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ABSTRACT

Climate Variability and International Migration: The Importance of the Agricultural Linkage[1]

While there is considerable interest in understanding the climate-migration relationship, particularly in the context of concerns about global climatic change, little is known about underlying mechanisms. We analyze a unique and extensive set of panel data characterizing annual bilateral international migration flows from 163 origin countries to 42 OECD destination countries covering the last three decades. We find a positive and statistically significant relationship between temperature and international outmigration only in the most agriculture-dependent countries, consistent with the widely-documented adverse impact of temperature on agricultural productivity. In addition, migration flows to current major destinations are especially temperature-sensitive. Policies to address issues related to climate-induced international migration would be more effective if focused on the agriculture-dependent countries and especially people in those countries whose livelihoods depend on agriculture.

JEL Classification: Q54, J10

Keywords: international migration, climate variability, agricultural productivity

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Introduction

Climate change has become an increasing global concern as its current and future impacts are understood in greater detail (IPCC, 2007). One widely cited response to such impacts is the potential for large-scale displacement of segments of human population (Myers, 2002; Stern, 2007; Warner et al., 2009; Marchiori et al., 2012). Among all climate-induced migrants, those crossing the political borders would be a matter of particular concern as both receiving and sending countries are affected. Identification of the mechanisms underlying the climate-migration relationship would be useful to national governments and international agencies devising policies to manage migration flows.

Despite growing interest from policymakers and the general public, the quantitative literature on weather- and climate- induced migration is still in its infancy.[2] The empirical results so far are mixed – while many studies support a significant relationship between migration and climatic factors such as natural disasters, temperature, and precipitation (Reuveny and Moore, 2009; Feng et al., 2010; Marchiori et al., 2012; Gray and Muller, 2012; Feng and Oppenheimer, 2012), some researchers find that climate is an inconsequential factor compared to other drivers of migration (Mortreux and Barnett, 2009; Naudé, 2010). The apparent inconsistencies among the outcomes of various studies arise partly because such studies are mostly context-specific – they differ in the geographic regions covered and the time frames of study. The effects of climate on human migration are likely to be heterogeneous across time and space, as climate may

[2] While we acknowledge the difference between climate and weather, the terms "climate" and "weather" will be used interchangeably in this paper. Our analysis is performed with annual temperature and precipitation for the period of 1980-2010.

interact with region-specific factors, such as other environmental and socio-economic conditions, cultural and lifestyle characteristics, and social networks (Black et al., 2011).

To move this literature forward and gain a more complete picture of the climate-migration relationship, one can either continue to accumulate such context-specific evidence or conduct the analysis at a more aggregate level and focus on the most important linkage(s). This paper takes the second approach, and considers agriculture to be a possible intermediate link between climate and (international) migration. We do so for the following reasons. First, a large body of literature has already established a significant sensitivity of crop yields to climatic changes, especially temperature increases (Lobell et al., 2008; Schlenker and Roberts, 2009; Lobell et al., 2011). Second, agriculture is an important economic sector in many countries, especially in the developing world, where a large proportion of the population still directly depends on agriculture for a living. Thus it is a plausible hypothesis that agriculture plays an important role in the climate-migration relationship.

In this paper, we use a comprehensive bilateral annual migration dataset covering 163 origin countries and 42 OECD destination countries over the period of 1980-2010 to study the climate-migration relationship empirically. We first estimate a reduced-form model that links origin country weather variations to its international outmigration, while controlling for an important migration determinant – income (approximated by GDP per capita) – as well as unobserved time-invariant country-pair factors and country-specific time trends. To investigate the role of agriculture, interaction terms between weather and agricultural dependence are included in the model.[3] We find that the effect of temperature on outmigration is positive and

[3] Agricultural dependence is a dummy variable, where the top 25% agriculture-dependent countries are assigned with 1, and the remaining countries are assigned with 0. Agriculture-

statistically significant only in agriculture-dependent countries. Because most agriculture-dependent countries are also relatively poor, we use the instrumental variables approach to provide more direct evidence on the agricultural linkage to rule out the alternative hypothesis that the sensitivity of outmigration to climate is due to a country's being poor per se. We estimate the yield-migration relationship, using temperature and precipitation as instruments for cereal yields. We find that outmigration is highly responsive to climate-induced yield shocks, but only in agricultural countries. Our results thus suggest that, globally, agriculture is an important intermediate link between climate and international migration. It should be noted that the relation between the sensitivity of past migration to climate/weather variability and future migration due to long term climate change is uncertain. Here we focus on the former which provides insights on current motivations for migration while potentially informing projections of the latter.

The rest of the paper proceeds as follows. The next section reviews the emerging literature on climate-induced migration. Then we present a theoretical model of international migration that incorporates climate formally, followed by our empirical strategy. Following that are our empirical results. Then the final section concludes.

Literature Review

There is a large literature on the determinants of human migration that encompasses several disciplines. Income maximization is usually considered to be one of the most important migration determinants (Roy, 1951; Borjas, 1989; Clark et al., 2007; Mayda, 2010). Simply put, a potential migrant is assumed to compare the income differences between origin and several

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dependent countries (or agricultural countries, used interchangeably in our paper) are defined as those with relatively high share of agriculture value added in GDP.

destinations and the cost of migration, and select a destination which maximizes income. The income maximization framework can be extended to utility maximization in order to incorporate non-pecuniary determinants of migration (Borjas, 1989), such as cultural and linguistic distance, political pressures, conflicts and wars, networks of family and friends, educational and social benefits, immigration policies, and amenities (Massey et al., 1993; Borjas, 1999; Clark et al., 2007; Pedesen et al., 2008; Ortega and Peri, 2009; Mayda, 2010; Adsera and Pytlikova, 2012).

