Climate, Migration, and Labor Market Opportunities: Evidence from Temperature Shocks in the United States

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Abstract

This paper studies the impacts of high temperature days on out-migration from sub-state regions in the United States. Using data from two different sources – covering 10 and 24 year periods respectively - we find that an increase in the incidence of high temperature days in a year leads to more out-migration compared to moderate temperature days. The effect of temperature on out-migration does not vary by multiple observable characteristics like race, family structure, income, age, or sex. Finally, we explore employment effects of temperature shocks and find that increased incidence of high temperatures on average does not have a statistically significant effect on employment. While we do not find strong employment effects in areas that depend on agriculture (where the climate-income relationship might be most obvious), we still find significant out-migration from these areas, suggesting more nuanced pathways than direct labor-market-impacts for climate to affect mobility.

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Introduction

While migration due to climate change has been offered as an important adaptation mechanism, micro evidence on whether people move due to higher temperatures in developed countries has only become a focus of research very recently. The burgeoning literature in this area has focused largely on extreme events that cause severe disruptions to the economy and well-being. For example, Mahajan and Yang (2017) show that people move away from places that experience devastating hurricanes, Hornbeck (2012) finds that migration was the primary adaptation mechanism used by those affected by the American Dust Bowl in the late 1930s, and Boustan, Kahn, and Rhodes (2012) study migration responses to natural disasters in the 20th century. Additionally, there is increasing evidence from developing countries where incomes are much more closely tied to climate due to a higher reliance on agriculture (Cai et al. 2016). For example, Bohra-Mishra, Oppenheimer, and Hsiang (2014) find migratory responses to climate shocks in Indonesia; Mueller, Gray, and Kosec (2014) examine the relationship between heat stress and long-term migration in Pakistan; and Marchiori, Maystadt, and Schumacher (2012) provide evidence on weather anomalies and migration in sub-Saharan Africa.

While such papers are indeed important in identifying a climate-migration connection, it is also useful to consider non-catastrophic sources of weather variation in contexts where other climate coping mechanisms might be present (these can range from direct adaptation mechanisms such as air conditioning to income smoothing resources such as social safety nets). Indeed, there are many reasons to hypothesize that such effects might be important. Recent work in economics has highlighted the role of environmental factors in determining economic growth (Hsiang et al., 2017; Dell, Jones, and Olken 2011), worker productivity (Graff Zivin and Neidell 2012), and cognition (Garg, Jagnani, and Taraz 2017). The motivating questions of this investigation are whether and in what settings might increased temperatures serve as “push” factors for migration and how important labor market opportunities might be as a channel of action for such a relationship. To these ends, we will examine whether high temperatures impact migration in the United States, and whether temperature shocks lead to changes in labor market opportunities (in particular non-agriculture labor market opportunities) that might be the driving force behind the decision to migrate.

Using annual migration and labor market data from the continental U.S., we find that extreme temperatures in a given location are associated with moderate increases in out-migration from that area, but that increased temperatures are not linearly associated with local employment. These results are not driven by spatial heterogeneity in time invariant characteristics that might matter for temperature and labor markets simultaneously, as we employ an empirical design that exploits temperature variation *within* local areas. The local regions of study are MigPUMAs (Migratory Public Use Microdata Areas) from the Census's American Community Survey (ACS) and counties from the Internal Revenue Service's (IRS) Statistics on Income (SOI) migration data. We utilize a 10-year period from 2005-2015 for the individual survey data from the ACS and the 24 years from 1990-2014 for the IRS SOI data which tracks the flow of tax returns, claimed exemptions, and aggregate income between every two counties in the U.S. each year. State-by-year macroeconomic factors are also held constant using appropriate fixed effects. Hence, we are utilizing short-run, idiosyncratic variation in temperatures at a fairly local level over time to identify our effects. We restrict our ACS sample to working age adults (25-64), and the IRS data only captures information regarding earners and their dependents. This ensures that our results are not driven by elderly people moving away from colder climates for health reasons (as would be implied by the results in Deschenes and Moretti 2009).

Using the ACS and IRS data – along with county-level, labor-market data from the Bureau of Labor Statistics (BLS) – linked to temperature data from NOAA (the Global Historical Climatology Network – GHCN), we are able to estimate migration and labor market impacts of temperature fluctuations. Following Deschenes and Greenstone, 2011, as has become common in this literature, we use counts of days with mean temperatures in 10-degree Fahrenheit bins in the year as our temperature measure. For our migration results, we exploit the fact that the ACS reports respondents' MigPUMA of residence in the prior year, and that the IRS data tracks the address from which tax documents are filed and compares this information to the filing address from the prior year. Using these data, we are able to construct annual counts of the number of out-migrants from each MigPUMA and use the analogous counts produced by the IRS for each county and year.

Although the climate of an area (i.e.- the distribution of weather conditions) can be known and considered in the decision of whether to leave or locate in an area, the specific realization of weather conditions in a given year (or other relevant time period) can be considered to be effectively random for the current residents. It is the variation in the conditions experienced in a location in a given year, which we leverage to estimate the effects of temperatures on migration decisions.

Following a similar approach, we also examine labor market impacts of high temperature days using two sources of labor market data. First, we use employment questions asked in the ACS to estimate unemployment rates among the working age population in each MigPUMA, and we use data from the BLS on annual average unemployment rates and labor force size in each county. Estimates of the relationship between temperatures and unemployment rates do not exhibit a clearly systematic relationship (linear or otherwise), and specifically our results do not suggest that high temperatures result in lower employment. Indeed, our results present a bit of a puzzle, as we find no average effects even in areas heavily dependent on agriculture.

An important question arises about whether our migration results have economic meaning in light of the fact that we do not find effects on employment. For example, if climate shocks simply reallocate factors of production in a costless manner, then the fact that climate shocks make people move, while revealing an interesting behavioral aspect, might not have any bearing on overall welfare. To the extent that mobility is not costless, the fact that we observe migration at all implies some potential welfare losses if people are unable to move in response to temperature shocks. Our paper therefore highlights the fact that even if we do not find direct employment or economic effects of climate shocks, the fact that people move in response to higher temperatures might be used as an important statistic to understand welfare impacts.

Our paper contributes to a burgeoning literature in environmental economics on the effects of extreme temperature (or more generally climate shocks) on migration. In doing so we complement the existing literature focusing on catastrophic climate shocks or moderate climate shocks in developing countries, by providing evidence on the impacts of non-catastrophic temperature changes in a developed country like the United States. Closely related to this paper is the work of Feng, Oppenheimer and Schlenker (2012) who examine net-migration flows in the United States due to changes in crop yields (which in turn are affected by the weather) in the Corn Belt. While agricultural incomes no doubt play a role in determining push and pull factors, our paper takes a broader view of this question by asking whether temperature in general acts as a push factor in migration.[3] Our motivating idea is that there could be factors other than income that climate affects, and thinking about whether temperature affects migration even in areas where the income link is not obvious is therefore a relevant starting point.

