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Death Scares

How Potential Work-Migrants Infer Mortality Rates from Migrant Deaths

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Abstract

This paper studies how potential work migrants infer mortality rates from incidents of migrant deaths. In the context of migrant workers from Nepal to Malaysia and the Persian Gulf countries, the study finds that the death of a migrant from a district lowers migration outflows in subsequent months. Furthermore, this migration response is stronger when there have been more migrant deaths in recent months. Using relevant elasticities, this study finds that the migration response implies large changes in mortality rates perceived by potential migrants. Models of learning fallacies better explain the observed responses than a standard model of rational Bayesian learning.

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

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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 nine months of 2016, over 3,600 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). The 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 the death of migrants in the 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 Shrestha (2017) 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 not 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

[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).

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 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 (à la Kahneman and Tversky, 1974; Tversky and Kahneman, 1973). It could be that they think recent deaths represent the scenario more accurately, or that the 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 (à la 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 Shrestha (2017), 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 translates 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.

Moreover, this paper presents a context where fallacious learning, albeit about extreme and rare events, could have large welfare costs. Many studies find migration to be welfare improving for the marginal migrant and their family (see Bryan, Chowdhury, and Mobarak, 2014; McKenzie, Stillman, and Gibson, 2010, for a few examples). These studies also find the levels of migration to be sub-optimally low. This paper, through a stark example, shows how fallacious learning could potentially lead to lower levels of migration.

The remainder of the paper is organized as follows: Section 2 describes the migration process in context of Nepal and the data sources, Section 3 outlines the empirical strategy, Section 4 discusses the effect of migrant deaths on subsequent migrant flow, Section 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 6 concludes.

2 Context and Data

2.1 Migration from Nepal

Historically, migration of Nepali workers outside the country was low and was limited mostly to India. As Table 1 shows, before 2001, the 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 the Indian or British army was one of the very few options available to Nepali commoners to migrate abroad. Only since the mid-1990s, the 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. Figure 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 32 percent by 2015 (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

[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.

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 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 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 is 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 shows, outflow of migrants is increasing in recent years for most destinations. By 2013, over 1,100 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 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 rupees) 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 shows, only a third of the workers identified going to work that can be classified as not being in the 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 Shrestha (2017), 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.

2.3 Data on migrant deaths

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 of death, district of residence in Nepal and the cause of death reported in the death certificate. Figure 3 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).

Though considered an accurate source of information on the number of migrant deaths, this data

[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.

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 4). 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. The 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 5). The figure also shows that death rates in Malaysia and Saudi Arabia are slightly higher than death rates in Qatar and the UAE.

3 Empirical strategy

I use a 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

$$y_{odt} = \alpha_{od} + \gamma_{ot} + \xi_{td} + \sum_{i=-12}^{12} \tau_i D_{od,t-i} + \varepsilon_{odt} \tag{1}$$

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.

[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 effects 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.

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

$$y_{odt,x} = \beta D_{odt} + \alpha_{od} + \gamma_{ot} + \xi_{dt} + \varepsilon_{odt} \tag{2}$$

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 (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 (1). However, since these specifications use a 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 (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) 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

$$y_{odt,x} = \beta D_{odt} + \delta\left(D_{odt} \times X_{odt}\right) + \zeta X_{odt} + \alpha_{od} + \gamma_{ot} + \xi_{dt} + \varepsilon_{odt} \tag{3}$$

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) 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

$$y_{ot,x} = \beta D_{ot} + \alpha_o + \gamma_t + \nu_{ot} \tag{4}$$

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

$$y_{ot,x} = \beta D_{ot} + \delta\left(D_{ot} \times X_{ot}\right) + \zeta X_{ot} + \alpha_o + \gamma_t + \nu_{ot} \tag{5}$$

where X_{ot} represents the variable of interest.

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 deaths are generated by an i.i.d process.

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 6, 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 12 months after 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 the migration decision of those who have already made all the preparations and investments to migrate.

There is also evidence of some substitution to other destinations following migrant death in an origin district - destination cell (Figure 6, 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 6, bottom two plots). The migration flows in neighboring districts (expressed in logarithm of flow per district per destination per month) respond 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 districts to the same destination fall and migration flows from neighboring districts to other destinations slightly increase.

The estimates of these effects using Equation (2) show similar results. Consistent with the event study plots, Table 3 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 3).

