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Abstract

Climate change has altered the severity and frequency of extreme weather events for the worse. These weather shocks have direct and indirect effects on economic and demographic factors that influence the migration decision of individuals and households. This paper investigates the relationship between climate and migration within the Philippines, a country considered vulnerable to the effects of climate change and is marked by high levels of internal migration. Using panel data, I exploit the exogenous variation in the frequency of temperature and precipitation shocks across provinces to estimate bilateral migration rates using a Poisson pseudo-maximum likelihood estimator. I find that an increase in the monthly frequency of drought and wet spells in the origin province is associated with higher outmigration. Though temperature shocks are not significant drivers of provincial outmigration, there is evidence that the slow-onset rise in baseline provincial temperature impacts migration. Furthermore, younger individuals and those with lower levels of educational attainment display a higher sensitivity to precipitation shocks when it comes to migration. I infer that these differences are driven by income variability and earning potential. However, my main findings are only partially robust to alternative characterizations of weather shocks and the empirical specification.

Zusammenfassung

Der Klimawandel hat die Stärke und Häufigkeit von extremen Wetterereignissen deutlich verstärkt. Diese Wetterschocks haben direkte und indirekte Auswirkungen auf ökonomische und demografische Faktoren, welche die Migrationsentscheidung von Individuen und Haushalten beeinflussen. Diese Arbeit untersucht die Beziehung zwischen Klima und Migration innerhalb der Philippinen, ein Land durch die Auswirkungen des Klimawandels als stark betroffen gilt und durch hohe Binnenmigration gekennzeichnet ist. Auf der Basis von Paneldaten nutze ich die exogene Variation in der Häufigkeit von Temperatur- und Niederschlagsschocks, um die bilaterale Migrationsrate der Provinzen mit einem Poisson Pseudo-Maximum-Likelihood-Schätzer zu schätzen. Daraus ließ sich ableiten, dass eine Zunahme der monatlichen Häufigkeit von Dürre und Nässeperioden in der Ursprungsprovinz in Zusammenhang mit einer höheren Auswanderungsrate steht. Obwohl Temperaturschocks nicht als treibende Kraft von provinzieller Auswanderung gelten, gibt es Nachweise dafür, dass die langsam einsetzende Erhöhung der provinziellen Grundtemperatur einen Einfluss auf Migration hat. Weitergehend ist zu beobachten, dass junge Individuen und Individuen mit niedrigem Bildungsniveau im Bereich der Migration eine höhere Empfindlichkeit gegenüber Niederschlagsschocks aufzeigen. Daraus schließe ich, dass diese Unterschiede vor allem durch schwankendes Einkommen und Einkommenspotential entstehen. Allerdings sind die Hauptergebnisse teilweise robust gegenüber alternativen Interpretationen von Wetterschocks und empirischen Spezifikationen.

Contents

Introduction

Increased climate variability resulting from climate change has altered the frequency and severity of extreme weather events for the worse (International Panel of Climate Change [IPCC], 2021). At most risk from them are low- and middle-income countries that tend to have low financial resources and weak institutions that cannot adapt quickly to environmental changes (Kahn, 2005).

In response to this, individuals and households look to migration as a possible adaptation strategy. The environmental factor typically works through its effect on the economic, demographic, social, and political drivers behind migration (Black et al., 2011). Economic factors continue to have the strongest influence on the decision to move, as evidenced by migration flows induced by wage and productivity differentials across locations (Kennan & Walker, 2011; Lucas, 1997; Narayan & Smyth, 2006). These differences can be driven by temperature, as increasing temperatures and a higher frequency of temperature shocks negatively affect agricultural productivity, economic growth, and health outcomes (Cai et al., 2016; Dell et al., 2012). While there is mixed evidence on the relationship between precipitation shocks and economic outcomes (Bohra-Mishra et al., 2017; Maccini & Yang, 2009), their immediate impacts can be large in magnitude; tropical cyclones, for instance, cause significant damage to infrastructure and leave persistent negative effects. At the household level, the migration of family members can act as a form of insurance against environmentally-associated economic risks, such as income variability from drought (Black et al., 2013; Yang & Choi, 2007).

In this paper, I further explore the climate-migration relationship by examining how weather shocks drive internal migration in the Philippines. I work with a stylized gravity model of migration where interprovincial migration is determined by the weather characteristics in the migrants' province of origin. I exploit the exogenous variation in the frequency of temperature and precipitation shocks at the provincial level to estimate bilateral migration rates using a Poisson pseudo-maximum likelihood (PPML) estimator. As the PPML estimator can be used with multiplicative models, I overcome the selection bias associated with the exclusion of zero-valued migration observations when multiplicative models are converted into their additive form through a log transformation.

The Philippines is a suitable setting to study climate-induced migration. First, the country is highly exposed to climatic variations and extreme weather events as it lies along the Pacific typhoon belt and the Pacific Ring of Fire. It is hit by 20 typhoons annually, with five considered as destructive (Asian Disaster Reduction Center [ADRC], 2018). Due to the increasing severity of weather extremes affecting the country, it has been listed as one of the 12 countries most vulnerable to climate change, with natural disasters having affected 109 million people from 1980 to 2009 (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2018). The country's topology magnifies the impact of these events; 60% of its municipalities and cities are by the coast and many areas lie below sea level, including its capital region. As a result, a large percentage of the country is susceptible to the impact of typhoons, floods, and drought (ADRC, 2018).

Second, the Philippines is characterized by high levels of internal migration. Majority of individuals who changed residences between 2005 and 2010 were either long-distance (interprovincial) or short-distance (intercity) movers (UNESCO, 2018).

Migration behavior differs across demographic groups; while women in Mindanao move for familial reasons such as marriage, men tend to move for economic reasons (Quisumbing & McNiven, 2006). There is also evidence that climate variability is a driver of internal migration, with men, individuals with higher levels of educational attainment, and the younger population as the most sensitive to climate variability when it comes to provincial migration (Bohra-Mishra et al., 2017).

