The Impact of Weather and Conflict-Driven Internal Migration on Labor Markets in Nepal*

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Abstract

While an emerging literature relates income shocks as major determinants of migration, scant evidence exists on how such migration impacts the labor markets of receiving communities in developing countries. We address this knowledge gap by investigating the impact of weather- and conflict-driven migration on internal labor markets in Nepal. Contrary to the conventional narrative, we find prevailing factors entice workers with positively selected attributes to migrate. Marked skill differences between migrants and the native population accentuate wage effects in the formal sector: a 1 percentage point increase 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 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.

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1 Introduction

It is well understood that extreme floods, droughts, and pestilence render significant damages to agricultural production and long-term growth (Dercon 2004 ; de la Fuente and Dercon 2008). Rural workers search for employment elsewhere to mitigate income losses temporarily or move permanently if the damages are severe (Halliday 2006 ; Feng, Krueger, and Oppenheimer 2010 ; Dillion, Mueller, and Sheu 2011 ; Gray and Mueller 2012 a,b ; Marchiori, Maystadt, and Schumacher 2012 ; Gray and Bilsborrow 2013 ; Mueller, Gray, and Kosec 2014). Measures of the consequences of migratory flows on the labor markets of hosting communities in developed countries are ubiquitous (Card 1990 ; Borjas 2005 ; Borjas 2006 ; Card 2005 ; Boustan, Fishback, and Kantor 2010 ; Ottaviano and Peri 2012; Pugatch and Yang 2011). In developing countries, the issue has been investigated, either from the migrants′ perspectives (Beegle, de Weerdt, and Dercon 2011; Grogger and Hanson 2011; de Brauw, Mueller, and Woldehanna 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 or conflict-driven migration (Kleemans and Magruder 2012; El Badaoui, Strobl, and Walsh, 2013; Strobl and Valfort 2013). We address this knowledge gap by investigating the impact of weather- and conflict-driven migration on internal labor markets in Nepal.

Standard models predict immigration is detrimental to workers that show high degree of substitutability with migrants (Johnson 1980a, 1980b; Altonji and Card 1991; Borjas 2003; Borjas 2006; Card and Lemieux 2001; Borjas and Katz 2007; Ottaviano and Peri 2012). Migrants are implicitly assumed to be low-skilled, and substitute natives with comparable skills. Recent work in Uganda supports these assertions (Strobl and Valfort 2013). Elsewhere, migrants are characterized as high-skilled, yet displace low-skilled workers (Kleemans and Magruder 2012). The authors speculate binding constraints (e.g., 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 disadvantage 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], environmental degradation, and their linkages to rural-urban migration[2] lends Nepal an interesting context to study the spillover effects of adaptation, with a direct focus on nearby labor markets. We apply the methodology of Boustan, Fishback, and Kantor (2010) to address biases inherent in the immigration literature: the self-selection of migrants at origin, the selection of migrant destinations, and native displacements. We provide a few modifications to improve identification in the first stage and adapt to the contextual setting of our study. First, we model net-migration rates between districts in Nepal accounting for lagged weather anomalies, conflict and historical migration flows, and their interactions with river density, thus expanding the push-pull factors previously considered while introducing a dynamic estimation framework. Controlling for historical migration flows is particularly important 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 from theoretical predictions in the literature (Altonji and Card, 1991; Kleemans and Magruder, 2012).

Our dynamic model of out-migration rates indicates weather extremes are a prominent driver of out-migration in Nepal, corroborating earlier work (Feng, Krueger, and Oppenheimer 2010; Dillion, Mueller, and Sheu 2011; Gray and Mueller 2012a, 2012b; Marchiori, Maystadt, and Schumacher 2012; Gray and Bilsborrow 2013; Mueller, Gray, and Kosec, 2014). A 1 standard deviation

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

[2]Environmental degradation and weather shocks have been argued to increase rural-urban migration in Nepal (Shrestha and Bhandari 2005; Massey, Axinn and, Ghimire 2010).

increase in the exposure of floods (droughts) reduces out-migration rates by approximately 18 percent (20 percent) in areas with mean river density. The effect of flooding reverses for individuals in areas densely populated with rivers. Increasing the number of conflict events by 1 standard deviation also encourages out-migration on the order of 6 percent.

Incorporating historical migration rates in our dynamic model provides two interesting perspectives. First, including auxiliary controls is crucial in this literature, as their omission can bias parameter estimates. Second, it suggests that weather extremes are of equal importance to these omitted factors. A 1 standard deviation increase 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 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 the native population accentuate wage effects in the formal sector: a 1 percentage point increase in net-migration reduces wages in the formal sector by 4.8 percentage points.

