	0.005	0.007*	0.006	0.002	0.002
1 yr ago	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Normalized daily monsoon	0.002	0.000	0.002	-0.000	0.003	0.002
2 yr ago	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.355	0.359	0.346	0.350	0.414	0.413
p-value of joint test	0.123	0.332	0.185	0.344	0.359	0.431
Migration to India						
Normalized daily monsoon	0.007***	0.007***	0.007**	0.007**	0.004*	0.003*
1 yr ago	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Normalized daily monsoon	0.008***	0.002	0.008***	0.001	0.007***	0.004**
2 yr ago	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.079	0.119	0.082	0.117	0.084	0.192
p-value of joint test	0.001	0.008	0.005	0.035	0.001	0.000
Migration to non-India						
Normalized daily monsoon	-0.001	-0.002	0.000	-0.001	-0.002	-0.001
1 yr ago	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Normalized daily monsoon	-0.006***	-0.002	-0.006***	-0.001	-0.005**	-0.002
2 yr ago	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	2260	2260	1560	1560	700	700
Adj R-squared	0.422	0.466	0.424	0.474	0.429	0.465
p-value of joint test	0.000	0.146	0.001	0.472	0.018	0.253

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of past two years' monsoon on migration rates using Equation (3.1). The first pair of columns show the effect for all the PSUs. The second and third pairs of columns split the sample into rural and urban areas respectively. The even numbered columns add linear time trends for each region. The top panel shows the effect on all international migration. The second panel shows the effect on migration rates to India. The third panel shows the effect on migration rates to non-India destinations. All regressions are weighted by NLSS-III sampling weights. The explanatory variable measures previous year's average daily rainfall in the village during the monsoon months normalized by the historic rainfall in the village. Data for all years (1981, 1991, 2001, 2008, 2010) are used with district level rates for 1981 and 1991. Standard errors, reported in parenthesis, are clustered at the district level. $^{*}: p < 0.1;^{**}: p < 0.05;^{***}: p < 0.01$.

Table 3.7: Future rainfall and International migration (1981-2008)

	All		Rural		Urban	
	(1)	(2)	(3)	(4)	(5)	(6)
All International Migration						
Normalized daily monsoon	0.001	0.000	-0.000	-0.001	0.002	0.003
1 yr later	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	1808	1808	1248	1248	560	560
Adj R-squared	0.296	0.300	0.286	0.289	0.407	0.414
Migration to India						
Normalized daily monsoon	0.002	0.002	0.001	0.001	0.003	0.004
1 yr later	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	1808	1808	1248	1248	560	560
Adj R-squared	0.058	0.093	0.062	0.089	0.068	0.231
Migration to non-India						
Normalized daily monsoon	-0.001	-0.002	-0.002	-0.002*	-0.001	-0.001
1 yr later	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1808	1808	1248	1248	560	560
Adj R-squared	0.422	0.474	0.425	0.481	0.432	0.472

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of the following year's monsoon on migration rates using Equation (3.1). The first pair of columns show the effect for all the PSUs. The second and third pairs of columns split the sample into rural and urban areas respectively. The even numbered columns add linear time trends for each region. The top panel shows the effect on all international migration. The second panel shows the effect on migration rates to India. The third panel shows the effect on migration rates to non-India destinations. All regressions are weighted by NLSS-III sampling weights. The explanatory variable measures previous year's average daily rainfall in the village during the monsoon months normalized by the historic rainfall in the village. Data for years 1981, 1991, 2001, and 2008 are used with district level rates for 1981 and 1991. Year 2010 excluded because rainfall data not available for 2011. Standard errors, reported in parenthesis, are clustered at the district level. $^{*}: p < 0.1$;$^{**}: p < 0.05$;$^{***}: p < 0.01$.