I use Philippine census data to construct the bilateral migration rates for the 1990-1995 and 1995-2000 periods at two levels of aggregation. First, I use migration rates derived from total migration flows to estimate the total effect of weather shock frequency. Second, I use the migration rates for different demographic subgroups to compare their sensitivity to weather shock frequency, allowing me to infer the mechanisms behind the climate-migration relationship. I quantify the frequency of weather shocks in each province using standardized climate indices for precipitation and temperature. The main advantage of these indices is that they are spatially and temporally consistent, making deviations in monthly rainfall and temperature observations comparable across different locations within the same reference period (World Meteorological Organization [WMO], 2012).

I find that among weather shocks, only precipitation shocks influence internal migration. A higher frequency of drought and wet spells in the province of origin are linked to increased bilateral migration rates, with wet spells having a stronger push effect. This result remains consistent when estimating the effect of weather shocks on the migration rates of different demographic subgroups pertaining to sex, age, and educational attainment. Younger individuals and those with lower levels of educational attainment are the most sensitive to weather shocks when it comes to migration. I infer that differences in sensitivity are related to the impact of weather shocks on income. However, my main findings are only partially robust to alternative characterizations of weather shocks and the empirical specification.

I contribute to the environmental migration literature by providing further evidence of the role that weather plays in shaping internal migration in the Philippine context. The study by Bohra-Mishra et al. (2017) has already explored how outmigration is impacted by provincial variation in average temperature and precipitation conditions. Slow-onset changes in these baseline climatic conditions are accompanied by an increased frequency in rapid- and medium-onset weather shocks, which are associated with increased rates of internal migration (Black et al., 2013). I complete the picture of climate-induced migration in the country by focusing on how more immediate temperature and precipitation shocks can influence human mobility. To the best of my knowledge, this paper is the first to utilize a gravity model to investigate climate-driven internal migration in the Philippines.

The rest of my paper is structured as follows. In Chapter 1, I discuss the developments and major findings in the environmental migration literature thus far. In Chapter 2, I present the random utility maximization (RUM) model of migration that informs the empirical specification used in this paper. In Chapter 3, I discuss the empirical challenges associated with studying migration and how these are addressed by with the PPML estimator. In Chapter 4, I present my data sources and how the variables utilized in estimation are constructed. In Chapter 5, I present the estimated effects of weather shock on provincial outmigration and test the robustness of my results. The final section concludes.

Chapter 1

Review of Related Literature

A meta-analysis by Hoffmann et al. (2020) of 30 papers from the environmental migration literature shows that the changing climate is a relevant driver of international and internal migration. However, the climate is a result from the interaction between climate variables that are spatially correlated, have individual effects on the natural world, and whose historical distributions are now being altered by human activity (Abatzoglou et al., 2020; Auffhammer et al., 2013). Migration is also driven by economic, demographic, social, and political factors that are not just tied to each other and to the environment, but can also either magnify or minimize the impact of environmental shocks (Black et al., 2011; Locke, 2009). The complexity involved in characterizing these processes individually and their linkages has made it difficult to reach a consensus on the overall direction of the climate-migration relationship (Hoffmann et al., 2020).

Empirical studies instead focus on how migration is impacted by changes in climatic factors at the center of climate change discussions, such as temperature and precipitation (IPCC, 2021). A key finding is that temperature has a significant effect on migration. Poston et al. (2009) show that state-level temperature variation in the

United States drives net internal migration. States with more favorable temperatures attract more migrants while holding the effects of other climate and sociocultural factors constant. In Indonesia, a temperature increase from baseline high temperatures induces permanent outmigration to other provinces (Bohra-Mishra et al., 2014).

There is mixed evidence on the impact of precipitation on migration. Rainfall shortages are attributed to higher migration in sub-Saharan Africa (Barrios et al., 2006; Henry et al., 2004), while above average rainfall is associated with a lower likelihood of interprovincial migration in South America (Thiede et al., 2016). However, while both positive and negative rainfall shocks increase outmigration within post-apartheid South Africa (Mastrorillo et al., 2016), they reduce the probability of rural outmigration in Malawi (Lewin et al., 2012). Other studies even find that precipitation shocks have no effect on international migration (Beine & Parsons, 2015). Overall, (Hoffmann et al., 2020) find that the estimated effect of a change in precipitation on migration is smaller in magnitude compared to an equivalent change in temperature.

The literature also explores the other channels behind climate-induced migration. The environmental migration framework developed by Black et al. (2011) emphasizes that the environment has indirect effects on migration through its other drivers. Its primary driver is the economic motive, as geographic differences in income is as a significant determinant of internal and international migration flows (Kennan & Walker, 2011; Lucas, 1997; Narayan & Smyth, 2006). These differences can be attributed to hotter temperatures that have an adverse effect on per-capita income especially in agriculture-dependent areas. Declining crop yields and crop failure resulting from rising temperatures reduce the income of agricultural workers and induce outmigration (Dell et al., 2014; Feng et al., 2012; Lobell et al., 2011).

Precipitation shocks also have an adverse effect on income (Brey & Hertweck, 2019; Dercon, 2004; Silva & Matyas, 2014). Households and individuals may consider migrating in order to mitigate the risk of income loss. In the Philippines, where a period of low rainfall is followed by a period of reduced household income and consumption, families with a migrant member are able to recover up to 60% of lost income through the remittances they receive and are able to maintain their consumption level in the period following a negative rainfall shock (Yang & Choi, 2007). Gröger and Zylberberg (2016) also find that households in Vietnam cope with tropical cyclones, an excess rainfall event, through the labor migration of household members into urban areas where they can find jobs quicker. This allows them to immediately send remittances that compensate for the income loss back home.

Demographic and socioeconomic groups have varied responses to environmental changes that are reflected in their migration behavior (Fotheringham et al., 2004). In Nicaragua, urban households belonging to the second quintile of the wealth distribution are likely to move after being exposed to a rainfall shock. This suggests that urban poor households are incentivized to move as long as they are not the poorest and can cover the cost of migration (Carvajal & Medalho Pereira, 2009). Meanwhile, rural poor households are the most vulnerable to weather extremes from their inability to adopt alternative coping mechanisms, including migration, due to liquidity constraints (Beine & Parsons, 2015; Dell et al., 2014).

