Weather Anomalies, Crop Yields, and Migration in the US Corn Belt

Shuaizhang Feng[♣], Michael Oppenheimer[♠], and Wolfram Schlenker[♡]

Working Paper - September 2013

Abstract

We investigate the influence of weather anomalies on net migration in the Eastern United States using a county-level panel for the period from 1970 to 2009. One major mechanism is through the effect of weather on agricultural yields, which we examine in further detail using an instrumental variables approach. Our preferred model uses the seasonality of the sensitivity of corn yields to extreme heat over the growing season, which peaks during corn flowering, as instrument. The reduced-form estimate of the migration response to extreme heat closely mirrors the seasonality of corn yield. Our IV approach will provide an unbiased estimate of the responsiveness of outmigration to yield unless other determinants of migration, such as peoples direct preference for weather, perfectly align with the pattern of corn flowering. This is unlikely given that the exact dates of corn flowering vary from year to year. Our estimated semi-elasticity ranges from -0.3 to -0.4 depending on the chosen time trend, i.e., a one percent change in yields leads to an opposite 0.3-0.4 percentage point change in the net migration rate. The migration response is strongest for young adults and not significant for senior citizens. Extrapolating from this relationship, we project that climate change would induce significant outmigration in the U.S. Corn Belt.

We cordially acknowledge the contribution to this paper by Alan Krueger before he started his government position as the chairman of the Council of Economic Advisers. We appreciate comments from participants at the Norface Migration Conference at University College London. All remaining errors are ours.

♣ School of Economics. Shanghai University of Finance and Economics. Department of Economics, the Chinese University of Hong Kong. Email: shuaizhang.feng@gmail.com

♠ Department of Geosciences and Woodrow Wilson School. Princeton University. Email: omichael@princeton.edu

♡ School of International and Public Affairs (SIPA) and Earth Institute. Columbia University. Email: wolfram.schlenker@columbia.edu.

We investigate the effect of weather variability on migration patterns of the U.S. population, especially through its impact on agricultural productivity. The associations among changes in climatic conditions, agricultural productivity, and human migration have been most vividly illustrated by the famous "American Dust Bowl," one of the greatest environmental catastrophes in U.S. history. In the 1930s, exceptional droughts (Schubert et al. 2004), amplified by human-induced land degradation (Cook, Miller & Seager 2009), greatly depressed agricultural productivity in the Great Plains and led to large-scale and persistent net outmigration from those regions. Between 1935 and 1941, around 300,000 people migrated from the southern Great Plains to California (McLeman 2006). Hornbeck (2009) compares counties with different levels of soil-erosions in the Great Plains, and finds that the 1930s Dust Bowl generated persistent population loss in the following decades. In addition, the overall decline in population did not occur disproportionately for farmers, but had ramifications beyond the agricultural sector. This suggests a general economic decline that extends beyond the direct effect on agriculture. Many other businesses in agricultural areas, e.g., banking and insurance, are directly linked to the agricultural sector as they serve the agricultural community. Hornbeck (2009) argues that the economy mainly adapted through outmigration, not adjustment within the agricultural sector or increases in industry.

The "American Dust Bowl" happened under very different conditions from today's. It overlapped the Great Depression and a lack of credit may have limited the local capacity for adaptation. Since then, the American agricultural sector has undergone immense changes. On the one hand, it is much more mechanized and uses great amounts of chemical fertilizer and pesticides. As a result, it now accounts for a much smaller part of the overall economy and a smaller fraction of the population directly depends on agricultural outcomes. On the other hand, better communication and transportation networks may make the present generation of Americans more mobile. In either case, one might expect today's relationship between migration and agricultural productivity to be different from the 1930s. To assess the possible magnitudes of migration flows under future climate change, it is necessary to base empirical work on more recent experience, which we do in this paper.

