The Impact of Global Warming on Rural-Urban Migrations: Evidence from Global Big Data*

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Abstract

This paper examines the impact of temperature changes on rural-urban migration using a 56km×56km grid cell level dataset covering the entire world during the period 1970-2000. We find that rising temperatures reduce rural-urban migration in poor countries and increase such migration in middle-income countries. We propose a simple model reconciling these asymmetric migration responses to climate. The results suggest that expected warming in the next century will encourage further urbanization in middle-income countries such as Argentina, while it will slow down urban transition in poor countries such as Malawi and Niger.

Key Words: Rural-Urban Migrations, Global Warming, Rural Productivity
JEL Codes: O18, Q10, Q54, R11

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1. Introduction

Internal and international migrations are crucial ways for individuals to pursue economic opportunities. In aggregate, rural-urban mobility is an important channel through which structural transformation occurs. Internal migration leads to urbanization, which in turn induces economic growth (e.g., Au and Henderson, 2006). Within this industrialization process some migrants move to other countries, but more often they move internally due to limits and regulations on international migration. Economic development that has deeply transformed countries in recent decades is often associated with heavy internal migration, especially movements from rural areas to urban areas within a country. Examples include the massive rural-to-urban migration in China (see Zhao et al., 2018 and Baum-Snow et al., 2017) and the urbanization of Africa (see Cobbinah et al., 2015).[1]

Within the context of economically driven internal migration, we analyze the effect of temperature changes. Significant temperature increases (as predicted in future decades) may affect agricultural productivity and income potential, especially in the poor rural areas of developing countries (see, for example, Dell et al., 2012).[2] While productivity in urban areas is not immune to the effects of warming, it is less vulnerable than rural productivity because rural areas are more dependent on agriculture which is highly sensitive to weather. Hence, global warming may have important consequences on migration flows from rural to urban areas. On the one hand, global warming may increase incentives to leave rural areas by making them less productive, which may speed up internal migration flows toward urban areas. On the other hand, if a country is still in poverty and rural populations have limited migration opportunities due to a lack of resources, deteriorating agricultural productivity may lower their income further, making it harder for them to pay migration costs. As a result, rural-to-urban migration could decrease, perpetuating a poverty trap.

This paper is the first to assess the impact of temperatures on countries' internal migration patterns using data on net migration rates from an extremely detailed and comprehensive grid of cells covering the entire world. Each cell in our data is 0.5×0.5 square degrees (approximately 56km×56km at the equator) and their aggregate covers the total surface area of Earth. The dataset is available for the period between 1970 and 2000 at 10 year intervals. We combine this migration dataset with data on population, temperatures and precipitation at the same level of geographical detail as well as with national-level data to study the impact of temperature on net migration.

We first document the general pattern of migration in which individuals move out of rural areas into urban areas. In addition, we find that the intensity of rural-to-urban migration differs across country groups—middle-income countries have greater rates of rural-to-urban migration than poor and rich countries. This observation is consistent with a simple model of economic incentives and costs of migration. Middle-income countries are those in which the process of industrialization has started. Therefore, the rural income levels are high enough to pay migration costs. Furthermore, large rural-urban income differentials create a strong incentive to move to urban areas. On the other hand, in poor countries, fewer individuals have enough income to pay migration costs due to rural poverty, leading to lower rural-to-urban migration. Rich countries also have lower rural-to-urban migration as rural-urban income differentials and rural populations are small.

[1] For example, the migration rate in rural China increased from 20% to nearly 30% over the period 2003-2012 (Zhao et al., 2018). Baum-Snow et al. (2017) report that China's urban population was 29% of the total population in 1990, and that figure rose to 50% by 2010. Cobbinah et al. (2015) document that the urban population in Africa increased from 14% to 40% during 1950-2010.

[2] Average annual temperatures in 2050 are expected to be higher than the 1990 level by about 4°C under the worst case scenario (World Bank, 2018). Herring (2012) also notes that results from many climate models suggest that mean global temperature could be between 1.1 to 5.4°C higher in 2100 compared to current levels. Lastly, according to IPCC (2013), under the most extreme scenario the mean global temperature is expected to rise by 2.6 to 4.8°C by 2081-2100, relative to 1986-2005.

We employ this model to predict the effects of higher temperatures on migration from rural areas to urban areas, assuming that global warming mainly impacts rural areas, which disproportionately rely on agriculture. In such a context, a temperature rise reduces out-migration from rural areas in poor countries because it deteriorates rural productivity, worsening the liquidity constraint and making migration infeasible. However, the same temperature change increases out-migration from rural areas in middle-income countries because it widens rural-urban income gaps, strengthening individuals' incentives to migrate.

These asymmetric responses to weather shocks across countries are consistent with a collection of previous empirical findings. A large number of articles document that adverse weather shocks increase out-migration from affected areas (e.g., Kleemans and Magruder, 2018, Bohra-Mishra et al., 2014, for Indonesia). In contrast, studies on extremely poor countries such as Malawi (e.g. Suckall et al., 2017), find that negative climate shocks from droughts and flooding reduce internal migration by decreasing individuals' capabilities to move to other areas. Using data from Tanzania, Kubik and Maurel (2016) show that negative weather shocks increase or decrease internal migration depending upon households' initial income because migration decisions are made based on the ability to pay migration costs.

While these results from prior studies are suggestive of heterogeneous migration responses to weather shocks, possibly further depending upon national income levels, this paper is the first to test a general theory using a grid cell level dataset covering the entire world. We find strong evidence that higher temperatures reduce out-migration from rural areas in poor countries, and increase out-migration from such areas in middle-income countries. The temperature effects on migration are insignificant in rich countries, as these countries tend to be less agriculture-based and employ advanced technologies that are less sensitive to climate change.

The results of our grid cell level analysis are then confirmed using country-level observations constructed by aggregating the grid cell level data. Our results are robust for a wide range of different sample selection criteria and specifications. They suggest that global warming will increase the speed of transition to urban economies in countries where structural transformation has already started, but it will slow down such transformation in countries where this transition has not yet started. As a result, global warming may accentuate polarization (and therefore reduce convergence) of the level of economic development in countries.

This paper contributes to the literature on the impact of weather shocks on migration patterns.[3] Previous studies found that a rise in temperature induced out-migration (e.g., Zhou, 2011, for China; Joseph and Wodon, 2013, for Yemen; Marchiori et al., 2012, for Sub-Saharan Africa; and Bohra-Mishra et al., 2014, for Indonesia) and rainfall shortages also have similar effects (e.g., Kleemans and Magruder, 2018, for Indonesia; Nawrotzki et al., 2013, for Mexico; Barrios et al., 2006, and Henderson et al., 2017, for Sub-Saharan Africa; Strobl and Valfort, 2015, for Uganda; and Viswanathan and Kumar, 2015, for India). Catastrophic weather shocks such as typhoons were also shown to have induced internal migrations in Vietnam (Gröger and Zylberberg, 2016). However, Suckall et al. (2017) find that in Malawi—a very poor country—negative climate shocks reduced individuals capacity to migrate, which led to lower internal migration.

While country-specific evidence exists, there are only a few studies analyzing data from many countries to find a systematic relationship between the level of economic development and the economic or demographic responses

[3] The effects of weather changes, especially in the long-run, are channelled through their impact on agriculture-based economies. Some studies directly test the impact of climate change on agricultural output or income per capita (e.g., Kleemans and Magruder, 2018; Strobl and Valfort, 2015; and Viswanathan and Kumar, 2015). Burgess et al. (2014) find that, in India during the period 1957-2000, a greater number of high temperature days decreases agricultural yields and wages by 12.6% and 9.8%, respectively, and increases annual mortality by 7.3% in rural areas. Jayachandran (2006) finds that rainfall increased agricultural wages in India.

to weather shocks. Existing articles investigate the impact of weather shocks on GDP growth rate (Dell et al., 2012), agricultural productivity (Garcia-Verdu et al., 2019), local conflict (Bosetti et al., 2018), urbanization (Henderson et al., 2017), and *international* migration (Cattaneo and Peri, 2016).[4] The last two studies are most closely related to our paper. Henderson et al. (2017) analyzing Africa, show that weather shocks have differential impacts on rural areas, depending upon whether industrial cities are nearby or only agricultural-based centers exist. Their results are complementary to some of our findings and show that drier conditions reduce agricultural productivity, leading to rural-urban migration only when an industrial urban center is close. However, if the rural area is near less-developed cities, the same weather shock does not induce migration. Cattaneo and Peri (2016) find that higher temperatures increase international emigration from middle-income countries and reduces emigration from poor countries. Their results are similar to ours.

The remainder of the paper is organized as follows. The next section presents data sources and descriptive statistics. Section 3 proposes a simple model explaining the asymmetric temperature impacts on internal migration across countries. Sections 4 and 5 empirically test the relationship between temperatures and net migration using grid cell level data and country-level data, respectively. Section 6 offers concluding remarks.

2. Data and Descriptive Statistics

2.1. Definition and Sources for the Net Migration Variables

Our dataset is constructed using data from several sources. The data on net migration come from the *Global Estimated Net Migration Grids By Decade, v1 (1970-2000)* (de Sherbinin et al., 2015). These data provide estimates of net migration (in-migration minus out-migration) per $1km^2$ grid cell for the 1970s, 1980s and 1990s. While we provide a detailed description of how the data are produced in Appendix A, the main procedure is as follows. The data start with a very fine, census-based grid distribution of population in the year 2000, from the *Global Rural-Urban Mapping Project, Version 1*. Data on population growth during the previous decades for the same cross-sectional units, from the *History Database of the Global Environment, Version 3.1*, are then used to calculate population totals in 1970, 1980, 1990. In the next step, nativity and mortality rates that are specific to each nation, ethnicity group and decade are applied to each grid cell to estimate decennial births and deaths. Lastly, the fact that "births minus deaths plus net migration equals net population growth", is used to find net migration in each grid cell.[5]

We aggregate this highly detailed data to a 0.5×0.5 degree resolution. One grid cell used in the analysis in the current paper contains $56 \times 56 = 3,136$ of original grid cells. This aggregation reduces data volatility from small cells and leads to geographical units the size of which are roughly comparable to medium-sized cities and labor markets. We match the data on net migration with the population data obtained from Yamagata and Murakami (2015) at the same level of aggregation. Using these data, we construct net migration rates for grid cell (location) l of country c during the decade ending in year t as follows:

$$NetMigRate_{l,c,t} = 100 \times \frac{NetMig_{l,c,t}}{Pop_{l,c,t} - NetMig_{l,c,t}} \tag{1}$$

[4] Other related studies include Beine and Parsons (2015). They find that natural disasters induce international migrations. However, they do not focus on asymmetric reactions to weather shocks across countries.

[5] Appendix A describes the procedure in detail

where $NetMig_{l,c,t}$ denotes net migration (a positive or negative number of people) at location l of country c during the period between year $t-10$ and year t, where $t \in \{1980, 1990, 2000\}$. As we do not have population data in 1970 but do observe net migration in the 1970-80 period, the initial population in year $t-10$ is inferred as $Pop_{l,c,t} - NetMig_{l,c,t}$ and this is inserted in the denominator. Dividing by the initial population, equation (1) provides a net migration rate: the percentage change in population due to mobility.[6]

We also construct country-level measures of internal migration by aggregating grid cell level observations. The first measure of aggregate internal migration is constructed as follows:

$$AggMig^{\text{Total}}_{c,t} = \frac{1}{2} \sum_{l \in L_c} |NetMig_{l,c,t}| \tag{2}$$

where L_c is the set of all locations in country c. It shows that absolute values of net migration rates from all grid cells in country c are aggregated, and the sum is divided by two. If one individual migrates from a grid cell to another in the same country, net migration in the source location is -1 and in the destination location is $+1$. As there is only one individual who internally moved in this example, the absolute value of the sum is divided by two to obtain the total number of internal migrants in a country. This variable is indicated with superscript "Total" because it captures *total* internal migrations in a country.

We are particularly interested in emigration from rural areas of a country because rural areas are expected to be more sensitive to climate change. We therefore also construct different variables capturing this type of emigration. First, a set of grid cells in a country is divided into four groups–rural, middle-rural, middle-urban, and urban–based on the levels of population density in the (0-25th], (25th-50th], (50th-75th] and (75th-100th] percentiles within each country based on the population density data in the earliest available year 1980. Then, net out-migration from these grid cells is aggregated as follows:

$$AggMig^{\text{Rural Mid-rural}}_{c,t} = \sum_{l \in L_c^{\text{Rural Mid-Rural}}} |NetMig_{l,c,t}| \times \mathbf{1}_{(NetMig_{l,c,t}<0)} \tag{3}$$

$$AggMig^{\text{Rural}}_{c,t} = \sum_{l \in L_c^{\text{Rural}}} |NetMig_{l,c,t}| \times \mathbf{1}_{(NetMig_{l,c,t}<0)} \tag{4}$$

where in the first measure we aggregate grid cells in rural and middle-rural areas in country c, and in the second measure we only aggregate grid cells in rural areas. $\mathbf{1}_{(NetMig_{l,c,t}<0)}$ denotes an indicator variable taking unity if the net migration rate $NetMig_{l,c,t}$ is negative, and zero otherwise. Because these variables collect only negative net migration rates, these are a good approximation of out-migration from rural areas. Measure (3) captures out-migration from the rural and middle-rural and measure (4) quantifies that from rural areas only.[7]

Using each of these measures of total internal and rural out-migration, we construct the corresponding migration rates by dividing each by the country's population at the beginning of the decade as follows:

$$AggMigRate^{s}_{c,t} = 100 \times \frac{AggMig^{s}_{c,t}}{Pop_{c,t-10}} \tag{5}$$

[6] In the initial computation we include all cells in the world. Some of them may have zero population in some decades. When calculating the net migration rates in percent, we trim the values at or above 100% and at or below −100%. They are fewer than 0.1% of all cells and include those areas that go from zero to positive values and vice-versa.

[7] An alternative would be to sum all net migration from rural and semi-rural cells, including positive values. That variable is similar to the one constructed here, as rural and mid-rural cells have a large majority of negative net migration.

for $s =$ 'Total', 'Rural Mid-Rural', and 'Rural'. $Pop_{c,t-10}$ denotes the total population in country c in year $t-10$. Because country-level total population data are available from 1970, we can use the initial population level for the country-level internal migration measures in (5) unlike the grid cell level counterpart (1).

2.2. Definition and Sources for Climate Data and Country-level Data

We obtain data on temperatures and precipitation from the *Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01* (Matsuura and Willmott, 2007), and construct variables which capture their decennial change:

$$\Delta Temp_{l,c,t} = \overline{Temp}_{l,c,t} - \overline{Temp}_{l,c,t-10} \quad (6)$$

$$\Delta Prec_{l,c,t} = \overline{Prec}_{l,c,t} - \overline{Prec}_{l,c,t-10} \quad (7)$$

The average terms, $\overline{Temp}_{l,c,t}$ and $\overline{Prec}_{l,c,t}$, are defined as follows:

$$\overline{Temp}_{l,c,t} = \frac{1}{3}\sum_{k=0}^{2} Temp_{l,c,t-k} \quad \text{and} \quad \overline{Prec}_{l,c,t} = \frac{1}{3}\sum_{k=0}^{2} Prec_{l,c,t-k}$$

where $Temp_{l,c,t}$ and $Prec_{l,c,t}$ indicate the annual average temperature and the annual average precipitation at location l of country c in year t. These are three-year averages of annual average temperature and precipitation.

This grid cell level dataset is matched with country-level data using grid cell level country identifiers obtained from the *Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): National Identifier Grid* (van Donkelaar et al., 2015). The country-level variables are obtained from the *World Development Indicators* (World Bank, 2018, hereafter WDI).

2.3. Descriptive Statistics

Table 1 shows descriptive statistics of the grid cell variables, with the full sample as well as with sub-samples from each country group: poor, lower-middle income, upper-middle income, and rich.[8,9] The first row shows that the average net migration rate is −6.52%. This negative value implies that net emigration rates are, on average, greater than net immigration rates, which is explained by the fact that people tend to emigrate from low-population-density cells (hence larger negative values of the net migration rate) and immigrate to high density cells (hence lower positive values of the net migration rate).

It also shows that lower-middle income countries have the largest (in absolute value) negative average net migration rate among all groups. This implies that the level of rural-to-urban migrations is highest for that group of countries. This echoes the fact that middle-income countries have the greatest international emigration rates (see Dao et al., 2018; Clemens, 2014). It also describes the average temperatures and their average decennial changes, revealing an average warming of almost one degree (0.91) over the three decades. Precipitation levels are more stable and their decennial variations are small.[10]

[8] See Appendix A.2 for summary statistics of country-level variables.

[9] The country groups are based on the 25th, 50th, and 75th percentile of the income per capita distribution in the world in 1980. See Appendix B for a list of countries in each of the four groups.

[10] It also shows the population growth rates. These are not at the grid cell level, but rather at the country-level.

The four scatter plots in Figure 1 indicate the relationship between the net migration rates in rural areas (a negative value implies out-migration from rural areas) and the temperature changes during the more recent 1990-2000 decade available. Each panel includes countries from one income group and a line of the best fit. It shows that, in poor (and to some extent in lower-middle income) countries, a temperature rise is associated with attenuated rural out-migration rates, i.e. higher temperature corresponds to migration rates closer to zero. This suggests that a higher temperature reduces out-migration from rural areas of poor countries. In contrast, in upper-middle income countries, higher temperatures are associated with larger negative net migration rates, implying that rising temperatures induce stronger out-migration from rural areas. In rich countries, finally, the association is very weak.

Finally, Figure 2 shows similar correlations to Figure 1, using country-level data. In particular, we show the correlation between temperature changes and out-migration from rural areas, defined as $AggMigRate_{c,t}^{\text{Rural Mid-Rural}}$ shown in equation (3). As the vertical axis measures out-migration (negative net migration), the slopes are opposite to those in Figure 1 but the finding is the same. Specifically, there is a negative correlation between temperature change and rural out-migration in poor countries, while the relationship is null in lower-middle income countries, and positive in upper-middle income countries. These results suggest that a higher temperature reduces rural out-migration in poor countries while it increases such migration in middle-income countries.

3. A Simple Model

We consider a simple theoretical framework with agents who have costs and incentives to migrate within a country, similar to the model presented in Cattaneo and Peri (2016), which builds on in part Roy-Borjas (Roy, 1951; Borjas, 1987).[11] The goal is to explain some of the above stylized facts and to offer a prediction of the impact of temperature changes on rural-to-urban migration. Once we have derived our model's implications, we choose parameter values based on empirical observation. We then conduct numerical simulations to understand the effect of economic development and temperature shocks on rural-to-urban migration.

3.1. The model

Consider a country with two regions, "urban" and "rural", indicated by superscripts U and R respectively, which differ in productivity. Urban productivity realizations follow a stochastic process. Specifically, the productivity level in the urban region in period t, A_t^U, is as follows:

$$\ln(A_t^U) = \alpha_0 + \alpha_1 \ln(A_{t-1}^U) + e_t \tag{8}$$

where α_0 is the average productivity growth rate and α_1 is the degree of persistence of productivity over time. The term e_t denotes a random innovation and is distributed with zero mean and positive variance. On the other hand, rural productivity is determined by initial rural productivity and urban productivity. Specifically, as in Desmet and Rossi-Hansberg (2009), rural productivity is given by:

$$A_t^R = \rho A_t^U + (1-\rho) A_{t-1}^R \tag{9}$$

[11] Cattaneo and Peri (2016) considers the effect of negative temperature shocks on international emigration, while we consider the effect of the same type of shocks on rural-urban migration within a country.

which shows that rural productivity is a weighted average of urban productivity and past rural productivity. The parameter $\rho < 1$ captures the speed of technology diffusion from the urban to the rural region. A greater ρ leads to a higher speed of technology diffusion and therefore a faster convergence of rural productivity to urban productivity. The initial productivity in the two regions, A_1^U and A_1^R, is exogenously given and the urban area is more productive than the rural area in the initial period, $A_1^U > A_1^R$.

