Climatic Variability and Internal Migration in Asia: Evidence from Integrated Census and Survey Microdata

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Abstract
The potential effects of climate change on human migration have received widespread attention, driven in part by concerns about possible large-scale population displacements. Recent studies demonstrate that climate-migration linkages are often more complex than commonly assumed, and climatic variability may increase, decrease, or have null effects on migration. However, the use of non-comparable analytic strategies across studies makes it difficult to disentangle substantive variation in climate effects from methodological artifacts. We address this gap by using census and survey micro-data from six Asian countries (n=54,987,838), which today are collectively home to nearly one-quarter of the world's population, to measure climate effects on interprovincial migration. We examine climate effects overall and among sub-populations defined by age, sex, education, and country of residence. We also evaluate whether climate effects differ according to the distance and type of migration. We find non-linear precipitation effects across the sample, with exposure to precipitation deficits leading to substantively large reductions in out-migration. Both precipitation and temperature effects vary among focal sub-populations. Precipitation deficits reduce internal migration to both adjacent and non-adjacent provinces and, among the subset of samples with data on the reasons for migration, also reduce the probability of work-related moves. Temperature anomalies reduce work-, education-, and family-related moves. Our findings provide evidence of climate-related reductions in migration (i.e., trapped populations) and suggest these effects are driven largely by economic factors. Our analysis complements similar uses of harmonized data and methods in studies from South America and sub-Saharan Africa, which collectively reveal significant heterogeneity in demographic responses to climate variability around the world.

Keywords
Climate, migration, Asia, displacement, labor migration

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Introduction

The prospect of large-scale population displacements due to climate change has motivated a growing body of demographic research and drawn the interests—and, in many cases, concerns—of policymakers and the public. Research on this topic is increasingly sophisticated (Fussell et al. 2014; Gemenne & McLeman 2018) and reveals significant associations between climate variability and human migration patterns across a range of contexts (Cattaneo et al. 2019; Hoffmann et al. 2020; Kazan & Orgill-Meyer 2020). However, the nature of these effects is much more nuanced and complex than commonly assumed or portrayed in popular accounts. Importantly, though, the empirical record remains characterized by important limitations. The use of non-representative survey data has limited the generalizability of findings, and cross-study differences in key measures and methods have made it difficult to draw rigorous comparisons across analyses and contexts. As a result, it is often unclear whether inconsistencies in the strength or direction of estimated climate effects on migration reflect substantive processes, methodological artifacts, or some combination of both.

A limited number of studies have addressed these issues by harmonizing nationally representative microdata from multiple countries and applying consistent methods.[1] These studies have been able to measure overall climate effects on migration and test for between-group and cross-national variation in these effects (Gray & Wise 2016; Mueller et al. 2020; Thiede at al. 2018). However, such approaches have not been applied outside of sub-Saharan Africa and South America to our knowledge. We extend this body of evidence by compiling and analyzing integrated census and intercensal survey data to examine climate-migration links in six Asian countries—China, Indonesia, Malaysia, Nepal, the Philippines, and Vietnam—over more than three decades.

These countries represent a useful set of contexts in which to understand the demographic impacts of climate change. They are demographically important: as of 2022, they were home to approximately 1.95 billion people, or about one-quarter of the world's total population (World Bank 2022b). They also face varying degrees and types of vulnerability to environmental change (Adger 1999; Lobell et al. 2008; Piao et al. 2010; Smit & Cai 1996; Yusuf 2009) and have experienced large but heterogeneous economic and demographic transformations over the decades we study. Attention to these contexts is also merited since there has been limited research on climate and migration in the countries we examine, with the exception of studies using household survey data from Indonesia and China (Bohra-Mishra et al. 2014; Gray et al. 2020; Thiede & Gray 2017). This paper will therefore fill a broader evidence gap and allow us to draw comparisons with similar big data analyses of climate-migration links across multiple countries in South America (Thiede et al. 2016) and sub-Saharan Africa (Mueller et al. 2022).

With this motivation in mind, our analyses measure the effects of exposure to temperature and precipitation variability on internal migration across Asia.[2] In addition to examining overall climate effects, we evaluate whether impacts vary among select sub-populations and for different types of migration, as defined by the distance of moves and reasons for moving. Our attention to variation in effects both across sub-populations and according to the type of migration provides

[1] A number of other studies have examined climate-migration links across multiple countries using aggregated data (Weinreb et al. 2020). While notable, we view these findings as distinct from the analyses of microdata that our study compares to given limitations to inference inherent in ecological analyses.

[2] Consistent with the demographic literature on climate change impacts, we measure responses to climatic variability: the deviation in temperatures and precipitation during relatively short, multi-year periods from long-term means. While climatic variability is distinct from climate change, responses to the former provide the best analogue for developing expectations about the impacts of the latter.

unique insights into the links between climate variability and migration in the Asian context. It also allows us to evaluate critical but largely untested assumptions about the nature of migratory responses to climatic variability.

The paper proceeds proceed as follows. In the next section, we describe the theoretical framework and existing empirical evidence that inform the study. The third section outlines our analytic strategy. We then present our results. Finally, we conclude by discussing the broader conceptual and practical implications of our findings. To preview the main results, we find evidence of non-linear precipitation effects on interprovincial migration, with exposure to precipitation deficits leading to significant reductions in the probability of migration. Tests for heterogeneity within our sample reveal significant differences in both temperature and precipitation effects by age, sex, educational attainment, and country of residence. We do not find evidence of substantively large differences in climate effects according to the distance of migration. Finally, our analysis of a subset of samples with information on the reasons for migration reveals that work-related moves are most sensitive to climate exposures, but education- and family-related moves are also affected by temperature anomalies. Together, these results provide additional evidence that exposure to adverse climatic conditions can reduce migration and suggest that such effects are largely—but perhaps not exclusively—driven by economic mechanisms.

Climate variability and migration

Temperature and precipitation variability often lead to significant changes in human and natural systems. The potential impacts of climate variability, and its second-order social and economic effects, on human migration have received extensive attention among social scientists, policymakers, and the public (Cattaneo et al. 2019; Hoffmann et al. 2020; Kazan & Orgill-Meyer 2020). Although much attention has been placed on the potential for climate variability to displace populations from affected areas (e.g., "climate refugees"), such environmental changes may also decrease migration (e.g., producing "trapped populations") (Black et al. 2011; DeWaard et al. 2022). The presence and direction of such climate effects reflect the relative influence of three mechanisms, which respectively capture the effects of environmental change on economic conditions, infrastructure and housing, and residential preferences.

