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Climate shocks, agriculture, and migration in Nepal

Disentangling the interdependencies

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Abstract: Climate change is expected to increase the risk in agricultural production due to increasing temperatures and rainfall variability. Smallholders can adjust by diversifying income sources, including through migration. Most existing studies investigate whether households send a migrant after experiencing weather shocks, but the literature lacks evidence on migration as an *ex-ante* measure. In this paper, we disentangle the direct effect of weather shocks on income from agriculture from the effect of changing weather patterns over a few years on migration as a diversification strategy. Using a novel household survey from Nepal combined with 35 years of rainfall and temperature data, we model migration and agricultural production using a simultaneous estimation methodology. The results confirm the simultaneity of these decisions and show that increasing uncertainty in weather patterns and a warming climate increase outmigration in rural Nepal. These results are in line with the hypothesis that migration acts as an income diversification strategy under climate change.

Key words: climate change, migration, agriculture, simultaneous estimation, Nepal

JEL classification: F22, O13, O15, Q54

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1 Introduction

Climate change is expected to affect communities and households in various ways: through shocks in the form of extreme weather events that make certain areas of the world uninhabitable (including sea level rise and frequent hurricanes, floods, and droughts) and through slow-onset changes that make some livelihood sources less profitable and reliable (including shorter and shifting growing seasons and increased frequency of dry spells, hotter days, and warmer nights). While the damages from extreme weather events tend to be more in urban areas with high population densities, slow-onset events may affect rural livelihoods dependent on rain-fed agriculture more by decreasing incomes and increasing risks (IPCC 2014).

In South Asia, climate change is expected to increase the number of hot days, warm nights, and the frequency of heat waves. Combined with decreases in crop productivity, these projections are expected to significantly increase food insecurity (IPCC 2014). This may consequently push rural people to migrate internally or abroad (ADB 2012), such as in India where inter-state out-migration is found to significantly increase in response to decreased rice and wheat yields (Viswanathan and Kumar 2015). Nepal is a low-income country, where most of the population resides in rural areas and is dependent on smallholder agriculture. Cai et al. (2016) observe that in agriculture-dependent countries a 1°C increase in temperature is associated on average with a 5 per cent increase in the number of international migrants. The unique topography of Nepal and the lack of infrastructure challenge market integration in many parts of the country. Migration, especially to international destinations, is so common that international remittances contribute to around 31 per cent of total gross domestic product (World Bank 2018). Despite the high incidence of migration and the vulnerabilities to climate change, the linkages between climate change and migration in Nepal have been rarely investigated so far in the applied economics literature, which is a gap addressed by this study.

Adaptation to climate change is one of the drivers of migration in the literature. Slow-onset events that change the risk profile of livelihood activities (in unexpected ways) can act as push factors for migration. The decision to migrate is both a function of the ability to migrate and the incentives to do so. Climate change is likely to decrease the former while increasing the latter (Black et al. 2011; Gemenne 2011). There is no general agreement on whether climate change will increase or decrease migration due to inherent non-linearity in this relationship, as well as differences between various durations and destinations of migration. Furthermore, the decision to send a household member as a migrant can present either a reaction (*ex-post*) to an adverse income shock or an (*ex-ante*) adaptation strategy to a changing climate where income diversification becomes more important, especially for households that rely on agriculture.

Studies on climate change and migration have mostly used cross-country analyses to identify significant correlations between temperature increases and emigration (Barrios et al. 2006; Cai et al. 2016; Cattaneo and Peri 2016). These correlations are more pronounced in countries that are highly dependent on agriculture. At the micro-level, there is growing evidence for significant effects of climate change, including increasing temperatures, variations in rainfall, and short-term shocks, on migration (Baez et al., 2017; Bohra-Mishra et al. 2014, 2017; Dallmann and Millock 2017; Jessoe et al. 2016; Mueller et al. 2020; Thiede et al. 2016; Williams and Gray 2019). Most of these studies, however, focus on migration as a response to weather shocks, rather than its potential as an *ex-ante* adaptation strategy, nor do they allow for the simultaneity in labour allocation decisions.

At the same time, there is increasing micro-econometric evidence on the effects of climate change on agricultural production. The increasing extreme weather events and slow-onset changes have been shown to significantly affect agricultural output not only directly but also through changes in input and technology use (Alem et al. 2010; Arslan et al. 2013, 2017; Asfaw et al. 2016; Kassie et al. 2015).[1]

We contribute to both strands of literature by disentangling the direct impact of climate change on the migration decision from the indirect effect through agricultural production in the context of a household's diversification strategy. Using unique household survey data enhanced by high-resolution climate data, we model the migration decision and agricultural productivity simultaneously by controlling for a set of climatic variables. In addition to standard variables to control for weather in the agricultural production model, we define variables that characterize long-run (LR) changes in levels and variability of weather preceding the migration decision. These variables help us capture both the strategic adaptation to a changing climatic environment as well as the pure impact of weather.

We estimate a system of equations allowing for correlation between the error terms without the requirement for exclusion restrictions. This approach also addresses the potential omitted variable bias in studies of weather impacts on migration that exclude income. Furthermore, it allows us to test and control for the simultaneity of household income diversification and agricultural production decisions. This is a distinction that is lost in studies of the unidirectional effect of income shocks on migration decisions.

We find that households in our sample use migration of a household member as an adaptation strategy to LR indicators of climate change. Seasonal rainfall and its positive deviation from the LR average significantly increase crop production, and only through this channel negatively affect the migration decision. Deviations of rainfall patterns, both in levels and variation, in the past 3 years compared with the past 35 years significantly affect the migration decision, as does a steeper increase in monsoon season temperature over the past 35 years. The more adverse the weather for crop production, the more likely households are to send a migrant to work abroad. The findings related to rainfall are independent of a household's engagement in other non-farm income generating activities, while households with larger non-farm income shares are significantly less likely to send a migrant in response to a steeper increase in temperature.

We review the literature in Section 2 and describe our household and climate data in Section 3. We lay out a conceptual framework in Section 4, followed by descriptive statistics in Section 5. We present our findings in Section 6 and conclude in Section 7.

2 Literature review

The question of whether and how climate change affects migration decisions has been receiving more attention recently due to its importance in the political discourse (e.g., Foresight 2011), as well as the increasing availability of better data, especially to measure weather and climate variations. The climate–economy literature uses long difference estimations for more robust estimates of the impact of climate on economic outcomes, but has found little difference between short and long-term effects (Dell et al. 2012; Hsiang 2016). In an aggregate analysis, Weinreb et al. (2020) find that decreases in rainfall and increases in variability of temperature in 41 Sub-Saharan

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[1] See Arslan et al. 2020 (the references therein) for a meta-analysis of this literature.

African countries increased rural net out-migration over the 1980–2015 period, and the effects intensified during this period. Two other studies investigate climate measures over longer time periods as drivers of migration decisions (Dallmann and Millock 2017; Falco et al. 2018)—inter-state in India and international, respectively. Their findings confirm that these LR weather changes also significantly increase out-migration rates.

Household-level evidence on the linkages between migration and slow-onset changes in climate is scant. Massey et al. (2010) find that perceived declines in productivity and declining land cover (among other reasons), which may be expected to get more severe with climate change, predict both short- and long-distance migration in Nepal, although the relationship is stronger for the former. Two recent studies by Mueller et al. (2020) and Gray and Wise (2016) show how weather anomalies over the past 2 years relative to the past 30 years significantly predict migration in Africa at individual and household levels, respectively. Conceptually closer to our study, Dillon et al. (2011) and Quiñones (2019) explore the use of migration as a household strategy to cope with *ex-ante* risk. Using data on the migration patterns of a sample of individuals in Northern Nigeria over a 20-year period, Dillon et al. (2011) find that households use domestic migration as a strategy to mitigate the agricultural risks linked to weather-related variability and shocks. Their study highlights strong findings that male household members migrate in response to *ex-post* shocks and provides only suggestive evidence that migration is also an *ex-ante* risk mitigation strategy. Quiñones (2019) examines how households in rural Mexico adjust labour allocation based on having observed climate-induced crop losses of other households in their community, but not having themselves experienced crop loss. Community-level crop losses are instrumented by a measure of extreme heat deviations (relative to the long-term average). The study finds strong impacts on domestic migration, especially among women, providing evidence that it is used as an *ex-ante* household adaptation strategy aimed at mitigating the risks of future crop shocks.

To the best of our knowledge no research has focused on the short- and long-term relationships between weather variations and migration decisions of rural households in Nepal. The contribution of this paper to the literature is threefold. Conceptually, we contrast household responses as part of the adaptation strategy with those of responses to a shock and provide evidence at the micro-level to a literature that is so far dominated by cross-country studies or studies at the aggregate level. Methodologically, the estimation of a simultaneous equation model captures the interdependency between decisions on agricultural production and migration of a household member in line with 'new economics of labour migration' (NELM) models, as opposed to a unidirectional relationship mostly found in the literature. Lastly, the findings of this study are relevant for policy given Nepal's high vulnerability to climate change and out-migration rates. Despite pressing needs for evidence on the impacts of climate on migration for this country, so far little exists.