The wage rate for an individual i in region J, $w_{i,t}^J$, is equivalent to labor productivity of the individual in that region and is given by:

$$w_{i,t}^J = A_t^J \delta^J(T_t) + \beta^J \epsilon_i \tag{10}$$

where A_t^J is the productivity of the region, $\delta^J(T_t)$ is a term capturing the potential productivity effect of temperature, and β^J indicates the location-specific return to skills. The term ϵ_i indicates human capital that is specific to individual i and transferable to other regions, and it is normally distributed with a zero mean and a standard deviation of unity. We assume that $\beta^U > \beta^R$, meaning that returns to skills are greater in the urban region than in the rural region for all workers.[12] Given that $A_t^R \leq A_t^U$ and that $\delta^R(T_t) \leq \delta^U(T_t)$ for all t (as we explain below), the urban region offers a higher wage than the rural region. This income differential generates incentives for rural-to-urban migration. Assuming the same price levels across regions for simplicity, income differentials are the only source of incentives to migrate.

A temperature rise reduces agricultural productivity in rural areas as shown in Dell et al. (2012) and Garcia-Verdu et al. (2019). We use the term $\delta^J(T_t)$ to capture the effects of an increase in temperatures. In particular, rural productivity decreases if temperatures rise above a certain threshold. On the other hand, the urban productivity is not affected by a temperature rise.[13] Specifically, the productivity terms $\delta^J(T_t)$ are:

$$\delta^U(T_t) = 1 \quad \text{for all} \quad T_t$$

and

$$\delta^R(T_t) = \begin{cases} 1 & \text{if } T_t \leq T^* \\ \gamma_t & \text{otherwise} \end{cases}$$

where T_t denotes temperature at time t; T^* is a threshold above which an increase in temperature reduces productivity; and $\gamma_t \in (0,1)$ is a parameter capturing reduced rural productivity due to high temperatures.

Consider an individual living for two periods. In the first period, she is in the rural region and works to earn income. At the end of the first period, she makes a decision to either migrate to the urban region or remain in the rural region. If she decides to move, she uses a part of her income to pay migration costs. Migration costs are denoted by $C > 0$, which includes costs for relocating, traveling, and searching for a job. In the second period, she works and earns in the location she chose. She needs to pay these costs in the first period in order to work in the urban region in the second period.

Therefore, an individual in the rural region makes a migration decision based on the wage she will receive in the second period (indicated as t) at the current location, in the urban region (i.e., post-migration) and the costs

[12] The assumption is supported by a number of studies estimating the spatial difference in the return to observable skills. See, for example, Moretti (2013) and Diamond (2016) for the evidence from the U.S and see Lucas (1997) and Lagakos et al. (2016) for the evidence from developing countries.

[13] Dell et al. (2012) and Garcia-Verdu et al. (2019) find significant impacts of weather shocks from poorer countries. Mendelsohn et al. (2001) and Mendelsohn et al. (2006) argue that economic development makes countries less sensitive to weather shocks because more developed countries use technologies that are less sensitive to climate as they are more capital-intensive and sophisticated.

of migration C. Assuming that aggregate and individual productivity are revealed at the beginning of period t, individual i migrates from the rural to the urban region at the beginning of period t if:

$$A_t^U + \beta^U \epsilon_i - C > A_t^R \delta^R(T_t) + \beta^R \epsilon_i \tag{11}$$

or simply

$$\epsilon_i > \frac{A_t^R \delta^R(T_t) - A_t^U + C}{\beta^U - \beta^R} \tag{12}$$

This condition is similar to what would arise in a Roy-Borjas model as the "selection equation". The parameter restriction $\beta^U > \beta^R$ implies that only individuals with high enough value of ϵ_i (proxy for skills) have an incentive to migrate. One can interpret this equation as an incentive-compatibility condition, which identifies individuals for whom migration is compatible with their economic incentives.

A second condition identifies individuals who are able to migrate; thus we call this condition the "feasibility constraint". An individual i needs enough income to pay the costs of migration at the end of the first period (indicated with $t-1$). Individual i migrates only if the cost of migration is not greater than savings at the end of the first period, which are $w_{i,t-1}^R = A_{t-1}^R \delta^R(T_{t-1}) + \beta^R \epsilon_i$. The feasibility constraint is therefore written as

$$A_{t-1}^R \delta^R(T_{t-1}) + \beta^R \epsilon_i > C$$

or

$$\epsilon_i > \frac{C - A_{t-1}^R \delta^R(T_{t-1})}{\beta^R} \tag{13}$$

Individual i migrates from the rural to the urban region if the two conditions, (12) and (13), are both satisfied.

Given the distribution of ϵ_i and using equation (12), the fraction of people who have an incentive to migrate from the rural to the urban region is

$$S_{\text{Selection},t}^R = 1 - \Phi\left(\frac{A_t^R \delta^R(T_t) - A_t^U + C}{\beta^U - \beta^R}\right) \tag{14}$$

where Φ denotes the cumulative distribution function of the standard normal distribution. The fraction of people whose feasibility constraint is not binding, using equation (13), is

$$S_{\text{Feasibility},t}^R = 1 - \Phi\left(\frac{C - A_{t-1}^R \delta^R(T_{t-1})}{\beta^R}\right) \tag{15}$$

While the selection equation depends on the current temperature T_t, the "feasibility constraint" depends on temperature from the previous period T_{t-1}.

The share of individuals who migrate from the rural to the urban region is therefore:

$$S_{\text{Migration},t}^R = \begin{cases} S_{\text{Feasibility},t}^R & \text{if } S_{\text{Selection},t}^R > S_{\text{Feasibility},t}^R \\ S_{\text{Selection},t}^R & \text{otherwise} \end{cases}$$

In the first case where $S_{\text{Selection},t}^R > S_{\text{Feasibility},t}^R$, there are some individuals who have incentives to migrate but whose feasibility constraints are binding. Thus the share of individuals who migrate is given by $S_{\text{Feasibility},t}^R$. If

$S^R_{\text{Selection},t} < S^R_{\text{Feasibility},t}$, instead, the overall income level is high enough that the feasibility constraint is not binding anymore. As a result, the share of individuals who migrate is given by $S^R_{\text{Selection},t}$.

3.2. Numerical Exercise: The Evolution of Rural-Urban Migration

To illustrate how the model works, we simulate a number of hypothetical transition paths of a country from poor to middle-income. Alternatively we can interpret the paths as representing an ordered set of identical countries at different levels of economic development.

3.2.1. Parameterization

We choose parameter values to match the summary statistics from a representative poor economy that has grown significantly in the considered decades, namely Vietnam. The industrial and agricultural value-added per worker from the World Development Indicators (WDI) are used as rural and urban productivity, respectively. The initial urban-to-rural productivity gap is assumed to be 6 because Vietnam's industry-to-agriculture productivity ratio equals that number in the earliest available year in the data, 1991. The productivity process is set to match the actual productivity growth in Vietnam, specified as $\ln(A^U_t) = 0.17 + 0.90\ln(A^U_{t-1}) + \epsilon_t$ where ϵ_t follows a normal distribution with zero mean and a standard deviation of 0.028. The initial log productivity is $\ln(A^U_1) = 1.5$, therefore $A^U_1 \approx 4.48$. The parameter determining the speed of technology diffusion is $\rho = 0.025$. A temperature rise is assumed to generate a 10% decline in rural productivity (i.e., $\delta^R = \gamma = 0.9$), and we analyze a new growth path with lower rural productivity.

The total costs of rural-to-urban migration is set to be 0.6 times the value of urban income, which is a reasonable assumption given that international migration costs are 1-6 times greater than urban income (Grogger and Hanson, 2011). We set returns from skills in the rural region to $\beta^R = 1.6$. Herrendorf and Schoellman (2018) find that returns to schooling are about 1.5 times greater in industry than agriculture. Therefore, returns from skills in the urban region is $\beta^U = 1.6 \times 1.5 = 2.4$. See Appendix C for more details about these assumptions.

3.2.2. Description of Numerical Simulation

We simulate 1,000 hypothetical paths of urban productivity. Given the realized urban productivity in each period, all other endogenous variables are obtained from the model. The error term in equation (8) generates a stochastic component. Figure 3 shows the average share of individuals willing to migrate implied from the selection equation as well the share who can feasibly migrate. The thinner solid (blue) line, representing the selection condition, shows that the incentive to migrate is higher in the earlier period due to the higher urban-rural productivity gap. The incentive declines as the country grows.

On the other hand, the thicker solid (green) line, indicating the feasibility constraint, describes how the share of individuals who can afford to migrate is lower at earlier stages of development. The lower rural income in earlier periods makes it difficult to migrate. However, as rural productivity rises, more people have enough income to pay migration costs. Interactions between these two conditions determine the share of individuals who are able and willing to migrate. The thick solid line in Panel A of Figure 4 shows that the net migration rate has a hump-shaped curve, reaching its maximum around period $t = 22$.

We now describe the effect of a temperature increase (above the threshold) on migration. The dashed lines in Figure 3 describe the share of people willing and able to migrate to the urban area when there is a 10% loss of rural productivity (with unchanged urban productivity) due to higher temperatures. Such negative shocks make the feasibility constraint tighter, while it increases the incentive to migrate. The dotted (red) line in Panel A of Figure 4 shows new migration rates with higher temperatures. Panel B shows the difference between migration with and without temperature shocks. A temperature rise reduces rural-to-urban migration in countries at lower levels of development. It is explained by the fact that the feasibility constraint prevails in these countries and negative temperature effects reduce individuals' income levels and, therefore, the capacity to migrate. On the contrary, in middle-income countries, the same temperature rise increases rural-to-urban migrations because it increases the urban-rural productivity gaps, providing stronger incentives to move to the urban region.

The key features of the numerical results are summarized as follows:

1 *The highest level of rural-to-urban migration is observed when a country is at an intermediate level of economic development.*

2 *An increase in temperatures decreases rural-to-urban migrations in poor countries while increasing such migration in middle-income countries.*

In Figure 5 we represent these implications in a stylized diagram with the vertical axis measuring the net migration rate and the horizontal axis measuring population density (rural areas on the left and urban areas on the right). Plotting average net migration rates in this space produces an upward-sloping net migration line crossing the zero horizontal line, as net migration rates are negative in rural regions and positive in urban regions. We call this upward-sloping relation the 'net migration line'.

The first implication of our model is that the net migration line is flatter in poor (and rich) countries and steeper in middle-income countries, as shown in Figure 5. The second implication has to do with the change in slope of the net migration line as a consequence of higher temperatures. The solid lines in the graph represent net migration rates before the temperature rise, while the dashed lines correspond to the one after the temperature rise. The temperature shock reduces, in absolute value, the net migration rates in poor countries. This causes a clockwise rotation of the net migration line. To the contrary, the same shock produces a counter-clockwise rotation of the line in middle-income countries because it leads to a large emigration (negative net migration) from rural areas and a large positive immigration into urban areas.

4. Empirical Analysis using Grid Cell Level Observations

Guided by the predictions in the previous section, we first estimate the slope of the net migration line for each of the four country groups. We then examine whether a temperature rise affects net migration rates, and if temperature effects depend on the income levels of countries.

4.1. Estimating the Slope of the Net Migration Lines

The first set of regressions addresses the following two questions. (1) What is the direction of internal migration? (2) Do we observe different levels of internal migration across countries at different stage of economic development? To answer these questions, we calculate average net migration rates over the period 1970-2000 in rural, middle-rural, middle-urban, and urban "cells" of each country, where these are defined by population density in the earliest available year, 1980, as described in section 2.1. Countries are divided into four groups: poor, lower-middle, upper-middle, and rich, as described in section 2.3.

Panel A of Figure 6 shows simple averages of the net migration rates (relative to the world average in each point in time) by plotting the coefficients of indicators for each of the four population density groups, which are measured on the horizontal axis. The bands are the 95% confidence intervals. Panel B of Figure 6 plots the same coefficients controlling for country- and grid cell-specific characteristics, obtained by estimating the following regression:

$$NetMigRate_{l,c,t} = \alpha_1 \Delta Temp_{l,c,t} + \sum_{g \in G} \alpha_3^g D_{l,c}^g + \alpha_2 \Delta Prec_{l,c,t} + \mathbf{X}_{l,c,t}\alpha_4 + u_{l,c,t}. \tag{16}$$

The dependent variable $NetMigRate_{l,c,t}$ denotes the net migration rate in location (grid cell) l of country c during the decade $t-10$ to t. $\Delta Temp_{l,c,t}$ and $\Delta Prec_{l,c,t}$ are decennial changes in average temperatures and precipitation, respectively. The variables $D_{l,c}^g$ indicate dummy variables taking one if location l is in area g for g = rural, middle-rural, middle-urban, and urban in country c, and G is the set of the four areas. We drop the intercept from the regression so that we can include all of the four dummies. The $\mathbf{X}_{l,c,t}$ is a vector of cell-level control variables including the population growth rate, and country fixed effects. $u_{l,c,t}$ denotes an error term. We estimate equation (16) separately for each of the four groups of countries.

Panels A and B of Figure 6 show similar trends with or without controls, and with a different standardization. We observe an upward-sloping relation of net migration rates in each country group with relative density. Cells in urban and middle-urban areas have positive net migration rates (i.e., receiving people on net), while cells in rural and middle-rural areas have negative net migration rates on average (i.e., sending people on net). This implies that net internal migrations are from rural areas to urban areas.

It also shows a clear across-group difference in net internal migration. Poor and upper-middle/ rich countries exhibit a flatter net migration line, while lower-middle income countries have the steepest net migration line.[14] These patterns are consistent with our model's prediction that rural-to-urban migration becomes greatest at intermediate levels of development. We note that this is also consistent with previous studies, for instance, Dao et al. (2018) and Clemens (2014). They show that emigration from a country increases as the country becomes richer, but after a certain level, further development reduces emigration from the same country. We find that internal migration also follows the same pattern.

4.2. Effects of a Temperature Increase

4.2.1. Regression Model to Estimate the Temperature Effect with Grid

This section investigates the effects of temperatures on the net migration rates. We allow for different migration responses to temperature shocks across areas of different population density and across income groups of countries. Specifically, our regression equation includes interaction terms between the three dummies capturing relative

[14]The estimates imply that rural and middle-rural areas of lower-middle income countries experience emigration that reduces their population by 15-20% every decade. Emigration from rural and mid-rural areas of poor countries is, instead, 5-15% of the population in each decade. That same rate is down to 0-5% of the population in rich and middle-rich countries. The urban regions of each country, considering the simple average chart, receive immigration in the order of 5-7% of their population in each decade.

population density within a country and temperature as well as precipitation changes. It is specified as follows:[15]

$$\begin{aligned} NetMigRate_{l,c,t} &= \alpha_0 + \alpha_1 \Delta Temp_{l,c,t} + \sum_{g \in G \setminus \{\text{Urban}\}} \alpha_1^g D_{l,c}^g \Delta Temp_{l,c,t} + \alpha_2 \Delta Prec_{l,c,t} \\ &\quad + \sum_{g \in G \setminus \{\text{Urban}\}} \alpha_2^g D_{l,c}^g \Delta Prec_{l,c,t} + \sum_{g \in G \setminus \{\text{Urban}\}} \alpha_3^g D_{l,c}^g D_t + \mathbf{X}_{l,c,t} \alpha_4 + e_{l,c,t} \end{aligned} \tag{17}$$

where $D_{l,c}^g$ are the dummies taking unity in area g = rural, middle-rural, and middle-urban within country c. D_t denotes a time (decade) dummy. The 'urban area' dummy $D_{l,c}^{\text{Urban}}$ is excluded from the interaction terms, as indicated in the expression. As a result, the coefficient on temperature changes, α_1, measures the impact of temperature shocks in urban areas. The coefficients on the interaction terms capture differences in the temperature effects from urban areas. For example, α_1^{Rural} measures the difference between the temperature effects in urban areas and in rural areas, and the linear combination $\alpha_1 + \alpha_1^{\text{Rural}}$ quantifies the temperature effects in rural areas. $\mathbf{X}_{l,c,t}$ is a vector of control variables including the population growth rates interacted with the rural-urban dummies and country fixed effects. $e_{l,c,t}$ indicates an error term. We estimate regression (17) separately for the four groups of countries.

The regressions test the implications described in Figure 5. First, in poor countries, higher temperatures flatten the net migration line. In other words, rising temperatures reduce out-migration from rural areas and have a small effect on urban areas. Therefore, we expect the following:

$$\textbf{Temperature effects in poor countries:} \;\; \alpha_1^{\text{Rural}} > \alpha_1^{\text{Middle-rural}} > \alpha_1^{\text{Middle-urban}} > \approx 0.$$

The coefficient α_1^{Rural} is positive because rising temperatures induce fewer people to emigrate from rural areas, increasing the net migration rate.

However, in middle-income countries a temperature increase steepens the net migration line. Hence, we expect the following results:

$$\textbf{Temp. effects in middle-income countries:} \;\; \alpha_1^{\text{Rural}} < \alpha_1^{\text{Middle-rural}} < \alpha_1^{\text{Middle-urban}} < 0.$$

Contrary to the case of poor countries, the coefficient α_1^{Rural} is negative because higher temperatures induce more people to emigrate, reducing the net migration rate. The absolute value of the coefficient declines as we move toward urban areas, as these areas are less affected by temperature shocks. Lastly, if rich countries exhibit limited rural-urban migration, as income differentials are small and once the economic and urbanization transitions have fully taken place, we expect the following:

$$\textbf{Temp. effects in rich countries:} \;\; \alpha_1^g \approx 0 \;\text{ for }\; g = \text{Rural, Middle-rural and Middle-urban.}$$

Armed with these conjectures, we find the temperature effects by estimating equation (17) separately for each income group of countries.

[15] In the baseline estimation, standard errors are clustered at the grid cell level. We consider possible spatial correlation of the error term because one grid cell is fairly small (about $50km \times 50km$) and climatic conditions are correlated across space, which may lead to standard errors which are smaller than they are supposed to be. In order to correct for possible spatial error correlations, in Appendix E.2, we show three other sets of standard errors clustered at more aggregated grid cells. We find that our baseline results remain largely unchanged.

4.2.2. Baseline Results on the Temperature Effect with Grid Cell Level Data

Table 2 summarizes our baseline results and Figure 7 plots the linear combinations of the estimated coefficients that gives the effect of temperature on net migration in each density area. The four graphs in Panel A show the effect of a 1°C rise in temperatures on the net migration rate, in percentage points, with 95% confidence intervals.[16] They show two important results. First, rural areas of a country are more affected by temperatures than urban areas. Second, there are clear cross-country differences that are consistent with the theory: higher temperatures have a positive effect on the net rural migration rate in poor countries, and they have a negative effect on rural migration in upper-middle income countries.

To help readers understand the meaning of these temperature effects, Panel B of Figure 7 describes the average net migration rates with and without the estimated temperature effects. The dashed lines show the average net migration rates before the increase in temperature, while the solid lines indicates those which include the effect of increasing temperatures. The solid lines are obtained by calculating the effect of a significant rise in temperatures—defined as the 90th percentile of historical changes in the average temperature over the period 1970-2000—on the net migration rates.

Several interesting patterns emerge which are in line with our predictions. Most importantly, rising temperatures reduce rural out-migration in poor countries. The positive temperature effects are particularly significant in rural regions of poor countries—a 1°C rise in temperatures increases the net migration rate by 4.7 percentage points. The temperature effects are positive in middle-rural areas although these are insignificant. In contrast, temperature effects turn to be negative in urban areas. These results imply that a rise in temperature flattens the net migration line in poor countries by reducing rural-to-urban migration. However, a rise in temperature increases rural-to-urban migration in upper-middle income countries. The temperature effects on net migration rates are negative and most significant in rural areas, while they are close to zero in urban areas.

In rich countries temperature effects are small in magnitude and generally insignificant. Rural productivity may be less affected by temperature in rich countries as documented in prior studies (e.g., Dell et al., 2012). Moreover, the rural-urban productivity gap is smaller, and most of the population is in urban areas already. Thus these insignificant results are not surprising.

Lastly, in lower-middle income countries, a higher temperature reduces the net migration rate in urban regions and has an insignificant effect in rural regions. These effects are somewhat different from the theoretical predictions. This is presumably due to the fact that this group includes countries in the middle of a transition from being a poor country to a middle-income country, making it difficult to observe a clear-cut temperature effect. In the next section, we show that the temperature effects on this group is more consistent with the theory once non-linearity of temperature effects are taken into consideration.