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 low-skilled native workers from the labor market. We show immigration largely leads to the unemployment of low-skilled natives. A 1 percentage-point increase in net-migration leads to a 1.5 percentage-point increase 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 Indonesia) and causes low-skilled 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 mostly 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.

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 towards low-lying land (Banister and Thapa 198l; Shrestha 1989; Massey et al. 2010). Our analysis covers periods of unprecedented increases in the frequency and severity of floods and landslides (1999-2002, 2006-2009). In the first period, small-scale floods occurred (1999-2001) followed by widespread exposure (in 47 districts) displacing hundreds of thousands in 2002 (UN report, 2002). During the second period, the 2007 floods displaced over 19,000 households (Dartmouth Flood Observatory Data (DFOS) and the International Disaster Database (EMDAT)). 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 (UNICEF report, 2008). Flooding and landslides affected the far- and mid-west regions during the heavy monsoon period of 2009: 4000 households were displaced and the food stock of 25,000 families lost (UN Office for the coordination of Humanitarian Affairs).

Drought risk is rare and tends to occur during the winter, regular monsoon period. Western Nepal experienced consecutive droughts since 2000. These culminated to a severe drought over the November 2008 to February 2009 period, with precipitation falling 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 poorer areas. The decade-long conflict led to the loss of over 13,000 lives (Do and Iyer 2010). There was considerable variation in the intensity of conflict across the country; the Maoists controlled several districts in eastern and western Nepal by 2005 (Murshed and Gates 2005). Violent outbreaks lead 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) find that environmental decay, as indicated by falling agricultural productivity, served to increase the odds of local migration. The authors find 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 to human capital from migration. Among locally migrating adult males in Nepal compared to 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, more educated, and hold salaried jobs (Bohra-Mishra 2011). These disparities across movers and non-movers increase when migration is across districts.

The above migration trends suggest displacement associated with environmental disasters explains a small portion of 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 influences our decision to modify the Boustan et al. (2010) identification strategy to incorporate conflict and dynamic components to proxy additional drivers of migration.

Previous work on environmental and conflict displacement suggests the relatively skilled will tend to move out-of-district; between district migration being the scope of our study. Classifying workers by skill, according to the completion of more than 10 years of schooling, we observe high-skilled workers increasingly are employed in services (52 percent in 2003 and 54 percent in 2010). Low-skilled workers disproportionately are employed in agriculture (75 percent in 2003 and 77 percent in 2010). While the agricultural sector remains an important contributor to Nepal′s economy, from 1965-2010, the share of GDP accounted for by agriculture fell from 70 percent to 30 percent, while the share of services increased from 20 percent to over 50 percent (ILO, 2010). These trends suggest that immigration is likely to affect the sector which employs high-skilled workers. Moreover, labor market adjustments following a shift in labor supply may be constrained for the sectors that employ predominantly low-skilled labor given the declining trends in the role of agriculture to 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 Standard Measurement Survey (NLSS): 2003, and 2010. Second, the Armed Conflict Location and Event Dataset (ACLED) comprises geo-referenced conflict events through 2010 to measure conflict exposure. Third, to construct weather anomalies, we use 1×1 degree, gridded satellite-based weather data provided by the POWER project of the National Aeronautics and Space Administration (NASA) of the United States from 1981 to 2013. Fourth, gridded population data are extrapolated from the Center for International Earth Science Information Network (CEISIN) at Columbia University. Fourth, river networks and geographic characteristics (e.g. distance) are extracted from the

USGS HydroSHEDS (Hydrological data and maps based on Shuttle Elevation Derivatives at multiple scales). [3] We elaborate on how our outcomes and explanatory variables are constructed from these aforementioned datasets.

3.1 Definition of Variables

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) 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 4 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. [4] Population figures are then used to further convert the migration flows into shares of migrants moving in 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.

Conflict. A conflict event is defined as a single altercation in which one of more groups use force for 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, there were about 3,030 conflict events reported in the ACLED dataset for Nepal.

Weather Anomalies. We create seasonal flood and drought indicator variables, for the same period covering migration flows, for each 1×1 degree grid that

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

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

overlaps a district in a given year. Heavy monsoon is from June to September in a given year. 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 90^{th} 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 10^{th} percentile of the distribution.

Annual district level flood and drought indicators are set to one 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.

Labour Market Outcomes. Our labor supply variables focus on the employment status of the individual. An individual is considered employed, if he reports working in the last 12 months prior to his 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, where individuals having more than 10 years of schooling are characterized as high-skilled, and are otherwise 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 district-level consumer price indices to deflate 2003 wages into 2010 real terms. Monthly wages for formal sector workers are directly taken from the survey. For the majority of workers employed in the informal sector, we base earnings on revenues from own farms and enterprises. To construct individual monthly earnings, we divide monthly revenues by the number of members in the household reported employed in the enterprise.