However, the increase in migration flow to other destinations does not fully offset the negative effect in the same origin district - destination cell. Table 4 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 have earned 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 spillover effects of the death to neighboring districts 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.

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 does not seem to be the case. The event study plots in Figure 7 confirm this (top and bottom plots in third column). For both the plots, I cannot reject the null that all effects before the

[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 (Shrestha, 2017). 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 Shrestha (2017), 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.

death and after the death are zero. As Table 5 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 response by the intermediaries who may be able to vary the net benefit of migration locally in response to a migrant deaths, or 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 7 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 5 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.

4.3 Does recent history of migrant deaths matter?

The effect of a migrant death in changing migration decision in Section 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 are 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 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 6 shows that when there have been no deaths in the past six months in the origin district - destination cell, the migration flow 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

[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.

six months, a 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 the 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 is driven by origin district - destination cells which have experienced more than 1 migrant death 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 6 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 6, 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 3.

Table 7 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 seems 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 the mortality rate abroad.

One fallacy that generates an 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 a 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 deaths 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 than 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 the mortality rate of a Bayesian who does not commit this fallacy.

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 my companion paper (Shrestha, 2017). In the second part, I present a simple learning model of a Bayesian who believes that migrant deaths every month are generated by an i.i.d binomial process and computes 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.

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

In Section 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.

$$\Delta d = \frac{\Delta W}{VSL} = \frac{1}{VSL} \cdot \beta \cdot \frac{1}{\varepsilon} \cdot W \tag{6}$$

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 Shrestha (2017) 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 a 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.[15]

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

[13] As a robustness exercise, in Online Appendix A, 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 Table A.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 Shrestha (2017). I use the estimate from the experiment as it has better identification due to the experimental setup.

[14] Assuming that each component of equation (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 Shrestha (2017) of \$0.538m and elasticities of 0.7 from Shrestha (2017) and 1.2 from Online Appendix A produce estimates of Δd ranging from 2.1 to 6.7 per thousand, quite similar to each other.

[15] Alternatively, one could directly use the experimental estimate of elasticity of migration to perceived mortality rate from Shrestha (2017) to convert migration effects to induced change in perceived mortality rate. This method would not need the estimates for VSL and earnings elasticity of migration. This method also yields estimates of Δd between 3.7 and 5.9 per thousand, quite similar to the estimates discussed above. I present estimates using Equation (6) as it allows using alternative estimates of earnings elasticity to check robustness (as in the Online Appendix).

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.

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).[16]

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 a 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 matters in their inference. This feature rules out other

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

explanations of 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 learning 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 Shrestha (2017) 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.

6 Conclusion

This paper demonstrates two key features of how potential migrants form their beliefs on the 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 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.

This paper finds that the belief on mortality rate expressed by inexperienced potential migrants in Shrestha (2017) 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.

Finally, this paper presents a real world setting in which a learning fallacy can have large welfare consequences for potential migrants. Incidences of deaths, which should convey zero information to a fully informed potential migrant, seems to thwart migration substantially. Policies designed to make individuals less 'scared' of migrant deaths abroad could potentially have large welfare effects.

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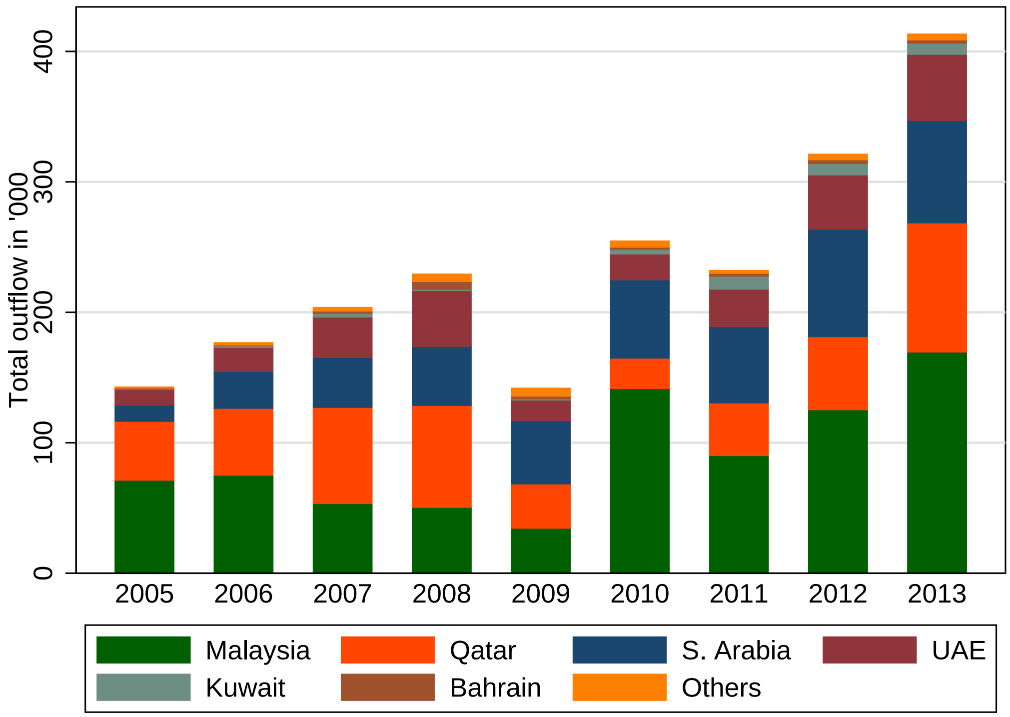
Figures and Tables