4.2.3. Robustness Checks using Grid Cell Level Data

This section addresses a number of potential critiques to our baseline results. First, prior studies show that temperatures have non-linear effects, meaning that rising temperatures have a negative impact on economic variables

[16] We report the coefficients of the temperature changes only. While we include the precipitation changes in the regressions, the coefficients on these variables turn out to be small and usually insignificant. Therefore, these are not reported. Table 2 shows results from the three country groups, leaving out rich countries, for which effects are always tiny. Nonetheless, Figure 7 plots temperature effects in rich countries as a reference.

above a certain threshold (e.g., Burke et al., 2015; Schlenker and Roberts, 2009; Bohra-Mishra et al., 2014).[17] To respond to this potential critique, we interact the temperature changes with a dummy variable taking one if average temperatures are above the 75th percentile of the world temperature distribution. It examines an additional effect of a temperature rise in grid cells that are already hotter than most.

Figure 8 presents estimated temperature effects, separately in hot grid cells and other grid cells. The temperature effects in poor countries are not very different between hot and less hot areas. On the other hand, temperature effects are different across hot and less hot areas in lower-middle income countries. Interestingly, less hot areas react to a higher temperature in the same way as poor countries, while hot areas respond to it as in upper-middle income countries. Our explanation for these results is the following. First, in less hot areas rising temperatures probably work to increase agricultural productivity because temperatures have a non-linear effect on agricultural production. As a result, a higher temperature improves economic conditions, inducing a fewer people to emigrate from those areas. Therefore, the negative net migration rates increase. Second, in hot areas rising temperatures reduce agricultural productivity, which induces emigration from those areas as in upper-middle income countries. The third panel shows that, in upper-middle income countries, rising temperatures have greater effects in hot areas, consistent with our prior.

Results from a series of other robustness checks are summarized in Figure 10. Panels A, B, and C show results from poor, lower-middle income, and upper-middle income countries, respectively. Each of of these panels includes four charts for rural, middle-rural, middle-urban, and urban, from left to right. Each chart shows point estimates and associated 95% confidence intervals for six different specifications as indicated in the chart for rural areas. Specification (1) drops observations with extreme temperature changes where these are defined as $\Delta Temp_{l,c,t}$ above the 95th percentile and below the 5th percentile of the distribution in the data used in the regression. Specification (2) omits observations with extreme precipitation, $\Delta Prec_{l,c,t}$, greater than the 95th or less than the 5th percentiles. Specification (3) drops extreme net international migration changes, defined as the top 1% and bottom 1% of the net international migration rates in the baseline sample. Specification (4) excludes observations from Sub-Saharan Africa, as previous studies argue that countries in the region are different in terms of the impact of weather shocks.[18] If so, our results may be driven by countries in the region. Specification (5) drops highly urbanized countries (with an urban population above the 75th percentile of the distribution) as they may have small impacts from agricultural productivity. Lastly, in Specification 6 we drop countries that are less dependent on agriculture (defined as those with agricultural value-added as a share of GDP less than the 25th percentile in 1990). Overall, the results show that these additional controls and variations do not change much the baseline results. Estimates from the cell-level analysis are quite robust and stable.

One may claim that our analysis does not demonstrate the channel through which rising temperatures affect migrations. We are unable to provide a direct test because there is no grid cell level data on agricultural productivity. Nonetheless, as an indirect test, we introduce a cropland dummy into our regression model to investigate if we

[17] Burke et al. (2015) show that global productivity is maximized when the annual average temperature is at 13°C and a further increase in temperatures reduces world production. Schlenker and Roberts (2009) focuses on the effect of temperatures on crop yield and finds that crop production increases up to 29-30°C before declining. Bohra-Mishra et al. (2014) show that the migration likelihood is also a non-linear function of temperature using the household-level data from Indonesia. Accordingly, some previous studies include the level of temperatures, its square term, and even higher order polynomials to allow non-linearity (e.g., Burke et al., 2015; Bohra-Mishra et al., 2014) or introduce a step damage function of temperatures by introducing dummies (e.g., Schlenker and Roberts, 2009; Garcia-Verdu et al., 2019).

[18] For example, Barrios et al. (2010) show that rainfall shortages in Sub-Saharan Africa during 1960-2000 are responsible for lower income levels in the region today. They also argue that the significant rainfall impacts are observed in poor Sub-Saharan African countries but not in other countries. Barrios et al. (2006) find that rainfall shortages induced urbanization in Sub-Saharan African countries and argue that climate-induced urbanization is not observed elsewhere.

observe stronger temperature effects from cropland areas. The data on cropland come from Ramankutty et al. (2008) and provide grid cell level data on cropland areas in the year 2000.[19] We create a dummy variable taking unity if the grid cell includes cropland areas more than the 95th percentile of the cropland distributions among all grid cells in each country. The cropland dummy is interacted with the temperature variable as well as the rural-urban dummies and year fixed effects.

Results are presented in Figure 9. It shows that significant temperature effects are almost exclusively coming from the cropland areas. For example, a 1°C rise in temperatures increases the net migration rate by 11.6 percentage points in cropland areas of poor countries while the same temperature shock raises it by 4.5 percentage points only in non-cropland rural areas. In lower-middle income countries, a 1°C rise in temperatures reduces the net migration rate by 11.6 percentage points in cropland areas and the temperature effects are close to zero in the other rural areas. We observe a similar pattern from upper-middle income countries as well. These results support our hypothesis that climate-related migrations are driven by declining agricultural productivity.

5. Analysis using Country-level Data

This section examines the impact of temperatures on rural-to-urban migration using aggregate data at the country-level. We first discuss our regression model and then present estimation results. The estimated coefficients from these regressions and the anticipated temperature changes in the next 80 years are then used to predict current and future internal migration rates.

5.1. Empirical Framework for Country-level Analysis

To analyze the impact of temperatures on rural-urban migration with the country-level data, we estimate the following equation:

$$AggMigRate^{s}_{c,t} = \gamma_0 + \gamma_1 \Delta Temp_{c,t} + \sum_{h \in \{\text{Poor, Lower-Middle}\}} \gamma_1^h D_c^h \Delta Temp_{c,t} + \mathbf{X}_{c,t}\gamma_3 + \epsilon_{c,t} \tag{18}$$

for s = "Total" and "Rural Mid-rural", and these dependent variables are defined in section 2.1. We use exclude rich countries because they exhibit little rural-to-urban migration and temperature effects are mostly insignificant. $\Delta Temp_{c,t}$ denotes changes in country-level long-run average temperatures. H is a set of groups of countries including poor, lower-middle, upper-middle, and rich. D_c^h indicates a dummy variable equal to one if country c is in group h and zero otherwise. Because we exclude observations from rich countries from the sample the coefficient of $\Delta Temp_{c,t}$, γ_1, measures the temperature effects in upper-middle countries. A linear combination of the two coefficients produces the effect on the other groups of countries. For instance, $\gamma_1 + \gamma_1^{\text{Poor}}$, measures the temperature effects on poor countries. The term $\mathbf{X}_{c,t}$ denotes a vector of country-level controls. Our baseline model includes GDP and population growth rates. These are long-run changes between the beginning and the end of the decade. We also include precipitation, the log of initial population, the log of initial GDP, the initial agricultural and manufacturing value-added as a share of GDP, and their decennial changes as a set of controls. $\epsilon_{c,t}$ is the error term.

We omit several small countries and islands where measurement errors in aggregation can be large, and we include countries for which we have some basic control variables (such as GDP) going back to 1970. These reduce

[19] See Appendix A for more details about the data.

the sample size substantially.[20] Rich countries are dropped from the regressions as well. As a result, the number of countries in the sample is 77.

5.2. Country-level Results

Baseline results are summarized in Table 3. Panel A shows the effects of a 1°C rise in temperatures on the total internal migration rate constructed using formula (2). Panel B shows the effect of the same rise in temperature on the rural out-migration rate defined in formula (3). Each panel presents linear combinations of the coefficients indicating the temperature effects as well. Column (1) includes the temperature changes only without introducing any interaction terms. Column (1) of the two panels shows an insignificant temperature effect.

Column (2) adds interaction terms between the temperature variable and the income-level dummies, allowing for heterogeneous migration responses to temperatures across income groups. It shows that, in upper-middle income countries, higher temperatures increase total internal migration rates by around 2 percentage points and rural out-migration rates by 0.6 percentage points. In contrast, in poor countries the same increase in temperatures reduces the two measures of internal migration rates by about 3 and about 2 percentage points, respectively.

Column (3) adds precipitation; the coefficients are basically unchanged. The levels of population and GDP as well as the industrial structures of the countries are controlled for in columns (4) and (5) respectively. In columns (4) and (5) of Panel A, the negative temperature effects in poor countries lose statistical significance, presumably due to the fact that total internal migration rates include all internal migrations in addition to rural out-migrations. However, as shown in Panel B, the temperature effects on the rural out-migration rates are significant in all columns. The significant temperature effects on rural out-migrations are consistent with the theory. The coefficients from lower-middle income countries are insignificant, which is consistent with the grid cell level results that, in that group of countries, rising temperatures have limited effects in less hot areas, and we observe poor-country-like effects in hot areas only. Overall, the results from the country-level data confirm our grid cell level evidence.

5.3. Robustness Checks for Country-level Results

We conduct a set of robustness checks and present results in Figure 11. Panels A and B presents the temperature effects on the total internal migration rates and the rural out-migration rates, respectively. Each of the two panels shows point estimates of poor, lower-middle, and upper-middle countries, from the left to the right. The vertical bars indicate the 95% confidence intervals. The first four plotted bars describe the results from columns (2)-(5) in Table 3.

The subsequent bars show the results from additional robustness checks. The fifth bar includes a dummy taking unity if the country's average temperature is above the 75th percentile of the world distribution. The sixth bar drops observations with extreme temperature changes, which is defined as temperature changes above the 95th percentile of the distribution. The seventh bar omits observations with extreme precipitation changes, defined using the 95th percentile of the distribution of precipitation changes. The eighth bar omits observations with extreme internal migration rates, defined as top 1% and bottom 1% of the observations. The results are similar to our baseline results.

The ninth bar omits urban countries defined as those with urban populations greater than the 75th percentile of the observations in 1970. The tenth bar excludes countries that are not agriculture-based, defined as those with

[20] See Appendix B for the list of the countries.

agricultural value-added as a share of GDP less than the 25th percentile in 1990.[21] Prior studies show that agricultural sectors are more subject to weather shocks (e.g., Mendelsohn et al., 2001; Mendelsohn et al., 2006; and Schlenker and Roberts, 2009). Therefore, these excluded countries are less suited to the model's underlying mechanisms leading to migratory responses to rising temperatures. Therefore, their exclusion is expected to magnify the temperature effects on the internal migration rates. Indeed, in Panel B the temperature effects on poor countries become about 0.2 percentage points larger and the effects on upper-middle income countries also become about 0.35 points greater in absolute values when excluding less agricultural countries. Overall, Figure 11 shows that our results are robust to dropping outliers and excluding some sub-sets of the baseline sample.

Lastly, we acknowledge that the temperature effects on the total migration rates are more imprecisely estimated and not very significant as shown in Panel A. While most temperature effects are significant in upper-middle income countries, those in poor countries are insignificant in all specifications in the robustness checks, because of large standard errors. This may be due to the fact that total internal migration is not a very precise measure of rural-urban migration.

5.4. Projecting Internal Migration Rates for 2020-2100

Having estimated these effects, we perform a forecast exercise. We calculate the expected internal migration rates for the period 2020-2100 using the estimated coefficients in regression (18) and projected temperature changes obtained from the *Climate Change Knowledge Portal* (World Bank, 2018). It provides projections under a scenario called A2, with higher carbon emissions and therefore higher increase in temperatures, and another scenario called B1 with a lower emission forecast. Projected median temperatures are shown in Figure 12 with a band describing the 10th and 90th percentiles of the projections. By the year 2100, all groups of countries are expected to experience a temperature rise about 4°C and 2.3°C under A2 and B1 scenarios, respectively.

Expected internal migration rates are obtained by using the estimated coefficients from the country-level regression (18), with all variables kept constant at the level in 2000, and only the temperature variable changing to its projected values in the coming decades, t = 2020-40, 2040-60, 2060-80, and 2080-2100, as follows:

$$Agg\widehat{MigRate}^{s}_{c,2000,t} = \hat{\gamma}_0 + \hat{\gamma}_1 \Delta Temp^{\text{Projection}}_{c,t} + \sum_{g\in G} \hat{\gamma}^g_1 D^g_c \Delta Temp^{\text{Projection}}_{c,t} + \mathbf{X}_{c,2000}\hat{\boldsymbol{\gamma}}_3 + \hat{\epsilon}_{c,2000}$$

where $Agg\widehat{MigRate}^{s}_{c,2000,t}$ denotes the predicted internal migration rates in country c during the decade between year $t-10$ and year t, including all internal migrations if s = 'Total' and only rural out-migrations if s = 'Rural Mid-Rural'. It includes subscript 2000 because it uses control variables, other than the temperature, taken from the period 1990-2000. $\hat{\gamma}_0$, $\hat{\gamma}_1$, $\hat{\gamma}^g_1$, and $\hat{\boldsymbol{\gamma}}_3$ denote the estimated coefficients and $\hat{\epsilon}_{c,t}$ are the residuals. We use the coefficients from column (3) of Table 3 to perform this exercise. $\Delta Temp^{\text{Projection}}_{c,t}$ are the projected temperature changes in every *two* coming decade, 2020-2040, 2040-2060, 2060-2080, and 2080-2100, compared with a control period of 1961-1999.[22]

[21] The data on urban population come from 1970 while the data on agricultural value-added share come from 1990. This inconsistency in the year when data were retrieved is due to a difference in availability of a large enough sample. The data are obtained from the WDI (World Bank, 2018).

[22] To match with our regression specifications exploiting historical *decennial* changes in the average temperatures, we divide these projected changes by two to find the *decennial* migration relative to the average temperature level during the period 1961-1999. As a result, computed migration rates are the ones expected when temperature levels rise to the projected levels relative to the average temperatures during 1961-1999.

Figure 13 plots the expected internal migration rates with the 90% confidence intervals.[23,24] Panel A shows that the average total internal migration rate in poor countries was 7.10% in 2000. This figure is expected to decline to 5.03% or 5.48% by 2080-2100 under the A2 and B1 scenarios, respectively. Panel B indicates that the average rural out-migration rate was 1.92% in 2000. This number is expected to decline to 1.37% or 1.89% by 2080-2100 under the two scenarios, respectively.

In contrast, upper-middle income countries are expected to see an increase in internal migration rates. Panel A indicates that the average total internal migration rate was 6.99% in 2000, increasing to 7.80% or 7.05% under scenarios A2 and B1, respectively. The rural out-migration rate in this group was 1.22% in 2000, and would increase to 1.44% or 1.24% under the two scenarios, respectively. The temperature effects on lower-middle income countries are between these two groups. Therefore the internal migration rates in this group are expected to remain rather stable or decline slightly.

We consider the forecast for a couple of representative countries. First, in Malawi, a poor country, the total internal migration rate was 4.63% per decade in 2000. This figure is expected to decline to 1.9% or 2.4% by 2080-2100 under the A2 and B1 scenarios, respectively. Given the population in 2000, 11.3 million, the total number of internal migrants is calculated to be 527,000, which is expected to decline to 216,000 or 271,000 under the two scenarios, respectively. This implies that 255,000-310,000 people per decade, who would have migrated, will instead remain in rural poverty as a consequence of lower agricultural income.

On the other hand, in Argentina, an upper-middle income country, the total internal migration rate was 8.8% per decade in 2000. This number is expected to increase to 10.1% or 9.4% by 2080-2100 under the A2 and B1 scenarios, respectively. Given Argentina's population of 37 million in 2000, the total number of internal migrants in 2000 is found to be 3.2 million, which will grow to 3.7 million or 3.5 million under the two scenarios, respectively. It suggests that rising temperatures would drive 300,000-500,000 more people per decade to move from sparsely populated areas to more urban environments in Argentina. These examples illustrate that global warming may affect the mobility of a large number of people in each country.

There are many reasons for taking the simulations with caution, and two of them are most important. First, we employ a linear model to project the effect of temperatures, but migration responses may not be linear, especially as adaptation may imply different effects in the long-run. Second, the predicted temperatures are subject to potentially large error: these predictions are beyond the historical experience and their increase is outside the range analyzed for the 1970-2000 period, so out of sample prediction may be inaccurate.[25] Nonetheless, this exercise gives us a sense of how severe the temperature effects could be in the coming decades.

To summarize, our results establish two facts regarding the most important effects likely to generate consequential changes in the next decades. First, rising temperatures will significantly reduce rural-to-urban migrations in poor countries. Second, for countries on their way to industrialization, in the upper-middle part of world income, a temperature rise may work to increase rural-to-urban migration. As a result, global warming may increase polarization of countries in the world in terms of their levels of economic development by further hurting development

[23] See Tables A11 and A12 in Appendix D for data associated with this figure. The average internal migration rates in 2000 shown in Figure 13 are slightly different from the ones in Figure F and Table A2 because some countries are dropped from the analysis in this section because of missing control variables for these countries. See Appendix F for more details.

[24] The 95% confidence interval becomes greater in 2040-2060 under B1 scenario because there is greater variance in the countries' expected temperature changes in 2040-2060 under the scenario.

[25] The predicted temperature increases—4°C rise or 2.5°C rise under A2 and B1 scenarios, respectively—are greater than the temperature changes during the sample period. According to Table 1, the average decennial rise in average temperatures during 1970-2000 was 0.15°C and its three standard deviation range was $[-0.96, 1.26]$. Clearly, the predicted increase in temperatures is outside this range.

in countries at the lower tail of the per-person income distribution, and encouraging it in the upper-middle part.

6. Conclusions

We have examined the impact of rising temperatures on internal migration using a 56km×56km grid cell level dataset at the 10-year frequency during the period 1970-2000. The results show that, within poor countries, rising temperatures reduced emigration out of rural areas. This is consistent with the well-established observation that increases in temperatures reduce rural income and exacerbate the poverty of rural residents, making the costs of migration prohibitive. On the other hand, in middle-income countries higher temperatures increased migration out of rural areas and into cities because they increased urban-rural income differentials and, hence, the incentive to migrate for a population that could afford to do so. The results also show that temperature effects on internal migration are insignificant in rich countries.

These asymmetric migration responses are also confirmed by the regressions with country-level data constructed by aggregating the grid cell level data. The results imply that a 1°C increase in average temperatures reduces the net migration rate by about 2 percentage points in poor countries. In contrast, the same rise in temperatures increases the internal migration rate by 0.5-1 percentage points in upper-middle income countries. We find particularly significant results when we employ rural out-migration rates as the dependent variable, suggesting that out-migration from rural areas responds most strongly to temperatures. These results on *internal* migration reinforce the country-level evidence on *international* migration documented in Cattaneo and Peri (2016).

Our results suggest that rising temperatures help urbanization in middle-income countries. However, a higher temperature works to exacerbate economic conditions and worsen the rural poverty trap in poor countries. We should interpret these forecasts with much caution given the simplicity of the estimates and the long span of time considered. However, given the inevitability of climate change and the important consequences of increased rural poverty predicted in this study, countries affected should take these indications seriously and consider policies that can offset this decline in rural-urban migration.

