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CLIMATE CHANGE AND MIGRATION: IS AGRICULTURE THE MAIN CHANNEL?

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Climate Change and Migration: Is Agriculture the Main Channel?

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Abstract

Migration and climate change are two of the most important challenges the world currently faces. They are connected as climate change may stimulate or hinder migration. One of the sectors most strongly affected by climate change is agriculture, where most of the world's poor are employed. Climate change may affect agricultural productivity and hence migration because of its impact on average temperatures and rainfall and because it increases the frequency and intensity of weather shocks. This paper uses data on more than 150 countries from 1960 to 2010, to analyse the relationship between weather variation, changes in agricultural productivity and international migration. Our main findings show that, in line with theoretical predictions, negative shocks to agricultural productivity caused by weather fluctuations significantly increase migration in middle and lower income countries but not in the poorest and in the rich countries. The results are robust to different econometric specifications.

Keywords: Climate change, Temperature, Agriculture, International Migration
JEL classification: F22, Q54, O13, Q15

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1 Introduction

Within the recent literature on climate change and migration, the impact of the increasing average surface temperature on agricultural productivity has been indicated as a possible key factor for the decision to migrate (Cai et al., 2016; Cattaneo and Peri, 2016). This is because, on the one hand, agriculture is the main sources of income and employment in the rural areas of developing countries, where the majority of migrants is coming from. On the other hand, agriculture is the sector most affected by climate change with important implications for agricultural productivity, rural livelihoods and food security, particularly in the developing world (Lobell et al., 2011; FAO, 2017).

Starting from the seminal work of Todaro (1969) and Harris and Todaro (1970), economists have interpreted migration as resulting from differences in economic opportunities or, more precisely, from expected wage differentials between origin and destination countries. In addition, migration is considered a way to diversify income sources (Stark, 1991), a way to deal with bad political institutions and conflicts, and a possible insurance mechanism against environmental shocks (McLeman and Smit, 2006; Drabo and Mbaye, 2015).

In the last decades an emerging literature using mostly individual data and household surveys investigated how weather variability and climatic shocks may affect migration (e.g. Feng et al. 2010; Dillon et al. 2011; Mueller et al. 2014; Gray and Mueller 2012; Gray and Bilsborrow 2013; Bohra-Mishra et al. 2014). The main findings show that, though climatic shocks often trigger both internal and international migration, the relationship appears complex and the effects are often country-specific (Gray and Wise, 2016). In addition, several conflicting results have emerged, such as the low or irrelevant effect of precipitations, relative to temperature (Mueller et al., 2014), or reverse effects, namely situations where adverse climate factors may reduce (and not increase) emigration flows (Gray and Mueller, 2012). One critical issue is also the lack of macro studies focusing on climate change and international migration, rendering the generalization of current (micro) evidence problematic.

More recently, important data collection, such as the bilateral migration dataset of Özden et al. (2011), have trigger a new wave of (macro) studies on the impact of climate change on international migration (e.g. Beine and Parsons 2015; Cattaneo and Peri 2016; Maurel and Tuccio 2016; Cai et al. 2016), confirming some of the previous micro-evidence, but also raising new issues. Importantly, when we focus the attention on the mechanisms driving the results, current empirical evidence is, at best, scant. This is an important limitation of the literature, especially because there is evidence suggesting that the effect of climate change on migration, if anything, tends to be mainly indirect and mediated by other socio-economic characteristics (Black et al., 2011; Beine and Parsons, 2015; Kubik and Maurel, 2016). Clearly, understanding the key mechanisms and channels through which climate change may affect migration is crucial to formulate evidence-based policy recommendations (Mbaye, 2017).

Using different approaches and different dataset, a few recent papers explicitly investigate the relationship between climate change and international migration, emphasizing the role of the agricultural channel (Feng et al., 2010; Cattaneo and Peri, 2016; Cai et al., 2016).[1] However, with the exception of Feng et al. (2010), who implemented a two stage least square (2SLS) approach to study the link between climate-driven changes in crop yields and migration, the actual evidence is mainly based on robust association, more than a careful identification of the true mechanism in place.

Thus, the idea that agriculture can be one of the key mediating channel in the climate change and migration relationship, is still an open and unresolved question.

Against this background, this paper uses a macro perspective to study the extent to which the effect of weather shocks on migration works mainly through the agricultural channel. We contribute to the existing literature in three main directions. First, guided by theory, we exploit a large data set of more than 150 countries observed from 1960 to 2010, to investigate the extent to which long-run climate-driven changes in agriculture affect directly migration. Second, we use a two stage least square (2SLS) approach, together with a particular research design, to test if there exists a causal relationship between changes in agricultural conditions and migration outcomes. Finally, we conduct sensitivity checks of our results to rule out the possibility that other concurrent explanations are driving the main findings.

Overall, our results provide convincing support to the idea that negative shocks in agricultural productivity, induced especially by a (long-run) increase in temperature, positively affect net migration outflows in middle-poor countries.

The remainder of the paper is organized as follows. Section 2 briefly considers the related literature, while Section 3 reviews the theory behind the econometric specification. Section 4 illustrates the empirical methodology used to identify the agricultural channel and Section 5 outline the data used for the empirical analysis and describes the main statistics. Section 6 presents the main results while robustness checks are reported in Section 7. Section 8 concludes.

2 Related literature

This paper relates to two main strands of the recent climate-economy literature.[2] On the one hand, several papers have studied the effects of weather and climate change on agricultural (and overall) productivity (Mendelsohn et al., 1994; Schlenker et al., 2006; Deschenes and

[1]Of course, there exist a large micro literature investigating both internal and international migration, highlighting the role of agriculture. See Berlemann and Steinhardt (2017) for a critical review.

[2]Important reviews with a broad coverage can be found in Dell et al. (2014) and Carleton and Hsiang (2016). Auffhammer and Schlenker (2014) survey the empirical literature on the weather and climate impacts on agriculture, while Berlemann and Steinhardt (2017) the literature on climate change, natural disaster and migration.

Greenstone, 2007; Lobell et al., 2011; Dell et al., 2012; Hsiang, 2016). On the other hand, there is the recent body of the literature that investigates the direct and indirect relationship between climate change and international migration (Beine and Parsons, 2015; Feng et al., 2010; Cattaneo and Peri, 2016; Cai et al., 2016; Maurel and Tuccio, 2016).

Looking at the first strand of literature, the seminal paper of Mendelsohn et al. (1994) uses an hedonic cross-sectional model to investigate the relationship between farm land price across US counties and growing season temperature and precipitations. The main finding is that a higher temperature significantly reduces land value, while higher precipitations tend to increase it, and that on the whole global warming has a very low impact on US agriculture. Using a similar cross-sectional approach, Schlenker et al. (2006) estimate the potential impacts on farmland values of a range of recent warming scenarios in the US agriculture. The results show that the aggregate impact for the US counties considered in the near to medium term is a 10%–25% decrease in aggregate land value, depending on the climate scenario chosen.

Unlike the previous contributions, Deschenes and Greenstone (2007) exploit the within time variation to identify whether agricultural profits in US counties respond to random fluctuations in weather. The main results show that climate change only marginally affects agricultural profit in the US. Importantly, they also demonstrate how the hedonic approach based on cross-sectional inference (the standard approach until then) is unreliable due to a sever problem of omitted variables bias.

After the contribution of Deschenes and Greenstone (2007), the use of panel data models become the standard approach within the climate econometric literature. For example, Schlenker and Roberts (2009) uncover important nonlinear effects of temperature on US crop yields that exacerbate the predicted decrease in yield due to global warming. Lobell et al. (2011) investigate the effect of weather trends on the main crops production, showing that global worming has been responsible for a decline in global corn and wheat production of about 3.8 and 5.5 percent, respectively. Dell et al. (2012) study the weather effects on both level and growth rate of per capita GDP. The results highlight a negative effect of an increase in temperatures on per capita GDP for poor countries: a 1° C increase in temperature in a given year reduces poor countries economic growth by 1.3 percentage points, an effect mainly driven by a reduction in agricultural output, and less by industrial output and political stability.

As discussed in detail by Dell et al. (2014), the key advantage of this time series identification strategy is that it accounts for unobservable differences between units through fixed effects, thus eliminating a potential source of omitted variables bias. An additional advantage, is that time variation in weather variables, after accounting for fixed effects, is exogenous to changes in socio-economic variables because it is driven by random geophysical processes. However, a shortcoming of using panel methods with yearly data is the inability of fully capturing adaptation to climate changes.

With the aim of addressing this critical issue, some papers have recently proposed a long differences approach (Dell et al., 2012; Burke and Emerick, 2016). The general idea of this strategy is that, because changes in climate are gradual, averaging across long time spans (e.g. a decade) should offer the possibility to capture both direct and belief effects (i.e. adaptation) of climate change. This is because populations only adjust their beliefs when environmental changes are expected to be persistent (Hsiang, 2016). However, studies that compared the weather effect using data at both short- and long-run frequency have found that the magnitude of the estimated effects of climate change on agricultural yields (and other economic variables) are not so different (Dell et al., 2012; Burke and Emerick, 2016), thus suggesting quite limited historical adaptation to climate change.