Our measure of informal earnings may under- or over-estimate 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 since we are unable to clarify which household members were employed by the enterprise on a permanent basis. We provide an additional proxy for informal earnings as a robustness check, consumption per capita.

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 on immigration 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. [5]

3.2 Summary Statistics

Table 1 compares the characteristics of migrants, non-migrants, and non-migrant heads in our sample. Migrants tend to be younger, more educated, and a greater percentage of them consist of women. The proportion of migrants that completed 10 or more years of schooling is 29 percent compared 14 percent of non-migrants in 2003. These differences widen by 2010, where 46 percent of migrants are considered skilled by our education definition compared to 18 percent of non-migrants. Given the skill differentials, it is not surprising that a greater

[5] The robustness of our results is also discussed when such a sample restriction is relaxed, at the cost of unduly duplicating observations within households and hence exacerbating measurement errors.

percentage of them work in the formal sector. [6]

Restricting the non-migrant sample to 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 non-migrants) which is persistent over time.

4 Methodology

We employ the Boustan, Fishback, and Kantor (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 (i.e., 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 4 years; a vector of demographic controls X that reflect one's earning potential (age, gender, education); a vector of location characteristics Q (urban destination), potentially affecting individual outcomes; 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.

To deal with the endogeneity of the net-migration rate M, we adopt the approach of Boustan et al. (2010). The predicted in- and out-migration rates are

[6] Table A.1 further breaks down the percentages of migrants and non-migrants employed by industry and skill. High-skilled migrants and non-migrants tend to work in similar proportions in the service industries, while low-skilled individuals tend to work in agriculture, forestry, and fishery.

used as instruments for the observed net migration rates. Errors are clustered at the district level to allow for correlation between individuals within district-level labor markets.[7]

We delineate how the predicted in-migration rate is computed from (2)-(4). Out-migration rates are calculated in a similar fashion to compute net migration rates. 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 flow in equation (2) divided by the district j's population in 1995.

$$
\begin{aligned}
IM_{jt} &= \sum_{k \neq j} \left(\widehat{O_{kt}} \times pop_{k1995} \right) \times \widehat{P_{kjt}}, \text{ with } t = [2003, 2010] && (2) \\
O_{kt} &= \alpha_2 + \theta_1 Z_{kt-1} + \theta_2 M_{kt-1} + \delta_k + \delta_t + \epsilon_{kt}, && (3) \\
\text{with} \quad & t = [2000, 2001, 2002, 2003, 2007, 2008, 2009, 2010] \\
P_{kjt} &= \alpha_3 + \phi f(d_{kj}) + \delta_t + \epsilon_{kt}, \text{ with } t = [1995, 2003, 2010] && (4)
\end{aligned}
$$

In (3), we modify the out-migration rate, O_{kt}, equation from Boustan et al. (2010) and later Strobl and Valfort (2013) threefold. First, the out-migration rate is influenced by origin weather shocks (flood and droughts) and their interaction with river density as well as past conflict events (Z_{kt-1}). Although the consistency of our results does not depend on the addition of these interaction terms and the conflict variables, such modifications are motivated by the vulnerability of Nepali households to floods described in Section 2. Second, we estimate the out-migration flows using a linear regression with district and time fixed effects.

[7]As pointed by Boustan et al. (2010) and based on Wooldridge (2002), standard two-stage least square inference is valid when instruments are functions of estimated parameters. Basically, it only adds noise to the first-stage estimations, while not affecting the inference of the second-stage regression.

Third, we improve the predictive power of out-migration rates by estimating a dynamic model, incorporating lagged migration rates. A standard system GMM dynamic model (Blundell and Bond 1998) is applied with robust standard errors.[8] The predictive power of the dynamic model is assessed against an alternative model, 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 for 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 to move 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 non-monotonic 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 origin level.

Our identification strategy hinges on the assumption that the predicted out-migration rates from sending districts only affect individual labor market outcomes at the destination through their effect on net-migration. By focusing on district level migration rates, we essentially reduce the potential for the exclusion restriction to be violated from the spatial correlation of shocks across cities and villages within the same district. Furthermore, by including district

[8] 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 the Fisher test for panel unit root using an augmented Dickey fuller test (Maddala and Wu 1999). For our main variables, we can reject the null hypothesis of non-stationarity in all variables at any reasonable confidence level. Results are available on request.

fixed effects, we control for unobserved factors at the destination that might be correlated with net-migration and affect labor market outcomes.