First, climatic variability has significant effects on economic conditions (Dell et al. 2014). Temperature and precipitation are important determinants of agricultural production. In Asia, for example, increases in both minimum temperatures and delays in monsoon onset have been implicated in declining rice production (Peng et al. 2004; Naylor et al. 2007). Likewise, global data reveal that temperature and precipitation variability can explain nearly 30 percent of the inter-annual variance in yields of major crops around the world (Lobell & Field 2007). These and similar climate impacts on agricultural production may have significant downstream effects on households' economic welfare via changes in income and food prices. Climatic variability may also affect economic welfare through non-agricultural channels, including through impacts on health, productivity, and energy consumption (Auffhammer & Mansur 2014; Burke et al. 2015; Graf Zivin & Neidell 2014; Mueller & Gray 2018; Zhang et al. 2018). Such climate-induced changes in households' economic status may influence the incentives for migration. Households may respond to adverse impacts by sending one or more members to less-affected locations, where they can generate income to offset the shock (i.e., geographic diversification). In other cases, however, the impacts of climatic stressors may leave the household without the resources needed to fund moves, thereby reducing the likelihood of out-migration.

Second, periods of anomalous environmental conditions (e.g., above-average annual precipitation) may also be characterized by the occurrence of natural disasters (e.g., floods, landslides, cyclones). To the extent that such events inflict costly damage and disrupt livelihoods and economies, they may affect migration via similar economic channels to those described above. For example, both Call et al. (2017) and Chen et al. (2017) find that flood exposures in Bangladesh reduce the likelihood of out-migration, which may reflect reductions in the economic resources needed to fund moves. However, such natural disasters may also cause destruction and directly displace populations. For example, Gray and Mueller (2012) show that local flood exposures actually have a displacing effect in Bangladesh, at least among women and the poor. Additionally, Bohra-Mishra et al. (2014) find that exposure to landslides increases the probability of permanent whole-household migration in Indonesia, and Berlemann and Tran (2021) find that tropical storms increase temporary migration in Vietnam.

Third, climatic variability may affect migration via matches (or mismatches) with individuals' residential preferences (i.e., the degree of residential satisfaction) (Hunter et al. 2015). Local environmental conditions represent one of multiple factors that influence decisions about where to live. All else equal, environmental changes may affect migration decisions as individuals and households move (or remain in place) to find (or remain in) a location with environmental conditions that meet their preferences (Albouy et al. 2016). While such changes in migration may be more sensitive to long-term changes in environmental conditions (i.e., climate changes) than shorter-term climatic variability (the focus of this paper), the latter may influence migration via changes in perceptions about the future (McLeman 2018). Importantly, however, there has been very little recent empirical research on this topic (to our knowledge).

While there are strong theoretical reasons to expect climate effects on migration, it is difficult to develop directional hypotheses since many of the proposed pathways can potentially increase or decrease migration, and because the mechanisms may not operate in a consistent manner. For example, higher temperatures may have adverse economic effects that reduce the resources needed to fund migration (decreasing incentives for migration) but lead to mismatches vis-à-vis preferences for moderate temperatures (increasing incentives for migration). Given such theoretical ambiguity, we treat the direction of climate effects as an empirical question. Consistent with these expectations, previous studies have documented many statistically and substantively significant associations between climatic variability and migration but revealed considerable variation in the direction of these effects. For example, Bohra-Mishra et al. (2017) found that higher temperatures increase out-migration in the Philippines, especially from rural and agriculturally-dependent provinces. In contrast, Quiñones and colleagues (2021) found that exposures to drought reduce migration in Vietnam, with the largest declines among poor households. Similar variation in the nature of climate effects abound in this literature, as documented by recent meta-analyses and syntheses (Cattaneo et al. 2019; Hoffmann et al. 2020; Kazan & Orgill-Meyer 2020).

Heterogeneity in the direction of climate effects is expected given the indeterminant theoretical predictions outlined above. However, it is often difficult to determine whether differences in results across studies reflect substantive processes (e.g., variation in the mechanism(s) that is driving observed changes), methodological artifacts (e.g., variation in data and methods), or some combination of both. Two studies have worked to address this issue by pooling census microdata from across multiple countries in South America (Thiede et al. 2016) and Africa (Mueller et al. 2020), respectively, and applying consistent statistical methods to measure climate effects. Both studies detect significant climate effects on migration, but also

reveal significant differences in the strength and direction of these effects among sub-populations (e.g., by sex, education) and countries in their samples. Given the use of harmonized data and methods, the results clearly demonstrate heterogeneity in the substantive processes linking climate and migration within South America and Africa.

While multiple studies have examined climate-migration links in contexts within Asia, no multi-national micro-level studies comparable to Thiede et al. (2016) or Mueller et al. (2020) have been conducted in the region. This evidence gap is notable given the demographic importance of the region and widespread evidence that environmental changes there are affecting migration and other demographic outcomes (Berlemann & Tran 2021; Bohra-Mishra et al. 2014; Gray et al. 2020; Koubi et al. 2016; McMahon & Gray 2021; Randell et al. 2021; Thiede & Gray 2017; Williams et al. 2020). The current study addresses this gap.

Objectives

Our overall goal is to understand whether and how exposures to temperature and precipitation variability—and the socioeconomic impacts implicit in those exposures—affect internal migration across a diverse set of countries in Asia. Toward this end, we address three specific aims. First, we measure overall climate effects on interprovincial migration across all six countries in our sample, testing for non-linearities in and interactions between temperature and precipitation effects. Second, we examine potential differences in climate effects on migration by age, sex, educational attainment, and country of residence. Each of these factors is expected to be correlated with individuals' vulnerability to environmental change and their propensity to alter migration behavior as a response. Third and finally, we evaluate whether climate exposures have differential effects according to the distance and cause of migration. We first differentiate between moves to adjacent and non-adjacent provinces and then—for a subset of three countries with detailed migration data—differentiate between work-, family-, and education-related moves.

Analytic strategy

Data

We compile demographic records from censuses and inter-censal surveys implemented in China (1990, 2000), Indonesia (1985, 1990, 1995, 2000, 2005, 2010), Malaysia (1991, 2000), Nepal (2001, 2011), the Philippines (2000, 2010), and Vietnam (1989, 1999, 2009) (Tables S1-2 of the Online Supplementary Information). We extract these data using the Integrated Public Use Microdata Series-International (IPUMS-I) database (Minnesota Population Center 2018), which provides random samples from the full census and survey datasets collected by national statistical agencies.[3] The analytic sample includes all available census and intercensal survey data (henceforth "census data" for brevity) from IPUMS-I that meet the following criteria: (1) were collected in Asia; (2) include harmonized geographic identifiers for place of residence at the time of the census and five years prior at the first subnational level (henceforth "province" for brevity); and (3) are from a country with at least two rounds of data that met the first two criteria.

