KNOMAD

Global Knowledge Partnership on Migration and Development

KNOMAD PAPER 55

Climate Variability and Internal Migration to Urban and Rural Areas: Evidence from Global Microdata

Brian C. Thiede

November 2023

The KNOMAD Paper Series disseminates work in progress funded by KNOMAD, a global hub of knowledge and policy expertise on migration and development. KNOMAD is supported by a multi-donor trust fund established by the World Bank. The European Commission, Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH commissioned by and on behalf of Germany's Federal Ministry of Economic Cooperation and Development (BMZ), and the Swiss Agency for Development and Cooperation (SDC) are the contributors to the trust fund.

The research presented in this paper is funded by the Thematic Working Group on Environmental Change and Migration. Please cite the work as follows: **Thiede, Brain C., 2023. Climate Variability and Internal Migration to Urban and Rural Areas: Evidence from Global Microdata, KNOMAD Paper 51**.

The views expressed in this paper do not represent the views of the World Bank or the sponsoring organizations. All queries should be addressed to KNOMAD@worldbank.org. KNOMAD working papers and a host of other resources on migration are available at www.KNOMAD.org.

Climate Variability and Internal Migration to Urban and Rural Areas: Evidence from Global Microdata*

Brian C. Thiede†

Abstract

Climate change is expected to have significant impacts on human population dynamics around the world, including on migration systems. The empirical evidence on climate-induced migration has expanded rapidly over the past decade, and it demonstrates significant but complex associations between temperature and precipitation variability and migration. Such environmental changes lead to shifts in migration behavior, but the direction and magnitude of such effects varies by context and across different sub-populations. The literature also remains characterized by important limitations, including a lack of generalizable evidence about whether and how climatic changes influence migration between rural and urban areas. Climatic changes are often believed to have disproportionate effects on rural-urban migration, but this assumption has been rarely tested empirically. This paper addresses this gap by measuring the effects of temperature and precipitation variability on inter-province migration to rural and urban areas in the developing world and developing statistical profiles of climate-affected migrants to urban areas. Drawing on integrated census and survey microdata from 23 countries, combined with high-resolution climate records, a series of multinomial logistic regression models are fit to measure the effects of climate exposures on internal migration to urban destinations and to test for heterogeneity in these effects across social and demographic groups. Subsequent analyses identify a population of climate-affected migrants in cities and develop statistical profiles of this group and comparison populations. Results show that climate exposures affect migration to urban but not rural provinces, with precipitation deficits strongly reducing the odds of urban-bound moves. Precipitation effects do not vary in a meaningful manner across many social and demographic groups or between rural and urban origins, but both temperature and precipitation effects vary significantly by world region. Statistical profiles of climate-affected migrants to cities suggest this population is remarkably similar to other streams of urban-bound migrants. The results should reduce concerns that climate change will disproportionately push the most disadvantaged populations to cities.

____

*The research presented in this paper was funded by KNOMAD's Thematic Working Group (TWG) on Environmental Change and Migration which is chaired by Alex Aleinikoff, Director, Zolberg Institute on Migration and Mobility, The New School, and co-chaired by Kanta Kumari Rigaud, Lead Economist, World Bank. The focal point for the TWG is Sonia Plaza, Senior Economist, World Bank. The paper was prepared under the guidance of Dilip Ratha, Head of KNOMAD.

†The author can be contacted at: 112C Armsby Building; The Pennsylvania State University; University Park, PA 16802; or via e-mail: bct11@psu.edu.

Table of Contents

Introduction

Climate variability and change are expected to have extensive social and economic costs, and to include many impacts on human population dynamics (Carleton & Hsiang 2016).[1] The possibility that climatic changes will alter human migration patterns has received widespread attention by academics, policymakers, and the public (Hoffman et al. 2020; Rigaud et al. 2018; The White House 2021), driven in part by concerns about climate-induced displacement and so-called climate refugees. However, the existing evidence supports a much more nuanced and complicated picture. Climate variability—and its downstream social and economic impacts—has the potential to both increase and decrease migration (i.e., displacing and trapping populations), with effects varying across sub-populations and types of migration (Black et al 2011; Boas et al. 2019; Fussell et al. 2014; Gemenne 2011).

Migratory responses to climate exposures can have important implications for wellbeing at the individual and household levels since mobility is often part of diverse livelihood strategies (Black et al. 2011a; Ellis 1998). Climate-related changes in migration may potentially also have broader impacts on the communities that receive migrants or remain home to trapped populations, including for local labor markets and socio-political stability (Koubi 2019). These impacts may be especially pronounced (or at least distinctive) for migration to urban areas, which in some parts of the world are characterized by high levels of unemployment, large informal settlements, and socio-political instability (Fink et al. 2014; Østby 2016). These conditions—and a common assumption that climate variability will drive rural-to-urban migration—fuel concern that climate-affected migrants to cities will fail to integrate and thereby contribute to social and economic challenges in those locations. Despite these claims, however, there is only limited evidence about the number and characteristics of climate-induced migrants to urban areas (for exceptions see Nawrotzki et al. 2017; Sedova & Kalkuhl 2020; Thiede et al. 2016; Weinreb et al. 2020).[2]

This paper helps to address that gap, and limitations to existing evidence, by measuring the effects of climate exposures on internal migration to urban and rural areas across 23 countries in the developing world. Drawing on over 142 million individual records from

---

[1] This study measures the effects of climate variability on human migration. As operationalized here, climate variability captures short-term deviations in temperature and precipitation from the respective long-term means in a particular location (e.g., how temperatures during a 5-year period deviate from a longer-term mean in a given location). The term "climate exposures" is also used to refer to individuals' exposure to climate variability throughout the text. The concept of climate variability is distinct from climate change, which represents a long-term change in the temperature and precipitation distributions for a particular location. This study follows current standards in the population-environment literature by using observed responses to climate variability to develop expectations about likely responses to future climate change, which is an imperfect but arguably best-available approach.

[2] More broadly, it is also important to note that many common claims about the impacts of migration to urban areas are overstated and (or) qualitatively incorrect. For example, contrary to the assumption that rural-urban migration is the main driver of urbanization globally, recent studies show that these contributions vary historically and spatially. In many places today, natural increase constitutes the main driver of urbanization (Bocquier et al. 2023; Menashe-Oren & Bocquier 2021).

harmonized microdata and high-resolution temperature and precipitation records, this study measures climate effects on migration to urban areas, draws comparisons with effects on migration to rural areas, and evaluates whether and how these effects vary across sub-populations and between different types of urban destinations. Statistical profiles of climate-affected migrants in urban destinations and relevant comparison groups are then generated to understand, descriptively, how this population differs from other groups of migrants and non-migrants.

To preview, the results support three headline findings. First, climate exposures affect migration to urban provinces but not rural provinces. In particular, precipitation deficits strongly reduce the odds of migration to urban areas. Second, climate effects are fairly consistent across many sub-populations, but vary significantly across world regions. Third, statistical profiles of climate-affected migrants in cities suggest this population is in many ways similar to other urban-bound migrants, reducing concerns that climate-induced migration streams will be negatively selected.

With these goals and overall findings in mind, the paper proceeds as follows. The next section describes the conceptual basis for expecting climate-induced changes in migration—with an emphasis on moves to urban areas—and outlines key findings from the existing literature. The third section describes the data, measures, and statistical methods used in the analysis. The fourth section presents the results, and the fifth section concludes with a discussion of key findings, their implications for policymakers and practitioners, and issues for future research to address.

Climate and migration to urban and rural areas

Climate exposures can have significant impacts on social and environmental systems, which can in turn shape individuals' incentives and abilities to migrate. These climate-induced changes in migration can operate through at least five mechanisms[3]: displacement dynamics, economic incentives, migrant health, residential preferences, and social networks (Black et al. 2011b; Hunter et al. 2015; Hunter & Simon 2022). Importantly, given the selective nature of migration (Bernard & Bell 2018; Bertoli et al. 2013; Lu 2010) and differences in vulnerability to climate exposures (Otto et al. 2017), these mechanisms are unlikely to operate consistently within and between contexts; and, as outlined below, these processes may have different implications for climate-migration dynamics in urban and rural areas.

First, climate impacts on migration may occur directly through physical displacement. Temperature and precipitation variability may be correlated with the occurrence of natural disasters (e.g., cyclones, floods, wildfires) that destroy or degrade housing and other property,

[3] The identification of these hypothesized mechanisms is based largely on the broader migration literature, which has identified correlates of migration that can be plausibly linked to climate variability. However, few studies in the climate-migration literature have systematically evaluated these mechanisms, representing an important limitation to this field (Cattaneo et al. 2019)

crops, and infrastructure, making it difficult or prohibitively costly to remain in affected areas (at least in the short run). For example, a recent global analysis revealed substantively important rates of flood-induced displacement in many locations, with countries such as Benin, Colombia, Pakistan, the Philippines, and Thailand all characterized by flood-induced displacement rates of more than 5 per 1000 (for the 2008-2013 study period) (Kakinuma et al. 2020). Over longer periods of time, climatic changes may also displace populations as sea-level rise inundates settlements, water and land resources are degraded (e.g., due to salinization), and temperatures rise to dangerous levels (Chen & Mueller 2018; Hauer et al. 2020; Raymond et al. 2020).