Educational attainment influences the direction of migration flows in Taiwan, where high precipitation in a province pushes the highly educated to migrate elsewhere while attracting the poorly educated (Nguyen, 2021). Extreme heat and cold also have detrimental effects on health and mortality rates; they disproportionately affect women, children, and the elderly and may be a push factor for migration (Dell et al., 2014; Deschênes & Moretti, 2009; Nguyen, 2021). In developing countries, there is evidence that migration behavior resulting from weather extremes differs by gender, with higher temperatures and droughts increasing the outmigration of men as opposed to women (Gray & Mueller, 2012; Mueller et al., 2014).

In the Philippine context, Bohra-Mishra et al. (2017) are the first to explore the relationship between climatic factors and internal migration using panel data. They exploit the provincial variation in summer temperatures, extreme precipitation levels in the dry and wet seasons, and typhoon incidence to estimate interprovincial migration. Their estimates show that higher temperatures and a higher frequency of typhoons in the origin province contribute to increased provincial outmigration, while changes in seasonal precipitation extremes have no significant effect. They further investigate potential channels that drive these results. First, agricultural productivity is found to be a direct channel. Higher temperatures and a higher frequency of typhoons reduce annual rice yields and increase outmigration from provinces with a higher share of rural population, which tend to be agriculture-dependent. Second, differences in the effect of climate variability on the outmigration of demographic subgroups suggest that demographic factors are indirect channels behind the climate-migration relationship. Men, the highly educated, and younger individuals are more sensitive to climate variability and more likely to migrate in response to changes in climatic conditions.

Chapter 2

Theoretical Framework and Empirical Specification

I derive my specification from the RUM model of migration as developed in Beine et al. (2011) and Beine and Parsons (2015). Assume that agents are homogenous and the locations refer to provinces within the agents' country. Let N_{it} be the initial population of province i at the beginning of period t. For each period, the agents choose their optimal location across all destination provinces k, including their origin province. The total number of agents in i with optimal destination province j is denoted by N_{ijt}. Assume that an agent's utility is dependent on the logarithm of their income, their province of origin, and the associated costs of moving. At period t, the utility associated with staying in the origin province i is

$$u_{iit} = \ln(w_{it}) + A_{it} + \epsilon_{it} \tag{2.1}$$

where w_{it} is their wage in province i, A_{it} is a vector of province-specification characteristics such as employment opportunities and weather, and ϵ_{it} is an independent and identically distributed (i.i.d.) extreme-value distributed random error term. Meanwhile, the utility associated with migrating from origin province i to destination province j at period t is given by

$$u_{ijt} = \ln(w_{jt}) + A_{jt} - C_{ijt} + \epsilon_{jt} \tag{2.2}$$

where C_{ijt} is the cost of migration from i to j.

As the random error term follows an i.i.d. extreme-value distribution, we can apply McFadden (1974) to determine the probability that an agent from i will move to j:

$$\Pr\left[u_{ijt} = \max_k u_{ikt}\right] = \frac{N_{ijt}}{N_{iit}} = \frac{\exp\left[\ln(w_{jt}) + A_{jt} - C_{ijt}\right]}{\sum_k \exp\left[\ln(w_{kt}) + A_{kt} - C_{ikt}\right]} \tag{2.3}$$

The bilateral migration rate between i and j, defined as the ratio of the total migrants from i to j at period t to the population who stayed in i (stayers) at period t, can then be expressed as

$$\frac{N_{ijt}}{N_{iit}} = \exp\left[\ln\left(\frac{w_{jt}}{w_{it}}\right) + A_{jt} - A_{it} - C_{ijt}\right] \tag{2.4}$$

Thus, the main determinants of the interprovincial bilateral migration rate in period t are the wage ratio between the origin and destination provinces $\frac{w_{jt}}{w_{it}}$, destination province characteristics A_{jt}, origin province characteristics A_{it}, and migration costs between the origin and destination provinces C_{ijt}.

I focus on the role of provincial extreme weather characteristics in determining outmigration across time periods. Wage is endogenous to climatic conditions (Dell et al., 2012), so I exclude the wage ratio as in Dallmann and Millock (2017). I utilize the following empirical specification, which is similar in form to an augmented constant-elasticity gravity model that accounts for multilateral resistance (Anderson & van Wincoop, 2003; Beine et al., 2011; Santos Silva & Tenreyro, 2006):

$$\frac{N_{ijt}}{N_{iit}} = \exp\left[\beta_0 + \beta_1 W_{it} + \theta X_{it}^{'} + \alpha_i + \delta_{jt}\right] + \epsilon_{ijt} \tag{2.5}$$

The independent variables of interest pertain to the exogenous extreme weather characteristics of the origin province (W_{it}). I characterize each province by their monthly frequency of precipitation shocks (drought and wet spell) and temperature shocks (cool and high temperature) for each period. Therefore, we interpret β_1 as the marginal effect of weather shocks on bilateral migration rates in the origin province.

I include a vector of origin province characteristics (X'_{it}) to control for other factors that can affect the bilateral migration rate. Ideal controls are variables that are not outcomes themselves within the specification; variables that do not fulfill this criteria but are included in the specification introduce selection bias in estimation (Angrist & Pischke, 2009). Thus, I only explicitly control for exogenous mean weather conditions in the origin province for each period. This allows me to estimate the effect of weather shocks on bilateral migration rate net of the influence of baseline provincial weather characteristics, which can be significant depending on the climate variable being examined (Bohra-Mishra et al., 2017).

The criteria for control variable selection excludes provincial economic factors from my specification. This includes the wage ratio, which has an endogenous relationship with climatic factors. While this has the benefit of eliminating the selection bias resulting from bad controls, this may also introduce omitted variable bias in estimation. This arises from the positive correlation of the wage ratio with weather shock frequency in the origin province and their simultaneous influence on the bilateral migration rate. If the wage ratio is time-variant, then its omission would lead to an upward bias on the estimated effect of climatic shocks on internal migration.

I utilize two fixed-effect (FE) variables to account for other provincial characteristics that can determine the bilateral migration rate. Along with economic factors, these include migration costs, geographic features, presence of armed conflict, and other forms of environment shocks such as earthquakes and volcanic eruptions. First, the destination-period FE (δ_{jt}) absorbs the pull effect of time-invariant and time-variant destination province characteristics. Second, the origin FE (α_i) controls for time-invariant origin province characteristics. This enables me to estimate the push effect of time-varying frequency of weather shocks across origin provinces.

