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Abstract

While an emerging literature cites weather shocks as migration determinants, scant evidence exists on how such migration impacts the markets of receiving communities in developing countries. We address this knowledge gap by investigating the impact of weather-driven internal migration on labor markets in Nepal. An increase of 1 percentage point in net migration reduces wages in the formal sector by 4.8 percentage points. The absence of wage effects in the informal sector is consistent with the exit of low-skilled native workers from the labor market. Understanding entrepreneurial constraints and drivers of labor market exits will inform pathways to resilience.

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1 Introduction

Migration is understood to be a key mode of adaptation to extreme climatic events (IPCC (2014)). Rural workers search for employment elsewhere to mitigate income losses temporarily or move permanently if the damages are severe (Halliday (2006);Feng et al. (2010); Dillion et al. (2011); Gray and Mueller (2012b) Gray and Mueller (2012a); Marchiori et al. (2012); Gray and Bilsborrow. (2013); Bohra-Mishra et al. (2014); Mueller et al. (2014)). An emerging challenge in the climate change debate is to reconcile whether such adaptation bears additional consequences for human security and livelihoods (IPCC (2014)).

Studies of the consequences of migratory flows on the labor markets of hosting communities in industrialized countries are ubiquitous (Card (1990);Card (2005); Borjas (2005); Borjas (2006); Boustan et al. (2010); Ottaviano and Peri (2012); Pugatch and Yang (2011)). In developing countries, the issue has been investigated from the perspectives of either the migrants(Beegle et al. (2011); Grogger and Hanson (2011); De Brauw et al. (2013)), their countries of origin (Adams and Page (2005); Hanson (2009), for a review), or the households directly linked to migrants (Woodruff and Zenteno (2007); Yang (2008)). Scant evidence exists on how internal migration impacts the labor markets of receiving communities in developing countries, let alone the implications of disaster-driven migration (Kleemans and Magruder (2012); El Badaoui et al. (2014); Strobl and Valfort (2013)). We address this knowledge gap by investigating the impact of weather-driven migration on internal labor markets in a conflict-prone country, Nepal.

Standard models predict immigration is detrimental to workers that show high degree of substitutability with migrants (Johnson (1980a); Johnson (1980b); Altonji and Card (1991); Borjas (2003); Card and Lemieux (2001); Borjas and Katz (2007); Ottaviano and Peri (2012)). Migrants are implicitly assumed to be low skilled and to substitute natives with comparable skills. Recent work in Uganda supports these assertions (Strobl and Valfort (2013)). Elsewhere, migrants are characterized as highly skilled, yet displace low-skilled workers (Kleemans and Magruder (2012)). Kleemans and Magruder (2012) speculated that binding constraints (such as minimum wage laws) in the formal sector can create a wedge between formal- and informal-sector wages. These conditions further render substitution effects more pronounced among disadvantaged natives. Thus, immigration displaces low-skilled workers, causing a decline in the wages of (less educated) native workers predominantly employed in the informal sector (Kleemans and Magruder (2012)).

Exposure to civil war[1] and environmental degradation, and the linkages of these factors to rural-urban migration[2] render Nepal an interesting context in which to study the spillover effects of adaptation, with a direct focus on nearby labor markets. We apply the methodology of Boustan et al. (2010) to address biases inherent in the immigration literature: the self-selection of migrants at origin, the selection of migrant destinations, and native displacements. The methodology allows for the full exploitation of bilateral migration flows in order to identify plausibly exogenous push factors at origin and pull factors at destination. The instruments for the net migration rate (predicted in-migration and out-migration rates) in the wage regression are based on multiples of the predicted probability of moving bilaterally from one district to another and the predicted bilateral (in- and out-) migration flows. These two factors are predicted using models prior to the first stage. The first stage then uses two sets of instruments for net migration: the constructed in- and out-migration rates jointly and the net-migration rate derived from subtracting the first instrument from the first. This is in direct contrast to earlier work which uses spatially lagged weather shocks as instruments, raising concerns regarding the validity of the exclusion restriction due to spatial spillovers resulting from these shocks.[3]

We provide a few modifications to the Boustan et al. (2010) methodology to improve

[1] Urbanization and labor markets have been affected by conflicts in other settings (Kondylis (2010); Maystadt and Verwimp (2014); Alix-Garcia and Bartlett (2012); Alix-Garcia et al. (2013)).

[2] Environmental degradation and weather shocks have been argued to increase rural-urban migration in Nepal (Shrestha and Bhandari (2007); Massey et al. (2010)).

[3] The problem of spatial spillovers is less of an issue when using approximations of shocks at origin to study international migration (Munshi (2003); Pugatch and Yang (2011)), since shocks occur outside the labor markets under investigation and the existence of spatial spillovers can be directly tested. In our study of internal migration in Nepal, we will nonetheless follow Pugatch and Yang (2011) to directly test the existence of spatial spillovers.

identification and adapt the methodology to the contextual setting of our study. First, we model out- and in- migration flows between districts in Nepal (which are later used to construct our instruments), accounting for lagged weather anomalies, *in addition to* conflict and historical migration flows, and their interactions with river density. Thus, we expand on the push-pull factors previously considered in the migration literature while introducing a dynamic estimation framework. Controlling for historical migration flows is crucial to decipher the relative importance of natural disasters and conflict events on immigration consequences. Second, we differentiate consequences on the labor market by native worker skills to interpret the empirical findings in relation to theoretical predictions in the literature (Altonji and Card (1991); Kleemans and Magruder (2012)).

Our dynamic model of out-migration (estimated prior to the first stage) indicates weather extremes are a prominent driver of out-migration in Nepal, corroborating earlier work on environmental migration patterns (Gray and Mueller (2012a), Mueller et al. (2014)). An increase by 1 standard deviation in the exposure to floods (droughts) reduces out-migration rates by approximately 18 percent (20 percent) in areas with mean river density. The effect of flooding is reversed for individuals in areas densely populated with rivers. Increasing the number of conflict events by 1 standard deviation also encourages out-migration to a lower degree, by 6 percent.

Incorporating historical migration rates in a dynamic model provides two interesting perspectives. First, including auxiliary controls is crucial in the environmental migration literature, as their omission can bias parameter estimates. Second, it suggests that weather extremes are of equal importance to these omitted factors. An increase of 1 standard deviation in the lagged out-migration rate increases future out-migration rates by about 22 percent. The corresponding increase for in-migration rates is even larger (at about 62 percent), reflecting strong network effects.

We find such prevailing factors push a more distinct group of individuals to migrate (Kleemans and Magruder (2012); Strobl and Valfort (2013)). Approximately half of the migrant population had completed 10 years of schooling, relative to 18 percent of natives, in 2010. These high-skilled migrants potentially saturate the formal sector, where one-fourth of natives are employed. These marked imbalances between the characteristics of the migrants and of the native population accentuate wage effects in the formal sector: an increase of 1 percentage point in net migration reduces wages in the formal sector by 4.8 percentage points[4].

Wage effects are concentrated in the formal sector, despite observed reductions in the employment of natives in the informal sector. The absence of wage effects in the informal sector is consistent with the exit of native workers from the informal labor market. We additionally show immigration largely leads to the unemployment of low-skilled natives. An increase of 1 percentage point in net migration leads to an increase of 1.5 percentage points in the unemployment of unskilled workers.

Our findings have implications for both the immigration and environmental migration literatures. First, migration is found to strongly affect labor outcomes in hosting districts in Nepal. While migrants bring skills to host economies, their presence depresses the wages of workers in the formal sector (in contrast to the findings of Kleemans and Magruder (2012) in Indonesia) and causes workers to exit the labor market altogether. Second, our results suggest vulnerability to weather extremes is not limited to those at the source of exposure. Conflict and flooding in areas populated by rivers displace people. The vulnerability of populations in external communities has spillover effects on migrant hubs. If the highly skilled workers are most affected, reductions in their purchasing power likely incur losses to providers of their services and goods. Understanding the constraints migrants face in starting their own enterprises and the drivers of labor market exits among the low-skilled natives will inform pathways to labor market resilience.

[4] Kleemans and Magruder (2012) report an increase in th migrant share of the population by 1 percentage point reduces overall income by 1.9 percentage points. Similarly, Altonji and Card (1991) and Ottaviano and Peri (2012) find 1-2 percent declines in wages among low-skilled workers in the U.S. Our results are just over double in magnitude.

2 Vulnerability and Labor Market Conditions in Nepal

Flooding is not uncommon in Nepal and can potentially lead to an increase in migration, away from rivers and toward low-lying land (Banister and Thapa (1981); Shrestha (1999); Massey et al. (2010)). Our analysis covers periods of unprecedented increases in the frequency and severity of floods and landslides (Figure 2.1). Small-scale floods occurred (prior to 2002) followed by widespread exposure (in 47 districts), displacing hundreds of thousands by 2002 (UN report 2002). The 2007 floods displaced more than 19,000 households (Dartmouth Flood ObservatoryDartmouth Flood Observatory (2014) data and the International Disaster Database,CRED (Centre for Research on the Epidemiology of Disasters) (2014)). A flood of an even larger magnitude occurred in eastern Nepal in 2008 as a result of a breach in an embankment at the Indo-Nepali border, displacing 42,000 households across several villages (UN Office for the coordination of Humanitarian Affairs (2008)). Flooding and landslides affected the far western and midwest regions during the heavy monsoon period of 2009: 4,000 households were displaced and the food stock of 25,000 families lost (UN Office for the coordination of Humanitarian Affairs (2009)).

Drought risk is rare and tends to occur during the winter, the regular monsoon period. Western and eastern Nepal have experienced episodes of consecutive droughts since 2000[5]. These culminated in a severe drought over the period November 2008 to February 2009, with precipitation 50 percent below the seasonal average (Wang et al. (2013)).

Civil conflict was also a major factor driving migration in Nepal from 1999 to 2006 (Bohra-Mishra (2011)). A Maoist insurgency began in the Rolpa district in western Nepal and much of the conflict was concentrated in mountainous and hilly terrain, and in poorer areas. The decade-long conflict led to the loss of more than 13,000 lives (Do and Iyer (2010)). There was considerable variation in the intensity of conflict across the country;[6] the Maoists controlled several districts in eastern and western Nepal by 2005 (Murshed and Gates (2005)).

[5] See Figure A.1 in the appendix.
[6] See Figure A.2 in the appendix.