An important caveat is in order: this paper focuses only on climate as a “push” factor in migration, not as a “pull” factor. Given that we know migrants’ destinations as well as their origins, it is tempting to analyze whether temperature variation in a location attracts people. However, this is a much harder question to credibly address because the destination choice set is not known, and is likely highly heterogeneous. A valid empirical approach to identifying “pull” effects of temperatures would require the evaluation of a destination’s climate as well as those of other potential candidate destinations. For example, whether the perfect weather in San Diego attracts a migrant is only relevant relative to the weather in other locations considered by the migrant, holding other factors constant. Given the structural approach necessary for credibly answering such a question, we currently only examine push factors in a reduced form framework.

Data

We currently rely on two independent sources of data for information regarding migration in the United States. The first is the ACS, which provides repeated, annual cross-sections of the American population back to 2000. Questions regarding place of residence one-year prior to the enumeration date have been included since 2005, and therefore our analytic sample will begin in that year.[4] All analyses in this investigation rely on the Census-provided person-level observation weights, which ensure that estimated statistics are nationally representative.

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[3] In our setting, we find we can replicate the Feng, Oppenheimer and Schlenker (2012) finding that high temperatures drive unemployment, but only in Corn Belt counties with high-levels of agriculture. This relationship does not appear to exist generally or even in high-ag areas in other regions of the country.

[4] 2005 is also the year in which the ACS became a stable 1-in-100 random national sample (randomized at the household level), which serves our purposes well. Prior to 2005, the ACS had a varying sample ratio around 1-to-240.

Publicly available geographic information regarding ACS respondents is limited to identifiable areas containing at least 100,000 persons. For location of current residence, geographic information is provided at the level of Public Use Microdata Areas (PUMAs); however, migration information is reported at the more-aggregate level of Migratory PUMA (MigPUMA). Boundaries of PUMAs and MigPUMAs never cross state lines and are redrawn following each decennial census. The 2012 ACS survey was the first to be organized by PUMA and MigPUMA definitions based on the 2010 Census. The first two panels of Figure 1 represent the 2000- and 2010-based PUMA and MigPUMA boundaries in light grey and black borders respectively for New Jersey and the surrounding area.

ACS data is reported at the level of the individual respondent. We include all respondents of working age, 25-64 in our analysis, and aggregate these individual observations to the MigPUMA level in order to reduce the number of observations with zero values for the considered outcome variables and reduce the computational burden of the investigation. Summary statistics for the aggregated ACS sample are provided in Panel A of Table 1.

Our second source of information on internal migration are the Statistics of Income (SOI) data from the Internal Revenue Service (IRS), which identify the flows of tax filings between counties on a yearly basis.[5] Migration flows are reported in both directions each year for every county-pair going back to 1990. In particular, the number of returns filed with addresses in County 1 by individuals in a given year that filed from addresses in different counties in the prior year are reported as migratory inflow for County 1. The number individuals that filed tax returns from addresses in County 1 in the prior year but filed from an address in a different county this year are reported in the outflow data for County 1. These outflow measures are the data we currently leverage in this investigation.

In addition to the number of gained and lost returns from and to each county, the SOI data also reports the number of exemptions claimed and aggregate income (beginning in 1992) reported on the “moving” returns. The count of returns serves as a proxy for the number of households that

[5] Additional information and raw data is available: https://www.irs.gov/uac/soi-tax-stats-migration-data.

migrate, while the number of exemptions proxies for the number of individuals that migrate between counties.

The IRS SOI data is limited in that it does not precisely capture the number of migrating individuals. It is also important to note that households that do not file taxes in a given year aren't captured by the data at all. As a result, the poor and elderly are likely underrepresented in the IRS SOI data.[6]

Throughout this analysis, we will be considering two measures of migration. The first includes all moves that cross the boundary of the smallest observable geographic unit, MigPUMA for the ACS data and county for the IRS SOI data. This removes from consideration any changes of address within these units, which are likely to represent changes in accommodation rather than migration. The second measure of migration considers only moves across state boundaries. Moves which involve a change in the reported state of residence are generally more likely to be associated with a true migration. Hereafter, the first measure will be called All Migration and will not be the center of the current investigation while the second measure will be referenced as Interstate Migration and will be the focus of the discussion and analysis of this paper. Moves to and from foreign countries are included in Interstate Migration, but represent a very small portion of such moves.

In order to assess the impacts of ambient temperatures on migration, the migration flows must be linked to relevant temperature conditions. The temperature measures used in this analysis are annual counts of days with reported mean temperatures falling in nine distinct temperature bins in a given year for a given MigPUMA/county. The bins capture counts of days with mean temperatures in 10-degree Fahrenheit ranges from 20 °F to 90 °F, with the remaining bins counting days <20 °F and >90 °F. Day-bin-counts are calculated for each monitor in NOAA's Global Historical Climatology Network for the relevant period and counts are assigned to MigPUMAs/counties based on the inverse distance weighted average of these counts from all monitors within 300km of the centroid of the relevant MigPUMA/county (following Dell, Jones,

[6] The IRS SOI data also only capture information from returns which are filed before September of the filing year – which is the year following the relevant tax year. While 95 to 98% of fillings are received by this cutoff, any filings after September are not captured. This may lead to lower representation of the very rich in the data as the complication of the tax returns of such individuals is more likely to warrant extensions beyond the September cutoff (Gross, 1999).

and Olken, 2014).[7] Only data from the continental United States – excluding Virginia – are included in the samples for analysis.

Table 1 summarizes the migration leaving (outflow) MigPUMAs/counties in each year for each of the analytic samples. Generally, we see comparable rates of inflow and outflow migration for each measure with 5-7% All Migration and 2-3% Interstate Migration each year.

Figure 2 presents the population-weighted average of All and Interstate Migration rates along with the average mean daily temperature (also, population weighted based on 2000 MigPUMAs) for the 1990-2014 period. Note that although we have ACS data through 2015, the last survey in this series is informative about moves that took place during 2014.

Empirical Strategy

Causal identification in this setting relies on random variation in the realized weather in a given locality in a given year. The independent variables of interest will therefore be the counts of days in a given calendar year on which mean temperatures fall in each of our 10 °F-width bins. These bins cover the temperature range from 20°F to 90°F with the remaining bins counting days <20°F and >90°F. The average number of days in each bin in each year are reported in Table 1, note that days with mean temperatures >90°F are quite uncommon.