3 Data

3.1 Household data

Household data were collected in August 2017 and capture detailed information on migration as well as on agricultural production, employment, and income of 1,002 rural households (Nepa School of Social Sciences and Humanities 2017). The sample was drawn using stratified three-stage random sampling from five districts (of which it is representative), and covers two ecological zones (hills and the Terai region) and five former developmental regions. The five districts (Jhapa, Makwanpur, Nawalparasi, Rolpa, and Achham) were purposefully selected in consultations with local experts to reflect the agro-ecological diversity of the country and based on available information about migration flows and stocks from the most recent census. In each district, first five village development committees (VDCs) and then two wards in each VDC were randomly selected. In each sampled ward, 20 households were randomly selected through a stratification based on the presence of a migrant in the household to ensure that households with migrants represent around half of the sample.

The questionnaire covers detailed information on the characteristics and determinants of different types of migration including current, past, international, internal, and seasonal migration. It also includes a detailed module on agricultural production. Given that agriculture in Nepal is not specialized on one crop only, we use the value of total agricultural production from all crops cultivated by a household in the last 12 months.

For the analysis, we only use households with at least one member working as a farmer (96 per cent of the total sample) resulting in 964 households, of which 470 have a current migrant. Migrants are household members, defined in terms of sharing food from a common source with other members when present, who currently live in another locality or country. Among all migrant households, 80 per cent have a migrant in another country, 15 per cent within Nepal, and 5 per cent both, while 40 per cent (189 households) have migrants that moved within the year before the survey. Given that our estimation strategy models migration and agricultural decisions simultaneously, the sample used in the analysis consists of the 189 households with recent migrants and 494 households without a current migrant.

3.2 Climate data

The data on climatic trends and weather variations used for this study include various measures of rainfall and temperature. We use data captured in dekads, each 10 days of a month, over the period from 1981 to 2016. The amount of total rainfall per dekad was obtained from the Climate Hazards Group InfraRed Precipitation with Station data. It was measured at the 0.05 grid level (~5×5 km at equator) and then calculated for the study areas (wards, districts, provinces). Average, maximum, and minimum temperature per dekad come from the European Reanalysis Interim source at 0.75° spatial resolution (~80 km at equator) and were equally calculated for the study areas. The geo-referenced household locations are used to merge household and climate data.

4 Conceptual framework and econometric specification

4.1 Conceptual framework

We follow the NELM literature and model migration as a household decision in the context of market failures (Stark and Bloom 1985). Agricultural households are assumed to be utility maximizing and engaging both in consumption and in production. Under imperfect markets, risk averse agents will not be able to separate consumption from production decisions (de Janvry et al. 1991). Production decisions, therefore, will be expected to depend also on factors such as household composition and wealth (Benjamin 1992), and the migration decision can be driven by, as well as have an effect on, both consumption and production.

Utility depends on consumption and leisure, subject to budget and time constraints. Income is generated through agricultural production and migration. Production depends on labour (both family and hired), capital, inputs, land, and weather. The weather is exogenous; land is assumed to be fixed and is treated as exogenous. The choice variables are capital, inputs, and labour. The decisions related to labour are closely related to the migration decision. The returns to migration are the wages at destination minus migration costs. If these are above the shadow wage of leisure at home, migration is positive, but it reduces the amount of time that remaining household members can split between agricultural labour and leisure, implying an increase in the shadow wage (De Brauw 2010; Wouterse and Taylor 2008). This could directly affect production through a decline in agricultural labour if labour markets are imperfect. However, the net-effect also depends on the cross-price elasticities of other inputs, whether they are complements or substitutes, and how their adoption is affected by migration. These effects cannot be predicted theoretically and must be established empirically.

Climate change enters this setting through the effect of weather on income generation. Weather shocks can directly affect output (e.g., by ruining crops), but they can also affect input and technology choices (Alem et al. 2010; Arslan et al. 2013, 2017, 2020; Asfaw et al. 2016; Kassie et al. 2015) and labour allocation. Increasing occurrence of extreme weather events imply an increase in risk, so that risk averse agents are likely to reduce adoption of risky inputs and increase adoption of risk-reducing inputs. Migration is one way to reduce risk by diversifying income sources across space and activities. Internal or international migration implies that income is either earned outside of agriculture and is less dependent on weather variation, or even if it is in agriculture it takes place in destinations with climatic conditions that are uncorrelated or negatively correlated with those in the origin. At the same time, migration reduces agricultural labour supply, which affects productivity in the absence of perfect labour markets. The decisions about whether to send a household member as a migrant and which inputs to allocate to agricultural production can thus be seen as simultaneous and are directly and indirectly shaped by changing weather patterns.

4.2 Empirical strategy

Following the conceptual framework, the empirical analysis models the simultaneous decisions on migration and agricultural production. This helps us to test the simultaneity and disentangle the direct effect of climate change on the migration from the indirect effect mediated through agricultural production. The migration decision of household i is a function of changing LR weather patterns in village v, W_v^{LR}, income from various sources, Y_i, and household characteristics, X_i. Income sources are non-agricultural activities (from self-employment Y_i^{na} and wage work Y_i^{wage}), as well as agricultural productivity, Y_i^a:

$$M_i = M\left(W_v^{LR},\ Y_i\left(Y_i^a, Y_i^{na}, Y_i^{wage}\right), X_i\right) \tag{1}$$

Agricultural productivity itself depends on the weather during the cropping year, W_v. It also depends on capital including land, household labour, and purchased inputs (I_i), such as fertilizers and hired labour, as well as household characteristics relevant for the agricultural production process (Z_i).[2] Household labour implicitly captures migration as the labour units available depend on household size. The agricultural production function can thus be written as:

$$Y_i^a = AP(W_v,\ I_i, Z_i, M_i) \tag{2}$$

We focus on agricultural productivity (measured by value of production per hectare) based on the assumption that the simultaneous decision regarding input and labour allocation relates to efficiency concerns (i.e. to equalize the marginal returns across activities). We also run the

[2] X and Z both indicate household characteristics, but the set of characteristics is different. X is related to characteristics relevant for the migration decision, whereas Z includes those relevant for the agricultural production process. They are listed in detail later.

regressions using the total value of agricultural production (not per hectare) and discuss results in Section 6.3.

If the two decisions are made at the beginning of the year, sending a household member away has direct implications for the labour available and other input choices, thus affecting agricultural productivity and other incomes. We, therefore, estimate both functions in a fully recursive system of equations:

$$M_i = f\left(W_v^{LR}, Y_i^a, Y_i^{na}, Y_i^{wage}, X_i\right) + \epsilon_i \tag{3}$$

$$Y_i^a = g(W_v, I_i, Z_i, M_i) + \varepsilon_i \tag{4}$$

Agricultural productivity is measured by the total value of all crops harvested per cultivated hectare and is estimated using an ordinary least square specification.[3] The variables capturing weather are the total rainfall in the monsoon season (June–September) in 2016 (the growing season that determines the production value reported in 2017) and its squared term to allow for a non-linear relationship.[4] We also include the percentage deviation of the seasonal rainfall from its long-term average to control for positive or negative rainfall shocks. Temperature is not included because of its high correlation with rainfall in the year 2016 across study areas.[5] *I* is the vector of inputs: total land size, number of working-age household members as proxy for household labour, crop diversification index, and the expenses on purchased inputs (chemical and organic fertilizers, pesticides and herbicides, hired labour). Household characteristics, Z_i, include an indicator for whether the household head belongs to the majority ethnic group of a district to capture access to networks for informal insurances and markets. Other controls are household head's age (capturing experience) and gender, as women often face socially imposed constraints in accessing essential inputs resulting in lower productivity. The highest education level of adult household members is used as a measure for available knowledge. We also include a dummy variable for the Terai agro-ecological zone, which is highly correlated with altitude in the sample.

The migration variable, M_i, is equal to one if the household has sent a migrant within the preceding 12 months and is estimated using a probit specification. Main climatic variables of interest in this model aim to capture slow-onset changes. These variables include the coefficient of variation (CoV) of seasonal rainfall for the past three years prior to the year of migration relative to the CoV of the LR (1981–2016). This variable captures the change in the variability of rainfall, which is expected to increase the variability of agricultural productivity. To capture the changes in levels of rainfall (temperature), we use the *z*-score, which is computed as the deviation of average seasonal rainfall (temperature) over the past 3 years from the LR average standardized by the LR standard deviation of rainfall (temperature). This is a measure commonly used in the climate change literature (Gray and Wise 2016). We construct two separate variables for each of these anomaly measures: the absolute value of positive and negative deviations. This allows anomalies in different directions to have different impacts on migration. Finally, we use a novel variable to capture the

[3] Crops include cereals, tubers, legumes, and vegetables. Harvest is valued using median unit values at the ward or district level and quantities of harvest reported by the households.