During recent decades, the migration literature has paid more and more attention to climatic and environmental factors, such as sea level rise, environmental degradation, weather-related crop failures, and extreme weather events (Hugo, 1996; Myers, 2002; Warner et al., 2009; Piguet et al., 2011; Foresight, 2011; Gray and Mueller, 2012). Many studies found a significant influence of climate on human migration. Using unbalanced panel data, Barrios et al. (2006) found that rainfall affects rural-to-urban migration in sub-Saharan Africa. Feng et al. (2010) and Feng and Oppenheimer (2012) used a Mexican state-level panel data of migration flows, and found a significant semi-elasticity of migration from Mexico to the United States with respect to climate-driven changes in crop yields. Gray and Mueller (2012) showed that crop failures driven by rainfall deficits have a strong effect on mobility in Bangladesh, while flooding has a modest effect. Using a country-level panel data of sub-Saharan Africa, Marchiori et al. (2012) found that weather anomalies increase internal and international migration through both amenity and economic geography channels. Mueller et al. (2014) found that flooding has modest impact on migration, while heat stress increases the long-term migration in Pakistan.

In contrast, some other studies have not found a significant role for climate. Based on a survey conducted in Tuvalu, Mortreux and Barnett (2009) showed that the vast majority of potential migrants do not consider climate change as a possible reason for leaving the country.

Naudé (2010) also reported that natural disasters do not have significant effects on international migration across sub-Saharan African countries. However, these studies did not consider possible indirect impact of climate through income differences and other channels. For example, in the survey data used by Mortreux and Barnett (2009), migrants might not be aware of the possibility that climate change implicitly contributes to socio-economic shocks which directly affect migration, and thus do not cite climate change as a reason to leave. When discussing the insignificant effects of natural disasters on migration, Naudé (2010) also acknowledged that natural disasters may affect conflict and job opportunities and, as such, have an indirect impact on migration.

Due to data limitations, previous studies on the determinants of migration usually relied on analyses of migrants moving from one origin to one destination (Massey and Espinosa, 1997; Feng et al., 2010) or multiple destinations (Hanson and McIntosh, 2010), or from multiple origins to one destination (Clark et al., 2007; Vogler and Rotte, 2000). More recently, researchers have begun to rely on multi-country bilateral migration data, which not only increases the sample size but also allows controls for country-pair specific factors through the fixed effects model and facilitates drawing more general conclusions (Pedersen et al., 2008; Ortega and Peri, 2009; Mayda, 2010; Adsera and Pytlikova, 2012). Nevertheless, its application in the climate-migration studies remains limited. Reuveny and Moore (2009) used a cross-sectional data of bilateral international migration flows to 15 OECD destination countries in the late 1980s and 1990s to investigate the effects of environmental degradation, e.g., weather-related natural disasters. Beine and Parsons (2012) used a panel of bilateral migration for the period of 1960-2000 to study the impact of climatic change. Their dataset has only five panels of foreign population stock data based on the last five completed censuses. Thus their migration flow data are approximated by the change in migration stocks between census years. We use a more comprehensive bilateral annual migration dataset covering 42 OECD destination countries and 163 origin countries over the period of 1980-2010 to study the climate-migration relationship.

Theoretical model

Suppose there is a fictitious country (FC), which is a small open economy compared with the rest-of-the-world (ROTW). Initially FC is populated by a mass normalized to 1. The utility of person *k* in FC is:

$$U_k = w + p + a_k \tag{1}$$

where w is the wage, p is the deterministic part of the non-pecuniary utility, and a_k is the individual deviation from the average non-pecuniary utility. To simplify this model, people in FC are assumed to have the same wage. By construction, the expectation of a_k is 0, with cumulative distribution function $F(.)$. The higher a_k, the more person *k* prefers to remain in FC.

Suppose we allow people from FC to migrate to ROTW (but not otherwise). Let the wage level in ROTW be w_r. For simplicity, we assume that people originally from FC do not enjoy any non-pecuniary utility in ROTW. Thus, a person *k* would have the utility level of just w_r in ROTW. Alternatively, one can consider $p + a_k$ as the utility premium for person *k* to live in FC.

To migrate from FC to ROTW, a person must also incur a cost of c. Thus the equilibrium condition for any person *k* to remain in FC is:

$$w + p + a_k \geq w_r - c \tag{2}$$

The marginal person *l* is defined as the one who is just indifferent between living in FC and migrating to ROTW, i.e., for person *l*,

$$w + p + a_l = w_r - c \tag{3}$$

Thus, in the equilibrium, the total population in FC is $N = 1 - F(a_l)$, where a_l is implicitly defined as in Eq. (3).

Suppose in FC, the aggregate production function is $Y = [\alpha A + (1-\alpha)B]K^{\beta}N^{1-\beta}$, where K is capital, N is total labor force, which equals the total population for simplicity, A is the productivity of agricultural sector, B is the productivity of non-agricultural sector, and we assume that $B > A$, i.e., non-agricultural sector is more productive. α is the proportion of agricultural sector in the economy. β is the output elasticity of capital, and $1-\beta$ is the output elasticity of labor. If the labor market is competitive, the real wage equals the marginal productivity of labor. Thus the equilibrium wage level in FC is determined by the first order condition:

$$w = \frac{\partial Y}{\partial N} = (1-\beta)[\alpha A + (1-\alpha)B](K/N)^{\beta} \tag{4}$$

Now, let's consider how climate change affects outmigration from FC. Let C stand for the adverse climate factors. Based on empirical findings of Dell et al. (2012), we assume climate affects the productivity of agricultural sector but not that of non-agricultural sector, i.e., $\frac{\partial A}{\partial C} < 0$ and $\frac{\partial B}{\partial C} = 0$.[4] We also allow the possibility that adverse climate condition would affect people's expected amenities in FC, and $\frac{\partial p}{\partial C} \leq 0$. Rewrite Eq. (3), we have:

$$(1-\beta)[\alpha A(C) + (1-\alpha)B](K/N(C))^{\beta} + p(C) + F^{-1}(1-N(C)) = w_r - c \tag{5}$$

[4] We make the assumption that climate does not affect non-agricultural sectors for simplification. In reality, climate change may have effects on non-agricultural sectors (Feng et al., 2012).