The only credible threat to identification would come from spatial correlation between the variables used to predict out-migration from sending districts and unobserved local labor market conditions at the district level (Boustan et al. 2010; Pugatch and Yang 2011). That is certainly one of rationale for lagging these variables when predicting 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 with spatially-lagged political and environmental shocks that explicitly control for possible 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 2). A one standard deviation increase in flood incidence during the heavy monsoon (i.e. 0.387) reduces the out-migration rate by 0.0009 (at mean river density).[9] Given the mean value of the out-migration rate (i.e. 0.005), the impact corresponds to a reduction of 18 percent. Flood exposure, particularly in areas with dense river networks, 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. A one standard deviation increase in flood incidence elevates their chance of out-migration by 3 percent.

Inferences on the flooding parameters are similar when based on the dynamic

[9] Descriptive statistics for district-level variables, needed to compute the average partial effects, are given in Table 3.

model (column 6, Table 2). At the cost of imposing an additional assumption with respect to the exogenous nature of past migration[10], 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 less than flooding and droughts. A 1 standard deviation increase in historical out-migration rate augments out-migration rates by 22 percent. This can be compared to an 18 percent and 20 percent reduction in out-migration rates caused by flood and drought exposure, respectively, from an equivalent increase in those variables. While the number of conflicts also has a consistently positive effect on out-migration rates, the effects are smaller with a 1 standard deviation increase leading to a 6 percent increase in out-migration rates.

We briefly remark on the in-migration rate regression (column 12, Table 2). Lagged-migration is the only statistically significant determinant. A 1 standard deviation increase 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 and j and vice versa (4). Both specifications suggest a convex relationship between the probabilities of moving and distance. For example, 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}) and positively correlated

[10]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.

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

Table 4 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.

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 our dependent variable is the logarithm of monthly real wage, distinguishing between the formal and informal sectors. The 2SLS estimates under just-identified (column 2) or over-identified (column 3) 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 Kleemans and Magruger (2012), the negative impact is only found in the formal sector (columns 4-6, Table 5).[11] These effects are consistent with migrants predominantly engaged in activities in the formal sector relative to non-migrants.[12]

Our descriptive statistics also reveal that the difference between migrants and non-migrants may be driven by distinctions in skills: in 2010, 46 percent of migrants are considered skilled compared to 18 percent of non-migrants. It is therefore not surprising to observe that net- migration also negatively affects the real wages of high-skilled non-migrants (columns 7-9, Table 5). A 1 percent increase in net migration rates would also translate into a decrease in real wages

[11] Results are robust to the substitution of consumption per capita for informal sector workers.

[12] Restricting our sample to household heads bears little consequences on the findings.

by around 5 percent. Interestingly, the estimated impact is close to the coefficients for low-skilled wages, in the context where labor substitutability among low-skilled workers is the proposed mechanism (e.g., 1-2 percent declines found in Altonji and Card (1991) or Ottaviano and Peri (2012)).

The non-effect on low-skilled wages is in accord with observed informal sector wages. However, Tables 6 and 7 point to another source of vulnerability for low-skilled workers. Low-skilled workers face a lower probability of employment (columns 8 and 9, Table 6) and higher probability of unemployment (columns 8 and 9, Table 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. In turn, employment and unemployment probabilities have the expected sign for the skilled workers, although statistically significant for the probability to be unemployed (columns 5 and 6, Table 7). Such contrasting results are consistent with a displacement of low-skilled workers out of the labor markets.

The seemingly contrasting results between employment and wage outcomes deserve further investigation. In particular, the displacement of low-skilled workers out of the labor market cannot be explained by the labor substitution mechanism. Our results are consistent with two alternative mechanisms which warrant exploration. First, immigration may change demand in ways differentially affecting the skilled and unskilled-intensive sectors which is supported by a general equilibrium model (Altonji and Card 1991). Second, although our findings are somewhat consistent with predictions in Kleemans and Magruder (2012), our informal wage effects suggest binding constraints in the informal sector preclude the absorption of workers (e.g., registration requirements may prevent the entry of new enterprises, and credit constraints prevent enterprise expansion). We examine these hypotheses in the next draft of the manuscript.

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 4). The F statistics range between 12 and 14 for our preferred dynamic specification, which exceeds the Stock and Yogo critical values with 15 percent absolute bias.[13] We also note that the predicted net migration rates positively affect observed net migration rates. That is reassuring given the fact just-identified estimates are median-unbiased.

Second, it is intuitively plausible that the predicted migration rates do not affect the labor market outcomes through another channel other than the 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 make the exclusion restriction more plausible. One possible violation of the exclusion restriction would nonetheless result from (weather and political) shocks in neighboring districts having direct impacts on the labor market outcomes. 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 weighs the values of each variable for one district by the inverse of the Euclidean distance 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 presented in Tables 5, 6 and 7.[14] We can therefore rule out the possible threat to our identification strategy that would result from spatial spillovers from environmental

[13]The Hansen J test when using the predicted out-migration and in-migration rates as separate instruments features a p-value above 0.100. It should be noted that both instruments are similar in nature and the test assumes that at least one instrument is valid.