In particular, we examine whether net migration rates over five year intervals between 1970 and 2009, defined as the fraction of people leaving a county net of new arrivals and deaths, are related to contemporaneous observed weather variations. We find a significant relationship in counties of the Corn Belt (which include all Midwestern states and Kentucky), but not outside the Corn Belt. We show that the main mechanism for the observed weather-migration relationship in the Corn Belt is through agricultural productivity, and not a direct preference for climate. If anything, people tend to favor hotter and drier climates that are detrimental for agricultural productivity. This poses a challenge to using traditional weather variables as instruments, such as degree days and precipitation over the growing season (Schlenker & Roberts 2009). A direct preference for climate will result in a biased estimate of the migration responsiveness. To circumvent such a problem, our preferred model uses novel instruments based on the seasonally varying sensitivity of corn yields to extreme heat over the growing season, which is highest during corn flowering. Unless people's distaste for heat peaks the same time that corn flowers, changes in agricultural productivity rather than some unobserved confounders drive the observed climate-migration relationship. Moreover, we find that the relationship inside the Corn Belt is driven mainly by young adults, while senior citizens, who are often believed to be more responsive to climatic conditions show no responsiveness.

Based on our preferred model specification, we find a statistically significant semi-elasticity of -0.3 to -0.4 between the net outmigration rate and yields for the population aged 15 to 59. I.e., for every percent corn yields during a five-year interval were below the historic normal, on net, 0.3-0.4 percent of a county's population left the county. In view of the relatively small proportion of people directly employed in agriculture,[1] our estimated elasticity may seem large. However, there might be considerable spillover effects from agriculture to other sectors of the economy, similar to what Hornbeck (2009) observed for the Dust Bowl migrants. To shed further light on this issue we examine the responsiveness of overall employment to crop yields. Consistent with the literature on the "Dust Bowl," we find that weather-induced yield shocks significantly impact non-farm employment. During years when agriculture is doing well, non-farm employment is expanding, while years with bad yields imply contractions in non-farm employment. The semi-elasticity for non-farm employment is larger than for farm employment and statistically significant. Farm labor is shielded from agricultural losses as we find an almost 1:1 increase in subsidy payments for weather-induced reduction in agriculture yields. At the same time, decreasing yields lead farms to merge, which might result in efficiency gains in the sense that less services or machinery are required, including the labor to sell, finance, and maintain them.

Our estimated semi-elasticities are specific to the period of 1970-2009 and may change in the future depending on many factors, such as the structures of the economy, demographic profiles, and government policies. Nevertheless, we believe it is an informative exercise

[1]For counties in the Corn Belt, the median fraction of employment in agriculture is 4.6% according to the 2000 decennial Census, based on data from Table QT-P30 of the Census 2000 summary file 3 (factfinder.census.gov).

to use the best estimate available to make projections, in order to illustrate the possible magnitudes of future outmigration flows for counties of the Corn Belt, as further warming is expected to directly affect these agricultural areas in the United States. Our projections are ceteris paribus in nature and should not be regarded as predictions of what will actually happen in the future. Based on the Hadley III model B2 scenario, with other factors held constant, we find that climate change would on average induce an additional 13 percent of the adult (15-59) population in non-urban counties (less than 100,000 inhabitants) to migrate out of Corn Belt counties in the medium term (2020-2049) compared to a baseline of 1960-1989. For comparison, the standard deviation in historic migration rates for our five-year intervals is 7 percent. The predicted effect equals two standard deviations. The estimated outmigration effect increases to 30% in the long-term (2070-2099) as extreme heat is predicted to significantly increase under continued warming. Of course, long run projections should be interpreted with greater caution as people's migration responses in the longer term might be considerably different from short-term responses.

Since predicted changes in the climate of the Corn Belt vary more between climate model runs than within a given model run, we also provide projections under uniform climate change scenarios, i.e., assuming only one aspect of climate (either temperature or precipitation) changes, and that the change is uniform across the whole Corn Belt. Specifically, we produce projected outmigration rates for each degree increase in temperature (up to 5°C) as well as increases and decreases of precipitation up to 50%. These can be used to construct corresponding migration estimates for any combination of temperature and precipitation forecasts made for any future time period by any General Circulation model under any emission scenario.

The rest of the paper is structured as follows. Section 1 reviews general internal U.S. migration patterns and the role of U.S. agriculture. Section 2 introduces our empirical methodology and data sources. The main estimation results are reported in Section 3. Section 4 presents projections of future migration flows, and is followed by our conclusions in section 5.

