Climate and Migration in the United States

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Abstract

We study whether households engage in climate-related migration in the United States, a country where most of the population does not regularly experience natural disasters or work in climate-exposed industries. With comprehensive, long-run data from both the Census and from tax filings, we document that warm temperatures induce net out-migration, while cooler temperatures do not. By comparing estimates from models using different lengths of temporal variation, we further show that migration is a medium-run response to high temperatures: decadal and longer shifts in weather have larger annualized impacts than year-over-year changes. Finally, comparisons across county types suggest amenity value is an important mechanism behind climate-related migration in the United States.

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1 Introduction

Throughout human history, migration has played a pivotal role in shaping societies. The United States in particular has been defined by waves of migration, beginning with the arrival and westward expansion of European settlers and continuing through the Dust Bowl and Great Migration. In this paper, we consider a possible driver of the next wave of American migration: climate change. Specifically, we ask two questions essential to understanding the future path of climate-driven migration in the United States. First, to what degree has historical variation in temperature led to internal migration? Second, to what extent are migratory responses to short-term variations in temperature informative regarding responses to more persistent temperature shifts of the sort expected from climate change?

Globally, climate change is expected to drive substantial migration both within and across countries (Xu et al. 2020). To date, most studies in this space have primarily focused on migration responses to acute, or "fast-onset" climate-related disasters such as droughts, floods, and typhoons (Cattaneo et al. 2019; Boustan et al. 2020; Chen and Lee 2022; Sheldon and Zhan 2022), or on population movements in or from the the developing world, where much of the population is engaged in activities and sectors which are sensitive to climatic conditions and where the scope for in situ adaptation is limited (Millock 2015; Cattaneo et al. 2019; Piguet, Kaenzig, and Guélat 2018).[1]

Temperature changes relative to local norms are likely to be the most widely experienced effect of global climate change, and whether to migrate is among the most consequential decisions made by individuals and households. Migration in response to rising temperatures represents a costly adaptation to climate change (Jia et al. 2023) and will also determine risk exposure profiles of future populations.

Standard models of spatial equilibrium, e.g., Roback (1982), consider household loca-

1. See, for example: in Ecuador (Gray and Bilsborrow 2013), Indonesia (Bohra-Mishra, Oppenheimer, and Hsiang 2014), Mexico (Saldaña-Zorrilla and Sandberg 2009; Feng, Krueger, and Oppenheimer 2010), and Pakistan (Mueller, Gray, and Kosec 2014), five countries in Africa (Gray and Wise 2016), and others (Barrios, Bertinelli, and Strobl 2006; Ash and Obradovich 2020).

tion as driven by three generalized factors: wages, rents, and quality of life. Work on the economic and social impacts of high temperatures predicts changes in outcomes due to climate change which directly or indirectly influence each of these factors and should therefore be expected to alter households' decisions to migrate (Carleton and Hsiang 2016).

Whether households in wealthy countries are likely to migrate in response to higher temperatures is an open question. Economic activity in high-income countries tends to be less exposed to outdoor conditions and richer households may have greater access to insulating technologies such as air conditioning. On the other hand, more affluent households may face proportionally lower moving costs: they have more financial resources to support the relocation process and are more likely to be able to retain their current source of employment in spite of moving. They may also place more value on non-economic factors such as the amenity value of cooler or warmer locations. As countries around the world become richer, their migration responses to climate change are likely to more closely resemble those of a historically rich country like the United States. By the end of the century, many of the world's largest countries are predicted to be above or near the level of GDP per capita in the United States during the period we study from the 1950s through 2018 (see Fig. A.2).

On the scale of human lifespans, climate change induced deviations of weather from historic norms are effectively permanent. To understand temperature-driven migratory responses to climate change, we must then understand both if migration responds to temperature variation and how such responses evolve as the persistence of local temperature deviations from long-term norms increases to more closely approximate the permanent changes in conditions expected from climate change.

In this paper, we empirically examine the relationship between temperature and internal migration using 1) decadal, county-level net migration data derived from the Census for the period from 1950–2010 and 2) annual, county-level in- and out-migration data derived from tax filings with the IRS from 1983–2018. Onto these migration data we map daily measures of weather conditions aggregated to the annual and decadal counts of heating and cooling degree-days. Consistent with the climate impacts literature (Dell, Jones, and Olken 2014), the fixed effects regression models we specify isolate the causal relationship between temperature realizations and migration at the county level. We consider the effects of variation in short-, medium-, and long-term changes in temperature conditions using several empirical specifications and the two datasets.

Using decadal variation in weather and the Census data, we find that warmer temperatures—specifically, an increase of 100 cooling degree-days per annum, approximately the average national increase in CDDs since the start of the 20th century—decrease net migration by 0.92 percentage points on an annualized basis, or about 0.47 standard deviations. By contrast, the estimates of the effect of cooler temperature—annual increases of 100 additional heating degree-days—are close to zero and generally not statistically different from zero.

The magnitudes of the warm temperature responses are larger when longer-term variation in temperatures is used for identification: our estimate from the Census data increases to 1.92 percentage points when considering temperature changes realized across the full sixty years of our Census sample. Using the annual migration data based on IRS tax returns, we identify qualitatively similar patterns: annual variation in weather results in almost no immediate migration, but the effect size increases as we consider longer time spans. Using the IRS data, which provide separate measures of in- and out-migration, we also document both less in-migration and more out-migration in the face of warmer temperatures driving the net effect.

To our knowledge, this work is among the first to directly measure the migration response to temperature change for the contiguous United States and the first to quantitatively consider the importance of the persistence of temperature shocks in driving migration. In these regards we expand upon Feng, Oppenheimer, and Schlenker (2015) and Winkler and Rouleau (2021), respectively. Feng, Oppenheimer, and Schlenker (2015) examine historical migration and climate data from the U.S., but focus exclusively on the Corn Belt and find migration responses only for rural counties. Winkler and Rouleau (2021) show that more high temperature days and the increased incidence of local wildfires in one year decrease in-migration and increase out-migration for US counties in the subsequent year. Our work builds on the single-year temperature responses identified in these investigations to consider how such responses evolve as temperature shifts persist beyond a single year.

Our evidence also complements model-based predictions of migratory sorting under climate change in the United States (Fan, Fisher-Vanden, and Klaiber 2018; Sinha, Caulkins, and Cropper 2018; Bilal and Rossi-Hansberg 2023) by supplying reduced-form, causal estimates of how realized temperature shocks have already reallocated population across counties. For example, our estimates can help calibrate and validate the dynamic spatial framework developed by Bilal and Rossi-Hansberg (2023). While their model infers future relocations from agents' forward-looking optimization, our results pin down the magnitude and direction of the moves that have actually taken place in response to historical warming, offering an empirical yardstick for the model's simulated migration paths. It is likewise complementary to recent work that tracks how aggregate population change—births, deaths, and migration combined—responds to temperature variation over time (Leduc and Wilson 2023).

Our work is distinct in that we provide direct evidence of both a migration response to temperature variation for the entire contiguous United States since the 1950s and importantly, how the magnitude of this response increases as identifying variation is limited to more persistent temperature changes. Our findings also help inform previous efforts to leverage cross-sectional climate variation to identify preferences for different climates (Albouy et al. 2016; Sinha, Caulkins, and Cropper 2018) and papers examining cross-sectional or short-duration correlations between other types of weather variation and migration (Clark, Nkonya, and Galford 2022). Finally, the evidence we present that higher temperatures drive out-migration is in line with associations between heat and emigration from middle-income and agriculturally dependent countries, though direct comparisons of effect magnitudes are not feasible (Cattaneo and Peri 2016; Cai et al. 2016).

We make three empirical contributions to the literature on climate-driven migration. First, we show a direct causal link between persistent temperature increases and migration within the United States over the last seventy years, with effect magnitudes growing across longer time scales. Second, we present evidence that increasing temperatures drive existing residents to leave as well as dissuading potential new residents from choosing to in-migrate. Third, we show how these effects are stable across a range of dimensions of economic heterogeneity, suggesting that changing amenity values, in addition to other economic factors, are likely contributing to our findings. As a result, there is little reason to expect climate-related migration to abate as the U.S. economy continues to evolve away from climate-exposed industries such as agricultural production. Our estimates suggest that as households and countries become wealthier, shifts in climate-related amenities could become an increasingly important mechanism for climate-related migration around the world.

2 Data

Our empirical investigation is based primarily upon Census data and measures of net migration at the county level for each decade from the 1950s to the 2000s. We also conduct a secondary set of estimations using data from the Internal Revenue Service (IRS) which capture annual measures of in- and out-migration at the county level for the period from 1983 to 2018. We link these measures to decadal and annual weather data compiled from daily measurements provided by Schlenker (2020) and PRISM Climate Group (2004).

2.1 Decadal migration (Census)

We obtain counts of net migration for each county-decade from a dataset compiled by Winkler, Johnson, Cheng, Beaudoin, et al. (2013). This dataset combines the efforts of several previous research teams (White, Mueser, and Tierney 1992; Voss et al. 2005; Fuguitt, Beale, and Voss 2010; Winkler, Johnson, Cheng, Voss, et al. 2013; Bowles et al. 2016) to identify net migration by county from the 1950s to the 2000s. We refer readers interested in a detailed description of the dataset to Winkler, Johnson, Cheng, Beaudoin, et al. (2013) and summarize here.[2]

Net migration counts in this data are estimated using the "forward residual method," which follows the logic that changes in population counts are completely determined by births, deaths, and moves into or out of a county. Because population, births, and deaths are all precisely measured, this method obtains an equally precise measure of net migration by examining how populations change net of births and deaths. Its drawback is that it is not possible to use this method to generate separate counts of in-migration and out-migration. Appendix A.1 describes the forward residual method in more detail.

This method can also be used within subsets of the data to identify, e.g., net migration counts for individuals within specific age brackets. We refer to this dataset as the "Census data" hereafter. The migration rate is calculated as the number of net migrants over each decade divided by the population at the start of the decade.[3] The data include more than 3,000 counties observed for all decades between 1950 and 2010, and we construct overall and age-group specific net migration rates for 0–18, 18–55, and 55+ from these data, where age is given as the age at the end of the decade.

2.2 Annual migration (IRS)

We derive measures of migration for the second dataset from publicly available IRS Statistics of Income (SOI) Tax Statistics - Migration Data, which is based on year-to-year address changes on individuals' tax filings. These data provide counts of inflow and outflow migration for each county-year. To facilitate the comparison of estimates based on the Census data, we calculate net migration rates as the difference of inflow minus outflow migration counts divided by the starting population. Inflow and outflow rates are also calculated as

2. Other potential data sources include the global gridded datasets of net migration produced by Sherbinin et al. (2015) and Niva et al. (2023), but these are less directly useful for our study since they use the same source data as Winkler, Johnson, Cheng, Beaudoin, et al. (2013) but are not specifically designed to examine within-U.S. migration and cover shorter time periods.

3. Census population data for 1950 are taken from Boustan et al. (2020) as they are not included in the data compiled by Winkler, Johnson, Cheng, Voss, et al. (2013).

the ratio of each to the county's start-of-year population.