[14]Results are provided in Table A3.

and political shocks.

5.4 Conclusion

We employ the Boustan et al. (2010) multi-stage procedure to identify the effects of weather and conflict-induced migration on the labor markets of hosting communities. We modify their procedure for constructing the instrumental variables to incorporate additional variables which are relevant to our setting (e.g., conflict exposure), district and time fixed effects, as well as a dynamic component. We show the dynamic model is preferred to the standard OLS model 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 observed in the U.S. and elsewhere (4.8 percent). Labor substitution is imperfect in the Nepal case, 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 Kleemans and Magruder (2012). Imperfect substitution coupled with fixed labor demand in the formal sector may partially explain why wage losses are more pronounced than in other settings.

Although migrants are positively selected as in Indonesia (Kleemans and Magruder 2012), we find informal sector employment (not wages) is negatively affected. The wages of the informal sector adjust due to the exit of unskilled workers from the labor market. To inform which mechanisms might foster resilience in hosting economies, in the next version of the manuscript we will explain what drives the non-wage effects. First, we will examine whether there are compositional shifts in the demand for goods attributable to migration which is consistent with the general equilibrium framework developed in Altonji and Card (1991). High-skilled workers preliminarily appear to shift their consumption towards food. If the informal sector largely consists of food enterprises and the unemployed are leaving non-food enterprises, our findings would lend credence to the demand argument. Second, we will unveil constraints in the informal sector. In particular, we will describe whether expansion constraints are greater in the informal sector and whether low-skilled workers appear more constrained to start their own businesses.

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Table 1: Summary Statistics, Individual Characteristics of Migrants and Natives aged 18-65, weighted

	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=7303)	(n=241)		(n=14367)	(n=401)		(n=2742)	(n=5230)
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)
High 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	(n=7303)	(n=241)		(n=14367)	(n=401)			
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=6572)	(n=180)		(n=12068)	(n=233)		(n=2660)	(n=4707)
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=2413)	(n=63)		(n=798)	(n=1080)
Real wage	10276	10221	0.996	13445	8653	0.569	14765	17582
(|empl. & formal)	(80981)	(18267)		(63605)	(8107)		(114300)	(89454)
	(n=2713)	(n=84)		(n=5700)	(n=75)		(n=1323)	(n=2034)
Real wage[1]	1566	1584	0.912	3245	4049	0.783	1890	3676
(|empl. & informal)	(5561)	(2919)		(24501)	(10973)		(7301)	(27204)
HH real wage [2]							3176	5570
(|empl. & informal)							(8721)	(30137)

Notes: Real wages expressed at the monthly level in 2010 Rupees. High skilled is defined when the individual. has 10 or more years of schooling. [1] Real monthly wage for individual in informal sector constructed using agricultural or enterprise revenue.

Table 2: 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]
Outmigration				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 HV 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(1) (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
Hansan 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. AB stands for Arellano-Bond. HM for heavy monsoon and RM for Regular monsoon. Robust standard errors in parentheses. Based on Conley (1999) a correction for spatial dependency with a cut-off point of 64 kilometers is applied for OLS specifications. *. **. ***: significant at 10% 5% and 1%.

Table 3: Descriptive statistics for district-level variables, period 2000 to 2003 and 2007 to 2010 (districts=69, n=552)

	Mean	Standard Deviation
Probability of flood heavy monsoon (unweighted)	0.183	(0.387)
Probability of drought during heavy monsoon (unweighted)	0.308	(0.462)
Total conflicts per square KM	0.002	(0.009)
River density (length of river KM per KM squared)	0.171	(0.023)
Actual migration outflow rate from district	0.005	(0.007)
Actual migration Inflow rate to district	0.003	(0.005)
Aggregate actual Net Migration Rate (cumulative 4 year)	0.005	(0.031)
(weighted by sample size in each district)		

Table 4: Relationship between Predicted and Actual Migration Rates (First Stage)

Dependent Variable	Out-Migration Rate		In-Migration Rate	
	IV(1)	IV(2)	IV(1)	IV(2)
Predicted Net Migration Rate	1.45850***		2.10741***	
(cumulative 4yr)	(0.533)		(0.668)	
Predicted Out Migration Rate		-0.58000**		-4.82919
(cumulative 4yr)		(0.241)		(5.123)
Predicted In Migration Rate		1.91777***		2.16551**
(cumulative 4yr)		(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	0.00017	0.00021	0.00019
	(0.000)	(0.000)	(0.000)	(0.000)
Individual Education Years	-0.00000	-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 on joint significance	58.28***	63.92***	61.67***	64.5***
Weak Identification test[a]	13.784	12.464	22.861	13.223
Stock-Yogo critical values				
10percent maximal IV size	16.380	19.930	16.380	19.930
15percent maximal IV size	8.960	11.590	8.960	11.590
20percent maximal IV size	6.660	8.750	6.660	8.750
25percent maximal IV size	5.930	7.250	5.930	7.250

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%, 5% and 1%.