In addition to information on province of current residence and residence five years prior, the records contain information on age, sex, and educational attainment. We restrict the sample to individuals aged 15 to 49 years at the start of the migration interval (i.e., five years prior to the census) to capture the ages of peak migration (Bernard et al. 2014a, 2014b). We exclude individuals who reported living abroad, in select semi-autonomous zones, or in an unknown

[3] We apply person-level weights provided by IPUMS-I throughout all analyses to account for differences in the sampling fraction.

location at the start of the migration interval.[4,5] By default, our sample also excludes individuals who moved out of the countries in our sample during the migration interval. Our final analytic sample includes 54,987,838 individuals and is representative of a population of approximately 1.9 billion individuals. These data are summarized in Tables S1 and S2 of the Online Supplementary Information; the countries and sub-national administrative units used in the analysis are mapped in Figure 1.

(Figure 1)

Measures

Our primary outcome is interprovincial migration, which we measure by comparing individuals' place of residence at the time of the census to their location five years prior (i.e., using a five-year migration interval). We use IPUMS-I's harmonized identifiers of baseline and current province of residence to account for province boundary changes over time, and we classify individuals as migrants if these two places of residences do not match. Our sample yields an overall interprovincial migration rate of approximately 2.9 percent.

In addition to the main binary measure of migration, we also model distance- and cause-specific migration. The former is operationalized as a three-category variable that distinguishes between non-migrants, migrants who moved between adjacent provinces, and migrants who moved between non-adjacent provinces. The rate of migration to adjacent provinces is approximately 1.3 percent, with an additional 1.7 percent of the target population classified as migrants to non-adjacent provinces.[6]

We measure cause-specific migration among the three countries in our sample which had two or more censuses collect sufficiently detailed information on the reasons for migration (China, Indonesia, and Nepal; n = 15,295,018; Table S1). This information allows us to categorize migrants as moving for work-, education-, and family-related reasons; we also include a residual "other" category (the process for harmonizing these categories is described in detail within the Online Supplementary Information). Work-related migration includes moves associated with an individual's employment; education-related migration includes moves due to schooling or higher education; and family-related migration includes moves associated with another family member (e.g., for marriage, following a spouse who migrated for work). Using the restricted analytic sample for which this outcome is available, the overall interprovincial migration rate is approximately 2.7 percent, with 1.8 percent of individuals classified as work-related migrants, 0.6 percent as family-related migrants, 0.2 percent as education-related migrants, and 0.1 percent as individuals who moved for other reasons.

Our main predictors of interest are temperature and precipitation exposures. We link our demographic data to monthly temperature and precipitation estimates produced by the Climatic Research Unit (CRU) at the University of East Anglia (Harris et al. 2014). 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 population-environment research (Call et al. 2019; Gray & Wise 2016; Mueller et al. 2020; Thiede et al. 2016). Using time-stable shapefiles

[4] We also exclude individuals in select semi-autonomous zones (e.g., Tibet, Hong Kong) since the data lack sufficient geographic identifiers to measure climate exposures and because of unique barriers to migration to and from many such regions.

[5] As a result of these restrictions, we dropped 327,390 cases (448 for China, 44,391 for Indonesia, 27,545 for Malaysia, 32,045 for Nepal, 191,511 for Philippines, and 31,450 for Vietnam).

[6] The difference between the sum of these values and the overall migration rate is due to rounding error.

provided by IPUMS, we extract these climate data as province-level spatial means and construct a series of climate exposure variables.

We operationalize exposures as temperature and precipitation anomalies measured over each five-year migration interval in an individual's baseline province of residence. Anomalies are constructed by taking the difference between the mean temperature or total precipitation during the exposure period and the long-term (defined as 1981-2020) mean for all other consecutive 60-month periods in a province, standardized over the long-term standard deviation for that location (i.e., z-scores). 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. 2021). By construction, the mean temperature and precipitation exposures in our sample are near zero (-0.111 for temperature, 0.031 for precipitation), but range from -1.816 to 1.889 for temperature and -2.506 to 2.135 for precipitation.

Methods

We measure climate effects on migration by fitting a series of logistic regression models in which the odds of migration are a function of climate exposures (as defined above), controls (age, sex, and education), and province and decade fixed effects. Province fixed effects are measured using individuals' residence at the start of the migration interval and account for province-level characteristics so long as they are time invariant. Decade fixed effects are measured using the year of the census and capture all decade-on-decade changes that are common across the sample. Standard errors are adjusted for clustering within the province of residence at baseline, which is the level at which our focal exposure variables are measured.

We begin with a model of overall climate effects across the sample. Here, we fit a set of models that respectively include linear climate terms, test for temperature-by-precipitation interactions, and test for non-linearities in climate effects by including quadratic terms for temperature and precipitation. Using our preferred specification—determined by the strength of the joint test of climate terms in each model—we then proceed to test for heterogeneity by age, sex, and educational attainment. We do so by fitting models that interact each factor, one at a time, with our climate exposure terms. We then conduct an exploratory analysis of spatial variation in climate effects by fitting country-specific binary logistic regression models. Finally, we evaluate whether climate effects vary across different types of migration by fitting a pair of multinomial regression models of migration by distance and by cause. These multinomial models include the same set of controls and fixed effects as the binary models, and operationalize climate exposures using the preferred specification as described above.

Results

Overall estimates

The first set of models measure the overall effects of climate exposures on interprovincial migration (Table 1). We begin by assuming a monotonic association between climate exposures and migration, including only linear temperature and precipitation terms (Model 1). The results show no significant association between temperature and interprovincial migration but indicate that precipitation exposures are positively associated with such moves ($\beta = 0.198$, odds ratio (OR) = 1.218). Each standard-deviation increase in precipitation is associated with an approximately 21.8 percent increase in the odds of migration, with comparable reductions during periods with

precipitation deficits. Droughts—and their corresponding social and economic impacts—seemingly reduce individuals' ability and (or) propensity to engage in interprovincial migration. Such migration-suppressing effects run contrary to popular narratives about environment-induced displacement but are consistent with many recent findings from around the world (DeWaard et al. 2022; Mueller et al. 2020; Nawrotzki et al. 2018; Thiede et al. 2022). The effect sizes implied by the coefficient estimates are substantively meaningful by most standards: for instance, the results imply a change in migration odds exceeding 40 percent in response to a precipitation anomaly of two standard deviations, which is well within the range observed in our data.

(Table 1)

The next two models account for potential complexities in climate effects by respectively testing for interactions between temperature and precipitation (Model 2) and for nonlinearities in each (Model 3). We find no evidence of statistically meaningful interactions between temperature and precipitation exposures. However, estimates from Model 3 reveal statistically significant nonlinearities in precipitation effects. To interpret these results, we generate predicted probabilities of interprovincial migration across a plausible range of precipitation exposure values (i.e., -2 to 2), holding all other variables at their means (Figure 2). We find that migration declines steeply during periods with precipitation deficits, but generally changes less—although in more complex ways—in response to periods of above-average precipitation. For example, a reduction in precipitation from average (z = 0) to two standard deviations below average (z = -2) reduces the probability of migration from 0.020 to 0.008. This decline occurs in a relatively linear manner between the two points. We do not find comparable changes in migration probabilities associated with exposure to above-average precipitation, and in the upper half of the precipitation distribution other non-linearities are apparent. For example, the predicted probability of migration increases from 0.020 to 0.022 as precipitation increases from average to one standard deviation above average, but then declines to 0.018 when precipitation is two standard deviations above average. In general, these results show that exposures to precipitation deficits—which are typically associated with adverse agricultural and economic conditions—are more meaningful predictors of migration behavior than exposures to above-average precipitation.