In situations such as the one investigated in the present paper, the idea that people may decide to migrate internationally as a response to yearly variations in weather is, admittedly, difficult to defend (Jessoe et al., 2016). This is because the migration decision has to be viewed as a long-run adaptation strategy intended to cope with the direct effects of permanent, not transitory, weather changes. For this reason, in our framework we identify the effects of weather-driven agricultural changes on migration using a long-run (decennial) variation in the variables of interest (a choice also dictated by data limitation). As discussed by Burke and Emerick (2016), this approach offers substantial advantages over the cross-sectional and (short-run) panel methods. For example, it better approximates the ideal experiment, it addresses potential omitted (time-invariant) variable bias and, at the same time, should capture medium-run adaptations that farmers put in place against trends in weather. In addition, as argued by Dell et al. (2014), also intensification effects should be captured, namely situations when climate change may cause demages that are not revealed by small weather changes, but that can be relevant in agriculture.[3]

Moving to the literature on migration and climate change, with special attention to the role of agriculture, Marchiori et al. (2012) study the impact of weather anomalies on migration in sub-Saharan Africa. Assuming that agriculture, and hence rural areas, are the most vulnerable places to weather changes, the authors argue that the more a country depends on agriculture, the stronger the impact of weather anomalies on migration. Using an instrumental variable (IV) approach for GDP per capita, the results show that climate anomalies spur both internal and international migration, and that urbanization might mitigate the effects of climatic factors on international migration, mainly in rural areas. Beine and Parsons (2015) investigated natural disasters and long-run climatic factors (temperature and precipitations) as potential determinants of international migration. Using a gravity-like approach they find that by affecting wage differentials long-run climatic factors have only indirect effects on bilateral migration. In addition, some of their results depend upon country's agriculture share of

[3] For example, situations where the permanent reduction of precipitations strongly affects the reservoir availability of water to agriculture.

GDP (similar results can also be found in Maurel and Tuccio, 2016 and in Drabo and Mbaye, 2015).

Coniglio and Pesce (2015) follow the same macroeconomic approach and explicitly consider the heterogeneity of climatic shocks (type, size, sign of shocks and seasonal effects) with specific attention devoted to expectations. Given the data used, the authors can account only for emigrants to OECD countries, thus importantly limiting the scope of their analysis as a huge amount of migrants displace in neighboring developing countries. Nevertheless, the results are in line with other empirical papers according to which the occurrence of adverse climatic events in the origin country has significant direct and indirect effects on out-migration from poor to rich countries, especially from areas with large agricultural sectors.

Using data from 115 countries between 1960 and 2000, Cattaneo and Peri (2016) test two main predictions derived from an extension of the Borjas (1985) migration decision model, where the key assumption is that income in poor and middle income countries, being largely dependent on the agricultural sector, is more affected by weather variability. Accordingly, they find a positive impact of warming trends on the probability to emigrate in middle-income countries, while in poor countries a negative pattern emerges due to liquidity constraints.

Finally, two studies are directly related to our paper. As in the present paper, Feng et al. (2010) use a 2SLS estimation strategy with weather variables as instrument for agricultural productivity, to investigate the extent to which climate-driven yield changes have a causal effect on emigration. Exploiting migration data from Mexico to the US in two consecutive five year periods (1995-2000 and 2000-2005), they find that 10% decrease in yields would cause an additional 2% of population to emigrate. However, Auffhammer and Vincent (2012) show that, by omitting time fixed effects from their specification, the climate-induced emigration effects of Feng et al. (2010) cannot be distinguished by other simultaneous shocks occurred in the same period, such as the effect of NAFTA, the Peso crisis, and changes in US border controls after 2001. Thus, these factors, and not climate change, were responsible for the change in emigration rates.[4] Cai et al. (2016) use bilateral annual data over the period 1980-2010 covering 163 origin and 42 destination countries (mainly OECD) and, controlling for country pair fixed effects, use cereal yields and the share of agricultural value added in GDP to account for the role of agriculture in explaining international migration. Their main finding is that temperature (but not precipitations) has a positive and statistically significant effect on international migration outflows only for agriculture-dependent countries. However, besides the use of bilateral migration data, the role of the agriculture channel is still identified indirectly, and not through a structural model devoted to quantify the migration elasticity to agricultural income shocks.

[4] In a recent working paper, Feng et al. (2015) use a similar two stage least square approach. Focusing on US agriculture over the period 1970-2009, they find an inverse relationship between temperature and yields which leads to a reduction of population through migration.

All the above considerations suggest that there is scope for further analysis. On the one hand, papers using a structural approach, such as the 2SLS research design of Feng et al. (2010), produced results apparently not robust to potential (omitted) confounding factors. On the other hand, the different strategy used by Cai et al. (2016) and Cattaneo and Peri (2016), although robust from an econometric point of view, confirm only the existence of an indirect association between climate change, the importance of agriculture and migration. Thus, whether weather-driven changes in agricultural productivity have a causal effect on international migration is still an unanswered question. This is what motivates the present paper.

3 Theoretical background

In order to outline our empirical model it is covenient to refer to the theoretical predictions in Cattaneo and Peri (2016). Their two-period model builds on the migration decision framework proposed by Roy (1951) and formalized by Borjas (1987), according to which an individual i will migrate if his expected wage at destination d is higher than the expected wage at origin o, in a given time t. The key assumption is that the wage at origin and at destination depend on a basic income which may vary according to, first, the importance of the agricultural and non-agricultural sector within the country and, second, to a skill measure which accounts for the selection process (see, among others, Stark and Bloom, 1985; Docquier and Rapoport, 2012).

In the first period the individual earns a specific local wage according to his skills, while in the second period he may choose to migrate as a consequence of a comparison between his wage at origin and his potential wage at destination, bear in mind that incurring in the migration process will entail some costs.

Analytically, at origin an individual i will earn the wage $w_{io,t} = \gamma_{o,t} W_t + C_t + \alpha_{o,t}\epsilon_{i,t}$, where $\gamma_{o,t}$ is the individual income depending on W_t weather factors such as variations in temperature and precipitations, C_t are costs associated with the migration process and $\alpha_{o,t}$ is the return to skills, with $\epsilon_{i,t} \sim (0, \sigma_i^2)$ being a measure of individual skill.

The wage at destination d is given by $w_{id,t} = \gamma_{d,t} + \alpha_{d,t}\epsilon_{i,t}$, with $\gamma_{d,t}$ not depending on weather variables. This is mainly due to the fact that, following the literature, climatic and weather factors are assumed to affect mainly basic income derived from agriculture, which is the main wage source in poor and middle-poor countries. These countries are in the framework proposed by Cattaneo and Peri (2016) taken to be the sending countries; on the contrary, income in middle-rich and rich countries does not depend exclusively on the agricultural sector, so that variations in temperature and precipitations could impact differently.

Thus, an individual will migrate if:

$$\gamma_{d,t} + \alpha_{d,t}\epsilon_{i,t} > \gamma_{o,t}W_t + C_t + \alpha_{o,t}\epsilon_{i,t} \quad (1)$$

that is, if the expected wage at destination is higher than the expected wage at origin net of migration costs, assuming that return to skills are perfectly transferable from origin to destination countries.

Taking into account the selection process according to which only a portion of individuals at origin can migrate, that is only the skilled ones have the incentive to migrate due to a potential gain in migration, equation (1) can be rewritten as:

$$\epsilon_i > \frac{\gamma_{o,t}W_t - \gamma_{d,t} + C_t}{\alpha_{d,t} - \alpha_{o,t}} = \epsilon^* \quad (2)$$

Equation (2) indicates that a shock in W_t at the origin (e.g. higher temperature) will increase the probability to migrate ($\frac{\delta\epsilon^*}{\delta\gamma_{o,t}} > 0$). However, poor individuals may face feasibility-liquidity constraint at origin so that the migration process may occur only if savings exceed the monetary cost of migration. While we are aware of this fact, in our empirical work to be presented below, we aggregate poor and middle-poor individuals on the one hand, and middle-rich and rich individuals on the other hand. Therefore, we focus the attention on Proposition 1 of Cattaneo and Peri (2016) where an increase in average temperature is associated with an increase in the emigration rate for middle-income countries only, assuming that an increase in temperature decreases basic agricultural productivity. Analytically, the share of migrants, which is highly dependent on the probability to emigrate, can be formalized as follows:

$$\frac{Mig_{c,t}}{Pop_{c,t}} = 1 - \Phi\left(\frac{\gamma_{o,t}W_t - \gamma_{d,t} + C_t}{\alpha_{d,t} - \alpha_{o,t}}\right) \quad (3)$$

where emigration $Mig_{c,t}$ is weighted by the total population $Pop_{c,t}$ of a country c and Φ is the CDF of a standard normal distribution. More specifically, in equation (3) it has been assumed that the probability to emigrate, and hence the share of migrants, among other things, depends on a variation in weather W_t which could decrease basic income (affecting income differences between origin and destination countries). Therefore, in the case of poor countries, this represents largely a variation in agricultural outcomes ($\gamma_{o,t}$), highlighting a negative relationship between weather-induced agricultural shocks with respect to emigration.