Table 3.8: Conflict and migration

	All (1)	Rural (2)	Urban (3)
All International Migration			
Conflict related deaths per 1000	0.008	0.005	0.031**
	(0.006)	(0.006)	(0.015)
Observations	1356	936	420
Adj R-squared	0.275	0.267	0.335
Migration to India			
Conflict related deaths per 1000	0.005	0.003	0.020
	(0.005)	(0.006)	(0.012)
Observations	1356	936	420
Adj R-squared	0.046	0.046	0.077
Migration to non-India			
Conflict related deaths per 1000	0.003	0.002	0.011
	(0.003)	(0.003)	(0.008)
Observations	1356	936	420
Adj R-squared	0.351	0.365	0.314

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of conflict intensity in district on migration rates using Equation (3.1). The first column shows the effect for all the PSUs. The second and third columns split the sample into rural and urban areas respectively. The top panel shows the effect on all international migration. The second panel shows the effect on migration rates to India. The third panel shows the effect on migration rates to non-India destinations. All regressions are weighted by NLSS-III sampling weights. Data for years 2001, 2008, and 2010 are used in this estimation. The conflict variable measures the conflict related deaths in the district during 1996-2001 for 2001, during 2002-2006 for 2008, and is set to 0 for 2010. Standard errors, reported in parenthesis, are clustered at the district level. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 3.9: Growth in destination and migration

	All destinations			Non-India destinations		
	(1)	(2)	(3)	(4)	(5)	(6)
1 yr growth in manu	0.015**			0.033***		
and cons CO2 emission	(0.007)			(0.009)		
2 yr growth in manu		0.012*			0.026***	
and cons CO2 emission		(0.006)			(0.007)	
3 yr growth in manu			0.011**			0.011***
and cons CO2 emission			(0.005)			(0.004)
Observations	4068	4068	4068	2712	2712	2712
Adj R-squared	0.179	0.178	0.178	0.466	0.458	0.442

Source: Author's calculation from the PSU level panel assembled from various surveys. See text for details.
Note: This table shows the impact of recent growth in construction and manufacturing sectors in the destination categories on migration rates using Equation (3.2). The first three columns include India, Malaysia, and the Persian Gulf countries (Qatar, Saudi Arabia, and the UAE) in the destination categories. The last three columns exclude India. All regressions are weighted by NLSS-III sampling weights. Data for years 2001, 2008, and 2010 are used in this estimation. The explanatory variable measures the growth in CO_2 emission by manufacturing and construction in each of the destinations over the previous 1, 2 and 3 year period preceding the survey years. Standard errors, reported in parenthesis, are clustered at the district level. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

3.B Calibrating migration thresholds

The interpretation of the empirical results in this paper depends upon the wealth distribution and the position of the affordability and desirability thresholds. In this subsection, I describe how the cut-offs for Figure 3.2 are calibrated. For this exercise, I set $p = 1$, so that the rich get the full peace premium.

Wealth, w, used in the theoretical framework is a measure of pre-migration permanent wealth and is separate from consumption. I use the monetary value of total amount of land owned by the household as a measure of w. I estimate the distribution of this measure in the Nepal Living Standards Survey - I (NLSS-I) of 1995/96 amongst the landed population using a log-normal approximation. Then I scale this distribution to its 2010 level by adjusting for inflation as well as allowing real wealth to grow between these two periods. I used the growth rate of real per-capita consumption amongst landed households without migrants between these periods. Similarly, I get distributions of per-capita consumption and farm income from NLSS-I after appropriate scaling to their 2010 level.

Then I simulate a dataset of 100,000 households with wealth, consumption and farm income drawn randomly from this distribution. I set r equal to the difference between farming income net of consumption. The costs and earnings from migration are as reported in Table 3.2 scaled by the CPI to year 2010. I assume a migration episode of 2 years. That is, households choose between 2 episodes of migration to India, each lasting 9 months or one episode of migration to the Gulf countries or Malaysia, lasting 2 years. I use NLSS-III to estimate income loss in farming resulting from migration of a member[20].

Using these calibrations and the simple cut-off rule implied by the theoretical framework, I classify each household as a non-migrant household, or a household with India migrant or a household with non-India migrant. I find that about 27 percent of the households choose to have a migrant in India, and 19 percent choose to have a migrant outside India. These numbers are only slightly bigger than the household migration rates observed in NLSS-III in 2010. In the NLSS-III data, about 15 percent of the households have a migrant in India and about 16 percent of the households have a migrant in non-India destinations.