Second, the effects of climate variability on economic activity may change individuals' incentives for migration and the resources needed to fund moves (Carleton & Hsiang 2016; Dell et al. 2012). For example, temperature and precipitation are important determinants of agricultural production (Lobell et al. 2011; Ortiz-Bobea 2021; Ray et al. 2015), which can affect economic welfare and incentives for migration via changes in income and food prices. Consistent with this expectation, evidence from Tanzania shows that weather-induced reductions in agricultural income increase the probability of out-migration in the next year (Kubik & Maurel 2016). Beyond the agricultural sector, climate variability can also affect economic conditions through effects on labor productivity (e.g., heat stressors reducing productivity; Graff Zivin & Neidell 2014) and through impacts on macroeconomic performance (e.g., natural disasters reducing economic growth; Klomp & Valckx 2014). Households may respond to such changes by sending one or more members to less-affected locations to generate income (i.e., livelihood diversification). Conversely, households who face large climate-related resource constraints may retain individuals who would have otherwise migrated and thereby reduce out-migration (sometimes referred to as a trapped population dynamic) (DeWaard et al. 2022; Kaczan & Orgill-Meyer 2020).[4]

Third, climate exposures can affect human health, which is often an important correlate of migration. Indeed, in some contexts, migrants are positively selected on health, which reflects the physical and psychological demands that migration (especially longer-distance migration) entails (Crimmins et al. 2007; Riosmena et al. 2017). Changes in temperature and precipitation have diverse health impacts. For example, exposure to high temperatures is associated with increased rates of malnutrition and worse psychological wellbeing among affected adults (Mueller & Gray 2018; Palinkas & Wong 2020). High temperatures and low precipitation are also associated with worse health outcomes among children, including elevated risks of malnutrition and other illnesses (Blom et al. 2022; Thiede & Stube 2020; Wang et al. 2022). To the extent that such health impacts occur among potential migrants or their family members, their poor health or increased caregiving responsibilities may reduce the likelihood of out-migration.

[4] The concept of a trapped population is consistent with the broader literature on migration, which shows that migration tends to be low among the poor and increase as incomes grow (De Haas 2007). The implication is that migration is generally uncommon among the poorest households, who lack the resources to move (especially long distances). Of course, this proposed income-migration relationship is a general empirical regularity. There may certainly be circumstances in which poor and vulnerable populations may experience climate-related displacement.

Fourth, changes in temperature and precipitation, as well as correlated changes in other aspects of the natural environment (e.g., bodies of water, glaciers, forests) can affect migration by increasing or decreasing the match between environmental conditions or amenities and individuals' residential preferences or satisfaction (Hunter 2005). The local environment is one of many factors that influence decisions about where to live or relocate to (McLeman & Gemenne 2018).[5] For example, temperature, precipitation, and humidity levels are associated with patterns of inter-province migration among skilled individuals in China (Liu & Shen 2013). Holding other factors constant, environmental changes may affect migration decisions as individuals move (forgo moves) to find (remain in) a location with environmental conditions that match their preferences. It is important to note that aspects of residential preferences (e.g., place satisfaction) may also moderate how environmental changes influence migration (Adams & Adger 2013). For example, place attachment among residents in the Peruvian highlands (which is associated with environmental and non-environmental factors) reduces their likelihood of out-migration even in the face of significant climate shocks (Adams 2016).

Fifth, to the extent that climate variability changes migration patterns through the four mechanisms described above, it may also have second-order effects via migration networks. A non-trivial share of individuals who migrate do so in response to the mobility decisions of others (Massey et al. 1993). For example, if an individual moves to seek new employment opportunities, their spouse, children, and (or) members of their social network may subsequently migrate as well (e.g., for family reunification, to seek their own employment opportunities) (Fussell 2010; Garip 2012). Likewise, a decision by a potential migrant to remain in place reduces the likelihood that family members and other individuals in their social network migrate via the same network effects. The implication is that climate-induced changes in migration will subsequently change the migration probabilities of other individuals in their social networks. It is important to note, however, that such social network effects often unfold over long periods of time and may therefore not be detected in the immediate aftermath of a given environmental change.

While the hypothesized mechanisms linking climate exposures and migration are relevant for many populations and types of moves, the salience of each may vary. Populations around the world vary significantly in their vulnerability to environmental changes given large socioeconomic, demographic, and ecological inequalities (Adger 2006; Otto et al. 2017). In the context of climate-related migration, such differences in climate vulnerability may interact with more generalized patterns of migrant selectivity (i.e., when the migrant population is systematically different than then non-migrant population). Vulnerability and selection often occur along similar lines, including class, gender, and location (Bernard & Bell 2018; Bertoli et al. 2013; Black et al. 2011a; DeWaard et al. 2022; Thiede et al. 2016). Yet it is difficult to predict how they may interact. For example, assume that migrants are typically better educated than non-migrant peers in their place of origin, and that less-educated individuals are more vulnerable to the effects of climate shocks than their better-educated peers. If vulnerability is correlated with the likelihood of being displaced (i.e., out-migration) by a climate shock, this process will offset the baseline selection dynamics (i.e., reduce the educational disparities in migration). However,

[5] The relative importance of residential preferences may vary across contexts and between groups (Hunter 2005).

such vulnerability may also ‘trap’ less-educated individuals in place by further reducing the resources that are needed to migrate. In the latter scenario the baseline selection process would be amplified (i.e., educational disparities would grow). Similar, difficult-to-predict dynamics may play out with respect to other dimensions of vulnerability and selection, such as gender, as well.

Climate exposures may also have heterogeneous effects across different types of moves. For example, climate-induced resource constraints (e.g., due to reductions in income) may reduce international migration given the relatively high costs of such moves (Riosmena et al. 2018; Sedova & Kalkuhl 2020), while having a weaker or positive effect on internal migration (Mueller et al. 2014).[6] Importantly for this analysis, the salience of these mechanisms may also vary across the rural-urban continuum (e.g., between rural and urban origins and destinations)—the focus of this paper. Here, at least three considerations are worth underlining. First, climate variability can have strong effects on agriculture (Lobell et al. 2011; Ortiz-Bobea 2021; Ray et al. 2015), which disproportionately affect rural populations and incentivize diversification into non-agricultural livelihoods that may be concentrated in urban areas (Henderson et al. 2017). This process may increase the sensitivity of rural-urban migration to climate exposures more than other forms of migration. Second, baseline levels of migration between and within rural and urban areas are not uniform across countries or over time. Rural-urban migration is significant in developing-country contexts with large rural populations (e.g., in sub-Saharan Africa) while urban-urban migration is more common within urbanized contexts (e.g., in Latin America) (De Brauw et al. 2014; Selod & Shilpi 2021). These dynamics shape the pattern of migration networks (and other factors associated with the costs of migration), which may in turn affect the sensitivity of migration flows to climate variability. Third, rural and urban areas may face unique climate-related natural hazards, which may influence individuals’ decisions about whether and where to migrate. While considerable attention has been placed on the vulnerability of rural areas to climate shocks (e.g., via impacts on agriculture), urban areas also face many risks (e.g., flooding, sea-level rise, excessive heat) (Garschagen & Romero-Lankao 2015; Hauer et al. 2019; Tuholske et al. 2021), which may incentivize out-migration from cities and make such places less attractive destinations.[7,8]

Given the multiple mechanisms that may link climate and migration, and the complex ways in which they operate, it is difficult to develop strong directional hypotheses about the effects of climate variability on migration to urban relative to rural areas. The above considerations nonetheless provide a strong rationale for new analyses that explicitly account for climate effects on migration to urban and rural areas. This rationale is also provided by a limited number of existing studies that have examined the effects of climate variability on migration to urban and (or) rural areas. For example, Sedova and Kalkuhl (2020) measure the effects of climate

---

[6] Of course, this is not always the case. Studies have also found climate-induced increases in international migration. In at least some of these cases, however, international moves are occurring in contexts where well-established migration networks reduce the costs of cross-border migration (Nawrotzki et al. 2016).

[7] Such hazards may be amplified in informal and otherwise marginal settlements that migrants are most likely to settle in.

[8] This study focuses solely on the effects of environmental exposures at the place of origin. Conditions in potential destinations are important and should be addressed in future research.

shocks on out-migration in rural India and find that adverse weather conditions reduce rural-rural and international migration but increase rates of inter-state rural-urban migration. They also show that favorable environmental conditions increase rural-urban migration within states. Nawrotzki et al. (2017) measure climate effects on migration between and within rural and urban areas in Mexico, revealing that exposures to precipitation deficits increase both rural-rural and rural-urban migration but reduce the likelihood of urban-urban moves. Thiede et al. (2016) examine climate and migration across eight countries in South America and find that temperature effects have stronger and more consistent effects on migration to urban than rural destinations. Finally, Mueller et al. (2020) measure climate effects on migration to rural and urban destinations in Kenya and find that spells of low precipitation significantly increase migration to urban destinations.

Other studies provide more indirect insights into climate effects on migration to cities and rural areas by modeling either net rural migration or urbanization rates at the aggregate level. For example, Weinreb et al. (2020) examine climate effects on country-level net out-migration rates from rural (to urban) areas of sub-Saharan Africa. They find that low rainfall and high temperatures increase net rural out-migration among young adults. In a second example, Barrios et al. (2006) examine the relationship between rainfall and country-level urbanization rates across the developing world and find that rainfall deficits increase urbanization in sub-Saharan Africa (but not other regions). Finally, Henderson et al. (2017) examine the effects of drying on district-level urbanization in Africa, showing that dry conditions increase urbanization in regions where manufacturing is common in cities (i.e., in non-agriculturally-dependent regions).