4 Econometric approach

On the basis of the theoretical model described in the previous section, we assume that the emigration rate ($\frac{Mig_{c,t}}{Pop_{c,t}}$), which is our dependent variable in the empirical analysis, is driven by the willingness to migrate. Hence, by increasing the probability to migrate, climatic shocks shall increase, as a consequence, the emigration rate.

Our country level analysis is based on a two stage least square (2SLS) approach similar in spirit to the analysis of Feng et al. (2010), though with important differences, in the use of fixed effects, in the (macro) level of the analysis, in the identification strategy, and in the use of a long-run econometric approach.

The empirical model can be written as follow:

$$m_{it} = \beta x_{it} + f(t) + c_i + \varepsilon_{it} \tag{4}$$

$$x_{it} = \gamma W_{it} + f(t) + c_i + v_{it} \tag{5}$$

Equation (4) represents our regression of interest, where the (log) of emigration rate, m_{it}, from country i to the world at time t, is regressed on our key variable, the (log) of agricultural output or productivity, x_{it}. We aim at estimating an unbiased β coefficient that represents the elasticity of net emigration with respect to agricultural outcomes.[5] However, what happens in the agricultural sector tends to be endogenous relative to the migration decision since, for example, any increase in the rate of emigration from rural areas, for reasons other than agricultural shocks (e.g. conflicts), will directly affect the level of agricultural output. Hence, in our first stage equation (5), the agricultural endogenous variable, x_{it}, is assumed to be a function of weather shocks, W_{it}, that represent our instrumental variables. Both the first and the second stage, respectively equations (5)-(4), include a full set of year controls, $f(t)$, and country fixed effects, c_i. Finally, ε_{it} and v_{it} are the errors of the two equations, assumed to be normally distributed. On the basis of equations (4) and (5) we purport to test whether the effect of climate change on migration is mainly indirect and mediated by the agricultural channel.

The most critical assumption is the validity of our instruments, W_{it}, namely their relevance and exogeneity (exclusion restriction). As is well known, relevance implies that our instruments should be sufficiently correlated with the instrumented variable, i.e. $corr(W_{it}, x_{it}) \neq 0$, so that the first stage, equation (5), is consistently identified. The exclusion restriction, instead, requires instruments not to have any other direct effect on the outcome variable (emigration), other than the one mediated by the agricultural channel, i.e. $corr(W_{it}, \varepsilon_{it}) = 0$, after controlling for relevant covariates.

That weather variations affect agricultural yields is well established, given the large amount of evidence from agronomic models and, in the last decades, from the climate econometrics literature (see Auffhammer and Schlenker, 2014). In particular, as explained above, the first stage (as well as the second stage) equation is identified by exploiting gradual (decennial)

[5]From now on in this section we will refer to agricultural outcome, agricultural productivity and agricultural output interchangeably.

changes in weather with gradual changes in agricultural productivity (and migration). Because our econometric specification is always conditioned on year and country fixed effects, the estimated parameters of interest are identified from the country-specific decennial deviations in weather from the country-specific means, after controlling for shocks common to all countries. Under these conditions, the general idea is that weather variation is orthogonal to unobserved determinants of yields, a standard assumption made by the literature (see Dell et al., 2014).

More problematic is, in principle, the exclusion restriction of our instruments, namely that weather variations affect the migration decision only through their effects on agricultural outcomes. This is because, there is evidence showing that climate variability may affect a multiplicity of different economic and social outcomes potentially inducing people to migrate, such as economic growth and political instability (Dell et al., 2012), conflicts and wars (Burke et al., 2015a), and health outcomes (Deschenes and Moretti, 2009). Whether these additional channels are sufficiently controlled for in our research design is difficult to be properly established. What we can do is to make as convincing as possible our econometric identification.

Note that, by including country fixed effects, we control for time-invariant country specific factors, such as proximity to destination countries, network effects and other unobserved factors that could affect the migration process (Feng et al., 2010). In addition, time fixed effects $f(t)$ address all common factors that could affect both agriculture and migration trends, such as technological progress, and changes in agricultural policies (due to international price movements) as well as overall economic conditions both at origin and destination.

In addition, and importantly, guided by the predictions of Cattaneo and Peri (2016) discussed above, we estimate our model separately for: (i) poor and middle-poor countries (henceforth Poor); and (ii) middle-rich and rich countries (henceforth Rich). This is crucial for the credibility of our identification strategy. Indeed, similarly to Feng et al. (2015), in our research design Rich countries act as a control group. Basically, if changes in climate affect migration through channels other than agricultural outcomes, that is, the error term in equation (4) is correlated with the instrument ($corr(W_{it}, \varepsilon_{it}) \neq 0$), then our estimate for β would also be non-zero in the Rich countries subsample. Instead, the relationship between migration and climate change should be relevant only for the Poor country group, but not in the Rich one. This is because the agricultural income/wage effect, induced by climate change, is relevant only in countries where the agriculture sector is one of the key sources of individual income. Thus, while weather shocks should clearly affect agricultural yields in both Rich and Poor countries, and this will come out clearly from our first stage equation (5), in the second stage equation (4) our variable of interest, agricultural outcome, should be relevant and statistically significant only for the Poor countries' sample. Hence, by comparing the performance of the second stage regression in the two country groups (Poor vs Rich), we can be quite confident about the credibility of our empirical approach.

In conducting the investigation we start from a parsimonious specification that does not include control variables in the analysis other than country and year fixed effects, for two main reasons. First, in our framework, to estimate the impact on emigration of agricultural productivity, we uses only the portion of variations in productivity that is predicted by long-run variations in climate. Hence, because such variations tend to be exogenous to other factors potentially affecting migration, in principle it is not necessary to explicitly control for other social and economic determinants of emigration. Second, several controls such as economic, political and demographic variables may themselves be affected by agricultural productivity shocks (and vice-versa), so that including them may produce a bias in the estimation by introducing an over-controlling problem (see, among others, Hsiang, 2016). However, in a section on robustness check we also use the 2SLS approach with controls suggested by the most recent literature on climate change, such as GDP per capita, political institutions, conflicts and wars, and health indicators.

5 Data and descriptive statistics

In view of the empirical analysis, we construct a panel dataset covering all available countries in the world from 1960 to 2010 by merging different sources of data from which our key variables come from.

Firstly, data on international migration are taken from Özden et al. (2011). This dataset is a global matrix of bilateral migrant stocks from 115 countries to 115 countries spanning the period from 1960 to 2000 with ten year intervals. We extended it until 2010 using estimates from the same World Bank sources, so that we can benefit from one more decade of observations. These data are available every ten years due to the fact that the original sources of these data are national Censuses. As stressed by Cattaneo and Peri (2016), among others, these data are much more accurate in counting foreign-born individuals than flow measures and they allow us to study the long-run relationship between agricultural outcomes, weather variability and migration behavior. As seen above we construct our dependent variable by first summing all emigrants from each origin country and then computing emigration rate as the ratio between the aggregate net outflow relative to the origin country population at the beginning of each period considered. Thus, we compute net emigration as differences between stocks in two consecutive Censuses. As shown in Table 1 the average migration rate in the period considered (1960-2010) is equal to 2.5% with a maximum of 3.2% in 1980-1990 and a minimum of 1.5% in 2000-2010.

[Table 1 about here]

Secondly, data on mean temperature and precipitations are taken from Burke et al. (2015b) which extend the Dell et al. (2012) dataset. They are expressed as population-weighted (or area-weighted): average annual temperature in degrees Celsius while precipitations are in millimeters.[6] This dataset is the result of aggregation at the country level of worldwide monthly mean temperature and precipitation data at 0.5 x 0.5 degree resolution. Values are interpolated for each grid node from an average of 20 different weather stations, corrected for elevation. We then calculate the mean temperature and precipitation over ten years, harmonizing this part of the dataset with the one on migration.

In Figure 1 it is shown that high temperatures are mainly a feature of Poor countries, while moderate or low temperatures characterize Rich countries (see Dell et al., 2012 for similar results).

[Figure 1 about here]

Thirdly, we account for agricultural output and agricultural productivity. In the former case we obtain gross production values measured in constant 2004-2006 international dollars from FAOSTAT, create the mean value over ten years, and take the logarithm of this variable. In the latter case we compute the ratio between agricultural output and agricultural land and we transform it in logarithm.

In Table 1 we report the summary statistics for all countries and then splitting the sample according to the Poor and Rich countries definition. We consider poor and middle-poor countries (Poor) those belonging to the first and second quartiles of the per capita income distribution in 1990, while middle-rich and rich (Rich) those in the third and fourth quartiles. We end up with a sample of 107 Poor countries and 53 Rich ones. Agricultural output and agricultural productivity are higher in middle-rich and rich countries, while temperature and precipitations are higher in poor and middle-poor countries.

