# Extreme Weather and Migration in the United States

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**Abstract**

Extreme weather has become more frequent and intense over the past few decades. Its effect on migration in developed countries has been understudied. Given that the United States population has been historically highly mobile, direct and indirect effects of extreme weather could catalyze people to migrate. I test this empirically by exploiting spatial and temporal variation in extreme weather (temperature, precipitation and natural disasters) at the county level over 6 decades (1950-2010). A non-parametric estimation yields an inverted U-shape relationship between temperature and net-migration, where decades in which the temperature was further away from the 50-60 temperature bin exhibit lower net-migration; the effect is strongest at the extreme temperature bins. Specifically, one additional day in a year with temperature above 90 decreases net migration by approximately 1.5 migrants per 100 population. This result is important as migration could mitigate the detrimental effects of climate change in the developed world. In addition, it suggests that future increase in extreme weather could entail a migration response that will affect different markets, which should be taken into account when considering the general equilibrium effects of climate change.

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# 1 Introduction

Extreme weather has become more frequent and intense over the last few decades; high temperatures, heavy downpours, and natural disasters such as floods, droughts and storms are more common than ever. These trends are predicted to persist (Karl et al., 2009). The rise in extreme weather has garnered attention from policy makers, as well as the public, to become one of the most debated topics on the public agenda. Researchers have also weighed in, developing a vast body of literature examining the effects of extreme weather. In particular, its effect on migration has been studded extensively. In this paper, we expand the study of the effect of extreme weather on migration to a context that has been scarcely studied - the developed world.

Extreme weather could catalyze migration directly or indirectly. The former stems from natural human aversion to extreme hot or cold temperatures and wet conditions (Albouy et al., 2010). The latter stems from the the detrimental effects that extreme weather has been found to have on numerous economic, health, and social factors, which in turn could catalyze migration. These include, but are not limited to, reduced productivity (Burke et al., 2015; Schlenker and Roberts, 2009), reduced economic growth (Hsiang and Jina, 2014), increased mortality (Deschênes and Greenstone, 2011), and increased human conflict activities such as crime and political conflict (Hsiang et al., 2013).

These migration catalysts are combined with the fact that the United States has one of the highest rates of internal migration in the world. For example, in 2010, about 2% of the population migrated within the last year and about 12% migrated in the last 5 years (Molloy et al., 2011). The catalysts mentioned above, in conjunction with a dynamic, mobile population could make extreme weather an important determinant of migration. This is manifested in the Census's decision to add in 1998 the option for individuals to choose "change of climate" as a reason as to why they decided to move.

We estimate the effect of extreme weather on migration by exploiting variation in extreme weather within counties over six decades, as well as between counties, using a specification that allows the effects of extreme weather to vary across the weather distribution. We start by aggregating temperature and precipitation data from the daily-weather station level to the county-decade level, by counting the average number of days in a year (averaged over the decade) in which the temperature and precipitation were within certain bins; we also aggregate natural disasters data by counting the number of "disasters days" in a county-decade, which take into account both the frequency and severity of natural disasters. We then regress the county-decade net migration rate, defined as the increase/decrease in the population due to migration, on the temperature, precipitation and natural disasters measures including county and decade fixed effects. The estimates provide the separate effect of having the temperature, precipitation and natural disasters be within our assigned bins, relative to an omitted "moderate" weather bin.

Our results reveal an inverted "U-shape pattern for the effect of temperature, in which, as temperature moves further away from "moderate" temperatures towards hotter/colder temperatures, the net migration rate decreases, with the most negative estimates at both extremes temperatures - $>90°$ and $<10°$. For example, an additional day in a year (averaged over a decade) in which the temperature was above 90°, decreases the net migration rate by 1.33, relative to a day in which the temperature was 50°-59° . This is a considerable effect, given the distribution of the net migration rate. Although $>90°$ days are rare, they have been increasing in recent years, and are predicted to continue increasing; moreover, we find a statistically significant effects at the more prevalent temperatures as well, such as 80°-89° days. With respect to precipitation, we find that an additional day in which precipitation was above 15mm decreases the net migration rate by 0.31, relative to a day with no precipitation. The estimates for the effects of lower precipitation are all negative, but are imprecisely estimated. Similarly, our estimates for the effect of natural disasters on the net migration rate are statistically insignificant; nonetheless, they are negative, and are larger in magnitudes for the higher natural disaster measure.

We also run our analysis for different age groups, finding that, in line with predictions, extreme weather affects persons aged 25-45 more than it affects persons aged 45-65, and it has no effect on persons aged 65 or more. In addition, we run our analysis separately for agriculture dependent counties and non agricultural dependent counties, finding that extreme weather affects these counties similarly, suggesting that the effect that we find is not solely driven by the impact of extreme weather on agriculture, as is the case in nost developing country contexts.

This paper makes several contributions to the literature. First, it studies the effect of extreme weather on migration for a large country in the developed world, the entire United States, over a long period of time. Previous studies focused on the developing world, or specific parts of the United States, in which weather induced agricultural shocks catalyzed migration. We test whether extreme weather affects migration in broader contexts, that are not limited to agriculture. Finding an effect would suggest that individuals respond to climate change and that migration could be mitigating the effects of climate change not only in developing world, but in the developed world as well. This endogenous response should be taken into account when modeling the costs of climate change. Second, we estimate the effects using recent causal inference methods that do not impose as much structure as previous methods.Third, in contrast to previous papers, we combine in the same estimation, the three extreme weather measures; this is important to avoid omitted variable bias, where precipitation for example, would be attributed part of the effect coming from natural disasters that entail high precipitation, such as hurricanes, although the effects of those on migration isn't limited to high precipitation.