We refer to this dataset as the "IRS data" hereafter. Because the IRS data are based on tax filings, migration and population counts are tallies of "exemptions" claimed, which are considered to proxy for the number of individuals in the county. We use annual, county-level measures of net-, in-, and out-migration from the IRS data for 1983 through 2018. Relative to the Census data, the IRS data capture a shorter time period, are less representative of the full population as they capture only households which file taxes before the end of September in two successive years and can be linked between tax cycles (Gross 2003).

2.3 Weather and climate

We measure climatic variation using a fine-scaled gridded dataset of daily weather data provided by Schlenker (2020). These data are built on the PRISM Climate Group weather dataset (PRISM Climate Group 2004), but are distinct from their daily (AN81d) product as they are built from a balanced panel of weather stations, and are available at the daily level back to 1950 (whereas the PRISM Climate Group daily product is only available from 1980 onwards).

These data provide daily measures of temperature and precipitation from 1950 to 2019, computed for 4 kilometer square (roughly 0.05 by 0.05 degrees) grid cells covering the United States. We first compile measures of the number of heating and cooling degree days (HDD and CDD), where HDD is the sum of the degrees by which daily average temperatures fall below 18.3 C in a year and CDD is the sum of the count of degrees by which daily average temperatures exceeded 18.3 C. For example, a day with an average temperature of 25.3 C would add 7 CDD to the annual total. Then, we take population-weighted averages for each county using gridded population data from CIESIN (2017). The resulting county-year measures represent the average climate experienced by a household in a given county-year and are merged onto the IRS measures of migration. For the Census data, averages of annual conditions during each decade are merged onto each county-decade record.

2.4 Descriptive evidence

Tables A.1 and A.2 give descriptive statistics for the Census and IRS datasets. The Census data are a balanced panel covering nearly all of the counties in the contiguous United States from the six decades between the 1950s and the 2000s. The IRS dataset represents county-year net migration for nearly all of the counties in the contiguous United States between 1983 and 2018, although around 300 counties do not report migration counts in all 36 years.

To maintain consistency across the two datasets, we compute "annualized" net migration rates in percentage terms (i.e., decadal net migration divided by the population at the start of the decade, divided by 10 to annualize, and multiplied by 100 to be in percentage terms) for the decadal data. These annualized migration rates are distributed around zero, with an average of around 0.05%, and have a standard deviation of 1.95%. In the IRS data, we compute annual net migration rates for each county-year. Migration rates in the IRS data have a mean of 0.14% and a standard deviation of 1.56%. The IRS data also allow us to observe in- and out-migration separately, both of which average around 4,200 in- or out-migrants per county-year in our sample. Across our whole sample period, the average county in the United States experiences more HDDs (2,800) than CDDs (690) each year, and the standard deviations for HDDs and CDDs are 1200 and 440, respectively.

The left panels of Fig. 1 illustrate the average number of cooling degree days and net migration by county over the course of the Census data. Over the period of our sample, populations tended to flow out of the middle of the country toward the coasts and into the south—sometimes described as the "hollowing-out" of America (Molloy, Smith, and Wozniak 2011). As shown in the top left panel, these destination locations also tend to be warmer than the locations experiencing fewer incoming migrants. Because we are interested in studying how *changes* in climate conditions (rather than differences in *average* climate conditions) impact migration, we control for cross-sectional variation of the type represented by the visual comparison of the top and bottom panels on the left of Fig. 1 by comparing within-county changes between the 1950s and the 2000s in the number of CDDs and the migration rate, additionally controlling for differences between Census Region. This variation is illustrated by the maps in the right column of Fig. 1.

3 Methods

The objective of this study is to identify the causal effects of variation in climate of differing frequencies on migration patterns. To do so, we use two distinct empirical specifications, each of which is estimated using the Census data and the IRS data separately.

The first specification is a panel model with period-of-observation fixed effects that limits identifying variation to the period of observation, which is a decade for the Census data and a year for the IRS data (Timmins and Schlenker 2009; Kalkuhl and Wenz 2020; Kolstad and Moore 2020). The second specification—labeled "long differences"—allows for identification based on variation across the length of the sample periods, which are 60 and 36 years for the Census and IRS datasets respectively (Hsiang 2016; Burke and Emerick 2016; Kolstad and Moore 2020). In order to eliminate the consideration of cross sectional variation (and therefore the relationships visible in the left panels of Fig. 1), all of the models we estimate include county fixed effects or are estimated using within county differences. By design, the specifications differ in the period length of variation captured by the estimates.

The length of temporal variation captured by different estimations is a combination of the period represented by the observations and the estimation approach. The shortest temporal variation we capture is the panel model estimated on annual tax return data: this model is designed to capture immediate responses to unusual temperature realizations. Estimating the panel model on the decadal Census data will capture responses to unusual temperatures that manifest within the same decade they are realized. The long differences model estimated on the tax return data isolates longer-run effects of changes in temperature realized across 30 years. Finally, estimating the long differences model on the decadal data allows for effects occurring over 60 years.

Panel model. Letting i and t index counties and relevant time periods respectively, the panel model is estimated by the following specification:

$$\text{Migration rate}_{it} = \beta_H \text{HDD}_{it} + \beta_C \text{CDD}_{it} + \beta_P \text{Precip}_{it} + \phi_i + \phi_{rt} + \varepsilon_{it} \tag{1}$$

In Eq. (1), Migration rate_{it} is the annual migration rate for county i in period t. Our main measure of migration is net migration, though we also consider in- and out-migration rates based on the IRS data. In the Census data, for which the relevant period is a decade, variables capture the annual averages across decade, t. HDD_{it} and CDD_{it} are the annual number of heating and cooling degree days for the period (averaged for the decade in the case of the Census data). Precip_{it} is the total annual precipitation in the county-period. Because values represent annual measures in both datasets, coefficient magnitudes are comparable across the two and can be interpreted as the effect on annual migration rates of a one-unit-per-year change in the considered weather variable.

County and Census Region-by-period fixed effects are represented by ϕ_i and ϕ_{rt}. The model is identified using within-county variation in temperature after accounting for region-wide trends (separately for each of the four Census Regions) and period-specific idiosyncrasies in temperature realizations, consistent with the existing literature that estimates the impact of climate change on economic outcomes (Dell, Jones, and Olken 2014). In words, these estimates are causally identified using county-periods that had an unusually hot or cold period relative to both their own baselines and relative to other counties in their Census Region for that period.

We highlight that the panel model is identified from period-to-period variation, which is annual in the IRS data and decadal in the Census data. Given the pace of migratory decisions and flows, we consider year-to-year variation as short-term in this context, and decade-to-decade variation as medium-term.

Long differences model. To document long-run effects, we estimate a "long differences" model that uses within-Census Region variation by county to observe whether areas with different long-run changes in climatic conditions experienced different changes in migration rates. This approach is similar to the empirical design deployed by Burke and Emerick (2016) and is also described in Hsiang (2016).

More specifically, we estimate the model by computing the differences in net migration and climate measures between the beginning and end of our time period (e.g., the 1950s and the 2000s in the Census data) and regressing the differences in net migration on the differences in climate measures, along with a Census Region fixed effect. For the IRS data, the beginning and end periods are 5-year averages of the relevant variables. As the Census observations already represent multi-year aggregates, no additional smoothing is undertaken for specifications using the Census datasets.

To develop intuition for this model, consider the right panels of Fig. 1. These two maps show county-level changes between the 1950s and 2000s in the average number of cooling degree days each year and in net migration rates after controlling for average changes by Census Region. The logic of the model is to isolate long-run shifts in climate that are uncorrelated with other drivers of long-run migration. To do so, we estimate the following statistical specification:

$$\Delta \text{Migration rate}_i = \beta_H \Delta \text{HDD}_i + \beta_C \Delta \text{CDD}_i + \beta_P \Delta \text{Precip}_i + \phi_r + \varepsilon_i \tag{2}$$

Eq. (2) gives the estimating equation for the long differences approach, which we apply to both the Census and IRS datasets. The start and end periods are the 1950s and the 2000s in the Census data, and 1983–1987 and 2014–2018 in the IRS data. We denote differences in a variable between the start and end periods with the Δ symbol as follows: Δmigration rate$_i$ is the change in annual net migration rate, ΔHDD_i and ΔCDD_i are the changes in the average annual number of heating and cooling degree days, and ΔPrecip_i is the difference in the average annual precipitation. ϕ_r is a Census Region fixed effect, which controls for any Census Region-specific changes in migration, temperature, or precipitation and implies that our coefficient estimates β_H, β_C, and β_P are identified using within-county variation based on comparisons within the same Census Region.

4 Findings

4.1 Decadal estimates (Census)

Table 1 reports our main estimates based on annualized measures of net migration from the Census data, in which the panel estimates are based on decade-to-decade variation and the long-differences model leverages variation across 60 years. Negative coefficient estimates indicate lower net migration which could be arising from higher out-migration and/or reduced in-migration.

Column (1) of Table 1 reports estimates based on a model with county and decade fixed effects. We find that an increase in 100 CDDs, i.e., warming, depresses net migration in a county by 1.07 percentage points. By contrast, 100 more HDDs yields no shift in net migration. This model controls for unobserved variation between counties and across time but could still be confounded by correlated regional trends: for example, if the West, which experienced some warming as a region during our sample period, also saw increased migration during that time for reasons unrelated to its climate, it could bias the estimate on CDDs upward.

For this reason, estimates from our preferred panel specification, described by Eq. (1), are given in column (2). This specification replaces the decade fixed effects with Census Region by decade fixed effects to account for region-wide time trends or shocks. This additional set of fixed effects does not substantially alter the estimates, with each 100 CDDs depressing net migration by 0.92 percentage points, or about 0.47 standard deviations (SDs) of the net migration rate in our sample. As in the first column, 100 HDDs have virtually no effect on net migration.

Columns (3) and (4) of Table 1 reflect the long differences estimate described by Eq. (2) without, and then with, Census Region fixed effects. These long difference estimates capture the long-run effects of changes to climate over time. Compared to the panel model, we find similarly signed but larger in magnitude estimates, such that an increase of 100 CDDs leads to a decrease of 1.92 percentage points, or about 0.76 SDs, in net migration, based on the more saturated specification. Here we find a small positive coefficient on HDDs in column (3), suggesting a slight increase in net migration for counties with a long-term cooling trend, but the magnitude of this estimate remains small and its sign is reversed when using region fixed effects.

To benchmark the CDD effect size, the average county has experienced an increase of about 100 CDDs per year between the 1950s and 2000s. Our estimates imply that counties that experienced this amount of warming would see a decline in net migration of about 0.92–1.92 percentage points, depending on whether the medium-run (panel) or long-run (long differences) coefficient estimate is used.

The estimates in Table 1 model net migration as a function of the annual totals of heating and cooling degree days, which is equivalent to estimating a piecewise-linear function in temperature with a break at 18.3 C (similar to Schlenker and Roberts (2009)). Fig. 2 compares estimates from the degree-days specification using county and region-year fixed effects—column (2) of Table 1—with estimates from more demanding models that allow temperature to enter either in five degree bins or as a spline, following guidance in Carter et al. (2018). The figure shows that more flexible functional forms of temperatures capture comparable relationships in the data. For this reason, we focus on degree-day specifications for the remainder of the paper.