[4] While some households might also grow winter crops (Poudel and Kotani 2013), the survey does not allow us to differentiate between winter and monsoon production. Therefore, we estimate the model for total annual agricultural production using weather variables measured in the monsoon season, as it is the main rainfall and growing season. See Appendix Figure A1 for monthly rainfall in the past 35 years used to identify the main season.

[5] We estimate the model using temperature instead of rainfall and find that temperature is insignificant with the exception for higher maximum temperature in the sub-sample of households in the ecological zone of the hills (i.e. at higher altitudes). There, it has a negative effect on agricultural output.

effects of LR increases in temperature on migration. For each ward, we run a simple linear regression of average seasonal temperature over time (using all values over the 35 years) and use the estimated slope coefficients of the time dummy (the slope of the fitted line) for each ward as a measure of long-term changes in seasonal temperature.

The migration model also controls for household characteristics specific to the migration decision, X_i. These include household income diversification with dummies for whether the household earns any income from non-farm enterprises or wages. A dummy variable indicating whether a relative has migrated in the past controls for migration networks (Munshi 2003). The wealth index captures the potential liquidity constraints, as the poorest households are less likely to be able to afford migration (McKenzie and Rapoport 2007).[6]

4.3 Econometric considerations

The system of Equations (3) and (4) is estimated in a fully recursive conditional mixed process model that allows for error correlation. Our approach assumes that the input choices and migration decisions are made simultaneously. By restricting our sample only to households that have sent a migrant within the preceding 12 months, this assumption is more likely to hold as the households had to decide whether to send a migrant and how much labour (and other inputs) to dedicate to agricultural production subject to climatic expectations built over the preceding years.

Other studies exploit two data points over time in a panel data setting to identify the effect of weather shocks on migration by measuring changes between the two waves of the survey. Given our cross-sectional data, we use an innovative way to address simultaneity in the absence of panel data, which is difficult to come by. The climate-economy literature raises the issue of potential omitted variable bias when estimating the effect of climate on migration, arguing that weather variables could be correlated with other factors that affect migration, such as income. The simultaneous estimation allows for this correlation by modelling it directly. The inclusion of several relevant variables in the migration model should further reduce concerns about omitted variable bias.

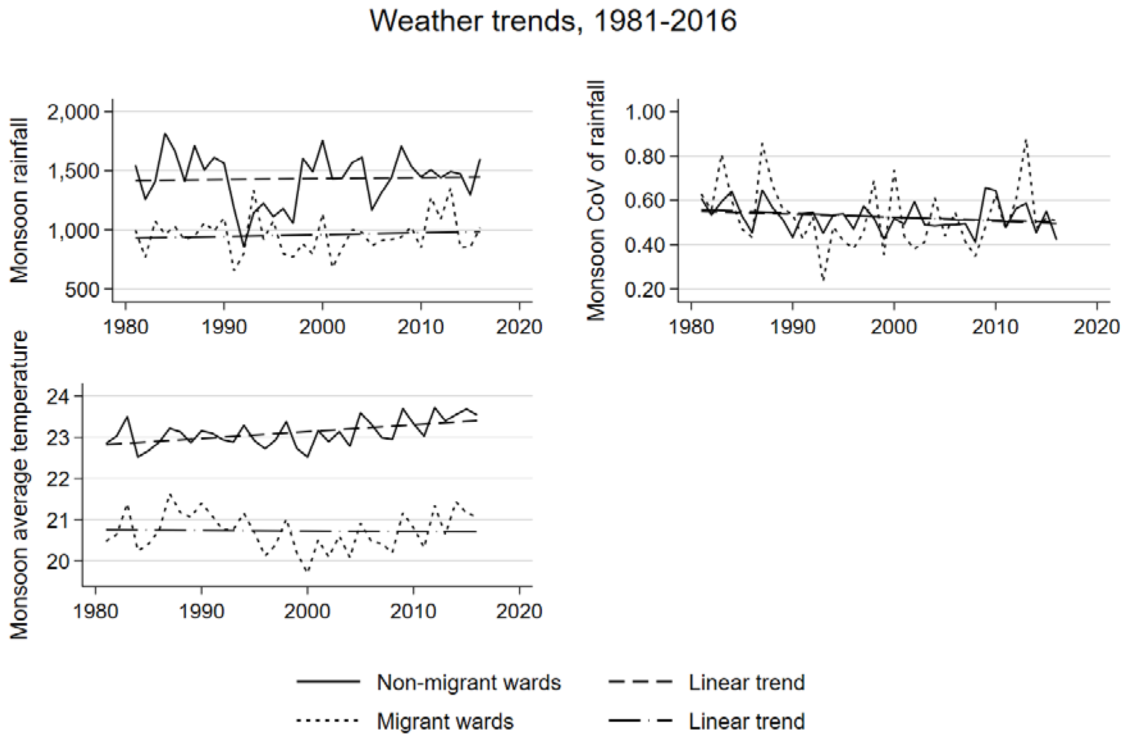
5 Descriptive statistics

5.1 Climate

Figure 1 shows the average monsoon rainfall and mean temperature at ward level over the past 35 years (1981–2016) with a fitted line that depicts the general trend over time. The CoV of dekadal rainfall is plotted next to it to capture the changes in rainfall variability over this period. For descriptive purposes, we differentiate between migrant wards (those with a share of migrant households above the median) and non-migrant wards (those with a share below the median). Although the total amount of monsoon rainfall has only increased minimally, its variability seems to have declined equally in migrant and non-migrant wards. Despite a similar trend in rainfall variability, migrant wards show relatively more extreme values of higher rainfall variability especially in more recent years (peaks in Figure 1).

[6] The wealth index is computed with principal component analysis from housing quality, drinking water source, electricity access, and the mode of transport to nearest town/market.

Figure 1: Trends in total monsoon rainfall, CoV of monsoon rainfall, and average monsoon temperature in wards with above and below median migrants



Note: CoV, coefficient of variation.

Source: authors' compilation.

Comparing the CoV of the past 3 years with that of the past 35 years is expected to show relatively more positive deviations in migrant than in non-migrant wards. Monsoon average temperature has increased by around 0.5°C in the same period motivating our measure of long-term temperature increase.[7] The upward temperature trend is steeper in non-migrant wards over the 35-year period. During the most recent years, however, temperature has been rising more in migrant than in non-migrant wards, with more years of positive deviations from the LR trend. We thus expect the temperature *z*-score to significantly affect the migration decision. Overall, most migrants come from wards in colder areas with lower levels of monsoon rainfall.

Poudel and Kotani (2013) show that increasing rainfall variance is associated with lower yields. This is attributed to the fact that smallholders in Nepal primarily rely on rain-fed farming. The observation that wards with larger migrant shares face generally lower rainfall but more variations and strong seasonal dependence under growing temperatures points at the vulnerabilities of farming households in these areas.

Table 1 presents summary statistics of our rainfall and temperature variables for migrant and non-migrant households. The first three are variables included in the agricultural production function: annual monsoon rainfall and its positive and negative deviations from the previous 35-year average. Average rainfall in the study year was between 1,500 and 1,600 mm and around 15 per

[7] The average minimum dekadal winter temperature at ward level in our sample has increased by almost 2°C in the period from 1981 to 2016.

cent above the LR average. There was no significant difference in rainfall experienced by migrant and non-migrant households. The lower panel ('Long-term weather variation relevant for migration decision') of Table 1 summarizes the variables measuring rainfall or temperature changes over several years prior to the study relevant for the migration decision. There are significant differences in the deviations from the LR measure between locations where migrant and non-migrant households live. Migrant households experienced relatively smaller positive and larger negative rainfall deviations over the past three years relative to the previous 35 years (positive *z*-score).

Table 1: Summary statistics of weather variables at ward level, by migrant status of households.

	Migrant households		Non-migrant households		Mean difference
	Mean	SD	Mean	SD	
Rainfall relevant for agricultural production					
Total ward rainfall (100 mm)	15.32	4.49	15.74	4.61	−0.41
Positive % deviation from LR average	15.03	10.81	16.13	10.97	−1.10
Absolute negative % deviation from LR average	0.00	0.05	0.01	0.09	−0.01
Long-term weather variation relevant for migration decisions					
Positive *z*-score of 3-year rainfall	0.22	0.24	0.32	0.36	−0.10***
Absolute negative *z*-score of 3-year rainfall	0.04	0.08	0.02	0.05	0.02***
Positive *z*-score of 3-year temperature	1.20	0.19	1.05	0.38	0.153***
Absolute negative *z*-score of 3-year temperature	0.00	0.00	0.00	0.04	−0.003
Absolute positive % deviation of CoV of 3-year rainfall from LR	0.00	0.00	0.04	0.79	−0.04***
Absolute negative % deviation of CoV of 3-year rainfall from LR	46.45	24.98	51.76	23.81	−5.31**
LR slope of average temperature	0.03	0.01	0.02	0.01	0.00
No. of observations	189		494		

Note: SD, standard deviation; LR, long run; CoV, coefficient of variation. Point estimates are sample means. Asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01.