(Figure 2)

Social and spatial heterogeneity

The next analyses test for differences in climate effects across demographic groups and between countries, which we expect given variation in vulnerability to climatic exposures and migration systems across our large sample. Since the inclusion of quadratic climate terms increases the explanatory power of the climate variables (Model 3), we consider that to be our preferred specification and proceed with additional analyses accordingly. The first interaction model tests for age-based differences in climate effects (Model 4, Table 1). Precipitation effects do not vary significantly by age (as indicated by the results of the joint test of interaction terms). However, we find that temperature effects do and are significantly weaker among older individuals in the sample. We illustrate these differences by plotting the predicted probability of migration among individuals aged 15 and 49 years at the start of the migration interval, who are respectively at the lower and upper bounds of our sample's age range (left panel, Figure 3). The predicted probability of migration among individuals aged 15 at the beginning of the migration interval is 0.072 during average temperatures, 0.031 during temperatures two standard deviations below normal, and 0.032

during temperatures two standard deviations above normal. The respective probabilities are 0.007, 0.010, and 0.012 for individuals aged 49 at the start of the migration interval.[7]

Next, we test for differences by sex (Model 5, Table 1). The results reveal significant differences in both temperature and precipitation effects between men and women. The predicted probability of migration among men is 0.024 during spells of average precipitation, 0.012 when precipitation is two standard deviations below normal, and 0.025 when precipitation is two standard deviations above normal. The respective probabilities are 0.028, 0.014, and 0.031 for women (center panel, Figure 3). Although the between-sex difference in temperature effects is statistically significant, the joint effects of temperature on migration are not statistically significant among either sub-population.[8]

(Figure 3)

The third interaction model allows for differences in climate effects by educational attainment (Model 6, Table 1). The magnitude of temperature and precipitation effects are both statistically different between individuals with and without a primary school education. Substantively, however, the differences are a matter of degree rather than kind. The predicted probability of migration among individuals with less than a primary school education is 0.021 during periods of average precipitation, 0.006 when precipitation is two standard deviations below normal, and 0.012 when precipitation is two standard deviations above normal. The respective probabilities are 0.033, 0.014, and 0.031 for individuals with a primary school education or more (right panel, Figure 3). Consistent with the analysis of between-sex differences, we detect significant between-group differences in temperature effects but find that the joint effects of temperature exposures on migration are not statistically significant for either group.[9]

The final analysis of heterogenous effects focuses on spatial variation. We do so by fitting a series of country-specific binary logistic regression models (Models 7-13). To summarize the results, we generate predicted probabilities of migration across a range of temperature and precipitation values, while holding all other variables at their means. We report these probabilities, as well as the results of joint tests on our focal climate variables, in Table 2 (regression coefficients are provided in Table S3 of the Online Supplementary Information). In contrast to the overall model, temperature is a significant predictor of migration in two of the countries in our sample. In Indonesia, exposures to both abnormally high and abnormally low temperatures are associated with increased interprovincial migration. For example, the predicted probability of migration increases from 0.020 to 0.044 as temperatures increase from average to two standard deviations above average and is 0.045 when temperatures fall to two standard deviations below average. In contrast, anomalous temperatures (both high and low) in Vietnam are associated with reductions in migration. The predicted probability of interprovincial migration drops from approximately 0.040 when temperatures are at average to near zero when temperatures are two standard deviations from average (in either direction).

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[7] Temperature anomalies of two standard deviations from average fall outside of our data's range. We therefore highlight additional estimates that fall within range: The predicted probability of migration for individuals aged 15 at the start of the migration interval during a period with temperatures one standard deviation below average is 0.061 and the predicted probability is 0.058 when temperatures are one standard deviation above average. For individuals aged 49 at the start of the migration interval, the respective probabilities are 0.008 and 0.007.

[8] The test of the joint effects for temperature in the results for Model 5 (Table 1) apply to the male population. The results of the test for joint temperature effects among the female population are χ^2=1.49, p=0.476.

[9] The test of the joint effects for temperature in the results for Model 6 (Table 1) apply to the population of individuals with less than a primary school education. The results of the test for joint temperature effects among the population with a primary school education or greater are χ^2=2.12, p=0.346.

(Table 2)

Consistent with the main model, precipitation is a significant predictor of migration in three countries: China, Malaysia, and Vietnam. In China, precipitation is positively associated with migration. The predicted probability of migration is approximately 0.015 when precipitation is at average levels but decreases during droughts and increases during period of above average rainfall. For example, when precipitation is two standard deviations below average, the predicted probability of migration is 0.011, but it is 0.037 when precipitation is two standard deviations above average. Precipitation effects are more complex in Malaysia and Vietnam. In Malaysia, precipitation anomalies in both directions are associated with reductions in migration. As precipitation decreases from average to two standard deviations below average, migration probabilities fall from 0.048 to 0.016; and they decrease (relative to average) to 0.024 when precipitation is two standard deviations above average. In Vietnam, exposure to above average precipitation increases migration, with predicted probabilities increasing from 0.040 to 0.083 as precipitation increases from average to two standard deviations above average. Exposures to below-average precipitation do not have symmetrical effects, with predicted probabilities of 0.038 and 0.044 during exposures of one and two standard deviations below average, respectively.

Migration by distance

The effects of climatic variability on migration may not only vary across demographic groups and countries, but also by the type of migration. We first examine whether climate exposures have differential effects on the odds of short- and long-distance moves, as respectively measured by migration between adjacent and non-adjacent provinces (Model 13, Table 3). We again proceed with the preferred specification that includes quadratic temperature and precipitation terms, as described above.

Precipitation exposures are significantly associated with moves to both adjacent and non-adjacent provinces, though there are modest differences in the direction of these effects across the distribution of precipitation exposures. We again interpret the substantive meaning of these non-linear effects by generating the predicted probability of each outcome across a range of precipitation exposures, while holding the value of other variables at their means (Figure 4). The relationship between precipitation exposures and migration to adjacent provinces (Panel a) is consistent with the model of our binary migration outcome. Exposures to precipitation deficits are associated with relatively steep and linear declines in the probability of migration (compared to migration probabilities under normal conditions), while exposures to above-average precipitation are associated with weaker, non-linear changes in migration. For example, the predicted probability of migration to adjacent provinces is 0.004 for average levels of precipitation and 0.001 during precipitation deficits of two standard deviations. However, the predicted probability of migration increases (from average) to 0.005 when precipitation is one standard deviation above average before declining slightly to 0.004 when precipitation is two standard deviations above average. The relationship between precipitation exposures and migration to non-adjacent provinces is generally weaker and more linear than for migration to adjacent provinces. For example, the predicted probability of migration to non-adjacent provinces is 0.011 during periods of average precipitation, 0.006 during precipitation deficits of two standard deviations, and 0.010 when precipitation is two standard deviations above average. Temperature is not a significant predictor of interprovincial migration, and this is true for moves to both adjacent and non-adjacent provinces.