The coefficient on CDD approximately doubles between columns (2) and (4) in Table 1, suggesting that responsiveness to long-term changes in temperatures are substantially larger than responses to decadal-scale temperature variation. The online appendix includes a range of sensitivity checks, none of which alter the substantive conclusions presented here: Figs. A.3 and A.4 show the sensitivity of the estimates to Winsorizing the net migration rate variable, using alternative sets of fixed effects, estimating unweighted regressions, and other possible combinations of those choices. Fig. A.8 estimates an alternative long-run estimation strategy called "trends-on-trends" with the Census data and finds similar results to those obtained with the long-differences estimation.

4.2 Annual estimates (IRS)

In order to consider responses to short-term variation, we turn to estimates based on annual measures of net migration from the IRS data. In contrast to the Census-based measures in the previous section, net migration in this dataset is directly measured from tax filings and is representative of the population that files taxes. In spite of these measurement and sample differences and the shorter time period covered, the estimates for the CDD coefficient in Columns (1) and (2) of Table 2 show consistent evidence that increased temperatures in a given county result in reduced net migration.

With the annual IRS data, panel estimates represent effects of year-to-year variation, while long-differences estimates capture the effects across the 30+ year span of the sample. Comparing estimates on CDDs reported in Columns (1) and (2) of Table 2, the estimated effect of 100 additional CDDs is a decrease of 0.03 percentage points based on the panel model and year-to-year variation, but 0.41 percentage points based on the long differences specification. Responsiveness of net migration to increasing temperatures in a given location is small in magnitude when only short-term variation is considered and is substantially stronger when longer term variation is considered. HDD estimates are again closer to zero, though in the long difference specification we observe a small negative effect of 0.15 percentage points.

4.3 In- and out-migration estimates (IRS)

The structure of the IRS data allows for the decomposition of net-migration rates into separate measures for in- and out-migration for each county and year. We can investigate these measures separately as a means of assessing the extent to which temperature variation impacts migration by "pushing" existing residents to leave versus "pulling" outside residents to move in. Estimates of the panel and long-differences models using the in- and out-migration rates as outcome variables are presented in columns (3)–(6) of Table 2.

Higher temperatures are associated with no significant responses in out-migration in the panel specification while estimates based on long-differences show that increases in CDDs drive significant out-migration. In-migration falls in response to increases in CDDs in both the panel and long-differences specifications, though the magnitudes are substantially larger with long-differences. The increases in unusually hot local conditions appear to reduce in-migration pull factors over both the short- and longer-terms, and increasing the push to out-migrate over the longer term. Notably, the coefficient magnitudes on CDDs for in- and out-migration are essentially equal in the long-differences specifications, suggesting that our main estimates are driven meaningfully by responses among both existing and potential residents. The effect of HDDs, by contrast, is isolated to effects on the out-migration rate, suggesting that out-migration increased in the face of long-run cooling trends, while in-migration was unaffected.

4.4 Determinants of decadal migration (Census)

Having established that migration in the United States is responsive to changes in climate and that those responses increase with the length of climate variation considered, we return to the Census data to investigate heterogeneity in responsiveness. We examine how the effects differ by the type of county, by age group, and by decade.

By county type. We first consider whether rural counties, which are likely to be more reliant on climate-exposed industries, experience larger magnitude responses to changes in climate. We find larger magnitude effects in urban counties. Though this difference fades later in the sample period (results not shown), these estimates suggest our main results are not driven solely by financial necessity or occupational considerations in rural areas.

The second set of estimates in Fig. 3 shows that effects do not differ for warm versus cool counties, suggesting regular exposure to high temperatures does not facilitate in situ adaptation to changes in climate. Finally, we consider whether wealthier counties demonstrate a higher propensity to migrate in response to temperature shocks, and find suggestive evidence they do, which may imply budget constraints still restrict migratory flows to some degree, even in rich countries.

These estimates should be interpreted with some caution for two reasons. First, they are reliant on cross-sectional variation in the response of migration to temperature, and could represent other correlated factors dictating migratory responses than those we quantify here. Second, we estimate analogous models for the long-run effect of CDDs on net migration using the IRS data in Fig. A.7 and find in the IRS migration data, rural counties respond more than urban counties, and rich counties do not respond any more (or less) than poor counties. Because the limitations of the IRS data (discussed in Section 2) are magnified by these increasingly demanding specifications, we place more evidentiary weight on the Census data and emphasize them here, though the later sample period of the IRS data could also be contributing to the differences in estimates.

By age. We next consider heterogeneity by age, using age-group-specific net migration rates from the Census data. As shown in Fig. 3, we find that responsiveness to high temperatures increases in age. While all age groups increase migration away from warming counties on net, the oldest groups have a larger response than working age groups, who have a larger response than the young. This pattern is again consistent with the identified migratory responsiveness to temperature resulting, at least in part, from changes in amenity values.

By decade. Finally, we examine the degree to which the effect of cooling degree days on net migration has changed over time. To do so, we estimate the same model but allow the effect of cooling degree days to vary by decade. We find that the effect is stable, suggesting that the secular transition away from agricultural employment over the study period is not an important feature driving our results.

The stable magnitude of the temperature-migration relationship over time also stands in contrast to the dramatic decline in the magnitude of the heat-mortality relationship identified by Barreca et al. (2016) over the latter half of the twentieth century. In light of that study's attribution of the shrinking of the heat-mortality effect to the diffusion of air conditioning, our results suggest that technological adaptation to heat via adoption of air conditioning has not supplanted migration as a means of adapting to higher temperatures.

5 Discussion

Temperature increases will be the most widely experienced impact of global climate change, and exposure to such higher temperatures is associated with a range of negative social and economic outcomes (Carleton and Hsiang 2016). In this paper, we first show that changes in temperature induce migration responses, even in one of the wealthiest (and in principle most climate-shielded) countries in the world. We find that the American population has responded to warming temperatures by shifting away from areas experiencing temperature increases relative to local norms. Second, we find that this response is attributable to temperature increases that persist over medium- to long-term horizons—exactly the type of warming expected to be brought on by global climate change.

This net migration response is driven both by increases in out-migration and decreases in in-migration at the county level. The former result is notably consistent with findings for out-migration from middle-income countries (Cattaneo and Peri 2016). We also show that the sensitivity of migration to locally-unusual high-temperature realizations has been consistent since the 1960s, even as penetration rates of residential air conditioning have risen dramatically. Our estimates are therefore plausibly informative about likely responsiveness to future temperature changes, even in emerging economies, as adaptive technologies such as air conditioning become ever more widely adopted.

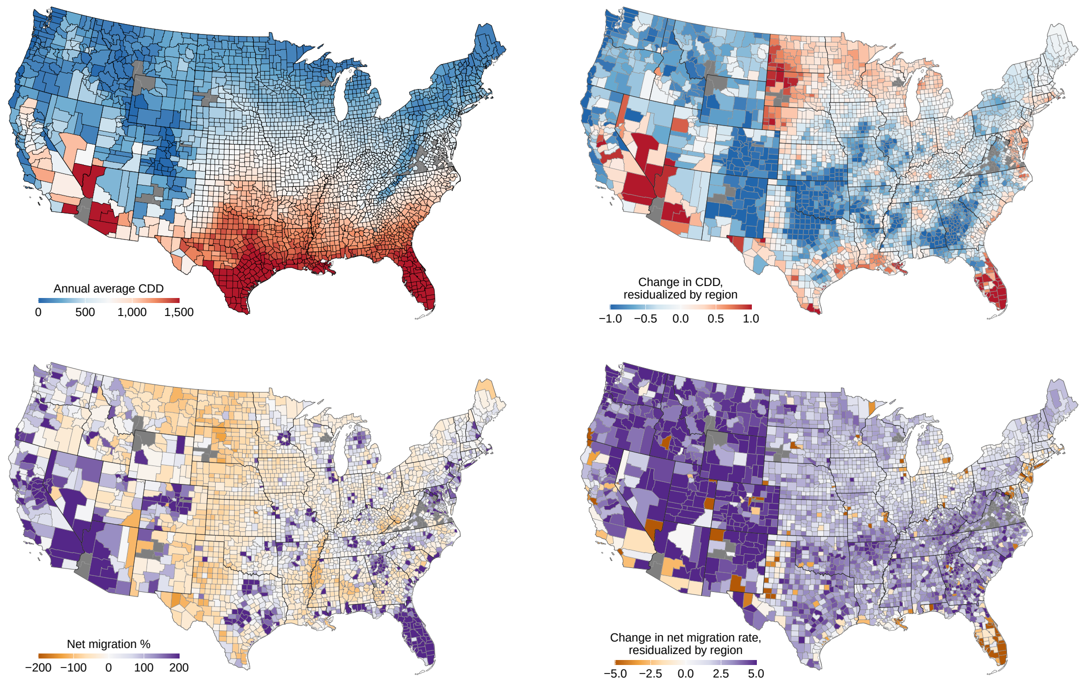
Migration in response to local temperature increases realized over the long-term represent a direct measure of adaptation to climate change. Our results provide direct evidence that populations in the United States are in fact adapting to changes in climate. Recognition of such adaptation is critical for valid estimation of future damages from climate change for two distinct reasons. First, large-scale migration in response to temperature changes produced by climate change represents a substantial additional—and underappreciated—adaptation cost, as even internal migration is costly (e.g., Kennan and Walker 2011; Bayer and Juessen 2012). Second, adaptation via migration will alter the profile of future climatic exposures realized under climate change as future population distributions may differ substantially from those observable today.

A limitation of this study is that we cannot use our estimates to project the effect of climate change on future migration patterns. In addition to the typical set of assumptions required for projections of climate impacts (fixed technology, preferences, adaptation, among others) in Auffhammer et al. (2013), projecting migration in the face of broader climatic shocks also requires overcoming a general equilibrium problem, i.e., changes in the climate of one county will affect migration patterns in other counties (Oliva 2024). We look forward to future work that addresses this important issue.

We are unable to directly compare the magnitudes of our estimates to other results examining international migratory flows (e.g., Cattaneo and Peri 2016; Cai et al. 2016), as the outcome measures and underlying migration decisions considered are not analogous. Our work, therefore, underscores the need for additional research comparing the responsiveness of low-friction, internal migration decisions to major, international emigration decisions.