The paper proceeds as follows: Section 2 surveys the related literature. Section 3 outlines our identification strategy. Section 4 details the data sources, the identifying variation, and provides descriptive statistics. Section 5 presents the results, and Section 9 concludes.

# 2 Related Literature

The majority of studies that relate extreme weather to migration have done so in the context of developing countries. Large share of households in these countries drive their income from agriculture. When extreme weather occurs, agriculture is adversely affected; moreover, households in developing countries lack the resources to adapt, as well as a sufficient social welfare net (Cai et al., 2016), leading some households to migrate as a risk-management strategy (Kubik and Maurel, 2016). Certain extreme weather events such as storms, landslides, fires and floods lead to forced migration (Bedarff and Jakobeit, 2017). These migrants have been referred to by the UN as "environmental migrants" (Chazalnoel et al., 2017).

These scenarios have been studied in numerous contexts throughout the developing world; in Tanzania (Kubik and Maurel, 2016), Mexico (Cai et al., 2016) and the Philippines (Bohra-Mishra et al., 2017), authors estimate the migration response to decline in agricultural yields due to extreme weather; in Indonesia, Kleemans and Magruder (2018) estimate the effect of migration on labor markets by instrumenting for migration with weather shocks; (Cai et al., 2016) link international migration to climate changes, and find that the a statistically significant relationship exists only for the most agriculture-dependent countries; Thiede et al. (2016) conduct similar analysis for South America.

Research on the effect of extreme weather on migration in the developed world is much more scarce, although a few papers exist. Poston Jr et al. (2009) estimates this effect for the United States during a short time period (1995-2000) by simply regressing migration on several contemporaneous weather measures at the state level. Feng et al. (2012) look at a longer time period (1970-2009), and at a finer geography (county), but do so only for the Eastern United States; as in the papers looking at the developing world, the authors instrument for corn yields with weather shocks and find a migration response for those counties heavily dependent on corn yields. Similarly, Rappaport (2009) considers a framework where "nice weather" is a commodity; empirically, he relates population growth rates to a few temperature and precipitation measures from 1970 to 2010 at the county level. Lastly, Boustan et al.

(2012) find that a migration response to natural disasters at the beginning of the twentieth century. Research in the context of the developed world has been limited, such that even an important article in JEP that surveys internal migration trends in the United States (Molloy et al., 2011), does not mention weather as a determinant of migration. This paper distinguishes itself from previous papers by examining a longer time period (1950-2010), for the entire United States, allowing weather to flexibly affect migration, whereas previous papers assumed a linear relationship, and by including temperature and precipitation with natural disasters simultaneously in the estimation.

# 3 Identifying Strategy

I am interested in estimating the effect of extreme weather on net migration. To do so, we exploit the intra-county variation in extreme weather across decades, and relative to the corresponding changes in other counties, by employing the following specification, in the spirit of Barreca et al. (2016):

$$\begin{aligned} mig\_rate_{ct} = &\sum_{i=1,i\neq 7}^{10} \beta_i \cdot temp\_bin\_i_{ct} + \sum_{j=1,j\neq 1}^{5} \gamma_j \cdot prec\_i_{ct} \\ &+ \delta_1 \cdot low_{ct} + \delta_2 \cdot high_{ct} + \theta_c + \lambda_t + \epsilon_{ct} \end{aligned} \tag{1}$$

Where $c$ indexes county and $t$ indexes the year. $mig\_rate_{ct}$ is the migration rate per 100; $temp\_bin\_i_{ct}$ is the number of days in a year in which the average daily temperature was in a given range, averaged over the decade. I include 9 temperature bins, ranging from <10° to >90° at 10° intervals; I omit the 50°-59° temperature bin. $prec\_i_{ct}$ is the number of days in a year in which the precipitation was in a given range, averaged over the decade. I include 5 precipitation bins (0mm, 0-3mm, 3-9mm, 9-15mm and ¿15mm); I omit the 0mm precipitation bin. $low_{ct}$ and $high_{ct}$ are dummies, taking the value 1, if the number of "disaster days" during the decade was between 1 and 30, or above 30, respectively; the omitted category is 0 disaster days. We include county fixed effects, $\theta_c$ to control for time-invariant differences across counties that might affect migration rates, such as differences in desirability, or distance from border; and decade fixed effects, $\lambda_t$, to control for nationwide factors that affect migration rates over time, such as common economic shocks.

This specification allows the effect of temperature, precipitation, and natural disasters to vary across their distributions. The $\beta_i$'s measure the effect of an additional day in a year, over a decade, in which the temperature was in bin $i$, relative to a day in the 50°-59° temperature bin. The $\gamma_j$'s measure the effect of an additional day in a year, over a decade, in which the precipitation was in bin $j$, relative to a day in the 0mm precipitation bin. Lastly, $\delta_1$ and $\delta_2$ measure the effect of low and high number of disaster days occurring during the decade, relative to having no disaster days occurring during the decade. Note that "an additional day in year, over a decade" could mean an additional day in each of the decade, or it could mean 10 additional days in one year, or anything in between. As we include county and decade fixed effects, the effect is identified from the changes in the temperature distribution within a county over time - and relative to the corresponding changes in other counties. The regressions are clustered at the state level to allow errors to correlate spatially within a state and across time.

# 4 Data and Identifying Variation

## 4.1 Data

*Temperature and Precipitation* - Data on temperature and precipitation come from the most comprehensive source of daily climate summaries from land surface weather stations in the United States - the National Climatic Data Center - Global Historical Climatology Network Daily (Menne et al., 2012). The dataset contains the maximum and minimum daily temperatures (at tenths of a degree Celsius, which I convert to Fahrenheit) and the precipitation (at tenths of a mm) at the weather station-day level for weather stations in the United States. I use data for the years 1950 to 2010, the years for which the migration data is available.