(Table 3)

(Figure 4)

Migration by cause

Finally, we extend our analysis by disaggregating migration according to the reported reason for moving. We differentiate between work-, education-, and family-related moves (as well as a residual "other cause" category) and fit a multinomial logistic regression model using the preferred specification described above (Model 14, Table 4). Recall that this analysis is restricted to the three countries (six censuses) that collected sufficiently detailed information on the reasons for migration.[10]

(Table 4)

The results show differential effects of climate exposures across types of migration. Consistent with widespread assumptions about the economic mechanisms linking climate exposures to migration, we find that work-related moves (i.e., labor migration) are most sensitive to environmental change. Both temperature and precipitation exposures are significant predictors of work-related migration, with the likelihood of such moves decreasing after periods of high temperatures and low precipitation, respectively. To interpret these non-linear relationships, we generate predicted probabilities of work-related moves across a range of precipitation and temperature levels while holding all other variables at their means (provided in Figures S1-S4 in the Online Supplementary Information).

Precipitation exposures are negatively associated with work-related migration. For example, a shift in precipitation from average to two standard deviations below average is associated with a reduction in the predicted probability of a work-related move from 0.013 to 0.006. Above-average precipitation is associated with increases in migration odds (e.g., 0.036 when precipitation z = 2). The relationship between temperature and work-related migration follows an inverted-U pattern, with both above- and below-average temperatures associated with reductions in migration. The predicted probability of work-related migration is 0.012 during average temperature exposures but declines to nearly zero when temperatures are two standard deviations below or above normal.[11] Assuming extreme temperatures and low precipitation are associated with poor economic conditions (e.g., due to reductions in agricultural output), these patterns are consistent with a dynamic in which adverse environmental conditions reduce migration.

Education- and family-related moves are also significantly associated with temperature variability but, contrary to the overall model, are not affected by precipitation exposures. The odds of both types of migration tend to decrease as temperatures deviate from normal, regardless of the direction of that deviation. The pattern of these effects largely mirrors the observed temperature effects on work-related moves (i.e., an inverted-U shape).[12] However, we note that the absolute probabilities of these forms of migration vary considerably and, in the case of education-related moves, are quite low.

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[10] To facilitate comparison with the other analyses, we also fit regression models of the binary migration outcome and the migration-by-distance outcome using this restricted analytic sample. We use the preferred specifications based on the overall model with the full analytic sample (i.e., Model 3, Table 1), which includes quadratic temperature and precipitation terms. The results are reported in Tables S4 and S5 within the Online Supplementary Information.

[11] We again note that temperature anomalies of two are outside the range of our data. We therefore also report two within-range results. The predicted probability of work-related migration is 0.003 when temperatures are one standard deviation below normal and 0.002 when temperatures are one standard deviation above normal.

[12] We find no association between climate exposures and all other forms of migration, the residual category, which is not unexpected given its small size and undefined nature.

Together, these results underline the salience of economic pathways between climate exposures and migration—as evidenced by the strong effects on labor migration—but show that other forms of migration are affected as well. Importantly, the consistency in the direction of temperature effects across labor-, education- and family-related moves suggests all three types of migration may be driven by a common set of mechanisms and (or) may be jointly determined (e.g., family-related moves are contingent upon labor migration decisions).

Discussion and conclusion

This paper uses a "big data" approach to measure the effects of climate exposures on internal migration across six Asian countries, which today are home to nearly one-quarter of the world's population. In addition to measuring overall effects across our large target population, we test for variation in climate impacts according to the demographic and geographic characteristics of exposed populations, as well as the distance of and reasons for migration. Our results provide novel evidence of climate effects on migration in Asia, including regions which have received relatively little attention in the climate-migration literature to date. Importantly, our results also help assess the validity of common assumptions about the direction of climate effects on migration, the populations that are most at risk, and the types of migration that are most sensitive to environmental change.

The results point to four overall conclusions. First, adverse environmental conditions—anomalously low precipitation or high temperatures—tend to reduce interprovincial migration across our target population and do so in a substantively meaningful way. For example, precipitation deficits of two standard deviations or more are associated with a halving of migration odds. Our results provide additional support for the expectation that climate exposures may suppress out-migration—a dynamic that some scholars have referred to as producing trapped populations (Black et al. 2011; DeWaard et al. 2020; Riosmena et al. 2018). The implications of such climate-related immobility are unknown. On the one hand, migration may help households adapt to the effects of climate shocks, leaving immobile populations least able to cope and therefore most at risk (Black et al. 2011). On the other hand, migration may involve significant costs, and reductions in migration may increase households' available resources and ability to adapt in situ (Bardsley & Hugo 2010).

Second, climate exposures have qualitatively similar effects on short- and long-distance interprovincial migration, as measured by moves to adjacent and non-adjacent provinces. The similarity in climate effects between short- and long-distance moves is in some respects unexpected given assumed differences in the costs of each type of migration. However, adjacency may be a poor proxy for distance and cost, it or may simply capture less meaningful differences than other potential comparisons (e.g., internal versus international).

Third, climatic variability has the strongest effects on labor migration, but also has non-trivial impacts on education- and family-related moves. The climate effects on labor migration provide support for the common assumption that most climate-related migration is driven by economic motives. However, the results demonstrate that such impacts are not strictly limited to labor migration. For example, the economic impacts of adverse climatic conditions may reduce the household resources needed to invest in education and (or) influence decisions about labor-education tradeoffs (Shah & Steinberg 2017). Likewise, climate-induced changes in labor migration may have second-order effects on the mobility of family members, whose movement may be tied to the (potential) labor migrant (i.e., family-related moves) (Bohra-Mishra et al. 2014).

Fourth, we find significant variation in climate effects across demographic groups and countries. While not all these differences are substantively meaningful, they collectively highlight the importance of accounting for heterogeneity—especially among spatially and temporally extensive samples as we use here. These results also raise questions about the mechanisms that explain these differences, which is an important task for future studies.