Violent outbreaks led to the movement of political refugees away from conflict-prone areas. The predicted probability of migration decreased for moderate levels of violence and increased as violence became more intense (Bohra-Mishra (2011)).

Local migration in Nepal driven by environmental and political factors is concentrated among more skilled and educated workers. Massey et al. (2010) found that environmental decay, as indicated by falling agricultural productivity, serves to increase the odds of local migration. Specifically, the odds of moving are significantly higher for individuals with more years of schooling and holding salaried occupations, which is likely to indicate greater skill and therefore greater potential returns on human capital from migration. Among locally migrating adult males in Nepal compared with non migrants, the former are younger and more educated (Fafchamps and Shilpi (2013)). Similar to environmentally driven migration, within conflict areas, migrants who move both within and across districts tend to be younger and more educated, and to hold salaried jobs (Bohra-Mishra (2011)). These disparities across movers and nonmovers increase when migration is across districts.

The above migration trends suggest displacement associated with environmental disasters explains only a small portion of the mobility patterns in Nepal. Acknowledging additional push-pull factors, such as conflict and economic drivers, is crucial to provide an unbiased understanding of migration and its consequences on neighboring districts. This fact influences our decision to modify the Boustan et al. (2010) identification strategy to incorporate conflict and a dynamic component to proxy additional drivers of migration.

Previous work on environmental and conflict displacement suggests the relatively skilled will tend to move out of district. Our study focuses on between-district migration and classifying workers by sector in our LSMS data, we observe both migrants and non migrants tend to be employed in the informal sector (Table 2.1). However, the share of migrants employed in the formal sector is larger than the share of non migrants in this sector. A greater proportion engage in service-sector work; 39 percent of migrants compared to 17 percent of non migrants in 2003 (Table 2.1). Non migrants are also disproportionately employed in agriculture. While the agricultural sector remains an important contributor to Nepal′s economy, from 1965 to 2010, the share of gross domestic product accounted for by agriculture fell from 70 percent to 30 percent, while the share accounted for by services increased from 20 percent to more than 50 percent (International Labor Organization (2010)). These trends suggest that immigration is likely to affect services, the sector that employs the greatest share of migrants. Moreover, labor market adjustments following a shift in labor supply may be constrained given the declining role of agriculture in the economy.

3 Data

Our analysis draws from several data sources. First, migration and employment data are taken from two waves of the nationally representative Nepal Living Standards Survey (NLSS): 2003 and 2010. Second, we use the Armed Conflict Location and Event Dataset (ACLED), which documents georeferenced conflict events through 2010, to measure conflict exposure. Third, to create weather anomaly variables, we use 1×1 degree gridded satellite-based weather data provided by the POWER (Predicted of Worldwide Energy Resource) project of the National Aeronautics and Space Administration (NASA) of the United States for the years 1981 to 2013 (US National Aeronautics and Space Administration (2014)). Fourth, gridded population data are extrapolated from the Center for International Earth Science Information Network at Columbia University. Fifth, river networks and geographic characteristics (such as distance) are extracted from the United States Geological Survey HydroSHEDS (Hydrological Data and Maps Based on Shuttle Elevation Derivatives at Multiple Scales dataset). [7] Below we elaborate on how our outcomes and explanatory variables are constructed from the aforementioned datasets.

[7] The data source is: *http://hydrosheds.cr.usgs.gov/index.php*.

3.1 Definition of Variables

3.1.1 Migration

We create migration flows using the migration information of 7,000 and 14,000 individuals (residing in 3,954 and 5,556 households in 69 districts[8]) in 2003 and 2010, respectively. Inflows are based on individuals who reported moving to district k from district j in year t using NLSS sampling weights for population-based inferences. Bilateral migration outflows are similarly defined. We restrict our focus to inflows and outflows for four years preceding the 2003 and 2010 surveys to minimize the impact of recall bias and ensure sufficient coverage of conflict and weather events in the period observed.[9] Population figures derived from the 1995 NLSS are then used to further convert the migration flows into shares of migrants moving into and out of each district k from each district j for each year. This procedure creates two 69×69 matrices of bilateral in- and out-migration rates at the district level, which are used to predict net migration rates, the key variable for the identification of the impact of migration in the labor regressions.

3.1.2 Conflict

A conflict event is defined as a single altercation in which one or more groups use force for a political end (Raleigh et al. (2010)). Following this definition, the number of conflict events per square kilometer is defined by district-year for the four years prior to 2003 and 2010. Between 1996 and 2006, the end of the civil war, about 3,030 conflict events were reported in the ACLED dataset for Nepal.

[8] In total, six districts are excluded from our panel because they were omitted from the 2003 and 2010 surveys. In 2003, Accham, Mustang, and Rasuwa districts were unreachable due to conflict. Dolpa, Ilam, and Manang districts were omitted in 2010.

[9] Modifying the number of years over which migration is observed has little impact on the estimation of predicted migration rates.

3.1.3 Weather Anomalies

We create seasonal flood and drought indicator variables, for the same period covering migration flows, for each 1×1 degree grid that overlaps a district in a given year. Heavy monsoon is from June to September. Regular monsoon is from November in the previous year through February of the current year. A flood shock indicator, for each grid in a given year, is set to 1 if cumulative rainfall over the heavy monsoon season exceeds the 90th percentile of the time-series distribution. Similarly, a drought shock indicator, for each grid in a given year, is set to 1 if cumulative rainfall over the regular monsoon season falls below the 10th percentile of the distribution.

Annual district-level flood and drought indicators are set to 1 if a flood or drought occurs in any grid overlapping the district. The flood and drought variables are interacted with river density data to capture an additional dimension of district exposure to the weather anomalies. River density is calculated as the length of the river segments in kilometers divided by each district area.

3.1.4 Labor Market Outcomes

Our labor supply variables focus on the employment status of the individual. An individual is considered employed if he reported working in the last 12 months prior to the survey interview. Otherwise, the individual is categorized as unemployed (did not work nor engage in domestic activities in the last 12 months) or inactive (did engage in domestic activities in the last 12 months).

Two stratifications are made in the analysis to facilitate the interpretation of results. The first stratification is based on the sector of employment, which relies on the NLSS definition. We also stratify the sample by skill, whereby individuals having more than 10 years of schooling are characterized as highly skilled and others are considered low skilled.

Individual and household earnings over a 12-month period are used to construct monthly formal- and informal-sector wages, respectively. We use the national consumer price index to convert 2003 wages into 2010 real terms. Monthly wages for formal-sector workers are taken directly from the survey. For the majority of workers employed in the informal sector, we proxy for earnings with revenues from own farms and enterprises. To construct individual monthly earnings, we divide monthly revenues by the number of members in the household reported to be employed in the enterprise.

Our measure proxy for informal earnings may under- or overestimate true individual earnings in the informal sector. We might systematically overestimate revenues per capita by omitting hired employees from the denominator (because they were missing from the agricultural module). On the other hand, we may underestimate individual earnings because we are unable to clarify which household members were employed by the enterprise on a permanent basis.

Because household enterprises are more the rule than the exception, we restrict the analysis of migration impacts to the sample of household heads. Particularly for the informal sector, adding members from larger households may attenuate the effect of immigration inasmuch as their employment status may depend on their relative position in the household and other joint household decisions. Since restricting the focus to household heads sufficiently reduces the initial sample size, we detail how heads differ from the rest of the natives in the Summary Statistics section.

3.2 Summary Statistics

Table 2.1 compares the characteristics of migrants, nonmigrants, and household heads of both groups in our sample. Migrants tend to be younger and more educated than nonmigrants, and a greater percentage are women. The proportion of migrants that completed 10 or more years of schooling is 29 percent, compared with 14 percent of non-migrants in 2003. These differences widen by 2010, when 46 percent of migrants are considered skilled according to our definition, compared with 18 percent of nonmigrants. Given the skill differentials, it is not surprising that a greater percentage of migrants work in the formal sector.

Restricting the nonmigrant sample to household heads changes the distribution of gender and age characteristics with negligible effects on educational endowment. Focusing on the heads produces a sample closer to full employment. As expected, household heads obtain greater formal- and informal-sector wages on average (than the complete sample of nonmigrants), and the difference is persistent over time.

4 Methodology

We employ the Boustan et al. (2010) methodology to account for changes in native labor market outcomes attributable to immigration, using the following empirical model:

$$Y_{ijt} = \alpha_1 + \beta M_{jt} + \lambda X_{ijt} + \gamma Q_{jt} + \delta_j + \delta_t + \epsilon_{ijt}, t = [2003, 2010] \tag{1}$$

The dependent variable Y represents the non-migrant labor outcomes (employed, unemployed, and log monthly wages) for individual level i, living in area j at time t. Labor supply and wage variables are a function of several factors: the net labor migration rates M to area j over the last four years, a vector of demographic controls X that reflect one′s earning potential (age, gender, education), a location variable Q (urban destination), a location fixed effect δ_j to reflect labor market differences at the regional level, and a time fixed effect δ_t to account for time trends. Errors are clustered at the district level, for the 69 districts, to allow for correlation between individuals within district-level labor markets.

To deal with the endogeneity of the net migration rate M, predicted in- and out-migration rates are used as instruments for the observed net migration rates (Boustan et al. (2010))[10]. We also subtract the predicted out-migration rate from the predicted in-migration rate to create the predicted net migration rate and use this one instrument for the net-migration

[10] We follow Boustan et al. (2010) in how we compute the standard errors in the first- and second-stage regressions. The first-stage regressions use block-bootstrapped standard errors (clustering at the district level) to account for the fact that the predicted in- and out-migration rates are generated regressors.

rate. Thus we have two sets of instruments, predicted in- and out-migration rates together, or the predicted net migration rate as an instrument for the net migration rate in a just identified model.