To control for unique characteristics of given areas and idiosyncratic regional shocks, MigPUMA/county fixed effects and state-year fixed effects are included in all analyses. The main specification for analysis of the ACS data is as follows:

$$MR_{msy} = \alpha + \sum_{t=1}^{10} \widehat{\beta_t} * \widehat{T_{tmy}} + \delta * f(prec_{msy}) + \gamma_m + \mu_{sy} + \varepsilon_{msy}$$

$$MR_{csy} = \alpha + \sum_{t=1}^{10} \widehat{\beta_t} * \widehat{T_{tcy}} + \delta * f(prec_{csy}) + \gamma_c + \mu_{sy} + \varepsilon_{msy}$$

[7] The inverse of the squared distance is actually used so that the contribution of more distant monitors is quite steeply discounted.

Where MR_{msy} and MR_{csy} are migration rates from MigPUMA or county m or c respectively in state, s, and year, y. $\widehat{T_t}$ is the vector of temperature bin counts where t identifies the bins and y denotes the year of the observation. $\widehat{\beta_t}$ is therefore a vector of the estimated coefficients of interest, the interpretation of which is the effect of an additional day each year with a mean temperature in bin *t* relative to a day in the omitted category (as is common in the literature, we omit the 60-70°F bin). $f(prec_{csy})$ is a function of MigPUMA or county precipitation, γ represents the local area (MigPUMA or county) fixed effects, and μ_{sy} represents the state-year fixed effects. ε_{csy} is the idiosyncratic error term.

ACS regressions are weighted by working age population (population aged 25-64) in each MigPUMA. Regressions based on the number of returns and total aggregate income variables in the IRS SOI data are weighted by the number of returns in each county while the estimates based on the count of exemptions are weighted by the number of exemptions in each county.

When the MigPUMA/counties which define the observations are the place of origin (that is, migratory outflows are being considered), the temperature (and precipitation) variables capture the conditions in the location from which the population considers leaving. Because realized weather in a given locality in a given year is random, the estimated effects of such variation can be interpreted causally. The analyses of if and how temperatures in a location might "push" residents to leave therefore provide estimates of causal effects.

Results

Migration

Table 2 presents our main results on the effects of temperature on out-migration using the ACS data aggregated to the MigPUMA level. The omitted category is number of days with mean temperatures in the range of 60-70°F; hence, all coefficients are interpreted as relative to days in that temperature range. The columns represent increasing levels of fixed effects, and our preferred specification is column 4 that accounts for MigPUMA and state by year fixed effects. However, going from Column 1 to Column 4 does provide some interesting insights. Col 1 for example shows that in general people tend to out-migrate when the number of hot and cold days increases, relative to days in the 60-70°F range. However, the opposite is true in column 2 when

MigPUMA fixed effects are added. The estimates in these columns indicate the need for fixed effects that capture area-specific characteristics of the local geographic areas of examination. The last two columns use time fixed effects in addition to the MigPUMA fixed effects, and the last column makes the time fixed effects state-specific, which accounts for macroeconomic factors at the state and year level that might affect migration. This is a key fixed effect, as migration certainly depends on broad economic factors, but our estimates are based on variation that is idiosyncratic from area norms and state-level trends and shocks.

Column 4 of Table 2 (as well as Figure 3) shows that days in the higher temperature categories (above 80°F) induce outmigration. Estimates are statistically significant for the 80-90°F bin (and for a single >80°F bin when the top two bins are combined – results not shown). All estimates are reported in the number of movers per 100,000 working-aged individuals at the start of the period, and all marginal effects report the impact of a single additional day with a mean temperature in the relevant bin in an entire year.

It is important to note that slightly warmer days compared to the omitted category (i.e. days in the 70-80°F range) induce less out migration, while an increase in hot days leads to a higher number of individuals leaving the state. This is an interesting non-linearity in the migratory response to local temperatures that will have important implication for the anticipated overall effects of climate change, as anticipated increases in warm days will lead to very different predicted outcomes than increases in the number of hot days.

Table 3 repeats the addition of geographic and then temporal fixed effects, culminating in the main specification, however this time the estimates are based on the number of returns that file in a different county the following year (per 100,000 filed in the county of interest) from the IRS SOI data. We see generally the same responses to the addition of more stringent spatial and temporal controls in this data set. Deviations in temperature from the human ideal of 60-70°F lead to out-migrations generally in Column 1. The addition of location-specific (county in this data set) fixed effects reverse these signs for many bins, and temporal fixed effects significantly reduce the magnitude of estimates. Column 4 again represents our preferred specification, accounting for both location-specific and state-year idiosyncrasies (see also Figure 4). Again, we see that higher temperatures are associated with higher levels of out-migration. Interestingly, in this data, there is no migration-reducing response to an additional day in the 70-80°F bin.

The estimates in Table 3 represent our preferred specification applied to the three migration-related outcome measures in the IRS data. The number of returns – proxying for the number of households – and the number of exemptions – proxying for the number of individuals – show a consistent pattern of increases in the number of warm and hot days leading to higher levels of out-migration. While the coefficient on the >90°F temperature bin is larger in the exemptions sample than the returns sample, it is not significantly so. Nevertheless, the general comparability of the magnitudes of the coefficients on the warm- and hot-day indicators in Columns 1 and 2 suggest that it is small households being driven to migrate by increases in hot days. Smaller households are likely to be younger and face fewer mobility frictions, so it is not surprising that such households are more responsive to adverse shocks.

The smaller magnitude of the out-migration characterized by the estimates based on the IRS data relative to the ACS data may be due to the segments of the population not captured by the IRS data (those who don't pay taxes by the September deadline in consecutive years – i.e.: the poor, those with low earnings, the negligent, and the rich). It could also be that the IRS proxy for individuals (i.e.: exemptions) underestimates the number of people actually moving.

The third column of Table 4 presents the marginal effects of realized temperatures on the aggregate income reported in year *t* on the returns of those that left the county in year *t* as a share of the total aggregate income reported in year *t* by all those that filed their taxes from the county in year *t-1* (the previous year). This measure is clearly less straightforward than the other two, but the positive coefficients on the higher temperature bins suggest that some income is being earned outside a given county after hotter temperature realizations that would have been earned in the county but-for the higher temperatures.

Taken together, the estimates reported in Tables 2-4 generally indicate that higher temperatures, and in particular hot days, drive increases in out-migration. To better understand the channels through which higher temperatures might contribute to increased migration, we now consider how such higher temperatures impact local labor market conditions.

Unemployment

Beginning with the ACS data, we look at the reported employment status at the time of enumeration of those who lived in a given MigPUMA one year prior to enumeration. Column 1 of Table 5 and Figure 5 present the coefficients from the main specification (including

MigPUMA and state-year fixed effects) estimated on the share of the working-age population that reported being unemployed at the time of the survey. Outcomes are now measured as population shares (between 0 and 1) rather than rates per 100,000. While the coefficient on the top temperature bin is marginally significant, the negative sign on the estimate suggests that hot days lower the unemployment rate. This is unlikely to be a driving factor for the out-migration responses identified previously.