Aside from determining the effect of extreme weather shocks on aggregate migration flows, I also look at their effect on interprovincial migration flows for different demographic subgroups. This allows me to infer the mechanisms that drive the environment-migration relationship, as demographic sensitivity to climate change can be linked to economic and socioeconomic factors that may affect subgroups differently (Black et al., 2013). To this end, I use the following specification:

$$\frac{N_{hijt}}{N_{hiit}} = \exp\left[\beta_0 + \beta_1 W_{it} + \theta X'_{it} + \alpha_i + \delta_{jt}\right] + \epsilon_{ijt} \tag{2.6}$$

The dependent variable in this specification is the bilateral migration rate of demographic subgroup h between i and j at period t. I focus on the sensitivity of subgroups by sex, age, and level of educational attainment to migrate with respect to the frequency of climatic shocks.

Chapter 3

Estimation Strategy

The log transformation of a multiplicative constant-elasticity gravity specification transforms the model into an additive model, making it possible to estimate the model using ordinary least squares (OLS). Despite the straightforward appeal of this approach, taking the natural logarithm of the dependent variable excludes observations of zero migration flows between province pairs from estimation and this presents empirical challenges. First, the absence of migration flows is a determined outcome of the agents' utility-maximizing decision. The exclusion of such observations introduces selection bias in estimation, making the resulting OLS estimator inefficient (Beine et al., 2016). Second, if the variance of the error term ϵ_{ijt} is dependent on the regressors of $\frac{N_{ijt}}{N_{iit}}$, then its expected value is also dependent on the regressors in the presence of zero-value observations (Santos Silva & Tenreyro, 2006). Thus, their exclusion also results in inconsistent OLS estimates.

I overcome these challenges with the use of the PPML estimator that can be applied to constant-elasticity multiplicative specifications and, in general, to panel data models (Honoré & Kyriazidou, 2000; Santos Silva & Tenreyro, 2006). Its main advantage is that the bilateral migration rate does not need to be log transformed, excluding selection bias in estimation. Additionally, the PPML estimator is efficient in the presence of heteroskedasticity and a high percentage of zero-valued observations. It also remains consistent even if the underlying data distribution is not Poisson.

Another estimation issue relates to multilateral resistance (MR). It is defined by Bertoli and Fernández-Huertas Moraga (2013) as the influence of alternative destination characteristics on the bilateral migration rate, which introduces bias in estimation if not appropriately controlled for. They advocate the use of the correlated common effects estimator (Pesaran, 2006) that conforms to the form of the theoretical resistance term. However, this approach is infeasible in the context of this paper, as it requires a sufficiently large number of panels in the data. Another approach is utilizing time-varying destination FEs that leads to consistent estimates in the presence of MR (Feenstra, 2002). I follow this method and include destination-period FEs in my specification, which have also been used in other studies on environmental migration (Beine & Parsons, 2015; Dallmann & Millock, 2017).

Chapter 4

Data

4.1 Migration

I construct my measures for migration using the Philippine 2000 Census of Population and Housing conducted by the Philippine Statistical Authority and made available online by IPUMS International. The dataset is a 10% sample of the Philippine population constructed through systematic cluster sampling at the city/municipal level and includes person-weights that I apply accordingly. It has information on the place of residence in 1990, 1995, and 2000 for individuals above 5 years old when the census was conducted. It also has individual-level data on age, sex, and level of educational attainment.

In my analysis, migrants are individuals whose province of residence changed between the beginning and end of the time periods 1990-1995 and/or 1995-2000. For these time periods, I first calculate the aggregate migration flows and migration flows per demographic group for each unique origin-destination province pair. I then compute the aggregate number of stayers and stayers per demographic subgroup in each province.

Table 1. Descriptive statistics

Variables	1990-1995 Obs.	Mean	Std. Dev.	1995-2000 Obs.	Mean	Std. Dev.
Bilateral migration rates						
Aggregate	6,162	0.00034	0.0014	6,162	0.00035	0.0012
Male	6,162	0.00032	0.0014	6,162	0.00032	0.001
Female	6,162	0.00037	0.0015	6,162	0.00038	0.0013
Achieved primary education or lower	6,162	0.00023	0.0008	6,162	0.00024	0.00077
Achieved secondary education	6,162	0.00041	0.0017	6,162	0.00047	0.0017
Achieved tertiary education or higher	6,162	0.00053	0.0026	6,162	0.00053	0.0021
Age 20-29	6,162	0.0006	0.0028	6,162	0.00065	0.0024
Age 30-49	6,162	0.0003	0.0011	6,162	0.00032	0.001
Age 50-65	6,162	0.00016	0.00075	6,162	0.00017	0.00063
Climatic variables						
Monthly frequency of drought	6,162	21.11	3.07	6,162	14.86	3.33
Monthly frequency of wet spells	6,162	7.92	3.89	6,162	19.22	4.48
Monthly frequency of cool temperatures	6,162	0.09	0.33	6,162	0.16	0.51
Monthly frequency of high temperatures	6,162	2.22	1.76	6,162	14.46	2.49
Average precipitation	6,162	188.6	39.85	6,162	213.83	44.13
Average temperature	6,162	25.9	1.36	6,162	25.96	1.38

Source: Author's calculations from the Philippine Census of Population and Housing 2000 and Climatic Research Unit Time-Series datasets

Afterwards, I use these data to construct aggregate and demographic bilateral interprovincial migration rates for every origin-destination province pair at each time period. As I am primarily interested in internal migration, these measures exclude observations for which the origin or destination is listed as a foreign country.

4.2 Precipitation Shocks

Numerous standardized indices have been created to characterize periods of drought and excess rainfall. I use the Standardized Precipitation and Evapotranspiration Index (SPEI) by Vicente-Serrano et al. (2010) derived from monthly water balance, or the difference between precipitation level and potential evapotranspiration. For a specified reference period, the SPEI is constructed by first fitting the water balance observations for a particular timescale in a location to a gamma distribution. It is then translated into its corresponding value within a standard normal distribution. If a single month is set as the timescale, the corresponding SPEI value for a particular month-year observation, eg. July 1990, represents the probability of occurrence of the July 1990 water balance observation relative to the historical distribution of July water balance within the reference period. The index can be calculated for timescales beyond a single month, as the effects of precipitation shocks on the environment vary depending on their duration.[1]

I construct 3-month SPEI (SPEI-3) for each province with 1952-2013 as my reference period. I first extract data on provincial water balance using the Climate Research Unit Time Series (CRU TS), a 0.5°x 0.5° gridded data set containing monthly data on climate variables including precipitation level and potential evapotranspiration. With QGIS[2] , I extract the monthly observations for both variables at the provincial level using zonal statistics, which returns the weighted average of the grid values that fall within provincial borders. Afterwards, I calculate the water balance in R and use the package `SPEI` to generate the index time series for each province.