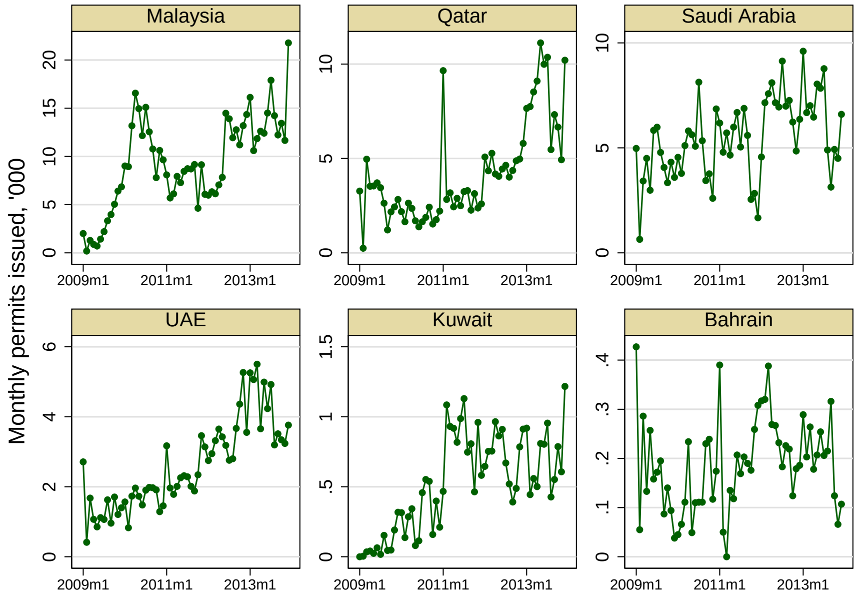
Figures

Figure 1: Permits granted by DoFE for work abroad



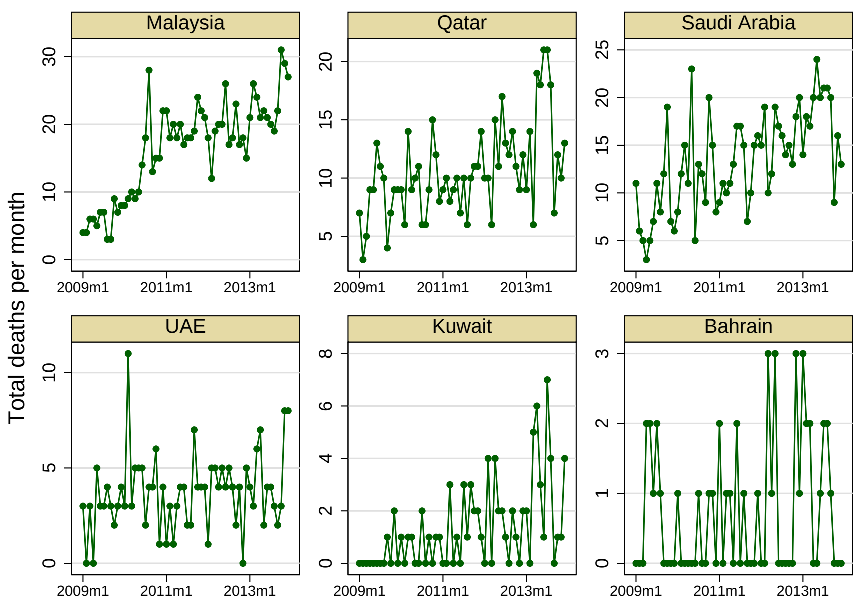
Source: Author's calculation on the data provided by Department of Foreign Employment (DoFE).
Note: This figure shows the number of work-permits issued by DoFE for work abroad by year and destination country.