[Figure 2 about here]

Panels (a) and (b) of Figure 2 show that variations in agricultural output and emigration rates tend to go in opposite directions in the case of the Poor sub-sample, so that a decrease in the agricultural output is inversely related to the emigration rate. On the contrary, for Rich countries a decrease in agricultural output is associated with a decrease in the emigration rate. The pattern is similar when we consider the variation in agricultural productivity, instead of agricultural output, as shown in Figure 3 (a-b).

Looking more closely at the differences among poor and rich countries, we also focus on three specific regional areas: Africa, Asia and Latin America countries. We include in the African region Eastern, Western, Middle and Southern African countries; in the Asian region East Asia and Pacific and South Asian countries, while Central and South American countries form Latin America. In Figure 2 and 3, panels (c-d-e) for all our three regions, there is a clear

[6] As a robustness check, we also used temperature and precipitation expressed in area-weighted terms. The results are not reported here but do not change qualitatively.

divergent trend between agricultural output or productivity and emigration rate with a more pronounced pattern for Asian and Latin America countries, but less so for African countries.

[Figure 3 about here]

Table 2 reports summary statistics by regions. Overall, the higher percentage of emigrants comes from Latin America, while African countries are those with the lowest level of emigration which could be due to income constraints making migration for Africans costly.[7] Asian countries are more agriculturally productive then the other two regions and, in addition, are those with a low level of precipitations. African countries are, on average, the hottest in our sample.

[Table 2 about here]

6 Econometric results

6.1 Reduced-form and OLS results

To substantiate our empirical approach, we start by estimating an equation in which the logarithm of the emigration rate is regressed directly on our weather variables (both linearly and squared), controlling for year and country fixed effects. This corresponds to the case where we estimate the reduced-form equation obtained from substituting (5) into (4). We do this in order to show the extent to which the main findings of the previous literature hold true for our extended dataset and sample of countries.

Table 3 presents the results for the full sample in column (1), for the sample of Poor countries in column (2) and for Rich countries in column (3) accounting for robust standard errors. Starting from the overall sample, we see that the emigration rate is increasing in temperature, but at a decreasing rate. This non-linear pattern also characterizes the effect of precipitations, though theses variables are never statistically significant. Weather variables, and particularly temperature, are significant at 10 percent level for Poor countries, but not for the Rich ones. Thus, an increase of temperature over the trend, during a 10-year period, induces people of poor and middle income countries to emigrate, an effect however that is not estimated with great precision. Taken together, these reduced form results are fairly consistent with previous evidence, and particularly with Cai et al. (2016): migration is mainly affected by temperature variability in a non-linear fashion, but only in the poor and middle income countries.

[Table 3 about here]

[7] Per capita GDP in the African region is, on average, 613 US$ while it is 2422 US$ in Asia and 1682 US$ in Latin America.

In the next set of results we focus on the relationship betweem migration and agriculture. Table 4 presents fixed effects (FE) OLS estimation results where we regress the emigration rate on our variables of interest, agricultural output or productivity and weather variables. As before, we consider the overall sample and respectively the Poor and Rich countries sub-samples separately. In Panel A we include only the agricultural regressors, besides country and time fixed effects. In Panel B we also add weather variables as controls, again with a quadratic spacification. These regressions serve as a reference for our 2SLS research design which will be presented in the next sub-section.

[Table 4 about here]

When measured as production output, the effect of agriculture on migration is negative and strongly significant in both the overall and the Poor sample but not in the Rich one. We find a similar pattern when we use agricultural productivity as regressor: a reduction in agricultural productivity increases the rate of emigration, though now the effect is (less strongly) significant also in the case of the Rich countries. Thus, controlling for country and time fixed effects, what happened in the agricultural sector appears to be very important for the decision to emigrate, and this is especially true for poor and middle income countries. Quantitatively, the estimated elasticity implies that a 1% reduction below the trend in agricultural output (or productivity) over a 10-year period induces an increase of the emigration rate ranging from 0.5% to 0.7%, considering the overall sample. The size of this (OLS) effect is of the same order of magnitude as the 2SLS estimate by Feng et al. (2015) for the US internal migration. As discussed above, the estimated effect of agriculture on the emigration rate could be biased due to reverse causality problems, as any variation in the emigration rate due to reasons other than agricultural shocks will affect directly agricultural production. In addition, these OLS estimates may suffer from omitted variable bias induced, for example, by international price shocks and the government reaction to these shocks through agricultural protection policies (Olper et al., 2014), both factors that could increase or offset the migration responses.

OLS regressions in Panel B add weather variables as controls. The agricultural output or productivity effect on migration is nearly unchanged in size and remains negative and strongly significant also in this specification. By contrast, and interestingly, when controlling for agriculture variables, migration decisions appear to be no longer a response to weather variability, a result in line with the finding of Beine and Parsons (2015) and Kubik and Maurel (2016), who argued that climatic shocks tend to have mainly indirect effects on migration. This result provides preliminary support to the idea that agriculture can be an important mediating channel in the relationship between weather and migration and, interestingly, it does not contradict the validity of our exclusion restriction.

6.2 2SLS estimation results

Table 5 reports the main results of estimating the system of equations (4) and (5), with the second stage results displayed in Panel A and the first stage results displayed in Panel B. Results are shown for the full country sample in columns (1) and (2), the Poor countries sample in columns (3) and (4) and the Rich countries sample in columns (5) and (6). As before, all specifications include time and country fixed effects.

We first address the issue of the relevance of our instruments and look at the evidence reported at the bottom of Panel A (first stage). We see that the p-value of the underidentification test suggests that the excluded instruments are relevant in all the specifications, confirming that they are correlated with the endogenous regressors. In addition the Kleibergen-Paap Wald F-statistic for the weak identification of our instruments satisfies the Stock et al. (2002) and Stock and Yogo (2005) critical values for several, but not all, regressions. The cases potentially more problematic are those related to the Poor countries sample, especially when agricultural productivity is used as the endogenous variable (see column 4). Here, the first stage Wald F-statistic, equal to 3.95, is admittedly far from the rule of the thumb value of 10. For this reason we report two additional weak instruments test. First, the Anderson and Rubin (1950) AR test statistics always rejects the null hypothesis that the coefficients of our endogenous variables in the structural equation are equal to zero. Second, the fractionally re-sampled Anderson and Rubin (FAR) test recently proposed by Berkowitz et al. (2012) which is able to obtain valid, but conservative, inferences when the instruments do not perfectly satisfy the exclusion restriction in the second stage. In our specifications, the FAR test rejects systematically the hypothesis that the second stage coefficient is zero at 1% level of significance, thus confirming that our instruments do a good job at identifying the first stage equation.[8]

The first stage regressions of Panel B show that temperature and its square have the expected non-linear effect on agricultural production, an effect that is strongly significant in nearly all the country samples considered. Interestingly, the magnitude of the temperature effect is, on average, twice larger in the Rich country sample than in the Poor one for both agricultural output and agricultural productivity. This difference is probably due to the quality of weather, and perhaps also agricultural, data notoriously lower in Poor countries. This translate in an error in variables in the Poor countries' sample that induce attenuation bias in a fixed effects specification (Auffhammer and Schlenker, 2014), a problem that is probably at the root of the low first stage F-statistic in some specifications discussed above.[9] Precipitations are never statistically significant, a result that is robust across samples and

[8]To apply the FAR test we used K=5 with 100 repetitions of the re-sampling procedure.

[9]Another important reason could be the low frequency of our data. As shown by Feng et al. (2015) the F-statistics of the first stage regression significantly decrease as the number of "yearly" observations go down, i.e. moving from yearly to 5-year averages.

estimation methods, as already shown in the previous tables.

Moving to the second stage results reported in Panel A, in line with theoretical predictions our findings strongly confirm that climate-driven changes in agricultural outcomes affect significantly net migration outflows so that a decrease in agriculture production leads individuals to migrate. Importantly, this effect is only relevant in the case of Poor countries (columns 3 and 4), where there are not technological adaptations and migration may be treated as a plausible coping strategy. No effects are detected on the contrary for Rich countries where the agricultural variables are never statistically significant (columns 5 and 6), even if the first-stage results suggested a similar pattern between agriculture and weather variables, as for the Poor countries.

The magnitude of the 2SLS estimated effect of agriculture is more than 3 times larger than that of the corresponding OLS effect in the previous table 4. For example, considering columns 3 and 4, a 1% decrease in agricultural production (resp. productivity) below its trend, over a 10-year period, induces an additional 1.9% (resp. 2.1%) increase of emigration rate, a sizeable effect from an economic point of view. In comparison, when Rich countries are considered, the estimated agricultural effect on emigration is never statistically significant, and even positive when the agricultural output is considered (see column 5). This pattern of the results therefore gives credence to our identification strategy, where the sample of Rich countries serves as a conterfactual scenario.