Following the methodology of Barreca et al. (2016), I aggregate temperature data to the county-decade level in the following manner. First, I calculate average daily temperature for each weather station-day as the simple average of the maximum and minimum temperature that day. Then, for each weather station-year, I count the number of days during that year in which the average daily temperature was within one of 10 temperature bins, ranging from $<10°$ to $>90°$ at $10°$ degree intervals. In order to aggregate up to the county-year level, I calculate a weighted average of the yearly temperature bin counts of all the weather stations that are within 300km of a county centroid, where the weight given to each weather station is it's inverse squared-distance from the county centroid; this gives higher weight to weather stations closer to the county centroid. Lastly, I aggregate the yearly temperature bins counts from the county-year level to the county-decade level using a simple average across the years in each decade. Precipitation data is aggregated to the county-decade level in the same manner, with five precipitation bins used (0mm, 0-3mm, 3-9mm, 9-15mm and >15mm).

I include all weather stations-years for which there are no missing data (i.e. no days in the year in which temperature or precipitation data are missing). Overall, this leaves

13,003 unique weather stations across the United States with the number of weather stations contributing to the calculation of temperature and precipitation at the county-decade level ranging between 50 and 500[1].

*Natural Disasters* - Data on natural disasters come from OpenFEMA Disaster Declaration data (FEMA, 2019). The dataset includes all federally declared disasters; for each, it includes its type (e.g. severe storm), beginning and end date[2], and the county effected. It includes natural disasters declared from 1964 onward[3]; I include natural disasters up to 2009, as the net migration data ends at the 2000's decade.

I define *disaster exposure* per county-decade according to the total number of disaster days declared in the county during that decade, and create dummies for each of the following categories accordingly:

- *No disasters* - 0 disaster days
- *Low # of disaster days*: 1< disaster days <30
- *High # of disaster days*: disaster days >30

*Migration* - Data on migration come from the University of Wisconsin - Madison Applied Population Laboratory Age-Specific Net Migration Estimates for US Counties, 1950-2010 (Winkler et al., 2013). It includes estimates of net migration for US counties for each decade from 1950 to 2010; it does not include the actual flows of in-migrants and out-migrants.

Net migration estimates were calculated using a residual method, based on US Census counts at the beginning and end of each decade and intercensal birth and death records, in the following way (for each county-decade) - first, "expected population" at the end of the decade was calculated as the population at the beginning of the decade plus births minus deaths that occurred during the decade; this would have been the population at the end of the decade if there was no in or out migration. Then, the expected population at the end of the decade is subtracted from the observed population; this is the estimate of net migrants, the change in the population over the decade due to migration, defined as in-migrants minus out-migrants. A positive estimate, for example, means that in-migrants outnumbered out-migrants; the actual flow is not obtained, just the net balance.

Using the estimate for net migrants, we calculate the migration rate, per 100 population - the change in a county's population during the decade, due to migration, defined as:

[1] A weather station can be within 300km of more than one county centroid, and therefore, could contribute to the calculation of weather in several counties

[2] As FEMA explained to me in an e-mail, the interval between the beginning and end date is "the time interval during which the disaster-causing incident occurs."

[3] The dataset includes disasters declared prior to 1964, but for those, it only includes state identifier.

$$mig\_rate_{ct} = \frac{net\_migrants_{ct}}{population_{ct}} * 100$$

Where $population_{ct}$ is the population of county $c$ at the start of decade $t$. Note that the average net migration rate doesn't distinguish between internal migration (United States citizens moving from one county to another) and international migration. The average net migration rate across counties is positive - although internal migration will decrease the population at one county, while increasing it at another, migration from outside the United States will increase the population only at the destination county.

## 4.2 Descriptive Statistics

Table 1 details the decade net migration rate at different percentiles of the net migration rate distribution. While at the $10^{th}$ percentile, counties were losing 17.3 residents per 100 population, at the $90^{th}$ percentile, counties were gaining 18.5 residents per 100 population. The median county was losing 1.2 residents per 100 population.

The table also provides descriptive statistics on the number of days in a year, averaged over a decade, in which the average temperature was above 90°, between 80° and 89°, and below 10°, at different percentiles of the temperature distribution. Although the number of days in a year in which the average temperature was above 90° are small (0.05 at the $50^{th}$ percentile; 1.23 at the $90^{th}$ percentile), the number of days in a year in which the temperature was between 80° and 89° is much higher (15.1 at the $50^{th}$ percentile; 68.9 at the $90^{th}$ percentile). This is important, as our estimation suggests a significant effect not only for additional days in which the temperature was above 90°, but also for days in which the temperatures are 80°-89°. Also, as noted previously, the number of days with above 90° are on the rise. Extreme cold weather is prevalent as well. the number of days in a year in which the average temperature was below 10° is 1.9 at the $50^{th}$ percentile, and 32.4 at the $90^{th}$ percentile. Figure 2, which shows the increase in extreme temperatures over time, will be discussed in the section 4.3.

Table 2 provides descriptive statistics on the natural disasters in our data, from the 1970 to 2009, the four full decades included in the data. During this period 45,915 natural disasters were federally declared by FEMA. Out of those, 34.2% were severe storms, 20.2% were hurricanes, 19.9% were floods, and 25.7% were other categories. I categorize "low-severity" natural disasters as those that lasted up to 3 disaster days, the $25^{th}$ percentile of disaster days, while "high-severity" are those that lasted 34 days or more, the $75^{th}$ percentile of disaster days. The data reveals a signiifcant increase in the number of natural disasters. While in the 1970's an average county experienced 1.6 disasters, lasting 13.1 days (throughout the whole decade). By the 2000's those numbers have increased considerably to 5.5 disasters, lasting 168.8 days.