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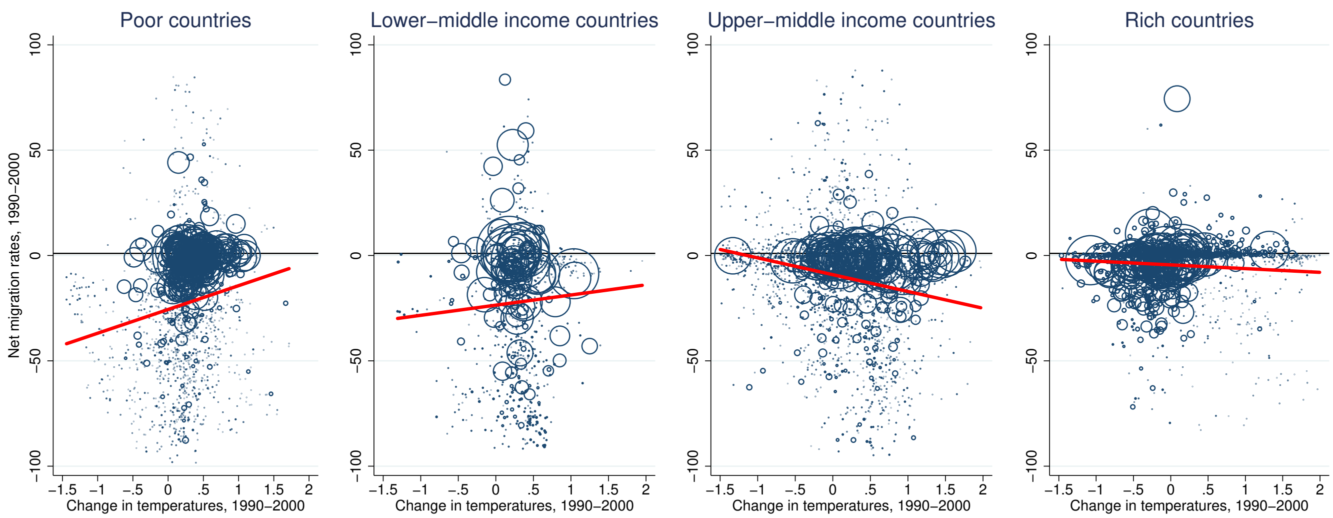
Tables and Figures

TABLE 1: SUMMARY STATISTICS OF THE DATA FOR GRID CELL LEVEL REGRESSIONS

	N	Mean	St. dev.	Min	Max
Net migration rates					
Full sample	96,792	-6.52	19.54	-98.51	88.85
Poor countries	24,236	-8.25	20.02	-98.51	87.93
Lower-middle income countries	12,703	-14.38	27.27	-98.19	88.31
Upper-middle income countries	33,695	-5.34	18.32	-97.63	88.85
Rich countries	26,158	-2.62	14.06	-96.39	88.74
Net migration rates (relative to the world average)					
Full sample	96,792	.00	19.51	-92.38	95.74
Poor countries	24,236	-1.73	20.00	-92.38	94.89
Lower-middle income countries	12,703	-7.87	27.26	-91.62	93.78
Upper-middle income countries	33,695	1.18	18.27	-92.04	95.74
Rich countries	26,158	3.90	14.04	-90.19	94.21
Long-run average temperatures (degree Celsius)					
Full sample	88,855	14.61	9.88	-19.86	35.21
Poor countries	23,191	18.62	9.33	-12.48	31.97
Lower-middle income countries	10,984	19.32	9.54	-13.26	30.52
Upper-middle income countries	31,787	13.63	9.80	-13.85	35.21
Rich countries	22,893	9.63	7.77	-19.86	31.36
Changes in the long-run average temperatures					
Full sample	88,855	.27	.66	-11.08	12.95
Poor countries	23,191	.23	.45	-2.79	4.29
Lower-middle income countries	10,984	.19	.52	-1.92	3.70
Upper-middle income countries	31,787	.29	.75	-11.08	12.95
Rich countries	22,893	.32	.74	-3.73	5.09
Long-run average precipitation (mm, at monthly scale)					
Full sample	88,855	73.86	58.47	.02	979.00
Poor countries	23,191	77.73	53.86	.10	457.20
Lower-middle income countries	10,984	98.56	76.07	0.02	666.97
Upper-middle income countries	31,787	70.10	63.18	0.07	979.00
Rich countries	22,893	63.33	39.67	2.13	426.02
Changes in the long-run average precipitation (mm, at monthly scale)					
Full sample	88,855	-.35	14.72	-448.88	584.34
Poor countries	23,191	-.55	15.24	-188.96	180.71
Lower-middle income countries	10,984	-2.09	17.19	-193.29	165.41
Upper-middle income countries	31,787	.17	15.31	-448.88	584.34
Rich countries	22,893	-.04	11.66	-133.44	116.06
Population growth rates					
Full sample	96,704	1.68	1.00	-1.83	5.17
Poor countries	24,236	2.17	.76	-1.83	5.14
Lower-middle income countries	12,615	2.35	.74	-1.70	4.59
Upper-middle income countries	33,695	1.52	1.03	-1.18	4.67
Rich countries	26,158	1.11	0.84	.02	5.17

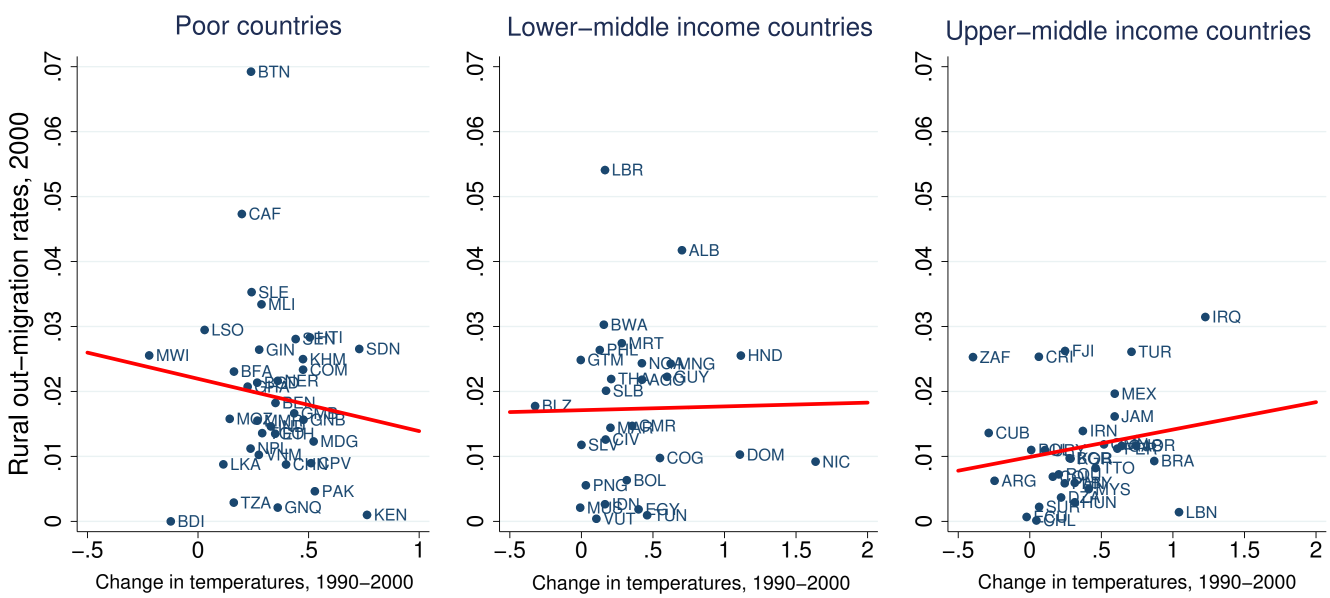
NOTE. The table shows summary statistics of the variables used in the grid cell level regressions. One observation represents one grid cell in a decade. The country groups are based on the 25th, 50th, 75th percentiles of the world distribution of GDP per capita in 1980. The population growth rates are a country-level variable.

FIGURE 1: NET MIGRATION RATES, RURAL LOCATIONS AND CHANGES IN TEMPERATURES, 1990-2000



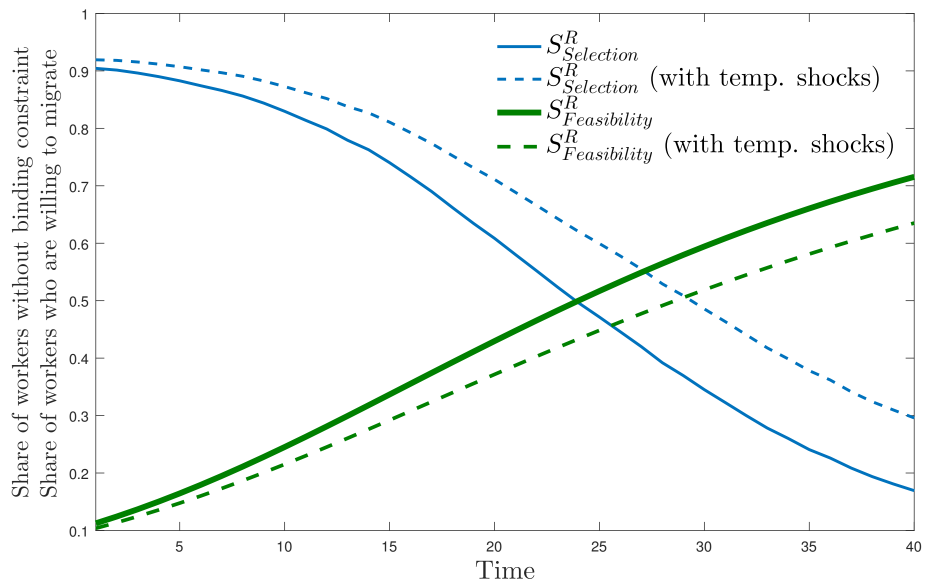
NOTE. The figure shows the relationship between the net migration rates in the rural areas and changes in temperatures in the decade 1990-2000. Each panel includes a different set of countries. The size of bubbles measures population size of grid cells.

FIGURE 2: RURAL OUT-MIGRATION RATES AND CHANGES IN TEMPERATURES, 1990-2000



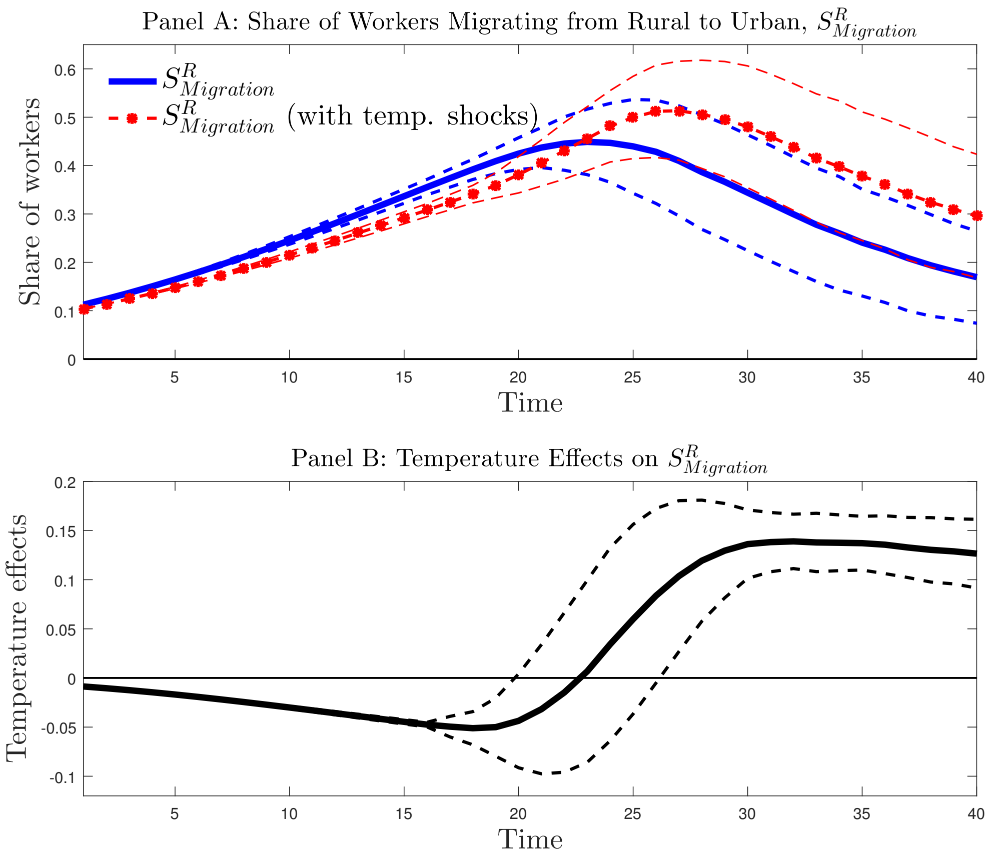
NOTE. The figure shows the relationship between the net migration rates in Rural and Mid Rural areas of each country and the changes in temperatures in the decade 1990-2000.

FIGURE 3: FEASIBILITY CONSTRAINTS AND SELECTION CONDITIONS WITH AND WITHOUT TEMPERATURE SHOCKS



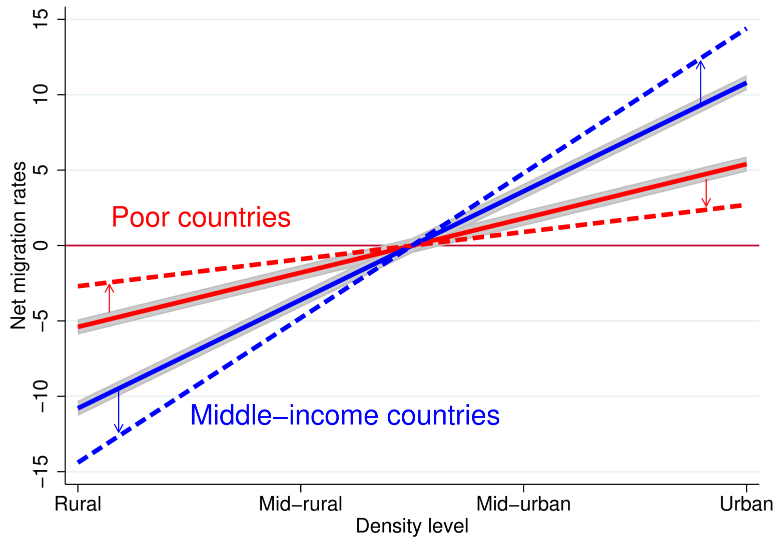
NOTE. The figure shows the simulated share of workers able/willing to migrate as implied by the feasibility/selection constraint with and without the temperature shock over time. The solid lines indicate the mean value implied by 1,000 growth paths from 1,000 simulations. The dashed lines indicate the ones with temperature shocks reducing the rural productivity. See Table A3 for parameter values.

FIGURE 4: THE IMPACT OF TEMPERATURE SHOCKS ON INTERNAL MIGRATIONS



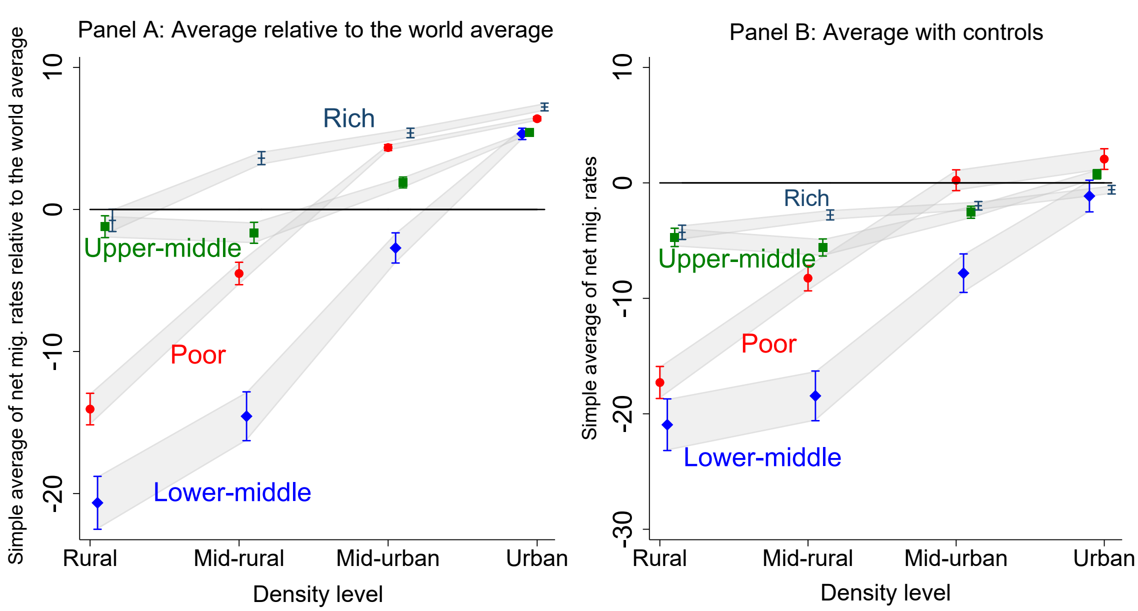
NOTE. I panel A we represent the share of people migrating without (blue line) and with (red line) temperature shocks average over 1000 simulations in 40 years. The dashed line represent the 95% confidence interval. IN Panel B we represent the different=ce in migration between the scenario with and without temperature shock, average over 1000 simulation. The dashed line represents the 95% confidence interval . See Table A3 for parameter values.

FIGURE 5: THE THEORETICAL IMPACT OF TEMPERATURE SHOCKS ON INTERNAL MIGRATIONS IN POOR AND MIDDLE-INCOME COUNTRIES



NOTE. The figure shows the qualitative impacts of rising temperatures on the internal migration rates in poor and middle-income countries. Dashed line represents the qualitative net migration without the temperature shock and the solid line with the shock

FIGURE 6: MEAN GRID CELL LEVEL NET MIGRATION RATES



NOTE. The vertical axis of the figure measures the average net migration rates, for three decades during 1970-2000, in percent, with 95% confidence intervals. Top 1% and bottom 1% of net migration observations are dropped as outliers. In Panel A, the net migration rates are normalized so as to set the mean value to zero for observations in each decade. Panel B shows the net migration rates (raw data, not relative to the world average) with control variables. See Table A4 for a regression table associated with this figure.

TABLE 2: GRID CELL LEVEL REGRESSIONS

Dependent variable = Net migration rates

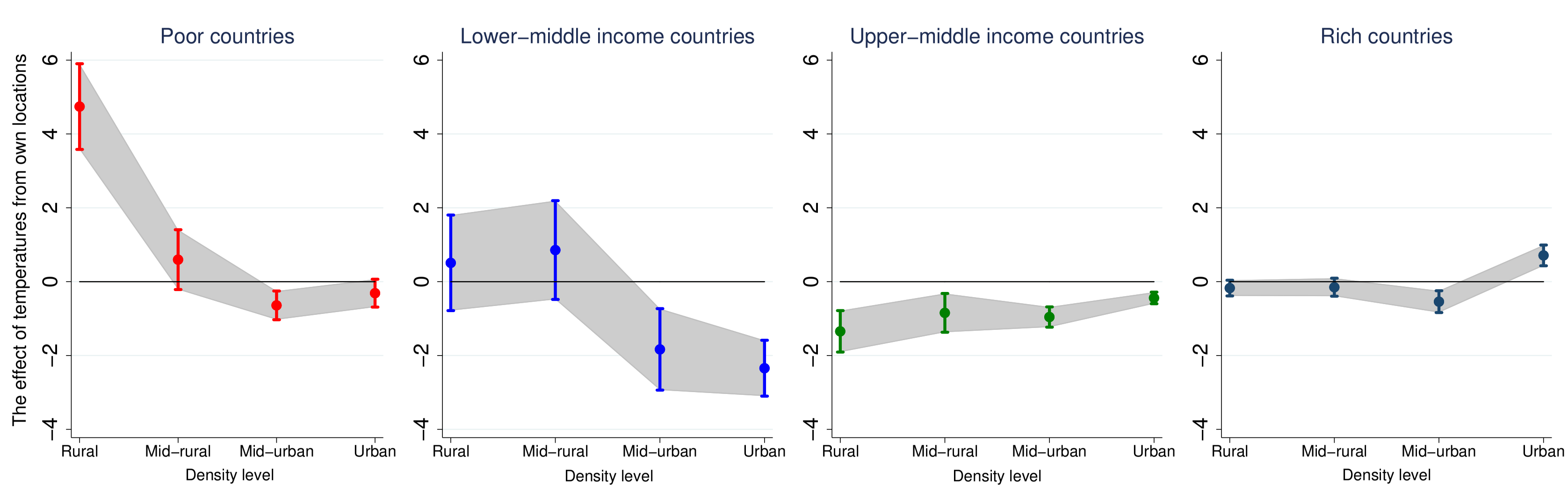
Definition of rural-urban areas is based on Population at the grid cell level