Source: authors' compilation.

Similarly, migrant households experienced relatively larger positive temperature deviations (positive *z*-score). There are only three observations with a negative temperature *z*-score, which explains the lack of variation. We saw in Figure 1 that rainfall variability has been decreasing over the 35 years preceding the survey. Yet, in the 3 years before the survey, this decrease was less pronounced in locations where migrant households live as the lower value of the absolute negative deviation of the CoV shows. There was only one observation with a positive value of the CoV deviation, so this variable drops from the analysis. There does not seem to be a significant difference in the 35-year temperature increase (measured by the estimated LR slope) between migrant and non-migrant households.

5.2 Household characteristics

Migrant and non-migrant households live equally distributed between the hills and the Terai region (Table 2). The average migrant household is slightly smaller and they have on average fewer working-age members than non-migrant households, confirming the expectation that migration implies a loss in household labour. Around 47 and 43 per cent of migrant and non-migrant households, respectively, belong to the majority ethnic group in their district in line with the fact that ethnic groups in Nepal are spatially concentrated. There is no indication that the migrant households are statistically more likely to have access to this kind of social network. However, migrant households are significantly more likely to have a relative, who has migrated in the past, pointing at the importance of migrant networks. In terms of destination of international migrants, the majority moved to the Gulf, and around 30 per cent to neighbouring India, followed by Malaysia. Migration to the Gulf or Malaysia require significant capital to finance the move mostly through agents, whereas the porous border to India allows for seasonal mobility also among poorer households.

Table 2: Main characteristics of migrant and non-migrant households

	Migrant households		Non-migrant households		Mean difference
	Mean	SD	Mean	SD	
Ecological zone	0.66	0.48	0.61	0.49	0.049
Household size (excluding migrant)	4.2	1.96	4.9	1.78	−0.747***
Number of working-age household members	2.46	1.46	3.04	1.29	−0.576***
Dominant ethnic group in district	0.47	0.50	0.43	0.50	0.032
Migration of relative of household	0.47	0.50	0.35	0.48	0.115***
Number of past migrants in household	1.19	1.07	1.28	1.14	−0.087
Ward share of migrants in India	0.30	0.36	0.27	0.35	0.031
Ward share of migrants in Gulf	0.48	0.33	0.52	0.32	−0.032
Ward share of migrants in Malaysia	0.17	0.20	0.17	0.18	0.003
Ward share of migrants in other destinations	0.05	0.09	0.05	0.09	−0.002
Wealth index	−0.01	0.10	-0.00	0.10	−0.014
Female household head	0.19	0.39	0.10	0.31	0.085***
Household head can read and write	0.50	0.50	0.57	0.49	−0.072*
Highest level of education in household (including migrant)					
Never attended school	0.07	0.02	0.16	0.02	−0.084***
Class 1–5	0.19	0.03	0.23	0.02	−0.042
Class 6–12	0.68	0.03	0.57	0.02	0.110***
Higher education	0.06	0.02	0.04	0.01	0.016
Agricultural production					
Productivity (value of agricultural production per hectare,100 rupees)	53,119	327,827	55,370	5,723,510	−2,252
Output (value of agricultural production, 100 rupees)	25,110	50,911	27,000	182,640	−1,890
Total land cultivated (hectare)	0.61	0.52	0.61	0.48	−0.0
Crop diversity index (count)	4.9	3.1	5.4	3.3	−0.4
Expenses on chemical fertilizers, pesticides, and herbicides, (100 rupees per hectare)	69	374	67	376	1.5
Expenses on organic fertilizers (100 rupees per hectare)	96	140	101	414	−4.8
Expenses for labour (100 rupees per hectare)	90	214	185	1,770	−94.5
Total household hours worked as farmer in past 12 months	3,040	2,368	3,027	2,122	13.2
Total per capita hours worked as farmer in past 12 months	807	649	648	464	159***
Income sources					
Non-agricultural self-employment income, dummy	0.14	0.35	0.22	0.41	−0.07**
Non-agricultural self-employment share of income	0.08	0.23	0.13	0.29	−0.05**
Non-agricultural wage work income, dummy	0.22	0.42	0.28	0.45	−0.06**

Non-agricultural wage work share of income	0.15	0.30	0.18	0.32	−0.03**
Income source diversity index (count)	2.3	0.93	2.6	0.99	−0.3**
Household received remittances in past 12 months	0.8	0.42	0.1	0.24	0.7**
Probability to receive remittances	0.4	0.09	0.4	0.09	−0.0**
Amount of remittances received in past 12 months (100 rupees)	2,684	19,964	572	11,252	2,111.4**
No. of observations		189		494	

Note: asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Income measures exclude remittances.

Source: authors' compilation.

There is no indication of a significant difference between migrant and non-migrant households in terms of the wealth index. Most migrants are male, and hence relatively more migrant households are female-headed (19 per cent versus 10 per cent). The heads of non-migrant households are on average better educated than those of migrant households, which could also be related to the fact that the latter are often female and that female school enrolment in Nepal has only recently caught up with male enrolment (World Bank 2017). When considering the highest level of education achieved in a household including migrant members, the picture changes. Relatively more migrant households have a member with higher education than non-migrant households. Migrants in our sample are on average the better educated household members, suggesting that families also lose substantial human capital.

The second panel ('Agricultural production') of Table 2 provides summary statistics of agricultural production. There is no statistically significant difference between migrant and non-migrant households in total or per hectare value of agricultural production. Households in our sample are smallholders with only around 0.6 hectare of farmland. Households grow on average around five different crops, without a statistically significant difference between migrant and non-migrant households. In terms of the amount spent on inputs such as fertilizers and labour, there is also no statistically significant difference between the two types of households. Hired labour is among the most expensive input, indicating that a loss in household labour due to migration is not easily substitutable through hired labour. While total hours of household labour dedicated to farming is not different between household types, per capita hours indicate that migrant household members work significantly more per person, potentially to compensate for the decrease in labour due to migration.

In terms of other income-generating activities, we present in the bottom panel ('Income sources') of Table 2 the summary statistics of engagement in non-agricultural income-generating activities (for self- or wage-employment), as well as income diversity index and remittance receipts.[8] Migrant households are significantly less likely to have a member running a non-farm business, which is also reflected in a significantly lower share of non-farm business income in the total household income (excluding remittances). The same applies for non-agricultural wage work. As expected, migrant households on average receive much larger amounts of remittances than non-migrant households.

[8] Remittance receipt is not restricted to remittances from current migrants. Thus, both migrant and non-migrant households may receive remittances from someone living outside of the household, who does not identify as a migrant household member in the data.

6 Findings

6.1 Main findings

In Table 3, we present the main results from the simultaneous estimation of the agricultural productivity function and the migration decision. The coefficients in the upper panel are those from the estimation of the probability that a household has a migrant controlling for different LR weather variables. The lower panel ('Log(Value of total crop production per hectare)') of Table 3 lists the estimates of agricultural output per hectare with the same control variables across columns. The final three coefficient rows (gamma1_2, gamma2_1, and atanhrho_12) stem from estimating a fully recursive system of equations and show the coefficients of the outcome variable of one model in the equation of the other model, as well as the correlation of the error terms between the two equations (atanhrho_12). Column 1 includes the positive and negative rainfall z-score, Column 2 the CoV of rainfall, Column 3 the indicator of the LR temperature increase, and Column 4 the positive temperature z-score. As noted, there were only three observations with negative temperature z-scores. These variables are included separately as the inclusion of all of weather variables simultaneously would create multicollinearity issues.[9]

Table 3: Results of fully recursive simultaneous regressions of migration decisions and agricultural productivity

	(1)	(2)	(3)	(4)
	Probability (migrant=1)			
Positive *z*-score of 3-year rainfall	−0.767**			
	(0.319)			
Negative *z*-score of 3-year rainfall	1.225*			
	(0.730)			
Negative absolute % deviation of 3-year CoV rainfall		−0.002		
		(0.002)		
35-year slope of average temperature increase			25.554**	
			(12.657)	
Positive *z*-score of 3-year temperature				1.952***
				(0.428)
Non-agricultural self-employment income (dummy)	−0.087	−0.055	−0.089	−0.246
	(0.096)	(0.097)	(0.095)	(0.155)
Non-agricultural wage work income (dummy)	−0.107	−0.088	−0.110	−0.234**
	(0.083)	(0.101)	(0.096)	(0.116)
Migration of relative of household	0.183*	0.125	0.181	0.384***
	(0.105)	(0.127)	(0.114)	(0.142)
Number of past migrants in household	−0.014	0.034	0.013	−0.027
	(0.040)	(0.030)	(0.032)	(0.063)
Ward share of migrants in India	0.201	−0.073	0.445	0.833**
	(0.318)	(0.310)	(0.401)	(0.421)
Ward share of migrants in the Gulf	0.220	0.047	0.169	0.169
	(0.186)	(0.201)	(0.176)	(0.364)
Asset index	−0.026	−0.063*	−0.027	0.034
	(0.039)	(0.037)	(0.043)	(0.073)
Household size	−0.084**	−0.077	−0.072	−0.128***

[9] All regressions are estimated using the cmp command in Stata. We run the same regressions using variables specified for 5 years, instead of 3 years, before migration for robustness checks. The results are presented in Appendix Table A1.