1 Background

Migration is a defining feature in the history of the United States, not just in terms of arrival of immigrants, but also in terms of internal population movements. During the last century, the mean center of the U.S. population moved about 324 miles west and 101 miles south (Hobbs & Stoops 2002) and the fraction of the population living in rural areas decreased significantly. One of the most important determinants of migration flows has been identified as relative economic opportunities in source and destination regions (see e.g., Borjas, Bronars & Trejo (1992)). For example, during the "great migration" in 1910-1970, millions from the South were attracted to the Northeast and Midwest, as farm and non-farm economic opportunities dwindled in the South while demand for labor increased in the industrializing destination regions (Eichenlaub, Tolnay & Alexander 2010). Empirical research also studied the effects of industry composition (Beeson, DeJong & Troesken 2001), natural characteristics such as oceans and rivers (Beeson, DeJong & Troesken 2001), and weather (Rappaport 2007, Alvarez & Mossay 2006) on domestic migration flows.

Agriculture has traditionally been an important driver of U.S. domestic migration flows. Early internal migrants were typically farmers seeking better farming opportunities, e.g., those who moved to the Ohio River Valley in the late eighteenth century and to the Great Plains before the middle of the nineteenth century (Ferrie 2003). Later on, developments in the manufacturing and service industries, together with technological changes in the agriculture sector, have prompted sustained rural-to-urban migration. Consequently, the rural proportion of the U.S. population has declined from 60% in 1900 to around 20% in 2000 (Hobbs & Stoops 2002).

Besides all the urban "pull" forces such as increased availability of employment opportunities in non-agricultural sectors and the possibly more attractive urban lifestyle, several "push" factors in the agricultural sector have been important in shaping this rural flight. First of all, long-run increases in farm productivity due to changes in the economic structure, technological progress, and better access to domestic and international markets, have diminished demand for labor in farms. Since the late 19th century, subsistence farming gradually gave way to commoditized agriculture, with increased access to credit and transportation (for example, railroads). This trend was further accelerated by mechanization starting in the 1940s, and more recently, the use of chemical fertilizers and pesticides. Previous studies showed that mechanization has had a significant impact on the relationship between agriculture and migration. For example, White (2008) studied the Great Plains region for the period of 1900-2000, and found that counties that witnessed an increased dependence on agriculture were also more likely to experience positive population growth in the pre-mechanization era, but the relationship reversed in the post-mechanization era (post-1940s).

Second, agricultural policy has also played an important role in rural-urban migration. New Deal policies in the 1930s, such as the Agricultural Adjustment Act (AAA), the Works

Progress Administration (WPA) and the Civilian Conservation Corps (CCC) proved critical in preventing even larger outmigration in certain areas of the Great Plains (McLeman et al. 2008). Even after the 1930s, income support programs have likely slowed the movement of labor out of the agricultural sector (Dimitri, Effland & Conklin 2005). On the other hand, the risk-reduction effects of price supports and the planting rigidities imposed by supply controls encouraged specialization, and may have facilitated outflow of farm labor. Since there has been a long history of interventionist policies to manage migration patterns, policy makers may be able to utilize migration forecasts under climate change to enhance local adaptive capabilities to reduce unnecessary outmigration and manage any remaining migration flows (Adger 2006, McLeman & Smit 2006).

Last but not least, variations and changes in environmental and climatic conditions affect agricultural productivity and can induce significant migration responses. The most extreme case we have witnessed so far occurred during the Dust Bowl in the 1930s. In those years, productivity in the Great Plains dropped precipitously because of sustained droughts. This triggered significant and sustained outmigration from the affected regions (Hornbeck 2009). At the same time, local adaptive capacity was already at a very low level before the Dust Bowl because of falling commodity prices and a general economic depression (McLeman et al. 2008). Adjustments within the agricultural sector and between different economic sectors were very limited due to a lack of credit, and the economy adjusted primarily through mass outmigration (Hornbeck 2009). Nevertheless, it is important to note that people with different demographic and socio-economic characteristics experienced very different levels of vulnerabilities and exhibited different adaptation responses. For example, McLeman (2006) found that migrants from rural Eastern Oklahoma to California in the 1930s were disproportionately young tenant farmers.