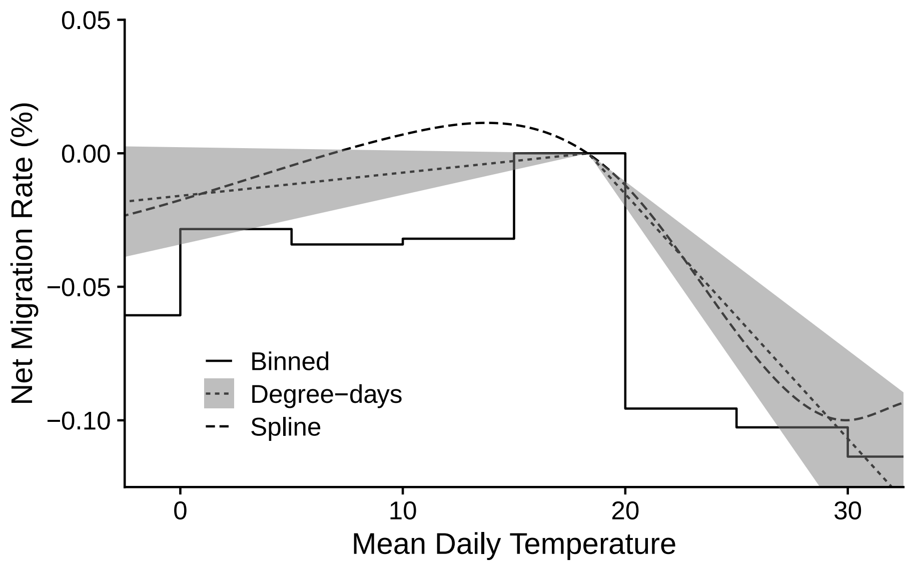
Still, our findings indicate that climate amenities are likely to be an important driver of migration in the United States. More speculatively, they suggest that as other countries continue to grow wealthier, global migration is likely to become more responsive to the amenity losses from climate change. Finally, our evidence suggests that while these migration responses may not be obvious over shorter time horizons, they will manifest in meaningful ways over longer periods of sustained climate change.

Figure 1: Climate and Net Migration, 1950s to 2000s



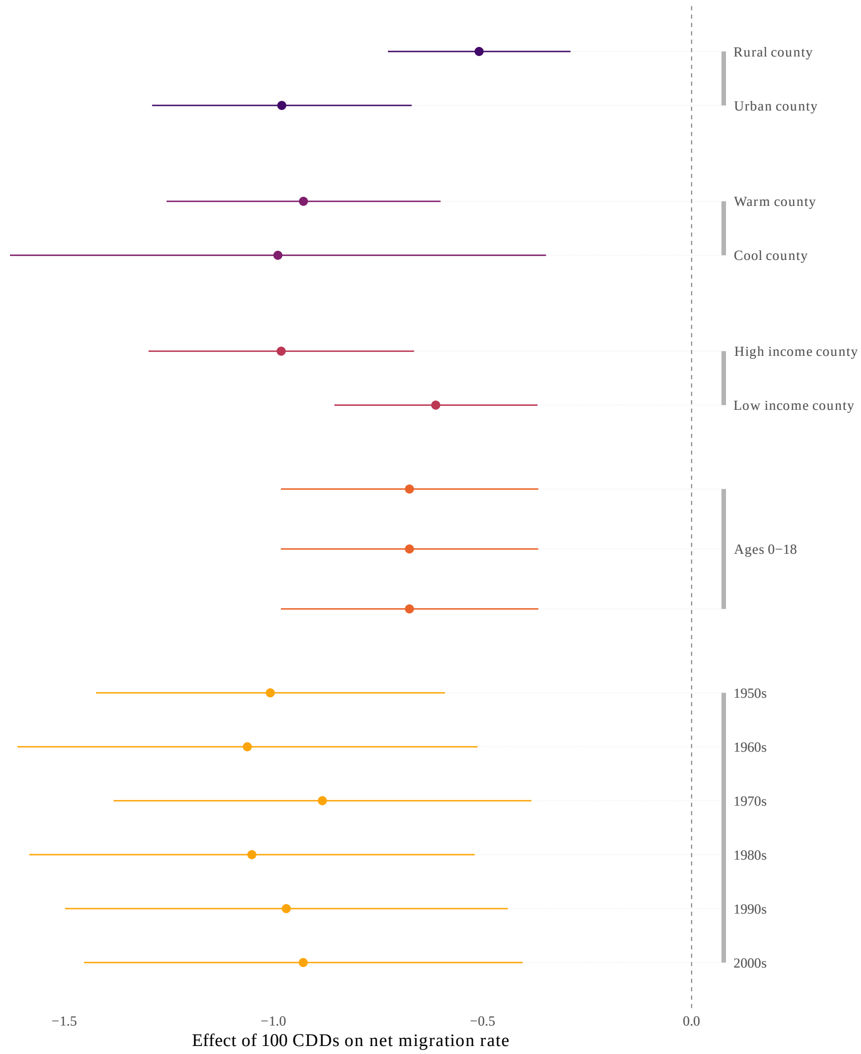
Notes: Maps show climate and net migration by county between the 1950s and the 2000s. *Top left*: Average annual cooling degree days between 1950 and 2009. *Bottom left*: Total net migration between the 1950s and 2000s as a percent of the county population in 1950. *Top right*: Change in the average number of cooling degree days between the 1950s and 2000s, residualized by Census Region. *Bottom right*: Change in net migration rates between the 1950s and 2000s, residualized by Census Region.

Figure 2: Impact of temperature on decadal net migration (Census)



Notes: Figure shows the impact of decadal temperature on net migration. The height of each line is the estimated impact of replacing one day per year with an average temperature of 18.3 C with one day per year at the indicated average temperature on the annualized net migration rate. Each line documents a separate regression using the given function of temperature. "Binned" shows five-degree bins of the count of days with average temperature in the given bin, with the 15-20 C bin omitted, "Degree-days" shows heating and cooling degree days, each computed relative to an average temperature of 18.3 C (65 F), and "Spline" shows a B-Spline in average daily temperature, with internal knots at 10, 20, and 30 C and boundary knots at 0 and 40 C. All regressions include county and region-decade fixed effects and are weighted by county population in 1950. The shaded 95% confidence interval on the degree-days model is computed using standard errors clustered by county.

Figure 3: Heterogeneous effects of CDDs on net migration (Census)



Notes: Figure shows coefficient estimates for effect of 100 CDDs on net migration rate (in percentages), split by various dimensions of heterogeneity. Except for the effects by age group, each set of estimates is produced by a regression of net migration rate on HDD, CDD, precipitation and their interactions with the given dimension, plus county and Census-Region-decade fixed effects. Urban counties are those in metropolitan areas with more than 250,000 residents in 1983, rural counties are all other counties. Warm counties are those with above-median average cooling degree days between 1950 and 2009. The effects by age group are estimated using separate models where the left-hand side variable is the net migration rate for the relevant age group. All regressions are weighted by county population in 1950. Standard errors clustered by county, bars represent 95% confidence intervals.

Table 1: Impact of climate on decadal migration (Census)

	Net migration rate (%)			
	Panel		LD	
	(1)	(2)	(3)	(4)
HDD (100s)	-0.04	-0.09*	0.14	-0.21
	(0.04)	(0.05)	(0.13)	(0.15)
CDD (100s)	-1.07***	-0.92***	-1.51***	-1.92***
	(0.13)	(0.14)	(0.24)	(0.28)
Precip. (100s mm)	-0.08**	-0.09**	-0.01	0.01
	(0.04)	(0.05)	(0.11)	(0.10)
County FE	✓	✓		
Decade FE	✓			
Region-Decade FE		✓		
Region FE				✓
Observations	18,120	18,120	3,020	3,020
Within R^2	0.07	0.04		0.13
Outcome mean	0.05	0.05	1.23	1.23
Outcome SD	1.95	1.95	2.53	2.53

Notes: Table shows estimates of heating and cooling degree-days on decadal net migration. Decadal net migration is the annualized rate of net migration as a percentage of total population at the start of decade. HDD (100s) and CDD (100s) are hundreds of heating and cooling degree days per year. Precip. (100s mm) is the amount of rainfall in a year in hundreds of mm. The first two columns show panel estimates, where each observation is a county-decade. The second two columns show long difference estimates, where observations are differences between the first and the last decades in the sample (1950s and 2000s). Regions are Census Regions. All regressions are weighted by county population in 1950. Standard errors clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Impact of climate on annual migration (IRS)

	Net migration rate (%)		Out-migration rate (%)		In-migration rate (%)	
	Panel	LD	Panel	LD	Panel	LD
	(1)	(2)	(3)	(4)	(5)	(6)
HDD (100s)	-0.01*	-0.15***	0.02***	0.18*	0.01*	0.03
	(0.01)	(0.05)	(0.01)	(0.09)	(0.01)	(0.09)
CDD (100s)	-0.03**	-0.41***	-0.01	0.23**	-0.04***	-0.19*
	(0.01)	(0.07)	(0.01)	(0.09)	(0.01)	(0.10)
Precip. (100s mm)	-0.01***	0.02	0.01***	0.04	0.00	0.06
	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)	(0.04)
County FE	✓		✓		✓	
Region-Year FE	✓		✓		✓	
Region FE		✓		✓		✓
Observations	107,638	3,003	107,638	3,003	107,638	3,003
Within R^2	0.00	0.05	0.00	0.01	0.00	0.01
Outcome mean	0.14	0.28	6.25	-0.90	6.39	-0.62
Outcome SD	1.56	1.40	2.07	1.62	2.47	1.82

Notes: Table shows estimates of heating and cooling degree-days on annual rates of net, in-, and out-migration by county. Net migration is the rate of annual net migration in percentages of total population at the start of the year. Out-migration is the rate of annual out-migrants leaving the focal county, and in-migration is the rate of annual in-migrants moving to the focal county. HDD (100s) and CDD (100s) are hundreds of heating and cooling degree days per year. Precip. (100s mm) is the amount of rainfall in a year in hundreds of mm. The first, third, and fifth columns show panel estimates, where each observation is a county-year. The second, fourth, and sixth columns show long difference estimates, where observations are differences between the averages of the first five and last five years in the sample (1983–1987 and 2014–2018). Regions are Census Regions. All regressions are weighted by county population in 1950. Standard errors clustered by county. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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ONLINE APPENDIX

This appendix includes supplementary material for Baylis, Bharadwaj, Mullins, and Obradovich (2025). Appendix A provides additional information on the data collection process. Appendix B documents sensitivity checks not included in the main paper.

A Detailed data description

A.1 The "forward residual" method

Formally, the forward residual method starts with the Census-measured population in each county at the start of each decade. It then estimates an expected population at the end of the decade by adding births and subtracting deaths from confidential datasets held by the National Center for Health Statistics. The count of net migrants is computed as the difference between the observed population at the end of decade and the expected population described above. Mathematically, net migration counts for a single county in time period t are computed as follows:

$$\text{Net migration}_t \equiv \text{Population}_t - \overbrace{\text{Population}_{t-1} + \text{Births}_t - \text{Deaths}_t}^{\text{Expected population}_t}$$

A.2 Summary statistics

Table A.1 documents summary statistics for the decadal dataset, and Table A.2 does the same for the annual dataset.

Table A.1: Decadal data summary (Census)

Coverage					
County-decades	18,120				
Counties	3,020				
Decades	6				
Years covered	1950 – 2010				
Variables					
	Mean	SD	Min	P50	Max
Net migration rate (%)	0.054	2	-10	-0.13	32
Net migrants (1,000s)	2.2	30	-749	-0.17	1171
Population (1,000s)	75	265	0	22	10526
HDD (100s)	28	12	0.4	27	64
CDD (100s)	6.9	4.4	0	6.1	25
Precip. (100 mm)	9.8	3.6	0.56	10	27

Notes: Table summarizes descriptive statistics for decadal (Census) dataset. Each observation is a county-decade. All 3,051 counties appear in all six decades of the data. Net migrants is the number (in thousands) of in-migrants minus out-migrants in that county-decade, accounting for births and deaths (see text for details). Population is the start of decade population. The net migration rate is the number of net migrants for a given county-decade divided by population, divided again by 10 (to annualize the rate), and multiplied by 100 (to represent a percentage). HDD and CDD are annual average counts of hundreds of heating degree days and cooling degree days, computed as the sum total number of degrees below or above 18.3 C, averaged across each year in the decade. Precipitation is the average total precipitation in each year in the decade.