Take derivatives with respect to C in both sides of Eq. (5),

$$\frac{dN}{dC} = \frac{(1-\beta)\alpha \frac{\partial A}{\partial C}(K/N)^{\beta} + \frac{\partial p}{\partial C}}{(1-\beta)\beta[\alpha A + (1-\alpha)B](K/N)^{\beta}(1/N) + F^{-1'}(1-N(C))} \tag{6}$$

According to Eq. (6), we have the following results:

(a) $\frac{dN}{dC} < 0$, i.e., adverse climate change would induce a decline in population, or outmigration from the country. This is assuming that $\alpha = 0$ (no agricultural sectors) and $\frac{\partial p}{\partial C} = 0$ (climate has no effects on amenities) do not hold simultaneously;

(b) For countries that are more agriculture-dependent, i.e., with larger α, an adverse climate change would trigger more outmigration. This follows as A<B;

(c) If amenities are not adversely affected by climate, i.e., $\frac{\partial p}{\partial C} = 0$, then for non-agricultural countries (with $\alpha = 0$), changes in climate would not trigger any outmigration ($\frac{dN}{dC} = 0$).

Empirical Model

To empirically test the main implications of the theoretical model, we estimate the following fixed-effects regression:

$$\ln M_{ijt} = \beta_0 + \beta_1 TMP_{it} + \beta_2 PCP_{it} + \delta_1 TMP_{it} * A_i + \delta_2 PCP_{it} * A_i + \phi x_{it-1} + \varphi z_{jt-1} + \theta_{ij} + d_i year_t + d_j year_t + \varepsilon_{ijt} \tag{7}$$

where $\ln M_{ijt}$ denotes the natural logarithm of migration rate, i.e., migration flow from origin country *i* to destination country *j* divided by the population of the origin country *i* at time *t*. TMP_{it} represents the population-weighted annual average of monthly mean temperature in the origin country *i* in degree Celsius.[5] PCP_{it} represents the population-weighted annual average of monthly total precipitation in the origin country *i* in millimeters.[6] A_i is a dummy variable that equals 1 if the origin country *i* is defined as agriculture-dependent, 0 otherwise. x_{it-1} and z_{jt-1} are other control variables specific to origin country *i* and destination country *j*, respectively, such as the natural logarithm of GDP per capita, which are commonly accepted as the main determinant of migration. The lagged value of GDP per capita is employed to address possible reverse causality that migration flow affects destination countries' income (Mayda, 2010). θ_{ij} denotes country-pair fixed effects, which capture time-invariant unobserved characteristics between two specific countries, such as distance, historical and cultural ties, linguistic distance, and many more. Using country-pair fixed effects, we only explore the variations over time within each country pair. $d_i year_t$ and $d_j year_t$ denote origin and destination country-specific linear time trend, which control for factors evolving over time within specific countries, such as urbanization, employment possibilities, welfare schemes, migrant networks or immigration

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[5] We use annual average temperature and precipitation data, since we focus on international migration and Piguet et al. (2011) summarized that "rapid onset phenomena lead overwhelmingly to short-term internal displacements rather than long-term or long-distance migration". It should be noted that rapid onset extreme events may affect the annual average weather data. For instance, a heat wave increases the average temperature, and flooding increases the total precipitation of a particular year.

[6] In studies of climate impact on agriculture, growing season weather variables are usually used. However, for cereal yields (including corn, rice, wheat, and many more) from all the countries, growing seasons are rather diverse, so annual weather variables are a better choice.

policy schemes. ε_{ijt} denotes the error term. In our empirical work, we always report robust standard errors clustered at the country-pair level to allow for within-country-pair correlation of the error term. $\beta_0, \beta_1, \beta_2, \delta_1, \delta_2, \phi,$ and φ are parameters to be estimated. The key parameters of interest are δ_1 and δ_2, which capture the differential weather effects in agriculture-dependent countries versus the other countries.

To provide more direct evidence on the role of agriculture as the intermediate linkage between weather and outmigration, we follow an empirical strategy similar to Feng et al. (2010) and estimate the elasticity of migration with respect to cereal yields. Our fixed-effects two-stage least-squares (FE-2SLS) regression model is as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 TMP_{it} + \beta_1 PCP_{it} + f_i + c_i year_t + \varepsilon_{it} \tag{8}$$

$$\ln M_{it} = \gamma_0 + \gamma_1 \ln Y_{it} + h_i + d_i year_t + \mu_{it} \tag{9}$$

In the first stage as Eq. (8), the natural logarithm of cereal yields, $\ln Y_{it}$, is regressed on annual average of monthly mean temperature and monthly total precipitation. In the second stage as Eq. (9), the natural logarithm of outmigration rate is regressed on predicted cereal yields from the first stage. f_i and h_i are country fixed effects, and $c_i year_t$ and $d_i year_t$ are the origin country-specific linear time trends. Unlike the reduced-form model shown in Eq. (7), we aggregate outmigration to all destination countries for each origin country in FE-2SLS.

Results

Data and summary statistics

We use a unique dataset on bilateral international migration flows and stocks of foreigners in 42 OECD destination countries from 163 origin countries during the period of

1980-2010.[7] It was collected by writing to selected national statistical offices of OECD countries to request detailed information on immigration flows and foreign population stocks in their respective country, sorted by origin country. Although our dataset presents substantial progress over similar datasets used in past research (Pedersen et al., 2008; Ortega and Peri, 2009; Mayda, 2010; Adsera and Pytlikova, 2012), it is not without limitations. First, the dataset is unbalanced, with missing migration flows and stocks for some countries in some years. However, missing observations become less of a problem for more recent years (Table A1). Second, as in the other existing datasets (Ortega and Peri, 2009), different countries use different definitions of an immigrant (Table A2). Nevertheless, these limitations are unlikely to be correlated with weather patterns and thus should not cause biases to our results. Besides, by using country-pair fixed effects, we only explore variations over time within each country pair, therefore different definitions of an immigrant should not be a concern here.