Equations (2) through (4) delineate how the predicted in-migration rate is computed. Out-migration rates are calculated in a similar fashion to compute net migration rates (equations (5) through (7)). To compute the in-migration rate for location j, we must first predict the in-migration flows, IM_{jt}, of migrants to location j. This is the product of the number of migrants leaving location k and the probability that these migrants move from location k to location j, $\widehat{P_{kjt}}$, where $\widehat{O_{kt}}$ denotes the out-migration rate. The instrument for the in-migration rate is the predicted inflow in equation (2) divided by district j's population in 1995. Predicted in-migration flows (equation (2)) are affected only by outmigration in all j states excluding own state k itself[11]. Predicted out-migration flows (equation (5)) is similar.

$$
\begin{aligned}
IM_{jt} &= \sum_{k \neq j} \left(\widehat{O_{kt}} \times pop_{k1995} \right) \times \widehat{P_{kjt}}, \text{ with } t = [2003, 2010] && (2) \\
O_{kt} &= \alpha_2 + \theta_1 Z_{kt-1} + \theta_2 M_{kt-1} + \delta_k + \delta_t + \epsilon_{kt}, && (3) \\
\text{with } & \quad t = [2000, 2001, 2002, 2003, 2007, 2008, 2009, 2010] \\
P_{kjt} &= \alpha_3 + \phi f(d_{kj}) + \delta_t + \epsilon_{kt}, \text{ with } t = [2003, 2010] && (4)
\end{aligned}
$$

In (3), we modify the out-migration rate, O_{kt}, equation from Boustan et al. (2010) and later Strobl and Valfort (2013) in three ways. First, the out-migration rate is influenced by origin weather shocks (floods, droughts and their interaction with river density), as well as by past conflict events (Z_{kt-1})[12]. Although the consistency of our results does not depend on the addition of these interaction terms and the conflict variables, such modifications are

[11] The use of migration out of (into) other states excluding own state helps to avoid the issue of endogeneity as discussed. In addition, excluding own state automatically implies excluding own state lagged weather and conflict variables used in equation (3) and (6) to predict out(in) migration flows which could indirectly affect the main dependent variables of the analysis.

[12] Weather and conflict variables are not used directly as instruments, only to construct predicted in and out migration rates which are the excluded instruments used in the analysis

motivated by the vulnerability of Nepali households to floods, as described in Section 2. Second, we estimate out-migration flows using a linear probability model with district and time fixed effects. Third, we improve the predictive power of out-migration rates by estimating a dynamic model, incorporating lagged migration rates. A standard system generalized method of moments (GMM) dynamic model (Blundell and Bond (1998)) is applied with robust standard errors.[13] The predictive power of the dynamic model is assessed against an alternative model, ordinary least squares (OLS) with standard errors robust to time and spatial correlation (Conley (1999)). We assume that spatial dependency disappears beyond a cutoff point of 64 kilometers, which corresponds to the maximum distance between the centroids of any pair of neighboring districts. We also allow for time dependency of up to two years, which is larger than the minimum time lag (T powered 0.25) recommended by Green (2003) and Hsiang (2010).

For each source location k, the probability of moving from location k to location j is then estimated by a dyadic model in equation (4), which depends on the proximity between locations k and j, d_{jk}. We define the proximity as a Euclidian distance between locations and allow for a nonmonotonic relationship with the introduction of a quadratic term. We estimate (4) using a linear probability model with time fixed effects δ_t to account for unobserved time-specific variables that influence migration. Standard errors are clustered at the origin level.

Thus far, we have explained how we predict in-migration rates. We must also predict out-migration rates to have the complete set of variables used as excluded instruments in equation (1) . Out-migration rates are computed in a similar fashion from equations (5)-(7)

[13] The method provides more efficient estimates than difference GMM estimations (Arellano and Bond (1991)) but requires an additional assumption with respect to stationarity. We apply Fisher$'$ test for panel unit root using an augmented Dickey-Fuller test (Maddala and Wu (1999)). For our main variables reported in Table 5.2, we can reject the null hypothesis of nonstationarity in all variables at any reasonable confidence level. One exception is the number of conflicts per square kilometer, but note that that our results do not depend on the inclusion of the conflict variables (Table 5.1).

below:

$$
\begin{aligned}
OM_{jt} &= \sum_{k \neq j} \left(\widehat{I_{kt}} \times pop_{k1995} \right) \times \widehat{P_{jkt}}, \text{ with } t = [2003, 2010] && (5) \\
I_{kt} &= \alpha_2 + \theta_1 Z_{kt-1} + \theta_2 M_{kt-1} + \delta_k + \delta_t + \epsilon_{kt}, && (6) \\
\text{with} \quad & t = [2000, 2001, 2002, 2003, 2007, 2008, 2009, 2010] \\
P_{jkt} &= \alpha_3 + \phi f(d_{jk}) + \delta_t + \epsilon_{kt}, \text{ with } t = [2003, 2010] && (7)
\end{aligned}
$$

Equation (5) denotes the predicted out-migration flow OM_{jt} of migrants from location j. The predicted out-migration flow from j is estimated as the sum over all destination districts k ($k \neq j$) of the number of migrants settling in destination district k who are estimated to come from source district j. Equation (6) provides the predicted in-migration rate for districts estimated in a similar form to equation (3). From (7), a function of distance across districts is used to estimate the likelihood of individuals leaving source region j to move to region k. Predicted district level observations of P_{jkt} and I_{kt} from equations (6) and (7) are used to create predicted out-migration flows in (5). The predicted out-migration flow from location j is divided by district j's population in 1995 to create the predicted out-migration rate used as an instrument, along with the predicted in-migration rate in the empirical estimation.

Our identification strategy hinges on the assumption that the predicted out-migration rates, predicted in-migration rates and predicted net migration rate affect individual labor market outcomes at the destination only through their effect on net migration.[14] By focusing on district-level migration rates, we essentially reduce the potential for the exclusion restriction to be violated due to the spatial correlation of shocks across cities and villages within the same district. Furthermore, by including district fixed effects, we control for unobserved factors at the destination that might be correlated with net migration and affect labor market outcomes.

[14] The average net migration rate (Table 5.2) is slightly lower than rates observed in the US literature but within the realm for internal migration in developing countries (Strobl and Valfort (2013)).

The only credible threat to identification would come from spatial correlation between the variables used to predict net-migration rates from sending districts and unobserved local labor market conditions at the district level (Boustan et al. (2010); Pugatch and Yang (2011)). This is certainly one rationale for lagging these variables when predicting in- and out-migration. Yet we cannot rule out that (lagged) political and environmental shocks are correlated across districts and feature enough persistency to threaten the validity of the exclusion restriction. We will therefore test the robustness of our analysis in Section 5.3 by augmenting the regressions in equation (1) with spatially lagged political and environmental shocks that explicitly control for spatial correlation across districts.

5 Results

5.1 Results from the Regressions Used to Predict Net Migration Rates

We first present the parameter and standard error estimates from the OLS version of (3) (column 3, Table 5.1). An increase of 1 standard deviation (that is, by 0.387) in flood incidence during the heavy monsoon (i.e. 0.387) reduces the out-migration rate by 0.0009 (at mean river density).[15] Given the mean value of the out-migration rate (0.005), the impact corresponds to a reduction of 18 percent. However, flood exposure, particularly in areas with dense river networks (floods*river density), can push individuals out of their locations of origin. For example, consider individuals living in areas where the river density is 2 standard deviations above the mean. An increase of 1 standard deviation in flood incidence elevates their chance of out-migration by 3 percent.

Inferences on the flooding parameters are similar when based on the dynamic model (column 6, Table 5.1). At the cost of imposing an additional assumption with respect to

[15] Descriptive statistics for district-level variables, which are used to compute the average partial effects, are given in Table 5.2.

the exogenous nature of past migration,[16], the dynamic model is found to offer a better specification fit. The F-test of joint significance in the first-stage equation is slightly higher for the instruments resulting from the dynamic model. Our instrumental variables (predicted migration rates) and the interpretation of the remaining parameters are therefore based on our preferred specification, the dynamic model.

A major advantage of the dynamic model is the ability to control for auxiliary factors that affect historical migration rates. To give perspective on the relative importance of flooding on out-migration rates, auxiliary factors, as proxied through the lagged out-migration rate, influence out-migration rates by a similar order of magnitude. An increase of 1 standard deviation in historical out-migration rate augments out-migration rates by 22 percent compared with an 18 percent reduction from an equivalent increase in flooding exposure. While the number of conflicts also has a consistently positive effect on out-migration rates, the effects are smaller with an increase of 1 standard deviation, leading to a 6 percent increase in out-migration rates.

We briefly remark on the in-migration rate regression (column 12, Table 5.1). Lagged migration is the only statistically significant determinant. An increase of 1 standard deviation in historical in-migration rates is predicted to increase in-migration by 62 percent, reflecting strong network effects.

We next turn to the models used to predict the probabilities of moving from district k to j and vice versa (4). Both specifications suggest a convex relationship between the probability of moving and distance: the probability is almost always negatively correlated with the linear term (for 124 and 127 of the 138 estimated pairs in P_{kj} and P_{jk}, respectively) and positively correlated with the squared term (for 132 and 136 of the 138 estimated pairs in the same two specifications). The small sample of district pairs, however, influences the precision of our estimates. About 25 percent of the coefficients on the linear and squared distance variables

[16] To validate the consistency of the GMM estimator, the test for the first-order serial correlation rejects the null hypothesis of no correlation, while the hypothesis for second-order serial correlation cannot be rejected. The Sargan test for over identification does not reject the null hypothesis of zero correlation between the instrumental variables and the error term.

are statistically significant at the 10 percent critical level in both probability specifications.

Table 5.3 presents the results from the first-stage regressions. Predicted migration rates calculated from formula (2) for in-migration (and a similar formula for out-migration) are used as instruments for actual net migration rates. We also provide a just-identified version of the first stage, using the predicted net migration rate as one instrument subtracting the aforementioned two formulas.

Figure 5.1 maps the predicted and observed net migration rates. Although strongly correlated in areas with major cities, the two maps substantially differ in that the predicted figures capture a subsample of the observed net migration rates. For Kathmandu, actual and predicted net-migration rates are strongly correlated. Actual net migration rates were 0.020 and 0.117, while predicted net migration rates were 0.023 and 0.064 in 2003 and 2010, respectively. In other cities, such as Nepalganj in the southwestern Banke district (Figure 5.1), the distinction between actual and predicted migration is much larger. The actual net migration rate is 0.046 and 0.010 in contrast to the predicted net migration rate of -0.003 and -0.004 in 2003 and 2010, respectively. The striking differences across predicted and observed net migration rates highlight that the interpretation of our results is not generalizable to any type of migrants in Nepal.