## 4.3 Identifying Variation

We are interested in examining whether decades in which the weather was more extreme coincide with decreases in net migration. To identify the effect we exploit the temporal variation in temperatures, precipitation and natural disasters within a county over time, as well as the spatial variation in those variables across counties. We illustrate this identifying variation in this section.

Figure 1 details the spatial variation in hot and cold temperatures in the 1950's. The left figure shows the number of days in a year (averaged across the decade) in which the average temperature was above 80°, while the right figure shows the number of days in a year (averaged across the decade), in which the average temperature was below 20°; the darker the shade, the higher the number of days of either extreme hot or cold weather. As expected, counties in the south experience a higher number of hot days, whereas counties in the north experience a higher number of cold days.

Figure 2 details the temporal variation in hot and cold temperatures. For each county, we calculated the absolute change in the number of days in a year (average across the decade) from the 1960's to the 2000's in which the temperature was above 80° (left figure), or below 20° (right figure). The left figure reveals significant increase in the number of hot days across the United States, but especially in the southern United States, where in a large number of counties, in as little as four decades, the number of hot days in a year increased by more than 20. The right figure reveals that the number of cold days decreased moderately across the United States. Note that these changes in the temperature distribution over time affected counties across the United States differentially, providing significant temporal and spatial variation required for estimation.

Lastly, Figure 3 details the spatial and temporal variation in natural disasters. The left figure illustrates the number of natural disasters in each county in the 1970's (left figure) and the 2000's (right figure) across United States counties; the darker the shades, the higher the number of natural disasters in that county X decade. While in the 1970's, lighter shades dominated the map, by the 2000's, darker shades dominated the map, implying a significant increase in the number of natural disasters. As noted in the previous section, their severity increased as well. In addition, similarly to the increases in hot days, counties across the United States experienced differential increases.

# 5 Results

## 5.1 Main Results

Figure 4 plots the estimates for the $\beta_i$s from estimating the main specification - equation 1; Table 3 details the corresponding estimates. To the right of the "moderate" temperature bin of 50°-59°, which is omitted in the estimation, the coefficients are negative, and they become more negative the higher the temperature bin, reaching the most negative coefficient at the hottest temperature bin (>90°). The coefficients of the 70°-79°, 80°-89° and >90° temperature bins are statistically significant at 99%. They suggest that an additional day in a year (averaged over a decade) in which the temperature is within these temperature bins, will decrease the net migration rate by 0.46, 0.63 and 1.33, respectively, relative to a day in which the temperature was 50°-59°. Meaning, during the decade, 0.46, 0.63 and 1.33 more migrants will move out of the county than migrants that will move into the county, for every 100 population that the county had at the beginning of the decade. Given the distribution of net migration, as detailed in 2, these magnitudes are sizeable. For example, for counties at the $90^{th}$ percentile of the net migration rate, an extra day in a year (averaged over a decade) in which the temperature is between 80°-89° will decrease the net migration rate by approximately 3.4%.

To the left of the 50°-59° temperature bin, the coefficients are negative, but are statistically insignificant, except the coefficient of the <10° temperature bin, the coldest temperature bin. This coefficient suggests that an additional day in a year (averaged over a decade) in which the temperature was lower than 10°, will decrease the net migration rate by 0.69 (significant at 99%).

Overall, the fact that at the extremes, the coefficients becomes more negative as we move away from the "moderate" temperature bin, in addition to the fact that they reach their largest magnitudes at the most extreme temperature bins, suggests that the effect of extreme weather on net migration takes an inverted "U-Shape".

Figure 5 plots the estimates for the $\gamma_i$s; Table 3 details the corresponding estimates. The coefficients to the right of the 0mm precipitation bin are all negative, but are statistically insignificant, except the coefficient of the highest precipitation bin (>15mm) - -0.31 (statistically significant at 95%), which suggest that heavy precipitation decreases net migration. Specifically, an additional day in a year (averaged over a decade) in which the precipitation is above 15mm, will decrease the net migration rate by 0.31, relative to a day in which the precipitation was 0mm.

Lastly, Table 3 details estimates for $\delta_1$ and $\delta_2$. Both are not statistically significant, but are negative, and the magnitude of the effect of high number of disaster days is higher than the magnitude of the effect of low number of disaster days.

Overall, the results suggest that extreme weather - temperature, precipitation, and natural disasters decrease net migration, meaning that either less people are moving into counties experiencing extreme weather, more people are moving out of these counties, or a combination of both.

## 5.2 Heterogeneous Effects

We conduct two additional analyses. First, we present evidence that in line with the literature, younger persons are more responsive to changes in extreme weather. Second, we provide evidence that the effects we find are not driven by agriculture dependent counties.

In general, the propensity to migrate falls with age, with young adults being the most mobile population. This is partly due to life transitional changes that occur at young adulthood and might motivate migration such as getting married, purchasing a home, or finding a job. As persons age, some costs associated with migration rise (loss of origin-specific human capital, psychological costs of separating from family, etc.), while the gains in expected earnings decline (lower employment opportunities, shorter time horizon to benefit from the gains, etc.) (Molloy et al., 2011; Benetsky et al., 2015; Zaiceva, 2014).