Column 2 of Table 5 and Figure 6 provide estimates from the same specification using annual average unemployment rates by county over the period from 1990-2015. This data was obtained from the BLS Local Area Unemployment (LAU) program.[8] The estimated effects of increased hot days are generally small and insignificant. The significant coefficients that do appear do not serve to explain the increased migration rates associated with higher temperatures. The results in Table 5 lead us to conclude that changes in unemployment rates are not the mechanism through which hotter temperatures driving out-migration.

Climate Projections

Models of climate change allow for the estimation of the differences in conditions between present day and future dates under various scenarios. Taking our estimated coefficients seriously (and assuming past responses fairly characterize future responses), we can undertake some back-of-the-envelope estimations of how out-migration might be expected to change as the climate warms. Beginning with the estimates of the changes in the level of out-migration in response to additional days in each temperature bin (from Column 4 in Tables 2 and 3), we then apply estimates of the expected increase in the number of days with a mean temperature falling in each bin relative to present day. For the latter information, we rely on Deschenes and Greenstone (2011), in which the number of days annually falling in each 10°F bin are estimated for the period from 2070-2099 using the Hadley Climate Centre's third Coupled Ocean-Atmosphere General Circulation Model assuming a business-as-usual emissions path (A1F1). The authors also error-correct the predictions from the model by comparing the model's predictions for the 1990-2002 period to realized weather conditions.

Specifically, we extracted the average number of days predicted nationally to fall in each temperature bin, and separately subtract the average number realized in our two samples (counts

[8] Available: https://www.bls.gov/lau/.

differ slightly between the MigPUMA-based ACS data and the county-based IRS data). This gives us the projected change in the number of days in each temperature bin between our sample and the 2070-2099 period for each of our two samples. These numbers are then simply multiplied by our estimated coefficients for the relevant sample and summed in order to approximate a net change in the migration rates that might be associated with conditions as forecast by the Hadley 3 model under the business-as-usual emissions path.

Uncertainty in the estimated conditions provided by the climate model is not accounted for, and all coefficient estimates are used, regardless of significance. The results of this approximation exercise are reported in Table 6 with the net-estimates presented at the bottom in the grey rows.

Column 1 reports the anticipated change in the number of days falling in each temperature bin averaged between our two samples (and rounded to the nearest integer). Even this simple representation suggests the dramatic rightward shift in the temperature distribution that is expected by the end of the century if the world continues on its current emissions trajectory. There will be many more hot days and fewer cold, comfortable and warm days (~11 fewer days in the omitted, 60-70°F, bin are expected). The upshot from these estimates is that migration rates could conceivably increase fairly substantially as the number of hot days increases. Our estimates imply 15.8% and 4% increases in annual out-migration due only to temperature increases by the end of the century.

Conclusion

We have shown that out-migration rates increase with the incidence of hot days. This relationship does not appear to be acting through temperature-driven labor market effects as we are unable to detect broad-scale impacts of high temperatures on unemployment levels. The magnitude of the migration inducing effect of hot days is moderate, such that predicted conditions at the end of the century will likely lead to increases in annual out-migration of less than 20%. Nevertheless, our estimates do not factor in the effects of increased natural disasters and coastal flooding also expected under climate change, and together these factors could contribute to significant levels of geographic displacement, even in a developed-country setting like the United States.

While the loss of community and intellectual capital (not to mention tax revenues) represented by out-migration may embody costs to a local region, it is not obvious that such movement represents a loss in social welfare. However, moving costs are certainly non-zero yet must be smaller than the costs faced by migrants in their places of origin. Additionally, it is likely that such moving costs are highly heterogeneous and that those facing greater mobility frictions would require larger shocks to drive them into migrant statuses. The moving decisions of groups with low mobility frictions may be informative about the costs absorbed by non-movers facing higher frictions.

Next steps for this project involve the examination of heterogeneity in the temperature-migration relationship to better characterize who is moving in response to hot days and why. A broader range of economic and employment outcomes will also be examined to better understand the factors that might be driving the identified temperature-migration connection. Finally, we hope to leverage the observable migration levels to infer the deeper societal costs imposed by increased incidence of high temperatures and consider more deeply the resulting implications under Climate Change.

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Table 1: Summary Statistics

Panel A: ACS Data: MigPUMA-Level

		Outflow
Years		2005-2015
# of MigPUMAs per Year		940-982
Mean Population Age 25-64		162,014
Ages 25-64	% All Moves	5.02%
	% Interstate Migration	2.26%
# Days <20°F		11.19
# Days 20-30°F		20.17
# Days 30-40°F		38.47
# Days 40-50°F		52.77
# Days 50-60°F		65.30
# Days 60-70°F		70.96
# Days 70-80°F		70.21
# Days 80-90°F		33.45
# Days >90°F		2.74
Annual Precipitation (cm)		101.82

Notes: Data is aggregated from individual level responses for all working-aged (25-64 year) adults surveyed by the American Community Survey. A move is defined as the respondent having lived in a different MigPUMA 12 months prior, and an interstate move is defined as a respondent having lived in a different state 12 months prior. Weather conditions are matched to the MigPUMA of origin, which is the location the respondent reported living 12 months prior to the survey. MigPUMA definitions shifted in 2012 based on the findings of 2010 Decennial Census.

Panel B: IRS SOI Data: County-Level

		Outflow
Year Range		1990-2014
# of Counties per Year		3107-3108
Total # Returns		33,609
Total # Exemptions		73,270
Total Aggr. Income ($1K)		1,689,632
All Moves	% of Returns	6.63%
	% of Exemptions	5.79%
	% of Aggregate Income	5.27%
Inter-State Moves	% of Returns	2.91%
	% of Exemptions	2.56%
	% of Aggregate Income	2.44%
# Days <20°F		10.59
# Days 20-30°F		19.96
# Days 30-40°F		39.37
# Days 40-50°F		54.64
# Days 50-60°F		65.77
# Days 60-70°F		71.70
# Days 70-80°F		69.83
# Days 80-90°F		31.37
# Days >90°F		2.01
Annual Precipitation (cm)		101.85

Notes: Returns proxy for the number of earners. Exemptions proxy for the number of individuals. Data only captures tax returns filed prior to September in the filing year (the year after the tax year), which can be matched to a taxpayer that filed in the previous year. The poor, elderly, and very rich are therefore likely under-represented in the sample. A move is defined as a return that is filed in a different county than the taxpayer filed in the previous tax year. An interstate move is defined as a return that is filed in a different state than the taxpayer filed in the previous tax-year. Weather conditions are matched to the county from which outflows are measured for the tax-year in question.