Analyses of urbanization and net migration provide useful insights into climate-related migration into cities but do not directly measure climate effects on rural-urban migration (or other types of moves, e.g., rural-rural migration). Urbanization rates are a function of both migration and natural increase (i.e., the number of births and deaths) in rural and urban areas. Net rural out-migration rates are simultaneously influenced by migration patterns to both rural and urban areas and do not differentiate between scenarios with high and low gross migration. While the analyses of individual-level migration outcomes discussed above overcome these limitations, such studies cover a limited number of contexts, are few in number, and as such represent only a small subset of the broader climate-migration literature.

Research objectives

The overall goal of this study is to understand the influence of climate variability on migration to urban areas across the developing world, drawing on “big microdata” collected in 23 countries between 1970 and 2017. Toward this end, this analysis addresses three specific objectives. The first objective is to measure the effects of climate variability on migration to urban areas and draw comparisons with migration to rural areas. The second is to evaluate whether and how climate effects on migration to urban (and rural) areas vary by individuals’ age, sex, educational attainment, and residence in rural or urban communities. Statistical models also measure variation in climate effects across world regions. In doing so, the analyses identify the sub-populations and areas that are most likely to experience climate-induced changes in migration to urban areas. The third objective is to identify a discrete population of what are referred to, here, as climate-affected migrants in urban areas, describe their social and demographic characteristics, and compare these characteristics to climate-affected migrants to rural areas, non-exposed migrants, and non-migrants.

The study makes four key contributions to knowledge on climate-induced migration. First, the analyses provide new evidence about the effects of climate variability on migration to urban areas. Although there are many implicit (and sometimes explicit) assumptions about the distribution of climate-related impacts on migration between urban and rural areas, few studies disaggregate origins and (or) destinations by urban and rural status (exceptions discussed above). Second, the regression analyses account for potential heterogeneity of climate effects across sub-populations. These analyses account for the systematic differences in vulnerability to climate variability that have been suggested in previous studies (Mueller et al. 2020; Thiede et al. 2016), as well as the possibility that groups may have different propensities to move to urban (or rural) areas in response to environmental stressors. Third, the study identifies and describes discrete groups of climate-exposed migrants, providing insights into the characteristics of such populations in urban and rural areas. Most previous studies have aimed to measure the marginal effects of climate exposures on migration probabilities, giving much less attention to the identification and characterization of climate-affected migrants. Fourth and most broadly, the conclusions from this study are based on the application of consistent methods to harmonized census microdata, which produce comparable estimates across a large number of countries. This effort builds on previous papers that have variously measured climate effects across multiple countries in Latin America (Thiede et al. 2016), Africa (Mueller et al. 2020), and Asia (Thiede et al. 2022), combining data from across world regions and placing renewed emphasis on migration between and within urban and rural areas.

Analytic strategy

Data

Migration and other demographic characteristics are measured using harmonized census and inter-censal survey microdata (henceforth census data for brevity) from 23 countries, which are accessed using the Integrated Public Use Microdata Series-International (IPUMS-I) database (Minnesota Population Center 2020). Among the census data available from IPUMS-I at the time of analysis, the analytic sample is restricted to samples that meet the following criteria: (a) are collected through censuses or inter-censal surveys[9]; (b) include a migration question with a five-year lookback (i.e., is the place of current residence different than five years ago?); (c) include georeferenced data on place of residence at both the baseline of the migration interval and time of enumeration; and (d) are sourced from developing countries for which at least two censuses meet the first three criteria.[10] The dataset is further restricted to include individuals who were of working age (15-64 years) at the start of the migration interval (i.e., five years prior to the census).

[9] The high-frequency labor force surveys provided by IPUMS-I are excluded.

[10] One country (Haiti) and a limited number of provinces within countries are excluded from the analysis because they lack variability in the outcome variable.

The decision focuses the analysis on populations who are likely to be most affected by the economic effects of climate variability and excludes individuals in ages when migration is rare (Bernard et al. 2014). After these restrictions, the analytic sample includes 142,947,304 observations from 23 countries, which are representative of a target population of more than 3.2 billion individuals. The geographic distribution of the sample is described in Table 1.

Table 1. Distribution of sample by country

Country	Sample size	Proportion of sample
Argentina	2,161,151	0.0151
Bolivia	621,225	0.0043
Botswana	78,488	0.0005
Brazil	12,747,205	0.0892
Chile	1,477,180	0.0103
China	63,847,023	0.4466
Colombia	2,299,765	0.0161
Costa Rica	284,892	0.0020
Dominican Republic	330,137	0.0023
Ecuador	815,432	0.0057
Guatemala	579,548	0.0041
Honduras	238,020	0.0017
Indonesia	33,615,645	0.2352
Malaysia	844,390	0.0059
Mexico	11,062,865	0.0774
Mozambique	632,230	0.0044
Nepal	1,035,603	0.0072
Nicaragua	218,940	0.0015
Paraguay	277,847	0.0019
Philippines	3,753,010	0.0263
Senegal	474,832	0.0033
Vietnam	5,329,672	0.0373
Uruguay	222,205	0.0016
Total	142,947,304	

Notes: the analytic sample is representative of target population of 3.245 billion individuals.

Climate exposures are measured using data from the University of East Anglia’s Climatic Research Unit Time Series (CRU). The CRU dataset provides 0.5°-resolution climate estimates based on the interpolation of data from more than 4,000 weather stations globally and has been widely used in previous population-environment research (Gray & Wise 2016; Weinreb et al. 2020). Total precipitation and average temperatures are extracted for all months between 1961 and 2020 as spatial means for first-level sub-national units (henceforth “provinces” for brevity) in the sample. These climate data are matched to the demographic files using individuals’ place of residence at the start of the migration interval, which was also measured at the province level.

Measures

The dependent variable is migration status. Individuals are defined as migrants if their province of residence at the time of the census differs from their province of residence at the start of the migration interval, five years prior. This approach captures inter-province moves of significant duration (i.e., 2.5 years on average if migration rates are inter-annually stable), while excluding moves that are of shorter duration and distance (e.g., temporary or intra-metropolitan moves); international moves are also excluded by default (see limitations section). I further differentiate between migrants to urban and rural areas, and in some analyses also differentiate between urban and rural places of origins. Provinces are classified as urban and rural according to population density, using a country-specific relative measure. Provinces with population densities in the top third of all province-year observations for a given country are classified as urban and all other provinces are classified as rural. This country-specific approach is appropriate since large regional differences in urbanization make the use of absolute thresholds difficult (i.e., some countries would have zero urban provinces). It is important to note, however, that this approach still differs considerably from the definitions of urban and rural used by countries' statistical agencies.

The focal predictor variables are temperature and precipitation variability. These measures are operationalized as anomalies, measured at the province level during the five-year migration interval. Anomalies capture the deviation of temperature and precipitation during a given period from the long-term mean in a location (in this case, at the province scale), standardized over the historical standard deviation (i.e., they can be interpreted as z-scores). The historical means and standard deviations are calculated from the full 1961-2020 climate history used in the analysis.[11] Anomalies are a preferred measure of climate exposures in the population-environment literature since they capture locally meaningful deviations from normal, should be uncorrelated with baseline climate, and empirically have been stronger predictors of demographic outcomes than unstandardized measures of temperature and precipitation (Gray & Wise 2016; Thiede et al. 2022).[12] Parts of the analysis require the use of categories that distinguish between populations that are exposed and non-exposed to temperature and precipitation shocks. In these cases, individuals are defined as being affected by temperature and precipitation shocks if they were respectively exposed to temperatures and precipitation levels more than one standard deviation above or below average during the migration interval.[13]

---

[11] The historical means and standard deviations are calculated for all consecutive 60-month periods in the climate history (e.g., running means and standard deviations).

[12] The ability for anomalies to capture locally meaningful deviations from normal is particularly important for analyses of spatially extensive datasets, in which the absolute thresholds that define above- or below-normal temperatures and precipitation are likely to vary. Alternatives, such as the number of days with temperatures above or below a specific threshold, may provide additional information in some contexts but lack relevance in others (e.g., where 90˚ F temperatures do not occur, but 80˚ F temperatures have meaningful impacts).

[13] For reference, and to assess potential non-linearities, I also fit a regression model that uses such categorical climate variables as focal predictors. Consistent with a reviewer comment, these supplemental analyses also include a model that uses the absolute temperature and precipitation anomalies as focal predictors. All supplemental analyses are reported in the appendix.

As described below, all analyses account for individuals' age (in years), sex, and primary school attainment, and the urban (rural) status of their province of residence (at migration interval baseline). Statistical profiles of climate-affected migrants and comparison populations also include measures of household size and household head sex (i.e., residence in a female-headed household). Supplemental analyses among populations with requisite data describe individuals' marital status, labor force status, disability status, and membership in indigenous groups.

Methods

The first set of analyses measure the effects of climate variability on migration to urban areas, also drawing comparisons with migration to rural areas. These estimates are generated by fitting multinomial logistic regression models of migration status, differentiating between migrants to urban and rural destinations (i.e., a three-category outcome with non-migrants as the reference group). Migration is modeled as a function of climate exposures (defined above), controlling for individuals' age, sex, primary school attainment, and rural (urban) status of baseline province of residence. The models also include sample fixed effects, which account for systematic differences between each of the samples (i.e., censuses and inter-censal surveys) from which the data are drawn. In practice, census fixed effects help to control for potential spatial and temporal confounders, including flexibly controlling for time trends within countries and accounting for common between-country differences.[14] Standard errors are adjusted for clustering within provinces, which is the level at which the focal predictor variables are measured.