As extreme weather affects various instigators of migration, such as economic conditions, and those in turn motivate younger persons to migrate, rather than older persons, we hypothesize that extreme weather will affect the migration of younger persons more than that of older persons. This in addition to aversion from extreme weather, that even if affects all age groups, might actually push to migrate the more dynamic age groups. In order to test this, we run the main specification - equation 1, separately for three age groups, with the dependent variable being the net migration rate that we calculate for each age group - persons aged 24-45, 45-64 and 65+. The results are presented in Figure 6, which plots the estimates for the $\beta i$s from these three separate regressions. As the figure shows, the coefficients for the 24-45 and 45-64 age groups display the same pattern as the main specification that included all persons, where the coefficients decline as temperature shifts from the "moderate" temperature bin to the more extreme temperature bins, either hot or cold. But, the effect is more pronounced at each temperature bins (meaning, the coefficients are more negative) for the 25-45 age group. Specifically, at the highest temperature bin (>90°), the coefficient for 25-45 age group is almost double the magnitude of the coefficient for the 45-65 age group. We find no effect of extreme weather on the oldest age group, 65+, as the coefficients are mostly small in magnitude and statistically insignificant.

Second, we test whether the effect that we find is driven by the impact of extreme weather on agriculture. In a large share of previous papers that examined the effect of extreme weather on migration in the developing world (Kleemans and Magruder (2018); Kubik and Maurel (2016); Cai et al. (2016) and many others), as well as in the developed world Feng et al. (2010), the main mechanism through which extreme weather affected migration, was through its effect on agriculture, the main source of income in the developing world and specific parts of the developed world as well, as higher temperatures reduce agricultural productivity and adversely affect crop yields (Wesselbaum and Aburn, 2019). To test this, we run the main specification - equation 1, separately for agriculture dependent and non agricultural dependent counties, with the dependent variable being the net migration rate of each respective group. We define counties as being in either category according to the United States Department of Agriculture 2015 categorization of counties across the US (of Agriculture, 2021). Counties were defined as "agricultural dependent" if "either 25 percent or more of average annual labor and proprietors' earnings derived from farming during 2010-12 or 16 percent or more of county jobs were in farming in the same period." 444 counties are categorized as such.

The results are presented in Figure 7, which plots the estimates for the $\beta i$s from these two separate regressions. As the figure shows, the coefficients for the two groups are not statistically different, and display the same patterns. This suggests that agriculture dependence does not drive our results, as suggested for developing countries, and for some specific United States counties. This could be partly since United States agricultural producers are more better able to adapt to changing weather conditions, for example through more advanced technology, or faster adaption of suitable crops.

# 6 Conclusion

This paper estimates the effects of extreme weather - temperature, precipitation and natural disasters on migration in the United States across 6 decades.

Although the effects of extreme weather on various outcomes have been studied extensively, its effect on migration in the developed world has been scarcely studied. The effect of extreme weather on migration has mostly been studied in the developing world, as well as in specific parts of the developed world, in contexts where the effect works through reduced agricultural output. This paper aims to fill this gap. Beside decline in agricultural output, extreme weather can induce migration indirectly through its effects on economic conditions, crime and health outcomes, as well as directly, as people are averse to extreme weather.

To test this, we exploit variation in extreme weather within a county over time, as well as between counties. By employing recent methodologies that allow the effect of extreme weather to vary across the weather distribution, we show that decades that had more extremely hot or cold days, more high precipitation days, and more natural disasters coincided with decreased net migration. We provide evidence that the effect is stronger for younger persons, and is not driven by agricultural dependent counties.

This paper adds to the vast literature on the effects of extreme weather, by studying its effect on an outcome that has considerable implications to the study of population flows, labor markets, housing markets, as well as other policy relevant contexts. We present evidence that persons in the developed world respond to extreme weather changes; meaning that migration could be mitigating the detrimental effects of extreme weather not only in the developing world, but also in the developed world, a fact that should be modeled in when considering the general equilibrium effects of climate change.

# Tables

Table 1: Net Migration and Temperature Descriptive Statistics

| | Percentiles | | | | |
|---|---|---|---|---|---|
| | 10 | 25 | 50 | 75 | 90 |
| **Net Migration Rate** | -17.3 | -9.0 | -1.2 | 6.9 | 18.5 |
| **Days>90** | 0.0007 | 0.005 | 0.05 | 0.26 | 1.23 |
| **80>Days<89** | 1.7 | 4.8 | 15.1 | 40.2 | 68.9 |
| **Days<10** | 0.003 | 0.11 | 1.9 | 9.2 | 32.4 |

| | |
|---|---|
| **Observations** | 18,757 County X Decades |
| **Weather Stations** | Approx. 13,000<br>50-500 Per county |

Notes: The table details the net migration rate at different percentiles of the net migration rate distribution. Observations are at the county X decade level. The net migration rate is the the net balance of migrants at the end of the decade (in-migrants minus out-migrants) out of 100 residents at the beginning of the decade (i.e. the increase/decrease in a county's population over the decade due to migration). The table also provides descriptive statistics on the number of days in a year, averaged over a decade, in which the average temperature was above 90°, between 80° and 89°, and below 10°, at different percentiles of the temperature distribution.

Table 2: Natural Disasters Descriptive Statistics

| | All | Low-severity | High-severity |
|---|---|---|---|
| **Severe Storm (%)** | 34.2 | 21.7 | 35.9 |
| **Hurricane (%)** | 20.2 | 5.2 | 29.6 |
| **Flood (%)** | 19.9 | 34.1 | 16.6 |
| **Total** | 45,915 | 12,166 | 11,933 |

| | |
|---|---|
| **Natural Disaster per County X Decade** | 1970s: 1.6 disasters (13.1 days)<br>2000s: 5.5 disasters (168.8 days) |

Notes: The table provides descriptive statistics on the natural disasters data provided by FEMA; it includes all federally declared natural disasters from 1964 to 2010. Data provides the natural disaster type and its beginning and end date, from which we calculate "disaster days". Low-severity disasters are those that lasted up to 3 days, the $25^{th}$ percentile of disaster days; high-severity are those that lasted 34 days or more, the $75^{th}$ percentile of disaster days.