Table 2: Out-Migration – Adding Fixed Effects – ACS Aggregated Data

	Interstate Moves	Interstate Moves	Interstate Moves	Interstate Moves
# Days <20°F	**10.38*** **	**-3.692** **	**-1.684**	**-6.045**
	(1.294)	(1.767)	(1.887)	(3.885)
# Days 20-30°F	**4.291*** **	**-6.779*** **	**-0.151**	**0.327**
	(1.642)	(1.602)	(1.815)	(3.161)
# Days 30-40°F	**12.09*** **	**-5.545*** **	**-3.649*** **	**-1.916**
	(1.243)	(1.311)	(1.354)	(2.064)
# Days 40-50°F	**10.72*** **	**-4.644*** **	**-2.754** **	**2.313**
	(1.101)	(1.246)	(1.328)	(1.938)
# Days 50-60°F	**7.621*** **	**-3.543** **	**-2.117**	**2.15**
	(0.823)	(1.509)	(1.593)	(2.265)
# Days 70-80°F	**7.746*** **	**-2.991*** **	**-3.841*** **	**-3.466** **
	(0.578)	(1.074)	(1.089)	(1.683)
# Days 80-90°F	**9.784*** **	**-1.588**	**0.443**	**4.367** **
	(0.636)	(1.172)	(1.365)	(1.939)
# Days >90°F	**15.33*** **	**-3.355**	**0.525**	**4.194**
	(1.234)	(2.458)	(2.573)	(3.528)
Observations	10,635	10,634	10,634	10,623
R-squared	0.778	0.635	0.646	0.647
MigPUMA FE	NO	YES	YES	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	YES	NO
State-Year FE	NO	NO	NO	YES

Notes: Robust standard errors reported in parenthesis. Only moves to other states are considered out-migration. All regressions are weighted by the number of working-aged individuals in the MigPUMA in the year prior to analyzed exposure and include a fifth-order polynomial terms in precipitation. Results reported per 100,000 working-age population. Independent variables capture weather conditions in the MigPUMA of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit. Sample size varies because of the number of singleton observations dropped depends on the specific fixed effects included.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Out-Migration – Adding Fixed Effects – IRS SOI Migration Data – Tax Returns

	Returns Interstate Moves	Returns Interstate Moves	Returns Interstate Moves	Returns Interstate Moves
# Days <20°F	**6.954*** **	**-13.13*** **	**-0.632**	**0.836**
	(0.606)	(0.392)	(0.400)	(0.777)
# Days 20-30°F	**-0.577**	**-6.574*** **	**-0.394**	**0.700**
	(0.769)	(0.367)	(0.370)	(0.599)
# Days 30-40°F	**14.63*** **	**-5.938*** **	**-3.958*** **	**0.544**
	(0.548)	(0.300)	(0.285)	(0.436)
# Days 40-50°F	**13.44*** **	**-5.782*** **	**-5.353*** **	**-0.621* **
	(0.419)	(0.262)	(0.247)	(0.368)
# Days 50-60°F	**6.930*** **	**-2.407*** **	**-3.892*** **	**0.571* **
	(0.384)	(0.282)	(0.267)	(0.345)
# Days 70-80°F	**8.230*** **	**-1.605*** **	**-1.373*** **	**1.822*** **
	(0.299)	(0.237)	(0.226)	(0.317)
# Days 80-90°F	**11.29*** **	**-0.349**	**-0.523* **	**0.888** **
	(0.303)	(0.257)	(0.269)	(0.374)
# Days >90°F	**22.21*** **	**1.044**	**-2.357*** **	**2.917*** **
	(0.802)	(0.640)	(0.595)	(0.753)
Observations	76,700	76,699	76,699	76,674
R-squared	0.808	0.879	0.902	0.916
County FE	NO	YES	YES	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	YES	NO
State-Year FE	NO	NO	NO	YES

Notes: Robust standard errors reported in parenthesis. Only moves to other states are considered out-migration. All regressions are weighted by the number of returns filed in a county for the year prior to analyzed exposure and include a fifth-order polynomial terms in precipitation. Results reported per 100,000 returns filed. Independent variables capture weather conditions in the county of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit. Sample size varies because of the number of singleton observations dropped depends on the specific fixed effects included.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Out-Migration – Three IRS SOI Measures

	Interstate Moves		
	Returns	Exemptions	Agg. Income
# Days <20°F	**0.836**	**0.785**	**1.21E-06**
	(0.777)	(0.794)	(0.000009)
# Days 20-30°F	**0.7**	**0.748**	**2.42E-07**
	(0.599)	(0.611)	(0.000007)
# Days 30-40°F	**0.544**	**0.289**	**3.59E-06**
	(0.436)	(0.446)	(0.000005)
# Days 40-50°F	**-0.621***	**-0.620***	**-3.03E-06**
	(0.368)	(0.373)	(0.000004)
# Days 50-60°F	**0.571***	**0.327**	**1.13e-05*****
	(0.345)	(0.361)	(0.000004)
# Days 70-80°F	**1.822*****	**1.383*****	**5.53E-06**
	(0.317)	(0.323)	(0.000004)
# Days 80-90°F	**0.888****	**0.949****	**6.26E-06**
	(0.374)	(0.378)	(0.000004)
# Days >90°F	**2.917*****	**1.736****	**1.73e-05****
	(0.753)	(0.742)	(0.000008)
Observations	76,674	76,674	70,484
R-squared	0.916	0.907	0.863
County FE	YES	YES	YES
State FE	NO	NO	NO
Year FE	NO	NO	NO
State-Year FE	YES	YES	YES

Notes: Robust standard errors reported in parenthesis. Only moves to other states are considered out-migration. Returns and Aggregate Income regressions are weighted by the total number of returns filed in the county for the year prior to analyzed exposure. Exemptions regressions are weighted by the total number of exemptions claimed. All regressions include a fifth-order polynomial terms in precipitation. Returns and Exemptions results are reported per 100,000 returns filed in prior year. Results for Aggregate Income are for share of total Aggregate income of prior year filers in a location. Independent variables capture weather conditions in the county of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit. Returns are generally considered to proxy for the number of earners and exemptions for the number of individuals. Sample is for 1990-2015. Aggregate Income data is not available until 1992.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Unemployment

	ACS: Unemployed as Share of Working-Age Population	BLS: Unemployment Rate
# Days <20°F	**-0.0000302**	**0.000957**
	(0.000043)	(0.001)
# Days 20-30°F	**8.36e-05****	**0.00437*****
	(0.000035)	(0.001)
# Days 30-40°F	**0.00000955**	**-0.00202****
	(0.000023)	(0.001)
# Days 40-50°F	**-0.0000105**	**0.001**
	(0.000021)	(0.001)
# Days 50-60°F	**-0.0000337**	**0.00033**
	(0.000025)	(0.001)
# Days 70-80°F	**-0.00000378**	**0.00380*****
	(0.000019)	(0.001)
# Days 80-90°F	**-0.00000505**	**-0.000427**
	(0.000021)	(0.001)
# Days >90°F	**-7.17e-05***	**-0.00189**
	(0.000039)	(0.001)
Observations	10,623	76,660
R-squared	0.838	0.906
MigPUMA/County FE	YES	YES
State FE	NO	NO
Year FE	NO	NO
State-Year FE	YES	YES