Table 5: Effect of Net Migration Rate on Wages for Non-Migrant 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)
Panel A	All			High Skill			Low Skill		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net Migration rate	-1,6014	1.745	0.992	-1.940*	-1.253	-1.202	-0.638	4.615	3.431
(cumulative 4yr)	(0.962)	(3.298)	(2.808)	(1.068)	(1.453)	(1.438)	(1.133)	(4.638)	(3.961)
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	1,075	1,075	1,075	4,154	4,154	4,154
R Squared (within)	0.510	0.508	0.509	0.464	0.464	0.464	0.480	0.478	0.479
Districts	69	69	69	60	60	60	69	69	69
Panel B	Formal Sector			Informal Sector					
	(10)	(11)	(12)	(13)	(14)	(15)			
Net Migration Rate	-5.072***	-4.753***	-5.066***	1.162	6.700	5.791			
(cumulative 4yr)	(0.560)	(0.855)	(0.671)	(1.554)	(5.129)	(4.597)			
Individual Control	Y	Y	Y	Y	Y	Y			
Occupation dummies	Y	Y	Y	Y	Y	Y			
Observations	2,121	4,119	4,119	3,113	3,113	3,113			
R Squared (within)	0.285	0.285	0.285	0.365	0.362	0.363			
Districts	69	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) refer to actual net migration rate instrumented with predicted net migration rate (IV(1)), and with in and out migration rates (IV(2)).

Table 6: Effect of Net Migration Rate on Employment for Non-Migrant 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			High Skill			Low Skill		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net Migration Rate	-0.721***	-0.934***	-0.981***	-0.113	-0.073	-0.098	-0.710***	-1.031***	-1.096***
(cumulative 4yr)	(0.110)	(0.154)	(0.161)	(0.170)	(0.189)	(0.173)	(0.163)	(0.212)	(0.217)
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)	0.055	0.055	0.055	0.182	0.182	0.182	0.111	0.111	0.110
Districts	69	69	69	64	64	64	69	69	69
Panel B	Formal Sector			Informal Sector					
	(10)	(11)	(12)	(13)	(14)	(15)			
Net Migration Rate	0.459*	0,594	0,725	-1.132***	-1.466***	-1.630***			
(cumulative 4yr)	(0.241)	(0.381)	(0.485)	(0.209)	(0.434)	(0.556)			
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)	0.055	0.055	0.055	0.040	0.040	0.040			
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 7: Effect of Net Migration Rate on Unemployment for Non-Migrant 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 4yr)	(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%.

Separate Appendices with Supplemental Material for:

The Impact of Weather and Conflict-Driven Internal Migration on Labor Markets in Nepal

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March 21, 2014

Abstract

This document contains a set of appendices with supplemental material.

Table A1. Summary Statistics, Classification of Migrants and Non-Migrants by Industry and Skill Level (|provide classification in survey)