Table 3: Main Specification Estimates

| | Temperature Estimates | | Precipitation Estimates | | Natural Disaster Estimates |
|---|---|---|---|---|---|
| $\beta$¡10 | -0.69*** | $\gamma_0$ | - | $\delta_0$ | - |
| | (0.21) | (omitted) | | (omitted) | |
| $\beta_{10-19}$ | -0.21 | $\gamma_{0-3}$ | -0.04 | $\delta_1$ | -0.14 |
| | (0.25) | | (0.06) | | (0.56) |
| $\beta_{20-29}$ | 0.01 | $\gamma_{3-9}$ | -0.20 | $\delta_2$ | -1.58 |
| | (0.16) | | (.13) | | 0.84 |
| $\beta_{30-39}$ | -0.24* | $\gamma_{9-15}$ | -0.12 | | |
| | (0.13) | | (0.27) | | |
| $\beta_{40-49}$ | -0.26* | $\gamma$¿15 | -0.31** | | |
| | (0.14) | | (0.14) | | |
| $\beta_{50-59}$ | - | | | | |
| (omitted) | | | | | |
| $\beta_{60-69}$ | -0.21 | | | | |
| | (0.17) | | | | |
| $\beta_{70-79}$ | -0.46*** | | | | |
| | (0.15) | | | | |
| $\beta_{80-89}$ | -0.63*** | | | | |
| | (0.20) | | | | |
| $\beta_{>90}$ | -1.33*** | | | | |
| | (0.36) | | | | |
| Observations | 12,122 | | | | |
| R-squared | 0.1901 | | | | |

**Note:** The table provides the estimates for the coefficients of interest from estimating equation 1. The dependent variables are the STI rates per 100. The 50°-59° temperature bin, the 0mm precipitation bin, and the ”no disaster days” dummy are omitted. Estimation includes county and decade fixed effects. Robust standard errors clustered at the state level are in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

# Figures

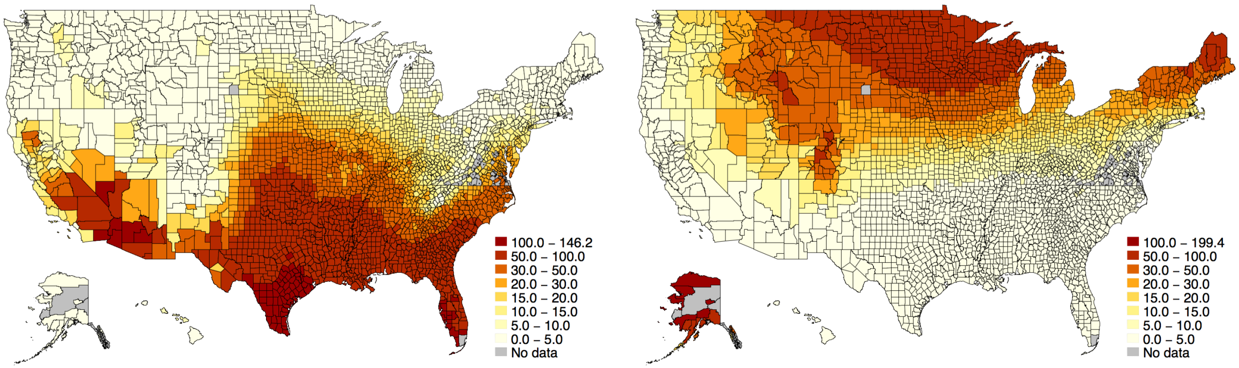


Figure 1: Number of Days of $>80^\circ$ (Left); Number of Days of $<20^\circ$ (Right); 1950's

Notes: The figure shows the spatial variation in temperatures across counties in the United States in the 1950's. The left figure shows the number of days in a year (averaged across the decade) in which the average temperature was above $80^\circ$, while the right figure shows the number of days in a year (averaged across the decade) in which the average temperature was below $20^\circ$.

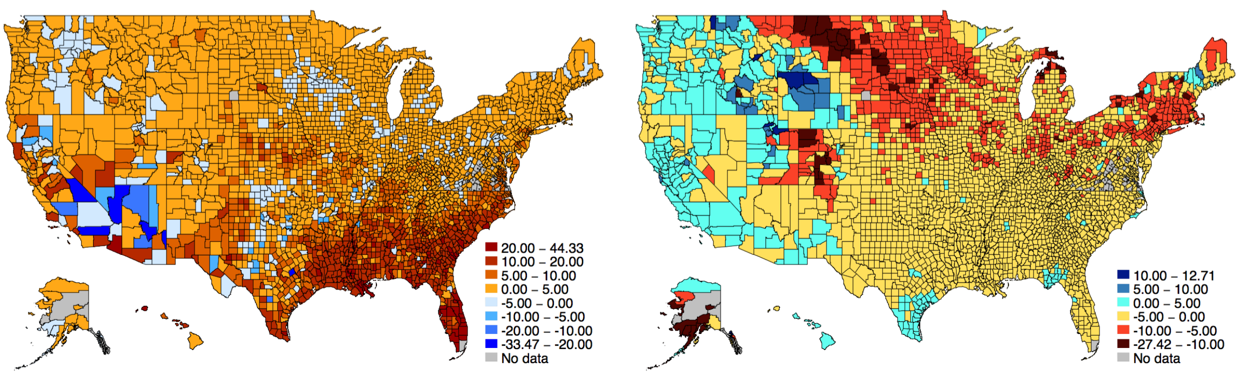


Figure 2: Change in the Average Number of $>80^\circ$ Days Per Year (Left); Change in the Average Number of $<20^\circ$ Days Per Year (Right); 1960's - 2000's

Notes: The figure shows the temporal variation in temperatures across counties in the United States; it details the change (in absolute terms) in the number of days in a year (averaged across the decade) in which the temperature was above $80^\circ$ (left figure), or below $20^\circ$ (right figure), from the 1960's to the 2000's.