	Poor		Lower-middle		Upper-middle	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Temp$	1.48***	-.31	-0.67**	-2.34***	-.87***	-.44***
	(.22)	(.19)	(.29)	(.39)	(.11)	(.08)
$D^{\text{Middle-urban}} \times \Delta Temp$		-.33		.51		-.52***
		(.25)		(.66)		(.14)
$D^{\text{Middle-rural}} \times \Delta Temp$		.91**		3.20***		-.41
		(.45)		(.76)		(.27)
$D^{\text{Rural}} \times \Delta Temp$		5.05***		2.85***		-.91***
		(.62)		(.77)		(.29)
N	23,191	23,191	10,898	10,898	31,787	31,787
Grid cells	7,851	7,851	3,734	3,734	10,770	10,770
R-squared	.26	.27	.25	.26	.14	.15
Temperature effects (Linear combination of coefficients)						
Middle-urban areas		-.64***		-1.83***		-.96***
		(.20)		(.56)		(.14)
Middle-rural areas		.60		.86		-.85***
		(.41)		(.68)		(.27)
Rural areas		4.74***		.51		-1.35***
		(.59)		(.66)		(.29)
$D^{\text{Rural-urban}} \times$ Year fixed effects		Yes		Yes		Yes
$D^{\text{Rural-urban}} \times \Delta$Precipitation		Yes		Yes		Yes

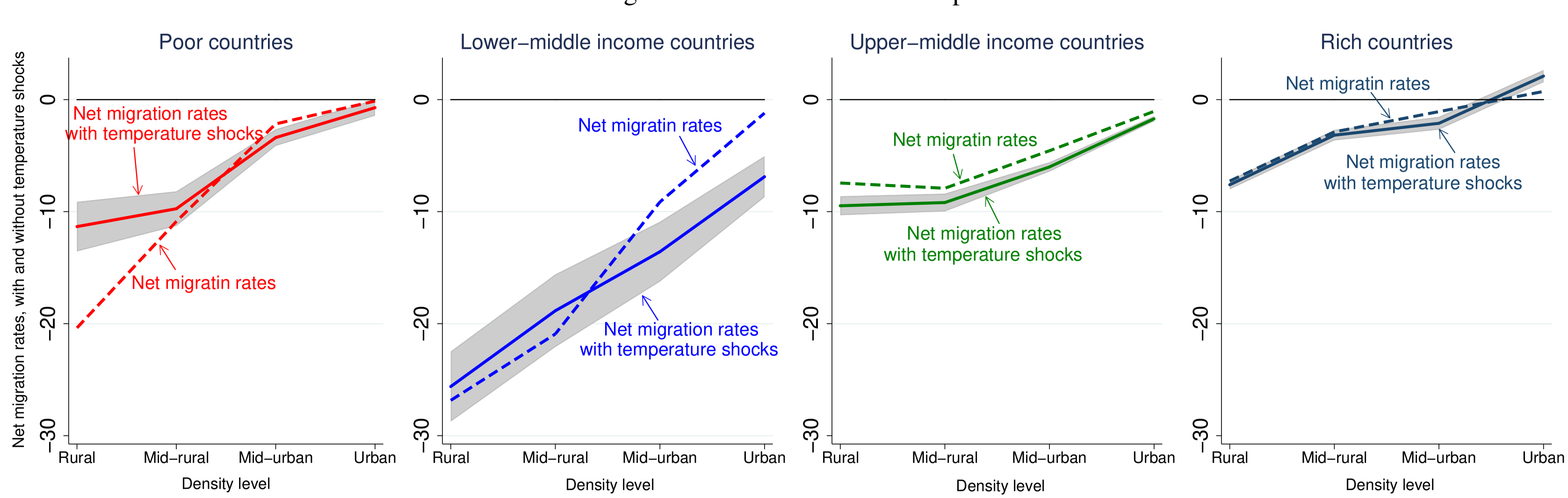
NOTE. Robust standard errors clustered at the grid cell level are in parentheses. All regressions include $D^{\text{Region}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Population growth rates, and country fixed effects, where $D^{\text{Rural-urban}}$ indicate the rural-urban dummies and D^{Region} denote the region dummies. * $p < .1$, ** $p < .05$, and *** $p < .01$.

FIGURE 7: THE IMPACTS OF TEMPERATURE SHOCKS ON THE NET MIGRATION RATES

Panel A: Temperature effects

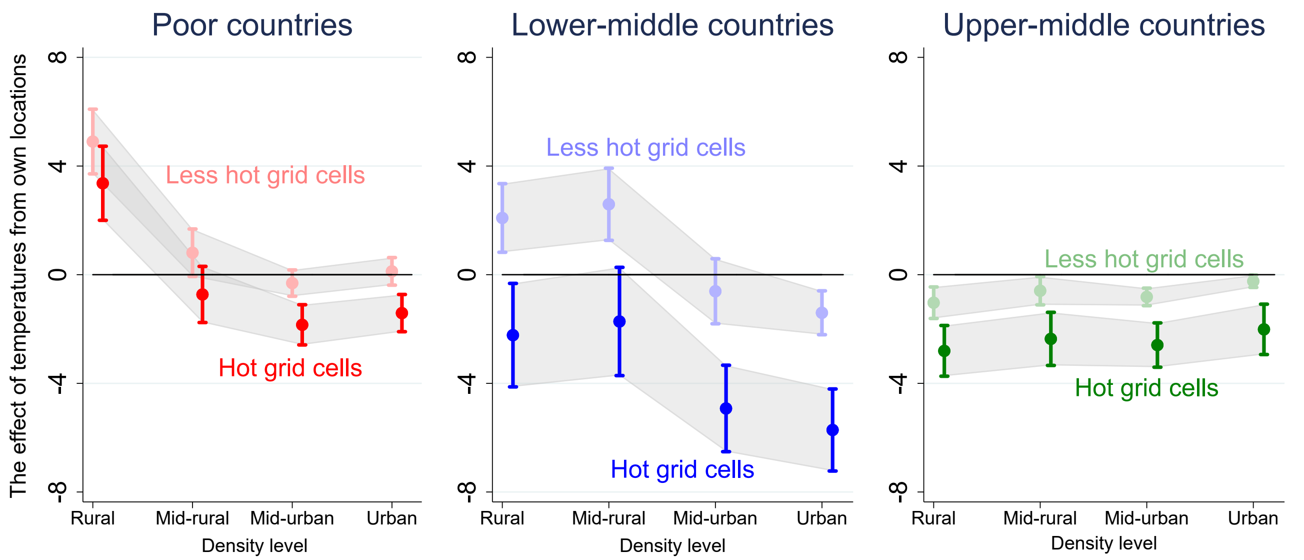


Panel B: Net migration rates with/without temperature shocks



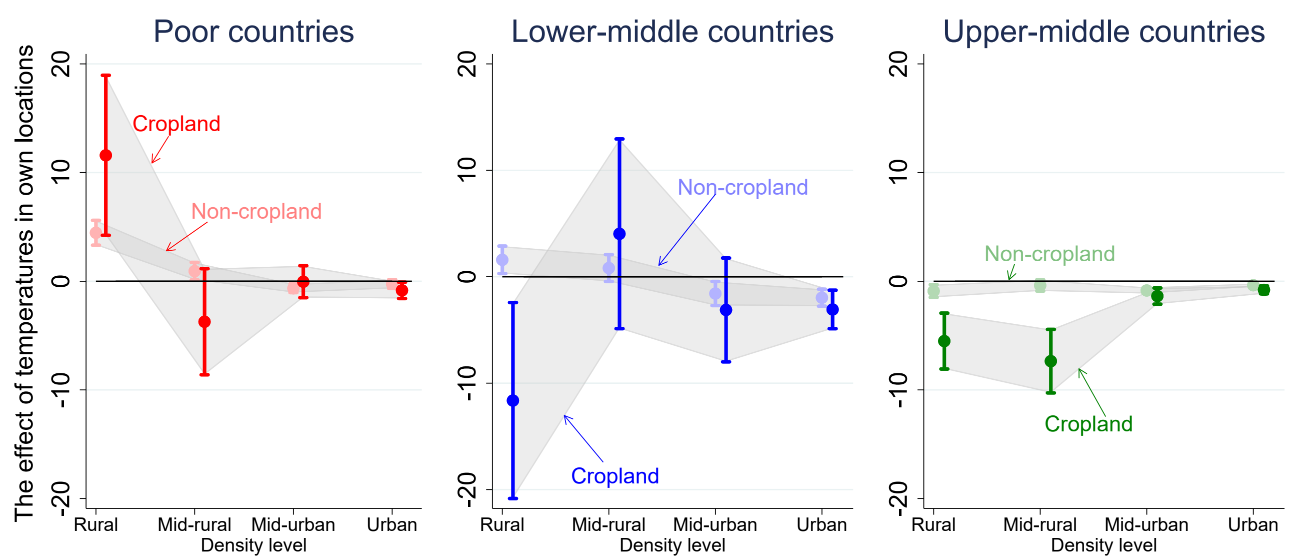
NOTE. Panel A shows the point estimates of a 1°C increase in temperatures on the net migration rate with 95% confidence intervals. The vertical axis net migration rates in percentage points so 1 represent net migration of one percent of the population. In Panel B, the dashed lines describe the average net migration rates. The solid lines show the average net migration rates with temperature shocks with 95% confidence intervals in grey color. The effects of temperatures are based on even number columns of Table 2. The temperature shocks are defined as the 95th percentile of cumulative long-run changes in annual mean temperatures from 1970 to 2000 in each of the four groups of countries.

FIGURE 8: GRID CELL LEVEL REGRESSIONS, ROBUSTNESS CHECKS, ADDRESSING NON-LINEARITY OF TEMPERATURE EFFECTS



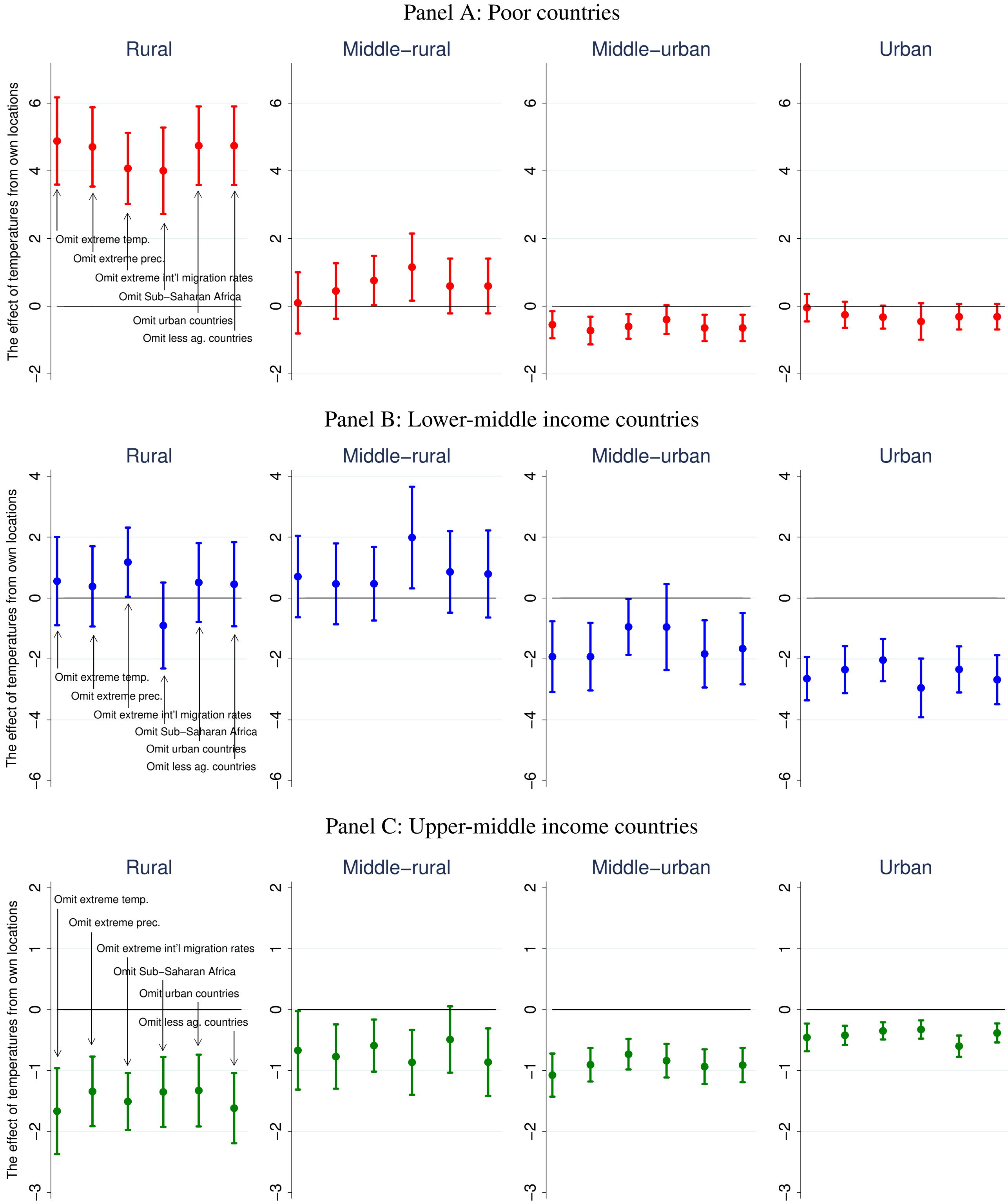
NOTE. The figure shows the point estimates of the impact of temperatures on the internal migration rates interacted with hot location dummies to address non-linear effects of temperatures. Dots in the middle of bars denote point estimates and the bands indicate the 95% confidence intervals. See Table A5 in Appendix D for a regression table associated with this figure. The results from odd number columns in the table are plotted.

FIGURE 9: GRID CELL LEVEL REGRESSIONS, ROBUSTNESS CHECKS, CROPLAND VERSUS NON-CROPLAND



NOTE. The figure shows the point estimates of the impact of temperatures on the internal migration rates interacted with the cropland dummy. Dots in the middle of bars denote point estimates and the bands indicate the 95% confidence intervals. See Table A6 in Appendix D for a regression table associated with this figure. The results from odd number columns in the table are plotted.

FIGURE 10: GRID CELL LEVEL REGRESSIONS, ROBUSTNESS CHECKS



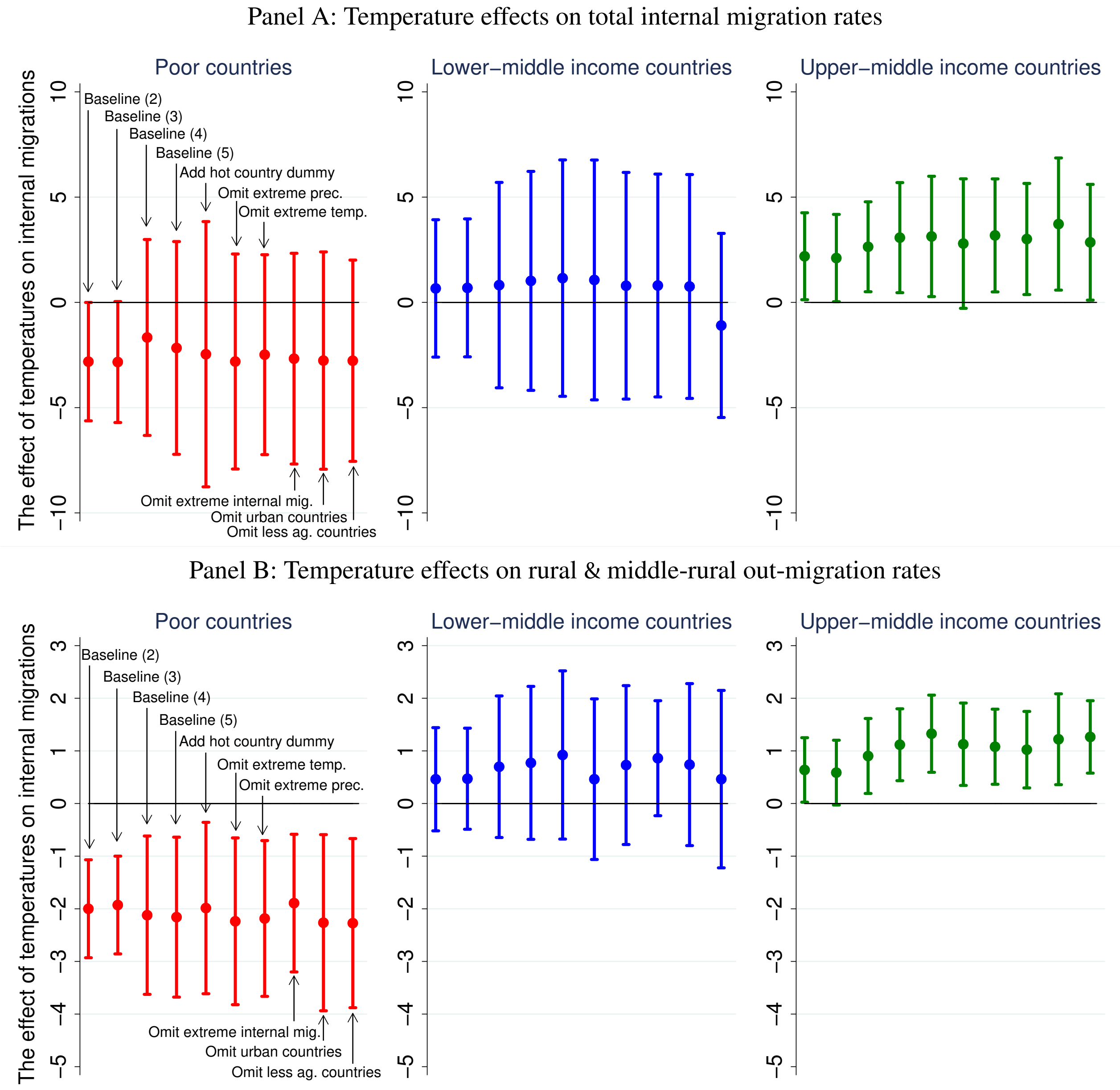
NOTE. The figure shows the point estimates of the impact of temperatures on the internal migration rates. The dots in the middle of the bars denote the point estimates and the bands indicate the 95% confidence intervals. See Table A7 in Appendix D for a regression table associated with this figure.

TABLE 3: COUNTRY-LEVEL REGRESSIONS, BASELINE RESULTS

	Panel A: Total internal migration rates				
	(1)	(2)	(3)	(4)	(5)
$\Delta Temp$	.61	2.19**	2.11*	2.64**	3.08**
	(.96)	(1.05)	(1.06)	(1.09)	(1.33)
$D^{\text{Lower-middle}} \times \Delta Temp$		-1.53	-1.42	-1.82	-2.05
		(1.92)	(1.93)	(2.75)	(3.12)
$D^{\text{Poor}} \times \Delta Temp$		-5.01***	-4.94***	-4.31*	-5.24*
		(1.71)	(1.74)	(2.49)	(3.07)
N	202	202	202	144	140
Countries	77	77	77	66	63
R-squared	.07	.07	.08	.24	.25
Temperature effects (Linear combination of coefficients)					
Lower-middle countries		.67	.69	.82	1.02
		(1.66)	(1.67)	(2.49)	(2.65)
Poor countries		-2.81*	-2.83*	-1.67	-2.16
		(1.43)	(1.47)	(2.37)	(2.58)
	Panel B: Out-migration rates, Rural and Middle-rural				
	(1)	(2)	(3)	(4)	(5)
$\Delta Temp$	.14	.64**	.59*	.90**	1.12***
	(.31)	(.31)	(.31)	(.36)	(.35)
$D^{\text{Lower-middle}} \times \Delta Temp$		-.18	-.12	-.20	-.35
		(.56)	(.55)	(.78)	(.83)
$D^{\text{Poor}} \times \Delta Temp$		-2.64***	-2.52***	-3.03***	-3.28***
		(.53)	(.52)	(.81)	(.87)
N	200	200	200	144	140
Countries	77	77	77	66	63
R-squared	.07	.09	.11	.25	.29
Temperature effects (Linear combination of coefficients)					
Lower-middle countries		.46	.47	.70	.77
		(.50)	(.49)	(.69)	(.74)
Poor countries		-2.00***	-1.93***	-2.12***	-2.16***
		(.48)	(.47)	(.77)	(.78)
Controls					
ΔPrecipitation			Yes	Yes	Yes
$\ln(Pop)$				Yes	Yes
$\ln(GDP)$				Yes	Yes
Ag. value-added share				Yes	Yes
Manu. value-added share				Yes	Yes
ΔAg. value-added share					Yes
ΔManu. value-added share					Yes

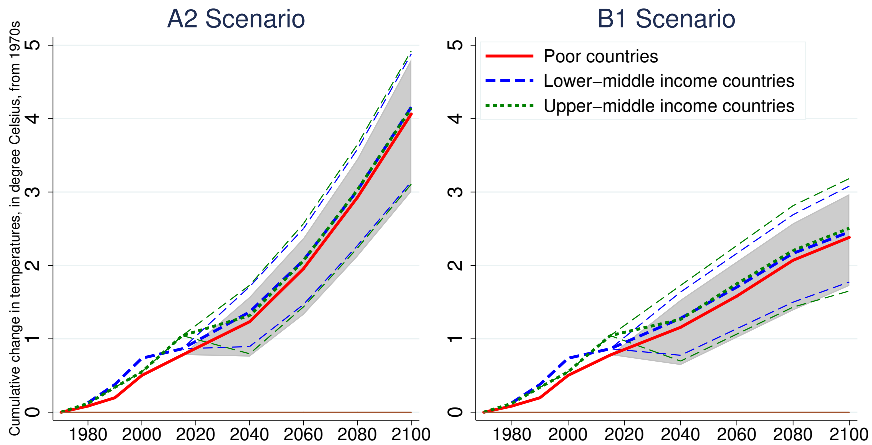
NOTE. All regressions include the population growth rates and the GDP growth rates during each decade as controls. Robust standard errors clustered at the country-level are in parentheses. * $p < .1$, ** $p < .05$, and *** $p < .01$.