It is useful to further investigate the effect for poor and middle-poor countries of climate-driven changes in agriculture outcomes on the decision to migrate. Recall that the findings by Cattaneo and Peri (2016) suggest that liquidity constraints faced by poor individuals at origin may represent an additional cost to emigration. Looking at the summary statistics for the sample disaggregated across regions reported in Table 2, we see that this problem can be especially severe in African countries, where the emigration rate, as well as agricultural productivity and per capita GDP are significantly lower than in the other regions considered. These figures suggest that the climate-driven changes in agriculture productivity on emigration should be weaker or even reversed in African countries. To test for this possibility, in Table 6 we restrict the empirical analysis to regions that are characterized by low per capita GDP levels, distinguishing between Latin America, Asia and Africa regions (columns 1 to 3), respectively, and using as control the effect on OECD countries (column 4).

[Table 6 about here]

The effect is significant for Asia and Latin America, while there is no significant effect for the Africa region where the estimated coefficient on agricultural variables is even positive, albeit statistically insignificant. This is plausible as the Africa region is the poorest in the sample, so that individuals may encounter liquidity constraints limiting the migration process. Asian and Latin America are the regions where changes in agriculture productivity affect the probability to migrate more: in this case we are dealing with middle-poor countries where the income constraint is becoming weaker. Clearly, other channels may be at work, for example there are different international agreements between Latin American countries and some OECD countries by virtue of which individuals may be facilitated in the migration process.[10] At any rate, these additional findings are in line with the underline theory on which our empirical analysis is based, giving further credence to the validity of the research design.

7 Robustness checks

7.1 Results with additional controls

The validity of our 2SLS results in Table 5 depends on the assumption that our weather variables have no direct effect on current emigration rates, after controlling for (instrumented) agricultural production and including country and time fixed effects. Although this assumption has been argued to be plausible, we now assess the evidence after directly controlling for several covariates that have been shown to be correlated with weather variables and migration outcomes. The approach is similar to Acemoglu et al. (2001), in that we try to assess the potential for omitted variable bias in the case of regressors that have time variation, since in our panel regressions included fixed effects absorb any time invariant omitted variable bias. The idea is that if the estimated coefficient of agricultural variables do not change as additional covariates are included in the regression, then they are less likely to change if we add some of the (time varying) omitted variables. In general we find that our results change remarkably little with the inclusion of additional controls and many variables emphasized in previous works are insignificant once the effect of agriculture is controlled for.

We consider four covariates suggested by the most recent literature on the impact of climate on socio-economic outcomes (see, e.g., Dell et al., 2014; Carleton and Hsiang, 2016). These are: (i) economy-level outcomes as measured by the log of per capita GDP, taken from the Penn World Tables; (ii) the number and frequency of conflicts and wars taken from the Arms&Conflict database; (iii) the quality of institutions as measured by the Polity 2 index of democracy taken from the Polity IV dataset (Marshall and Jaggers, 2007); (iv) a health indicator of the overall population as measured by the life expectancy at birth, taken from the World Development Indicators of the World Bank. In Table 7 we report the results of 2SLS regressions where these four controls are included simultaneously. In the appendix A, the contribution of each of these variables is investigated individually in our 2SLS regressions.

[Table 7 about here]

[10] For example, the Spain-Ecuadorian visa agreement signed in 1964 and effective from 1965 to 2000, which significantly facilitated the entrance of Ecuadorian immigrants into the Spanish and the EU labor market.

Because the theory on which our research design is based emphasized climate-driven income effects as the key determinant of the emigration decision, the first critical variable to be included to test the robustness of the agricultural channel is GDP per capita. Dell et al. (2012) and Burke et al. (2015b) found a strong (short-run) relationship between per capita GDP and temperature. While Dell et al. (2012) argued that the relationship holds only for a country whose income is below the median level, i.e. for poor countries, Burke et al. (2015b) showed that a similar (non-linear) relationship between temperature and overall economic growth holds for both poor and rich countries.

The results of 2SLS regressions in Table 7 (and Table A.1 in the appendix A) prove to be robust to the inclusion of per capita GDP in our context. In the first stage equations GDP per capita is positive and significant in some cases, reducing somewhat the effect of temperature on the instrumented agricultural variables, especially in the case of Poor countries (see columns 3 and 4 of panel B). However, and importantly, the magnitude of the estimated coefficients of agricultural variables in the second stage equations is virtually unchanged, after controlling for per capita GDP (see panel A), a variable that is never statistically significant in the Poor country sample.[11]

Another important variable to allow for is conflicts and wars. Recent works have emphasized how climatic conditions may influence the relationships between groups, increasing the probability of large-scale conflicts (Hsiang et al., 2013; Burke et al., 2015a), and conflicts and wars are clearly a primary source of migration decision (see, among others, Adhikari, 2013; Brzoska and Fröhlich, 2016). In addition, a few papers have shown how, in the modern warm period, the increase in temperature fosters collective violence, such as land invasions in Brazil (Hidalgo et al., 2010) or civil war intensity in Somalia (Maystadt and Ecker, 2014). If these wars induced by hot weather conditions are correlated with agricultural production and emigration, then our previous estimates will be biased. We see that controlling for conflicts and wars (see also Table A.2 in the appendix A) does not affect in any way the impact of agriculture production on emigration. Indeed, inspection of first stage results in Table 7 (panel B) suggests that the increasing breakouts of wars negatively affects agricultural production, an effect that is only marginally significant in column 3. In addition, and quite surprisingly, in our second stage regressions the wars variable does not affect at all the emigration rate (see Table 7, panel A).

Moving to the role of political institutions, a regime change toward autocracy may clearly

[11] Note that, once we control for agricultural variables, per capita GDP in our regressions should capture the variability of the income effect stemming from non-agricultural sectors, such as industry and services. Hence, our results implicitly suggest that non-agricultural income variability is not a major determinant of emigration, after controlling for agriculture. To investigate further this issue we ran a 2SLS regression where the instrumented variable is industrial output in constant dollars, rather than agriculture outcomes or productivity, within a specification identical to our regressions of Table 5. The results strongly confirm that weather induced variability in industrial production is not a significant determinant of emigration rate. The results are available from the authors upon request.

affect emigration directly, an impact that could be particular severe for rural people because there is evidence showing how autocratic governments tax the agricultural sector heavily (Olper et al., 2014). Furthermore, Dell et al. (2012) find evidence that higher temperature induces a general reduction in the quality of democracy or a deterioration of the quality of autocracy in poor countries, bringing more political instability and less growth (Alesina et al., 1996). Controlling for the quality of democracy using the Polity 2 index in our regressions does not change the effect of weather induced agricultural shocks on emigration and the Polity 2 index is never statistically significant in our 2SLS regressions (see Table 7 and Table A.3 in the appendix A).

As a final control we add to our specification health outcomes, as measured by life expectancy at birth. The presumption is that adverse weather shocks, induced by very hot (or very cold) temperature, by affecting mortality, morbidity and early life (Carleton and Hsiang, 2016), could induce people to migrate. Note that the effect could be both direct, i.e. people choose to migrate to cope with the physiological effects of high (low) temperature, but also could be indirect through the agricultural channel. This is because working in agriculture, especially in poor and middle income countries, being an outdoor activity, is affected by weather conditions more than other working indoor. Although our results show that some of these channels are plausible, controlling for health outcomes do not affect to any degree our 2SLS results. Indeed, though life expectancy strongly positively affects production and productivity in agriculture in our first stage equation (see Table 7, panel B), it has no effect on the second stage equations, where the effect of agricultural variables are virtually the same (see Table A.4 in the appendix A).

7.2 LIML estimation results

Our 2SLS results could be affected by weak instruments problems for two main reasons. First, the use of decennial time periods, though meaningfully for the credibility of our identification strategy - i.e. people do not migrate to cope with yearly weather variation but with gradual and persistent changes in weather conditions - by reducing the frequency of our weather variables, could make the identification more problematic. Second, weather data, especially in poor and middle income countries, are measured with errors (see e.g. Auffhammer and Schlenker, 2014) and this introduces attenuation bias in our fixed effects regressions. We already discussed this aspect when showing that both the underidentification test, the AR test as well as the most conservative FAR test, did not detect particular problems with our instruments. In addition, in the presence of weak instruments, the estimated coefficient of 2SLS should converge toward the OLS one (see Angrist and Pischke, 2008). This is never the case in our regression results, where the 2SLS coefficients of the agricultural variables are more than 3 times larger than the OLS ones (see columns 1-4 of Table 5).

However, to further check the robustness of our results with respect to weak instruments problems, in Table 8 we present results obtained using a Limited Information Maximum Likelihood (LIML) estimator.

[Table 8 about here]

This is approximately median unbiased for overidentified constant effects models and provides the same asymptotic distribution as 2SLS (under constant effects) but also a finite sample bias reduction. The estimated effect with the LIML estimator is qualitative and quantitatively similar to the 2SLS results, for both our agricultural variables of interest. Thus, the LIML results, together with those of the reduced form equations and the large difference between the OLS and 2SLS coefficients, represent a confirmation of the robustness of our key findings.