5.2 Impact of Migration on Hosting Labor Markets

We now present our estimates of the impact of net migration rates on labor markets outcomes. In Table 5.4, our dependent variable is the logarithm of monthly real wage, distinguishing between the formal and informal sectors. The two-stage least-squares estimates under just-identified (column 5) or over identified (column 6) equations indicate a strong negative impact in the formal sector. A 1 percent increase in net migration rates would translate into a fall in real wages by about 5 percent. Contrary to the findings of Kleemans and Magruder (2012), the negative impact is found only in the formal sector. These effects are consistent with migrants' being engaged in activities in the formal sector more than nonmigrants.

The formal-sector wage effects for each district are extrapolated from the regression results and presented in Figure 5.2. A 1 percent increase in net migration rates from increased frequency of droughts, floods, and conflict in this part of the world is expected to have profound effects on the economic geography of Nepal. There is quite a bit of variation in the wage effects across space which corresponds to district migration hot spots depicted in Figure 5.1, which suffers the most negative consequences.

Our descriptive statistics also reveal that the difference between migrants and nonmigrants may be driven by distinctions in skills: in 2010, 46 percent of migrants were considered skilled compared with 18 percent of nonmigrants. It is therefore not surprising to observe that net migration negatively affects the real wages of high-skilled nonmigrants (columns 1-3, Panel A, Table 5.5), in particular in the formal sector where most (relatively) high-skilled migrants are competing (columns 7-9, Panel B, Table 5.5). The magnitude of the wage effect resembles wage losses in the context of labor substitutability among low-skilled workers in the United States (for example, 1-2 percent declines found by Altonji and Card (1991) or Ottaviano and Peri (2012)). Nonetheless, the negative impact found in the formal sector for the low-skilled workers (columns 10-12, Panel B, Table 5.5) sheds doubt on a mechanism exclusively based on labor substitutability.

Tables 5.6 and 5.7 point to another source of vulnerability for low-skilled workers. Low-skilled workers face a lower probability of employment (columns 14 and 15, Table 5.6) and a higher probability of unemployment (columns 8 and 9, Table 5.7). Raising net migration by 1 percentage point increases the unemployment of unskilled workers by 1.5 percentage points. A slightly lower (reverse) elasticity is found for employment probability. Similarly, employment and unemployment probabilities have the expected sign for skilled workers, although statistically significant for the probability to be unemployed (columns 5 and 6, Table 5.7). Such contrasting results are consistent with a displacement of low-skilled workers out of the labor market.

5.3 Validity of the Instruments

The identification strategy hinges on two main identifying assumptions: the strength and the exogenous nature of the predicted net migration rates used as instruments. First, the individual t- and F-tests, assuming weak instruments, indicate the instruments are strong predictors of the actual net migration rate (Table 5.3). The Kleibergen Paap rk Wald F statistics range between 12 and 14 for our preferred dynamic specification, which exceeds the Stock and Yogo (2005) critical values with 15 percent absolute bias.[17] We also note that the predicted net migration rates positively affect observed net migration rates, which is reassuring given that just-identified estimates are median-unbiased.

Second, it is intuitively plausible that the predicted migration rates affect labor market outcomes *only* through observed migration rates. In Section 4, we rationalize the focus of the analysis at the district level and the use of lagged environmental and political shocks in predicting migration rates to satisfy the exclusion restriction. One possible violation of the exclusion restriction would nonetheless result if (weather and political) shocks in neighboring districts have direct impacts on labor market outcomes.[18] We therefore test the stability of our coefficients of interest in the second-stage regressions to the inclusion of spatially lagged variables. The spatially lagged variables are obtained by multiplying the variables used to predict migration in equation (3) with a distance-based spatial matrix that weights the value of each variable for one district by the inverses of the Euclidean distances to the geographical centers of all other districts (Anselin (2002)). The inclusion of these spatially lagged variables does not alter substantially the magnitude of the impact of migration on labor market outcomes.[19] We can therefore rule out the possible threat to our identification

[17] The F statistics on excluded IV is also above the rule-of-thumb of 10 provided by Stock and Yogo (2005). We also note that when using the predicted out-migration and in-migration rates as separate instruments, the Hansen J test features a p-value above 0.100. It should be noted that the two instruments are similar in nature and the test assumes that at least one instrument is valid.

[18] Past migration in equation (3) may also be endogenous. Our results are similar when past migration is omitted and the instruments are constructed using an OLS estimation (as shown in columns 1-3 and 7-9 in Table 5.1). The robustness of the two-stage estimates is provided in Tables A.1 and A.2 in the appendix.

[19] Results are provided in Table A.3. There is only one exception : the impact on wages for the low-skilled workers appears to be positive when spatially lagged variables are included. However, when restricted to the

strategy that would result from spatial spillovers from environmental and political shocks.

5.4 Reflections on the Role of the Informal Labor Market in Absorbing Displaced Workers

The seemingly contrasting results between employment and wage outcomes deserve further investigation. The displacement of low-skilled workers out of the labor market cannot be explained by the labor substitution mechanism. First, immigration may change demand in ways differentially affecting formal- and informal-sector workers (Altonji and Card (1991)). For example, a growing literature demonstrates immigration influences prices and consumption composition (Saiz (2003)Saiz (2007); Lach (2007); Cortes (2008)). Second, although our findings are somewhat consistent with the predictions of Kleemans and Magruder (2012), our informal-sector results suggest binding constraints preclude the absorption of workers (for example, registration requirements may prevent the entry of new enterprises, or credit constraints prevent enterprise expansion). We reflect on the plausibility of these hypotheses descriptively.[20]

We first examine whether native workers change their consumption patterns in response to migrant flows. It is important to note that the general equilibrium framework developed by Altonji and Card (1991) accounts for the increase in the demand for goods caused by the shift in the population from migration. We explore an additional effect on labor demand, which is through shifts in preferences for goods. If the purchasing power parity of workers declines with immigration, then we might expect to observe changes in consumption patterns. While total consumption remains unaffected by migration, native workers reduce the share

formal sector, we found a negative impact, similar to the one found in Table 5.5 (columns 11-12).

[20] These hypotheses are by no means exhaustive. The skilled may be differentially affected if migration affects innovation and technology boosting their marginal productivity (Kerr (2013)). Additionally, from a worker's perspective, the returns to his skills or education in the informal sector may be lower than his reservation wage, rendering unemployment more desirable than employment in the informal sector. Although testing the role of migration in innovation is beyond the scope of the paper, we find no descriptive evidence to support the reservation wage argument when comparing the returns on education across sectors in simple Mincerian wage regressions (Table A.4 in the appendix).

of service goods consumed in exchange for other nonfood essentials (Table 5.8). These compositional changes in demand do not explain labor market exits in the informal sector, but they do offer one explanation for why formal-sector workers are at most risk. A greater share of formal-sector workers are engaged in the service sector, in which services are likely to have a higher elasticity of demand.

We next assess how constraints on the creation and expansion of enterprises may affect the ability of the informal sector to absorb displaced workers. Descriptive statistics indicate that the majority of enterprises are financed through households' own savings (approximately 40 percent) (Table 5.9). Only a small percentage of enterprises tried to obtain a loan to operate or expand their business (23 percent in 2010) and fewer complained of unsuccessful attempts (3 percent). Overall, the environment for hired labor is low (for example, only 17 percent in 2010). Informal enterprises are more inclined to hire workers and a significantly greater number of workers per enterprise. The absence of financial capital may discourage enterprises in the informal sector from expanding or entrepreneurs from creating start-ups.

6 Conclusion

We employ the Boustan et al. (2010) multi-stage procedure to identify the effects of environmental migration on the labor markets of hosting communities. We modify these authors' procedure for constructing the instrumental variables to incorporate additional variables relevant to our setting (such as conflict exposure), district and time fixed effects, and a dynamic component. We show the dynamic model is preferred to the standard OLS accounting for spatial and time correlation (Conley (1999)). Inferences based on the dynamic model suggest droughts and floods are equally crucial determinants of migration as auxiliary factors, proxied by lagged migration. Predictions from the dynamic model are used to construct instruments for net migration rates in the second stage.

Our second-stage regressions indicate wage losses are slightly larger than those observed in the United States and elsewhere (4.8 percent). Labor substitution is imperfect in the Nepal case inasmuch as migrants appear more skilled than the average native worker in hosting communities. The demand for labor in the formal sector also appears binding in the short term following earlier work in Indonesia (Kleemans and Magruder (2012)). Imperfect substitution coupled with fixed labor demand in the formal sector may partially explain why wage losses are more pronounced here than in other settings.

Although migrants are positively selected, as in Indonesia, we find informal-sector employment (not wages) is negatively affected. The wages of the informal sector adjust due to the exit of workers from the labor market. Migration appears to change consumption patterns by reducing the share of service goods consumed. Service goods may have a higher elasticity of demand. Furthermore, formal-sector workers are at greater risk than informal-sector workers since a greater share are employed in the service sector. The informal sector's ability to absorb excess labor may also be limited by opportunities to access financial capital in Nepal to support new enterprises or encourage older enterprises to grow. Such descriptive evidence suggests the provision of grants to support enterprises following periods of disasters may foster resilience in hosting economies to forced migration (de Mel et al. (2012)).