While the Dust Bowl experience may be unique in American history, the extreme climatic conditions witnessed in the 1930s may become more frequent in current century as a consequence of global climate change. Recent researches suggests that climate change is expected to have significant negative impacts on crop yields in the United States. Lobell & Asner (2003) report that for each degree increase in growing season temperature, both corn and soybeans yields would decline by roughly 17%. Similarly, Schlenker & Roberts (2009) identify serious nonlinearities in the temperature-yield relationship. Increasing temperatures are beneficial for crop growth up to a point when they switch to becoming highly detrimental. These breakpoints vary by crop: 29°C or 84°F for corn, 30°C of 86°F for soybeans and 32°C or 90°F for cotton. The effect of being 1 degree above the optimal breakpoint is roughly ten times as harmful as being 1 degree below it. Area-weighted average yields are predicted to decrease by 30-46% before the end of this century under the slowest (B1) warming scenario and by 63%-82% under the most rapid warming scenario (A1F1) based on the Hadley III model. These newly available estimates were considerably larger than what previous modeling studies have suggested (Brown & Rosenberg 1997, Reilly 2002, Cline 2007).[2] It should also be noted that these estimates are based on the existing statistical relationship between yield and climate/weather, and have not incorporated CO_2 fertilization effects and adaptation possibilities beyond what is found in the historic time series. At the same time, recent evidence suggests that the actual CO_2 effect on crop yield is still uncertain and may be considerably less significant than previously thought (Long et al. 2006). Assuming no breakthroughs in technology, potential gains from adaptation may also be limited and may require considerable financial investments.

The magnitudes of the possible impact of changing climate conditions on yields warrant careful examination of the weather-migration and yield-migration relationship. The emerging empirical literature on climate-driven migration, as reviewed by Leighton (2009), is interdisciplinary in nature. Most studies rely on qualitative analyses of fairly small scale local phenomena. This paper contributes to the existing literature by utilizing a statistical approach to estimate the semi-elasticity of outmigration with respect to crop yields. Our approach is similar to Feng, Krueger & Oppenheimer (2010) who examine the effect of climate-driven yield declines in Mexico on Mexico-U.S. cross-border migration.

[2]To assess the impact of climate change on U.S. agriculture, three different approaches have been used in the literature, each with its own merits and shortcomings. The first one is the production function approach, in which the impact of weather/climate on crop yields is derived using controlled laboratory or field experiments. Some sort of CGE (Computed General Equilibrium) model is sometimes used to incorporate price feedbacks. This approach is usually adopted by agronomists, see for example Rosenzweig & Hillel (1998). The second one is the so called Ricardian approach, which estimates a cross-sectional relationship between land values and climate while controlling for other factors. The underlying assumption is that the value of farmland reflects the sum of discounted expected future earnings. This approach was originally due to Mendelsohn, Nordhaus & Shaw (1994). It utilizes the fact that farmers have adapted to local climatic conditions. The third and more recent approach is to use time series variations in climate to identify effect of climate on agricultural profit (Deschênes & Greenstone 2007) or crop yields (Schlenker & Roberts 2009). The advantage of this approach is that identification comes only from within variation. Other determinants of yield, such as soil quality and land management practices, which are usually correlated with climate and difficult to measure, would not bias the estimated weather-yield relationship.

2 Methodology and Data

2.1 Empirical Methodology: Reduced Form Regression

We start by linking the net outmigration rate m_{it}, defined as the fraction of people leaving a county net of new arrivals and deaths, in county i during the five-year interval started with year t to observed weather outcomes. Consecutive observations in our panel are five years apart as the population data is reported every five years.

$$m_{it} = \pi \mathbf{W}_{it} + f(t) + c_i + \epsilon_{it} \tag{1}$$

Our baseline model examines the ratio m_{it} of all people that were aged 15-59 at the beginning of interval t that outmigrated over the next five years, net of any new arrivals. If weather $\mathbf{W}_{it}$ explains migration, the coefficients π should be jointly significant.[3] A set of unrestricted county dummy variables, represented by c_i, are included to capture time-invariant county factors, such as proximity to urban centers and natural amenities. Time controls $f(t)$ capture all aggregate-level factors that affect migration trends, such as technological progress in agriculture, changes in agricultural policies, as well as changes in overall economic fundamentals in both source and destination counties. We use four time trends $f(t)$: (a) a linear time trend common to all counties; (b) a quadratic time trend common to all counties; (c) state-specific quadratic time trends; and (d) county-specific time trends that allow for the fact that the economic conditions might be trending differently in each location. The error ϵ_{it} might be spatially and serially correlated, and we hence cluster in the baseline regressions at the state level, which adjusts for arbitrary within-state correlations along both the cross-sectional and time-series dimensions.[4] In a sensitivity check, we also present results of an unweighted regression where we use a grouped bootstrap routine and draw entire 5-year interval with replacement, i.e., all counties that report in a given 5-year interval.