Notes: Robust standard errors reported in parenthesis. ACS regression is weighted by working age (25-64) population of the MigPUMA in the year prior to analyzed exposure, and measure represents the share of this population that reports being unemployed at the time of enumeration. Observations in the BLS regression are annual average unemployment rates by county as calculated by BLS. BLS regression is weighted by the size of the labor force in the county-year. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit. Both regressions include a fifth-order polynomial terms in precipitation.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Projected Difference in Annual Migration Rates per 100,000
Based on 2070-2099 Predicted Temperature Shifts

	Avg. Change in # of days in each bin annually 2070-2099	Diff. in 2070-2099 Rates Attributable to Projected Shift in Temperature Distribution	
		ACS: Out-Migration Wrk Age Pop	**IRS: Out-Migration Returns**
Day Under 20	-8	**49.51**	**-6.35**
		(31.82)	(5.90)
Day 20-30	-10	**-3.32**	**-6.97**
		(32.15)	(5.90)
Day 30-40	-12	**21.98**	**-6.72**
		(23.67)	(5.96)
Day 40-50	-11	**-22.6**	**7.23***
		(18.93)	(5.40)
Day 50-60	-16	**-32.89**	**-9***
		(34.65)	(5.45)
Day 70-80	-8	**28.45****	**-14.27*****
		(13.82)	(5.45)
Day 80-90	34	**145.2****	**31.38****
		(64.47)	(2.48)
Day Over 90	41	**171.37**	**121.31*****
		(144.14)	(13.23)
Change per 100,000		357.70	116.61
Net Implied Rate Change		0.0036	0.0012
Mean Annual Rate (Present Day)		0.0226	0.0291
% Change in Annual Rate		15.83%	4.01%

Notes: Standard errors do not account for uncertainty in climate projections. Projections based on the average national change in the number of days in each temperature bin in the period from 2070-2099 as calculated by Deschenes and Greenstone (2011) using the error-corrected Hadley 3 A1F1 Climate Model. Column 1 presents the rounded average change in the number of days in each bin between the two samples. Regressions are weighted as described for the underlying analyses.
*** p<0.01, ** p<0.05, * p<0.1