The analyses begin with a model that measures overall climate effects, across the entire sample (Model 1). The second set of analyses evaluate whether and how climate effects on migration to urban (and rural) areas vary by individuals' age, sex, educational attainment, and urban (rural) status of their province of residence. The goal is to identify the sub-populations whose migration behavior is particularly sensitive (or insensitive) to climate variability and, relatedly, the groups that are most likely to experience climate-induced changes in migration to urban areas. Differences are assessed by fitting multinomial regression models that include interactions between the temperature and precipitation terms and, respectively, individuals' age, sex, and primary school attainment, and the urban (rural) status of their province of residence (Models 2-5). This part of the analysis is then extended by exploring potential regional heterogeneity in climate effects. Here, three separate models are fit for each of the major world regions included in the data—Africa, Asia, and Latin America and the Caribbean.

The third and final analysis develops a statistical portrait of climate-affected migrants in urban areas and compares their characteristics to reference populations. Specifically, a set of descriptive profiles describe the age, sex, educational attainment, and household size and

[14] A more conservative approach would include province fixed effects and separate controls for global or region-specific time trends (see Mueller et al. (2020) and Thiede et al (2016) as examples using similar data and methods). However, the main models in this study could not be fit when replacing census fixed effects with province fixed effects and a separate time trend (i.e., they did not converge). Alternatively, I note that the current approach should provide more conservative estimates than a model with country fixed effects and a separate time trend, since sample fixed effects more-flexibly account for spatial-temporal confounders.

structure (i.e., sex of household head) of individuals exposed to climate shocks, as defined above. Comparable profiles are produced for climate-affected migrants to rural areas, non-affected migrants to both rural and urban areas, and non-migrants.

Results

Description of sample

The analysis begins by describing key features of the analytic sample (Table 2). Overall, 3.0 percent of individuals in the sample are classified as a migrant using the five-year migration question, with 1.9 percent of individuals moving to urban areas and 1.1 percent moving to rural areas. That is, a sizeable majority (62.7%) of migrants settle in urban destinations. There is considerable variation in the climatic conditions that individuals were exposed to during the migration intervals captured in the data. The average temperature anomaly was 0.321, with a standard deviation of 0.536 and a range of -1.948 to 2.248. Likewise, the average precipitation anomaly was 0.065, with a standard deviation of 0.815 and a range of -2.257 to 2.975. Individuals in the sample were exposed to the extreme conditions—at both the upper and lower ends of the temperature and precipitation distributions—that are expected to disrupt socioeconomic and environmental systems, and to change migration patterns.

Table 2. Description of analytic sample

Variable	Mean	SD	Min	Max
Migrant = urban destination	0.0190	-	0	1
Migrant = rural destination	0.0113	-	0	1
Temperature	0.3210	0.5363	-1.9457	2.2484
Precipitation	0.0654	0.8150	-2.2569	2.9754
Age	33.4	13.1	15	64
Sex = female	0.5014	-	0	1
Education = primary +	0.6935	-	0	1
Residence = urban	0.5350	-	0	1
Year	1992.0	8.5	1965	2012
Sample size		142,947,304		

Notes: see Table 1 for distribution of cases by country. Year is measured at migration interval baseline.

For reference, the demographic characteristics of the sample are also described, focusing on the variables included as controls in the regression model. The average age of individuals in the sample—which was restricted to working-age individuals aged 15 to 64 years—at the migration interval baseline was 33.4 (standard deviation = 13.1). Approximately 50.1 percent of the sample were women, 69.4 percent had a primary education or higher, and 53.5 percent resided in an urban province at the start of the migration interval.

Regression estimates

The next set of analyses aim to measure the effects of temperature and precipitation variability on internal migration to urban and rural areas using regression methods that control for potential confounding factors. This part of the analysis begins by measuring overall effects across the entire sample (Model 1, Table 3). The results yield no evidence of temperature effects on the likelihood of migration to urban destinations, but do show a positive association between precipitation exposures and urban-bound migration (β = 0.267, relative risk ratio (RRR) = 1.306). Each standard-deviation increase (decrease) in precipitation is associated with an approximately 30.6 percent increase (decrease) in the odds of migration to urban areas relative to no migration. To put this result into a more substantively meaningful context, predicted probabilities of migration to urban areas are generated across a range of precipitation exposures while holding all other variables at their means. The predicted probability of urban-bound migration under average precipitation levels is 1.2 percent. The probability of such moves decreases to just 0.7 percent when precipitation is two standard deviations below normal; and conversely would increase to nearly 2.1 percent when precipitation is two standard deviations above normal. Substantively, an implication of these findings is that drought exposures—and the adverse downstream impacts of droughts—reduce migration to urban areas, rather than increasing such moves as commonly assumed. The regression analyses also account for migration to rural destinations. Precipitation exposures have much weaker effects on moves to rural areas, both statistically ($p<0.10$) and substantively (β = 0.077, RRR = 1.080).

Table 3. Multinomial logistic regression models of inter-province migration to urban and rural destinations

	Model 1					
	Urban destination			Rural destination		
Variable	β		SE	β		SE
Temperature	-0.0044		0.1881	-0.1915		0.1367
Precipitation	0.2672	***	0.0671	0.0770	†	0.0415
Age	-0.0549	***	0.0052	-0.0427	***	0.0025
Sex = female	-0.0893	***	0.0218	-0.2190	***	0.0188
Education = primary +	0.5700	***	0.0684	0.2768	***	0.0381
Residence = urban	-0.1073		0.1423	-0.3627	***	0.0822
Sample fixed effects	Yes					
Joint test, all climate	16.09***			7.77*		
Pseudo R^2	0.0693					
Sample size	142,947,304					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001

Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

Given differences in vulnerability to climatic stressors and the use of migration as an adaptation strategy, the relationship between climate anomalies and migration odds may vary systematically across sub-populations. Therefore, an additional series of models that allow climate effects to vary by individuals' age, sex, educational attainment, and baseline residence in an urban or rural community are fit (Tables 4-5). The first of these models tests for differences by age (Model 2, Table 4). The strong precipitation effects on migration to urban areas identified above are not significantly moderated by age. While we did not identify a significant temperature effect on migration to urban areas in the overall model, we find evidence of variation in such effects by age (as indicated by a statistically significant temperature-by-age interaction term). However, further calculations show that the marginal effects of temperature exposures remain non-significant across the entire range of ages in our data. We also find evidence of age-temperature interactions when modeling moves to rural destinations. The marginal effect of temperature remains statistically non-significant for all but the oldest individuals in our sample, and for these individuals the effects are not substantively meaningful. For the example, the marginal effect of temperature (holding all other variables at their means) is just -0.001 for individuals aged 64 years at the start of the migration interval. Age does not significantly moderate precipitation effects on moves to rural destinations, which were only marginally significant in the main model.

The next model tests for differences in climate effects by sex (Model 3, Table 4). The positive association between precipitation exposures and migration to urban areas does not vary significantly between men and women. Both groups experience drought-induced reductions in migration to urban areas. The point estimates of temperature effects for men and women do vary significantly, but these differences lack substantive importance since marginal temperature effects are not statistically or practically meaningful for either group. We observe a similar dynamic for estimated temperature effects on migration to rural areas, where between-sex differences are statistically significant but the marginal climate effects for each group are not. Finally, we find significant differences in precipitation effects on migration to rural areas, which are non-significant among men but significant and positive among women ($\beta = 0.091$, RRR = 1.096). Each standard deviation increase (decrease) in migration is associated with an approximately 9.6 percent increase (decrease) in the odds of moves to rural areas among women.

The next interaction model allows temperature and precipitation effects to vary by individuals' educational attainment (Model 4, Table 5). Precipitation effects among individuals with less than a primary school education are statistically significant and positive ($\beta = 0.118$, RRR = 1.126). Each standard deviation increase (decrease) in precipitation is associated with an appropriately 12.6 percent increase (decrease) in the likelihood of migrating to an urban area. Precipitation effects operate in the same direction among better-educated individuals (with a primary school education or more) but are significantly stronger ($\beta = 0.289$, RRR = 1.335). Among this population, a standard deviation increase (decrease) in precipitation is associated with a 33.5 percent increase (decrease) in the probability of moving to an urban destination. The results also show significant between-group differences in temperature effects on moves to urban areas, but the marginal effects of temperature exposures for both groups are statistically non-significant. There is no evidence of substantively meaningful climate effects, and educational differences therein, on migration to rural destination

Table 4. Multinomial logistic regression models of inter-province migration to urban and rural destinations