In this simple simulation, I find that 19 percent of the households are below the affordability threshold for India and 23 percent are above the desirability threshold for the Gulf and Malaysia migration. The wealth distribution used for simulation and the resulting average thresholds of migration to India and non-India destinations is plotted in Figure 3.2.

In this simulated data (with a sample size of 5,000, the expected size of NLSS-III survey), I find that a random drop of Rs 7,500 (USD 100) increases India migration rate significantly by 3.7 percentage points (p-

[20]The estimating equation is $\log(Y_i) = \beta M_i + \varepsilon_i$ where M_i indicates whether a household has a foreign migrant, and Y_i is total farm income for the household. I estimate this specification on a sample of household with agricultural land. The OLS estimate of β is -0.088 with standard error of (0.041)

value of 0.004) whereas the cash transfer has an insignificant impact on migration to non-India destinations (p-value of 0.850). This is also consistent with what I find empirically[21].

3.C Monetizing rainfall and conflict

3.C.I Data and method

In this exercise, I try to monetize the conflict and rainfall shocks using three different cross-sectional surveys with consumption and income measures. I use three different waves of Nepal Living Standards Surveys (NLSS) conducted in 1995/96, 2003/04 and 2010 by the Central Bureau of Statistics using comparable instruments.

In the pooled cross-sectional data, I estimate

$$y_{it} = \beta X_{it} + \gamma_t + \mu_j + \varepsilon_{it}$$

where y_{it} is the consumption per-capita or farm income per-capita for PSU i observed in year t, X_{it} is the conflict or rainfall measure for the PSU for year t; γ_t captures the survey-year fixed effects. I employ different fixed effects to essentially create pseudo-panel data at the $j \times t$ level. I use Development Region $\times$ Ecological belt which results in 15 groups, district fixed effects which results in 74 groups and also use synthetic clusters of 97 clusters. I allow standard errors to be correlated across observations within the same group (j) and across survey periods.

As these surveys were cross-sections, the probability that the same PSU is observed more than once is quite low. However, several PSUs that are close to each other are observed across different periods. I therefore create a pseudo-panel at a level lower than the administrative districts by creating synthetic clusters of PSUs that are close to each other. A group of three (or more) PSUs within 10km of each other are in the same synthetic cluster. Any PSU within 10km of at least two of the PSUs in a cluster also belongs to the same cluster. In cases where this algorithm maps one PSU to more than one cluster, I assign it to the cluster with fewer PSUs. This method gives me a total of 97 synthetic clusters and covers 70 percent of the PSUs in the dataset. I dropped the unassigned PSUs from this specification. Since the 70 percent of the PSUs which are mapped to synthetic clusters are different from those that were not-mapped, this specification would produce biased estimates of β. As a simple check, I test whether income measures differ by whether a PSU is included in the synthetic cluster sample or not. I find that farm income per-capita is not different

[21] However, the outcome variables are not identical in the simulated data and the one used in the paper, so I cannot compare coefficients directly. In the simulated data, outcome variable is an indicator of whether the household has a migrant or not. In the paper, the outcome variable is a ratio of migrant to population in the village.

(p-value of 0.31) whereas consumption per-capita is different (p-value of 0.04) by their inclusion status in the synthetic cluster sample. When I assign higher level clusters to unassigned PSUs, I get qualitatively similar results as in other specifications with fixed effects (and clustering) at higher levels.