Table A.2: Annual data summary (IRS)

	Mean	SD	Min	P50	Max
Coverage					
County-years	107,638				
Counties	3,014				
Years	36				
Years covered	1983 – 2018				
Variables					
Net migration rate (%)	0.14	1.6	-32	0	61
In-migration (# Exemptions, 1000s)	4.2	11	0	1.1	258
Out-migration (# Exemptions, 1000s)	4.2	12	0.015	1.1	352
Net migrants (# Exemptions, 1000s)	0.026	3.1	-181	0	121
Population (# Exemptions, 1000s)	72	232	0.2	19	8100
HDD (100s)	27	12	0.062	27	67
CDD (100s)	7.1	4.5	0	6.3	28
Precip. (100 mm)	10	4	0.17	10	34

Notes: Table summarizes descriptive statistics for annual (IRS) dataset. Each observation is a county-year. Of the 3,045 counties, 2,706 appear in all 36 years of the data. In-migrants is the number of tax exemptions claimed in a year by newcomers to the county, out-migrants in the number of tax exemptions claimed by households who exited the county. Net migration is the in-migrants minus out-migrants. Population is the total number of tax exemptions claimed by households who began the year in the county. The net migration rate is net migration divided by population and multiplied by 100 (i.e., it is a percentage). HDD and CDD are annual counts of heating degree days and cooling degree days, computed as the sum total number of degrees below or above 18.3 C. Precipitation is the total precipitation in the year.

A.3 Additional county characteristics

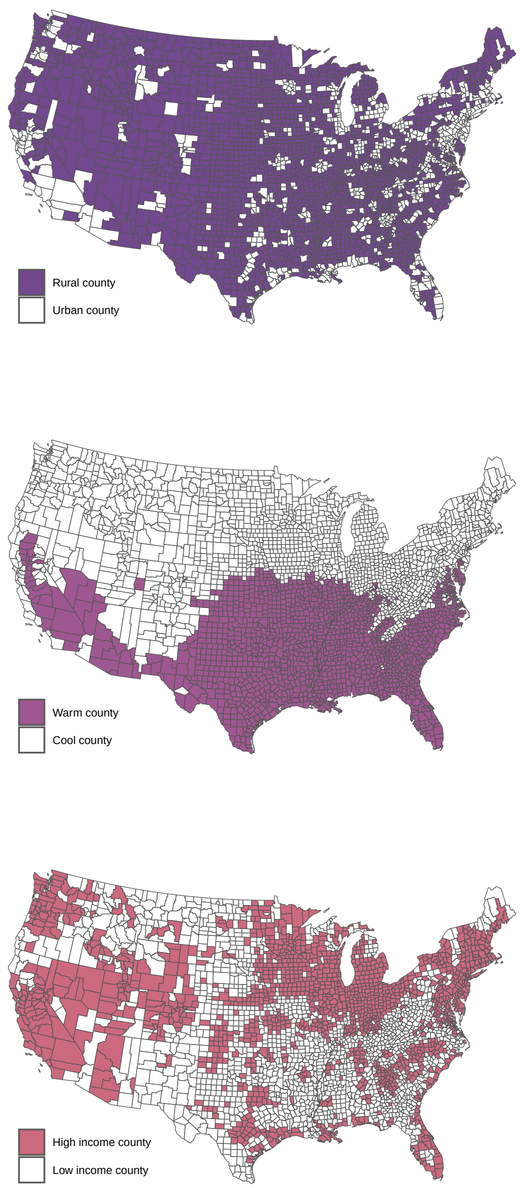
We include several time-invariant county characteristics in the data to classify counties as urban or rural, warm or cool, and high income or low income. In order to accurately represent the distribution of these characteristics across our sampling frame, we attempted to use measurements from as close to the midpoint of the time period we study (1950s to 2000s). We define those distinctions as follows, and Fig. A.1 provides the associated maps.

Urban / rural counties. The rural/urban indicator we use comes from the Rural-Urban Continuum Codes provided by the U.S. Department of Agriculture. We consider counties urban if they have a code of 1, 2, or 3, i.e., are in a metro area with a population of 250,000 people or more. We use the code from 1983 to approximate the middle of our time frame.

Warm / cool counties. We compute long-run average temperature cooling degree days by county from 1950 to 2010 and define counties as "warm" if their cooling degree days exceed the median – roughly 621 CDD – of the distribution over these averages. The remaining counties are defined as "cool".

High / low income. We define high income counties as those with household average income above the county median in 2000, which is around $34,000.

Figure A.1: County Characteristics

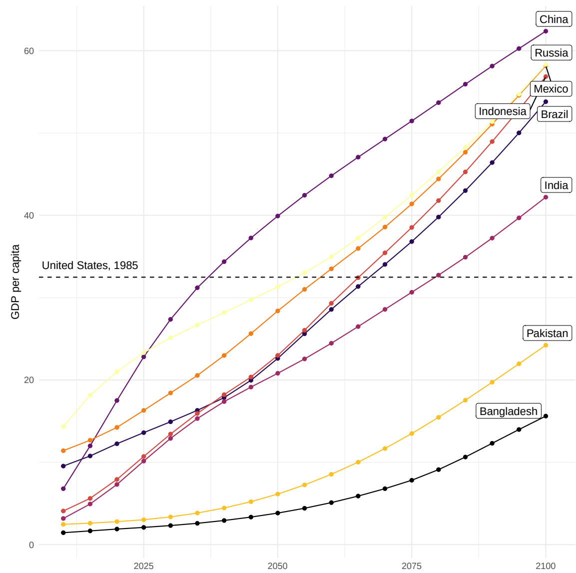


Notes: Maps of county characteristics. Rural and urban county definitions follow 1983 definitions of rural and urban counties from the U.S. Department of Agriculture. Warm counties are those with above median average annual CDDs, and high income counties are those with above median household income in 2000.

A.4 Projections of GDP per capita by country

Fig. A.2 presents projections of GDP per capita by country under the second shared socio-economic projection, SSP2 (Riahi et al. 2017). These projections are used as inputs for integrated assessment models of climate change. SSP2 is described by Riahi et al. (2017) as the "Middle of the Road (Medium challenges to mitigation and adaptation)" pathway.

Figure A.2: Projections of GDP per capita by country (SSP2)



Notes: Projections of GDP per capita by country under SSP2 (Riahi et al. 2017).

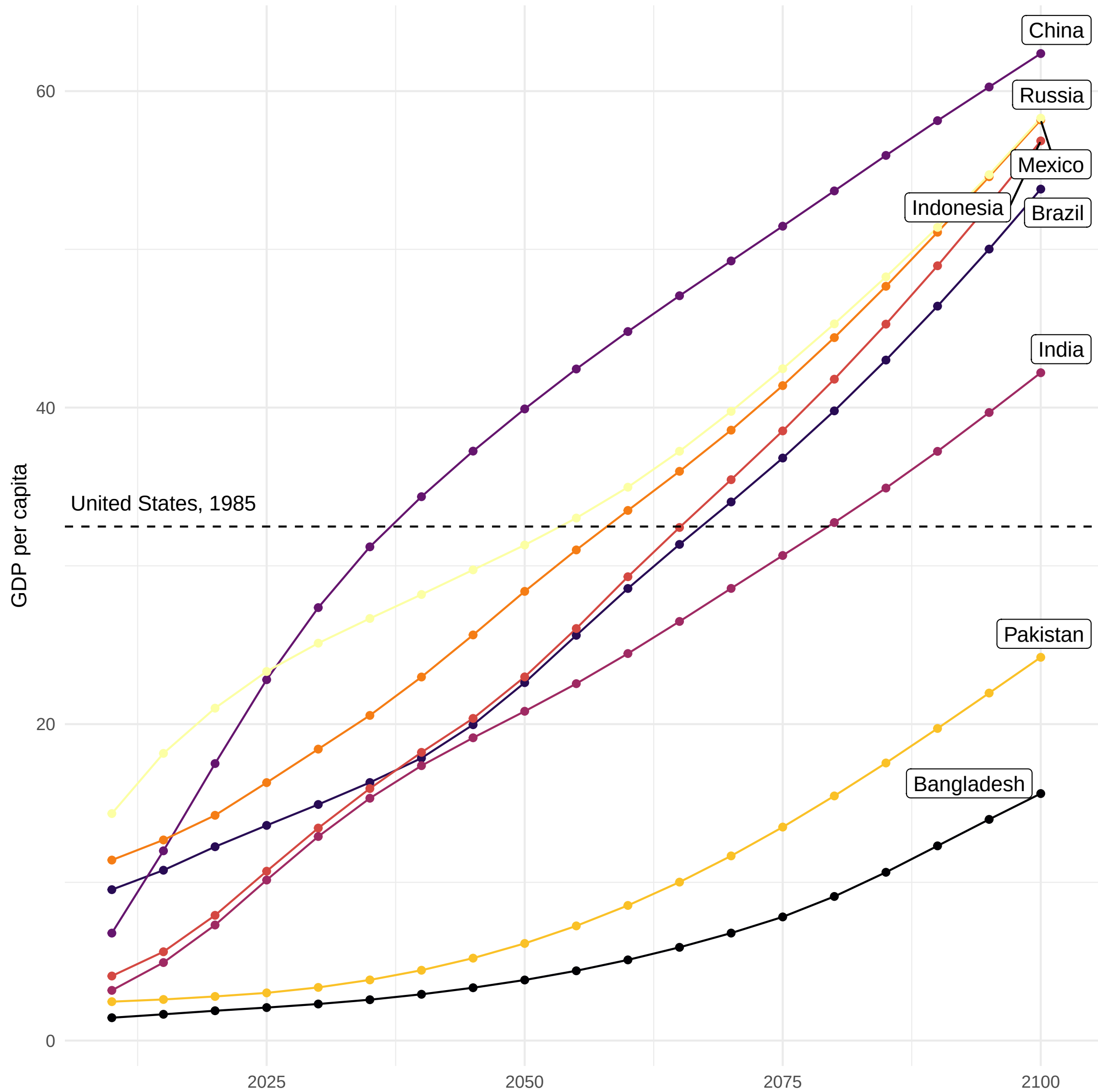
B Sensitivity

B.1 Sensitivity curves

This section documents the sensitivity of the estimates to various specification choices.