My measures for precipitation shocks are the monthly frequency of droughts and the monthly frequency of wet spells within each five-year period at the provincial level. An SPEI-3 value of less than or equal to -1 among monthly observations indicates drought for a particular monthly observation, while a value greater than or equal to 1 indicates a wet spell. I use these criteria accordingly to generate my measures of precipitation shocks.

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[1] The 3-month SPI (SPEI-3) value for July 1990, for instance, is calculated using the cumulative May-June-July 1990 water balance and is compared to the cumulative May-June-July water balance for all other years in the reference period.

[2] Quantum-GIS (QGIS) is an open source geographic information software.

4.3 Temperature Shocks

I create a 3-month Standardized Temperature Index (STI-3) following the methodology of the SPEI for the same reference period.[3] The monthly provincial observations from 1952-2013 are obtained using zonal statistics on the CRU TS data set, which also has data on average land surface temperature. I use the R package `STI` to translate the monthly observations into their respective index values.[4]

My measures for temperature shocks are the monthly frequency of cool temperatures and the monthly frequency of high temperatures within each five-year period at the provincial level. A month with an STI-3 value less than or equal to -1.5 indicates cooler temperatures, while a value greater than or equal to 1.5 indicates higher temperatures. I use these criteria accordingly to generate my measures of temperature shocks.[5]

4.4 Controls: Average Temperature and Precipitation

To control for baseline provincial weather characteristics, I use mean temperature and mean precipitation for each time period. These are calculated from monthly data on average land temperature and precipitation in each province from 1990-2000 using zonal statistics on the CRU TS raster data.

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[3] Unlike the SPEI which is calculated using cumulative water balance observations, the 3-month STI-3 value for July 1990, for instance, is calculated using the average temperature for May-July 1990 and is compared to the average May-July temperature for all other years in the reference period.

[4] Instead of fitting the temperature observations to a gamma distribution, the package instead uses maximum-likelihood estimation to determine the values of parameters necessary in characterizing a standard normal distribution.

[5] According to Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA, 2019), extreme temperature events occur less frequently than precipitation shocks in the Philippines. I set higher threshold values for monthly STI-3 observations to reflect this fact.

4.5 Limitations

There are two limitations that my data pose. First, my migration measures do not capture short-distance migration within the origin province and other interprovincial movement between the beginning and end of each time period. Second, in estimating the weather effects on migration for different demographic subgroups, I am not able to determine whether the differences across these groups are statistically significant or not. Due to how the bilateral migration rate for each demographic subgroup is constructed, I can only show that there are differences in the estimated effect of weather shocks on migration across these subgroups if the estimates are statistically significant for the particular subgroup.

Chapter 5

Results and Analysis

5.1 Main Results

Table 2 contains the estimates for Eq. (2.5) with robust standard errors clustered at each origin-destination pair. I apply the Ramsey Regression Equation Specification Error Test (RESET) test statistic that has been adapted for the PPML estimator (Santos Silva & Tenreyro, 2006) to check for model misspecification. It has the null hypothesis that the general functional form is correctly specified, which the test fails to reject for my main specification.

The results reveal that precipitation shocks are significant push factors by boosting interprovincial migration. An additional month of drought in the origin province is associated with a 2.26%[6] increase in the bilateral migration rate. As droughts reduce income and consumption among Filipino households, a higher level of outmigration from provinces with a higher frequency of rainfall deficits is expected; the migration

[6] In PPML, the estimated semi-elasticity for an independent variable measured in levels is $100(\exp(\hat{\beta})-1)\%$.

Table 2. Effect of weather shocks on internal migration: PPML estimates

Variables	(1)
Monthly frequency of drought	0.0223***
	(0.00577)
Monthly frequency of wet spells	0.0558***
	(0.0106)
Monthly frequency of cool temperatures	-0.00268
	(0.109)
Monthly frequency of high temperatures	-0.00309
	(0.00708)
Controls	
Average precipitation	-0.0146***
	(0.00255)
Average temperature	0.891*
	(0.483)
Origin FE	Yes
Destination-Period FE	Yes
Observations	12,324
Pseudo R-Squared	0.1170
RESET Test (p-value)	0.1413

Note: The dependent variable is the bilateral migration rate between origin province i and destination province j during five-year period t. Weather shocks are characterized in Chapter 4. Robust standard errors are indicated in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

of household members can mitigate income and consumption loss through remittances sent to their families back home (Yang & Choi, 2007). The monthly frequency of excess rainfall has the strongest push effect among weather shocks, with an additional month increasing the migration rate by 5.75%. Excess rainfall can be a proxy for short-term high rainfall events such as tropical cyclones, making this result consistent with findings that excess rainfall boosts local outmigration in the Philippines primarily through its adverse effect on income (Bohra-Mishra et al., 2017). The push effect on internal migration by precipitation shocks have also been observed in other agricultural countries (Brey & Hertweck, 2019; Gröger & Zylberberg, 2016).

On the other hand, temperature shocks in the origin province do not influence interprovincial migration. The monthly frequency of cool and high temperatures have negative estimated effects on outmigration, though they are statistically insignificant. One explanation for this is that recorded temperature shocks neither persist long enough nor deviate too far from the historical average in the country to have any meaningful impact on other migration drivers.[7] Generally speaking, the push effect of temperature is observed from slow-onset temperature change over longer time periods (International Organization of Migration [IOM], 2017). This is seen in the control variables, as an increase in the five-year average temperature in the province of origin has the expected positive effect on the bilateral migration rate. Thus, it is the variability in average provincial temperature that drives local outmigration among climatic variables instead of the frequency of temperature shocks, a result that aligns with existing findings in the Philippines (Bohra-Mishra et al., 2017) and in other countries (Bohra-Mishra et al., 2014; Mueller et al., 2014; Poston et al., 2009).