Cereal yields and the share of agriculture value added in GDP were collected from the World Bank (http://databank.worldbank.org). The purchasing power parity converted GDP Per Capita at 2005 constant prices was obtained from the Penn World Tables version 7.0 (Heston et al., 2011). Global gridded monthly mean temperature and total precipitation data from 1980 to 2010 were collected from NASA–Modern Era Retrospective Analysis for Research and Applications (Rienecker et al., 2011) with a resolution of 2/3 degrees in longitude and 1/2 degrees in latitude, and then aggregated to be country-level population-weighted, so that the

[7] The original OECD migration dataset covers 22 OECD destination and 129 origin countries over the period of 1989-2000 (Pedersen et al., 2008). It has been extended to cover 30 OECD destinations, all origin countries and the period of 1980-2010 (Adsera and Pytlikova, 2012).

weather conditions for populated regions within a country are given more weights. Data are available upon request.

Our bilateral migration data covers 163 origin countries, and 42 of them are also destination countries, with a total of 95,712 observations during the period of 1980-2010. On average, for an origin country, about 1,077 people migrate to another specific country during a specific year. During the period of 1980-2010, there were in total about 108 million people migrating to another country; among them, about 85 million (50 million) people migrated through the top 5% (1%) country pairs with large migration flows. Table 1 presents detailed information about our data. We observe that non-agricultural countries have higher outmigration rates. This may be due to the fact that most of agricultural countries are also poor, which usually have limited out-migration flows due to poverty constraints (Pedersen et al., 2008; Hatton and Williamson, 2002 and 2011). GDP per capita and cereal yields are lower for agricultural countries. Agricultural countries tend to have higher temperatures as they are more likely to be located in lower latitude regions than non-agricultural countries. Agricultural countries also tend to have higher precipitation.

The Reduced-form Regression Results

In Model 1 of Table 2, we regress the natural logarithm of migration rate (migration flow from one origin country to one destination country divided by the origin country population) on contemporaneous temperature and precipitation of origin countries. In Model 2 of Table 2, the interaction terms between weather and agricultural dependence are included to test if the weather effect is different between the top 25% agriculture-dependent countries and the remaining countries. In Model 3 of Table 2, our preferred specification as Eq. (7), we further include the natural logarithm of lagged GDP per capita for both origin and destination countries. All three models contain a set of country-pair fixed effects and the origin and destination country specific linear time trends. A positive and significant coefficient estimate for the interaction term suggests that the temperature effects are significantly different between agricultural and non-agricultural countries – and more likely to induce significant outmigration from agricultural countries. Specifically, based on Model 3 of Table 2, each 1°C increase in temperature implies a 5% increase in the outmigration from the top 25% agricultural countries (significant at the 1% level), as compared to only 0.4% increase (statistically insignificant) in outmigration from the remaining countries. This is in line with Marchiori et al. (2012) who also found that weather in agricultural countries induces outmigration. As shown in Models 2 and 3 of Table 2, our results hold whether we control for GDP per capita or not.

In Table 3, we present a number of robustness checks for the coefficient of the interaction term between temperature and agricultural dependence. Our main results are qualitatively the same whether we use different control variables (Panels A-F), different regression techniques (Panel G), different dependent and independent variables (Panels H and I), or slightly different samples (Panels J-L). When conducting robustness checks, we also allow different thresholds for the definition of agricultural countries – the top one-third (33%), top one-fourth (25%), and top one-fifth (20%) countries with higher share of agriculture value added in GDP, as shown in different columns in Table 3. In general, the differential temperature effects for agricultural countries become larger in magnitude and more statistically significant when a higher threshold is set to identify agricultural countries. The results are thus consistent with the idea that more agriculture-dependent countries are more likely to experience outmigration when temperature rises, as shown in the theoretical model.

The contemporaneous temperature effects become slightly weaker but still significant when the lagged terms up to five years are also included in the model (Panels A and B). This implies that temperature may have some lagged effects on outmigration as it may take time to stimulate some of international migration flow. Migration flows may be largely determined by the existing co-ethnic networks, i.e. networks of family members, friends and people of the same origin that have already lived in a host country (Munshi, 2003; Pedersen et al., 2008). In Panel C, we use migration stock (foreign population from country *i* residing in country *j*) as a proxy for migrant networks and find that our results still hold. We also use the lagged dependent variable – the natural logarithm of lagged migration rate as one of the independent variables (Panel D), since the migration rate may be serially correlated. Again, we obtained a similar estimate as our baseline specification. This specification in Panel D could be viewed as an alternative way to control for migrant networks as Panel C.

In Panel E, the temperature effects are still positive and significant when we include an origin country-specific quadratic time trend, which controls for some nonlinear determinants of migration trending over time for each origin country. We used the country-pair fixed effects in the baseline specification, while two separate country fixed effects – one for origin and the other for destination countries – were chosen as baseline specifications in some other studies (Ortega and Peri, 2009; Mayda, 2010). In Panel F, we control for the separate country fixed effects and other variables such as distance between the most populated cities, common language, colonial tie, and common border which were not included in the model with country-pair fixed effects since they were absorbed by country-pair fixed effects (Ortega and Peri, 2009). With this alternative fixed effects specification, the temperature effects are still positive and significant for all definitions of agriculture-dependent countries.

In panel G, we run a weighted least squares regression using the natural logarithm of origin country's total population as weights, which does not change our baseline results. We further use the natural logarithm of migration flow (Panel H), instead of the natural logarithm of migration rate, as dependent variable. The results are very similar to the baseline specification. Instead of estimating the contemporaneous temperature effects, we estimate the effects of the lagged temperature in Panel I, and find the lagged response of migration flow to temperature variability, which is consistent with our expectation based on Panels A and B.

We also study if the results are driven by specific countries or country pairs. During the past three decades, 85 million (50 million) out of 108 million migrants are in the top 5% (1%) migration routes (from one country to another) by the size of migration flow. Now we remove the data from the top 5% (1%) migration routes in Panel J (Panel K) and find that the temperature effects are still positive and statistically significant across all three definitions of agriculture dependence. In addition, about 11% of all the country pairs do not have any migration flows. In Panel L, we drop those zero migration flows from the sample. The coefficient estimates for the interaction term remain positive and statistically significant.