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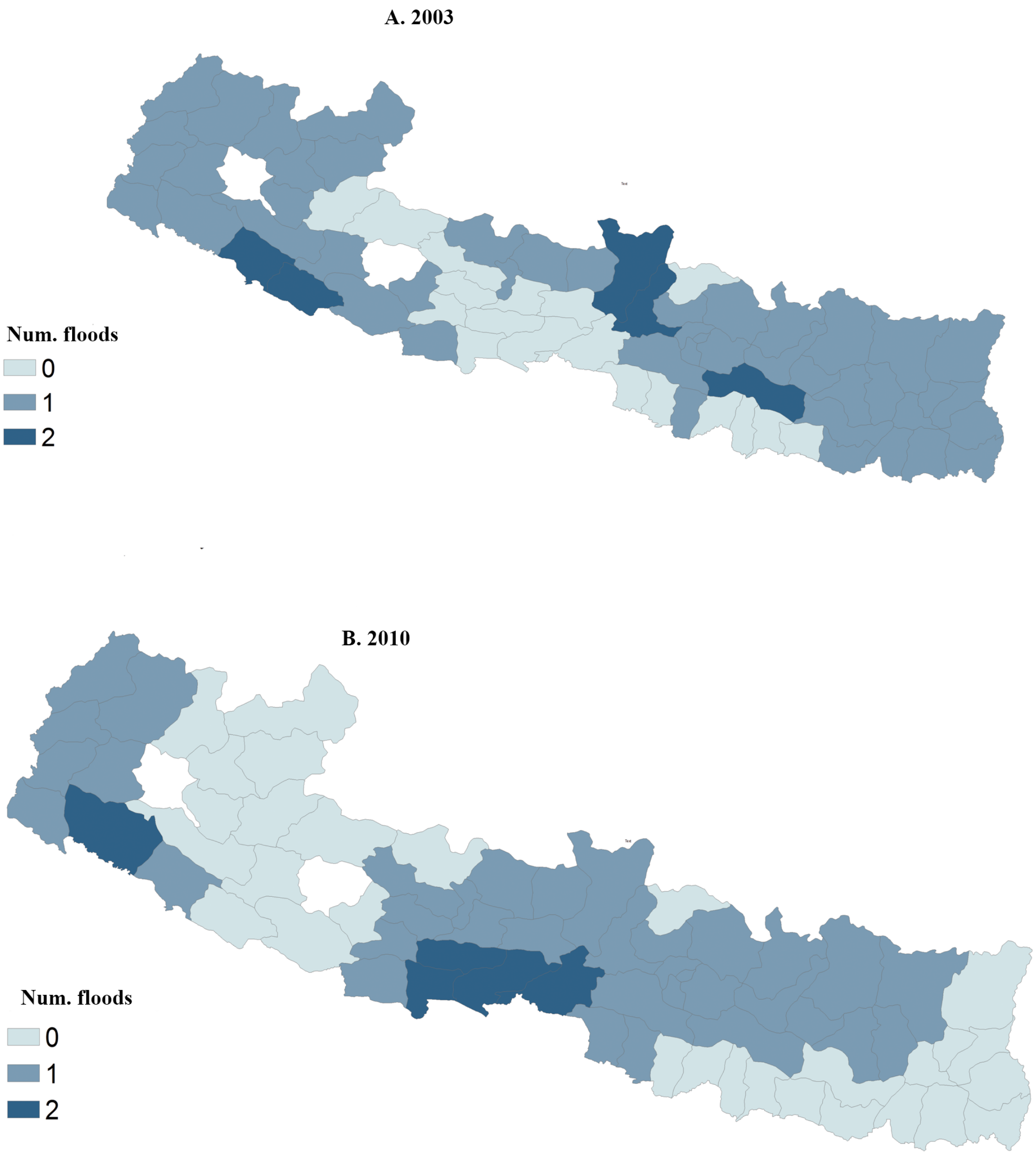
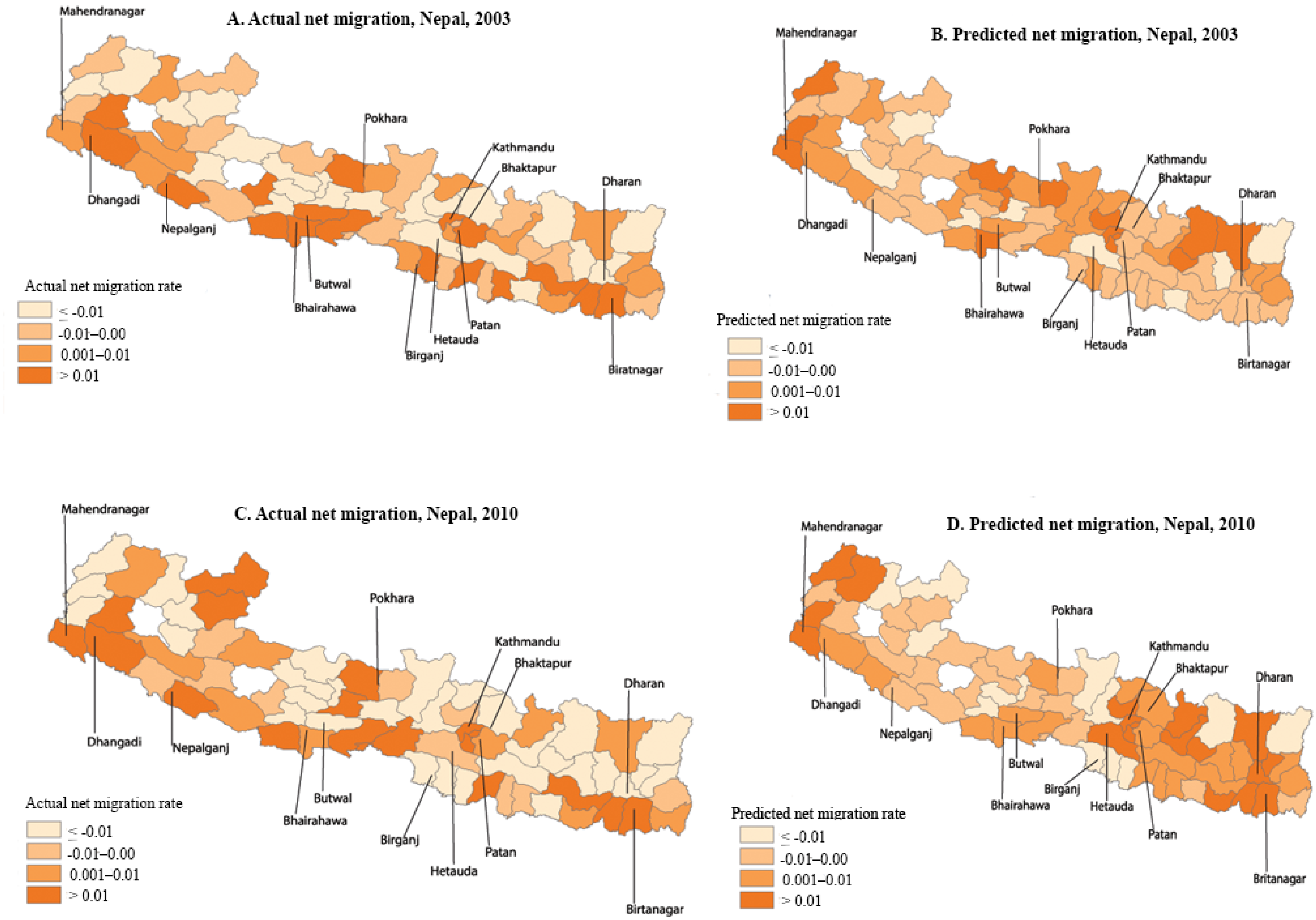
Figure 2.1—Floods in Nepal, cumulative over previous four years, 2003 versus 2010



Source: Authors' representation based on data from NASA (2014).
Note: Districts not used in analysis are omitted from maps.

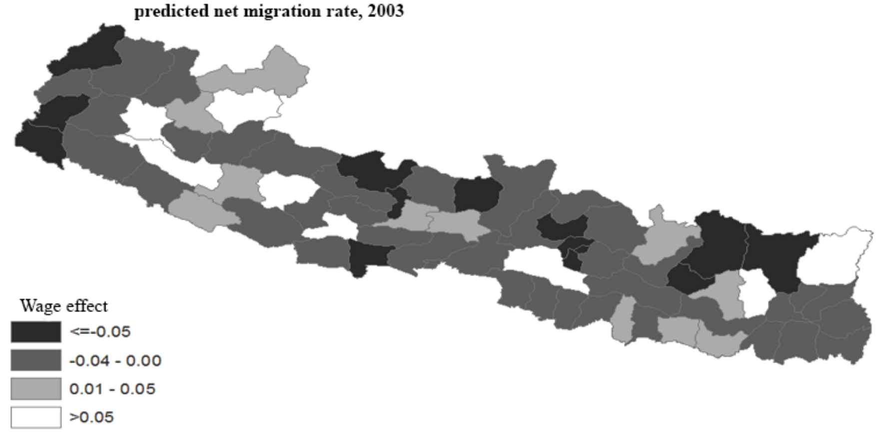
Figure 5.1 —Actual and Predicted Net Migration, Nepal, 2003 and 2010



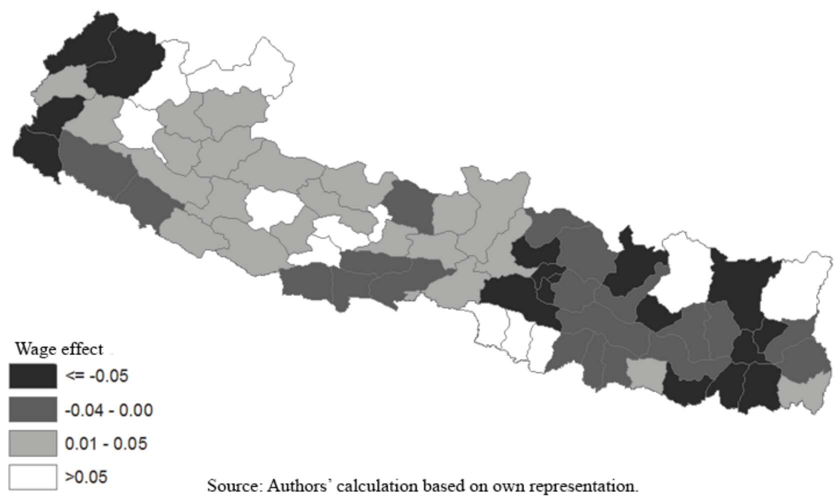
Source: Authors' representation based on own calculations.
Note: Districts not used in analysis are omitted from maps.

Figure 5.2—Estimated Effects of predicted net migration on formal-sector wages, Nepal, 2003 and 2010

A. Estimated effect on formal-sector wages of a 1 percent increase in within-district predicted net migration rate, 2003



B. Estimated effect on formal-sector wages of a 1 percent increase in within-district predicted net migration rate, 2010



Source: Authors' calculation based on own representation.
Note:Districts not used in analysis are omitted from map.