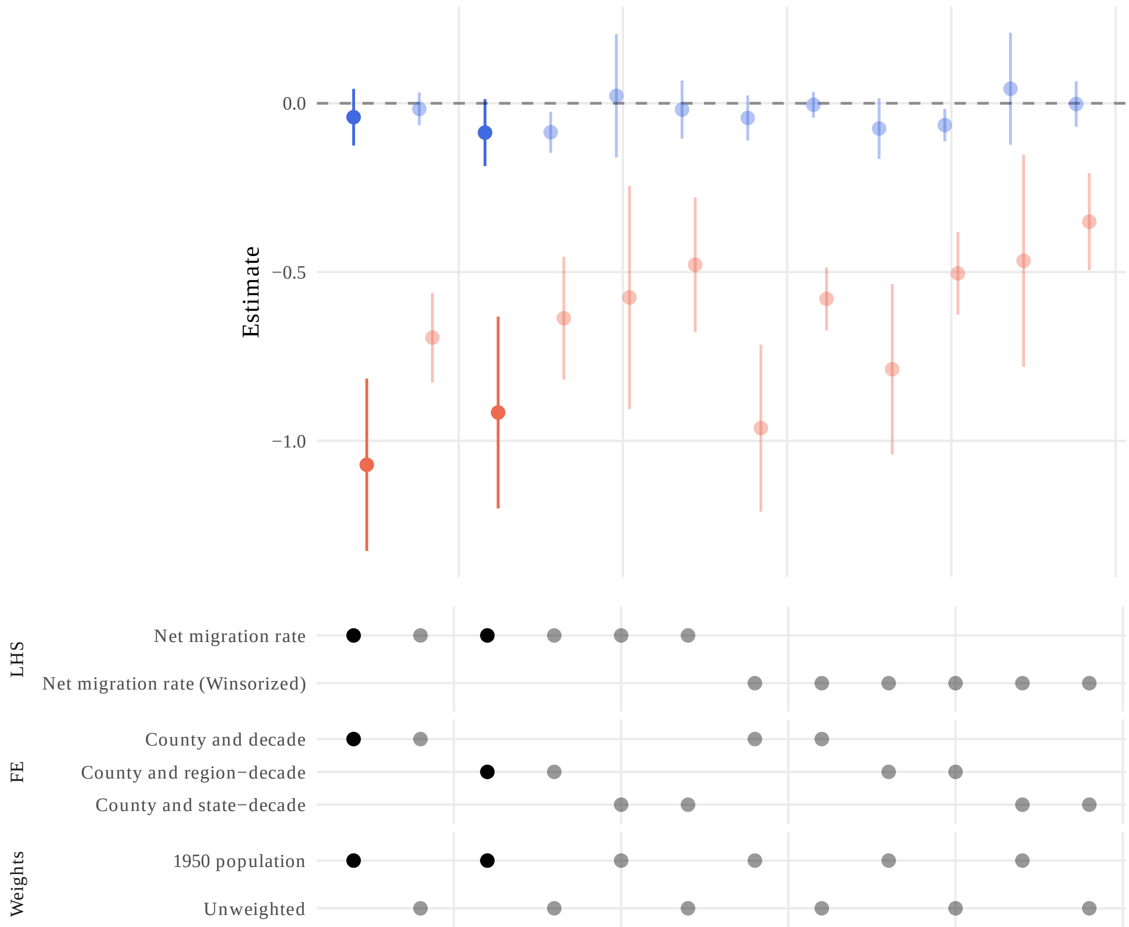
Figs. A.3 and A.4 show the sensitivity of the estimates using decadal (Census) data across panel and long-differences specifications. The estimates are consistently negative and statistically different from zero. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles.

Figure A.3: Sensitivity curves for decadal (Census) data – Panel models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the decadal (Census) data using panel models and the given left-hand side (LHS), fixed effects (FE), and weights, where the right-hand side always includes HDD, CDD, and precipitation. Net migration rate is the number of net migrants divided by the population at the start of the decade. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Blue represents HDD estimates, red represents CDD estimates, and solid (non-transparent) points and lines indicate results included in the main text. Standard errors clustered by county, lines represent 95% confidence intervals.

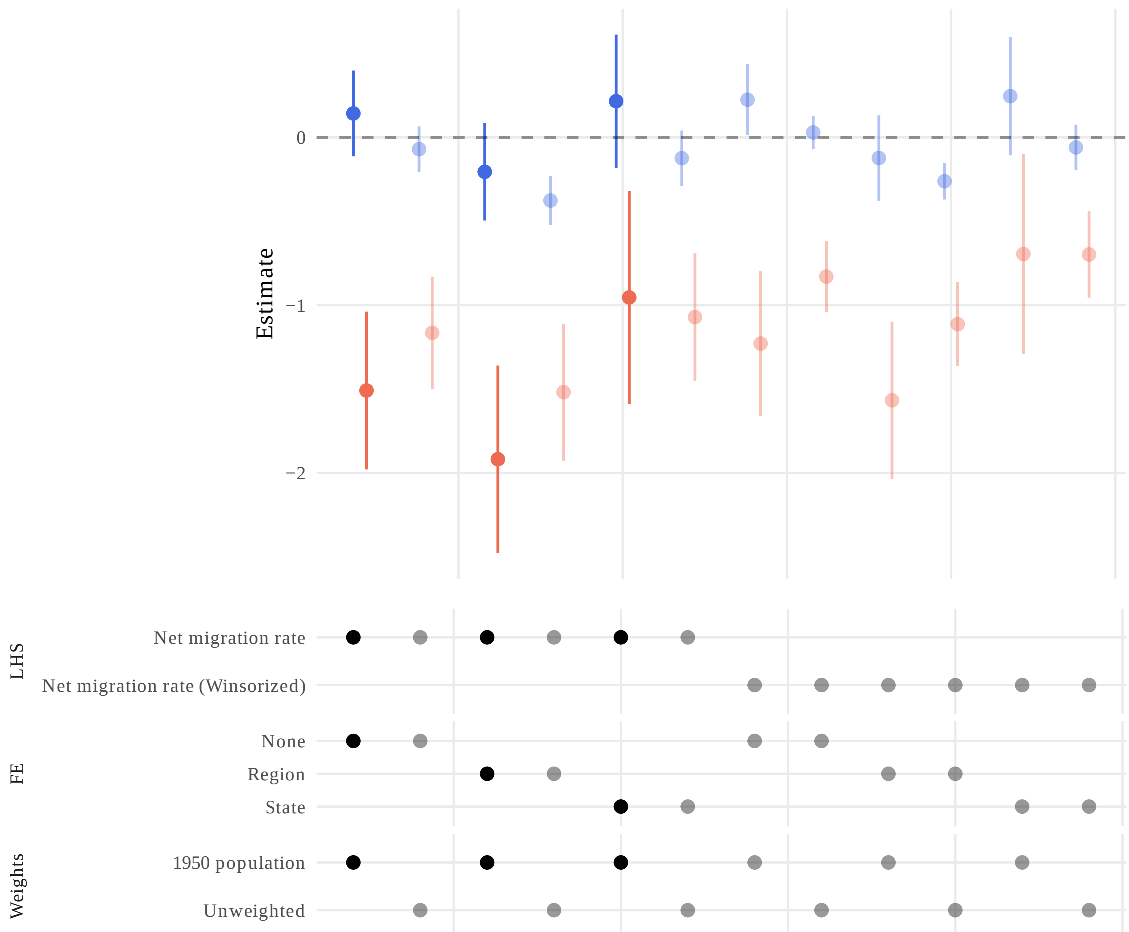
Figure A.4: Sensitivity curves for decadal data (Census) – Long differences models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the decadal (Census) data using long differences models and the given left-hand side (LHS), fixed effects (FE), and weights, where the right-hand side always includes HDD, CDD, and precipitation. Net migration rate is the number of net migrants divided by the population at the start of the decade. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Blue represents HDD estimates, red represents CDD estimates, and solid (non-transparent) points and lines indicate results included in the main text. Standard errors clustered by county, lines represent 95% confidence intervals.

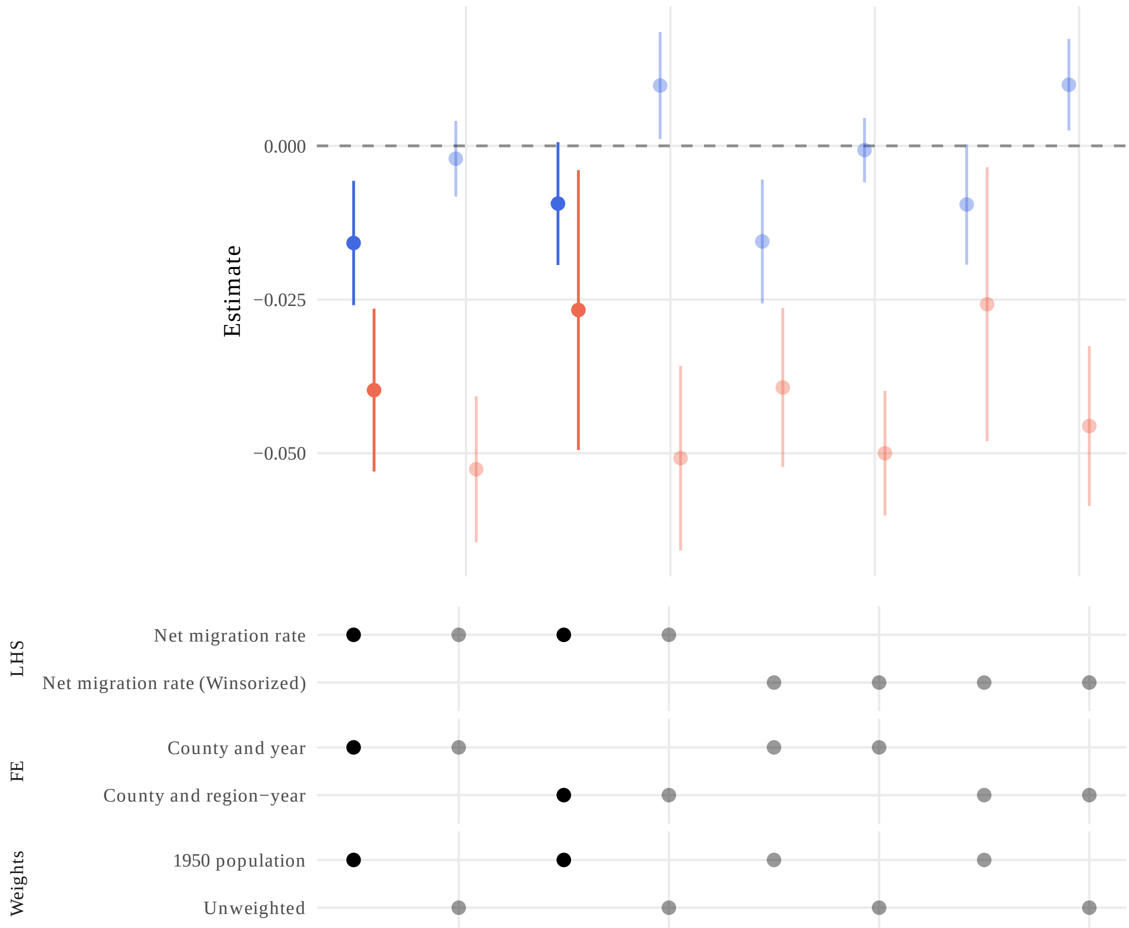
Figs. A.5 and A.6 show the sensitivity of the estimates using annual (IRS) data across panel and long-differences models. The estimates using these data are somewhat less consistent than those using the decadal (Census) data, but are also negative and statistically different from zero. We note that the magnitudes of the estimates are consistently larger for the long-differences specifications than the panel specifications, consistent with a growing response to more persistent climate shifts.