	Model 2				Model 3			
	Urban destination		Rural destination		Urban destination		Rural destination	
Variable	β	SE	β	SE	β	SE	β	SE
Temperature	0.1844	0.2266	-0.0408	0.1478	-0.0275	0.1866	-0.2196	0.1377
Precipitation	0.3587 **	0.1186	0.0917	0.0625	0.2566 ***	0.0651	0.0651	0.0416
Temperature × age	-0.0073 *	0.0034	-0.0055 ***	0.0013				
Precipitation × age	-0.0035	0.0033	-0.0005	0.0016				
Temperature × sex = female					0.0480 **	0.0147	0.0618 ***	0.0120
Precipitation × sex = female					0.0223	0.0137	0.0263 *	0.0126
Temperature × education = primary+								
Precipitation × education = primary+								
Temperature × residence = urban								
Precipitation × residence = urban								
Age	-0.0516 ***	0.0049	-0.0411 ***	0.0025	-0.0549 ***	0.0052	-0.0428 ***	0.0025
Sex = female	-0.0890 ***	0.0218	-0.2186 ***	0.0188	-0.1117 ***	0.0247	-0.2394 ***	0.0185
Education = primary +	0.5764 ***	0.0677	0.2807 ***	0.0383	0.5688 ***	0.0683	0.2750 ***	0.0380
Residence = urban	-0.1072	0.1423	-0.3624 ***	0.0821	-0.1072	0.1423	-0.3626 ***	0.0822
Sample fixed effects	Yes				Yes			
Joint test, all climate	9.59**		2.88		15.96***		7.12*	
Joint test, all climate interactions	5.28†		19.62***		12.41**		36.77***	
Pseudo R^2	0.0695				0.0694			
Sample size	142,947,304				142,947,304			

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001

Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

The fourth interaction model accounts for differences in climate effects between residents of rural and urban provinces at migration interval baseline (Model 5, Table 5). As such, this approach allows for the explicit measurement of temperature and precipitation effects on rural-urban, rural-rural, urban-urban, and urban-rural moves. Contrary to common assumptions, we find that precipitation effects on migration to urban areas do not vary between rural and urban places of origin. Substantively, this result means that droughts are likely to reduce both rural-urban and urban-urban migration flows. While the point estimates of climate effects on migration to rural areas do not vary significantly, we note that the marginal effects of precipitation are significant and positive (β = 0.132, RRR = 1.142) among individuals in urban but not rural provinces. The implication is that all but rural-rural migration is influenced by precipitation exposures.

The final component of the main regression analysis explores regional heterogeneity in climate effects (Table 6) by fitting region-specific models for Africa (Model 6), Asia (Model 7) and Latin America and the Caribbean (Model 8). In Africa, temperature is a stronger predictor of migration to urban areas than precipitation, which has a non-significant association with such moves. Exposure to high temperatures in the region is associated with large reductions in migration to urban areas (β = -2.411, RRR = 0.090). Point estimates suggest that a one standard deviation increase in temperatures is associated with a large, 91.0 percent reduction in the likelihood of migration to urban areas. Temperature exposures are also negatively associated with migration to rural areas in Africa. The point estimate on this temperature coefficient is also large in magnitude (β = -1.189, RRR = 0.305) but is less precise ($p<0.10$) and does not meet the standard threshold for statistical significance. In Asia, migration to urban areas is driven by precipitation exposures (β = 0.338, RRR = 1.402). Temperature exposures are only marginally associated with migration to rural areas (β = -0.389, RRR = 0.678, $p<0.10$). Finally, in Latin America and the Caribbean, results show that temperature exposures are significantly and positively associated with migration to urban areas (β = 0.365, RRR = 1.440); while migration to rural areas is positively associated with precipitation (β = 0.113, RRR = 1.119).

Table 5. Multinomial logistic regression models of inter-province migration to urban and rural destinations

	Model 4						Model 5					
	Urban destination			Rural destination			Urban destination			Rural destination		
Variable	β		SE	β		SE	β		SE	β		SE
Temperature	0.2487		0.1763	-0.1514		0.1320	-0.0076		0.2045	-0.1880		0.1461
Precipitation	0.1183	*	0.0558	0.0750	†	0.0448	0.2847	***	0.0764	0.0525		0.0450
Temperature × age												
Precipitation × age												
Temperature × sex = female												
Precipitation × sex = female												
Temperature × education = primary+	-0.3077	***	0.0778	-0.0554		0.0425						
Precipitation × education = primary+	0.1704	***	0.0429	0.0018		0.0366						
Temperature × residence = urban							0.0150		0.1048	-0.0331		0.0636
Precipitation × residence = urban							-0.0489		0.0979	0.0800		0.0610
Age	-0.0550	***	0.0052	-0.0427	***	0.0025	-0.0549	***	0.0052	-0.0427	***	0.0025
Sex = female	-0.0886	***	0.0218	-0.2186	***	0.0188	-0.0894	***	0.0218	-0.2189	***	0.0188
Education = primary +	0.6172	***	0.0627	0.2864	***	0.0364	0.5699	***	0.0684	0.2767	***	0.0383
Residence = urban	-0.1009		0.1413	-0.3620	***	0.0819	-0.1046		0.1401	-0.3598	***	0.0794
Sample fixed effects	Yes						Yes					
Joint test, all climate	5.63†			5.39†			14.20***			4.49		
Joint test, all climate interactions	24.73***			1.83			0.27			2.02		
Pseudo R^2	0.0697						0.0694					
Sample size	142,947,304						142,947,304					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001

Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

Table 6. Multinomial logistic regression models of inter-province migration to urban and rural destinations, by region

	Model 6: Africa						Model 7: Asia						Model 8: Latin America & Caribbean					
	Urban destination			Rural destination			Urban destination			Rural destination			Urban destination			Rural destination		
Variable	β		SE	β		SE	β		SE	β		SE	β		SE	β		SE
Temperature	-2.4110	***	0.6515	-1.1886	†	0.6336	-0.2943		0.2967	-0.3888	†	0.2075	0.3646	**	0.1257	0.0535		0.1237
Precipitation	0.0151		0.2014	-0.0867		0.1302	0.3381	***	0.0826	0.0458		0.0588	-0.0238		0.0468	0.1125	**	0.0428
Controls	Yes						Yes						Yes					
Sample fixed effects	Yes						Yes						Yes					
Joint test, all climate	13.73**			4.05			21.32***			5.84†			8.78*			6.93*		
Pseudo R^2	0.1022						0.0803						0.0396					
Sample size	1,185,550						108,425,343						33,336,411					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001

Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

Finally, several additional sets of analyses are conducted to supplement the main regression estimates (included in the appendix). First, the overall regression model (i.e., Model 1) is re-fit but allowing temperature and precipitation effects to interact (Model A1, Table A1) and allowing for non-linearities in temperature and precipitation effects via the inclusion of quadratic terms (Model A2, Table A1). The results suggest that temperature and precipitation may interact such that the migration-reducing effects of drought are amplified when they occur at the same time as periods of excessive heat; and that the precipitation effects reported in the main analysis may be driven by strong negative effects of precipitation deficits (versus positive effects of excessive precipitation). As another approach for examining non-linearities, a supplemental model using measures of absolute temperature and precipitation anomalies is fit (Model A3, Table A2). In a more restrictive approach than Model A2, this model assumes the effects of positive and negative anomalies will be identical. The results indicate that any deviations from normal temperature and precipitation are associated with reduced migration. This result is in some ways consistent with that of Model A2 but given the stronger assumptions should be interpreted with caution.

The final supplemental model uses a different outcome variable, which differentiates between moves to capital city regions—defined as a province that contains the capital city—and all other destinations (Model A4, Table A3). Interestingly, the results show that temperatures (but not precipitation) are associated with migration to capital cities ($\beta = 0.363$, RRR = 1.438). Precipitation (but not temperatures) is a significant predictor of migration to all other destinations ($\beta = 0.213$, RRR = 1.237). The implication is that the strong precipitation effect detected in the main analyses is likely to be driven by moves to non-capital cities.

Characterizing climate-affected migrations in urban areas

The final step in the main analysis is to generate statistical profiles of climate-affected migrants to urban areas and comparison populations, including climate-affected migrants to rural areas, non-affected migrants to both rural and urban areas, and both climate-affected and non-affected non-migrants (Table 7). The focus is on seven sociodemographic variables that can be measured consistently across the samples in the dataset.

This analysis begins by describing the age profile of climate-affected migrants to urban areas and comparison groups. With a mean age of 25.9 years, climate-affected migrants to urban areas have the youngest average age of all groups—although non-affected migrants to urban areas are only marginally older (mean age = 26.1 years). Migrants to rural areas—both climate-affected (mean age = 27.3 years) and those not affected by climate anomalies (mean age = 27.0 years)—have the next highest ages, while non-migrants are much older on average. Both climate-affected and non-affected non-migrant populations have an average age of 33.6 years.

Table 7. Demographic profiles of climate-affected migrants and reference populations

	Climate-affected urban migrants				Climate-affected rural migrants				Climate-affected non-migrants			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Age	25.94	10.46	15	64	27.34	10.93	15	64	33.62	13.00	15	64
Sex = female	0.4864	-	0	1	0.4625	-	0	1	0.5033	-	0	1
Education = primary +	0.8681	-	0	1	0.7567	-	0	1	0.6947	-	0	1
Baseline residence = urban	0.4437	-	0	1	0.4229	-	0	1	0.4693	-	0	1
Household size	2.6857	2.1254	1	94	2.7608	2.2667	1	92	2.7832	1.4245	1	96
Household head												
Female	0.1663	-	0	1	0.1505	-	0	1	0.1300	-	0	1
Not reported	0.1753	-	0	1	0.0903	-	0	1	0.0422	-	0	1
Sample size	998,391				844,733				50,538,377			

	Non-affected urban migrants				Non-affected rural migrants				Non-affected non-migrants			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Age	26.05	10.44	15	64	27.03	10.64	15	64	33.61	13.14	15	64
Sex = female	0.4748	-	0	1	0.4451	-	0	1	0.5020	-	0	1
Education = primary +	0.8434	-	0	1	0.7726	-	0	1	0.6872	-	0	1
Baseline residence = urban	0.5658	-	0	1	0.4554	-	0	1	0.5593	-	0	1
Household size	2.6911	2.4370	1	94	2.7825	2.6157	1	96	2.7675	1.4994	1	96
Household head												
Female	0.1491	-	0	1	0.1322	-	0	1	0.1279	-	0	1
Not reported	0.1721	-	0	1	0.1053	-	0	1	0.0458	-	0	1
Sample size	1,822,004				1,402,544				87,341,245			

Notes: climate-affected persons are individuals exposed to temperatures and (or) precipitation anomalies greater than |1|.