Table 2.1—Summary statistics, individual characteristics of migrants and natives aged 18-65, weighted, 2003 and 2010

	2003			2010			2003	2010
	Non-migrant	Migrant	Diff. (p-val)	Non-migrant	Migrant	Diff. (p-val)	Non-migrant HH head	Non-migrant HH head
	(n = 7,303)	(n = 241)		(n = 14,367)	(n = 401)		(n = 2,742)	(n = 5,230)
Age	36.70	28.50	0.000	37.80	25.70	0.000	43.40	43.70
	(13.60)	(11.60)		(13.60)	(10.10)		(11.60)	(11.50)
Male	0.53	0.43	0.000	0.43	0.24	0.000	0.85	0.72
	(0.50)	(0.50)		(0.50)	(0.43)		(0.36)	(0.45)
Schooling	3.69	6.52	0.000	4.25	8.24	0.000	3.36	3.98
	(4.57)	(4.71)		(4.81)	(4.58)		(4.36)	(4.51)
Highly skilled	0.14	0.29	0.174	0.18	0.46	0.000	0.12	0.14
	(0.34)	(0.46)		(0.39)	(0.50)		(0.32)	(0.35)
Labor Variables								
Employed	0.90	0.75	0.358	0.84	0.58	0.152	0.97	0.94
(last 12 months)	(0.30)	(0.43)		(0.37)	(0.50)		(0.17)	(0.24)
Unemployed	0.03	0.07	0.000	0.13	0.26	0.000	0.01	0.06
(last 12 months)	(0.18)	(0.25)		(0.34)	(0.44)		(0.12)	(0.23)
Inactive	0.07	0.18	0.000	0.03	0.16	0.375	0.02	0.004
(last 12 months)	(0.25)	(0.39)		(0.17)	(0.37)		(0.13)	(0.06)
	(n = 6,572)	(n = 180)		(n = 12,068)	(n = 233)		(n = 2,660)	(n = 4,707)
Work primary job	0.26	0.32	0.084	0.20	0.27	0.027	0.31	0.23
(|empl. in formal)	(0.44)	(0.47)		(0.40)	(0.44)		(0.46)	(0.42)
	(n = 1708)	(n = 57)		(n = 2,413)	(n = 63)		(n = 798)	(n = 1,080)
Real wage	10,276	10,221	0.996	13,445	8,653	0.569	14,765	17,582
(|empl. & formal)	(80,981)	(18,267)		(63,605)	(8,107)		(114,300)	(89,454)
	(n = 2,713)	(n = 84)		(n = 5,700)	(n = 75)		(n = 1,323)	(n = 2,034)
Real wage[1]	1,566	1,584	0.912	3,245	4,049	0.783	1,890	3,676
(|empl. & informal)	(5,561)	(2,919)		(24,501)	(10,973)		(7,301)	(27,204)
Share of Migrants by Industry								
	(n = 5,960)	(n = 151)		(n = 9,901)	(n = 173)		(n = 2,484)	(n = 4,264)
Agriculture,	0.70	0.52		0.71	0.53		0.70	0.67
Forestry & Fishery	(0.46)	(0.50)		(0.46)	(0.50)		(0.46)	(0.47)
Services	0.17	0.39		0.20	0.35		0.18	0.22
	(0.38)	(0.49)		(0.40)	(0.48)		(0.38)	(0.41)
Manufacturing	0.08	0.08		0.05	0.06		0.06	0.05
	(0.26)	(0.27)		(0.22)	(0.25)		(0.24)	(0.23)
Construction	0.05	0.02		0.04	0.05		0.07	0.06
	(0.21)	(0.13)		(0.21)	(0.23)		(0.25)	(0.24)

Notes: Real wages expressed at the monthly level in 2010 rupees. *Highly skilled* is defined as having 10 or more years of schooling. HH = Household. [1] Real monthly wage for individual in informal sector constructed using agricultural or enterprise revenues per worker. [2] Real monthly wage for Household in the informal sector is household agricultural or enterprise revenue.

Table 5.1—Determinants of in- and out-migration rates

Dependent variable	Out-migration rate						In-migration rate					
	OLS			Dynamic model			OLS			Dynamic model		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Flood in heavy	-0.002***	-0.002***	-0.014***	-0.002***	-0.002**	-0.008**	-0.000	-0.000	0.002	0.000	0.000	0.000
monsoon at $t-1$	(0.001)	(0.001)	(0.005)	[0.001]	[0.001]	[0.004]	(0.000)	(0.000)	(0.004)	[0.000]	[0.000]	[0.004]
Drought in regular	-0.001	-0.001	-0.000	-0.003**	-0.003**	0.005	-0.001	-0.001*	-0.001	0.001	0.001	-0.001
monsoon at $t-1$	(0.001)	(0.001)	(0.004)	[0.001]	[0.001]	[0.005]	(0.000)	(0.000)	(0.003)	[0.001]	[0.001]	[0.003]
No. of conflicts		-0.041	-0.041		0.028	0.031*		-0.100***	-0.100***		0.035	0.018
per sq km at $t-1$		(0.031)	(0.031)		[0.018]	[0.019]		(0.022)	(0.022)		[0.045]	[0.019]
Out-migration				0.171***	0.169***	0.159**				0.277***	0.356***	0.370***
rate at $t-1$				[0.055]	[0.058]	[0.062]				[0.090]	[0.094]	[0.100]
Flood in HM at $t-1\times$			0.068***			0.033*			-0.017			-0.001
River density			(0.025)			[0.019]			(0.023)			[0.021]
Drought in RM at $t-1\times$			-0.003			-0.043**			0.003			0.009
River density			(0.021)			[0.022]			(0.015)			[0.014]
Observations	552	552	552	552	552	552	552	552	552	552	552	552
R-squared	0.013	0.016	0.021				0.004	0.045	0.046			
AB test for AR(1) (p-val)				0.000	0.000	0.000				0.000	0.000	0.000
AB test for AR(2) (p-val)				0.627	0.576	0.737				0.701	0.731	0.708
Sargan test (p-val)				0.643	0.155	0.962				0.132	0.107	0.122
Hansen test (p-val)				0.160	0.307	0.331				0.371	0.152	0.332

Notes: Time and district - origin for specifications (1)–(6) and destination for specification (7)–(12)—fixed effects are included.
Robust standard errors in parentheses. Based on Conley (1999) a correction for spatial dependency with a cutoff point of 64 kilometers is applied for OLS specifications.
* significant at 10%, ** at 5%, *** at 1%. AB = Arellano and Bond(1991); HM =heavy monsoon; RM = Regular monsoon;
AR(1) = first-order autocovariance in residuals of order 1; AR(2) = first-order autocovariance in residuals of order 2

Table 5.2—Descriptive statistics for district-level variables, periods 2000 to 2003 and 2007 to 2010 (districts = 69, n = 552)

	Mean	St. dev.	Fisher's test
Flood during heavy monsoon (unweighted)	0.183	(0.387)	329***
Drought during heavy monsoon (unweighted)	0.308	(0.462)	443***
Total conflicts per square km	0.002	(0.009)	120
River density (length of river per square km)	0.171	(0.023)	343***
Actual migration outflow rate from district	0.005	(0.007)	358***
Actual migration inflow rate to district	0.003	(0.005)	329***
Aggregate actual net migration rate (cum. 4-year) (weighted by sample size in each district)	0.005	(0.031)	

Note: *** significant at 1%

Table 5.3—Relationship between predicted and actual migration rates (first stage)

	Actual net migration rate			
Dependent variable	Dynamic model		OLS model	
	IV(1)	IV(2)	IV(1)	IV(2)
Predicted net migration rate	1.459***		2.107***	
(cumulative 4-yr)	(0.533)		(0.668)	
Predicted out migration rate		-0.580**		-4.829
(cumulative 4-yr)		(0.241)		(5.123)
Predicted in migration rate		1.918***		2.165**
(cumulative 4-yr)		(0.672)		(0.862)
Individual age	-0.00000	-0.00001	-0.00001	-0.00001
	(0.000)	(0.000)	(0.000)	(0.000)
Individual male	0.00008	0.0002	0.0002	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
Individual education years	-0.0000	-0.00002	-0.00003	-0.00002
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.00015	0.00017	0.00025	0.00034
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	24.235	24.235	24.235	24.235
R-Squared	0.598	0.652	0.646	0.652
Number of districts	69	69	69	69
F-stat	58.28***	63.92***	61.67***	64.5***
F-stat on excl. IV	13.86***	12.53***	23.003***	13.34***
Weak identification test[a]	13.784	12.464	22.861	13.223
Stock-Yogo critical values				
10 percent maximal IV size	16.380	19.930	16.380	19.930
15 percent maximal IV size	8.960	11.590	8.960	11.590

Notes: Time and district fixed effects are included. [a] The weak identification test provides the Kleibergen-Paap rk Wald F statistic.
Standard errors in parentheses are bootstrapped and clustered at the district level.
* significant at 10%, ** at 5%, *** at 1%.

Table 5.4—Effect of net migration rate on wages for nonmigrant household heads aged 18-65 (second stage)

Dependent Variable	Log monthly real wages (2010 Nepal rupees)								
	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
	All			Formal sector			Informal sector		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net migration rate	-1.6014	1.745	0.992	-5.072***	-4.753***	-5.066***	1.162	6.700	5.791
(cumulative 4-yr)	(0.962)	(3.298)	(2.808)	(0.560)	(0.855)	(0.671)	(1.554)	(5.129)	(4.597)
Individual control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,234	5,234	5,234	4,119	4,119	4,119	3,113	3,113	3,113
R-squared (within)	0.510	0.508	0.509	0.285	0.285	0.285	0.365	0.362	0.363
Districts	69	69	69	67	67	67	69	69	69

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%. In all subsequent specifications, IV(1) and IV(2) use predicted net migration rates to instrument actual net migration rate, and predicted in- and out-migration rates as separate instruments for actual in- and out-migration rates, respectively.

Table 5.5—Effect of net migration rate on wages for nonmigrant household heads aged 18-65, by skill (second stage)

Dependent Variable	Log monthly real wages (2010 Nepal rupees)					
	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
Panel A	All sectors					
	High skill			Low skill		
	(1)	(2)	(3)	(4)	(5)	(6)
Net migration rate	-1.940*	-1.253	-1.202	-0.6378	4.615	3.431
(cumulative 4-yr)	(1.068)	(1.453)	(1.438)	(1.133)	(4.638)	(3.961)
Individual control	Y	Y	Y	Y	Y	Y
Occupation	Y	Y	Y	Y	Y	Y
Observations	1,075	1,075	1,075	4,154	4,154	4,154
R-squared (within)	0.464	0.464	0.464	0.480	0.478	0.479
Panel B	Formal sector					
	High skill			Low skill		
	(7)	(8)	(9)	(10)	(11)	(12)
Net migration rate	-1.675**	-1.518*	-1.593**	-5.397***	-4.655***	-5.376***
(cumulative 4-yr)	(0.705)	(0.818)	(0.790)	(0.745)	(1.326)	(0.939)
Individual controls	Y	Y	Y	Y	Y	Y
Occupation	Y	Y	Y	Y	Y	Y
Observations	573	573	573	1,530	1,530	1,530
R-squared (within)	0.171	0.171	0.171	0.250	0.250	0.250
Number of districts	45	45	45	66	66	66

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%. High skill refers to those individuals with at least 10 years of education.