Both temperature and precipitation variables are included in the baseline specification, due to their frequent use in the literature. We do not interpret the precipitation coefficients here, since statistical methods appear more reliable for temperature variables (Lobell and Burke, 2010); this may be explained by the fact that precipitation has higher spatial variability and thus is less well captured than temperature by the relatively coarse climate data (Burke et al., 2009), e.g., country-level in our study. However, it is still necessary to control for precipitation in our model since it is a possible confounding factor, which may be correlated with both temperature (independent variable) and migration (dependent variable).

We further study the role of different destination countries in climate-induced migration. In Table 4, we split our dataset into four parts determined by the popularity of destination countries (based on migration stock) for each origin country. In other words, each of these four sub-datasets includes all 163 origin countries, but only a quarter of destination countries. We find that our main results – positive temperature effects on outmigration from agricultural countries – are only detected in the migration routes to their top 25% migration destination countries (Table 4, column 4). The results imply that temperature tends to intensify migration mostly in the already established migration routes, while it has insignificant effect on migration to the countries which are previously not major destinations. This finding is in line with previous hypotheses that climate change will affect existing migration routes (McLeman and Hunter, 2010; World Bank, 2010).

Two-stage least squares regression results

The finding of a positive and statistically significant relationship between temperature and outmigration only for agricultural countries is quite revealing, but does not yet provide a definite answer on whether agriculture plays an important intermediate role, as many agricultural countries are also very poor. To rule out a poor-country effect, one needs to provide more direct evidence on the role of agriculture.

In this subsection, we estimate the relationship between cereal yields (an indicator of agricultural productivity) and international outmigration. To deal with the biases caused by omitted variables, we use temperature and precipitation to instrument for cereal yields and use FE-2SLS to estimate the Eq. (8) and (9). To the extent that weather factors are exogenous, the

FE-2SLS is consistent; see Feng et al. (2010) and Feng and Oppenheimer (2012) for more discussion of this point.

Tables 5 contains the second stage results of the instrumental variables approach for four country groups categorized based on the agricultural dependence. Cereal yields are found to be negatively associated with outmigration only in the top 25% agricultural countries (Table 5, column 4), suggesting that cereal yields appear to be an important factor for migration from such countries, consistent with earlier studies (Feng et al., 2010; Feng and Oppenheimer, 2012). In particular, the estimated elasticity of outmigration rate with respect to cereal yields in the top 25% agricultural countries is about -2.4. To put the number in perspective, for a country with 0.1% outmigration rate, a 10% reduction in cereal yields would raise the outmigration rate by around 24%, or to 0.124%. Table 5 shows that the FE-2SLS estimates are substantially different from the OLS estimates and more negative, which implies that the unobserved omitted variables jointly determining cereal yields and migration would bias the OLS estimates towards zero.

A concern for the instrumental variables approach is the weak instrument. In Table A3, although F-statistics of the instruments in the first stage are all significant at the 5% level, all of them are less than 10, a value usually used as a rule of thumb to detect weak instruments (Staiger and Stock, 1997). However, this rule of thumb is only for regular standard errors while we report robust standard errors clustered at the country level in this study. On the other hand, the slightly low F-statistics reported here might be due to imprecise measurements of weather and yields. Country-level data are relatively coarse for both weather and cereal yields; thus the correlation between them is expected to be less significant than is the case when finer subnational data are used. The slightly low F-statistics could also be due to the possible nonlinear relationship between temperature and yields (Schlenker and Roberts, 2009). Furthermore, cereal includes multiple crops such as corn, rice, wheat, and many more, which have different growing seasons, and also different sensitivities to weather variations. Additional noise is thus introduced when pooling them together, as we do in this paper.

Another concern is whether or not our exclusion restriction is valid. If weather affects migration through channels other than cereal yields, the FE-2SLS estimates would be biased. For instance, if people have a direct preference to live in less hot areas, our FE-2SLS estimates would be biased upward in absolute value. If this is the case, we would expect a negative and significant coefficient even for non-agricultural countries, i.e., non-agricultural countries serve as a control group in our empirical methodology. However, this is not the case. As shown in Table 5, for less agriculture-dependent countries (columns 1-3), we cannot reject the null of zero coefficients. This is also consistent with our findings reported in Table 2, which shows no reduced-form relationship between temperature and outmigration for non-agricultural countries.

In Table 6, we conduct several robustness checks for the coefficient of cereal yields in the second stage of instrumental variables approach. In this table, we only report the coefficient for agricultural countries as we reported in column (4) in Table 5. In addition to the FE-2SLS results, we also perform the fixed-effects limited-information maximum-likelihood (FE-LIML) estimations. The results are quite robust to various model specifications. First, to alleviate concerns regarding weak instruments, we use either only temperature or only precipitation as the instrument, as it is well known in the econometrics literature that the use of fewer instruments reduces the possible weak instrument bias (Angrist and Pischke, 2009). The results are shown in Panels A and B in Table 6. When temperature is used as the only instrument, the estimate is quite similar to the baseline specification. When precipitation is used as the only instrument, the coefficient is slightly smaller (still significant at the 10% level), as the average precipitation data at the country level may not be reliable.

In Panel C, we use the lagged (one-year) weather variables and cereal yields in the regression. In Panel D, we include GDP per capita as an additional control variable, as income is frequently used as a main explanatory variable in studies of international migration. In Panel E, we try an alternative definition of migration, using the natural logarithm of migration flows rather than the natural logarithm of migration rate as the dependent variable. In all these cases, the coefficient estimates remain negative and statistically significant.

Lastly, instead of using only the top 25% agricultural countries as in the baseline specification, we use the top 33% and top 20% agricultural countries in Panels F and G in Table 6, respectively. The estimated coefficients are very close to the baseline results, suggesting that the threshold for agricultural dependence that we use is not the key.

Conclusions

In this study, we have employed an empirical approach to quantify the effects of weather variations on global bilateral international migration flows. The results show that temperature has positive and statistically significant effect on outmigration, but only from agriculture-dependent countries. Therefore, among the intermediate links between weather and international migration, agriculture appears to be an important factor. Our results are robust to alternative model specifications.