[3] The exact weather measures are further explained in the next section where we outline the instrumental variable approach for yields.

[4] In a yearly panel regression of yields on weather, clustering by state or adjusting for spatial correlation using Conley's (1999) nonparametric routine gives comparable estimates (Fisher et al. 2012).

2.2 Empirical Methodology: IV Regression

To investigate our hypothesis that the weather-migration relationship are driven by changes in agricultural productivity, we use an instrumental variable approach:

$$m_{it} = \beta x_{it} + f(t) + c_i + \epsilon_{it} \tag{2}$$

$$x_{it} = \gamma \mathbf{W}_{it} + g(t) + k_i + \nu_{it} \tag{3}$$

We now regress the net migration ratio m_{it} of all people that were aged 15-59 at the beginning of interval t on the average log yield during the same 5-year period x_{it}.[5] Our key parameter of interest is β, the semi-elasticity of net outmigration with respect to log yields. Similar to equation (1), we use a set of unrestricted county dummy variables, represented by c_i and time controls $f(t)$. Error terms are clustered at the state level unless otherwise noted.

Because x_{it} may be correlated with ϵ_{it}, we only use yield shocks that are due to presumably exogenous variation in weather.[6] We again include county fixed effects k_i to control for baseline differences as well as time trends $g(t)$ as yields have been trending upward over time. The coefficient β is identified by deviations of the weather variables $\mathbf{W}_{it}$ from their time trends, which are presumably exogenous since we use the same time controls in both the first and second stage. Figure A2 in the appendix displays annual corn and soybean yields for the 13 states in the Corn Belt.[7] The figure displays actual yields as well as predicted yields using the four weather variables of Schlenker & Roberts (2009): two degree days variables as well as a quadratic in total precipitation.[8] Yield growth is approximately piecewise linear in temperatures: Moderate heat, as measured by degree days 10-29°C for corn and degree days 10-30°C for soybeans, is beneficial for plant growth. Extreme heat, as measured by degree days above 29°C for corn and degree days above 30°C for soybeans are very harmful for crops. Our first model uses these four weather variables summed over all days of the fixed growing season of March-August.

The best single predictor of yield among these four weather variables is extreme heat. The effect of extreme heat varies over the growing season for corn, as corn is most damaged

[5]We first take the log of annuals yields (or adjusted average of more than one crop, see below) and then average over the five years of each interval.

[6]In a sensitivity check in Table A7, we present results from a simple OLS regression for comparison, which are different from the IV regression.

[7]We aggregated to the state level as it is impossible to display the time series for each county.

[8]Degree days are simply truncated daily temperature variables summed over the growing season (March-August). For example, degree days above 30°C measure temperatures above 30°C, i.e., a temperature of 32°C would give 2 degree days. The daily measure is summed over all days of the growing season.

by heat during flowering (Berry, Roberts & Schlenker 2013). We therefore use a second model that only relies on extreme heat (degree days above 29°C for corn), but interacts (multiplies) the variable with a restricted cubic spline with 5 knots in the phase of the growing season that is normalized to length 1, i.e., 0 corresponds to the planting date and 1 to the harvest date (see the data section 2.3 below). Therefore, although extreme heat enters both models as instrument, in the first model the effect of an extra degree day above 29°C is restricted to be the same throughout the growing season, while the second model allows it to vary smoothly over time.

Our empirical analysis uses log *corn* yields in the baseline regression, since it is the crop with the largest growing area in the Corn Belt, which gave rise to the region's name. In a sensitivity check in the appendix we use log soybean yields, and the log of the adjusted average of the two. Both corn and soybeans yields are measured in bushels/acre, yet average productivity is significantly different. Corn yields are on average roughly three times as high. Since changes in average yields should not be driven by changing compositions of soybean and corn production, we need to adjust the yields to make them comparable. Regressions that use the log of the adjusted average yield therefore transform soybean yields into corn equivalents by multiplying them with the soybean to corn price ratio.[9] This makes the two crops comparable on a dollar/acre basis. Ultimately, agricultural returns are the difference between revenues and cost. By prorating yields with the average price ratio, we make them comparable on a revenue/acre basis, which would be an exact conversion under the assumption that the revenue/cost rato is comparable for the two crops. After making the yields comparable, we take the area-weighted average of the equivalent yields. Similarly, we take the area-weighted average of the crop-specific weather variables $\mathbf{W}_{it}$.