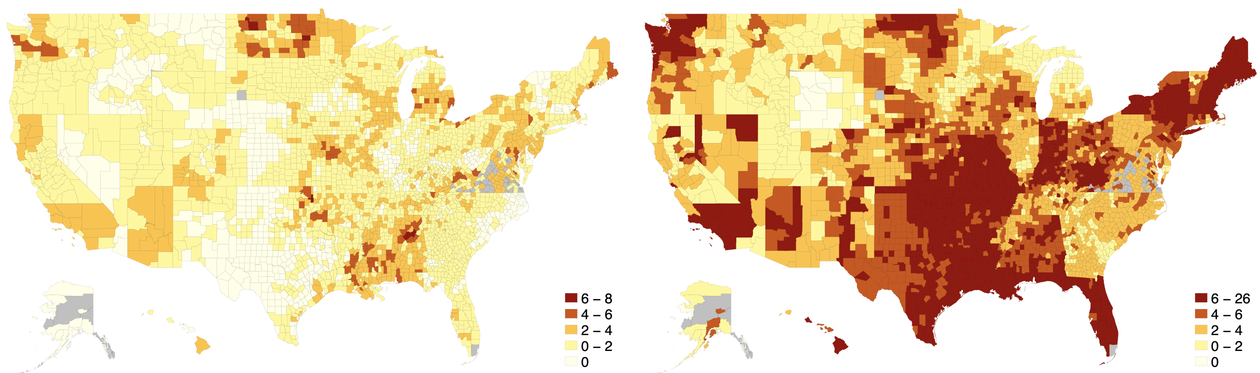


Figure 3: Number of Natural Disasters Per Decade; 1970's (Left); 2000's (Right).

Notes: The figure details the number of federally declared natural disasters across counties in the the United States in the 1970's (left figure) and in the 2000's.

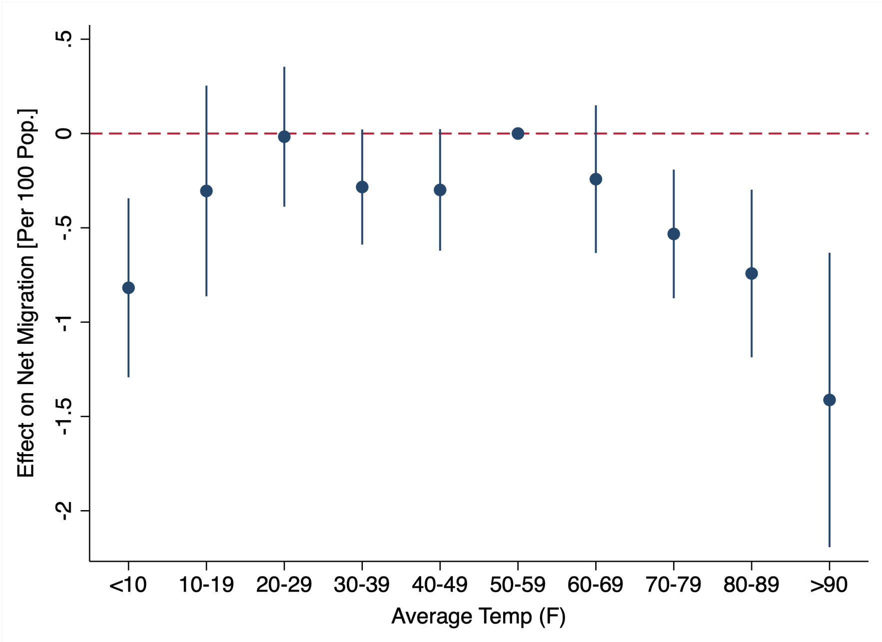


Figure 4: Estimated Effect of Temperature on Net Migration

Notes: The figure plots the estimates for the $\beta_i$s from estimating equation 1. The dependent variable is the net migration rate, per 100 population. The 50°-59° temperature bin is omitted. Estimation includes county and decade fixed effects. The bands represent the 95% confidence intervals, calculated using robust standard errors clustered at the state level.