Table 5.6—Effect of net migration rate on employment for nonmigrant household heads aged 18–65 (second stage)

Dependent variable	Employment probability (worked in last 12 months)								
	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
Panel A	All			Formal sector			Informal sector		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net migration rate	-0.721***	-0.934***	-0.981***	0.459*	0.594	0.725	-1.132***	-1.466***	-1.630***
(cumulative 4-yr)	(0.110)	(0.154)	(0.161)	(0.241)	(0.381)	(0.485)	(0.209)	(0.434)	(0.556)
Individual control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,965	7,965	7,965	7,965	7,965	7,965	7,965	7,965	7,965
R-squared (within)	0.055	0.055	0.055	0.055	0.055	0.055	0.040	0.040	0.040
Districts	69	69	69	69	69	69	69	69	69
Panel B	High skill			Low skill					
	(10)	(11)	(12)	(13)	(14)	(15)			
Net migration rate	-0.113	-0.073	-0.098	-0.710***	-1.031***	-1.096***			
(cumulative 4-yr)	(0.170)	(0.189)	(0.173)	(0.163)	(0.212)	(0.217)			
Individual control	Y	Y	Y	Y	Y	Y			
Occupation dummies	Y	Y	Y	Y	Y	Y			
Observations	1,358	1,358	1,358	6,604	6,604	6,604			
R-squared (within)	0.182	0.182	0.182	0.111	0.111	0.111			
Districts	64	64	64	69	69	69			

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses.
* significant at 10%, ** at 5%, *** at 1%.

Table 5.7—Effect of net migration rate on unemployment for nonmigrant household heads aged 18–65

Dependent variable	Unemployment probability (worked in last 12 months)								
	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
	All			High skill			Low skill		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net migration rate	1.011***	1.295***	1.372***	0.552***	0.570***	0.574***	1.147***	1.542***	1.675***
(cumulative 4-yr)	(0.211)	(0.172)	(0.163)	(0.163)	(0.182)	(0.173)	(0.329)	(0.257)	(0.215)
Individual control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,965	7,965	7,965	1,358	1,358	1,358	6,604	6,604	6,604
R-squared (within)	0.100	0.099	0.099	0.153	0.153	1,358	0.095	0.094	0.093
Districts	69	69	69	64	64	64	69	69	69

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses.
* significant at 10%, ** at 5%, *** at 1%.

Table 5.8—Effect of net migration rate on nonmigrant household expenditure patterns

	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
Panel A	Log per capita total Expenditures (real 2010 rupees)			Share food expenditures (real 2010 rupees)		
	(1)	(2)	(3)	(4)	(5)	(6)
Net migration rate	-0.549	1.133	1.105	0.003	0.031	0.016
(cumulative 4-yr)	(0.436)	(1.504)	(1.539)	(0.146)	(0.163)	(0.167)
Individual control	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y
Observations	7,965	7,965	7,965	7,965	7,965	7,965
R-squared (within)	0.449	0.447	0.447	0.242	0.242	0.242
Number of districts	69	69	69	69	69	69
	OLS	IV(1)	IV(2)	OLS	IV(1)	IV(2)
Panel B	Share nonfood expenditures excl. services (real 2010 rupees)			Share services expenditure (real 2010 rupees)		
	(7)	(8)	(9)	(10)	(11)	(12)
Net migration rate	0.555***	0.855***	0.879***	-0.558**	-0.886***	-0.895***
(cumulative 4-yr)	(0.117)	(0.188)	(0.191)	(0.225)	(0.147)	(0.126)
Individual control	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y
Observations	7,965	7,965	7,965	7,965	7,965	7,965
R-squared (within)	0.356	0.355	0.354	0.065	0.064	0.063
Number of districts	69	69	69	69	69	69

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table 5.9—Nonmigrant household financial and capacity constraints of enterprises (| own enterprise), weighted, 2003 and 2010

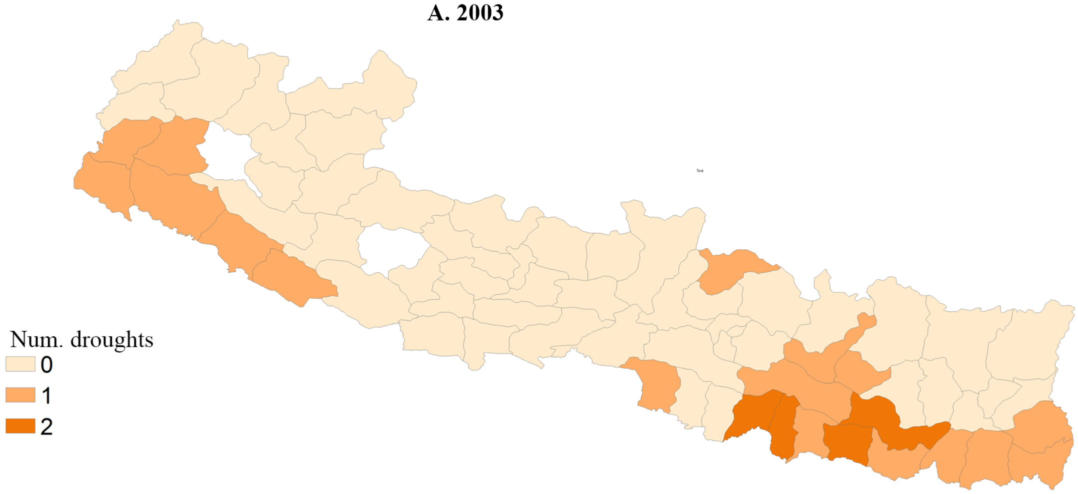
	2003 All	2010 All	2003 Low skill	2003 High skill	2010 Low skill	2010 High skill
	(n=865)	(n = 1,854)	(n = 695)	(n = 170)	(n = 1,469)	(n = 385)
Is the enterprise registered with the govermnent? (yes)	0.20	0.21	0.15	0.54	0.15	0.48
	(0.40)	(0.41)	(0.35)	(0.50)	(0.36)	(0.50)
What was the main source of money for setting up the enterprise?						
Didn't need any money	0.30	0.33	0.31	0.21	0.35	0.20
	(0.46)	(0.47)	(0.46)	(0.41)	(0.48)	(0.40)
Own savings	0.41	0.37	0.39	0.53	0.37	0.41
	(0.49)	(0.48)	(0.49)	(0.50)	(0.48)	(0.49)
Relatives or friends	0.14	0.13	0.15	0.10	0.13	0.16
	(0.35)	(0.34)	(0.36)	(0.30)	(0.34)	(0.37)
Bank (agricultural, commercial, Grameen type)	0.07	0.06	0.07	0.07	0.05	0.11
	(0.26)	(0.25)	(0.26)	(0.26)	(0.23)	(0.31)
Other financial institution	0.01	0.04	0.01	0.01	0.03	0.08
	(0.12)	(0.20)	(0.12)	(0.12)	(0.18)	(0.27)
Other	0.07	0.06	0.07	0.07	0.07	0.05
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.21)
Have you tried to borrow money to operate or expand your business in the past 12 months? (relative to no)						
Yes, successfully	0.20	0.23	0.20	0.18	0.22	0.31
	(0.40)	(0.42)	(0.40)	(0.39)	(0.41)	(0.47)
Yes, unsuccessfully	0.04	0.03	0.04	0.03	0.03	0.04
	(0.19)	(0.17)	(0.19)	(0.17)	(0.17)	(0.20)
Did you hire anyone over the past 12 months? (yes)	0.13	0.17	0.11	0.30	0.14	0.35
	(0.34)	(0.38)	(0.31)	(0.46)	(0.34)	(0.49)
How many workers do you normally hire during a month when the enterprise is operating?						
(| hired in last 12 months)	8.88	9.98	4.99	17.80	11.00	7.84
	(32.10)	(38.60)	(20.60)	(48.20)	(42.80)	(28.40)
What problems, if any, do you have in running your business?						
No major problem	0.35	0.49	0.36	0.30	0.51	0.38
	(0.48)	(0.50)	(0.48)	(0.46)	(0.50)	(0.49)
Caiptal or credit problem	0.15	0.13	0.15	0.22	0.13	0.16
	(0.36)	(0.34)	(0.35)	(0.41)	(0.33)	(0.36)
Lack of customers	0.31	0.14	0.32	0.24	0.13	0.17
	(0.46)	(0.34)	(0.47)	(0.43)	(0.34)	(0.37)
Other	0.18	0.25	0.17	0.25	0.23	0.30
	(0.39)	(0.43)	(0.38)	(0.44)	(0.42)	(0.46)

Appendix

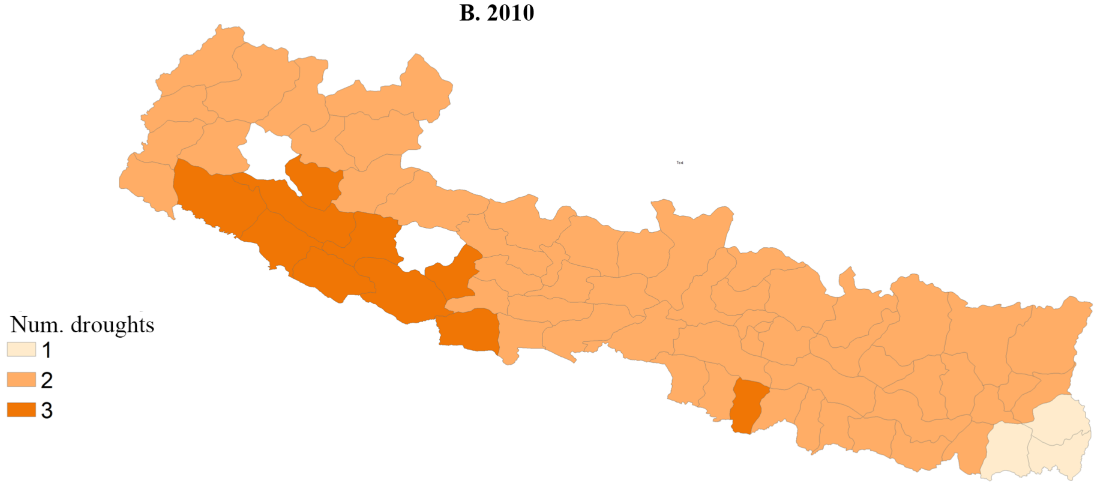
August 11, 2014

Figure A.1—Droughts in Nepal, cumulative over previous four years, 2003 versus 2010