5.2 Migration Sensitivity by Demographic Group

I also estimate the migration sensitivity of different demographic subgroups in relation to weather shocks. Table 3 contains the estimates for Eq. (2.6) with robust standard errors clustered at each origin-destination pair. The RESET test statistic either rejects the null hypothesis or cannot be computed for the specifications estimating the bilateral migration rate for males, the age group 20-29, and individuals who have finished secondary education only, so I exclude them from my analysis.[8]

[7]On average across provinces, one standard deviation change in the STI corresponds to a change of 0.43°C with respect to the historical monthly average temperature.

[8]I still include the estimates for these excluded models in Table 3 for transparency.

Table 3. Effect of weather shocks on internal migration by demographic group: PPML estimates

	Sex		Educational Attainment in 2000			Age		
Variables	Male	Female	Primary and below	Secondary	Tertiary	20-29	30-49	50-65
Monthly frequency of drought	0.0215***	0.0232***	0.0370***	0.0234***	0.0110*	0.0218***	0.0250***	0.0136
	(0.00652)	(0.00608)	(0.00823)	(0.00627)	(0.00600)	(0.00669)	(0.00712)	(0.0130)
Monthly frequency of wet spells	0.0587***	0.0530***	0.0628***	0.0393***	0.0474***	0.0454***	0.0617***	0.0623***
	(0.0159)	(0.00963)	(0.0138)	(0.0104)	(0.0136)	(0.0131)	(0.0153)	(0.0207)
Monthly frequency of cool temperatures	-0.00789	0.00269	0.0146	-0.0755	-0.00775	-0.0417	0.0760	-0.0294
	(0.103)	(0.120)	(0.149)	(0.0962)	(0.0849)	(0.0613)	(0.144)	(0.198)
Monthly frequency of high temperatures	-0.0117	0.00509	-0.00314	-0.00463	0.000640	-0.00316	-0.00279	0.00786
	(0.00810)	(0.00721)	(0.00923)	(0.00770)	(0.00805)	(0.00868)	(0.00877)	(0.0143)
Controls								
Average precipitation	-0.0158***	-0.0134***	-0.0181***	-0.0117***	-0.00749**	-0.0124***	-0.0149***	-0.0148***
	(0.00355)	(0.00244)	(0.00351)	(0.00262)	(0.00291)	(0.00338)	(0.00337)	(0.00515)
Average temperature	1.614**	0.202	0.979**	0.476	0.217	0.742	1.627**	0.898
	(0.674)	(0.438)	(0.684)	(0.481)	(0.541)	(0.649)	(0.675)	(0.984)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,324	12,324	12,324	12,324	12,324	12,324	12,324	12,246
Pseudo R-Squared	0.1098	0.1252	0.0823	0.1384	0.1520	0.1559	0.0991	0.0914
RESET Test (p-value)	-	0.1956	0.0123	-	0.5717	0.0014	0.4161	0.7240

Note: The dependent variable is the bilateral migration rate for the indicated demographic subgroup between origin province i and destination province j during five-year period t. Weather shocks are characterized in Chapter 4. Robust standard errors are indicated in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Looking at the subpopulation of females, their outmigration is impacted by precipitation shocks and have estimated effects that are comparable to the results in Table 2. An additional month of a wet spell is associated with a 5.44% marginal increase in the bilateral migration rate among females. This is stronger than the positive push effect of the frequency of drought, whose marginal effect is a 2.35% rise in outmigration.

I measure the sensitivity of population subgroups by educational attainment, which is a suitable proxy for socioeconomic status, job search outcomes, and human capital. I find that precipitation extremes are the only weather shocks that induce higher rates of provincial outmigration, with the poorly educated displaying higher sensitivity to these shocks. While one additional month of drought increases the bilateral migration rate by 1.11% among individuals with tertiary education, it increases the rate by 3.77% for those who have reached primary education or lower. This difference in sensitivity can also be seen when looking at the effect of the frequency of wet spells, as a one-month increase raises the bilateral migration rate by 4.85% among the highly educated and 6.48% among the poorly educated.

A potential mechanism behind the differential effects of precipitation shocks by educational attainment is the type of labor that these demographic subgroups tend to engage in. Agriculture is the sector that is most vulnerable to droughts and excess rainfall, whose net effects are deemed to be negative as they lower land productivity and lead to large losses in the economic well-being of Filipino households (Anttila-Hughes & Hsiang, 2013; Israel & Briones, 2013). Additionally, this sector does not attract those with higher levels of educational attainment; it has the least educated workforce, with a third of agricultural workers not having finished primary school (Briones, 2017). Therefore, the poorly educated are more exposed to the adverse effects of precipitation shocks on agricultural income and household consumption as compared to the highly educated. It can be argued that this leads them to have a higher sensitivity to drought and wet spell frequency when it comes to outmigration.

Finally, I examine how the influence of extreme weather shocks on migration differs by age for the age brackets 30-49 and 50-65. While temperature shocks do not have an impact on outmigration for both age groups, excess rainfall is a common push factor for them. The marginal effect of a month under a wet spell for these groups is comparable, as it leads to a 6.36% and 6.43% increase in the bilateral migration rate of the 30-49 and 50-65 age brackets respectively. On the other hand, drought frequency has a statistically significant influence only on the outmigration of younger age bracket as it increases the bilateral migration rate by 2.53%. Overall, the younger cohort exhibits sensitivity to the most number of weather shocks in their province of origin, consistent with earlier findings in the Philippine context (Bohra-Mishra et al., 2017). Income may also be a channel that drives this difference, as migration among younger individuals is more common than among older individuals in low- to middle-income countries since they have more years to collect their returns from their migration investment (Borjas, 2012).