Figures

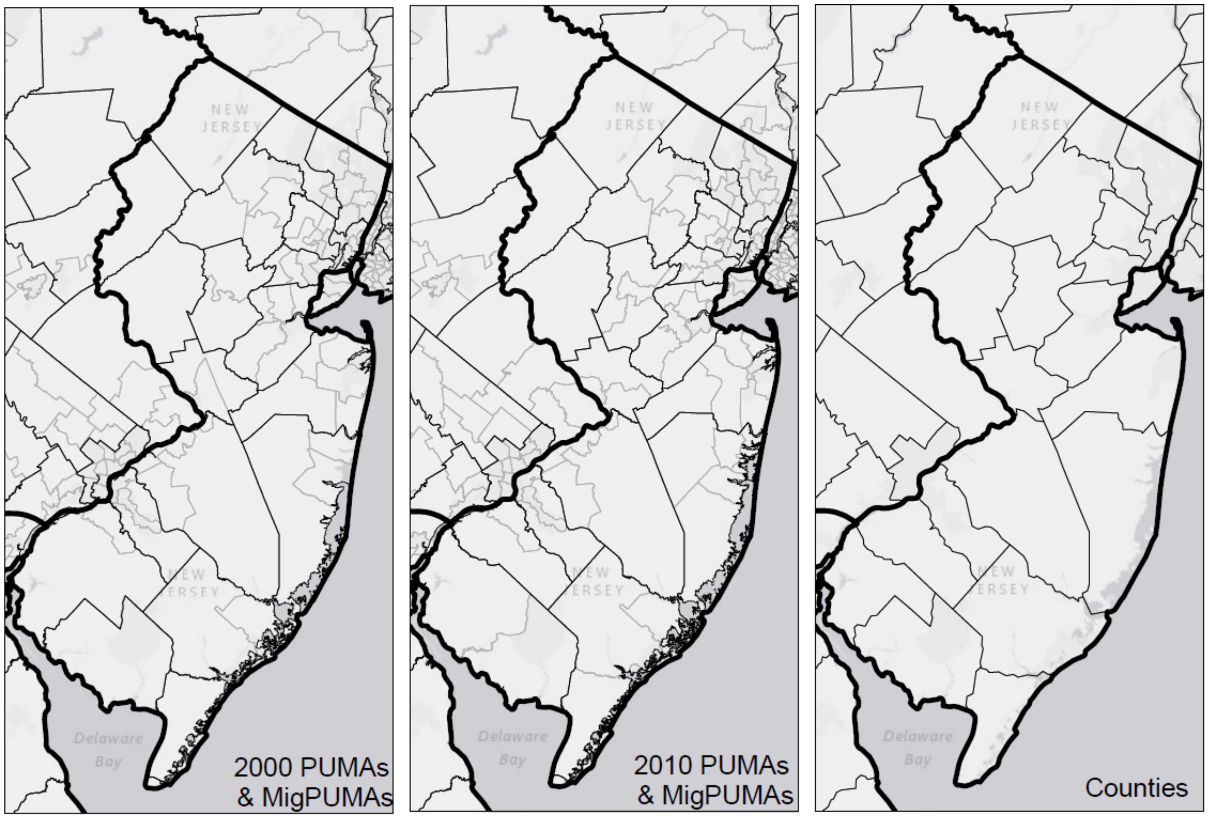

Figure 1: PUMA and MigPUMA boundaries based on 2000 and 2010 Censuses

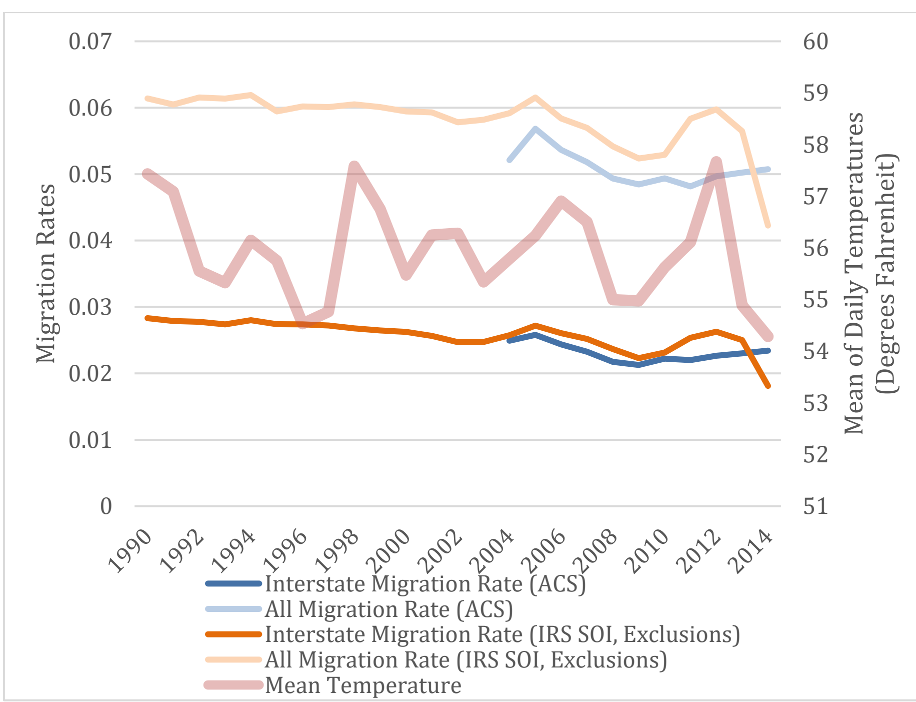

Figure 2. Implied MigPUMA Average Migration Rates and Temperatures by Year

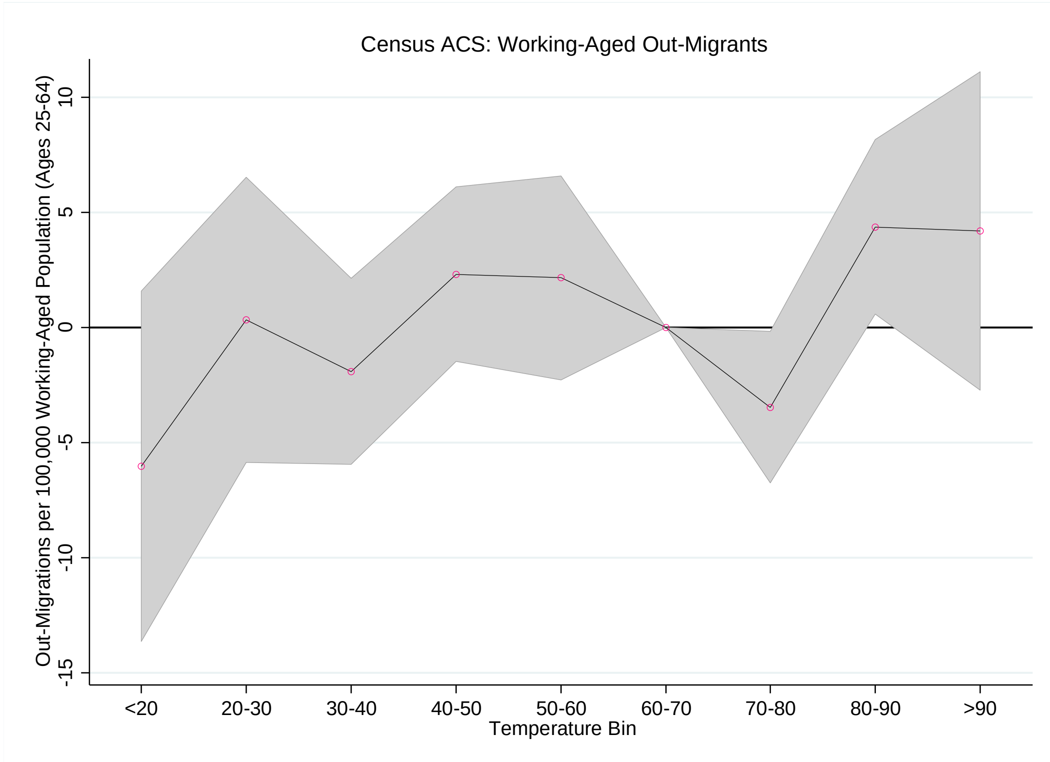

Figure 3: Coefficient Estimates for ACS Out-Migration

Notes: 95% confidence intervals based on robust standard errors shown in grey. Only moves to other states are considered out-migration. Regression includes MigPUMA and State-year fixed effects as well as a fifth-order polynomial in precipitation. Observations are weighted by the number of working-aged individuals in the MigPUMA in the year prior to analyzed exposure. Results reported per 100,000 working-age population. Independent variables capture weather conditions in the MigPUMA of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit.

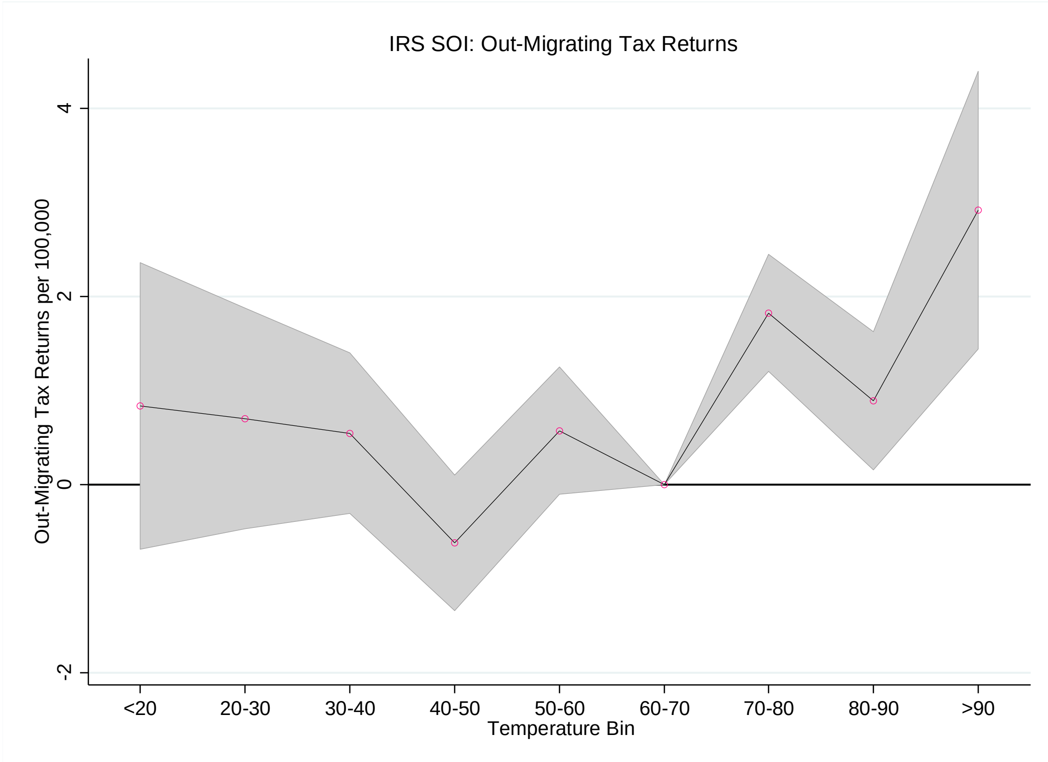

Figure 4: Coefficient Estimates for IRS SOI Out-Migration

Notes: 95% confidence intervals based on robust standard errors shown in grey. Only moves to other states are considered out-migration. Regression includes County and State-year fixed effects as well as a fifth-order polynomial in precipitation. Observations are weighted by the number of tax returns filed in the county in the year prior to analyzed exposure. Results reported per 100,000 returns filed. Independent variables capture weather conditions in the county of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit.