We estimate the model separately for (i) counties in the Corn Belt; and (ii) counties in the eastern United States outside the Corn Belt and the state of Florida. Areas in the Corn Belt predominately grow corn and soybeans. Our null hypothesis is that β is negative for the Corn Belt, but approximately equals zero for areas outside the Corn Belt, where corn and soybean production are less important as a fraction of overall economic activity. Eastern areas outside the Corn Belt serve as a control group in our research design - if changes in climate affect changes in outmigration through channels other than crop yield (i.e., the error term ϵ_{it} is correlated with the instrument $\mathbf{W}_{it}$), then β would also be non-zero for the sample of counties outside the Corn Belt.

If people have a preference for warmer and drier climate as suggested by the establishment

[9]We use average prices over our sample period 1970-2009, so there is no endogenous price feedback.

of retirement communities in the South, our estimate for β would be biased towards zero as people might migrate for reasons that are detrimental to crop growth. This poses a serious challenge to the exogeneity assumption of the instruments (growing season degree days and precipitation) used in our first model. On the other hand, for the instruments used in our second model, we can compare the seasonality of the sensitivity of corn yield to extreme heat to the seasonality of the reduced form relationship between migration and extreme heat. If migration is most sensitive to extreme heat when corn yield is most sensitive, the response is most likely driven through the agricultural channel unless humans dislike heat the most when corn flowers, which seems unlikely as the exact flowering time varies year-to-year.

2.3 Data and Summary Statistics

Since there is no accurate count of number of people migrated at the county level for the 40-year time period that we are focusing on, we use the residual approach to derive the outmigration ratio m_{it} for each county for each five-year period between 1970 and 2009.[10] For example, for the 15-59 age group, in the baseline model in our analysis, we use

- $m_{it[15,60)}$: net outmigration rate for those aged $[15, 60)$ at time t in county i.
- $p_{it[15,60)}$: total population aged $[15, 60)$ in county i at the beginning of the 5-year interval that started in t.
- $p_{i[t+5][20,65)}$: total population aged $[20, 65)$ in county i at the end of the 5-year interval that started in t.
- $d_{it[15,60)}$: number of people aged $[15, 60)$ in county i at the beginning of the 5-year interval t that died by the end of it.

To construct the net outmigration ratio

$$m_{it[15,60)} = \frac{p_{it[15,60)} - p_{i[t+5][20,65)} - d_{it[15,60)}}{p_{it[15,60)}} \tag{4}$$

We use publicly-available population data from U.S. Census Bureau for $p_{it[15,60)}$ and $p_{i[t+5][20,65)}$ and state- and age-group-specific mortality data from National Center for Health Statistics

[10] There are two alternative approaches: First, the Census Bureau has county-level migration information in each Decadal Census. Individuals are asked where they lived 5 years ago. Since the Census occurs every 10 years, there is no migration information for the 5-year period directly following the previous Census. The Census data hence is not a full panel but misses every other 5-year interval. Second, the Internal Revenue Service has yearly migration data between pairs of counties. The advantage of this data is that it has information on the destination county. The downside is that the data are only available since 1992 (Duquette 2010). Moreover, it is based on tax returns, and hence might under-represent the poor and the elderly.

to estimate $d_{it[15,60)}$.

Annual yields for corn and soybeans between 1970 and 2009 are from the U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS), where yields equal county-level production divided by harvested acres. For our main analysis, we use log corn yields, and the appendix gives results for soybeans. Climate variables are constructed over the growing season of corn and soybeans (March-August). We calculate total growing-season degree days instead of mean temperatures to capture the nonlinear effect of temperature on crop yields, as well as total precipitation in the growing period. More details on the sources and reliabilities of yield and climate data can be found in Schlenker & Roberts (2009), which are extended beyond 2005 in Berry, Roberts & Schlenker (2013). We follow the latter and allow the effect of the extreme heat to vary over the growing season. The phase of the growing season is defined from state-level planting and harvest dates that are available from USDA-NASS. We define the beginning of the growing season as the Monday of the week by the end of which at least 50% of the corn area in a state had been planted. Similarly, the end of the growing season is the last day of a week when at least 50% of the growing area had been harvested in a state.[11] Since there are hardly any degree days above 29°C towards the end point, we allow the effect of extreme heat to vary according to a restricted cubic spline with 5 knots between 0.1 and 0.75 of the growing season.[12]