While our results suggest that significant climate-induced international outmigration only happens in agriculture-dependent countries, the consequences may be substantial – we further find that climate-induced migration specifically enlarges the flow in already established migration routes, potentially presenting challenges to major migrant-receiving countries, mostly industrialized. Studies such as this one could provide a basis for advanced consideration of policies to address the consequences (both positive and negative) of potential increases in migration due to climate change. Our results provide some guidance to those developing policies to anticipate and manage these flows by focusing attention on agricultural countries and especially people in those countries whose livelihoods depend on agriculture. Agricultural adaptation, which builds resilience and enhances farmers' earnings capacities, may reduce incentives to migrate. Diversifying livelihoods for those who now depend on agriculture, such as by encouraging off-farm work, urbanization or structural upgrading, also has the potential to reduce migration.

Most previous studies are region-specific, thus generating mixed results when taken together and less likely to identify a universal underlying mechanism for the climate-induced international migration. Based on a comprehensive international migration dataset, this study provides robust empirical evidence that agriculture is an important factor influencing climate-induced international migration for the past three decades. Future research should further test our results as additional migration and climate/weather data becomes available. While we perform the analysis using the reduced-form model and instrumental variables approach, alternative methods and tools should also be used to study these relationships where appropriate.

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Table 1

Summary statistics.

	Four equal-sized country groups				All countries
	(1)	(2)	(3)	(4)	(5)
Total outmigration (millions)	38.6	24.0	34.7	8.2	108
Total outmigration in top 5% migration routes (millions)	30.8	18.6	29.3	4.6	85.4
Total outmigration in top 1% migration routes (millions)	17.8	10.4	18.9	2.2	50
Average annual outmigration rate	0.18% (0.18%)	0.30% (0.38%)	0.17% (0.32%)	0.10% (0.30%)	0.19% (0.31%)
GDP per capita (2005 US dollar)	23438 (13771)	8635 (6299)	3161 (2233)	1222 (1550)	9631 (12783)
Cereal yields (Kilogram per hectare)	3709 (2076)	2594 (1569)	2013 (1193)	1531 (962)	2463 (1711)
The percentage of agriculture, value added in GDP	3.55% (2.22%)	10.14% (4.36%)	20.48% (6.77%)	38.97% (11.41%)	18.15% (15.10%)
Monthly mean temperature (Degree Celsius)	15.712 (8.806)	18.485 (7.634)	19.127 (8.007)	23.397 (5.624)	19.309 (8.067)
Monthly total precipitation (Millimeters)	60.195 (39.230)	101.828 (77.894)	93.276 (70.284)	123.821 (82.684)	93.578 (72.888)

Note: Columns 1-4 are four country groups divided by the lower quartile, median, and the upper quartile in terms of the share of agriculture value added in GDP, where column (1) represents the least agriculture-dependent countries, and column (4) includes the most agriculture-dependent countries. Column (5) represents all the countries. Standard deviations are in parentheses.

Table 2

Climate and international migration: the reduced-form regression.

	Model 1	Model 2	Model 3
Temperature	0.011**	0.003	0.004
	(0.005)	(0.005)	(0.005)
Temperature × Agriculture		0.047***	0.046***
		(0.013)	(0.013)
Precipitation	0.0003	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Precipitation × Agriculture		0.0012***	0.0012**
		(0.0005)	(0.0005)
Log of lagged origin GDP per capita			-0.360***
			(0.045)
Log of lagged destination GDP per capita			1.081***
			(0.085)
Country-pair fixed effects	Yes	Yes	Yes
Origin and destination country-specific linear time trend	Yes	Yes	Yes
Observations	95,712	95,712	95,712
Number of origin countries	163	163	163
Adjusted R^2	0.9369	0.9369	0.9374
Temperature effect in agriculture-dependent countries		0.050***	0.050***
		(0.012)	(0.012)

Note: Dependent variable is the natural logarithm of migration rate from origin country *i* to destination country *j*. Temperature and precipitation variables are measured in country *i*. The dummy variable “Agriculture” in the interaction term is defined where the top 25% agriculture-dependent countries are assigned with 1, and the remaining countries are assigned with 0. Robust standard errors clustered by country pairs are reported in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3

Robustness checks for the reduced-form model.

	Alternative definitions of agricultural country		
	Top 33%	Top 25%	Top 20%
Baseline specification			
	0.019*	0.046***	0.055***
	(0.011)	(0.013)	(0.013)
Panel A: Controlling for lagged one year temperature and precipitation			
	0.008	0.031**	0.042***
	(0.010)	(0.012)	(0.013)
Panel B: Controlling for lagged temperature and precipitation (up to five years)			
	0.005	0.028**	0.041***
	(0.011)	(0.013)	(0.014)
Panel C: Controlling for the log of lagged migration stock			
	0.019*	0.044***	0.052***
	(0.011)	(0.013)	(0.014)
Panel D: Controlling for the log of lagged one year migration rate			
	0.013	0.025**	0.027***
	(0.009)	(0.010)	(0.010)
Panel E: Controlling for origin country-specific quadratic time trend			
	0.012	0.031***	0.043***
	(0.010)	(0.012)	(0.013)
Panel F: Controlling for both origin and destination country fixed effects			
	0.050***	0.076***	0.079***
	(0.013)	(0.016)	(0.017)
Panel G: Regressions weighted by the natural logarithm of origin country population			
	0.022**	0.049***	0.057***
	(0.011)	(0.013)	(0.014)
Panel H: Using the natural logarithm of migration flows as dependent variable			
	0.020*	0.046***	0.053***
	(0.011)	(0.013)	(0.013)
Panel I: Using lagged temperature and precipitation as independent variable			
	0.029***	0.038***	0.037***
	(0.011)	(0.013)	(0.014)
Panel J: Dropping observations with top 5% country pairs by migration flows			
	0.020*	0.047***	0.054***
	(0.011)	(0.013)	(0.013)
Panel K: Dropping observations with top 1% country pairs by migration flows			
	0.019*	0.046***	0.055***
	(0.011)	(0.013)	(0.013)
Panel L: Dropping observations with zero migration flows			
	0.028**	0.060***	0.066***
	(0.012)	(0.015)	(0.017)

Note: The coefficients of the interaction term between temperature and agricultural dependence are reported here, as the one reported in Model 3 in Table 2. Each column represents different definitions of agricultural countries, where the top 33%, top 25%, or top 20% agricultural countries are assigned with 1, and the remaining countries are assigned with 0. In Panel F, control variables such as distance between the most populated cities, common language, colonial tie, and common border are included in the model, since these country-pair variables are no longer controlled for without country-pair fixed effects. Robust standard errors clustered by country pairs are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4

Temperature effects by popularity of migration routes between origins and destinations.