FIGURE 11: RESULTS FROM COUNTRY-LEVEL REGRESSIONS



NOTE. The figure plots the point estimates and the 95% confidence intervals. The plotted point estimates labeled as Baselines (2)-(5) are from the regression results reported in Table 3, columns (2)-(5). See Table A8 in Appendix D for the other plotted point estimates.

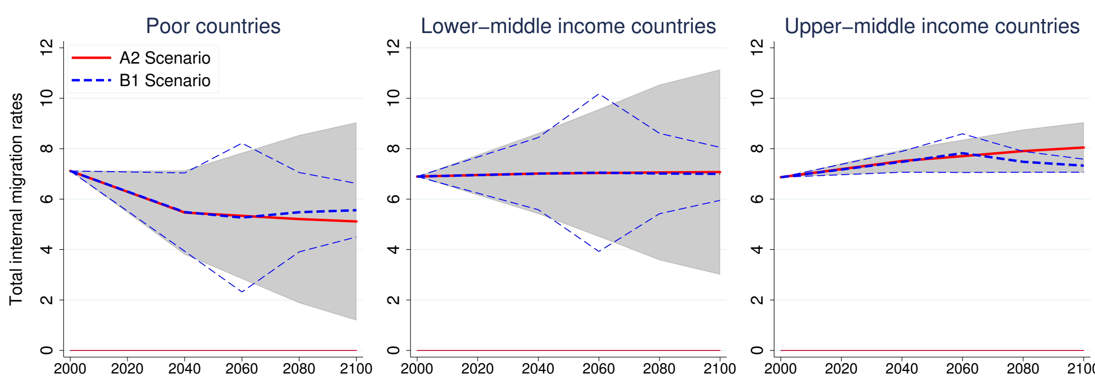
FIGURE 12: PROJECTED TEMPERATURE CHANGE



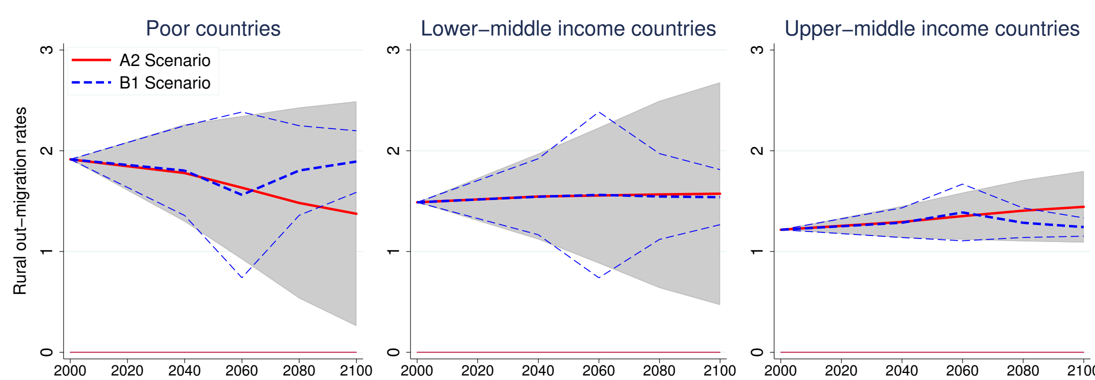
NOTE. The data come from the *Climate Change Knowledge Portal* (World Bank, 2018).

FIGURE 13: PROJECTED TEMPERATURE CHANGE AND PRECIPITATION CHANGE

Panel A: Predicted internal migration rates



Panel B: Predicted out-migration rates, Rural and middle-rural



NOTE. The figure shows the expected net migration rates based on temperature projections from the *Climate Change Knowledge Portal* (World Bank, 2018). The bands are 90% confidence intervals. See Tables A11 and A12 in Appendix F for data associated with this figure.

Online Appendix to "The Impact of Global Warming on Rural-Urban Migrations: Evidence from Global Big Data"

By GIOVANNI PERI AND AKIRA SASAHARA

A. Dataset

A.1. Data Sources

A.1.1. Net Migration Data

The net migration measure comes from the *Global Estimated Net Migration Grids By Decade, v1 (1970-2000)* (de Sherbinin et al., 2015).[26] It provides estimates of net migration (in-migration minus out-migration) per one-kilometer grid cell for three decades, 1970s, 1980s and 1990s. We present their method of imputing the net migration measure. The explanation below comes from de Sherbinin et al. (2015).

Step 1 The *History Database of the Global Environment, Version 3.1 (HYDE)* population grids are used to compute the rates of change in population in each decade.[27]

Step 2 The rates from Step 1 are applied to the *Global Rural-Urban Mapping Project, Version 1 (GRUMP)* population grids for 2000. It produces grids in 1970, 1980, and 1990 as well.[28]

Step 3 The global grids are adjusted to match country-level data in each year.

Step 4 To estimate the portion of population growth caused by natural increase (births minus deaths) for each grid cell, sub-national rates of natural increase are used. The natural increases in population in grids are adjusted to match the country-level natural increases.

Step 5 The population in period 1 (e.g., 1970) are subtracted from the population in period 2 (e.g., 1980) to find a change in population in each grid cell, and then subtract the natural increase in the grid cell to find an estimate of net migration in each grid cell. Specifically, it is computed as follows:

$$\text{Net migration} = \text{Population growth} - (\text{Births} - \text{Deaths}).$$

The unit of the net migration measure in the original dataset is the net change of the number of people due to migration per $1km^2$. We collapse the highly disaggregated observations to the 0.5×0.5 degree resolution. The original observations are aggregated by taking means. As a result, the unit of our net migration measure after aggregation is the number of people (due to migration) per $1km^2$ in a $56km \times 56km$ grid cell (at the equator). de Sherbinin et al. (2015) acknowledge that there could be measurement errors at a local-level such as counties and municipals. We assume that these measurement errors are somehow mitigated by aggregating the observations into the 0.5×0.5 degree resolution. One grid cell after aggregation contains $56 \times 56 = 3,136$ of original grid cells.

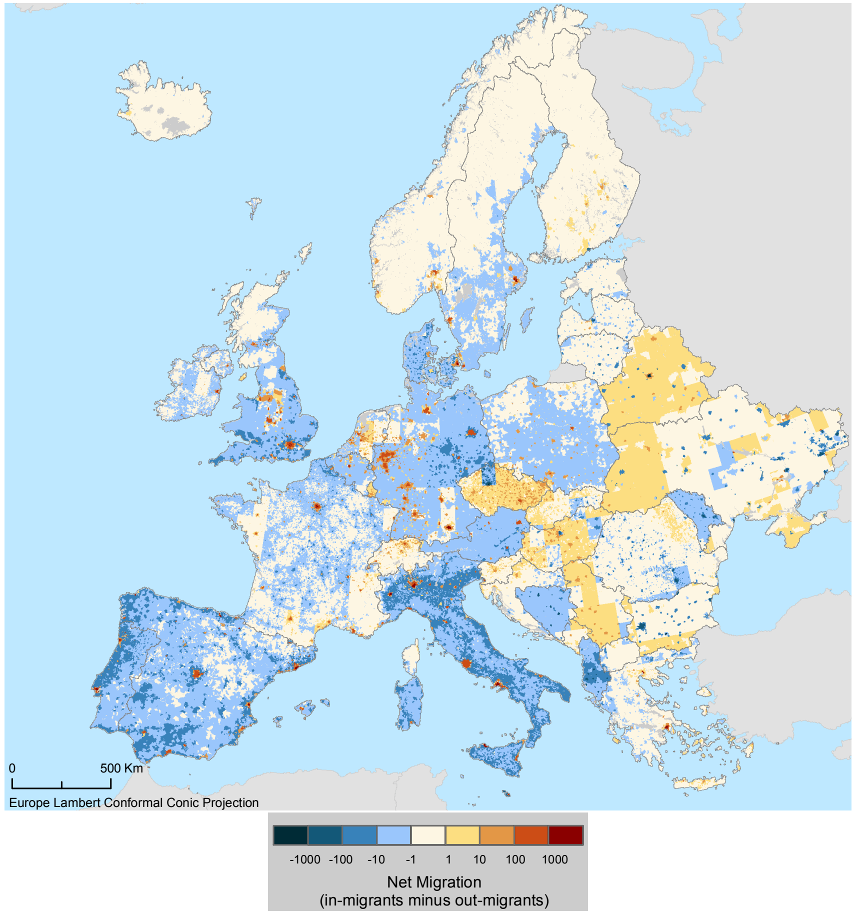
Figure A1 shows the net migration data produced by de Sherbinin et al. (2015) and the map is also directly obtained from them. It shows that many large urban areas (such as Paris, London, Rome, Berlin and Madrid) have positive net migrations while most of the remaining cells in Western Europe have negative net migration rates. Eastern Europe shows a mix of depopulating areas, including some cities and areas with population increase, near Russia or in central Europe.

[26] The same dataset on net migration is employed by de Sherbinin et al. (2012) in the context of environmental research. They investigate the association between the net migration and environmental factors such as risk of climate hazard. They find that, from 1970 to 2000, people tend to migrate from dryland and mountain areas toward coastal areas. Also, they find an opposite pattern for North America, i.e., there is a large influx of people in dry and high-latitude areas.

[27] Available at `http://themasites.pbl.nl/tridion/en/themasites/hyde/`

[28] Available at `http://sedac.ciesin.columbia.edu/data/collection/grump-v1`

FIGURE A1: NET MIGRATIONS, EUROPE, 1990-2000



Notes: The map comes from de Sherbinin et al. (2015).

A.1.2. Climate Data

We obtain the data on temperatures and precipitation from the *Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01* (Matsuura and Willmott, 2007). The dataset includes temperatures and precipitation at the 0.5×0.5 degree grid cell level (approximately $56km \times 56km$ at the equator) and it covers the global land surface. It provides monthly average temperatures and precipitation for each grid cell.

A.1.3. Other Grid Cell Level and Country-level Data

The data on GDP and population come from the *Global Dataset of Gridded Population and GDP Scenarios* (Yamagata and Murakami, 2015). This dataset gives global GDP and population in 0.5×0.5 degree grids between 1980 and 2010 by 10 years. The data in 1980–2010 are estimated by downscaling actual populations and GDP by country and we use the data from 1980, 1990, and 2000. They map the country-level population and GDP data into 0.5×0.5 degree grid cells by using spatial and economic interactions between cities, and by utilizing road network and land cover. See Murakami and Yamagata (2017) for further details.

The data on cropland come from *Farming the Planet: 1. Geographic Distribution of Global Agricultural Lands in the Year 2000* (Ramankutty et al., 2008). In the original data, grid cell sizes are 0.08333 decimal degrees (approximately 10km at the equator). These cells are aggregated into a 0.5×0.5 degree resolution to match with other variables. Although the original cropland information is coded as a dummy, 1 for cropland and 0 for non-cropland, after aggregating it by taking the average for each 0.5×0.5 grid cell makes this dummy variable continuous, taking a value between 0 and 1.

The country identifiers come from the *Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): National Identifier Grid* (van Donkelaar et al., 2015). We aggregate the grid cell level dataset to the country-level and run country-level regressions. The data on country-level GDP, GDP growth rates, population, population growth rates, urban population, agricultural value-added, and manufacturing value-added are retrieved from the *World Development Indicators* (World Bank, 2018).

A.2. Summary Statistics

This section presents summary statistics of variables used in the country-level regressions in section 5. Table A1 shows the summary statics where observations come from poor, lower-middle income, and upper-middle income countries for the three periods, '70s, '80s, and '90s. Table A2 shows summary statistics of the three internal migration variables by country group.

Figure A2 describes the country-level migration rates by country group and decade. All of the three measures (each represented in a different panel) imply that the level of internal migration is the greatest in lower-middle income countries. We observe a stark difference in the '70s and '80s.

TABLE A1: SUMMARY STATISTICS OF THE DATA FOR COUNTRY-LEVEL REGRESSIONS

	N	Mean	St. dev.	Min	Max
Total internal migration rates	349	7.09	5.41	.09	63.27
Out-migration rates (from rural and middle-rural areas)	349	1.82	2.03	.00	21.26
Out-migration rates (from rural areas)	349	.80	1.55	.00	21.20
Population growth rate (%)	349	2.04	1.13	-1.83	4.67
GDP growth rate (%)	242	3.28	2.45	-9.81	1.45
$\ln(GDP)$	264	23.10	1.95	18.62	27.98
$\ln(Population)$	349	15.64	1.68	10.99	20.85
Agricultural value-added share (% of GDP)	239	24.33	13.57	2.54	71.76
Manufacturing value-added share (% of GDP)	203	13.28	6.95	0.19	31.54
Δ Agricultural value-added share (% points)	238	-2.76	6.89	-21.82	21.70
Δ Manufacturing value-added share (% points)	195	.12	4.76	-22.57	14.91

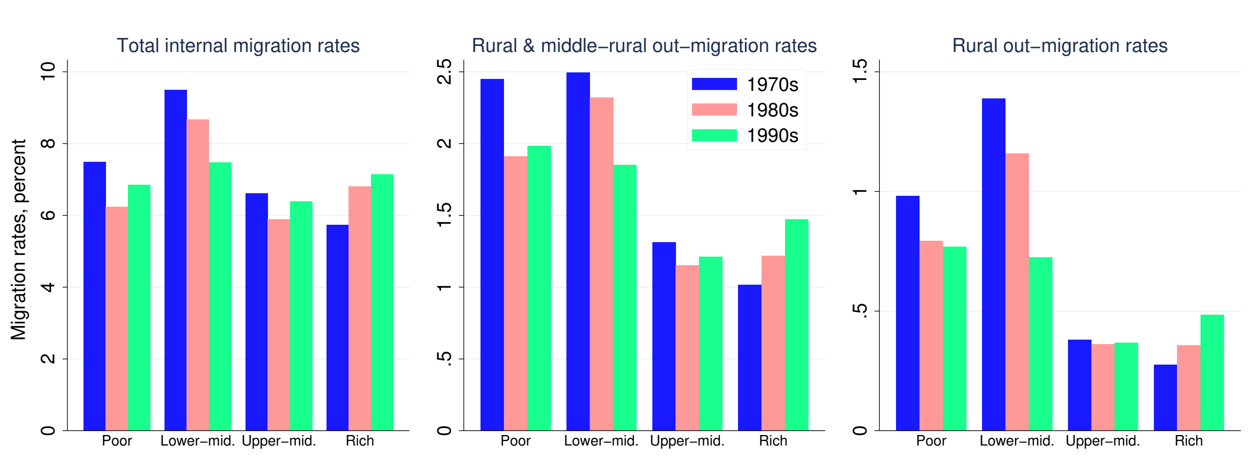
NOTE. The table shows summary statistics of the variables used in the country-level regressions.

TABLE A2: SUMMARY STATISTICS OF THE NET MIGRATION RATES BY INCOME-LEVEL OF COUNTRIES

	N	Mean	St. dev.	Min	Max
Total internal migration rates					
Full sample	448	6.98	5.30	.09	63.27
Poor countries	115	6.83	3.92	.09	25.70
Lower-middle income countries	105	8.50	7.87	.98	63.27
Upper-middle income countries	129	6.17	3.61	.75	15.92
Rich countries	99	6.58	4.89	.22	32.27
Out-migration rates from rural and middle-rural areas					
Full sample	448	1.69	1.94	.00	21.26
Poor countries	115	2.11	1.62	.10	8.56
Lower-middle income countries	105	2.26	2.94	.04	21.26
Upper-middle income countries	129	1.21	1.09	.00	5.13
Rich countries	99	1.24	1.53	.01	10.70
Out-migration rates from rural areas					
Full sample	448	.70	1.40	.00	21.20
Poor countries	115	.86	.73	.00	3.97
Lower-middle income countries	105	1.23	2.62	.00	21.20
Upper-middle income countries	129	.39	0.43	.00	1.86
Rich countries	99	.37	.56	.00	4.70

NOTE. The table shows summary statistics of the internal migration rates for each decade. The country groups are based on the 25th, 50th, 75th percentiles of the distribution of GDP per capita in 1980. See Section 2.1 for the definition of the variables.

FIGURE A2: COUNTRY-LEVEL AGGREGATE INTERNAL MIGRATION RATES, 1970-2000



NOTE. The figure shows the country-level rural to urban migration rates, for three decades and four country groups, during 1970-2000. The left panel shows the total measure and the middle one shows the out-migration from rural and middle-rural, the left panel shows the out-migration from rural areas only.

B. List of Countries

Countries are classified into four groups based on the income level.[29] Asterisk * indicates that the country is also included in country-level regressions. Poor countries (GDP per capita is less than 25th percentile) are:

> Bangladesh* (BGD), Benin* (BEN), Bhutan* (BTN), Burkina Faso* (BFA), Burundi (BDI), Cabo Verde* (CPV), Cambodia (KHM), Central African Republic* (CAF), Chad* (TCD), China* (CHN), Comoros* (COM), Democratic Republic of the Congo (COD), Equatorial Guinea* (GNQ), Eritrea (ERI), Ethiopia* (ETH), Gambia* (GMB), Ghana* (GHA), Guinea (GIN), Guinea-Bissau* (GNB), Haiti (HTI), India* (IND), Kenya* (KEN), Lesotho* (LSO), Madagascar* (MDG), Malawi* (MWI), Mali* (MLI), Mauritania (MRT), Mozambique (MOZ), Myanmar* (MMR), Nepal* (NPL), Niger* (NER), Pakistan* (PAK), Rwanda (RWA), Senegal* (SEN), Sierra Leone* (SLE), Sri Lanka (LKA), Sudan (SDN), Tanzania* (TZA), Togo* (TGO), Uganda (UGA), Uzbekistan (UZB), Vietnam (VNM), and Yemen (YEM).

Lower-middle-income countries (GDP per capita is between 25th and 50th percentile) are:

> Albania* (ALB), Angola* (AGO), Armenia (ARM), Belize* (BLZ), Bolivia* (BOL), Bosnia and Herzegovina (BIH), Botswana* (BWA), Cote d'Ivoire (CIV), Cameroon* (CMR), Rep. of Congo* (COG), Dominican Republic (DOM), Egypt* (EGY), El Salvador* (SLV), Guatemala* (GTM), Guyana* (GUY), Honduras* (HND), Indonesia* (IDN), Kiribati (KIR), Kyrgyzstan (KGZ), Liberia (LBR), Mauritius* (MUS), Mongolia* (MNG), Morocco (MAR), Nicaragua* (NIC), Nigeria* (NGA), Papua New Guinea (PNG), Paraguay (PRY), Philippines* (PHL), Saint Vincent and the Grenadines (VCT), Serbia and Montenegro (SRB), Solomon Islands* (SLB), Swaziland* (SWZ), Tajikistan (TJK), Thailand (THA), Timor-Leste (TLS), Tunisia* (TUN), Tuvalu (TUV), Vanuatu* (VUT), Zambia* (ZMB), and Zimbabwe* (ZWE).