Our findings contribute to ongoing academic and policy debates about how climatic variability—and longer-term climatic changes—will influence human migration around the world. In our view, the results from this study are particularly important given the large population that our data allow us to target, and our use of harmonized data and methods to produce comparable measures of climate effects across and within our sample. Importantly, however, our study and its limitations also raise a number of important issues for future research to address. First, our analysis is limited to interprovincial migration as measured using a five-year migration interval. Individuals who moved within provinces and (or) for relatively short periods of time within the migration interval are therefore treated as non-migrants. Likewise, individuals who moved internationally during the migration interval are necessarily excluded from the data. The impacts of climate exposures on these unobserved types of moves may differ from what we observed here. In general, we expect short-distance and -duration migration to be less costly than the interprovincial moves modeled in our analyses, but also less effective at mitigating risks via geographic diversification. We expect the opposite of international moves (i.e., more costly but also more effective at geographic diversification).[13] The net effect of these omissions on our estimates is therefore difficult to predict, but merits additional attention with appropriate data.

Additionally, while our big data approach has many advantages for generalizability and comparability of groups within the target population, the census data we pool to construct our sample have non-trivial limitations. For one, we necessarily use cross-sectional data: there are not comparable panel data from many countries that could be harmonized in the manner necessary for the type of analysis we conduct here. Although our empirical strategy accounts for many potential confounders, panel data would allow for approaches that could further reduce concerns about omitted variable bias. Additionally, censuses tend to focus data collection on core demographic outcomes and provide less information on social and economic characteristics. The nature of these data therefore limits the controls that can be included in the model and leaves our analysis of heterogeneous effects necessarily coarse. Other salient axes of inequality may occur along characteristics that are not included in our data and (or) differ among groups within our sample.

In addition to these specific limitations, our findings raise at least three general issues that merit further attention in future research. First, more research on the implications of climate-induced immobility is needed. Our results add further evidence that climate exposures can reduce migration, but to our knowledge there has been little study of how such immobile populations fare. Future studies should investigate whether such reductions in migration represent an inability to engage in adaptive migration (and are thus a source of vulnerability) or reflect effective in situ adaptations (which may be facilitated by a reduction in migration). It is essential that such evidence is collected and effectively communicated to policymakers and practitioners, among whom narratives emphasizing climate-induced displacement remain common.

Second, our study emphasizes the need to examine the links between climatic variability and migration across the economic development spectrum, not only in the world's poorest

[13] Our analysis of migration to adjacent and non-adjacent provinces provides some insight into potential differences in climate effects on short- versus long-distance moves. However, adjacency is only a proxy for distance and international migration involves unique costs above and beyond geographic distance.

countries. We detect significant climate effects on migration across a diverse set of countries, from Vietnam (income per capita: $3,694) to Malaysia (income per capita: $11,371) (using the most recent data from 2021) (World Bank 2022a). Along these lines, future research should continue to expand the diversity of contexts in which climate-migration links are studied.

Finally, despite the limitations noted above, the big data approach we use here—and that is facilitated by projects such as IPUMS-I—provides exciting opportunities for future research in the population-environment field. The spatial and temporal variation inherent in such data are necessary to detect many of the environmental effects of interest. Continued investments in and use of such data can therefore advance the field and provide the rigorous evidence needed to understand and address the ongoing climate crisis. Our findings provide a useful foundation from which future research can address these and other gaps in the climate-migration literature, and thereby contribute to both our understanding of the social costs of climate change and the determinants of migration in a dynamic world.

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Tables

Table 1. Binary logistic regression models of migration

	Model 1			Model 2			Model 3			Model 4			Model 5			Model 6		
	β		(SE)	β		(SE)	β		(SE)	β		(SE)	β		(SE)	β		(SE)
Climate																		
Temperature	-0.005		0.100	-0.007		0.097	-0.047		0.088	0.475		0.294	-0.091		0.089	0.094		0.108
Temperature^2							-0.114		0.097	-0.534		0.367	-0.115		0.098	-0.146		0.093
Precipitation	0.198	**	0.065	0.201	**	0.064	0.199	**	0.065	-0.055		0.191	0.188	**	0.067	0.157	*	0.067
Precipitation^2							-0.125	**	0.047	0.107		0.215	-0.168	**	0.054	-0.237	**	0.077
Temperature × precipitation				0.025		0.086												
Climate-by-group interactions																		
Age × temperature										-0.032	†	0.019						
Age × temperature^2										0.018		0.023						
Age × precipitation										0.021	**	0.008						
Age × precipitation^2										-0.016		0.014						
Age^2 × temperature										0.000		0.000						
Age^2 × temperature^2										0.000		0.000						
Age^2 x precipitation										0.000	**	0.000						
Age^2 x preciptiation^2										0.000		0.000						
Sex = female × temperature													0.094	*	0.037			
Sex = female × temperature^2													-0.003		0.029			
Sex = female × precipitation													0.022		0.025			
Sex = female × precipitation^2													0.092	*	0.037			
Primary school = yes × temperature																-0.162	*	0.069
Primary school = yes × temperature^2																0.036		0.038
Primary school = yes × precipitation																0.047	*	0.048
Primary school = yes × precipitation^2																0.124		0.050
Controls																		
Age	-0.099	**	0.018	-0.099	**	0.018	-0.100	**	0.018	-0.102	**	0.023	-0.100	**	0.018	-0.099	**	0.018
Age^2	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000
Sex = female	-0.152	**	0.030	-0.152	**	0.030	-0.152	**	0.031	-0.151	**	0.031	-0.205	**	0.041	-0.152	**	0.031
Primary school = yes	0.561	**	0.061	0.560	**	0.061	0.560	**	0.061	0.571	**	0.060	0.556	**	0.061	0.423	**	0.076
Decade fixed effects	Yes			Yes			Yes			Yes			Yes			Yes		
Province fixed effects	Yes			Yes			Yes			Yes			Yes			Yes		
Pseudo R^2	0.0926			0.0926			0.0931			0.0936			0.0933			0.0932		
Joint test, temperature interactions	-			-			-			10.30**			8.74*			8.25*		
Joint test, precipitation interactions	-			-			-			0.29			9.55**			7.39*		
Joint test, all climate interactions	-			-			-			10.86*			17.66**			10.26*		
Joint test, temperature	-			-			1.86			9.18**			2.79			2.76		
Joint test, precipitation	-			-			15.69**			6.84*			15.47**			12.17**		
Joint test, all climate variables	9.32**			10.14*			16.38**			11.54*			16.49**			12.45*		

†p<0.10, *p<0.05, **p<0.01

Note: Standard errors clustered on birth province.

Table 2. Predicted probabilities of migration derived from country-specific binary logistic regression models (Models 7-12)

	Temperature anomaly					Precipitation anomaly							
Country	-2	-1	0	1	2	-2	-1	0	1	2	Joint test, temperature	Joint test, precipitation	Joint test, all climate variables
China	0.004	0.012	0.014	0.007	0.001	0.008	0.011	0.015	0.023	0.037	0.41	10.29**	20.33**
Indonesia	0.045	0.025	0.020	0.025	0.044	0.013	0.018	0.021	0.019	0.015	12.05**	3.67	15.41**
Malaysia	0.530	0.102	0.048	0.089	0.453	0.016	0.035	0.048	0.042	0.024	3.06	7.32*	14.14**
Nepal	0.005	0.010	0.014	0.017	0.016	0.013	0.014	0.015	0.017	0.020	0.31	4.39	9.34†
Philippines	0.073	0.036	0.028	0.033	0.061	0.028	0.029	0.028	0.027	0.026	2.27	0.97	5.88
Vietnam	0.000	0.004	0.040	0.002	0.000	0.044	0.038	0.040	0.052	0.083	12.76**	20.15**	33.38**

†p<0.10, *p<0.05, **p<0.01

Note: Regression coefficients are provided in Table S3 of the Online Supplementary Information.