	(1)	(2)	(3)	(4)
Temperature	0.019	0.003	-0.001	0.002
	(0.013)	(0.010)	(0.009)	(0.009)
Temperature × Agriculture	0.020	-0.007	0.028	0.063***
	(0.022)	(0.019)	(0.021)	(0.023)
Precipitation	-0.001**	-0.000	0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation × Agriculture	0.001	0.001*	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Origin and destination log of lagged GDP per capita	Yes	Yes	Yes	Yes
Country-pair fixed effects	Yes	Yes	Yes	Yes
Destination and origin country-specific linear time trend	Yes	Yes	Yes	Yes
Observations	17,923	24,898	29,398	33,807
Number of id	1,677	1,844	1,821	1,882
Adjusted R^2	0.9000	0.8855	0.8887	0.9302

Note: We split the dataset into four parts determined by the popularity of destination countries (based on migration stock) for each origin country, where column (1) only includes destination countries with small migration stock from each origin country, and column (4) only includes destination countries with large migration stock from each origin country. Robust standard errors clustered by country pairs are reported in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5

The second stage results: International migration and cereal yields.

	(1)	(2)	(3)	(4)
	Panel A: FE-OLS			
Log of origin cereal yields	-0.016	-0.270**	-0.141	-0.548**
	(0.050)	(0.115)	(0.137)	(0.201)
	Panel B: FE-2SLS			
Log of origin cereal yields	-4.772	2.107	-1.859	-2.405**
	(20.650)	(1.542)	(1.218)	(0.974)
Country FE	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes
Number of Countries	40	39	38	38
Observations	1,158	1,125	1,069	1,138

Note: The dependent variable is the natural logarithm of total outmigration rate from one country to all the countries. Columns 1-4 are four country groups divided by the lower quartile, median, and the upper quartile in terms of the share of agriculture value added in GDP, where column (1) represents the least agriculture-dependent countries, and column (4) represents the most agriculture-dependent countries. Robust standard errors clustered by country are reported in parentheses.

FE-OLS is the fixed-effects ordinary least squares regression model. FE-2SLS is the fixed-effects two-stage least-squares regression model. The first stage of the FE-2SLS is reported in Table A3.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6

Robustness checks for the instrumental variables results.

	F-statistic (Prob > F) in the first stage	Coefficients of cereal yields in the second stage	
		FE-2SLS	FE-LIML
Baseline specification			
	6.34	-2.405**	-2.405**
	(0.0043)	(0.974)	(0.974)
Panel A: Using only temperature as instrument			
	9.99	-2.423**	-2.423**
	(0.0031)	(0.967)	(0.967)
Panel B: Using only precipitation as instrument			
	10.13	-2.375*	-2.375*
	(0.0029)	(1.159)	(1.159)
Panel C: Using lagged yield and climate variables			
	5.33	-3.029**	-3.131**
	(0.0093)	(1.245)	(1.312)
Panel D: Also controlling for origin country GDP per capita			
	6.50	-3.326**	-2.330**
	(0.0036)	(0.945)	(0.947)
Panel E: Using the natural logarithm of migration flows			
	6.34	-2.468**	-2.468**
	(0.0043)	(0.967)	(0.967)
Panel F: Using the top 33% agricultural countries			
	8.59	-2.098**	-2.157**
	(0.0006)	(0.833)	(0.869)
Panel G: Using the top 20% agriculture countries			
	5.95	-2.561**	-2.609**
	(0.0067)	(0.964)	(0.992)

Note: The coefficients reported in this table are for the top 25% agriculture-dependent countries only, as the FE-2SLS result reported in column (4) in Table 5. Panels A–E are based on the top 25% agriculture-dependent countries. Robust standard errors clustered by country are reported in parentheses.

FE-2SLS is a fixed-effects two-stage least-squares regression model. FE-LIML is a limited-information maximum-likelihood model.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix A

See Tables A1, A2, and A3.

Table A1

Country-year coverage migration flows.