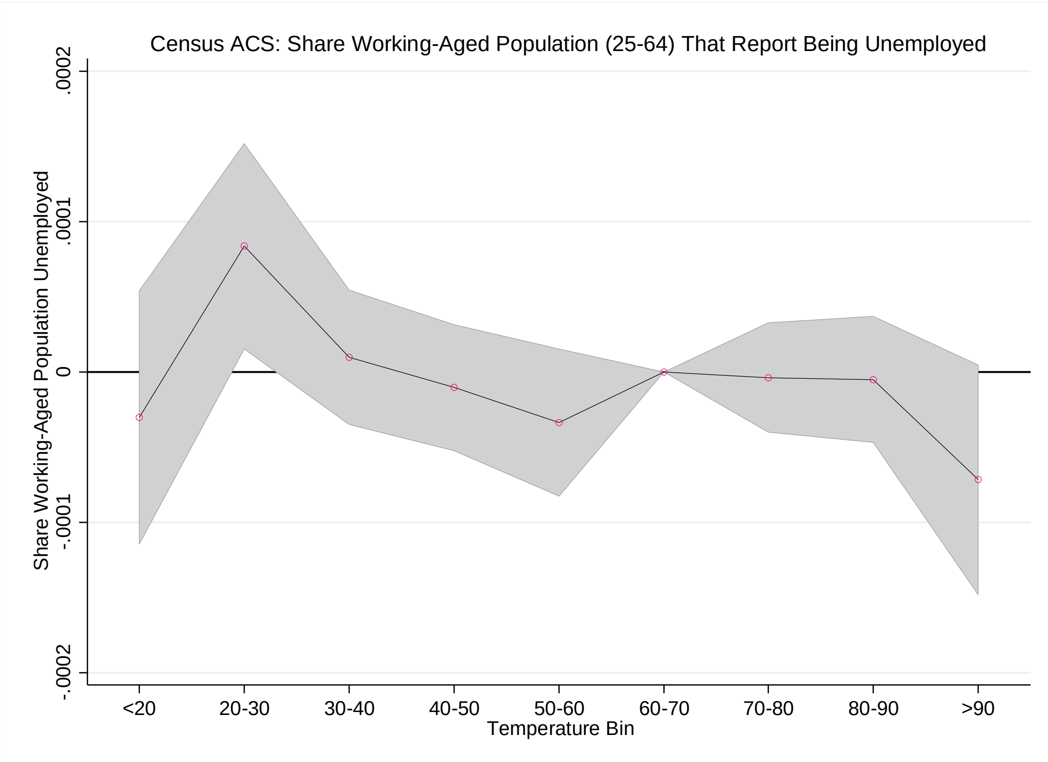

Figure 5: Coefficient Estimates for ACS Self-Reported Unemployment Rate

Notes: 95% confidence intervals based on robust standard errors shown in grey. Only moves to other states are considered out-migration. Unemployment rate is the number of working-aged (25-64 years) individuals in a MigPUMA-year that report being unemployed divided by the total number that report being employed or unemployed. Regression includes MigPUMA and State-year fixed effects as well as a fifth-order polynomial in precipitation. Observations are weighted by the number of working-aged individuals in the MigPUMA in the year prior to analyzed exposure. Results reported per 100,000 working-age population. Independent variables capture weather conditions in the MigPUMA of origin. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit.

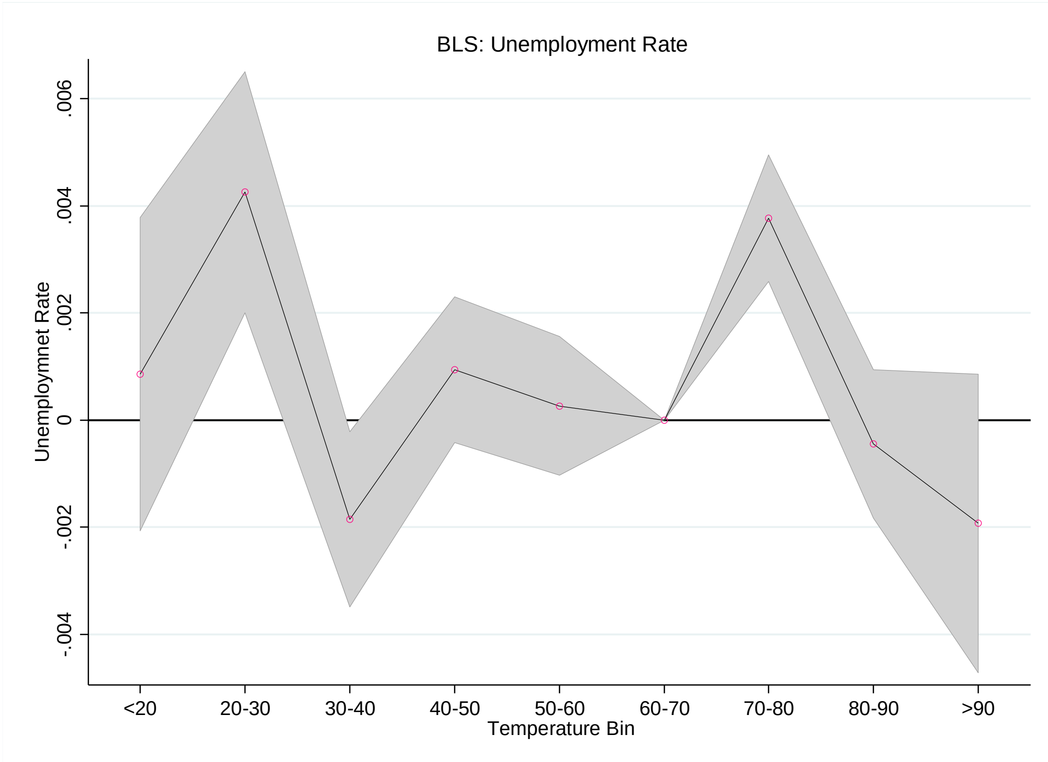

Figure 6: Coefficient Estimates for BLS Annual Average Unemployment

Notes: 95% confidence intervals based on robust standard errors shown in grey. Observations are annual average unemployment rates by county as calculated by BLS by dividing the number of unemployed individuals in the county by the size of the labor force. Regression includes County and State-year fixed effects as well as a fifth-order polynomial in precipitation. Observations are weighted by the size of the labor force in the county-year. Omitted category is the count of days with mean temperatures between 60 and 70 degrees Fahrenheit.