	(0.042)	(0.060)	(0.048)	(0.039)
Highest level of education in household including migrant (base=has never attended school)				
Class 1–5	0.437***	0.427***	0.460***	0.397*
	(0.144)	(0.166)	(0.144)	(0.219)
Class 6–12	0.760***	0.749***	0.786***	0.754***
	(0.122)	(0.192)	(0.128)	(0.186)
Higher education	0.914***	0.828***	0.912***	0.732**
	(0.230)	(0.285)	(0.239)	(0.357)
Constant	11.411***	8.153***	10.073***	5.937**
	(2.183)	(2.824)	(2.611)	(2.458)
	Log(Value of total crop production per hectare)			
Total monsoon rainfall	0.203***	0.151*	0.207***	0.189**
	(0.068)	(0.089)	(0.077)	(0.082)
Monsoon rainfall squared	−0.006***	−0.004	−0.006**	−0.005**
	(0.002)	(0.003)	(0.002)	(0.003)
Percentage deviation of seasonal rainfall from LR monsoon average				
Positive	0.012*	0.011	0.014**	0.011
	(0.007)	(0.007)	(0.007)	(0.007)
Negative	−0.004	0.043	0.052	0.012
	(0.116)	(0.134)	(0.122)	(0.181)
Log(total land cultivated in hectare)	−0.206***	−0.212**	−0.192**	−0.295***
	(0.070)	(0.086)	(0.080)	(0.059)
Crop diversity index (count)	0.049***	0.047**	0.045**	0.066***
	(0.016)	(0.020)	(0.019)	(0.014)
Log(expenses in 100 rupees per hectare)				
Chemical fertilizers, pesticides, and herbicides	0.037**	0.037*	0.033**	0.055***
	(0.016)	(0.020)	(0.016)	(0.018)
Organic fertilizers	0.000	0.001	0.002	0.005
	(0.011)	(0.012)	(0.011)	(0.017)
Hired labour	0.015*	0.013	0.013	0.020*
	(0.008)	(0.009)	(0.008)	(0.010)
Ecological zone (hills=1, Terai=0)	−0.070	0.005	0.037	−0.034
	(0.078)	(0.072)	(0.068)	(0.090)
Number of working-age household members	0.002	−0.002	0.008	0.028
	(0.018)	(0.016)	(0.017)	(0.023)
Member of dominant ethnic group in district	0.066	0.056	0.054	0.092
	(0.050)	(0.060)	(0.054)	(0.066)
Female household head	−0.081**	−0.081*	−0.085*	−0.129**
	(0.040)	(0.047)	(0.046)	(0.058)
Age of household head	0.000	0.001	−0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Highest level of education in household excluding migrant (base=has never attended school)				
Class 1–5	0.136**	0.170**	0.164***	0.068
	(0.055)	(0.069)	(0.059)	(0.073)
Class 6–12	0.241***	0.286***	0.262***	0.104
	(0.087)	(0.097)	(0.085)	(0.099)
Higher education	0.296**	0.309*	0.323**	0.092
	(0.148)	(0.159)	(0.152)	(0.135)
Constant	9.466***	9.785***	9.245***	9.882***

	(0.499)	(0.603)	(0.543)	(0.718)
Gamma1_2=coefficient of agricultural production in migration	−1.102***	−0.810***	−1.069***	−0.822***
	(0.202)	(0.271)	(0.237)	(0.199)
Gamma2_1=coefficient of migration in agricultural production	−0.176	−0.317*	−0.212	−0.002
	(0.108)	(0.192)	(0.148)	(0.057)
Atanhrho_12 (error correlation of two equations)	1.268***	1.275**	1.315***	0.591**
	(0.398)	(0.595)	(0.484)	(0.246)
Observations	625	625	625	625
Chi-squared	788.24	636.645	658.207	573.989

Note: CoV, coefficient of variation; LR, long run. Column 1 includes the positive and negative rainfall *z*-score, Column 2 the CoV of rainfall, Column 3 the indicator of LR temperature increase, and Column 4 the positive temperature *z*-score. Asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Standard errors in parentheses; they are clustered at ward level.

Source: authors' compilation.

The error correlation coefficients reported in the last row are always significant, confirming that production and migration decisions in our sample are correlated underlining the importance of modelling them simultaneously. Looking at the results for the migration model (upper panel ('Probability (migrant=1)'), Column 1), we find that the higher the *z*-score of dekadal rainfall of the most recent three monsoon seasons relative to the 35-year average, the less likely is a household to have a migrant; in turn, negative deviations of rainfall show a positive significant impact on migration even larger than the negative one. As all households in the sample are farmers, they do not send a migrant member when rainfall has been relatively high and thus are associated with higher agricultural productivity. This finding is also confirmed by the significant and negative coefficient of agricultural productivity in the migration regression (gamma1_2). Worsening climatic conditions in the form of lower rainfall leading up to the migration year, in turn, incentivizes households to send a migrant.

The indicators for households with non-farm income (either from wage work or self-employment) show negative but insignificant coefficients in the migration model. As expected, households with prior migration experience among their relatives are more likely to have a migrant, suggesting that migrant networks lower migration costs (both monetary and psychological), even though the number of previous migrants within the same household does not make a difference. In terms of most likely destinations for migrants which are associated with different types of migration, there is an indication of a higher likelihood for migration if relatively more migrants within a ward migrated to India, a destination more easily accessible for less wealthy households. This could be relevant in the context of subsistence agriculture. This coefficient, however, is only significant in Column 4.

The wealth index is not a significant predictor of migration in this specification. Household size is negatively correlated with migration as households with migrants are by definition smaller than those without migrants. Yet, as we simultaneously control for the agricultural production process where household labour was not significant, it appears that labour availability might not be a binding constraint in this setting. Finally, the significantly positive coefficients of better education in the majority of cases suggest a clear positive selection into migration. Even though not always significant, these relationships between the control variables and the migration decision remain the same across specifications.

Column 2 presents the results for the specification with negative deviations of the rainfall CoV, indicating decreasing variability. The positive deviation variable drops out of this model as there were only three observations with positive values. We do not find a significant relationship between the decline in 3-year rainfall variability relative to LR variability and the probability of migration. Yet, this measure might not be capturing the variability that matters for migration decisions as we saw from the significant results of the rainfall *z*-score. It should be noted that the CoV measures within-season dekadal variation, whereas farmers might pay more attention to between-season variation over several years, captured by the *z*-scores.

When we use the temperature variable to capture the effects of climate change (Columns 3 and 4), we find that increasing monsoon temperatures over 35 years significantly predicts migration (Column 3). Higher temperatures during the monsoon season can lead to crop loss and dryness, so that harvests are negatively affected increasing the need for income diversification outside of weather-dependent agriculture. In Column 4, we also look at temperature variability in the past 3 years relative to the LR measured by the *z*-score. In this model as well, higher temperatures are associated with a higher likelihood to have a migrant.[10]

We observe a consistent pattern in the estimated coefficients of the agricultural productivity independent of changes in the migration regression. In terms of weather, more rainfall has a significantly positive but decreasing effect on productivity, similar for positive rainfall shocks (*z*-score), whereas negative deviations of rainfall in the year preceding the survey from the LR average are not significant. Input coefficients are mostly as expected. There is evidence for the inverse farm size productivity relationship; higher crop diversity, chemical fertilizers, pesticides, and herbicides, all significantly increase productivity, and so does hired labour though to a lesser extent. The use of organic fertilizers, however, does not appear to improve productivity. Household labour measured by the number of working-age household members and belonging to the most common ethnic group in the area does not enter significantly in the productivity function. Productivity in the Terai region is not significantly different from that in the hills. Female-headed households are significantly less productive. This could be related to factors such as constrained access to credit, inputs, and information (for a review, see Croppenstedt et al. 2013), more domestic work hours, as well as to the fact that these households often lack household labour because of male migration (Lokshin and Glinskaya 2008). Education is a positive predictor of higher agricultural productivity even though insignificant in the specification in Column 4 of Table 3.