Destination	AUS	AUT	BEL	BGR	CAN	CHE	CHL	CYP	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	HRV	HUN	IRL	ISL	ISR	ITA
Year																							
2010	162	163			164				124	163	164	107	165	160					132	164	149		
2009	161	163	160		164	126	140		131	163	164	107	164	160		26			129	164	149	42	162
2008	159	163	159	164	164	126	140	164	134	163	164	107	164	160	113	21		164	130	164	149	42	161
2007	160	163	90	163	164	126	140	162	136	163	164	107	163	160	115	19	163	163	120	2	149	42	157
2006	162	163	91		164	126	140	162	135	163	164	102	163	160	114	32	163	163	122	2	149	42	159
2005	158	163	82		164	126	140	162	129	163	164	63	163	160	101	107			111	2	149	42	161
2004	160	163	68		164	126	140	162	136	163	164	55	163	160	100	101		163	100	2	149	42	161
2003	159	163	67		164	126	140	162	132	163	164	55		160	119	102		163	111	2	149	42	159
2002	158	163	67		164			160	131	163	164	55		160	120	92		161	102	2	149	42	160
2001	160	163	67		164			117	107	76	164	55		160	121	97		161	105	2	149	42	158
2000	158	163	67		164			161	104	75	164	54		160	121	103			108	2	149	42	160
1999	159	163	67		164				102	163	164	54	162	160	112	103		161	104	2	149	42	158
1998	155	163	67		164			117	113	163	164	54	162	160	112	107	161	116	106	2	149	42	160
1997	157	163	52		164				105	163	164	38		160	112	45	159		107	2	149		160
1996	156	163	52		164				110	163	164	53		160	112	49	163		108	2	149		157
1995	152		52		164				111	163	164	38		160	112	50	162		109	2	149		46
1994	152		52		164				102	163	164	38		160	113	25	163		109	2	149		31
1993	147		45		164				93	163	164	38		160		37	163		97	2	149		31
1992	148		45		164					159	164	43		160		43	163		103	2	149		31
1991	137		45		164					144	164	41		160		48	163		92	2	149		31
1990	134		45		164					41	164	41		160		38	161		95	2	149		31
1989	132		46		164					100	164	41		160		31			92	2	149		31
1988	127		24		164					100	164	41		160		38			95	2	149		31
1987	134		26		164					100	164			160		29			95	2	149		31
1986	132		26		164					100	164			160		33			99		149		31
1985	134		26		164					100	164			160		34			90		18		31
1984	131		26		164					100	164			160							18		
1983	139		26		164					100	164			160							18		
1982	136		26		164					100	164										18		
1981			26		164					100	164										18		
1980			26		164					100	164												

Note: Each cell in the table represents the numbers of origin countries for a given destination country in a particular year in our dataset.

Table A1 (continued)

Country-Year coverage migration flows.

Destination	JPN	KOR	LTU	LUX	LVA	MEX	MLT	NLD	NOR	NZL	POL	PRT	ROM	RUS	SVK	SVN	SWE	TUR	USA
Year																			
2010			163	131				160	162	163	113	136			163	164	163		161
2009	164	55	164	130	163	117		163	162	163	111	138		163	163	164	163	164	160
2008	163	54	164	135	164	116		162	162	163	163	132	70	163	163	164	163	163	161
2007	162	27	163	132	163	116	164	162	162	163	163	116		163	163	163	163	162	161
2006	161	10	163	131	163			160	162	163	163	119		164	163	163	163	161	161
2005	10	10	163	129	163			157	162	163	163	116		164	163	163	163	161	161
2004	10	10	163	128	163			161	162	163	163	109		164	163	163	163	161	163
2003	10	10	163	123	163			160	162	163	163	108		28	163	163	163	161	163
2002	10	10	162	116	161			163	162	163	163	116		26	163	161	163	161	164
2001	10	10	162	111	162		163	161	162	163	163	106		28	163	162	163	162	164
2000	14	10	162	114	162		118	160	162	163	163	105		28	163	162	163	162	163
1999	14		162	117	162		118	158	162	163	163	105		26	163	162	146	141	163
1998	14		162	112	162		118	160	162	163	16	131		26	163	162	149	140	163
1997	14			104				161	162	163	14	131			163	22	146	141	163
1996	14			101				159	161	163	14	131			163	22	151	135	163
1995	14			102				160	162	163	13	131					148	134	163
1994	14			97				156	162	163	13	131					152		163
1993	14			90				158	162	163	10	130					151		163
1992	14			97				148	162	163	10	131					142		164
1991	11			88				137	161	163	10						131		164
1990	11			93				139	161	163	9						130		164
1989	11			86				138	162	163	9						127		164
1988	11			88				137	162	163							121		164
1987	7			86				138	162	163							121		164
1986	7								161	163							124		164
1985	7								105	163							121		164
1984									163	163							114		164
1983									163	163							110		164
1982									163	163							109		164
1981									163	163							111		163
1980									163	163							111		162

Note: Each cell in the table represents the numbers of origin countries for a given destination country in a particular year in our dataset.

Table A2

Definitions of migration flows.

Destinations	Definition of “immigrant” based on
Australia	Country of Birth
Austria	Citizenship
Belgium	Citizenship
Bulgaria	Citizenship
Canada	Country of Birth
Chile	Citizenship
Cyprus	Citizenship
Czech Republic	Citizenship
Denmark	Citizenship
Estonia	Citizenship
Finland	Citizenship
France	Citizenship
Germany	Citizenship
Greece	Citizenship
Hungary	Citizenship
Iceland	Citizenship
Ireland	Country of Birth
Israel	Citizenship
Italy	Citizenship
Japan	Citizenship
Korea	Citizenship
Latvia	Citizenship
Lithuania	Citizenship
Luxembourg	Citizenship
Malta	Citizenship
Mexico	Citizenship
Netherlands	Country of Birth
New Zealand	Last Permanent Residence
Norway	1979-1984 Country of Origin, 1985-2010 Citizenship
Poland	Country of Origin
Portugal	Citizenship
Romania	Citizenship
Russian Federation	Citizenship
Slovak Republic	Country of Origin
Slovenia	Citizenship
Spain	Country of Origin
Sweden	Citizenship
Switzerland	Citizenship
Turkey	Citizenship
United Kingdom	Citizenship
United States	Country of Birth

Table A3

The first stage results: Cereal yields and climate.

	(1)	(2)	(3)	(4)
Temperature	-0.000	-0.037***	-0.026**	-0.030**
	(0.013)	(0.012)	(0.009)	(0.012)
Precipitation	0.000	0.000	0.000	0.001**
	(0.001)	(0.000)	(0.000)	(0.000)
Number of Observations	1,158	1,125	1,069	1,138
Number of Countries	40	39	38	38
Adjusted R^2	0.323	0.471	0.373	0.488
F-statistics	0.02	4.72	4.87	6.34
Prob > F	0.9785	0.0148	0.013	0.0043

Note: The dependent variable is the natural logarithm of cereal yields. Columns 1-4 are four country groups divided by the lower quartile, median, and the upper quartile based on the share of agriculture value added in GDP, where column (1) represents the least agriculture-dependent countries, and column (4) represents the most agriculture-dependent countries. Robust standard errors clustered by country are reported in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.