	MIGRANT				NON-MIGRANT				NON-MIGRANT HH HEAD			
	High Skill		Low Skill		High Skill		Low Skill		High Skill		Low Skill	
	2003	2010	2003	2010	2003	2010	2003	2010	2003	2010	2003	2010
Agriculture, Forestry & Fishery	0.40	0.33	0.60	0.62	0.37	0.38	0.75	0.77	0.37	0.32	0.73	0.72
	(0.50)	(0.47)	(0.49)	(0.49)	(0.48)	(0.49)	(0.43)	(0.42)	(0.48)	(0.47)	(0.44)	(0.45)
Non Agriculture **All**	0.60	0.67	0.40	0.38	0.63	0.62	0.25	0.23	0.63	0.68	0.27	0.28
	(0.50)	(0.47)	(0.49)	(0.49)	(0.48)	(0.49)	(0.43)	(0.42)	(0.48)	(0.47)	(0.44)	(0.45)
Services	0.53	0.58	0.23	0.24	0.52	0.54	0.13	0.13	0.54	0.62	0.13	0.16
	(0.50)	(0.50)	(0.42)	(0.43)	(0.50)	(0.50)	(0.34)	(0.34)	(0.50)	(0.49)	(0.34)	(0.37)
Manufacturing	0.07	0.04	0.13	0.08	0.08	0.05	0.07	0.05	0.04	0.04	0.06	0.06
	(0.25)	(0.19)	(0.33)	(0.27)	(0.27)	(0.22)	(0.26)	(0.22)	(0.21)	(0.19)	(0.24)	(0.23)
Construction	0.00	0.05	0.04	0.05	0.04	0.05	0.05	0.05	0.04	0.03	0.07	0.06
	(0.00)	(0.23)	(0.20)	(0.23)	(0.19)	(0.21)	(0.21)	(0.21)	(0.20)	(0.16)	(0.26)	(0.25)
Sample Size	49	68	109	105	940	2036	5030	7865	377	761	2107	3503
	MIGRANT				NON-MIGRANT				NON-MIGRANT HH HEAD			
	Informal		Formal		Informal		Formal		Informal		Formal	
	2003	2010	2003	2010	2003	2010	2003	2010	2003	2010	2003	2010
Agriculture, Forestry & Fishery	0.69	0.70	0.27	0.09	0.84	0.83	0.42	0.22	0.82	0.81	0.41	0.21
	(0.47)	(0.46)	(0.45)	(0.29)	(0.37)	(0.37)	(0.49)	(0.41)	(0.39)	(0.40)	(0.49)	(0.41)
Non Agriculture **All**	0.31	0.30	0.74	0.91	0.16	0.17	0.58	0.78	0.18	0.19	0.59	0.79
	(0.47)	(0.46)	(0.45)	(0.29)	(0.37)	(0.37)	(0.49)	(0.41)	(0.39)	(0.40)	(0.49)	(0.41)
Services	0.27	0.25	0.48	0.62	0.12	0.13	0.28	0.46	0.14	0.15	0.27	0.45
	(0.45)	(0.44)	(0.50)	(0.49)	(0.33)	(0.34)	(0.45)	(0.50)	(0.35)	(0.36)	(0.44)	(0.50)
Manufacturing	0.04	0.05	0.13	0.10	0.03	0.03	0.13	0.13	0.04	0.04	0.10	0.11
	(0.21)	(0.44)	(0.34)	(0.30)	(0.17)	(0.18)	(0.33)	(0.33)	(0.19)	(0.19)	(0.30)	(0.31)
Construction	0.00	0.00	0.13	0.20	0.01	0.00	0.17	0.20	0.01	0.01	0.23	0.23
	(0.00)	(0.00)	(0.33)	(0.40)	(0.09)	(0.07)	(0.38)	(0.40)	(0.08)	(0.09)	(0.42)	(0.42)
Sample Size	95	103	57	70	4129	7437	1553	2464	1648	3072	794	1192

High Skill denotes more than 10 years of schooling (completed secondary education). Low Skill is less than 10 years of schooling.

Table A2. Effect of Net Migration Rate on Consumption Per Capita of Workers in the Informal Sector (Alternative Wage Measures)

	(1) OLS	(2) IV(1)	(3) IV(2)
Net Migration Rate (cumulative 4yr)	-0.158	2.910	2.942
	(0.609)	(2.167)	(2.312)
HH Head controls	Y	Y	Y
HH Head Occupation dummies	Y	Y	Y
Observations	5,330	5,330	5,330
R Squared (within)	0.410	0.406	0.406
Number of districts	69	69	69

Table A3. Testing Exclusion Restrictions, including spatially lagged weather shock and climate variables in own district

	Log Monthly Real Wage (2010 Nepal Rupees)									
Panel A	*All*		*High Skill*		*Low Skill*		*Formal Sector*		*Informal Sector*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)
Net Migration Rate (cumulative 4yr)	14.091**	15.339**	-7.070	-4.136	18.839***	19.976***	-4.005*	-4.107**	18.013**	18.645***
	(6.151)	(6.356)	(8.189)	(9.021)	(6.931)	(7.142)	(2.209)	(2.041)	(7.134)	(7.105)
Spatially Lagged Flood in heavy monsoon at t-1	-7.944	-8.543	-13.787	-14.925	-5.794	-6.331	3.885	3.930	-11.400	-11.707
	(8.166)	(8.429)	(17.588)	(17.618)	(8.682)	(9.033)	(3.245)	(3.203)	(9.202)	(9.363)
Spatially Lagged Drought in regular monsoon at t-1	1.443***	1.482***	0.716	0.905	1.494***	1.525***	0.566	0.562	1.345**	1.363**
	(0.473)	(0.474)	(1.034)	(1.086)	(0.480)	(0.481)	(0.441)	(0.437)	(0.605)	(0.605)
River Density*Spatially Lagged Flood in heavy monsoon at t-1	50.499	53.906	88.791	94.657	37.890	40.994	-22.105	-22.360	71.901	73.662
	(45.276)	(46.408)	(101.539)	(101.279)	(47.313)	(49.036)	(17.493)	(17.210)	(52.377)	(53.116)
River Density*Spatially Lagged Drought in regular monsoon at t-1	-22.011***	-22.595***	-15.205	-16.557	-24.405***	-24.933***	-9.513**	-9.460**	-19.686**	-19.977**
	(6.557)	(6.626)	(11.579)	(11.415)	(7.091)	(7.188)	(4.715)	(4.672)	(9.061)	(9.110)
Spatially Lagged Total conflicts per square KM at t-1	313.888**	336.353***	-61.381	-7.512	357.506***	376.633***	77.478	75.548	261.236*	271.865*
	(124.942)	(128.865)	(152.113)	(161.851)	(135.438)	(139.279)	(56.922)	(55.259)	(144.203)	(144.914)
HH Head Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,234	5,234	1,075	1,075	4,154	4,154	2,120	2,120	3,113	3,113
R-squared	0.152	0.151	0.112	0.112	0.114	0.113	0.219	0.219	0.155	0.154
Number of districts	69	69	60	60	69	69	67	67	69	69