Figure A.5: Sensitivity curves for annual data (IRS) – Panel models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the annual (IRS) data using panel models and the given left-hand side (LHS), fixed effects (FE), and weights, where the right-hand side always includes HDD, CDD, and precipitation. Net migration is the in-migrants minus out-migrants. Population is the total number of tax exemptions claimed by households who began the year in the county. Net migration rate is the number of net migrants divided by the population. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Blue represents HDD estimates, red represents CDD estimates, and solid (non-transparent) points and lines indicate results included in the main text. Standard errors clustered by county, lines represent 95% confidence intervals.

Figure A.6: Sensitivity curves for annual data (IRS) – Long differences models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the annual (IRS) data using long differences models and the given left-hand side (LHS), fixed effects (FE), weights, starting period (First), and ending period (Last), where the right-hand side always includes HDD, CDD, and precipitation. Net migration is the in-migrants minus out-migrants. Population is the total number of tax exemptions claimed by households who began the year in the county. Net migration rate is the number of net migrants divided by the population. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Blue represents HDD estimates, red represents CDD estimates, and solid (non-transparent) points and lines indicate results included in the main text. Standard errors clustered by county, lines represent 95% confidence intervals.

B.2 Alternative standard errors

Tables A.3 and A.4 report versions of Table 1 using standard errors clustered by state and using the spatial clustering method from Conley (1999) with a 1,000 km cutoff, respectively.

Table A.3: Impact of climate on decadal migration (State clustered SEs)

	Net migration rate (%)			
	Panel		LD	
	(1)	(2)	(3)	(4)
HDD (100s)	-0.04	-0.09	0.14	-0.21
	(0.05)	(0.07)	(0.28)	(0.28)
CDD (100s)	-1.07***	-0.92***	-1.51***	-1.92***
	(0.21)	(0.28)	(0.41)	(0.59)
Precip. (100s mm)	-0.08	-0.09**	-0.01	0.01
	(0.06)	(0.04)	(0.12)	(0.11)
County FE	✓	✓		
Decade FE	✓			
Region-Decade FE		✓		
Region FE				✓
Observations	18,120	18,120	3,020	3,020
Within R^2	0.07	0.04		0.13
Outcome mean	0.05	0.05	1.23	1.23
Outcome SD	1.95	1.95	2.53	2.53

Notes: Table shows estimates of heating and cooling degree-days on decadal net migration. Decadal net migration is the annualized rate of net migration as a percentage of total population at the start of decade. HDD (100s) and CDD (100s) are hundreds of heating and cooling degree days per year. Precip. (100s mm) is the amount of rainfall in a year in hundreds of mm. The first two columns show panel estimates, where each observation is a county-decade. The second two columns show long difference estimates, where observations are differences between the first and the last decades in the sample (1950s and 2000s). Regions are Census Regions. All regressions are weighted by county population in 1950. Standard errors clustered by state. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Impact of climate on decadal migration (Conley SEs)

	Net migration rate (%)			
	Panel		LD	
	(1)	(2)	(3)	(4)
HDD (100s)	-0.04	-0.09	0.14	-0.21
	(0.06)	(0.07)	(0.29)	(0.28)
CDD (100s)	-1.07***	-0.92***	-1.51***	-1.92***
	(0.20)	(0.28)	(0.44)	(0.59)
Precip. (100s mm)	-0.08	-0.09**	-0.01	0.01
	(0.07)	(0.04)	(0.12)	(0.12)
County FE	✓	✓		
Decade FE	✓			
Region-Decade FE		✓		
Region FE				✓
Observations	18,120	18,120	3,020	3,020
Within R^2	0.07	0.04		0.13
Outcome mean	0.05	0.05	1.23	1.23
Outcome SD	1.95	1.95	2.53	2.53

Notes: Table shows estimate of heating and cooling degree-days on decadal net migration. Decadal net migration is the annualized rate of net migration as a percentage of total population at the start of decade. HDD (100s) and CDD (100s) are hundreds of heating and cooling degree days per year. Precip. (100s mm) is the amount of rainfall in a year in hundreds of mm. The first two columns show panel estimates, where each observation is a county-decade. The second two columns show long difference estimates, where observations are differences between the first and the last decades in the sample (1950s and 2000s). Regions are census regions. All regressions are weighted by county population in 1950. Standard errors robust to spatial correlation are computed using a 1000 km cutoff, following Conley (1999). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Comparing estimates from decadal and annual data

Table A.5 documents a comparison of estimates obtained from the Census (decadal) and IRS tax return (annual) datasets. The goal of this exercise is to highlight how the period examined affects the estimated relationship between climate and migration and to help reconcile the differences between the results in Table 1 and Table 2.

Column (1) shows the decadal estimate using the same specification given in Table 1, column (2), but restricted to only use data from 1980–2010. The remaining columns use the IRS data only, taking averages over the periods given: 1 year (no averaging), 3 years, 5 years, 7 years, and 10 years.

Column (1) is comparable to the estimate we document in the main paper, though the different time period yields a slightly smaller estimate. Column (2) estimates the panel model on the annual data from the IRS, i.e., it reproduces column (1) in Table 2 over a shorter sample period: the estimate is statistically different from zero, but more than an order of magnitude smaller than the one estimated in the decadal data. The remaining three columns show how the remaining estimates of the effect of CDDs become more similar to the decadal estimates when aggregating over 3, 5, 7, and 10 years.

B.4 Heterogeneity in estimates using IRS data

Fig. 3 in the main text estimates the effect of 100 CDDs on decadal net migration. Fig. A.7 here does the same using the annual IRS data. To increase the comparability of the estimates in terms of the temporal variation, we use the long differences specification used in column (2) of Table 2 plus interactions between HDD, CDD, and precipitation and the relevant dimension of heterogeneity.

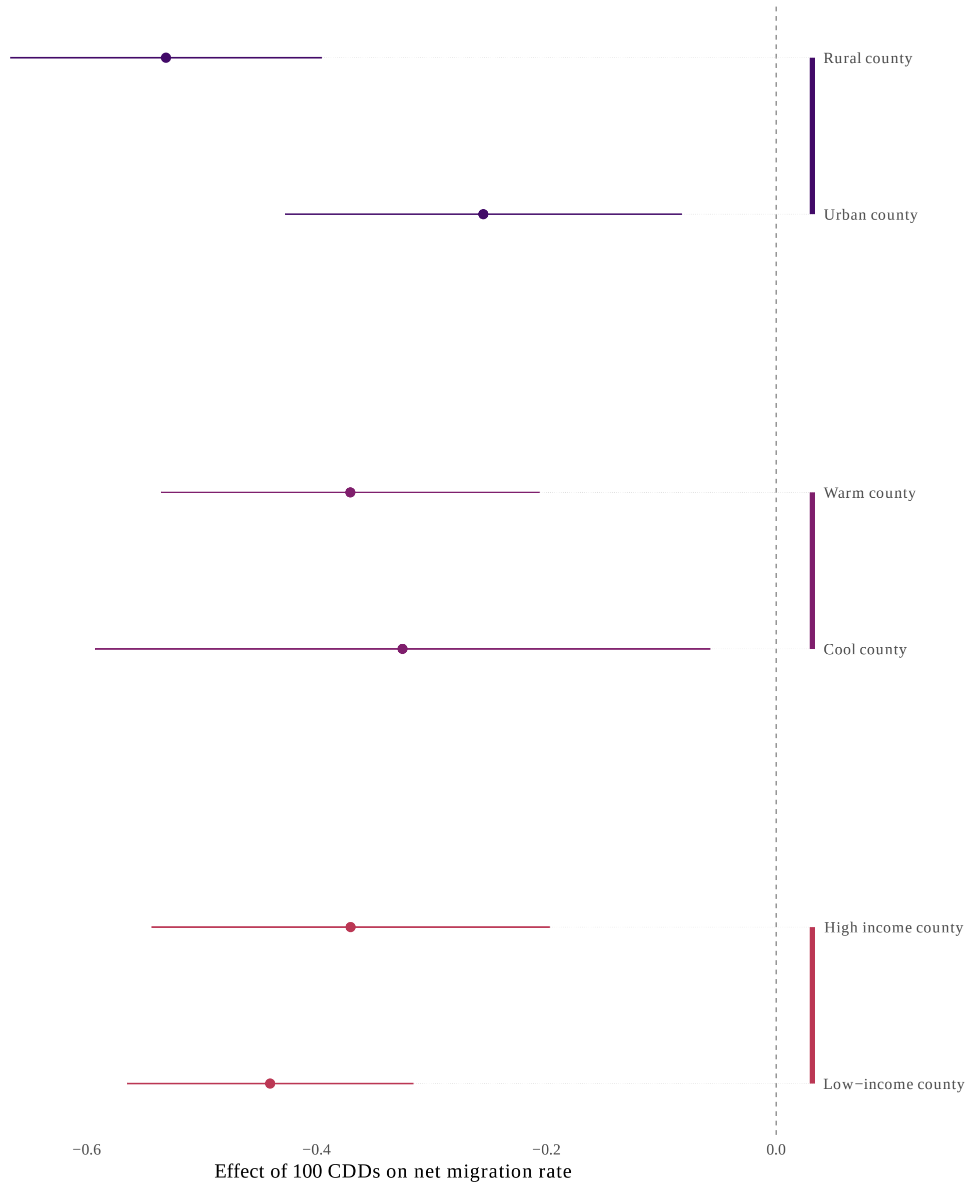
The pattern of estimates we document here is similar to the one we see in Fig. 3. The exception is for rural counties, which show a larger response to cooling degree days than urban counties in the IRS data. Given the limitations of the IRS data discussed in the main text, we place more weight on the comparison in the decadal data but present both for completeness.

Table A.5: Comparing estimates from decadal and annual data

	Net migration rate (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
HDD (100s)	-0.28***	-0.01	-0.01	-0.04	-0.12***	-0.15***
	(0.07)	(0.01)	(0.02)	(0.03)	(0.03)	(0.05)
CDD (100s)	-0.60***	-0.03**	-0.06*	-0.05	-0.20***	-0.34***
	(0.08)	(0.01)	(0.03)	(0.05)	(0.06)	(0.09)
Precip. (100s mm)	0.05	-0.01**	-0.01	0.04**	-0.02	0.02
	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Fixed effects						
County	✓	✓	✓	✓	✓	✓
Region-Decade	✓					
Region-Period		✓	✓	✓	✓	✓
Dataset	Census	IRS	IRS	IRS	IRS	IRS
Period	10 years	1 year	3 years	5 years	7 years	10 years
Observations	9,060	72,684	24,228	16,152	13,460	8,076
Within R^2	0.05	0.0007	0.001	0.003	0.009	0.02
Outcome mean	0.27	0.20	0.22	0.20	0.19	0.24
Outcome SD	1.4	1.5	1.4	1.4	1.3	1.4

Notes: Table shows the impact of decadal temperature on net migration, compared across estimates from Census (decadal) and IRS tax returns (annual) datasets. Coefficients are the estimated impact of one hundred additional heating or cooling degree-day each year on the annualized net migration rate (in percentages). The first column uses census data from 1980 to 2009. The remaining columns use a balanced panel of IRS tax return data from 1983 to 2009, taking averages of all variables within the given period before estimating the model. Periods are defined as groups of years starting in 1980 of the given period length. To compute the net migration rate for multi-year averages for the IRS data, we first sum the total in- and out-migration (as measured by tax exemptions claimed) for each county across each period and then divide it by the total number of exemptions claimed in the year prior to that period. All regressions are weighted by county population in 1950 and standard errors are clustered by county.