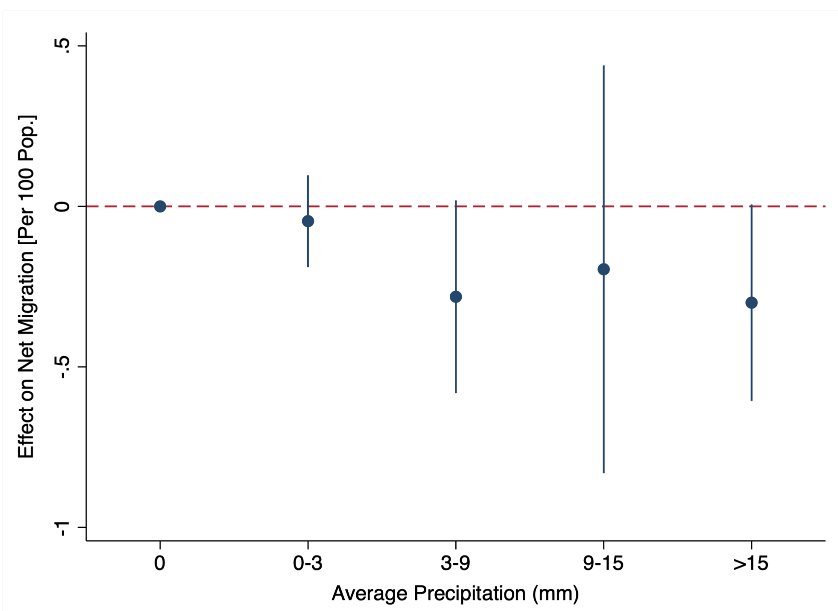


Figure 5: Estimated Effect of Precipitation on Net Migration

Notes: The figure plots the estimates for the $\gamma_j$s from estimating equation 1. The dependent variable is the net migration rate, per 100 population. The 0mm precipitation bin is omitted. Estimation includes county and decade fixed effects. The bands represent the 95% confidence intervals, calculated using robust standard errors clustered at the state level.

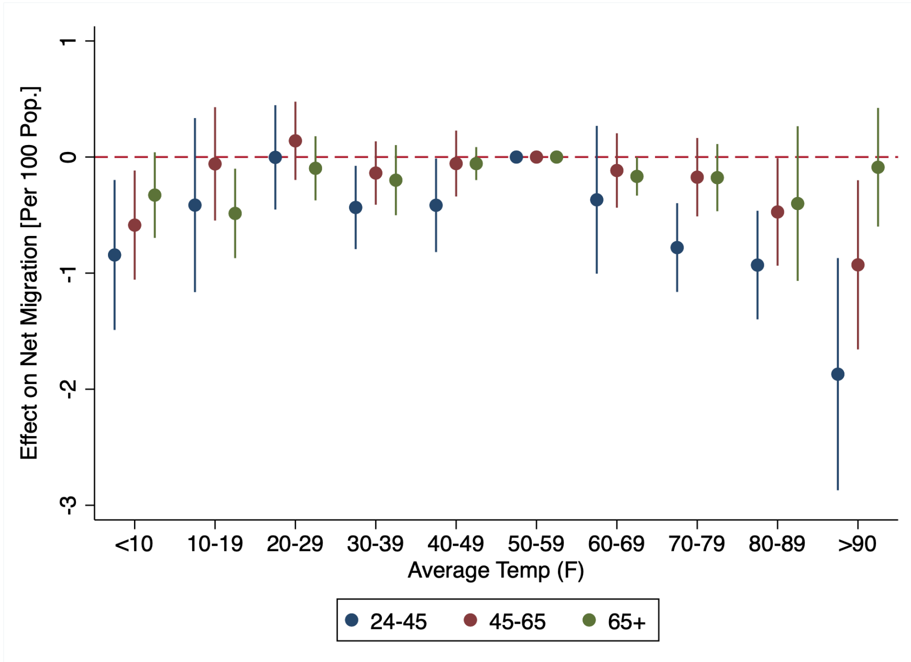


Figure 6: Estimated Effect of Temperature on Net Migration, by Age

Notes: The figure plots the estimates for the $\beta_i$s from estimating equation 1, separately for each of the three age groups. The dependent variable is the net migration rate, per 100 population. The 50°-59° temperature bin is omitted. Estimation includes county and decade fixed effects. The bands represent the 95% confidence intervals, calculated using robust standard errors clustered at the state level.

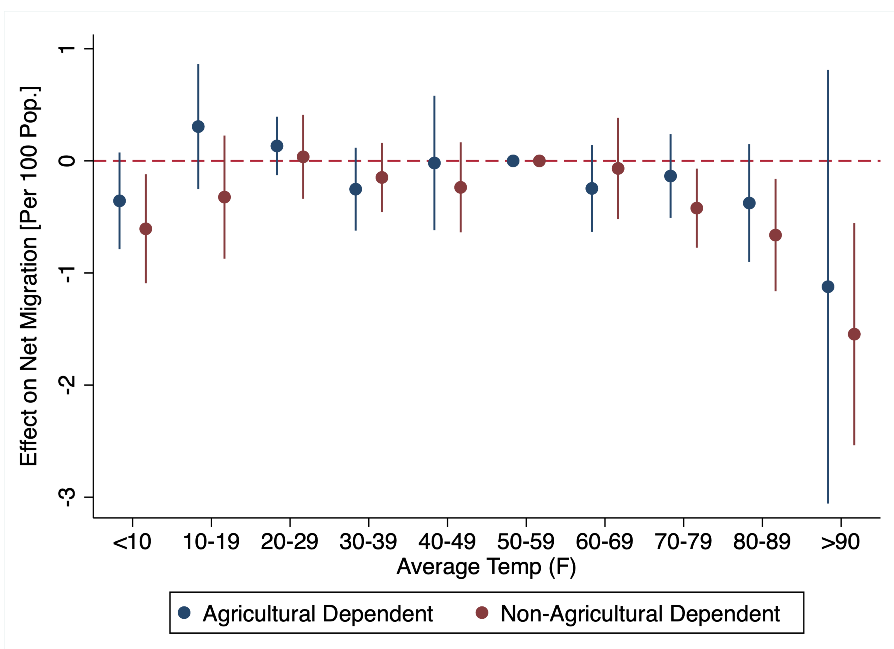


Figure 7: Estimated Effect of Precipitation on Net Migration, by Agriculture Dependence

Notes: The figure plots the estimates for the $\beta_i$s from estimating equation 1, separately for agricultural dependent and non-agricultural dependent counties. The dependent variable is the net migration rate, per 100 population. The 50°-59° temperature bin is omitted. Estimation includes county and decade fixed effects. The bands represent the 95% confidence intervals, calculated using robust standard errors clustered at the state level.

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