8 Discussion and conclusions

This paper has been motivated by the recent and growing literature on the relationship between climate variability and migration. At both micro and macro levels a growing body of research has established the existence of an empirical link between weather variables, such as temperature and precipitations, and migration decisions. Several studies emphasize the agricultural sector as one of the main mediating channel through which climate change may affect migration. To date no paper, especially at the macro level, has tested the structural relationship of this climate-driven changes in agricultural outcomes and migration decision hypothesis. Guided by the theoretical framework of Cattaneo and Peri (2016), we explicitly tested whether changes in agricultural outcomes, induced by decennial variations in temperature and precipitation, are at the root of climate induced international migration decisions.

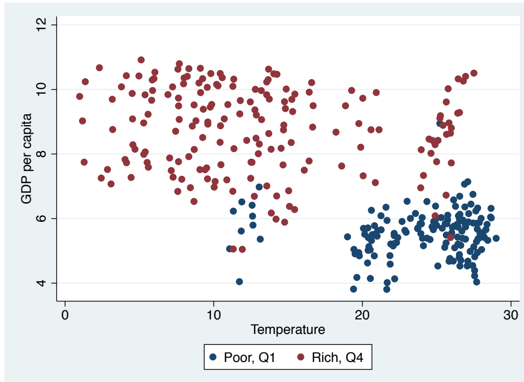
We find a strong confirmation to this hypothesis using both OLS and 2SLS approaches. Our preferred second stage results indicate that, on average, a reduction in agricultural output (or productivity) of 1% from its decennial trend induces an increase in the emigration rate of about 2% in the sample of poor and middle income countries, whereas for rich countries the effect is never statistically significant. This migration elasticity to agricultural outcomes is precisely estimated and it is robust to the use of different agricultural variables (overall output and productivity per hectare) and to the addition of several covariates suggested by the literature as plausible determinants of emigration. Quantitatively our finding show that the 2SLS effect is about three times larger than the OLS one, suggesting that, by not considering the endogeneity of agricultural variables relative to the migration decision, one significantly underestimates the magnitude of this elasticity. In addition, we have shown that the significant effect in the Poor country sample of the climate-induced agriculture effect on migration is driven mainly by Asian and Latin American countries, while there is no effect for the (poorest) African countries. This result is consistent with the hypothesis according to which liquidity constraint faced by poor individuals at origin may represent an additional cost to emigration. Hence, our findings confirm that the effect of climate on migration may have two opposing influences. On the one hand, a deterioration of economic conditions can motivate people to migrate, but at the same time undercutting household resources needed to migrate could hinder the migration process.

Understanding the extent to which climate-induced changes in agricultural outcomes cause migration is of vital importance from a policy perspective. This is because any policy action finalized to mitigate the effect of climate change on migrations needs to be well informed about the main channels at work. Using a particular research design and after several robustness checks, we argue that our main finding has a causal interpretation. However, it is also important to keep in mind the limitations of our results.

First, we are not arguing that climate-driven changes in agricultural outcomes are the only factor inducing migration decisions, but there exist other, perhaps more important, determinants of migration flows, as suggested by a large literature. Second, in our framework the role of agriculture as key mediating channel emphasizes direct income effects, i.e. how agricultural income shocks change the opportunity costs to stay or to migrate. Admittedly, though this can be one of the relevant mechanism, there are reasons to believe that the transmission channel from agricultural income shocks to migration, can be more complex, differentiated across countries, and involving other key variables, such as food security, resource conflicts or farm holdings heterogeneity.[12] Future work should be directed to better understand the mechanism through which weather-induced changes in agricultural income affect migration decisions in developing countries.

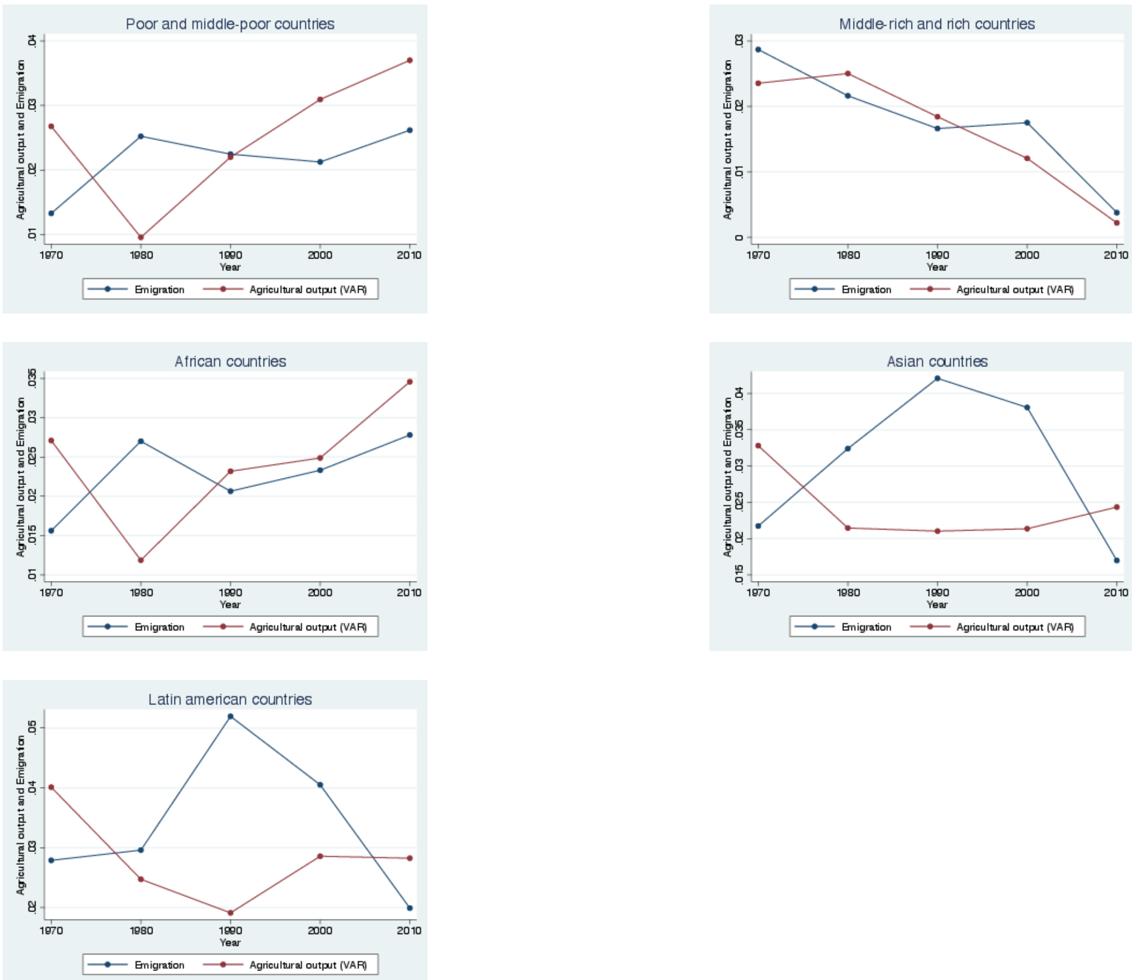
[12]See, for example, McGuirk and Burke (2017), who studied the relationships between food price changes and conflicts in Africa countries, or Bazzi (2017) who showed that positive agricultural income shocks increase or decrease emigration in Indonesia, depending on the size distribution of landholders.

Figure 1: GDP per capita and temperature (population weight)