We exclude all counties west of the 100 degree meridian and the state of Florida, as agriculture in those areas is heavily dependent on subsidized irrigation (see Reisner (1993) and Schlenker, Hanemann & Fisher (2005)). Figure 1 graphically displays all counties in our study with corn data.[13] We label counties in the following 13 states Corn Belt counties: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.[14] Counties outside these states that lie east of the 100 degree meridian except Florida are labeled the "non-Corn Belt" areas.

[11] If a planting or harvest date is missing for a year in a county, we replace it with the average planting and harvest date for that county.

[12] The average exposure to extreme heat over the growing season is shown in Figure A3. Note that there is almost no occurrence of temperatures above 29°C outside the interval $[0.1, 0.75]$, i.e., in spring or late fall.

[13] Figure A1 gives the results for soybeans. Our analysis uses counties with planting dates (right graph of each figure) even for the model with a fixed growing season March-August to keep the set of counties consistent.

[14] According to USDA National Agricultural Statistics Service (http://quickstats.nass.usda.gov/), the following states have the largest combined planted acreages of corn and soybeans in 2000: Iowa (23 mil), Illinois (21.7 mil), Minnesota (14.5 mil), Nebraska (13.15 mil), Indiana (11.2 mil), South Dakota (8.7 mil), Missouri (8 mil), Ohio (8 mil), Kansas (6.4 mil), Wisconsin (5.05 mil), Michigan (4.25 mil), Arkansas (3.53 mil), North Dakota (2.98 mil), and Kentucky (2.51 mil), i.e., we include all with the exception of Arkansas, which is not part of the Corn Belt. However, our results are robust if we include Arkansas in the Corn-Belt sample.

Table A1 presents sample summary statistics for the counties with planting and harvest dates. We exclude all counties with more than 100,000 population in 2000 in our baseline analysis as those counties are more likely to be urban centers and less dependent on agriculture.[15] There are 1,336 counties in our sample, 892 in the Corn Belt sample and 444 in the non-Corn Belt sample.[16] For comparison purposes, we have averaged all variables over each five-year period during 1970-2009. Panels A and B present sample means and standard deviations for the Corn Belt and non-Corn Belt samples, respectively. There is substantially more net outmigration for the Corn Belt sample than the non-Corn Belt sample as the Midwest has lost population over the last 40 years. Average county-level crop acreages in the Corn Belt states are also larger, especially for corn, as are average crop yields. For example, during the most recent recent 5-year period (2005-2009), both corn and soybean yields are around 30% higher in the Corn Belt sample than in the non-Corn Belt sample. This likely reflects effects of various factors such as geographic/climatic conditions, technology, and policies. Non-Corn Belt areas experience more extreme heat above 29°C and more precipitation.

3 Results

3.1 The Weather-Migration Relationship

We start with the reduced form relationship between our weather variables and net migration: do weather anomalies over 5-year intervals in a county, which are arguably exogenous, influence net outmigration rates? The results of the regression specified in equation (1) above are given in Table 1. Each column lists the results from a regression of the net outmigration rate on the four classical weather variables that have been shown to influence corn yields, summed over the fixed growing season March-August.[17] Coefficients on the time trends and county fixed effects are suppressed to save space. All regressions are population-weighted to adjust for the heteroscedasticity of the data.[18] The first four columns (1a)-(1d) of Table 1

[15]We present sensitivity checks where counties with more than 100,000 inhabitants are included in the appendix. The results are unchanged in unweighted regressions, but do change if we weight by the population in a county.

[16]In some alternative specifications we use either soybean yields or the average of corn and soybeans yields, which results in a different number of counties in our sample as sometimes only one of the two crops is grown.

[17]The four weather variables are: extreme heat as measured by degree days above 29°C, moderate heat as measured by degree days 10-29°C, as well as a quadratic in season-total precipitation.

[18]Outmigration ratios fluctuate less for counties with a larger population as individual decision to leave are averaged over a larger base.

give the results for counties inside the Corn Belt, while the last four columns use counties outside the Corn Belt. Within each set, columns differ by the included time controls: columns (a) uses a common linear time trend for all counties, columns (b) use a common quadratic time trend, columns (c) use a state-specific quadratic time trend, and columns (d) use a county-specific linear time trend.