Upper-middle-income countries (GDP per capita is between 50th and 75th percentile) are:

> Algeria* (DZA), Argentina* (ARG), Azerbaijan (AZE), Belarus (BLR), Brazil* (BRA), Bulgaria* (BGR), Chile* (CHL), China (Hong Kong SAR) (HKG), Colombia* (COL), Costa Rica* (CRI), Cuba* (CUB), Ecuador* (ECU), Estonia (EST), Fiji* (FJI), Gabon* (GAB), Georgia (GEO), Hungary (HUN), Iran* (IRN), Iraq* (IRQ), Jamaica* (JAM), Jordan* (JOR), Kazakhstan (KAZ), Rep. of Korea* (KOR), Latvia (LVA), Lebanon (LBN), Libya* (LBY), Lithuania (LTU), Macedonia (MKD), Malaysia* (MYS), Maldives (MDV), Mexico* (MEX), Namibia (NAM), Oman* (OMN), Panama* (PAN), Peru* (PER), Poland (POL), Portugal (PRT), Romania (ROU), Russian Federation (RUS), Slovakia (SVK), South Africa (ZAF), Suriname* (SUR), Trinidad and Tobago (TTO), Turkey* (TUR), Turkmenistan (TKM), Ukraine (UKR), and Uruguay* (URY).

Rich countries (GDP per capita is more than 75th percentile) are:

> Andorra (AND), Australia (AUS), Austria (AUT), Bahamas (BHS), Belgium (BEL), Canada (CAN), Denmark (DNK), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Ireland (IRL), Israel (ISR), Italy (ITA), Japan (JPN), Luxembourg (LUX), Netherlands (NLD), New Zealand (NZL), Norway NOR), Puerto Rico (PRI), Saudi Arabia (SAU), Spain (ESP), Sweden (SWE), United Kingdom (GBR), United States of America (USA), and Venezuela (VEN).

C. Parameter Values for the Numerical Exercise

This section discusses the parameter values in the numerical exercise in section 3.2, which are summarized in Table A3. We choose key parameter values to match a representative poor country, Vietnam.

Productivity in the urban and rural regions: We use the industrial and agricultural value-added per worker as a measure of rural and urban productivity, respectively. The data on the industrial and agricultural value-added per worker (USD, 2010 constant prices) are obtained from the WDI (World Bank, 2018). Vietnam's industry-to-agriculture productivity ratio is six in the earliest available year in the dataset, 1991. Therefore, we set our initial urban-to-rural productivity gap to six.

[29] We use the data on GDP per capita in 1980 to define the four groups of countries. Poor countries, lower-middle, upper-middle, and rich countries are those in $[0th, 25th)$, $[25th, 50th)$, $[50th, 75th)$, and $[75th, 100th)$, respectively. The 1980 data on GDP per capita are not available for some countries. Therefore, we use the percentiles based on all available countries in 1990 and 2000 to include countries as many as possible. If GDP per capita is not available in 1980 but available in 1990, for example, then the 1990 data are used to define the country's income level. The data on GDP per capita come from the WDI (World Bank, 2018)

TABLE A3: PARAMETER VALUES

Parameters		References
Productivity in the urban region		
$\ln(A_t^U) = 0.17 + 0.90\ln(A_{t-1}^U) + \epsilon_t$		Assumed
with $\ln(A_1^U) = 1.5$ (i.e., $A_1^U = 4.48$)		Assumed
ϵ_t follows a normal distribution with		
mean zero and standard deviation 0.028		Assumed
Productivity in the rural region		
$A_t^R = \rho A_{t-1}^U + (1-\rho)A_{t-1}^R$ with $A_0^R = A_0^U / Gap$		
where the initial productivity gap is $Gap = 6$		Based on the data from the WDI
and the speed of technology diffusion is $\rho = 0.025$		Assumed
Temperature shocks		
Constant 10% productivity decline throughout the periods		Assumed
Other parameters		
Costs of migration	$C = 0.6 \times A_1^U = 2.69$	Grogger and Hanson (2011)
Return from skills in rural	$\beta^R = 1.6$	Assumed
Return from skills in urban	$\beta^U = 1.5 \times \beta^R = 2.4$	Herrendorf and Schoellman (2018)

The average annual growth rates of the agricultural and industrial productivity are 1.85% and 3.89%, respectively, during the period 1991-2016 in Vietnam. Parameters governing the urban (industry) productivity evolution are chosen to match these average annual growth rates. As a result, in the process, $\ln(A_t^U) = 0.17+0.90\ln(A_{t-1}^U)+\epsilon_t$, ϵ_t follows a normal distribution with zero mean and standard deviation of 0.028. We set the initial log productivity to $\ln(A_1^U) = 1.5$ therefore $A_1^U \approx 4.48$. Given these, urban productivity paths are simulated for 1,000 times. The parameter determining the speed of technology diffusion ρ is chosen to match the annual average rural (agricultural) productivity growth rate, 3.89%. As a result, $\rho = 0.025$. We first simulate a path without any disruptive effect from excessively high temperature, so that $\delta^R = 1$ in each period. Then it introduces deterministic temperature shocks along the growth path. We assume that a temperature shock results in a 10% decline of the rural productivity (i.e. assuming $\delta^R = \gamma = 0.9$).

Costs of migration: Existing literature does not provide much guidance about the costs of rural-urban migration within a country. Therefore, we adapt estimates of international migration costs to provide a rough approximation for these costs. Grogger and Hanson (2011) estimate international migration costs in 2000. They find that, for individuals in Dominican Republic, migration costs to relocate to the U.S. are 0.64 times its industrial value-added per worker. Internal migration costs should be lower than this. Therefore, we assume that the total costs of rural-to-urban migration costs in a poor country are equal to 0.6 times the value of one year of urban income.

Returns from skills: An arbitrary value of returns from skills, β^R, suffices for an illustration of the model and we assume that the one for the rural region is $\beta^R = 1.6$. We choose a value of β^U based on the relative returns to schooling in agriculture (which we assume rural) and industry (which we assume urban) in a poor country. Herrendorf and Schoellman (2018) estimate these using the data from poor countries such as India and Indonesia. Panel A of Figure 1 in that paper suggests that returns to schooling is about 1.5 times greater in industry than agriculture. Therefore, we set $\beta^U = 1.6 \times 1.5 = 2.4$.

D. Regression Tables associated with Figures in the Main Text

Our theoretical model predicts different patterns of rural-urban migrations depending on the income level of countries. By allowing different reactions to temperatures across locations, we have a number of point estimates. To help readers understand our results, we have used graphical presentation of the results. This section presents regression tables that are plotted in figures in the main text. Specifically, regression results in Tables A4, A5, A7, and A8 are associated with Figures 6, 8, 10, and 11 in the main text, respectively.

TABLE A4: GRID CELL LEVEL REGRESSIONS, AVERAGE NET MIGRATION RATES BY AREA, 1970-2000

Dependent variable = Net migration rates
Definition of rural-urban areas is based on Population at the grid cell level

Panel A: Average relative to the world average

	Poor	Lower-middle	Upper-middle	Rich
	(1)	(2)	(3)	(4)
Urban	6.39***	5.32***	5.43***	7.21***
	(.08)	(.20)	(.08)	(.14)
Middle-urban	4.36***	-2.71***	1.90***	5.39***
	(.11)	(.54)	(.20)	(.17)
Middle-rural	-4.51***	-14.56***	-1.64***	3.61***
	(.40)	(.88)	(.38)	(.23)
Rural	-14.05***	-20.65***	-1.21***	-.77*
	(.57)	(.95)	(.39)	(.40)
N	24,236	12,703	33,695	26,158
Grid cells	8,219	4,345	11,439	8,772

Panel B: Average with controls

	Poor	Lower-middle	Upper-middle	Rich
	(1)	(2)	(3)	(4)
Urban	2.06***	-1.14	0.74***	-0.59***
	(.46)	(.70)	(.21)	(.19)
Middle-urban	0.23	-7.82***	-2.54***	-1.98***
	(.46)	(.85)	(.27)	(.19)
Middle-rural	-8.26***	-18.45***	-5.60***	-2.78***
	(.56)	(1.10)	(.38)	(.22)
Rural	-17.29***	-20.95***	-4.72***	-4.28***
	(.71)	(1.14)	(.41)	(.32)
N	23,191	10,898	31,787	22,893
Grid cells	7,851	3,734	10,770	7,654

NOTE. Regressions do not include a constant term. Panel B include $\Delta Temp$, $\Delta Prec$, and the population growth rate as controls. Robust standard errors clustered at the grid cell level are in parentheses. Point estimates shown in Panels A and B are plotted in Panels A and B in Figure 6, respectively. * $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A5: GRID CELL LEVEL REGRESSIONS, RURAL-URBAN DUMMIES BASED ON POPULATION, ADDRESSING NON-LINEARITY OF TEMPERATURE EFFECTS

Dependent variable = Net migration rates

Definition of rural-urban areas is based on Population at the grid cell level

	Poor		Lower-middle		Upper-middle	
	Uniform cutoff	Group-based cutoffs	Uniform cutoff	Group-based cutoffs	Uniform cutoff	Group-based cutoffs
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Temp$	.12	-.10	-1.40***	-2.02***	-.24**	-.12
	(.26)	(.22)	(.41)	(.39)	(.12)	(.13)
$D^{\text{Hot}} \times \Delta Temp$	-1.54***	-1.53***	-4.31***	-1.34	-1.77***	-2.22***
	(.47)	(.53)	(.82)	(1.07)	(.45)	(.41)
$D^{\text{Middle-urban}} \times \Delta Temp$	-.43*	-.40*	.79	.50	-.58***	-.54***
	(.25)	(.24)	(.65)	(.66)	(.18)	(.20)
$D^{\text{Middle-rural}} \times \Delta Temp$	.69	.79*	4.00***	3.31***	-.35	-.32
	(.45)	(.45)	(.76)	(.77)	(.29)	(.30)
$D^{\text{Rural}} \times \Delta Temp$	4.78***	4.88***	3.49***	2.83***	-.79**	-.76**
	(.63)	(.62)	(.74)	(.77)	(.31)	(.32)
N	23,191	23,191	10,898	10,898	31,787	31,787
Grid cells	7,851	7,851	3,734	3,734	10,770	10,770
R-squared	.26	.26	.27	.26	.14	.14
Temperature effects (Linear combination of coefficients)						
Middle-urban areas	-.31	-.49**	-.61	-1.52**	-.82***	-.66***
	(.25)	(.22)	(.61)	(.59)	(.16)	(.17)
Middle-rural areas	.81*	.70	2.59***	1.29*	-.59**	-.44
	(.45)	(.43)	(.68)	(.68)	(.27)	(.27)
Rural areas	4.90***	4.79***	2.09***	.81	-1.03***	-.88***
	(.61)	(.60)	(.64)	(.67)	(.30)	(.29)

NOTE. All regressions include $D^{\text{Hot}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times \Delta$Precipitation, $D^{\text{Region}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Population growth rates, and country fixed effects as controls. The hot country dummy D^{Hot} in columns (1), (3), and (5) takes unity if the mean temperatures during 1970-2000 are above the 75th percentile of the distribution in all locations. The hot country dummy D^{Hot} in columns (2), (4), and (6) takes unity if the mean temperatures during 1970-2000 are above the 75th percentile of the distribution in locations in each group of countries. Robust standard errors clustered at the grid cell level are in parentheses. Figure 8 plots point estimates shown in odd number columns. * $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A6: GRID CELL LEVEL REGRESSIONS, RURAL-URBAN DUMMIES BASED ON POPULATION, CROPLAND VERSUS NON-CROPLAND

Dependent variable = Net migration rates			
Definition of rural-urban areas is based on Population at the grid cell level			
	Poor	Low-middle	Up-middle
	(1)	(2)	(3)
$\Delta Temp$	-.26	-1.97***	-.37***
	(.21)	(.41)	(.08)
$D^{\text{Rural}} \times \Delta Temp$	4.72***	3.56***	-.53*
	(.62)	(.78)	(.31)
$D^{\text{Middle-rural}} \times \Delta Temp$	1.19***	2.79***	-0.02
	(.45)	(.74)	(.27)
$D^{\text{Middle-urban}} \times \Delta Temp$	-.39	.39	-.48***
	(.26)	(.69)	(.15)
$D^{\text{Cropland}} \times \Delta Temp$	-.58	-1.11	-.42**
	(.42)	(.99)	(.19)
$D^{\text{Cropland}} \times D^{\text{Rural}} \times \Delta Temp$	7.13*	-13.22***	-4.60***
	(3.81)	(4.75)	(1.35)
$D^{\text{Cropland}} \times D^{\text{Middle-rural}} \times \Delta Temp$	-4.66*	3.22	-6.97***
	(2.52)	(4.60)	(1.51)
$D^{\text{Cropland}} \times D^{\text{Middle-urban}} \times \Delta Temp$	.60	-1.54	-.52
	(.76)	(2.54)	(.39)
N	23,191	10,898	31,787
R-squared	.29	.26	.15
Temperature effects (Linear combination of coefficients)			
Rural, non-cropland	4.46***	1.59**	-.90***
	(.58)	(.66)	(.30)
Mid-rural, non-cropland	.93**	.82	-.38
	(.41)	(.64)	(.26)
Mid-urban, non-cropland	-0.64***	-1.58***	-.85***
	(.20)	(.58)	(.15)
Urban, non-cropland	-.26	-1.97***	-.37***
	(.21)	(.41)	(.08)
Rural, cropland	11.59***	-11.63**	-5.51***
	(3.76)	(4.70)	(1.31)
Mid-rural, cropland	-3.73	4.04	-7.36***
	(2.49)	(4.55)	(1.49)
Mid-urban, cropland	-.04	-3.12	-1.36***
	(.75)	(2.49)	(.38)
Urban, cropland	-.84**	-3.07***	-.79***
	(.38)	(.92)	(.19)

NOTE. All regressions include $D^{\text{Cropland}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times \Delta$Precipitation, $D^{\text{Region}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Population growth rates, and country fixed effects as controls. The hot country dummy D^{Cropland} takes unity if the share of croplands in the cell is greater than the 95th percentile of the distribution among all grid cells in each country. Robust standard errors clustered at the grid cell level are in parentheses. Figure 9 plots the point estimates. * $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A7: GRID CELL LEVEL REGRESSIONS, RURAL-URBAN DUMMIES BASED ON POPULATION, ROBUSTNESS CHECKS

Temperature effects (Linear combination of coefficients)
Dependent variable = Net migration rates
Definition of rural-urban areas is based on Population at the grid cell level

	Omit extreme temp.	Omit extreme prec.	Omit extreme internal migration	Omit Sub-Saharan Africa	Omit urban countries	Omit less ag. countries
	Panel A: Poor countries					
	(1)	(2)	(3)	(4)	(5)	(6)
Urban areas	-.04	-.25	-.32*	-.45	-.31	-.31
	(.21)	(.20)	(.17)	(.27)	(.19)	(.19)
Middle-urban areas	-.55***	-.72***	-.60***	-.40*	-.64***	-.64***
	(.20)	(.21)	(.19)	(.22)	(.20)	(.20)
Middle-rural areas	.10	.45	.76**	1.16**	.60	.60
	(.46)	(.42)	(.37)	(.51)	(.41)	(.41)
Rural areas	4.88***	4.71***	4.07***	4.00***	4.74***	4.74***
	(.66)	(.60)	(.54)	(.65)	(.59)	(.59)
N	23,055	22,724	22,875	23,191	14,078	23,191
Grid cells	7,851	7,838	7,821	7,851	4,759	7,851
	Panel B: Lower-middle income countries					
	(1)	(2)	(3)	(4)	(5)	(6)
Urban areas	-2.65***	-2.35***	-2.04***	-2.95***	-2.34***	-2.68***
	(.36)	(.39)	(.35)	(.49)	(.39)	(.41)
Middle-urban areas	-1.93***	-1.93***	-.95**	-.95	-1.83***	-1.66***
	(.59)	(.57)	(.47)	(.72)	(.56)	(.60)
Middle-rural areas	.71	.47	.47	1.99	.86	.79
	(.68)	(.68)	(.62)	(.85)	(.68)	(.73)
Rural areas	.55	.38	1.18**	-.90	.51	.45
	(.74)	(.67)	(.58)	(.72)	(.66)	(.71)
N	10,821	10,508	10,577	10,898	7,011	10,532
Grid cells	3,734	3,722	3,700	3,734	2,408	3,609
	Panel C: Upper-middle income countries					
	(1)	(2)	(3)	(4)	(5)	(6)
Urban areas	-.50***	-.44***	-.38***	-.35***	-.63***	-.41***
	(.12)	(.08)	(.07)	(.08)	(.09)	(.08)
Middle-urban areas	-1.00***	-.88***	-.68***	-.78***	-.88***	-.86***
	(.18)	(.14)	(.13)	(.14)	(.15)	(.15)
Middle-rural areas	-.63***	-.75***	-.56***	-.91***	-.54***	-.86***
	(.33)	(.27)	(.22)	(.28)	(.28)	(.29)
Rural areas	-1.80***	-1.41***	-1.62***	-1.43***	-1.36***	-1.71***
	(.36)	(.29)	(.24)	(.30)	(.30)	(.30)
N	30,769	31,078	31,305	28,007	30,074	29,462
Grid cells	10,763	10,755	10,717	9,505	10,185	9,981

NOTE. All regressions include $D^{\text{Rural-urban}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times \Delta$Precipitation, $D^{\text{Region}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Population growth rates, and country fixed effects as controls. Robust standard errors clustered at the grid cell level are in parentheses. Figure 10 plots point estimates presented in the table. * $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A8: COUNTRY-LEVEL REGRESSIONS, ROBUSTNESS CHECKS

	Add hot country dummy	Omit extreme temp.	Omit extreme prec.	Omit extreme internal migration	Omit urban countries	Omit less ag. countries
	Panel A: Total internal migration rates					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Temp$	3.13**	2.79*	3.18**	3.01**	3.72**	2.86**
	(1.46)	(1.57)	(1.37)	(1.35)	(1.60)	(1.40)
$D^{\text{Lower-middle}} \times \Delta Temp$	-1.98	-1.73	-2.39	-2.21	-2.97	-3.95
	(3.12)	(3.49)	(3.21)	(3.15)	(3.34)	(2.69)
$D^{\text{Poor}} \times \Delta Temp$	-5.59	-5.60*	-5.67*	-5.68*	-6.49*	-5.63*
	(3.76)	(3.14)	(2.98)	(3.05)	(3.45)	(2.95)
N	140	137	136	140	130	134
Countries	63	63	61	63	59	61
R-squared	.29	.27	.27	.27	.27	.25
Temperature effects (Linear combination of coefficients)						
Lower-middle countries	1.15	1.07	.79	.80	.76	-1.10
	(2.87)	(2.91)	(2.75)	(2.70)	(2.71)	(2.23)
Poor countries	-2.46	-2.81	-2.48	-2.67	-2.76	-2.77
	(3.22)	(2.61)	(2.42)	(2.55)	(2.63)	(2.44)
	Panel B: Out-migration rates, Rural and Middle-rural					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Temp$	1.33***	1.13***	1.08***	1.02***	1.22***	1.27***
	(.37)	(.40)	(.36)	(.37)	(.44)	(.35)
$D^{\text{Lower-middle}} \times \Delta Temp$	-.40	-.66	-.35	-.16	-.48	-.80
	(.85)	(.91)	(.87)	(.69)	(.93)	(.95)
$D^{\text{Poor}} \times \Delta Temp$	-3.31***	-3.36***	-3.26***	-2.92***	-3.49***	-3.54***
	(.96)	(.89)	(.86)	(.75)	(1.03)	(.90)
N	140	137	136	138	130	134
Countries	63	63	61	62	59	61
R-squared	.31	.30	.30	.32	.28	.31
Temperature effects (Linear combination of coefficients)						
Lower-middle countries	.92	.46	.73	.86	.74	.46
	(.82)	(.78)	(.77)	(.56)	(.79)	(.86)
Poor countries	-1.99**	-2.24***	-2.18***	-1.89***	-2.26***	-2.27***
	(.83)	(.81)	(.76)	(.67)	(.85)	(.82)

NOTE. All regressions include population growth rates, GDP growth rates, and ΔPrecipitation as controls. Robust standard errors clustered at the country-level are in parentheses. Figure 11 plots point estimates shown in the table. * $p < .1$, ** $p < .05$, and *** $p < .01$.