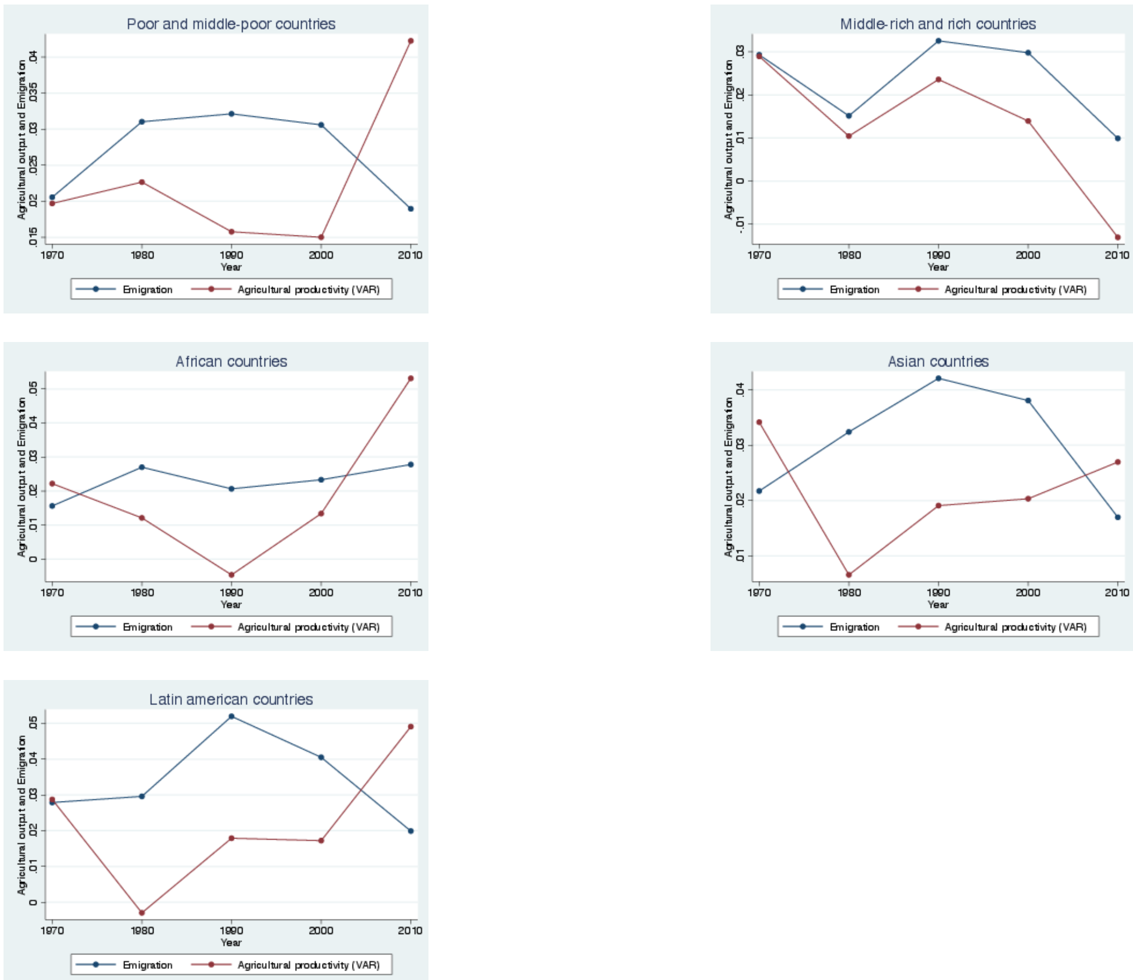
Source: authors' calculations based on Özden et al. (2011), Burke et al. (2015b) and World Bank data.

Figure 2: Emigration rate and agricultural output by regions



Notes: Decennial mean variation in migration rate and agricultural output. Authors' calculations based on Özden et al. (2011) and FAOSTAT data.

Figure 3: Emigration rate and agricultural productivity by regions



Notes: Decennial mean variation in migration rate and agricultural productivity. Authors' calculations based on Özden et al. (2011) and FAOSTAT data.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
All Countries					
Emigration rate	0.029	0.046	0	0.681	753
Agricultural output (PPP $)	10037.045	34750.955	10.954	536769.651	692
Agricultural productivity (PPP$/ha)	63.825	86.171	0.406	651.034	692
Temperature PW (deg. C)	19.316	7.186	-2.18	28.998	715
Precipitations PW (mm)	11.394	7.288	0.049	42.019	715
GDP per capita (log)	6.985	1.49	3.812	10.916	665
Wars	1.082	2.64	0	10	753
Democracy	0.493	0.5	0	1	753
Life expectancy	61.299	11.33	27.22	81.294	751
Poor and Middle-poor Countries					
Emigration rate	0.029	0.041	0	0.351	516
Agricultural output (PPP $)	8325.361	35982.005	10.954	536769.651	506
Agricultural productivity (PPP$/ha)	45.563	62.79	0.406	582.031	506
Temperature PW (deg. C)	22.355	5.178	-2.18	28.998	512
Precipitations PW (mm)	12.536	7.779	0.206	42.019	512
GDP per capita (log)	6.446	1.171	3.812	9.849	467
Wars	1.268	2.782	0	10	512
Democracy	0.432	0.496	0	1	512
Life expectancy	57.195	10.595	27.22	78.150	512
Middle-rich and Rich Countries					
Emigration rate	0.03	0.055	0	0.681	241
Agricultural output (PPP $)	14693.560	30767.663	41.119	237480.869	186
Agricultural productivity (PPP$/ha)	113.506	116.528	2.533	651.034	186
Temperature PW (deg. C)	11.652	5.68	0.978	26.038	203
Precipitations PW (mm)	8.513	4.798	0.049	24.125	203
GDP per capita (log)	8.257	1.389	4.988	10.916	198
Wars	0.689	2.267	0	10	241
Democracy	0.622	0.486	0	1	241
Life expectancy	70.091	7.043	38.964	81.294	239

Notes: PW refers to population weighted as in Burke et al. (2015b). Agricultural output has been rescaled by 1000.

Table 2: Summary statistics by main region

Variable	Mean	Std. Dev.	Min.	Max.	N
African Region					
Emigration rate	0.023	0.029	0.001	0.2	193
Agricultural output (PPP $)	1886.986	3897.879	10.954	36403.196	187
Agricultural productivity (PPP$/ha)	21.764	36.818	0.637	269.441	187
Temperature PW (deg. C)	24.514	2.787	18.911	28.998	190
Precipitations PW (mm)	12.361	5.735	1.541	28.432	190
GDP per capita (log)	5.792	0.888	3.812	8.997	172
Wars	1.005	2.433	0	10	193
Democracy	0.332	0.472	0	1	193
Life expectancy	49.133	7.77	30.001	72.399	193
Asian Region					
Emigration rate	0.033	0.049	0	0.351	225
Agricultural output (PPP $)	13280.447	48647.871	13.149	536769.651	225
Agricultural productivity (PPP$/ha)	73.092	72.739	0.465	456.727	225
Temperature PW (deg. C)	21.483	6.001	-2.18	27.986	225
Precipitations PW (mm)	16.68	7.357	1.619	42.019	225
GDP per capita (log)	7.102	1.185	4.339	10.916	205
Wars	1.16	2.846	0	10	225
Democracy	0.618	0.487	0	1	225
Life expectancy	64.492	8.369	27.22	79.954	225
Latin American Region					
Emigration rate	0.036	0.056	0.001	0.351	97
Agricultural output (PPP $)	8692.067	19310.381	41.119	140549.477	97
Agricultural productivity (PPP$/ha)	35.82	32.18	2.436	157.599	97
Temperature PW (deg. C)	21.202	4.279	9.598	26.892	97
Precipitations PW (mm)	16.069	7.813	5.532	42.019	97
GDP per capita (log)	7.114	0.952	5.382	10.916	97
Wars	1.031	2.737	0	10	97
Democracy	0.711	0.455	0	1	97
Life expectancy	65.539	7.232	43.993	78.78	97

Notes: see Table 1.

Table 3: Migration and climate: reduced form FE regressions

	All (1)	Poor (2)	Rich (3)
Dependent variable: log of emigration rate			
Temperature (deg. C)	0.323	0.793*	0.064
	(1.20)	(1.90)	(0.14)
Temperature ^{2}	-0.009	-0.021*	-0.004
	(-1.27)	(-1.94)	(-0.22)
Precipitations (mm)	-0.039	-0.037	-0.015
	(-0.79)	(-0.54)	(-0.22)
Precipitations ^{2}	0.000	0.000	-0.005
	(0.00)	(0.14)	(-0.85)
R^2	0.717	0.725	0.745
Obs.	715	512	203

Notes: the weather variables are population-weighted. Robust t-statistics in parentheses. * refer to the following cases: * p<0.10, ** p<0.05, *** p<0.01. Column (1) refers to the full sample, column (2) refers to poor and middle-poor countries, column (3) refers to middle-rich and rich countries, on the basis of their 1990 per capita GDP. All specifications include 10-year and country fixed effects.

Table 4: Migration, agriculture, and weather: OLS FE regressions

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Panel A: Migration and agriculture						
Agriculture	-0.529***	-0.705***	-0.610***	-0.668***	-0.366	-0.876*
	(-3.83)	(-4.27)	(-3.91)	(-3.69)	(-0.98)	(-1.94)
R^2	0.722	0.725	0.728	0.728	0.741	0.747
Panel B: Migration, agriculture, and weather						
Agriculture	-0.489***	-0.663***	-0.563***	-0.631***	-0.605	-1.013**
	(-3.47)	(-3.94)	(-3.70)	(-3.51)	(-1.32)	(-2.02)
Temperature (deg. C)	0.112	0.160	0.539	0.589	0.001	-0.116
	(0.38)	(0.56)	(1.19)	(1.31)	(0.00)	(-0.24)
Temperature ^{2}	-0.005	-0.006	-0.016	-0.018	-0.004	-0.001
	(-0.63)	(-0.87)	(-1.45)	(-1.57)	(-0.19)	(-0.07)
Precipitations (mm)	-0.034	-0.036	-0.033	-0.035	0.103	0.072
	(-0.50)	(-0.54)	(-0.53)	(-0.55)	(0.51)	(0.37)
Precipitations ^{2}	0.000	0.000	0.000	0.000	-0.010	-0.008
	(0.03)	(0.12)	(0.26)	(0.29)	(-1.31)	(-1.15)
R^2	0.724	0.726	0.732	0.733	0.750	0.755
Obs.	692	692	506	506	186	186

Notes: the weather variables are population-weighted. Robust t-statistics in parentheses. * refer to the following cases: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Columns (1-2) refer to the full sample, columns (3-4) refer to poor and middle-poor countries, columns (5-6) refer to middle-rich and rich countries, on the basis of their 1990 per capita GDP. All specifications include 10-year and country fixed effects.