Finally, the estimated coefficients of each dependent variable in the other regression of our fully recursive model show that the value of crop production per hectare significantly affects the likelihood to have a migrant in all regressions. This is an important finding as it supports our hypothesis that migration decisions are not simply the reaction to a weather shock in a given year, as they are commonly modelled. We show that contemporaneous rainfall is a highly significant predictor for crop production in the corresponding year and these changes in agricultural production in turn affect the migration decision. When we run the migration model by itself including the monsoon rainfall directly, the coefficient of rainfall is significant and negative.[11] However, when we include seasonal rainfall in the migration decision in the simultaneous model, it becomes insignificant, but the coefficient of agricultural production remains significant. Thus, seasonal rainfall affects the migration decision only through its effect on agricultural productivity. We note that the coefficient of agricultural productivity in the simultaneous model is always

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[10] One might claim that a potential reason for this may be that increasing temperatures improve productivity, and hence, are an *enabling* condition for migration (if migration cost was a binding constraint) rather than being a *push* factor. This argument can be refuted by the negative coefficient of productivity in migration decisions (gamma1_2) as well as the insignificant coefficient of average temperature and significant negative coefficient of positive maximum temperature deviation in production regression (results are available upon request).

[11] Results are available upon request.

negative indicating that higher farm incomes decrease the need or incentive to send a member away. In contrast, the deviations of the level of rainfall in the 3 years preceding the migration decision from their values observed over several decades are significant predictors of migration. This confirms the hypothesis that migration decisions are taken as part of an adaptation strategy of households facing a changing environment. On the other hand, the migrant dummy appears significantly in the crop production function only in one specification and is always negative. Having a migrant implies losing household labour (that also tends to be more educated) for farm production, and it appears that in our sample households are not always able to compensate for the lost labour by hiring labour or working more on their farms.

Appendix Table A1 presents the same estimation results using 5-year climate variables instead of 3-year averages. The results for both the agricultural production and the migration decision persist. Negative rainfall deviations (z-score) are a significant and positive predictor of migration. The more bad years a household experienced over the past 5 years, the more likely it is to diversify through migration controlling for other non-farm income sources. If weather patterns have been stable over 5 years, households are less likely to send migrants, whereas they are more likely to do so when faced with continuously deteriorating and unpredictable weather patterns.

6.2 Heterogeneous effects by non-farm income diversification and asset wealth

In Section 6.1, we found that long-term weather variation is a significant predictor of migration decisions in our sample. Given the high dependence of households on agriculture in rural Nepal and relatively poorer areas, we investigate heterogeneous effects. We focus on two variables with potential heterogeneity, diversification into non-agricultural income and wealth.

First, we split the sample in two: households that have non-agricultural income sources and those that do not. Based on the household model presented in the conceptual framework (Section 3), the hypothesis is that households that are diversified outside of agriculture might already have a buffer against weather-induced income shocks and may be less likely to diversify through migration. Second, we split the sample at the median of the wealth index. Migration is often found to be subject to a credit constraint and most migration in our sample is international and associated with significant costs. We thus expect wealthier households under climate distress to be more likely to send a migrant member than their poorer and credit-constrained counterparts.

Table 4 presents the results of the migration model only, as the results of the crop production function are not affected by the sample split. To further save space, we focus on one type of climatic variable shown to be a significant predictor of migration in Table 3: rainfall variability measured as positive and negative z-scores. Further, by splitting the variable into positive and negative deviations, we allow for non-linear responses to these positive and negative shocks. Columns 1 and 2 present the results of the sample split along income diversification outside of agriculture. While both sub-samples are significantly less likely to send a migrant in response to a positive rainfall shock, the effect is smaller for diversified households. These households are expected to be less sensitive to weather shocks, as not all their income depends on it. Furthermore, sending a migrant significantly reduces the agricultural productivity of these households (gamma2_1 in Column 2) pointing at higher opportunity costs for them to send a household member off the farm as they are already diversified into non-agricultural activities.

Table 4: Results of fully recursive simultaneous regressions of migration decision and agricultural production with interaction terms

	(1)	(2)	(3)	(4)
	Probability (migrant = 1)			
Sub-samples	Non-agricultural income		Wealth index	
	No	Yes	Below median	Above median
Positive *z*-score of 3-year rainfall	−0.921**	−0.721**	−1.641***	−0.436
	(0.422)	(0.318)	(0.370)	(0.289)
Absolute negative *z*-score of 3-year rainfall	1.718	0.794	0.823	2.133**
	(1.282)	(0.579)	(1.705)	(0.970)
Gamma1_2 = coefficient of agricultural production in migrant function	−0.946***	−1.122***	−0.962***	−0.927***
	(0.271)	(0.260)	(0.322)	(0.270)
Gamma2_1 = coefficient of migrant dummy in agricultural production function	−0.107	−0.272*	0.027	−0.270*
	(0.110)	(0.160)	(0.076)	(0.138)
Atanhrho_12	0.787*	1.785***	0.656	1.171***
	(0.436)	(0.434)	(0.431)	(0.423)
Other controls	Yes	Yes	Yes	Yes
Observations	358	267	330	295
Chi-squared	208.5	144.6	615.0	234.9

Note: asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Standard errors in parentheses; they are clustered at ward level. The wealth index is constructed using principal component analysis of housing characteristics, drinking water and electricity access, and transport modes. The results presented are from the probit model of the migration decision from the fully recursive simultaneous regression. The results of the agricultural production regression are not presented.

Source: authors' compilation.

In Columns 3 and 4, we test the credit constraint hypothesis. Again, in both sub-samples households are significantly less likely to send a migrant if they experience a positive rainfall shock, especially if they are poorer. In contrast, if they experience a negative shock, only the richer households (Column 4) are significantly more likely to send a migrant. This is in line with the literature showing that the migration probability increases with income (for a review, see Clemens 2014) and the poorest households may not be able to engage in migration because of high upfront costs. Thus, migration of a household member is not a feasible response to climate change for all households. These results show that while weather variation is an important predictor for migration decisions in rural Nepal, the responses are heterogeneous across households. Credit constraints and opportunity costs of household labour are important mediating factors.

6.3 Sensitivity checks

We conduct a series of sensitivity tests to confirm the robustness of our results. First, when we replace outlier values of agricultural production and input expenses with the 99th or 1st distribution percentile, respectively, the results remain stable as presented in Appendix Table A2.[12] Second, one can argue that decisions for internal and international migration may differ significantly. However, we cannot directly compare the results of international and internal migrants because of the very small sample size with internal migrants; running the regression only on the sample of international migrants yields the same results (see Appendix Table A2). As shown

[12] Results also remain unchanged when we control for livestock income, which enters insignificantly.

by Williams and Gray (2019), weather shocks might trigger different migration pathways in Nepal, thus our results may not hold for internal migration.

Another important variable of interest for the migration decision is remittances or expected remittances. Many studies have shown that remittances influence agricultural investment decisions and, therefore, should be accounted for in the agricultural production function (Taylor and Lopez-Feldman 2009; Taylor et al. 2003; Quisumbing and McNiven 2009). We include the remittance amount received by the household within the past 12 months from anyone living outside the household in the agricultural productivity regression and find that it is not significant and does not alter other findings (Appendix Table A2).

While the models we presented focus on agricultural productivity based on the assumption that the simultaneous decision regarding input and labour allocation relates to efficiency concerns (i.e. to equalize the marginal returns across activities), we also run the regressions using total agricultural production instead of productivity and present results in Appendix Table A3. The effects of long-term weather changes on migration remain as before; only the LR temperature trend becomes insignificant. The main difference with the productivity results is that migration does not enter significantly in the agricultural production function (gamma2_1) and total agricultural production does not always enter significantly in the migration decision (gamma1_2) and if so only weakly significantly, while productivity does. Furthermore, atanhrho_12 is almost always insignificant. Jointly, this confirms the appropriateness of our model choice.

7 Conclusions

This research aimed at disentangling the direct effect of weather shocks on agricultural production from the long-term effect of changing weather patterns on household decisions to diversify income sources through migration in rural Nepal. By estimating a fully recursive simultaneous equation model, we allow for agricultural production and migration decisions to influence each other to test the simultaneity of these decisions. A new household survey matched with 35 years of village level weather data allowed us to control for long-term changes in weather patterns just before the migration decision was taken, as well as seasonal weather variables that affect production. Our results confirm that longer-term changes influence expectations about future income streams and, thus, household diversification decision through migration.