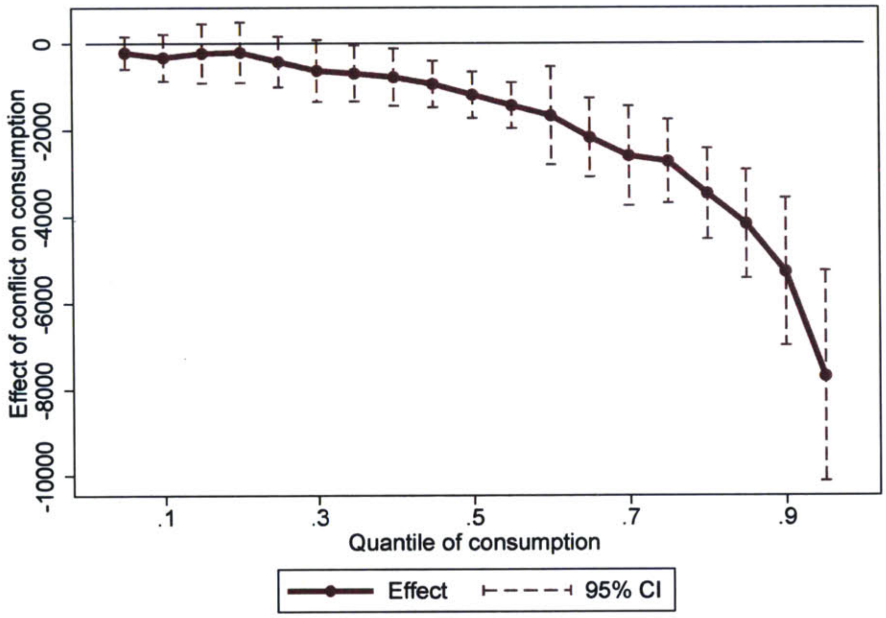
The measure of rainfall is identical to the measure used in the rest of the text adapted to different survey years. Conflict measures are set to 0 for NLSS-I and NLSS-III (years 1995/96 and 2010) whereas it measures conflict related deaths in a given district between 1996 and 2002 normalized by district population in 1991 for NLSS-II (year 2003/04). Since the conflict variable is measured at the district level, I only use specification with fixed effects at the district or a higher aggregation. All of my consumption and income measures are converted to 2010 prices.

Table 3.C.1 shows the result of the estimation restricted to households that do not receive any remittance income. I use column (3) as my preferred specification for the income equivalent of rainfall shock and column (5) as my preferred specification for the income equivalent of conflict shock.

The theoretical framework postulates that the wealthy suffer more from conflict. However, Table 3.C.1 only looks at the average effect of conflict on consumption. I use quantile regressions to investigate whether conflict affects consumption differently in different parts of the consumption distribution. Figure 3.C.1 shows the estimates of the same equation at different consumption quantiles. Indeed, conflict does not affect the consumption of poorer households but reduces consumption of the richer households. At the topmost decile, the effect is larger than Rs 5,000, almost five times the effect at the median.

3.C.II Figures and Tables for 3.C

Figure 3.C.1: Effect of conflict on different quantiles of consumption



Note: Bootstrap standard errors used to estimate the confidence interval. Regression estimates are unweighted.

Table 3.C.1: Income effects of conflict and rainfall

	Farm income per-capita			Consumption per-capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Normalized daily monsoon 1 yr ago	2051**	1921	2444**	2133	2323	484
	(880)	(1481)	(1034)	(1297)	(1955)	(858)
Observations	8081	8081	5207	8081	8081	5207
Adj R-squared	0.110	0.133	0.101	0.063	0.140	0.149
Conflict related deaths per 1000				-4719	-3488**	
				(2839)	(1477)	
Observations				8081	8081	
Adj R-squared				0.065	0.141	
Year FE	Y	Y	Y	Y	Y	Y
Region x Belt FE	Y			Y		
District FE		Y			Y	
Synthetic cluster FE			Y			Y

$* : p < 0.1; ^{**} : p < 0.05; ^{***} : p < 0.01$. Standard errors reported in parenthesis clustered at the level of the group fixed effects. Regression run in pooled Nepal Living Standards Survey of 1995/96, 2003/04 and 2010 and are weighted by their respective sampling weights. Sample further restricted to households that do not receive any remittance income. Conflict variable set to 0 for 1995/1996 and 2010 and counts the deaths from 1996-2002 for year 2003/2004. All consumption and income deflated to 2010 prices. All regressions have survey year fixed effects.
Columns (1) and (4) have Development region × Ecological belt fixed effects (15 groups). Columns (2) and (5) have district fixed effects (74 districts). Columns (3) and (6) have synthetic cluster fixed effects (97 clusters). Synthetic clusters group PSUs into one cluster if they are within 10km of each other.

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