A. 2003



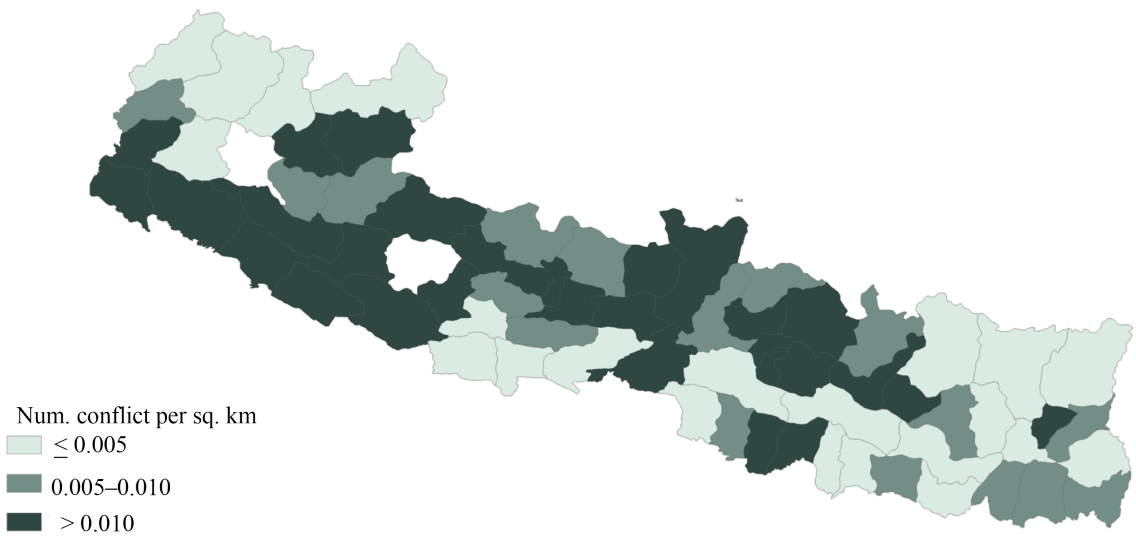
B. 2010



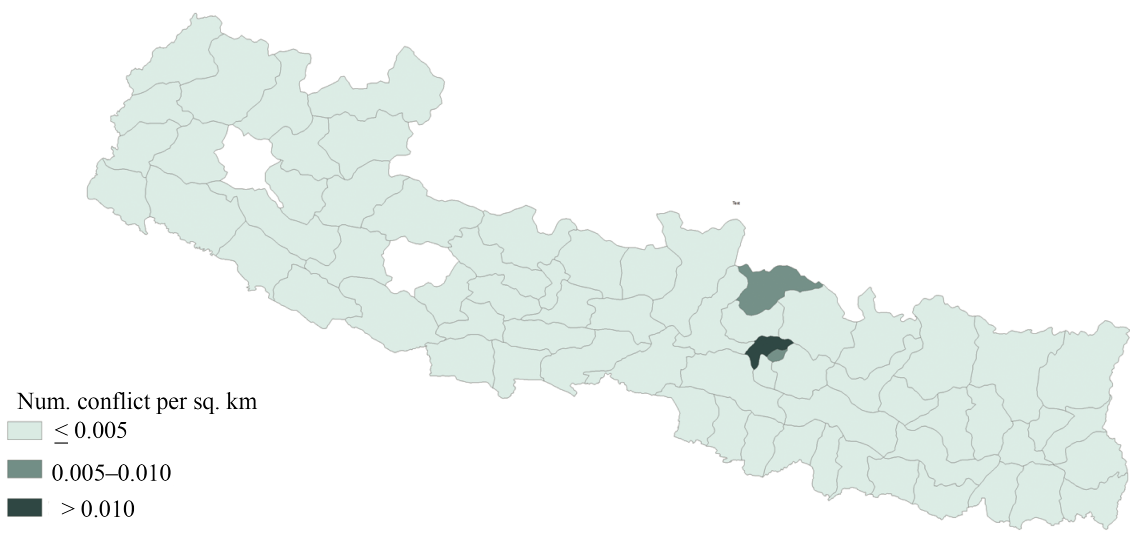
Source: Authors' representation based on NASA (2014).
Note: Districts not used in analysis are omitted in maps.

Figure A.2—Conflicts in Nepal, cumulative over previous four years, 2003 versus 2010

A. 2003



B. 2010



Source: Authors' representation based on ACLED (20104).
Note: Districts not used in analysis are omitted from Maps.

Table A.1—Effect of net migration rate on wages using alternate instruments derived from adjusted OLS method for nonmigrant household heads aged 18-65 (second stage)

Dependent variable	Log monthly real wages (2010 Nepal rupees)					
	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)
	All		Formal sector		Informal sector	
	(1)	(2)	(3)	(4)	(5)	(6)
Net migration rate	0.290	0.126	-5.2797***	-5.3236***	4.6988	4.5644
(cumulative 4-yr)	(2.395)	(2.303)	(0.603)	(0.583)	(4.021)	(3.945)
Individual control	Y	Y	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y	Y	Y
Observations	5,234	5,234	2,119	2,119	3,113	3,113
R-squared (within)	0.509	0.509	0.285	0.285	0.364	0.364
Number of districts	69	69	67	67	69	69

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table A.2—Effect of net migration rate on wages using alternate instruments derived from adjusted OLS method for nonmigrant household heads aged 18-65, by skill (second stage)

Dependent Variable	Log monthly real wages (2010 Nepal rupees)			
	IV(1)	IV(2)	IV(1)	IV(2)
Panel A	All sectors			
	High skill		Low skill	
	(1)	(2)	(3)	(4)
Net migration rate	-1.444	-1.794	2.403	2.309
(cumulative 4-yr)	(1.368)	(1.229)	(3.405)	(3.359)
Individual control	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y
Observations	1,075	1,075	4,154	4,154
R-squared (within)	0.464	0.464	0.479	0.480
Number of districts	60	60	69	69
Panel B	Formal sector			
	High skill		Low skill	
	(5)	(6)	(7)	(8)
Net migration rate	-1.7355**	-1.7758**	-5.8440***	-5.9253***
(cumulative 4-yr)	(0.807)	(0.808)	(0.828)	(0.803)
Individual control	Y	Y	Y	Y
Occupation dummies	Y	Y	Y	Y
Observations	573	573	1,530	1,530
R-squared (within)	0.171	0.171	0.250	0.250
Number of districts	45	45	66	66

Notes: Time and district fixed effects included. Standard errors , clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%. High skill refers to those individuals with at least 10 years of education.

Table A.3—Testing exclusion restrictions, including spatially lagged weather shock and climate variables in own district

	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)
Panel A	Log monthly real wage (2010 Nepal rupees)					
	Formal		High skill		Low skill	
	(1)	(2)	(3)	(4)	(5)	(6)
Net migration rate	-4.005*	-4.107**	-7.070	-4.136	18.839***	19.976***
(cumulative 4-yr)	(2.209)	(2.041)	(8.189)	(9.021)	(6.931)	(7.142)
Observations	2,120	2,120	1,075	1,075	4,154	4,154
R-squared	0.219	0.219	0.112	0.112	0.114	0.113
Number of districts	67	67	60	60	69	69
Panel B	Employed (worked in last 12 months)					
	Formal sector		High skill		Low skill	
	(7)	(8)	(9)	(10)	(11)	(12)
Net migration rate	1.240*	1.497*	-1.668*	-1.551*	-0.956**	-1.008***
(cumulative 4-yr)	(0.739)	(0.829)	(0.916)	(0.890)	(0.377)	(0.380)
Observations	7,967	7,967	1,358	1,358	6,604	6,604
R-squared	0.055	0.055	0.088	0.088	0.090	0.090
Number of districts	69	69	64	64	69	69
Panel C	Unemployed (worked in last 12 months)					
	All		High skill		Low skill	
	(13)	(14)	(15)	(16)	(17)	(18)
Net migration rate	1.319***	1.383***	1.950**	1.860**	1.305***	1.381***
(cumulative 4-yr)	(0.363)	(0.378)	(0.850)	(0.872)	(0.395)	(0.406)
Observations	7,965	7,965	1,358	1,358	6,604	6,604
R-squared	0.077	0.077	0.103	0.103	0.079	0.078
Number of districts	69	69	64	64	69	69
	Included in Panels A, B, and C					
Spatially lagged variables	Y	Y	Y	Y	Y	Y
HH head controls	Y	Y	Y	Y	Y	Y

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses. * significant at 10%, ** at 5%, *** at 1%. Spatially lagged variables include the spatially lagged versions of all weather and conflict variables used in Table 2. HH = Household.

Table A.4—Relationship between skill and wages for nonmigrant household heads, aged 18-65

Dependent Variable	Log real wage per month (2010 Nepal rupees)					
	All		Formal sector		Informal sector	
	(1)	(2)	(3)	(4)	(5)	(6)
Yrs of schooling	0.044***		0.051***		0.057***	
	(0.006)		(0.005)		(0.008)	
Schooling by category (relative to less than primary, 0–4 yrs of school) :						
Completed primary to		0.103**		0.166***		0.280***
less than secondary (5–9 yrs of school)		(0.050)		(0.046)		(0.058)
Completed secondary to less than		0.340***		0.354***		0.602***
higher secondary (10–11 yrs of school)		(0.065)		(0.067)		(0.079)
Completed higher secondary or more		0.730***		0.663***		0.653***
(12 or more years of school)		(0.112)		(0.058)		(0.154)
Individual controls	Y	Y	Y	Y	Y	Y
Observations	5,234	5,234	2,121	2,121	3,113	3,113
R-squared (within)	0.401	0.405	0.275	0.276	0.365	0.365
Number of districts	69	69	69	69	69	69

Notes: Time and district fixed effects included. Standard errors, clustered at the district level, in parentheses.
* significant at 10%, ** at 5%, *** at 1%.