Figure A.7: Heterogeneous effects of CDDs on net migration (IRS)



Notes: Figure shows coefficient estimates for the effect of 100 cooling degree-days on the net migration rate (in percentages), split by various dimensions of heterogeneity. Each set of estimates is produced by a long differences regression of the change in net migration rate on changes in HDD, CDD, precipitation and their interactions with the given dimension, plus Census Region fixed effects. Urban counties are those in metropolitan areas with more than 250,000 residents in 1983, rural counties are all other counties. Warm counties are those with above-median average cooling degree days between 1950 and 2009. All regressions are weighted by county population in 1950. Standard errors clustered by county and bars represent 95% confidence intervals.

B.5 Trends-on-Trends

We consider an alternative approach to estimating long-run changes in climate. This approach follows Burke and Tanutama (2019), who use this "trends-in-trends" model to estimate the impact of climate shifts on economic growth. Similar to the long-differences approach, this methodology uses variation spanning the entire period of the relevant sample. The trends-in-trends approach does this while also incorporating data from the entire study period. In our case, this specification isolates the effect of long-run average temperature trends realized across the whole extent of the considered sample on the same trends in net migration, effectively comparing migration rates in counties which have warmed more quickly to those in counties which have warmed less quickly (or even cooled). For each county, we regress its migration rates, heating and cooling degree days, and precipitation on a linear time trend.

$$\begin{aligned}
\text{Net migration rate}_{it} &= \alpha_i + \lambda_i \text{Period}_t + \varepsilon_{it} \\
\text{HDD}_{it} &= \alpha_i + \beta_i^H \text{Period}_t + \varepsilon_{it} \\
\text{CDD}_{it} &= \alpha_i + \beta_i^C \text{Period}_t + \varepsilon_{it} \\
\text{Precip}_{it} &= \alpha_i + \beta_i^P \text{Period}_t + \varepsilon_{it}
\end{aligned}$$

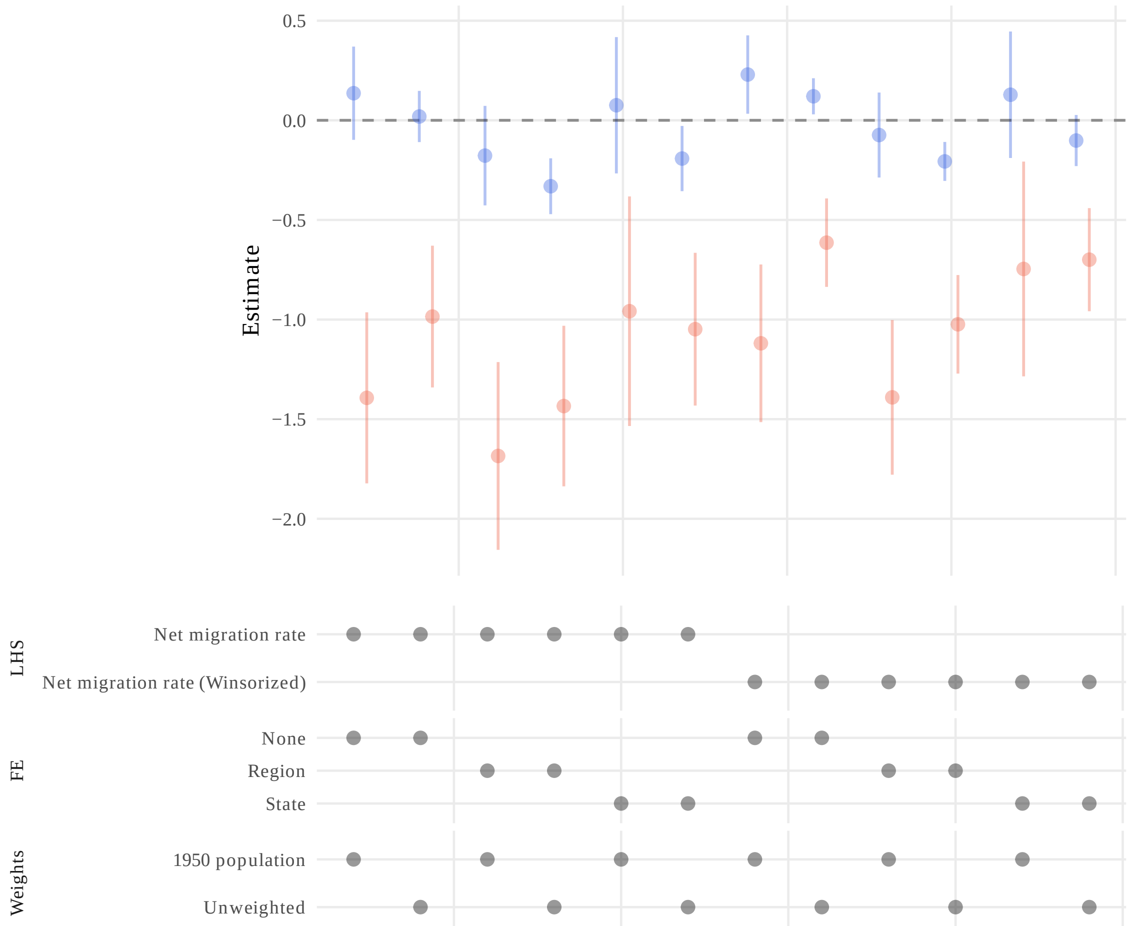
We then regress those trends on each other, along with Census Region fixed effects ϕ_r.

$$\hat{\lambda}_i = \alpha + \hat{\beta}_i^H + \hat{\beta}_i^C + \hat{\beta}_i^P + \phi_r + \upsilon_i \tag{3}$$

This specification accounts for unobservables in trends at the Census Region level using ϕ_r. Its identifying assumption is that trends in temperature and precipitation at the county level are uncorrelated with unobservable confounders that could change trends in both climate and migration. This method and its assumptions are similar to the long difference estimates, but by leveraging average trends rather than average changes over a long time period, estimates are less likely to be affected by outlying single-period shifts at the start or the end period used for long differences.

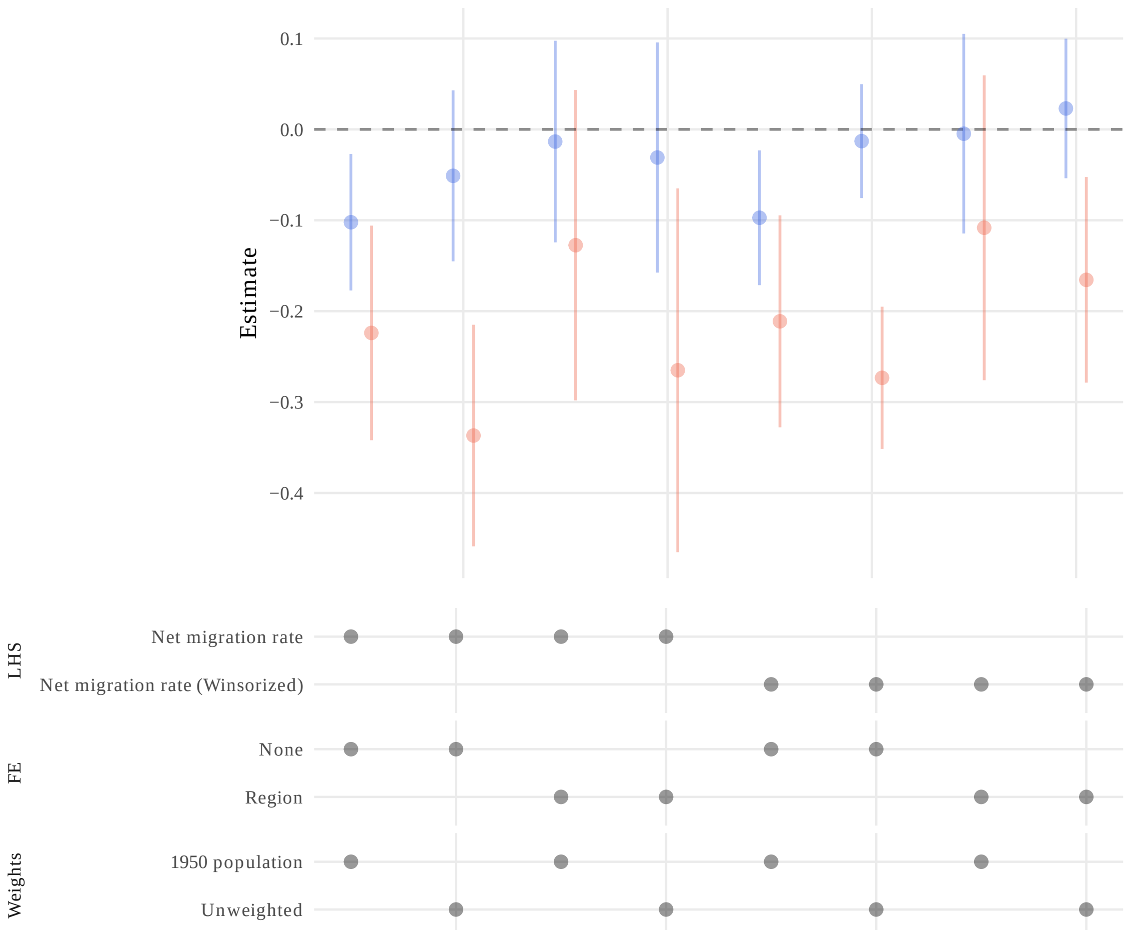
Fig. A.8 and Fig. A.9 show the sensitivity of the trends-on-trends estimates to alternative specification choices for the decadal and annual datasets respectively. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles.

Figure A.8: Sensitivity curves for decadal data (Census) – Trends-on-trends models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the decadal (Census) data using trends-on-trends models and the given left-hand side (LHS), fixed effects (FE), and weights, where the right-hand side always includes HDD, CDD, and precipitation. Net migration rate is the number of net migrants divided by the population at the start of the decade. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Estimates in blue are for HDDs and red are for CDDs. Standard errors clustered by county, lines represent 95% confidence intervals.

Figure A.9: Sensitivity curves for annual data (IRS) – Trends-on-trends models



Notes: Figure shows coefficient estimates for the estimates of the effects of 100 heating degree-days (HDDs) and 100 cooling degree-days (CDDs) on the net migration rate measured in the annual (IRS) data using trends-on-trends models and the given left-hand side (LHS), fixed effects (FE), and weights, where the right-hand side always includes HDD, CDD, and precipitation. Net migration is the in-migrants minus out-migrants. Population is the total number of tax exemptions claimed by households who began the year in the county. Net migration rate is the number of net migrants divided by the population. Net migration rate (Winsorized) is the net migration rate truncated at the 1st and 99th percentiles. Estimates in blue are for HDDs and red are for CDDs. Standard errors clustered by county, lines represent 95% confidence intervals.