The literature on the climate change and migration nexus traditionally focused on aggregate level analyses linking climate shocks to larger migration patterns, and more recently household level analyses linking climate data to migration decisions. Whether the main impact channel between climate change and migration is the impact of climate change on agriculture has been either indirectly tested or unidirectionally modelled, where climate affects agriculture, which in turn affects migration. This paper complements and expands this literature by showing that migration is not simply a reaction to shocks, but it is also an important *ex-ante* adaptation strategy to an increasingly uncertain environment. Therefore, the two decisions should be modelled jointly as they significantly (negatively) affect each other. Our results further suggest that migration acts as a substitute for non-agricultural income generation, and that the poorest households are less likely to migrate in response to negative shocks. Increasing rural outmigration (but not of the poorest) may thus be expected as the impacts of climate change intensify if no alternative adaptation strategies are available to households.

The findings have important policy implications. Outmigration is a key strategy for diversifying rural livelihoods and helping farming households manage increasing climate risks. It is, therefore, important to ensure that policies and interventions facilitate the voluntary and safe migration of people to make migration a choice rather than a necessity. Greater attention should be paid to enhance inclusiveness of the poorest in rural areas, as they are likely the most vulnerable to climate change but the least able to access migration as an adaptation strategy. It is, therefore, important to identify groups that are trapped in low-productivity work in rural areas and support their adaptive capacities through alternative measures, such as social protection, financial inclusion, and income diversification.

The need to strengthen such adaptive capacities beyond migration is especially important in Nepal, where a large share of rural households has international migrants. While some migration might reinvigorate rural areas through remittances, the effect of large-scale migration from rural areas is much more conspicuous. When an overwhelming majority of households engage in migration, this may lead to significant demographic, social, and economic consequences, especially as migrants tend to be younger and better educated, and remittances are not always invested efficiently in receiving communities. Attention should be paid to interventions to facilitate productive investments using remittances as well as knowledge accumulated by migrants that can improve adaptive capacities over time.

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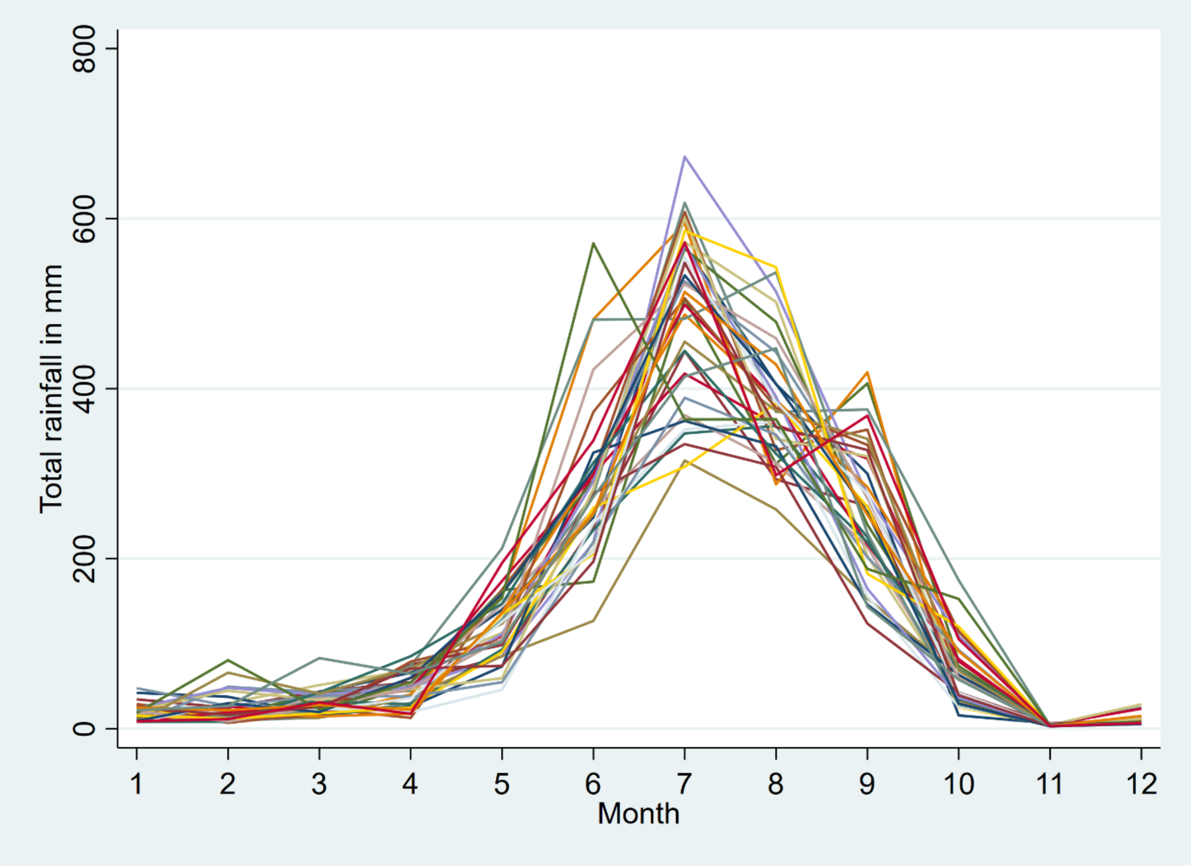
Appendix

Figure A1: Average monthly rainfall per year in study areas from 1981 to 2016



Source: authors' compilation based on survey data.

Table A1: Results of fully recursive simultaneous regressions of migration decision and agricultural production and climate variables of past 5 years relative to LR

	(1)	(2)	(3)
	Probability (migrant=1)		
Positive *z*-score of 5-year rainfall	−0.828**		
	(0.331)		
Negative *z*-score of 5-year rainfall	5.203*		
	(2.838)		
Negative absolute percentage deviation of 5-year CoV of rainfall		−0.012	
		(0.015)	
Positive *z*-score of 5-year temperature			2.594***
			(0.533)
Non-agricultural self-employment income (dummy)	−0.050	−0.098	−0.189
	(0.074)	(0.195)	(0.144)
Non-agricultural wage work income (dummy)	−0.054	−0.144	−0.170
	(0.064)	(0.180)	(0.104)
Migration of relative of household	0.130	0.200	0.332**
	(0.095)	(0.245)	(0.137)
Number of past migrants in household	0.000	0.054	−0.073
	(0.029)	(0.047)	(0.065)
Ward share of migrants in India	0.307	−0.457	1.260***
	(0.356)	(0.783)	(0.429)
Ward share of migrants in Gulf	0.252	−0.042	0.214
	(0.178)	(0.352)	(0.315)
Asset index	−0.030	−0.067	0.033
	(0.033)	(0.064)	(0.059)
Household size	−0.061	−0.115	−0.114***
	(0.042)	(0.097)	(0.038)
Highest level of education in household including migrant (base=has never attended school)			
Class 1–5	0.414***	0.467**	0.439**
	(0.135)	(0.185)	(0.205)
Class 6–12	0.729***	0.822***	0.710***
	(0.121)	(0.180)	(0.172)
Higher education	0.899***	0.880***	0.685**
	(0.197)	(0.296)	(0.345)
Constant	12.162***	7.296**	7.139***
	(2.253)	(3.591)	(2.367)
	Log(value of total crop production per hectare)		
Total rainfall in monsoon (ward)	0.189***	0.169	0.184**
	(0.065)	(0.108)	(0.081)
Monsoon rainfall squared	−0.005***	−0.004	−0.005*
	(0.002)	(0.003)	(0.003)
Percentage deviation of seasonal rainfall from LR monsoon average			
Positive	0.010	0.011	0.010
	(0.007)	(0.007)	(0.007)
Negative	0.039	0.045	−0.089
	(0.095)	(0.161)	(0.187)
Log(total land cultivated in hectare)	−0.172**	−0.256**	−0.284***
	(0.080)	(0.110)	(0.065)

Crop diversity index (count)	0.041**	0.058**	0.064***
	(0.018)	(0.028)	(0.014)
Log(expenses in 100 rupees per hectare)			
Chemical fertilizers, pesticides, and herbicides	0.033**	0.046*	0.053***
	(0.015)	(0.028)	(0.018)
Organic fertilizers	−0.002	0.002	0.004
	(0.008)	(0.017)	(0.017)
Hired labour	0.011	0.017	0.021**
	(0.007)	(0.013)	(0.010)
Ecological zone (hills=1, Terai=0)	−0.077	0.019	−0.044
	(0.079)	(0.091)	(0.082)
Number of working-age household members	−0.000	0.001	0.025
	(0.015)	(0.029)	(0.023)
Member of dominant ethnic group in district	0.046	0.069	0.096
	(0.045)	(0.086)	(0.061)
Female household head	−0.066*	−0.100*	−0.126**
	(0.039)	(0.056)	(0.054)
Age of household head	0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)
Highest level of education in household excluding migrant (base=has never attended school)			
Class 1–5	0.160***	0.129	0.063
	(0.047)	(0.138)	(0.064)
Class 6–12	0.283***	0.221	0.108
	(0.068)	(0.235)	(0.092)
Higher education	0.370***	0.224	0.097
	(0.134)	(0.312)	(0.131)
Constant	9.478***	9.797***	9.883***
	(0.430)	(0.680)	(0.726)
Gamma1_2=coefficient of agricultural production in migration function	−1.176***	−0.664	−0.963***
	(0.203)	(0.438)	(0.184)
Gamma2_1=coefficient of migrant dummy in agricultural production function	−0.244**	−0.193	−0.006
	(0.115)	(0.309)	(0.048)
Atanhrho_12	1.550***	0.887	0.720***
	(0.501)	(0.966)	(0.256)
Observations	625	625	625
Chi-squared	533.8	413.6	602.4

Note: LR, long run; CoV, coefficient of variation. Asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Standard errors in parentheses; they are clustered at ward level.