Migrants of all types, as defined here, are disproportionately male vis-à-vis the non-migrant population. While more than half of the non-migrant groups (both climate-affected and non-affected) are female, between 44.5 and 48.6 percent of each migrant population is female (i.e., fairly large majorities of migrants are males). Of all four groups, it is notable that climate-affected migrants to urban (48.6% female) and rural (46.3% female) destinations have slightly higher representation of women than their non-affected counterparts (47.5% of non-affected urban migrants are female; 44.5% of non-affected rural migrants are female). The implication is that women may be slightly more likely to be represented among climate-affected migrant populations than within migration streams associated with other factors.

The educational attainment of migrants is considered next. Nearly 87 percent (86.8%) of climate-affected urban migrants have a primary education or more, which is much higher than climate-affected rural migrants (75.6%) and non-migrants (69.5%). However, it is only 2.5 percentage points higher than the share of non-affected migrants to urban areas with a primary school education or more (84.3%). Still, the implication is that climate-affected migrants to cities are either not selected or positively selected on education vis-à-vis non-affected urban migrants. Non-affected rural migrants and non-affected non-migrants have lower educational attainment, with primary school completion rates of 77.3 percent and 68.7 percent, respectively.

Climate-affected migrants to urban areas are disproportionally likely to come from rural provinces. Only 44.4 percent of this group originated in an urban province, which is much lower than the 56.6 percent of non-affected migrants to urban areas. Only among climate-affected migrants to rural areas was the share from urban origins lower (42.3%), followed by non-affected rural migrants (45.5%) and climate-affected non-migrants (46.9%). More than 55 percent (55.9%) of non-affected non-migrants lived in urban provinces.

The final two comparisons in this main descriptive analysis focus on household characteristics—household size and female headship. The average household size of climate-affected urban migrants is the lowest of all groups, but within a rounding error of the average for non-affected urban migrants (i.e., both average 2.7). This similarity—and the consistency of average household size among all other groups (around 2.8)—suggests that the slightly smaller household size is characteristic of urban-bound migrants in general rather than climate-affected populations in particular. Finally, I note that the share of individuals living in female-headed households is highest among climate-affected urban migrants (16.6%), followed by climate-affected rural migrants (15.1%), and non-affected urban migrants (14.9%). Approximately 13 percent of individuals in the three other comparison groups live in female-headed households.

These main descriptive profiles are supplemented with additional analyses of other variables that were only available for some of the censuses and surveys used to construct the analytic sample. I include these results in full in Table A3 of the appendix, which presents the descriptive statistics and indicates the number of samples and countries for which valid data were obtained. Here, I highlight four key conclusions. First, climate-affected migrants to urban areas are more likely to be single and never married than non-migrants and migrants to rural areas. However, the share single (33.1%) is comparable to that among non-affected urban migrants

(32.1%). Second, climate-affected migrants in urban areas have a low employment rate (64.1%) compared to all other groups. Similarly affected rural migrants (65.2%) and non-affected migrants in urban areas (66.0%) have the most comparable employment rates, which range between 68.6 percent and 72.8 percent among all other groups. Third, the rate of disability is lowest among climate-affected urban migrants (1.8%), with somewhat higher rates (between 2.2% and 2.4%) among other migrant populations and rates between 2.8 and 3.4 percent among non-migrant populations. Fourth and finally, approximately 8.4 percent of urban-bound climate-affected migrants identify as indigenous. This share is much higher than any other comparison group, among which rates vary between 4.8 and 5.9 percent.

Discussion and conclusion

This study leverages "big microdata" from around the developing world (Ruggles 2014) to measure the effects of climate variability on migration to urban areas, to characterize the population of climate-affected migrants living in urban areas, and to draw comparisons with migration to rural areas. The regression analyses and descriptive statistical profiles support at least four main substantive claims. First, climatic variability is affecting migration to urban areas across the developing world. Overall estimates across the entire 23-country sample show a strong positive association between precipitation exposures and migration to urban areas, with the implication that drought exposures will significantly reduce migration flows to urban areas. Importantly, this result runs contrary to the common assumption that climatic stressors will displace populations to cities—and as such it adds further evidence to the hypothesis that climatic changes may trap vulnerable populations in place. Second, climate variability does not have a significant overall effect on migration to rural areas. Movement between rural provinces, or from urban to rural provinces, is seemingly driven by factors not associated with recent climate exposures.

Third, the results yield limited evidence of heterogeneity in climate effects on migration to urban areas across social and demographic groups. The most substantively important finding is that better-educated individuals are more sensitive to precipitation exposures than less-educated individuals, and as such are less likely to migrate to urban areas after droughts. This dynamic potentially reduces the pool of highly-skilled migrants in urban areas. The results also yield notable heterogeneity in effects across world regions. Fourth and finally, the statistical profile of climate-affected migrant populations in urban areas and comparison groups suggests that climate-exposed urban migrants are largely similar to other streams of urban migrants or, in some respects (i.e., education), may even be positively selected. This finding is notable since such migrants are more likely than other groups to originate from rural provinces, which tend to be disadvantaged. These descriptive results, within the context of the regression estimates, should ease concerns that climatic stressors will displace marginalized populations, with poor chances of adaptation, into cities. Climate-affected migrants in cities are instead remarkably similar to other migrants.

The findings from this study contribute to the scholarly literature on climate-related changes in migration by giving explicit attention to climate-induced changes in migration to urban (and rural) areas, comparing climate effects on rural-urban migration with other types of moves (e.g., urban-urban), testing for social and spatial differences in climate effects using harmonized data and methods, and attempting to describe a discrete population of climate-affected migrants. They also raise important considerations for policymakers and practitioners working in the areas of climate adaptation, social protection, and cognate fields. Here, three important conclusions merit attention. First, climate stressors (in this case, drought) may reduce rather than increase migration to cities. Such evidence should alleviate—or, at least, reduce—concerns that climate change will lead to large population displacements into cities. In fact, this evidence may instead raise the opposite challenge—that cities will be deprived of migrants, who often play a dynamic role in local economies. A second and related finding is that climate-affected migrants appear similar to other streams of migrants to urban areas, and in some respects (i.e., education) may be more positively selected than other groups. The results of this analysis suggest that climate-affected migrants are likely to be relatively well positioned to adapt and integrate, at least in terms of the basic characteristics captured in these census data. Third and finally, there remains a need for nuanced interpretation and continued data collection and analysis. The exploratory analysis of regional variation in climate effects, for example, shows differences in the direction and magnitude of climate effects from region to region. Policymakers and practitioners should therefore be cautious to interpret global evidence through the lens of the particular context they are working in.

With these contributions and conclusions in mind, the study is still characterized by limitations that should be addressed in future research. First, the analysis only captures intra-national moves between provinces that are of sufficient duration to be captured using a five-year lookback period. As such, it does not capture moves within provinces and may miss a substantial share of short-duration moves (e.g., individuals who left their original province of residence within the migration Interval but returned prior to the census). It also excludes international migrants (i.e., individuals who moved into or out of the country of enumeration during the migration interval). The implications of these exclusions are not easily predicted or characterized in general terms. The role of each type of migration in households' adaptation strategies is likely to vary systematically. For example, international migration may serve more of an adaptation function in some contexts, or for some types of households, than others (Riosmena et al. 2018; Sedova & Kalkuhl 2020).

Second, the study relies exclusively on census data. While such data have many strengths for these purposes, they may also be characterized by relevant biases. Specifically, censuses may undercount vulnerable populations (e.g., individuals living in informal urban settlements) who may also be uniquely affected by the impacts of climate variability. Consider a hypothetical example in which economically vulnerable populations in rural areas are displaced to informal settlements in cities, where they are systematically undercounted in a census. In this case, census-based estimates will produce downwardly-biased estimates of climate effects on rural-urban migration. The extent to which such biases occur is an open and very important question, which should be investigated in future studies using alternative data.

Third, the study focuses on the effects of climate variability, as operationalized by five-year temperature and precipitation anomalies. This approach is merited given the geographic heterogeneity within the sample and the relatively long intervals used to measure migration, which necessitates the use of globally relevant measures. However, it may miss effects that more fine-grained, context-specific measures would have detected (e.g., measuring heat exposure as the number of days above a locally relevant absolute temperature threshold). The climate anomalies used here may likewise not fully capture acute shocks (e.g., months with extreme heat or precipitation) and (or) natural disasters (e.g., floods) that are masked by five-year averages or are only weakly correlated with temperature or precipitation (e.g., flood exposures may not be correlated with local rainfall given the topography and hydrology of a given region, Chen et al. 2017).[15] This limitation highlights to need to complement large-scale, regional or global analyses with more geographically limited studies that can uncover critical nuances (albeit with some costs to generalizability).