E. Further Robustness Checks

E.1. Is China Special?

This section considers the case of China because a number of studies document that China is special in terms of its patterns of internal migrations. For example, Au and Henderson (2006) examine the effect of immigration restrictions in China called the Hukou system. They show that restricted internal migrations led to insufficient agglomeration of economic activities, resulted in a GDP loss. Inspite of the Hukou system, the migration rate increased from 20% to 30% during the period 2003-2012 (Zhao et al., 2018). These suggest that China might be special in terms of its internal migration patterns. Therefore, we re-estimate grid cell level regressions without China.

TABLE A9: GRID CELL LEVEL REGRESSIONS, POOR COUNTRIES, EXCLUDING CHINA

Dependent variable = Net migration rates
Definition of rural-urban areas is based on Population at the grid cell level

	Baseline		Excluding China		Only China	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Temp$	1.48***	-.31	.64*	.31	2.28***	.23**
	(.22)	(.19)	(.34)	(.24)	(.31)	(.10)
$D^{\text{Middle-urban}} \times \Delta Temp$		-.33		-.93**		.27*
		(.25)		(.39)		(.15)
$D^{\text{Middle-rural}} \times \Delta Temp$		.91**		-1.07		1.55**
		(.45)		(.75)		(.66)
$D^{\text{Rural}} \times \Delta Temp$		5.05***		4.10***		2.66***
		(.62)		(1.22)		(.75)
N	23,191	23,191	14,900	14,900	8,291	8,291
Grid cells	7,851	7,851	5,068	5,068	2,783	2,783
R-squared	.26	.27	.30	.31	.12	.16
Temperature effects (Linear combination of coefficients)						
Middle-urban		-.64***		-.62*		.50***
		(.20)		(.33)		(.12)
Middle-rural		.60		-.77		1.79***
		(.41)		(.71)		(.66)
Rural		4.74***		4.40***		2.90***
		(.59)		(1.21)		(.74)
Controls						
$D^{\text{Rural-urban}} \times$ Year fixed effects		Yes		Yes		Yes
$D^{\text{Rural-urban}} \times \Delta$Precipitation		Yes		Yes		Yes

NOTE. All regressions include $D^{\text{Region}} \times$Year fixed effects, $D^{\text{Rural-urban}} \times$Population growth rates, and country fixed effects, where $D^{\text{Rural-urban}}$ indicate the rural-urban dummies and D^{Region} denote the region dummies. Rural-urban locations are defined by population at the grid cell level. Robust standard errors clustered at the grid cell level are in parentheses. * $p < .1$, ** $p < .05$, and *** $p < .01$.

In our sample China is included as a poor country due to its low income level in 1980. Therefore, we re-estimate regressions with grid cell level data from poor countries without China. The first two columns of Table A9 show baseline results with grid cells from China as a reference. These come from columns (1) and (2) in Table 2. Columns (3) and (4) show results from excluding grid cells from China. The results qualitatively stay the same — the temperature effects are positive in rural areas and basically there is essentially no effect in urban area. Columns (5) and (6) present results from grid cells from China only. Column (6) shows that temperature effects on the net migration rates are positive in all areas — 0.23 (urban), 0.50 (middle-urban), 1.79 (middle-rural), and 2.90 (rural)

— and these are all statistically significant. However, the magnitude of the temperature is greater for rural areas, which is consistent with our hypothesis that rural areas are more sensitively affected by rising temperatures. These results suggest that internal migration patterns in China still fit to our theoretical framework.

E.2. Spatial Correlation of the Error Term

This section takes possible spatial correlation of the error term into consideration. The size of one grid cell is fairly small — 50km × 50km around the equator — and there may be correlation of climatic conditions across space. To address this, we cluster standard errors at more aggregated grid cells.

TABLE A10: DIFFERENT STANDARD ERRORS

Panel A: Poor countries

	Coefficients	Clustering robust standard errors			
		I (Baseline)	II	III	IV
Urban	-.31	(.27)	(.26)	(.60)	(.77)
Middle-urban	-.64	(.28)**	(.24)***	(.61)	(.69)
Middle-rural	.60	(.48)	(.45)	(.87)	(.96)
Rural	4.74	(.81)***	(.79)***	(1.41)***	(2.00)**
N. of grid cells in one cluster		1	3	85	253
N. of clusters		7,851	2,553	92	31

Panel B: Lower-middle income countries

	Coefficients	Clustering robust standard errors			
		I (Baseline)	II	III	IV
Urban	-2.34	(.58)***	(.46)***	(1.17)**	(1.78)
Middle-urban	-1.83	(.78)**	(.68)***	(1.19)	(1.33)
Middle-rural	.86	(.92)	(.77)	(1.80)	(2.33)
Rural	.51	(.98)	(.79)	(1.87)	(2.79)
N. of grid cells in one cluster		1	3	37	98
N. of clusters		3,734	1,411	102	38

Panel C: Upper-middle income countries

	Coefficients	Clustering robust standard errors			
		I (Baseline)	II	III	IV
Urban	-.44	(.10)***	(.10)***	(.22)***	(.31)
Middle-urban	-.96	(.19)***	(.17)***	(.37)**	(.31)***
Middle-rural	-.85	(.37)**	(.34)**	(.71)	(.77)
Rural	-1.35	(.38)***	(.35)***	(.64)**	(.63)**
N. of grid cells in one cluster		1	3	67	207
N. of clusters		10,770	3,683	160	52

NOTE. The table reports different clustering robust standard errors corresponding to point estimates shown in even number columns in Table 2. * $p < .1$, ** $p < .05$, and *** $p < .01$.

Table A10 shows point estimates of the temperature effects on the internal migration rates reported in the even number columns in Table 2. Panels A, B, and C summarize results from poor countries, lower-middle income countries, and upper-middle income countries, respectively. For each point estimates for urban, middle-urban, middle-rural, and rural areas, it shows robust standard errors clustered at four different cross sectional units.

We construct more aggregated grid cells by using longitude and latitude of original grid cells. Because we do not take countries' borders into consideration, two grid cells from different countries may be included in one aggregated grid cells (e.g., a grid cell from Belgium and a grid cell in Luxembourg may be included in one aggregated grid cell).

Column I shows the baseline standard errors clustered at the 0.5×0.5 grid cell level. Column II reports standard errors clustered at more aggregated grid cells. One cluster includes 2,553, 1,411, and 3,683 grid cells in poor countries, lower-middle income countries, and upper-middle income countries, respectively. It shows that standard errors in column B are similar to those in column I. Therefore, statistical significance remains the same.

Column III reports standard errors clustered at even more aggregated grid cells. One cluster includes 85, 37, and 67 grid cells in poor countries, lower-middle income countries, and upper-middle income countries, respectively. The results show that it increased standard errors. As a result, the coefficients from middle-urban areas in poor countries, middle-rural areas in lower-middle countries, and middle-rural areas in upper-middle countries turn to insignificant.

Lastly, column IV presents clustering robust standard errors based on the largest aggregation. One cluster includes 253, 98, and 207 grid cells in poor countries, lower-middle income countries, and upper-middle income countries, respectively. This increases standard errors substantially. As a result, the coefficient from middle-urban areas in poor countries lost its significance. It also makes all coefficients from lower-middle income countries insignificant. The coefficient for urban areas in upper-middle income countries turns to be insignificant as well. However, the most important results remain the same. A higher temperature increases the net migration rate in rural areas of poor countries and reduces it in rural areas of upper-middle income countries.

F. Expected Internal Migration Rates

This section describes the procedures to find the expected internal migration rates in 2010-2080. As described in section 5.4, we compute the expected internal migration rates using the estimated coefficients and the projected temperature changes provided by the World Bank. Tables A11 and A12 summarize the estimated expected internal migration rates shown in Figure 13. Panels A, B, and C present results for poor, lower-middle, and upper-middle countries, respectively. Panel D summarizes the overall impact on them.

F.1. Procedures and details

Column (1) of Panels A-C in A11 shows the actual average internal migration rates during 1990-2000 and the implied number of migrants. These average internal migration rates are slightly different from the ones in Table A2 because we focus on countries actually used in country-level regressions here. We use the average internal migration rates and the total population in the year 2000 — 3,218 million, 758 million, 1,093 million in poor, lower-middle, and upper-middle countries, respectively — to find the total number of migrants shown in column (1).[30]

In the regressions, we use $AggMigRate^s_{c,t} = 100 \times AggMig^s_{c,t}/Pop_{c,t-10}$ as the dependent variable where $AggMig^s_{c,t}$ denotes country c's aggregate internal migrations during the decade from year $t-10$ to year t and $Pop_{c,t-10}$ indicates population in year $t-10$ for s = 'Total' and 'Rural Mid-Rural'. It shows that we use initial population in the denominator. However, in Tables A11 and A12, we use population data from the year 2000 to infer how many people would have migrated during the decade 2000-2010. The projection is found using the population in 2000, assuming that the internal migration rates and other economic conditions were the same as the previous decade 1990-2000. We find that 228 million, 53 million, and 76 million of people would internally migrate during 2000-2010 in poor, lower-middle, and upper-middle countries, respectively.

The expected internal migration rates presented in columns (3)-(6) are estimated using the method explained in section 5.4 in the main text. We have two different estimates based on A2 and B1 scenarios for each group of countries. Temperature changes used for column (3) are $(Temp_{c,2020-2040} - Temp_{c,1961-1999})/4$ where $Temp_{c,2020-2040}$ denotes projected country c's average temperature during 2020-2040 and $Temp_{c,1961-1999}$ is the average temperature during 1961-1999 in the same country. It is divided by four to make it a decennial change. Temperature

[30] We obtain the population data from the WDI (World Bank, 2018). All available countries' populations are included (not just countries used in the country-level regressions).

changes used in column (4) are $(Temp_{c,2040-2060} - Temp_{c,2020-2040})/2$ where it is divided by two to make it a decennial change. Temperature changes used in Columns (5) and (6) are found using the same equation as column (4).

Because we use the temperature changes from the previous column for columns (4)-(6), the expected internal migration rates in those columns are based on decennial change in temperatures from the previous decade rather than the cumulative changes from the level 1961-1999. We use these expected internal migration rates and the population data in 2000 to infer the total number of people who are expected to migrate due to projected temperature changes.

Column (2) shows the expected migration rates during the period 2000-2015. We use actual temperature changes (from the level in 1961-1999 to the level in 2015) to find the expected migration rates.[31] We take different calculation steps to find the expected internal migration rates for the period because cross-country variations in actual temperature changes for 2015 are different from the World Banks' projections for 2020-2100 probably due to the fact that some countries experienced weather anomalies.

The internal migration rates in 2000-2015 are found by taking the following steps. First, we compute the average temperature change between the 1961-1999 level and the 2015 level. For example, for poor countries, this figure is 0.356°C. Second, we find the average projected temperature change from the 1961-1999 level to the 2020-40 level. Third, the expected migration rate in 2000-15, $AggMigRate^{s}_{h,2000-15}$, is computed as follows:

$$\begin{aligned}
AggMigRate^{s}_{h,2000-15} &= AggMigRate^{s}_{h,2020-40} - \\
&\quad (AggMigRate^{s}_{h,2020-40} - AggMigRate^{s}_{h,1990-2000}) \times \frac{\Delta Temp^{2015}_{h,1961-1999}}{\Delta Temp^{2020-40}_{h,1961-1999}} \\
&= 5.38\% - (5.38\% - 7.10\%) \times \frac{0.356^{\circ}C}{1^{\circ}C} \\
&= 6.49\%.
\end{aligned}$$

This leads to $AggMigRate^{s}_{h,2000-15} = 5.40\% - (5.40\% - 7.10\%) \times 0.356^{\circ}C/1^{\circ}C = 6.50\%$ under B1 scenario.

F.2. Results

F.2.1. Poor countries

Panel A of Table A11 shows the expected total internal migration rates for poor countries. Although the exercise here is informative, we may cautiously interpret the results because the temperature effects on poor countries are insignificant when we employ the total internal migration rate as the dependent variable. Column (1) shows that the actual internal migration rate during 1990-2000, $AggMigRrate^{Total}_{h,1990-2000} = 100 \times AggMig^{Total}_{h,1990-2000}/Pop_{h,1990}$ is 7.1%. By multiplying the total population in the year 2000, we find that 228.5 million people would have internally migrated during 2000-2010.

Column (2) uses the actual temperature changes during 2000-2015 to find the internal migration rates and the number of migrants. The only difference between column (1) and column (2) is temperature changes. Therefore, temperature rises during 2000-2015 alone imply a 8.6% decline of internal migrations under A2 scenario and a 8.5% decline under B1 scenario. Columns (3)-(4) show the expected internal migration rates in the period 2020-2100. These show that rising temperatures reduce total internal migrations by 29% and 23% by 2080-2100 under A2 and B1 scenarios, respectively.

Panel A of Table A12 present the expected rural out-migration rates computed using the same procedure. It shows that the number of rural out-migrations is expected decline from 61.6 millions to 44.2 millions by 2080-2100

[31] The average temperature level for 2015 is calculated as follows. First, we find the average temperatures during the period 2010-2015 for each country using the data from the *Climate Change Knowledge Portal* (World Bank, 2018). We use the average of the six years 2010-2015 to reduce the impact of weather anomalies. Second, we compute the group average of these country-level average temperatures during 2010-2015. Third, we find the change in the average temperatures from the 1961-1999 level, which is denoted as $\Delta Temp^{2015}_{h,1961-1999}$ for country group h.

under A2 scenario. On the other hand, B2 scenario leads to a decline of 0.7 millions.

F.2.2. Lower-middle income countries

Panel B of Table A11 shows that, the total number of migrations was 53.2 millions in the beginning of the century and it is expected to increase to 54.6 millions under A2 scenario. B1 scenario implies more moderate increase of 1.7%. Panel B of Table A12 indicates that, under A2 scenario, the number of rural out-migrations is expected to increase by 0.6 million, a 5.7% rise. This figure remains at 3.5% under B1 scenario. We acknowledge that the country-level regressions find insignificant temperature effects on lower-middle income countries. Therefore, we may cautiously interpret the results.

F.2.3. Upper-middle income countries

Panel C of Table A11 describes the expected total internal migrations for upper-middle income countries. The number of internal migrations was 76.4 millions in the beginning of this century. Under A2 scenario, it is expected to increase to 85.2 millions by 2080-2100, a 11.7% rise from the beginning of the century. However, under B1 scenario, it remains at a 0.9% rise by 2080-2100. We find the largest response of 8.5% rise in internal migrations during 2040-60 because changes in temperatures are expected to be greatest during the period. Panel C of Table A12 presents the expected rural out-migrations. It shows that, under A1 scenario, the number of rural out-migrations is expected to change to 15.8 millions by 2080-2100, a 18.7% increase from the beginning of the century. In contrast, B1 scenario leads to a 2.2% rise.

TABLE A11: EXPECTED TOTAL INTERNAL MIGRATION RATES

Panel A: Poor countries

	(1) 1990-2000*	(2) 2000-2015**	(3) 2020-40	(4) 2040-60	(5) 2060-80	(6) 2080-2100
A2 Scenario						
Total internal migration rates	7.10%	6.49%	5.38%	5.25%	5.13%	5.03%
# of migrants (million)	228.5	208.8	173.1	169.1	164.9	161.9
Rate of change from 2000		-8.6%	-24.2%	-26.0%	-27.8%	-29.1%
B1 Scenario						
Total internal migration rates	7.10%	6.50%	5.40%	5.19%	5.40%	5.48%
# of migrants (million)	228.5	209.0	173.8	167.0	173.8	176.3
Rate of change from 2000		-8.5%	-24.0%	-26.9%	-23.9%	-22.8%

Panel B: Lower-middle income countries

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
Total internal migration rates	7.02%	7.04%	7.15%	7.17%	7.19%	7.20%
# of migrants (million)	53.2	53.4	54.2	54.3	54.5	54.6
Rate of change from 2000		.3%	1.9%	2.1%	2.4%	2.7%
B1 Scenario						
Total internal migration rates	7.02%	7.04%	7.14%	7.18%	7.15%	7.13%
# of migrants (million)	53.2	53.4	54.1	54.5	54.2	54.1
Rate of change from 2000		.3%	1.8%	2.3%	1.9%	1.7%

Panel C: Upper-middle income countries

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
Total internal migration rates	6.99%	7.13%	7.24%	7.45%	7.65%	7.80%
# of migrants (million)	76.4	77.9	79.1	81.5	83.7	85.2
Rate of change from 2000		2.0%	3.6%	6.7%	9.6%	11.7%
B1 Scenario						
Total internal migration rates	6.99%	7.11%	7.21%	7.58%	7.20%	7.05%
# of migrants (million)	76.4	77.7	78.8	82.9	78.7	77.1
Rate of change from 2000		1.8%	3.2%	8.5%	3.1%	0.9%

Panel D: Number of people affected by rising temperatures

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
# of affected people (million)		21.4	59.1	65.7	72.2	76.9
As a share of population		.42%	1.17%	1.30%	1.42%	1.52%
B1 Scenario						
# of affected people (million)		21.0	58.2	69.3	58.1	53.8
As a share of population		.42%	1.15%	1.37%	1.15%	1.06%

NOTE. The table shows the average expected total internal migration rates. Column (1) shows the expected internal migration rates during 1990-2000 and the implied number of migrations during 2000-2010 given the level of population in the year 2000. Column (2) reports the expected internal migration rates and the implied number of migrations during 2000-2015 given the actual change in temperatures during the period 2000-2015. Columns (3)-(6) are those based on the projected temperature changes. See the text for details.

TABLE A12: EXPECTED RURAL OUT-MIGRATION RATES

Panel A: Poor countries

	(1) 1990-2000*	(2) 2000-2015**	(3) 2020-40	(4) 2040-60	(5) 2060-80	(6) 2080-2100
A2 Scenario						
Total internal migration rates	1.92%	1.87%	1.78%	1.63%	1.48%	1.37%
# of migrants (million)	61.6	60.1	57.3	52.6	47.7	44.2
Rate of change from 2000		-2.5%	-7.1%	-14.7%	-22.6%	-28.2%
B1 Scenario						
Total internal migration rates	1.92%	1.88%	1.80%	1.56%	1.80%	1.89%
# of migrants (million)	61.6	60.3	58.0	50.3	58.1	60.9
Rate of change from 2000		-2.1%	-5.8%	-18.4%	-5.8%	-1.1%

Panel B: Lower-middle income countries

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
Total internal migration rates	1.49%	1.50%	1.55%	1.56%	1.57%	1.57%
# of migrants (million)	11.28	11.36	11.72	11.80	11.88	11.93
Rate of change from 2000		.7%	3.9%	4.6%	5.3%	5.7%
B1 Scenario						
Total internal migration rates	1.49%	1.50%	1.54%	1.56%	1.55%	1.54%
# of migrants (million)	11.28	11.36	11.71	11.84	11.72	11.67
Rate of change from 2000		.7%	3.7%	5.0%	3.9%	3.5%

Panel C: Upper-middle income countries

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
Total internal migration rates	1.22%	1.26%	1.29%	1.35%	1.41%	1.44%
# of migrants (million)	13.3	13.8	14.1	14.8	15.4	15.8
Rate of change from 2000		3.6%	6.4%	11.1%	15.6%	18.7%
B1 Scenario						
Total internal migration rates	1.22%	1.26%	1.29%	1.39%	1.29%	1.24%
# of migrants (million)	13.3	13.7	14.1	15.2	14.1	13.6
Rate of change from 2000		3.3%	5.7%	14.1%	5.7%	2.2%

Panel D: Number of people affected by rising temperatures

	1990-2000*	2000-2015**	2020-40	2040-60	2060-80	2080-2100
A2 Scenario						
# of affected people (million)		2.1	5.7	11.0	16.6	20.5
As a share of population		.04%	.11%	.22%	.33%	.40%
B1 Scenario						
# of affected people (million)		1.8	4.8	13.8	4.8	1.4
As a share of population		.04%	.09%	.27%	.09%	.03%

NOTE. The table shows the expected rural out-migration rates. Column (1) shows the expected internal migration rates during 1990-2000 and the implied number of migrations during 2000-2010 given the level of population in the year 2000. Column (2) reports the expected internal migration rates and the implied number of migrations during 2000-2015 given the actual change in temperatures during the period 2000-2015. Columns (3)-(6) are those based on the projected temperature changes. See the text for details.