Source: authors' compilation based on survey data.

Table A2: Sensitivity checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	International migrant sample			Outliers included without adjustments			Outliers replaced with 1st or 99th percentile		
	Probability (international migrant=1)								
Absolute negative % deviation of 3-year monsoon CoV from LR	−0.002			−0.003			−0.003		
	(0.002)			(0.003)			(0.003)		
Positive *z*-score of 3-year monsoon rainfall		−0.712**			−0.712**			−0.683**	
		(0.361)			(0.300)			(0.302)	
Negative *z*-score of 3-year monsoon rainfall		1.287*			1.341			1.302*	
		(0.763)			(0.873)			(0.761)	
LR slope of average temperature in monsoon			22.550*			21.058			21.146
			(12.807)			(21.272)			(13.132)
Gamma1_2	−0.872***	−1.124***	−1.108***	−0.511**	−0.680***	−0.639***	−0.663***	−0.876***	−0.854***
	(0.289)	(0.213)	(0.251)	(0.217)	(0.209)	(0.231)	(0.245)	(0.203)	(0.233)
Gamma2_1	−0.376**	−0.207*	−0.264*	−0.358	−0.266	−0.244	−0.368	−0.241*	−0.259
	(0.178)	(0.119)	(0.150)	(0.336)	(0.165)	(0.435)	(0.231)	(0.131)	(0.206)
Atanhrho_12	1.421**	1.282***	1.411***	0.996	1.019**	0.925	1.176*	1.155***	1.163**
	(0.586)	(0.422)	(0.490)	(0.732)	(0.426)	(0.952)	(0.630)	(0.406)	(0.580)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	598	598	598	672	672	672	673	673	673
Chi-squared	210.909	543.371	366.641	480.281	512.521	664.969	649.838	802.832	728.294

Note: CoV, coefficient of variation; LR, long run. Columns 1–3 use only migrant households with international migrants, Columns 4–6 include outliers of agricultural productivity and input values, and Columns 7–9 replace these outliers. Asterisks represent level of statistical significance of t-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Standard errors in parentheses; they are clustered at ward level.

Source: authors' compilation based on survey data.

Table A3: Results of fully recursive simultaneous regressions of migration decision and agricultural production (total production)

	(1)	(2)	(3)	(4)
	Probability (migrant=1)			
Positive *z*-score of 3-year rainfall	−0.934***			
	(0.291)			
Negative *z*-score of 3-year rainfall	1.639			
	(1.276)			
Negative absolute percentage deviation of 3-year CoV of rainfall		−0.005		
		(0.006)		
35-year slope of average temperature increase			25.182	
			(17.338)	
Positive *z*-score of 3-year temperature				2.156***
				(0.396)
Non-agricultural self-employment income (dummy)	−0.144	−0.107	−0.136	−0.274
	(0.167)	(0.224)	(0.226)	(0.166)
Non-agricultural wage work income (dummy)	−0.188	−0.170	−0.198	−0.274*
	(0.117)	(0.147)	(0.150)	(0.146)
Migration of relative of household	0.225	0.163	0.210	0.384**
	(0.176)	(0.261)	(0.255)	(0.162)
Number of past migrants in household	−0.083	0.005	−0.036	−0.101
	(0.076)	(0.055)	(0.083)	(0.071)
Ward share of migrants in India	0.568	−0.017	0.687*	1.224***
	(0.366)	(0.547)	(0.400)	(0.406)
Ward share of migrants in Gulf	0.181	−0.036	0.077	0.161
	(0.317)	(0.371)	(0.320)	(0.413)
Asset index	−0.047	−0.086	−0.050	0.049
	(0.086)	(0.112)	(0.152)	(0.082)
Household size	−0.112***	−0.123**	−0.109**	−0.127***
	(0.041)	(0.059)	(0.045)	(0.044)
Highest level of education in household including migrant (base=has never attended school)				
Class 1–5	0.328*	0.356*	0.351*	0.281
	(0.186)	(0.197)	(0.192)	(0.234)
Class 6–12	0.665***	0.687***	0.709***	0.651***
	(0.165)	(0.234)	(0.194)	(0.203)
Higher education	0.767**	0.725*	0.757**	0.619
	(0.323)	(0.382)	(0.344)	(0.392)
Constant	1.383	0.286	0.188	−2.576**
	(0.944)	(0.905)	(0.811)	(1.021)
	Log(value of total crop production per hectare)			
Total rainfall in monsoon (ward)	0.255***	0.231***	0.254***	0.239***
	(0.075)	(0.082)	(0.075)	(0.079)
Monsoon rainfall squared	−0.007***	−0.006**	−0.007***	−0.006**
	(0.002)	(0.003)	(0.002)	(0.003)
Percentage deviation of seasonal rainfall from LR monsoon average				
Positive	0.014*	0.012	0.015*	0.011
	(0.008)	(0.008)	(0.008)	(0.008)
Negative	0.011	0.054	0.048	0.075
	(0.206)	(0.214)	(0.213)	(0.204)

Log(total land cultivated in hectare)	0.541***	0.566***	0.549***	0.573***
	(0.057)	(0.055)	(0.063)	(0.049)
Crop diversity index (count)	0.076***	0.074***	0.074***	0.076***
	(0.011)	(0.012)	(0.013)	(0.012)
Log(expenses in 100 rupees per hectare)				
Chemical fertilizers, pesticides, and herbicides	0.215***	0.214***	0.212***	0.223***
	(0.076)	(0.080)	(0.079)	(0.078)
Organic fertilizers	0.033***	0.032***	0.031***	0.033***
	(0.011)	(0.011)	(0.011)	(0.011)
Hired labour	−0.079**	−0.080**	−0.077**	−0.081**
	(0.040)	(0.039)	(0.039)	(0.041)
Ecological zone (hills=1, Terai=0)	−0.002	0.064	0.056	0.038
	(0.104)	(0.095)	(0.094)	(0.093)
Number of working-age household members	−0.001	−0.011	−0.001	0.022
	(0.027)	(0.037)	(0.039)	(0.024)
Member of dominant ethnic group in district	0.119**	0.106*	0.114*	0.116*
	(0.057)	(0.064)	(0.061)	(0.060)
Female household head	−0.117*	−0.113*	−0.119*	−0.128*
	(0.064)	(0.067)	(0.066)	(0.069)
Age of household head	0.001	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Highest level of education in household excluding migrant (base=has never attended school)				
Class 1–5	0.096	0.125	0.111	0.061
	(0.067)	(0.101)	(0.091)	(0.069)
Class 6–12	0.137	0.179	0.155	0.044
	(0.089)	(0.158)	(0.157)	(0.078)
Higher education	0.073	0.107	0.090	−0.031
	(0.136)	(0.188)	(0.191)	(0.108)
Constant	3.767***	3.774***	3.675***	3.775***
	(0.657)	(0.693)	(0.641)	(0.688)
Gamma1_2=coefficient of agricultural production in migration function	−0.192**	−0.062	−0.165*	−0.071
	(0.090)	(0.102)	(0.090)	(0.082)
Gamma2_1=coefficient of migrant dummy in agricultural production function	−0.148	−0.231	−0.177	0.002
	(0.126)	(0.335)	(0.311)	(0.052)
Atanhrho_12	0.456*	0.510	0.484	0.062
	(0.277)	(0.620)	(0.598)	(0.140)
Observations	625	625	625	625
Chi-squared	7,138.3	5,642.9	7,375.4	14,603.9

Note: CoV, coefficient of variation; LR, long run. Asterisks represent level of statistical significance of *t*-test/chi-squared test of difference in means: *0.1, **0.05, ***0.01. Standard errors in parentheses; they are clustered at ward level.

Source: authors' compilation based on survey data.