Table 3. Multinomial logistic regression models of migration, by distance

	Model 13					
	Adjacent			Non-adjacent		
	β		(SE)	β		(SE)
Climate						
Temperature	-0.015		0.082	-0.058		0.130
Temperature^2	-0.058		0.132	-0.146		0.103
Precipitation	0.289	*	0.119	0.142	**	0.044
Precipitation^2	-0.184	**	0.053	-0.089		0.069
Controls						
Age	-0.097	**	0.023	-0.101	**	0.019
Sex = female	-0.135	**	0.034	-0.166	**	0.037
Primary school = yes	0.447	**	0.083	0.642	**	0.071
Decade fixed effects			Yes			
Province fixed effects			Yes			
Pseudo R^2			0.1076			
Joint test, temperature		0.38			2.10	
Joint test, precipitation		14.73**			10.83**	
Joint test, all climate variables		17.00**			11.55*	

†p<0.10, *p<0.05, **p<0.01

Note: Standard errors clustered on birth province.

Table 4. Multinomial logistic regression models of migration, by type

	Model 14											
	Work			Education			Family			Other		
	β		(SE)	β		(SE)	β		(SE)	β		(SE)
Climate												
Temperature	-0.252		(0.291)	0.160		(0.174)	-0.046		(0.103)	0.033		(0.242)
Temperature^2	-1.799	**	(0.519)	-0.744	*	(0.321)	-0.682	**	(0.245)	-0.652		(0.599)
Precipitation	0.475	**	(0.135)	-0.009		(0.074)	0.089		(0.062)	0.149	†	(0.084)
Precipitation^2	0.036		(0.180)	0.025		(0.082)	0.117		(0.096)	0.103		(0.125)
Controls												
Age	-0.076	**	(0.025)	-0.795	**	(0.035)	-0.108	**	(0.019)	-0.035		(0.037)
Sex = female	-0.584	**	(0.065)	-0.643	**	(0.045)	1.492	**	(0.104)	-0.393	**	(0.078)
Primary school = yes	0.541	**	(0.107)	4.530	**	(0.250)	0.243	**	(0.095)	0.048		(0.087)
Decade fixed effects	Yes											
Province fixed effects	Yes											
Pseudo R^2	0.1320											
Joint test, temperature	12.04**			10.95**			8.10*			2.55		
Joint test, precipitation	15.48**			0.23			2.77			3.66		
Joint test, all climate variables	36.93**			23.90**			8.73†			5.07		

†p<0.10, *p<0.05, **p<0.01

Note: Standard errors clustered on birth province. Analytic sample restricted to China 1990, 2000; Indonesia 1995, 2005; Nepal 2001, 2011.