Figure 2: Total permits issued by DoFE for top destination countries



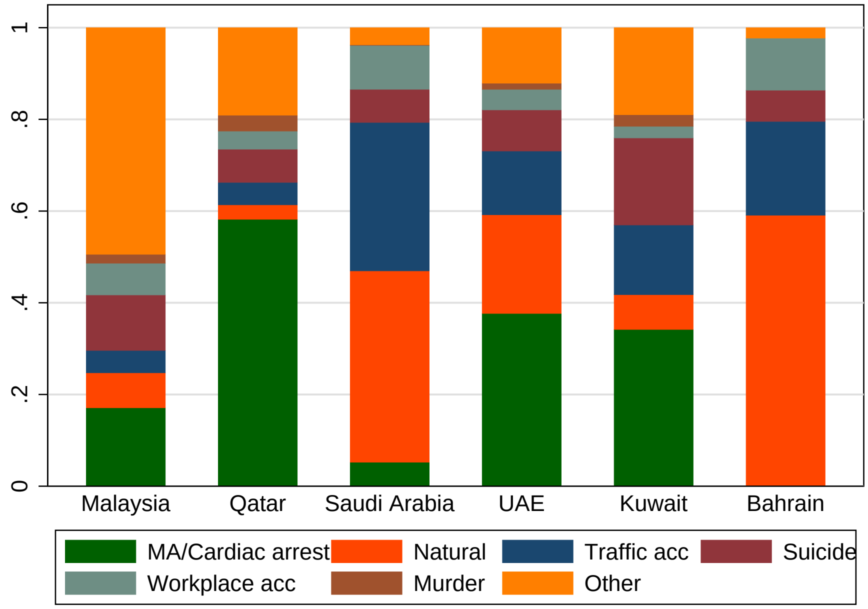
Source: Author's calculations from DoFE database
Note: This figure shows the number of work permits issued every month for the period of the study (2009-2013) to the top six destination countries. This does not include migration flows to India.

Figure 3: Monthly deaths in top destinations



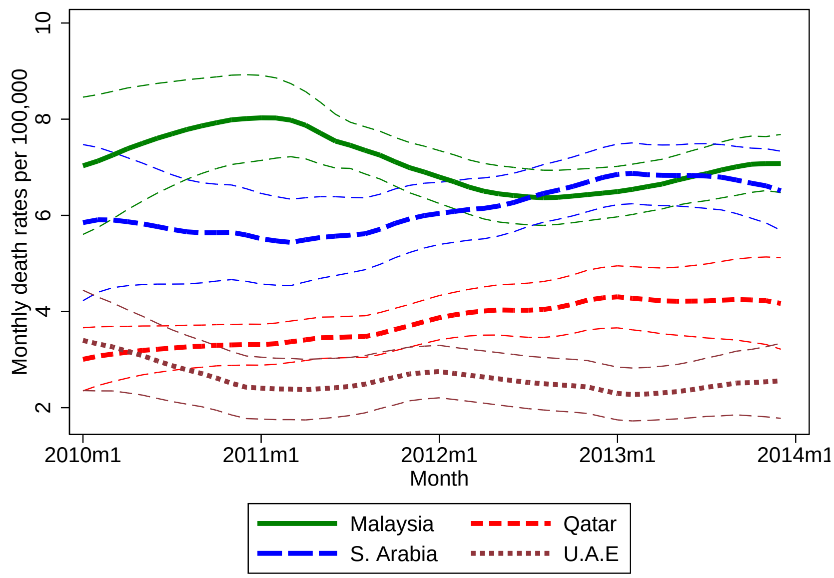
Source: Author's calculations from FEPB database
Note: This figure shows the number of deaths of registered Nepali migrants every month for the period of the study (2009-2013).