Fourth and relatedly, the study measures climate exposures in the place of origin. While this approach is consistent with much of the micro-level evidence on this topic to date (Gray & Wise 2016; Mueller et al. 2020), it makes strong assumptions about the characteristics of possible destinations that affected populations consider and, relatedly, does not measure how climatic conditions in possible destinations influence migration decisions. The limited attention to "pull-side" conditions in migration decision-making in this paper, and the climate-migration literature more broadly, represents an important gap that should be addressed using new analytic approaches (see Entwisle et al. 2020 as an example).

Finally, the analysis draws on a spatially extensive dataset, which enhances the generalizability of the estimates but is characterized by at least two limitations. First, the study prioritized the construction of an extensive dataset over one that included more information, which would have been available for a much smaller number of countries. This decision limited the number of variables that could be included as possible controls, moderators, or mediators, restricting the scope of the substantive questions that could be answered. For example, richer panel data that included questions about income, food prices and consumption, and health would allow for tests of hypothesized mechanisms. Of course, such approaches would need to be geographically limited and therefore lack the generalizability of the current estimates. Second, despite the spatial extent of the dataset, the necessary data on migration are still missing for many countries around the world. The availability of requisite census data may reflect countries' resources (e.g., data collection and dissemination capacity), which may be correlated with vulnerability to climate shocks and potentially bias estimates.

---

[15] Even standardized measures of monthly extremes are poorly suited for this analysis given spatial variation in the intra-annual distribution of precipitation and the inability to control for such spatial differences (e.g., via province fixed effects). For example, consider a case in which one defines negative precipitation shocks as when precipitation is more than one standard deviation below the monthly mean. If location A typically experiences little-to-no rainfall for 3 months of the year, it will not be "at risk" of negative precipitation shocks those months (i.e., because precipitation cannot fall below 0). If location B typically experiences non-zero rainfall all 12 months of the year, it will therefore by systematically more at risk of negative precipitation shocks.

Despite these limitations, the current study provides new insights into the effects of climate variability on migration to urban and rural areas across the developing world. Within the context of the large literature on climate and migration, the limited attention to urban- and rural-specific migration streams has been surprising. These findings, and the limitations identified above, should spur new research on this topic, which is essential to develop appropriate policy interventions as global climate change continues to unfold.

References

Adger, W. N. (2006). Vulnerability. Global Environmental Change, 16(3), 268-281.

Barrios, S., Bertinelli, L., & Strobl, E. (2006). Climatic change and rural–urban migration: The case of sub-Saharan Africa. Journal of Urban Economics, 60(3), 357-371.

Bernard, A., & Bell, M. (2018). Educational selectivity of internal migrants: A global assessment. Demographic Research, 39, 835-854.

Bernard, A., Bell, M., & Charles-Edwards, E. (2014). Improved measures for the cross-national comparison of age profiles of internal migration. Population Studies, 68(2), 179-195.

Bertoli, S., Moraga, J. F. H., & Ortega, F. (2013). Crossing the border: Self-selection, earnings and individual migration decisions. Journal of Development Economics, 101, 75-91.

Black, R., Bennett, S. R., Thomas, S. M., & Beddington, J. R. (2011a). Migration as adaptation. Nature, 478(7370), 447-449.

Black, R., Adger, W. N., Arnell, N. W., Dercon, S., Geddes, A., & Thomas, D. (2011b). The effect of environmental change on human migration. Global environmental change, 21, S3-S11.

Blom, S., Ortiz-Bobea, A., & Hoddinott, J. (2022). Heat exposure and child nutrition: Evidence from West Africa. Journal of Environmental Economics and Management, 115, 102698.

Boas, I., Farbotko, C., Adams, H., Sterly, H., Bush, S., Van der Geest, K., ... & Hulme, M. (2019). Climate migration myths. Nature Climate Change, 9(12), 901-903.

Bocquier, P., Menashe-Oren, A., & Nie, W. (2023). Migration's contribution to the urban transition: Direct census estimates from Africa and Asia. Demographic Research, 48, 681-732

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. Science, 353(6304), aad9837.

Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., ... & Schraven, B. (2019). Human migration in the era of climate change. Review of Environmental Economics and Policy.

Chen, J., & Mueller, V. (2018). Coastal climate change, soil salinity and human migration in Bangladesh. Nature Climate Change, 8(11), 981-985.

Chen, J. J., Mueller, V., Jia, Y., & Tseng, S. K. H. (2017). Validating migration responses to flooding using satellite and vital registration data. American Economic Review, 107(5), 441-45.

Crimmins, E. M., Kim, J. K., Alley, D. E., Karlamangla, A., & Seeman, T. (2007). Hispanic paradox in biological risk profiles. American Journal of Public Health, 97(7), 1305-1310.

De Brauw, A., Mueller, V., & Lee, H. L. (2014). The role of rural–urban migration in the structural transformation of Sub-Saharan Africa. World Development, 63, 33-42.

De Haas, H. (2007). Turning the tide? Why development will not stop migration. Development and Change, 38(5), 819-841.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66-95.

DeWaard, J., Hunter, L. M., Mathews, M. C., Quiñones, E. J., Riosmena, F., & Simon, D. H. (2022). Operationalizing and empirically identifying populations trapped in place by climate and environmental stressors in Mexico. Regional Environmental Change, 22(1), 1-11.

Ellis, F. (1998). Household strategies and rural livelihood diversification. The Journal of Development Studies, 35(1), 1-38.

Entwisle, B., Verdery, A., & Williams, N. (2020). Climate change and migration: New insights from a dynamic model of out-migration and return migration. American Journal of Sociology, 125(6), 1469-1512.

Fink, G., Günther, I., & Hill, K. (2014). Slum residence and child health in developing countries. Demography, 51(4), 1175-1197.

Fussell, E. (2010). The cumulative causation of international migration in Latin America. The Annals of the American Academy of Political and Social Science, 630(1), 162-177.

Fussell, E., Hunter, L. M., & Gray, C. L. (2014). Measuring the environmental dimensions of human migration: The demographer's toolkit. Global Environmental Change, 28, 182-191.

Garip, F. (2012). Discovering diverse mechanisms of migration: The Mexico–US Stream 1970–2000. Population and Development Review, 38(3), 393-433.

Garschagen, M., & Romero-Lankao, P. (2015). Exploring the relationships between urbanization trends and climate change vulnerability. Climatic Change, 133(1), 37-52.

Gemenne, F. (2011). Why the numbers don't add up: A review of estimates and predictions of people displaced by environmental changes. Global Environmental Change, 21, S41-S49.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. Journal of Labor Economics, 32(1), 1-26.

Gray, C., & Wise, E. (2016). Country-specific effects of climate variability on human migration. Climatic Change, 135(3), 555-568.

Hauer, M. E., Fussell, E., Mueller, V., Burkett, M., Call, M., Abel, K., ... & Wrathall, D. (2020). Sea-level rise and human migration. Nature Reviews Earth & Environment, 1(1), 28-39.

Henderson, J. V., Storeygard, A., & Deichmann, U. (2017). Has climate change driven urbanization in Africa?. Journal of Development Economics, 124, 60-82.

Hoffmann, R., Dimitrova, A., Muttarak, R., Crespo Cuaresma, J., & Peisker, J. (2020). A meta-analysis of country-level studies on environmental change and migration. Nature Climate Change, 10(10), 904-912.

Hunter, L. M. (2005). Migration and environmental hazards. Population and Environment, 26(4), 273-302.

Hunter, L. M., Luna, J. K., & Norton, R. M. (2015). The environmental dimensions of migration. Annual Review of Sociology, 41, 377.

Hunter, L. M., & Simon, D. H. (2022). Time to mainstream the environment into migration theory?. International Migration Review, 01979183221074343.

Kaczan, D. J., & Orgill-Meyer, J. (2020). The impact of climate change on migration: a synthesis of recent empirical insights. Climatic Change, 158(3), 281-300.

Kakinuma, K., Puma, M. J., Hirabayashi, Y., Tanoue, M., Baptista, E. A., & Kanae, S. (2020). Flood-induced population displacements in the world. Environmental Research Letters, 15(12), 124029.

Klomp, J., & Valckx, K. (2014). Natural disasters and economic growth: A meta-analysis. Global Environmental Change, 26, 183-195.

Koubi, V. (2019). Climate change and conflict. Annual Review of Political Science, 22, 343-360.

Kubik, Z., & Maurel, M. (2016). Weather shocks, agricultural production and migration: Evidence from Tanzania. The Journal of Development Studies, 52(5), 665-680.

Liu, Y., & Shen, J. (2014). Jobs or amenities? Location choices of interprovincial skilled migrants in China, 2000–2005. Population, Space and Place, 20(7), 592-605.

Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. Nature Climate Change, 1(1), 42-45.

Lu, Y. (2010). Rural-urban migration and health: Evidence from longitudinal data in Indonesia. Social Science & Medicine, 70(3), 412-419.

Massey, D. S., Arango, J., Hugo, G., Kouaouci, A., Pellegrino, A., & Taylor, J. E. (1993). Theories of international migration: A review and appraisal. Population and development review, 431-466.

Menashe-Oren, A., & Bocquier, P. (2021). Urbanization is no longer driven by migration in low- and middle-income countries (1985–2015). Population and Development Review, 47(3), 639-663.

McLeman, R., & Gemenne, F. (2018). Environmental migration research: Evolution and current state of the science. Routledge Handbook of Environmental Displacement and Migration, 3-16.

Minnesota Population Center. (2020). Integrated Public Use Microdata Series, International: Version 7.3 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D020.V7.3

Mueller, V., & Gray, C. (2018). Heat and adult health in China. Population and Environment, 40(1), 1-26.