Figures

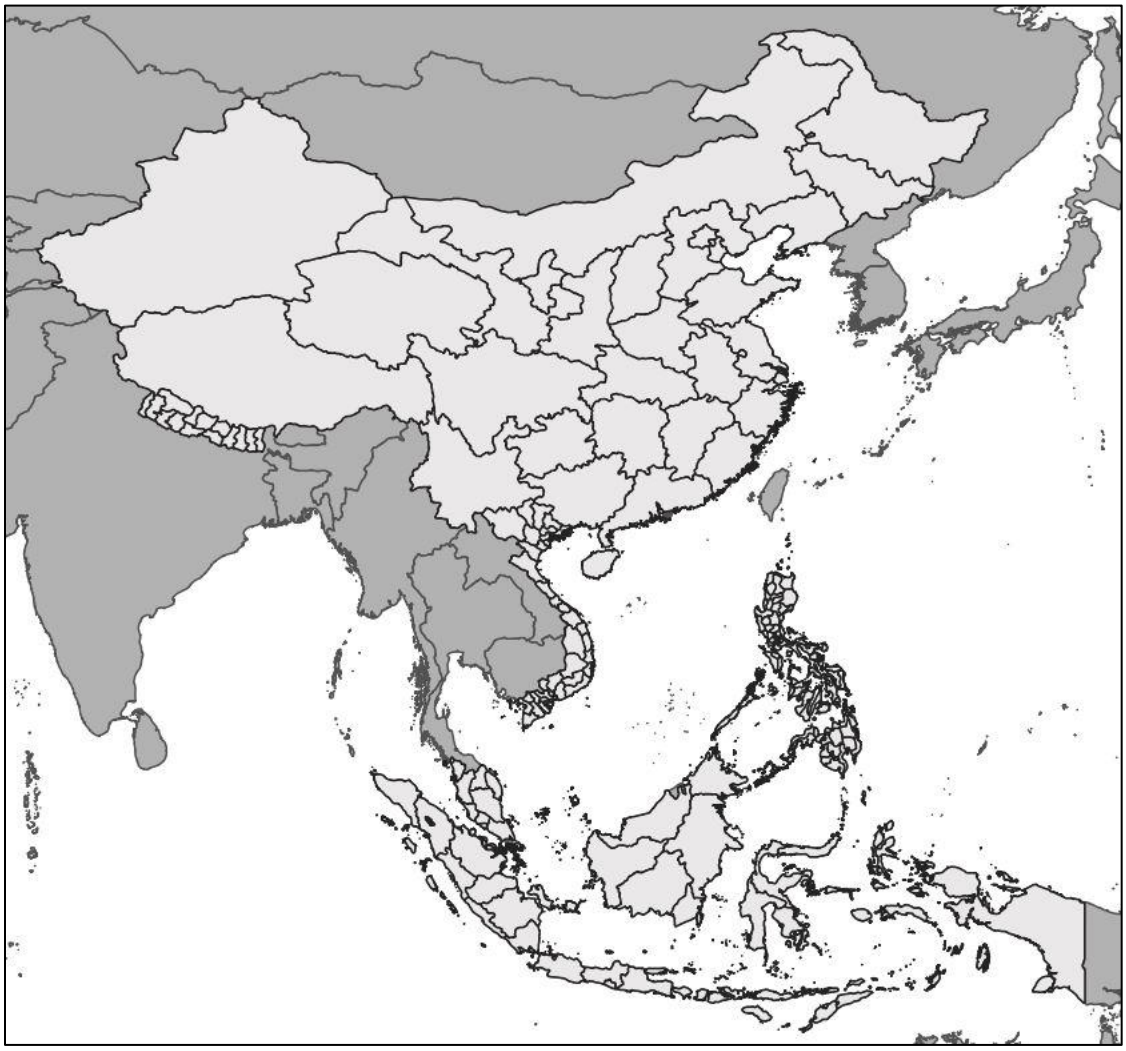

Figure 1 Countries and administrative units included in the analytic sample

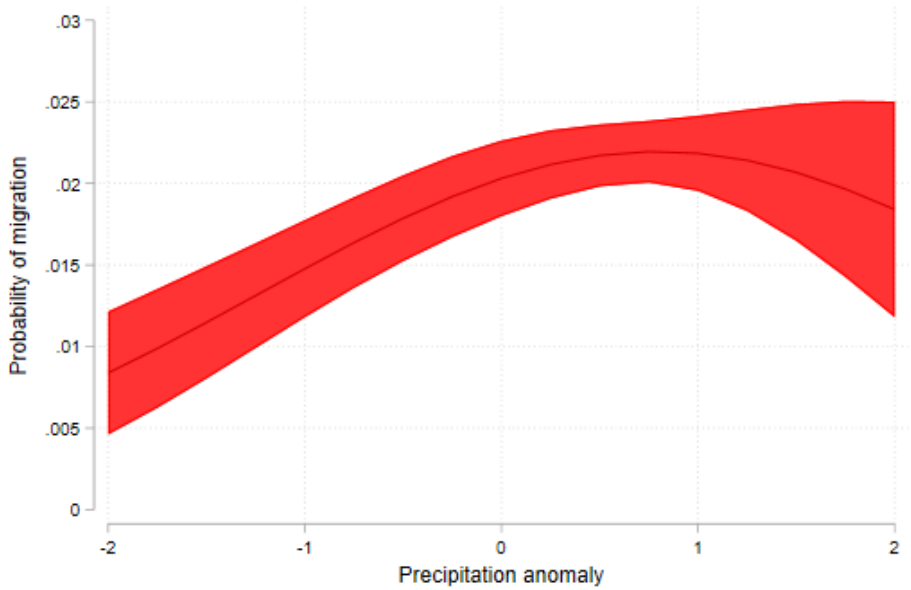

Figure 2 Predicted probability of migration, by precipitation exposure

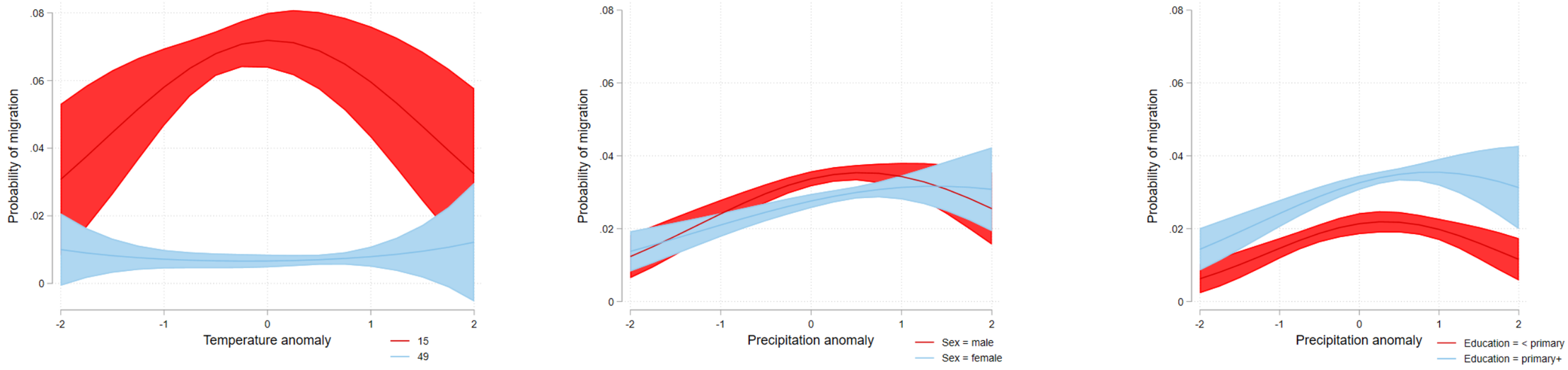

Figure 3 Predicted probability of migration by age (left), sex (middle), and education (right), by climate exposures

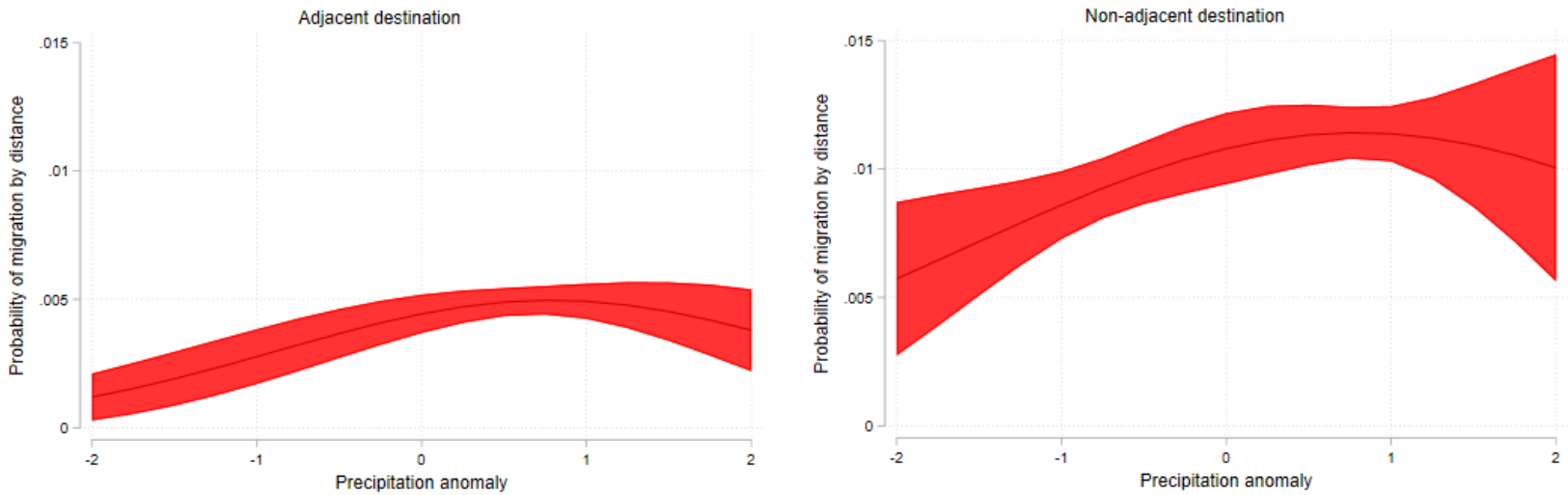

Figure 4 Predicted probability of migration to adjacent provinces (left) and non-adjacent provinces (right), by precipitation exposure