	Employed (worked in last 12 months)									
Panel B	*All*		*High Skill*		*Low Skill*		*Employed in Formal Sector*		*Employed in informal Sector*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)
Net Migration Rate (cumulative 4yr)	-1.071***	-1.122***	-1.668*	-1.551*	-0.956**	-1.008***	1.240*	1.497*	-2.292***	-2.600***
	(0.323)	(0.329)	(0.916)	(0.890)	(0.377)	(0.380)	(0.739)	(0.829)	(0.873)	(0.984)
Spatially Lagged Flood in heavy monsoon at t-1	-0.218	-0.191	0.676	0.632	-0.390	-0.363	-1.117	-1.255	0.918	1.084
	(0.498)	(0.508)	(1.171)	(1.171)	(0.580)	(0.589)	(1.231)	(1.270)	(1.382)	(1.441)
Spatially Lagged Drought in regular monsoon at t-1	-0.113***	-0.114***	0.016	0.022	-0.118***	-0.119***	-0.050	-0.045	-0.064	-0.070
	(0.034)	(0.034)	(0.104)	(0.106)	(0.035)	(0.036)	(0.082)	(0.082)	(0.091)	(0.091)
River Density*Spatially Lagged Flood in heavy monsoon at t-1	1.384	1.231	-2.999	-2.776	2.294	2.139	6.685	7.461	-5.423	-6.355
	(2.813)	(2.866)	(6.513)	(6.503)	(3.335)	(3.378)	(7.024)	(7.203)	(7.753)	(8.036)
River Density*Spatially Lagged Drought in regular monsoon at t-1	0.296	0.314	-0.832	-0.877	0.476	0.493	-0.165	-0.252	0.461	0.566
	(0.454)	(0.459)	(1.031)	(1.029)	(0.513)	(0.517)	(0.849)	(0.842)	(1.082)	(1.091)
Spatially Lagged Total conflicts per square KM at t-1	-2.482	-3.367	-23.142	-20.972	-0.118	-0.953	19.296	23.784	-21.672	-27.054
	(6.646)	(6.866)	(18.577)	(18.027)	(7.884)	(8.104)	(14.815)	(16.150)	(17.738)	(19.591)
HH Head Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,965	7,965	1,358	1,358	6,604	6,604	7,967	7,967	7,966	7,966
R-squared	0.082	0.082	0.088	0.088	0.090	0.090	0.055	0.055	0.040	0.040
Number of districts	69	69	64	64	69	69	69	69	69	69

	Unemployed (in last 12 months)					
Panel C	*All*		*High Skill*		*Low Skill*	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV(1)	IV(2)	IV(1)	IV(2)	IV(1)	IV(2)
Net Migration Rate (cumulative 4yr)	1.319***	1.383***	1.950**	1.860**	1.305***	1.381***
	(0.363)	(0.378)	(0.850)	(0.872)	(0.395)	(0.406)
Spatially Lagged Flood in heavy monsoon at t-1	-0.093	-0.127	-0.170	-0.136	-0.039	-0.079
	(0.580)	(0.599)	(1.205)	(1.217)	(0.614)	(0.633)
Spatially Lagged Drought in regular monsoon at t-1	0.087	0.088	0.005	0.000	0.089	0.090
	(0.058)	(0.058)	(0.108)	(0.108)	(0.057)	(0.057)
River Density*Spatially Lagged Flood in heavy monsoon at t-1	0.464	0.658	0.249	0.079	0.270	0.499
	(3.414)	(3.515)	(6.787)	(6.838)	(3.607)	(3.705)
River Density*Spatially Lagged Drought in regular monsoon at t-1	0.145	0.123	1.696	1.731	-0.096	-0.122
	(0.744)	(0.743)	(1.116)	(1.102)	(0.798)	(0.797)
Spatially Lagged Total conflicts per square KM at t-1	-2.953	-1.831	17.950	16.292	-8.021	-6.789
	(7.130)	(7.493)	(16.572)	(16.777)	(7.984)	(8.333)
HH Head Controls	Y	Y	Y	Y	Y	Y
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