5.3 Robustness

I perform a series of robustness checks. First, the estimated effects on interprovincial migration can be sensitive to how the shock variables are defined. I analyze the robustness of my main findings to higher threshold values in absolute terms of my climate shock indices. Precipitation shocks are redefined as the monthly frequency of severe and extreme drought (SPEI-3 $\leq$ -1.5), as well as severe and extreme wetness (SPEI-3 $\geq$ 1.5). Temperature shocks are redefined as the monthly frequency of extreme cold (STI-3 $\leq$ -2) and extreme heat (STI-3 $\geq$ 2). Table 4 contains the resulting estimates and I find that they only partially match my main results. While precipitation shocks both have positive marginal effects on the bilateral migration rate, only the corresponding variable for excess

Table 4. Effect of severe and/or extreme weather shocks on internal migration: PPML estimates

Variables	(1)
Monthly frequency of severe and extreme drought	0.004
	(0.00588)
Monthly frequency of severe and extreme wetness	0.0372***
	(0.00642)
Monthly frequency of extreme cold	-0.421***
	(0.0874)
Monthly frequency of extreme heat	-0.0266***
	(0.00623)
Controls	
Average precipitation	-0.00716***
	(0.00180)
Average temperature	0.167
	(0.327)
Origin FE	Yes
Destination-Period FE	Yes
Observations	12,324
Pseudo R-Squared	0.1170
RESET Test (p-value)	0.1413

Note: The dependent variable is the bilateral migration rate between origin province i and destination province j during five-year period t. Weather shocks are redefined with higher index value thresholds. Robust standard errors are indicated in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

rainfall remains a relevant determinant. Both extreme cold and hot temperatures are now also statistically significant and exert a negative influence on provincial outmigration. The frequency of extreme temperature shocks can hamper migration, as shocks that are stronger in magnitude adversely impact agricultural output and, in turn, household income. Thus, even if households would want to migrate, their liquidity constraint prevents them from paying the costs associated with moving elsewhere.

Second, I explore the validity of alternative specifications that include lags of the weather variables as well as the population in the province of origin. The results are reported in Table 5. Consistent with my main results, precipitation shocks in the current period remain the only shock variables that are associated with increased bilateral mig-

Table 5. Effect of severe and/or extreme weather shocks on internal migration: PPML estimates

Variables	(1)	(2)	(3)	(4)
Monthly frequency of drought	0.0206***	0.0216***	0.0209***	0.0217***
	(0.00652)	(0.00726)	(0.00685)	(0.00775)
Lag of monthly frequency of drought	-0.00116	0.00348	-0.00130	0.00339
	(0.00500)	(0.00543)	(0.00495)	(0.00545)
Monthly frequency of wet spells	0.0632***	0.0610***	0.0631***	0.0609***
	(0.0104)	(0.0107)	(0.0104)	(0.0107)
Lag of monthly frequency of wet spells	0.00685	0.000748	0.00688	0.000849
	(0.00575)	(0.00827)	(0.00578)	(0.00858)
Monthly frequency of cool temperatures	-0.0174	0.00508	-0.0196	0.00394
	(0.120)	(0.116)	(0.125)	(0.123)
Lag of monthly frequency of cool temperatures	-0.0201	-0.0170	-0.0199	-0.0170
	(0.0265)	(0.0260)	(0.0267)	(0.0259)
Monthly frequency of high temperatures	-0.0470***	-0.0500***	-0.0465***	-0.0498***
	(0.0113)	(0.0119)	(0.0121)	(0.0126)
Lag of monthly frequency of high temperatures	-0.0164***	-0.0186***	-0.0163***	-0.0186***
	(0.00324)	(0.00415)	(0.00331)	(0.00415)
Average precipitation	-0.0144***	-0.0137***	-0.0144***	-0.0137***
	(0.00267)	(0.00265)	(0.00269)	(0.00268)
Lag of average precipitation		0.000349		0.000291
		(0.00477)		(0.00491)
Average temperature	1.218**	1.143*	1.199**	1.132*
	(0.500)	(0.595)	(0.506)	(0.618)
Lag of average temperature		-0.0323		-0.0323
		(0.0212)		(0.0212)
Ln(Population)			-0.0420	-0.0196
			(0.278)	(0.284)
Origin FE	Yes	Yes	Yes	Yes
Destination-Period FE	Yes	Yes	Yes	Yes
Observations	12,324	12,324	12,324	12,324
Pseudo R-Squared	0.1171	0.1171	0.1171	0.1171
RESET Test (p-value)	-	-	-	-

Note: The dependent variable is the bilateral migration rate between origin province i and destination province j during five-year period t. Robust standard errors are indicated in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Effect of weather shocks on internal migration with time-invariant FEs: PPML estimates

Variables	(1)	(2)	(3)	(4)	(5)
Monthly frequency of drought	0.0250***	0.0177**	0.0208***	0.0177**	0.0214***
	(0.00624)	(0.00701)	(0.00771)	(0.00739)	(0.00827)
Lag of monthly frequency of drought		0.000913	0.000395	0.000909	-3.76 x 10^{-5}
		(0.00535)	(0.00647)	(0.00527)	(0.00647)
Monthly frequency of wet spells	0.0534***	0.0616***	0.0621***	0.0616***	0.0620***
	(0.0112)	(0.0123)	(0.0124)	(0.0122)	(0.0123)
Lag of monthly frequency of wet spells		0.00129	0.00324	0.00129	0.00372
		(0.00704)	(0.00958)	(0.00702)	(0.00990)
Monthly frequency of cool temperatures	-0.00717	-0.0234	-0.00556	-0.0235	-0.0110
	(0.105)	(0.127)	(0.121)	(0.132)	(0.126)
Lag of monthly frequency of cool temperatures		-0.0141	-0.0196	-0.0141	-0.0198
		(0.0311)	(0.0290)	(0.0312)	(0.0289)
Monthly frequency of high temperatures	-0.00715	-0.0205**	-0.0512***	-0.0205*	-0.0501***
	(0.00866)	(0.0101)	(0.0126)	(0.0111)	(0.0135)
Lag of monthly frequency of high temperatures		-0.0110***	-0.0183***	-0.0110***	-0.0182***
		(0.00350)	(0.00424)	(0.00351)	(0.00425)
Average precipitation	-0.0156***	-0.0126***	-0.0142***	-0.0126***	-0.0143***
	(0.00346)	(0.00321)	(0.00299)	(0.00321)	(0.00303)
Lag of average precipitation			0.000877		0.000587
			(0.00486)		(0.00496)
Average temperature	1.123*	0.654	1.247*	0.653	1.194*
	(0.682)	(0.585)	(0.642)	(0.584)	(0.664)
Lag of average temperature			-0.0165**		-0.0169**
			(0.00729)		(0.00724)
Ln(Population)				-0.00130	-0.0955
				(0.313)	(0.315)
Origin FE	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes
Observations	12,324	12,324	12,324	12,324	12,324
Pseudo R-Squared	0.1162	0.1162	0.1163	0.1162	0.1163
RESET Test (p-value)	-	-	-	-	-

Note: The dependent variable is the bilateral migration rate between origin province i and destination province j during five-year period t. Robust standard errors are indicated in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

ration. However, the monthly frequency of high temperatures in the current period and in the preceding period are now also statistically significant determinants. However, I cannot establish the validity of these specifications, as the RESET test statistic for each of them cannot be calculated.