Figure 4: Official cause of migrant deaths by destination



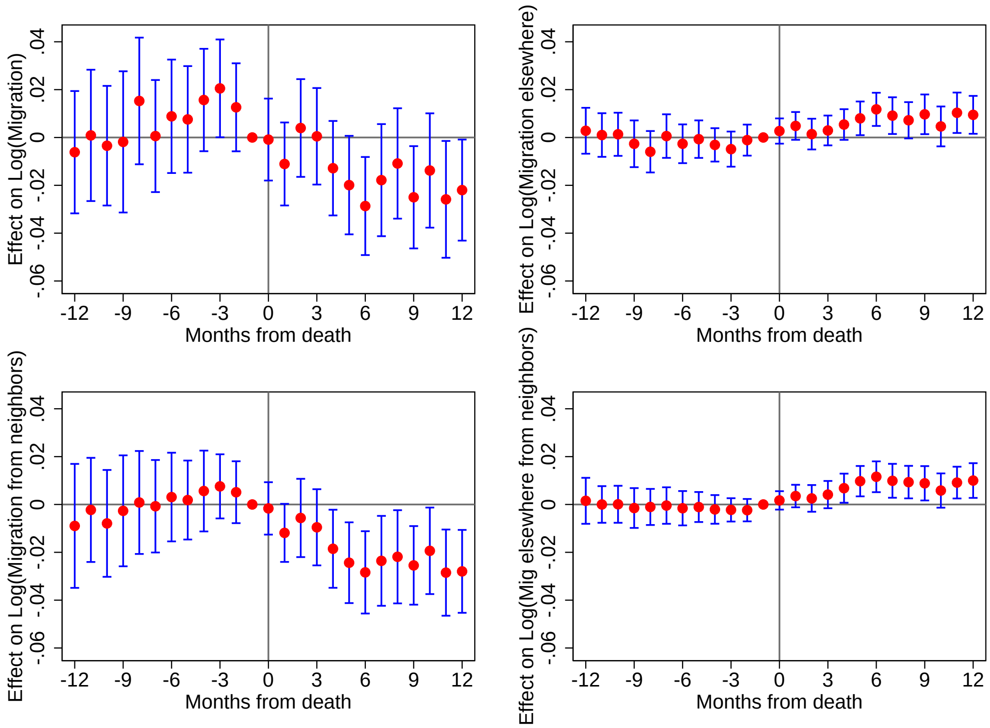
Source: Author's calculations from FEPB database
Note: This figure shows the official cause of deaths of Nepali migrants for each of the major destination countries

Figure 5: Deaths rates over time for top destination countries



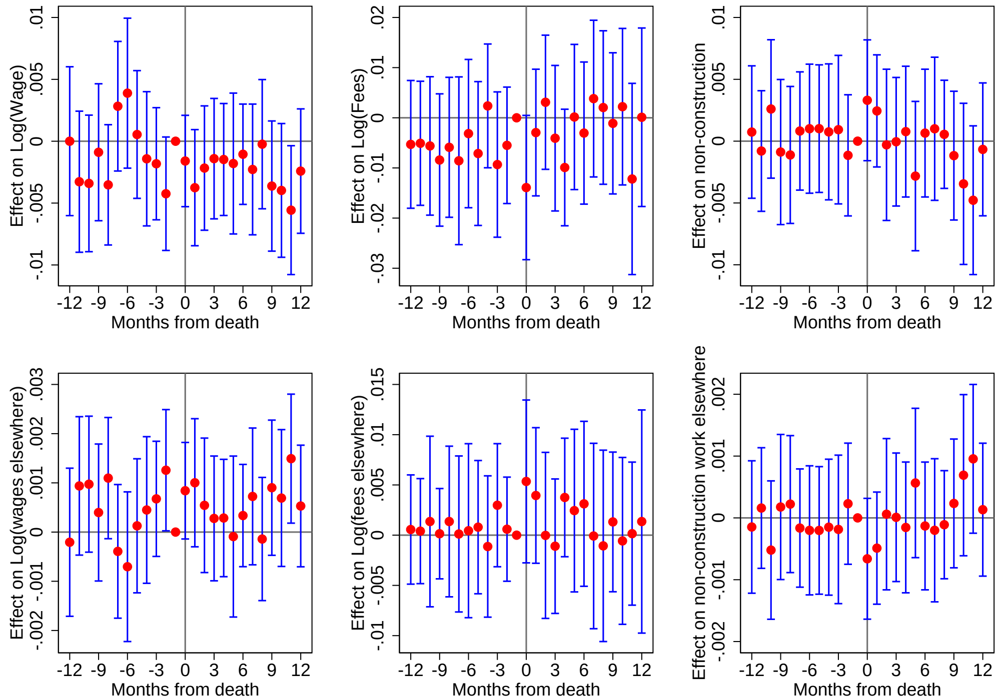
Source: Author's calculations from FEPB database and the 2011 Population and Housing Census Public Use Microdata Sample
Note: This figure shows the smoothened monthly death rates (per 100,000 migrants) of Nepali workers in the top destination countries. Locally linear regression with epanechnikov kernel 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 6: 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 (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 7: 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 (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.