Mueller, V., Gray, C., & Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. Nature Climate Change, 4(3), 182-185.

Mueller, V., Gray, C., & Hopping, D. (2020). Climate-Induced migration and unemployment in middle-income Africa. Global Environmental Change, 65, 102183.

Nawrotzki, R. J., DeWaard, J., Bakhtsiyarava, M., & Ha, J. T. (2017). Climate shocks and rural-urban migration in Mexico: exploring nonlinearities and thresholds. Climatic Change, 140(2), 243-258.

Nawrotzki, R. J., Hunter, L. M., Runfola, D. M., & Riosmena, F. (2015). Climate change as a migration driver from rural and urban Mexico. Environmental Research Letters, 10(11), 114023.

Nawrotzki, R. J., Runfola, D. M., Hunter, L. M., & Riosmena, F. (2016). Domestic and international climate migration from rural Mexico. Human Ecology, 44(6), 687-699.

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. Nature Climate Change, 11(4), 306-312.

Østby, G. (2016). Rural–urban migration, inequality and urban social disorder: Evidence from African and Asian cities. Conflict Management and Peace Science, 33(5), 491-515.

Otto, I. M., Reckien, D., Reyer, C. P., Marcus, R., Le Masson, V., Jones, L., ... & Serdeczny, O. (2017). Social vulnerability to climate change: A review of concepts and evidence. Regional environmental change, 17, 1651-1662.

Palinkas, L. A., & Wong, M. (2020). Global climate change and mental health. Current Opinion in Psychology, 32, 12-16.

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. Nature Communications, 6(1), 1-9.

Raymond, C., Matthews, T., & Horton, R. M. (2020). The emergence of heat and humidity too severe for human tolerance. Science Advances, 6(19), eaaw1838.

Rigaud, K. K., De Sherbinin, A., Jones, B., Bergmann, J., Clement, V., Ober, K., ... & Midgley, A. (2018). *Groundswell.* Washington, DC: The World Bank. Available at: https://openknowledge.worldbank.org/handle/10986/29461.

Riosmena, F., Kuhn, R., & Jochem, W. C. (2017). Explaining the immigrant health advantage: Self-selection and protection in health-related factors among five major national-origin immigrant groups in the United States. Demography, 54(1), 175-200.

Riosmena, F., Nawrotzki, R., & Hunter, L. (2018). Climate migration at the height and end of the great Mexican emigration era. Population and Development Review, 44(3), 455.

Ruggles, S. (2014). Big microdata for population research. Demography, 51(1), 287-297.

Sedova, B., & Kalkuhl, M. (2020). Who are the climate migrants and where do they go? Evidence from rural India. World Development, 129, 104848.

Selod, H., & Shilpi, F. (2021). Rural-urban migration in developing countries: Lessons from the literature. Regional Science and Urban Economics, 91, 103713.
The White House (2021). *Report on the impact of climate change on migration*. Washington, DC: The White House. Available at: https://www.whitehouse.gov/wp-content/uploads/2021/10/Report-on-the-Impact-of-Climate-Change-on-Migration.pdf.

Thiede, B., Gray, C., & Mueller, V. (2016). Climate variability and inter-provincial migration in South America, 1970–2011. Global Environmental Change, 41, 228-240.

Thiede, B. C., Randell, H., & Gray, C. (2022). The Childhood Origins of Climate-Induced Mobility and Immobility. Population and Development Review, 48(3), 767-793.

Thiede, B. C., Robinson, A., & Gray, C. (2022). Climatic Variability and Internal Migration in Asia: Evidence from Integrated Census and Survey Microdata. SocArXiv Working Paper. Available at: https://osf.io/preprints/socarxiv/hxv35/.

Thiede, B. C., & Strube, J. (2020). Climate variability and child nutrition: Findings from sub-Saharan Africa. Global Environmental Change, 65, 102192.

Tuholske, C., Caylor, K., Funk, C., Verdin, A., Sweeney, S., Grace, K., ... & Evans, T. (2021). Global urban population exposure to extreme heat. Proceedings of the National Academy of Sciences, 118(41), e2024792118.

Wang, P., Asare, E., Pitzer, V. E., Dubrow, R., & Chen, K. (2022). Associations between long-term drought and diarrhea among children under five in low-and middle-income countries. Nature Communications, 13(1), 1-10.

Weinreb, A., Stecklov, G., & Arslan, A. (2020). Effects of changes in rainfall and temperature on age-and sex-specific patterns of rural-urban migration in sub-Saharan Africa. Population and Environment, 42(2), 219-254.

Appendix

Table A1. Multinomial logistic regression models of inter-province migration to urban and rural destinations

	Model A1						Model A2					
	Urban destination			Rural destination			Urban destination			Rural destination		
Variable	β		SE	β		SE	β		SE	β		SE
Temperature	-0.0104		0.1876	-0.1878		0.1354	0.2267		0.1626	-0.1640		0.1242
Temperature^2							-0.3709	**	0.1116	-0.0678		0.0777
Precipitation	0.2036	**	0.0587	0.0450		0.0414	0.2759	***	0.0660	0.0736	†	0.0414
Precipitation^2							-0.1544	**	0.0489	0.0075		0.0408
Temperature × precipitation	0.1469	*	0.0675	0.0937	*	0.0469						
Controls												
Sample fixed effects												
Joint test, temperature	-			-			35.33***			2.13		
Joint test, precipitation	-			-			13.80**			3.16		
Joint test, all climate	16.67***			10.18**			39.57***			8.70†		
Pseudo R^2	0.0695						0.0704					
Sample size	142,947,304						142,974,304					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001
Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval.
Sample fixed effects indicate the census or survey that the observation was drawn from.

Table A2. Multinomial logistic regression models of inter-province migration to urban and rural destinations

	Model A3					
	Urban destination			Rural destination		
Variable	β		SE	β		SE
Temperature |z|	-0.2116	*	0.1067	0.0097		0.0752
Precipitation |z|	-0.4923	*	0.2192	-0.3393	*	0.1700
Controls	Yes					
Sample fixed effects	Yes					
Joint test, all climate	11.65**			5.64†		
Pseudo R^2	0.0687					
Sample size	142,947,304					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001

Notes: standard errors clustered at the province level. Temperature and precipitation are measured as absolute anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

Table A3. Multinomial logistic regression model of inter-province migration to capital cities and other destinations

	Model A4					
	Capital city destination			Other destination		
Variable	β		SE	β		SE
Temperature	0.3633	**	0.1177	-0.1288		0.1647
Precipitation	0.0027		0.0469	0.2131	***	0.0558
Controls	Yes					
Sample fixed effects	Yes					
Joint test, all climate	9.56**			17.01***		
Pseudo R^2	0.0737					
Sample size	142,947,304					

†p<0.10, *p<0.05, **p<0.01, ***p<0 .001
Notes: standard errors clustered at the province level. Temperature and precipitation are measured as anomalies during the 5-year migration interval. Sample fixed effects indicate the census or survey that the observation was drawn from.

Table A4. Demographic profiles of climate-affected migrants and reference populations, select variables among valid samples

				Climate-affected urban migrants				Climate-affected rural migrants				Climate-affected non-migrants			
Variable	Sample size	Number of countries	Number of samples	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Marital status	136,234,085	22	73												
Single, never married				0.3307	-	0	1	0.2446	-	0	1	0.1497	-	0	1
Married or in union				0.5804	-	0	1	0.6464	-	0	1	0.7589	-	0	1
Other				0.0889	-	0	1	0.1090	-	0	1	0.0914	-	0	1
Labor force status	109,313,748	19	68												
Employed				0.6409				0.6518				0.6940			
Unemployed				0.0547	-	0	1	0.0550	-	0	1	0.0512	-	0	1
Inactive				0.3002	-	0	1	0.2903	-	0	1	0.2526	-	0	1
Unknown				0.0042	-	0	1	0.0029	-	0	1	0.0022	-	0	1
Disability status = disabled	92,074,535	7	35	0.0175	-	0	1	0.0236	-	0	1	0.0283	-	0	1
Indigenous = yes	51,950,472	10	20	0.0835	-	0	1	0.0572	-	0	1	0.0587	-	0	1

				Non-affected urban migrants				Non-affected rural migrants				Non-affected non-migrants			
Variable	Sample size	Number of countries	Number of samples	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Marital status	136,234,085	22	73												
Single, never married				0.3206	-	0	1	0.2445	-	0	1	0.1495	-	0	1
Married or in union				0.6128	-	0	1	0.6754	-	0	1	0.7600	-	0	1
Other				0.0666	-	0	1	0.0801	-	0	1	0.0905	-	0	1
Labor force status	109,313,748	19	68												
Employed				0.6602				0.6860				0.7275			
Unemployed				0.0516	-	0	1	0.0393	-	0	1	0.0342	-	0	1
Inactive				0.2864	-	0	1	0.2727	-	0	1	0.2372	-	0	1
Unknown				0.0018	-	0	1	0.0020	-	0	1	0.0011	-	0	1
Disability status = disabled	92,074,535	7	35	0.0218	-	0	1	0.0240	-	0	1	0.0342	-	0	1
Indigenous = yes	51,950,472	10	20	0.0484	-	0	1	0.0563	-	0	1	0.0516	-	0	1

Notes: climate-affected persons are individuals exposed to temperatures and (or) precipitation anomalies greater than |1|. Labor force statistics exclude individuals outside of universe of valid samples.