Table 5: Migration, agriculture, and weather: 2SLS FE regressions

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Panel A: 2SLS						
Agriculture	-0.959*	-1.623**	-1.939**	-2.101**	0.192	-0.234
	(-1.92)	(-2.19)	(-2.21)	(-2.13)	(0.37)	(-0.31)
Underidentification test (P-value)	0.0000	0.0000	0.0004	0.0058	0.0000	0.0004
Kleibergen-Paap rk Wald F statistic	12.48	8.59	4.41	3.95	6.75	8.42
AR (P-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100
FAR (P-value)	0.0000	0.0000	0.0100	0.0000	0.0300	0.0300
R^2	0.717	0.707	0.677	0.680	0.737	0.743
Obs.	692	692	506	506	186	186

Dependent variables:	AO	AP	AO	AP	AO	AP
Panel B: First stage						
Temperature (deg. C)	-0.464***	-0.270***	-0.261***	-0.153**	-0.559***	-0.449***
	(-6.84)	(-5.20)	(-2.75)	(-2.04)	(-4.41)	(-4.73)
Temperature ^{2}	0.011***	0.006***	0.005*	0.003	0.018***	0.013***
	(5.93)	(3.78)	(1.89)	(1.13)	(4.14)	(4.14)
Precipitations (mm)	0.011	0.004	0.010	0.006	0.036	-0.009
	(0.61)	(0.27)	(0.44)	(0.30)	(0.82)	(-0.22)
Precipitations ^{2}	0.000	0.000	0.000	0.000	-0.002	0.001
	(0.13)	(0.55)	(0.38)	(0.53)	(-0.89)	(0.46)
R^2	0.990	0.986	0.988	0.983	0.994	0.990
Obs.	692	692	506	506	186	186

Notes: see Table 4. AO denotes agricultural output, AP denotes agricultural productivity. Panel A presents results of the 2SLS (second stage) estimates, while Panel B reports first stage results. All specifications include 10-year and country fixed effects.

Table 6: Migration and agriculture: 2SLS results for regional samples

	LAM (1)	Asia (2)	Africa (3)	OECD (4)
Dependent variable: log of emigration rate				
Agricultural output	-3.531**	-2.177**	1.196	-0.756
	(-2.48)	(-2.13)	(0.87)	(-0.62)
R^2	0.724	0.766	0.635	0.705
Agricultural productivity	-1.920**	-3.038**	1.220	-1.695
	(-2.31)	(-2.32)	(0.88)	(-1.17)
R^2	0.821	0.737	0.649	0.713
Obs.	97	225	209	117

Notes: see Table 1 and 5. LAM denotes the Latin American region. All specifications include 10-year and country fixed effects.

Table 7: Migration, agriculture, and weather: 2SLS FE regressions with additional controls

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Panel A: 2SLS						
Agriculture	-0.926*	-1.508*	-2.083**	-2.412**	0.034	-0.750
	(-1.73)	(-1.96)	(-2.24)	(-2.14)	(0.04)	(-0.73)
GDP per capita (log)	-0.176**	-0.097	0.038	0.098	-0.338**	-0.278
	(-2.26)	(-1.25)	(0.33)	(0.76)	(-2.16)	(-1.48)
Wars	0.010	0.012	0.009	0.017	-0.050	-0.053**
	(0.71)	(0.89)	(0.59)	(1.12)	(-1.59)	(-1.99)
Democracy	0.029	0.008	0.035	0.030	-0.183	-0.223
	(0.28)	(0.08)	(0.30)	(0.26)	(-0.50)	(-0.63)
Life expectancy	0.008	0.011	0.016	0.011	0.022	0.044
	(0.48)	(0.63)	(0.77)	(0.55)	(0.46)	(1.08)
R^2	0.725	0.719	0.672	0.666	0.771	0.782
Obs.	641	641	465	465	176	176
Dependent variables:	AO	AP	AO	AP	AO	AP
Panel B: First stage						
Temperature (deg. C)	-0.575***	-0.349***	-0.383**	-0.202	-0.386***	-0.324***
	(-7.51)	(-5.62)	(-2.42)	(-1.44)	(-2.84)	(-3.42)
Temperature ^{2}	0.012***	0.007***	0.006*	0.003	0.013***	0.011***
	(6.02)	(4.24)	(1.67)	(0.91)	(2.77)	(3.13)
Precipitation (mm)	0.008	0.007	0.008	0.010	-0.018	-0.062*
	(0.40)	(0.39)	(0.33)	(0.49)	(-0.40)	(-1.93)
Precipitation ^{2}	0.000	0.000	0.000	0.000	0.001	0.003**
	(0.42)	(0.41)	(0.56)	(0.34)	(0.51)	(2.30)
GDP per capita (log)	0.027	0.067***	0.071*	0.086***	0.032	0.072*
	(0.96)	(2.73)	(1.93)	(2.67)	(0.73)	(1.85)
Wars	-0.005	-0.002	-0.005	-0.001	-0.008	-0.005
	(-1.39)	(-0.53)	(-1.19)	(-0.35)	(-1.12)	(-0.75)
Democracy	-0.048*	-0.043	-0.047	-0.043	-0.037	-0.096
	(-1.67)	(-1.61)	(-1.57)	(-1.55)	(-0.41)	(-1.06)
Life expectancy	0.022***	0.015***	0.020***	0.015***	0.033***	0.023***
	(7.17)	(5.11)	(6.02)	(4.52)	(3.31)	(2.93)
R^2	0.992	0.989	0.991	0.987	0.995	0.993
Obs.	641	641	465	465	176	176

Notes: see Table 5. Robust t-statistics in parentheses. All specifications include 10-year and country fixed effects.

Table 8: Migration and agriculture: LIML regressions

	All		Poor		Rich	
	Output (1)	Productivity (2)	Output (3)	Productivity (4)	Output (5)	Productivity (6)
Dependent variable: log of emigration rate						
Agricultural output	-0.980*	-1.694**	-2.258**	-3.000*	0.242	-0.125
	(-1.87)	(-2.13)	(-2.03)	(-1.73)	(0.44)	(-0.14)
R^2	0.716	0.704	0.649	0.600	0.736	0.741
Obs.	692	692	506	506	186	186

Notes: see Table 5. Robust t-statistics in parentheses. All specifications include 10-year and country fixed effects.

Appendix A

Table A.1: 2SLS adding GDP per capita as control

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Agriculture	-0.826**	-1.414**	-2.165**	-2.553**	-0.257	-0.321
	(-2.01)	(-2.20)	(-2.20)	(-1.98)	(-0.72)	(-0.64)
GDP per capita (log)	-0.186**	-0.110	-0.032	0.022	-0.188	-0.170
	(-2.43)	(-1.45)	(-0.27)	(0.16)	(-1.37)	(-1.21)
R^2	0.727	0.722	0.643	0.632	0.780	0.782
Obs.	639	639	460	460	179	179

Notes: see Table 5. Robust t-statistics in parentheses. All specifications include 10-year and country fixed effects.

Table A.2: 2SLS adding wars as control

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Agriculture	-0.627	-1.322*	-2.057**	-2.348*	-0.226	-0.273
	(-1.52)	(-1.94)	(-2.16)	(-1.94)	(-0.63)	(-0.52)
Wars	0.015	0.013	0.003	0.014	-0.033	-0.033
	(1.10)	(0.97)	(0.16)	(0.75)	(-1.47)	(-1.47)
R^2	0.727	0.723	0.652	0.648	0.779	0.782
Obs.	639	639	460	460	179	179

Notes: see Table A.1.

Table A.3: 2SLS adding political institutions (democracy) as control

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Agriculture	-0.644	-1.328*	-2.116**	-2.419*	-0.166	-0.193
	(-1.54)	(-1.94)	(-2.19)	(-1.94)	(-0.47)	(-0.37)
Democracy	0.065	0.046	0.103	0.081	-0.284	-0.285
	(0.64)	(0.47)	(0.99)	(0.76)	(-0.75)	(-0.76)
R^2	0.727	0.723	0.648	0.643	0.779	0.781
Obs.	639	639	460	460	179	179

Notes: see Table A.1.

Table A.4: 2SLS adding life expectancy as control

	All		Poor		Rich	
	Output	Productivity	Output	Productivity	Output	Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log of emigration rate						
Agriculture	-0.712	-1.524**	-2.060**	-2.276**	-0.479	-0.496
	(-1.51)	(-2.04)	(-2.24)	(-2.03)	(-0.81)	(-0.63)
Life expectancy	0.002	0.009	0.013	0.007	0.024	0.016
	(0.11)	(0.60)	(0.71)	(0.42)	(0.70)	(0.51)
R^2	0.726	0.718	0.653	0.653	0.779	0.782
Obs.	639	639	460	460	179	179

Notes: see Table A.1.

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