Third, I investigate how relaxing the assumption of the presence of multilateral resistance alters the estimates in relation to my main specification and in the alternative specifications used previously. I do this by utilizing time-invariant FEs for both the origin and destination provinces, the results for which are seen in Table 6. Compared to the results in Table 1, the analogous specification (1) presents a stronger effect for drought frequency and a weaker effect for wet spell frequency, though they both remain positive. For the alternative specifications (2) and (4) where only lagged shock variables are added, the effects of statistically significant shocks in the current period and in the preceding period are lower in magnitude in relation to the estimates in Table 5. When the complete set of lag variables are used as in (3) and (5), the effect of drought frequency and the lag of high temperature frequency become lower in magnitude while the effect of wet spell and high temperature frequency become higher. Overall, these estimated effects are still consistent with previous estimates in other tables. However, like the specifications in Table 5, I cannot establish the validity of all these specifications as their RESET test statistics cannot be computed.

Lastly, I compare my findings with the estimates obtained with an alternative estimator. The panel structure of my data allows me to use the first difference (FD) estimator, which excludes the bias from unobserved time-invariant provincial characteristics (Wooldridge, 2010). I derive my new specification by applying a log transformation to Eq. (2.5) and then computing the first time difference for each panel to obtain the first

Table 7. Effect of weather shocks on internal migration: First-difference estimates

Variables (first-differenced)	(1)	(2)
Monthly frequency of drought	9.25×10^{-6}***	1.03×10^{-5}***
	(2.19×10^{-6})	(2.4×10^{-6})
Monthly frequency of wet spells	2.24×10^{-5}***	2.24×10^{-5}***
	(6.78×10^{-6})	(6.86×10^{-6})
Monthly frequency of cool temperatures	9.72×10^{-6}	8.16×10^{-6}
	(1.56×10^{-5})	(1.48×10^{-5})
Monthly frequency of high temperatures	2.06×10^{-6}***	2.07×10^{-6}***
	(6.37×10^{-7})	(6.4×10^{-7})
Controls		
Average precipitation	-4.51×10^{-6}***	-4.59×10^{-6}***
	(9.33×10^{-7})	(9.75×10^{-7})
Average temperature	-2.78×10^{-6}	-2.14×10^{-6}
	(2.43×10^{-6})	(2.17×10^{-6})
Ln(Population)		-1.01×10^{-4}
		(1.11×10^{-4})
Observations	6,162	6,162
R-Squared	0.0104	0.0105

Note: The dependent variable is the difference in ln(Bilateral migration rate + 1) for origin province i and destination province j between the periods 1990-1995 and 1995-2000. Robust standard errors are indicated in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

difference equation:

$$\ln\left(\frac{N_{ij,t}}{N_{ii,t}}+1\right)-\ln\left(\frac{N_{ij,t-1}}{N_{ii,t-1}}+1\right)=\Delta\ln\left(\frac{N_{ij}}{N_{ii}}+1\right)=\beta_0+\beta_1\Delta W_i+\theta\Delta X_i'+\Delta\epsilon_{ij} \quad (5.1)$$

Using OLS, I obtain the results reported in Table 7 and I find they are largely consistent with my main findings. Though a higher frequency of precipitation shocks in the origin province still marginally increases outmigration in these specifications, the monthly frequency of high temperatures is now also linked to a positive push effect on migration. However, the estimated effects here are significantly lesser in magnitude compared to those in Table 1; the strongest push effect comes from the monthly frequency of drought in (2), with an additional month being associated with only an 0.001% increase in the bilateral migration rate.

The FD estimator has two drawbacks that are addressed by the PPML estimator. First, I estimate $\Delta\ln\left(\frac{N_{ij}}{N_{ii}}+1\right)$ instead of only $\Delta\ln\left(\frac{N_{ij}}{N_{ii}}\right)$ in this new specification. This prevents observations from being dropped, which occurs when either the current bilateral rate of the origin-destination pair or its lag is zero-valued. This data transformation can be used when there are few zero-valued observations (Wooldridge, 2015); however, this is not applicable for my data where zero migration accounts for approximately 35% of observations in each period. The is a non-issue when using the PPML estimator, as it accommodates data with a high number zero-valued observations and does not require the transformation of the multiplicative gravity model.

Second, the FD estimator only excludes the bias from unobserved time-invariant provincial characteristics. For panel data where $t = 2$, it is numerically equivalent to the FE estimator (Wooldridge, 2010). My data conforms to this requirement and thus, my approach in this final robustness check is equivalent to estimating a specification that includes time-invariant origin and destination FEs only. However, this approach does not account for the influence of MR on the bilateral migration rate, leading to biased estimates. By using the PPML estimator, I am able to estimate my multiplicative model that includes origin and destination-time FEs that can control for MR effects (Feenstra, 2002).

Conclusion

I investigate how the frequency of precipitation and temperature shocks influence provincial outmigration in the Philippines. I find that precipitation shocks are the only shocks that influence internal migration. An increase in the monthly frequency of drought and wet spells in the origin province is associated with higher bilateral migration rates, with wet spells having a stronger marginal effect. While temperature shocks do not have a statistically significant effect on bilateral migration, there is evidence that temperature effects on interprovincial migration instead comes with the slow-onset rise in baseline provincial temperatures. When estimating the bilateral migration rates of different demographic subgroups, precipitation shocks remain the only shocks that have a significant effect. Younger individuals and those with lower levels of educational attainment display a higher sensitivity to drought and wet spell frequency when it comes to migration. Income variability and earning potential are possible mechanisms that drive sensitivity differences across subgroups. However, my main results are only partially robust to an alternative definition of precipitation and temperature shocks and to alternative empirical specifications.

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