Tables

Table 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 2: 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)	Exchange 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 3: 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).

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 4: 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 (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 5: 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).
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 6: 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 (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 7: 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 (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. $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$

For Online Publication

A 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. The monthly exchange rate data comes from the historic database of the online forex trading platform OANDA.[17]

A.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:

$$\begin{aligned} \log\left(\frac{y_{dt}}{y_{Mt}}\right) &= \alpha_d + \gamma_t + \beta \log\left(\frac{W_{dt}}{W_{Mt}}\right) + \varepsilon_{dt} \\ \log\left(\frac{W_{dt}}{W_{Mt}}\right) &= \xi_d + \psi_t + \delta \log\left(\frac{E_{dt}}{E_{Mt}}\right) + \eta_{dt} \end{aligned} \tag{7}$$

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.

The relative exchange rates and relative migrant flow appear to be strongly correlated. As shown in Figure A.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 (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

[17] http://www.oanda.com/currency/average.

level produces standard errors that are 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.

A.II Results

For the top 6 destinations, the relative exchange rates show strong first stages and reduced forms. As Table A.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 A.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.

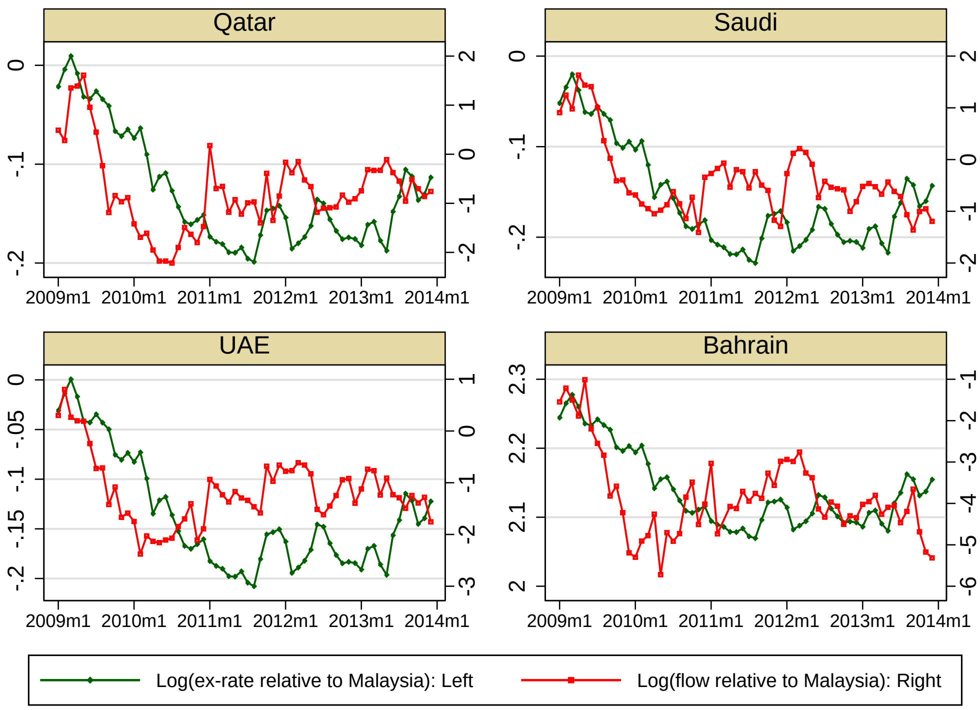
The point estimate of the elasticity is similar for the the top 10 destinations, but is estimated imprecisely (Table A.1, column 2). As discussed earlier, due to institutional restriction in other countries, migration flows do not respond as strongly to changes in relative exchange rates. The wage effect 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 A.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.

A.III Figures and Tables for Online Appendix

Figures

Figure A.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 A.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 (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. $^{***}: p < 0.01$; $^{**}: p < 0.05$; $^{*}: p < 0.1$