For counties inside the Corn Belt, there is a significant relationship between the net migration rates and the two temperature measures. The table also gives the F-statistic and p-values for a test for joint significance of all four weather variables, which are highly significant for Corn Belt counties. Coefficients are rather robust to the chosen time trend. Columns (d) rule out the possibility that climate and migration trends over time are driven by omitted county-specific factors which result in a spurious correlation, as the county-specific time trend would absorb such omitted trends.

While the measure on moderate heat is statistically significant, it has a counterintuitive sign: moderate heat is good for crop growth as shown in columns (1a)-(1d) of Table 2, which replicates columns (1a)-(1d) of Table 1 except that the dependent variable is no longer the net migration rate but instead log corn yields. Similarly, Table A3 replicates the analysis using an annual panel instead of 5-year intervals and finds that moderate heat is good for crop growth. Moderate heat improves yields and the economic livelihood of an agricultural area, which should decrease, not increase the net out-migration rate, as suggested by the positive reduced-form coefficient on moderate heat. The likely reason for the counter-intuitive sign in the reduced-form migration regression is a direct preference for climate that, which will bias our IV estimates. This observation motivated our use of the seasonality of the effect of extreme heat only as an instrument when we examine the yield-migration relationship in the next subsection.

Counties outside the Corn Belt show no significant response in Table 1: no weather measure is individually significant nor are they ever jointly significant at the customary 5% significance level. On the other hand, crops are significantly related to these weather variables both inside and outside the Corn Belt. Columns (1a)-(1d) of Table A4 replicate columns (2a)-(2d) of Table 1 using annual corn yields as the dependent variable instead of migration rates. The effect of extreme heat, as shown in the first row of each table, is statistically significant at explaining corn yields in both areas. As mentioned above, it is the single best predictor of year-to-year variability of yields in both areas, yet net migration only responds to extreme heat in Corn Belt areas.

One particularity of our "control" group on counties outside the Corn Belt is that they tend to be further in the South and hence hotter. We therefore further split these counties in counties in the North-East (all counties outside the Corn Belt in the right graph of Figure 1 that have a latitude higher than the Southern bound of the Corn Belt, i.e., are in Virginia or further North) and the South-East (remaining counties colored red in the right graph of Figure 1). Results are given in Table A5: The first four columns (1a)-(1d) show the results for counties in the Northeast, while the last four columns (2a)-(2d) show the results for the Southeast. In the former, the four weather variables are not jointly significant. For the Southeast, the four weather variables are jointly statistically significant and the driving force seems to be moderate degree days, which is significant in all specifications, but again has a counter-intuitive sign, suggesting that if people have a preference for climate, it goes against what we observe for crop growth.

3.2 First Stage: The Weather-Yield Relationship

We replicate the weather-yield relationship of Schlenker & Roberts (2009), as formerly specified in equation (3) above, in columns (1a)-(1d) of Table 2. There are three notable differences to earlier work: we aggregate the data to 5-year intervals, include only data for the Corn Belt sample, and weight the regressions by the population in a county. Columns (a)-(d) again vary the included temporal controls. Since year-to-year weather shocks are random, there is considerably more variation in the yearly data than in 5-year averages. Still, Table 2 reports significant results using 5-year averages of log yields and climate data from 1970 to 2009. The results confirm the significant nonlinear relationship between weather/climate and yields (Schlenker & Roberts 2009, Rosenzweig et al. 2002). An increase of 10 degree days in moderate heat (between 10 and 29°C) during the growing season would increase crop yields by 0.64-0.79%. On the other hand, extremely hot temperatures are very harmful - each degree day increase in extreme heat decreases yields by 0.50-0.58%, which is almost an order of magnitude higher. More rainfall is initially beneficial for crops, but at a decreasing rate, and becomes detrimental when it exceeds some optimum level. The null hypothesis that all coefficients of climate variables are jointly zero is rejected at even the 0.1% significance level.

The second set of columns (2a)-(2d) no longer uses all four weather variables, but only the effect of extreme heat and how it varies over the growing season (Berry, Roberts & Schlenker 2013). Season-total sum of extreme heat has the largest explanatory power of yields and is highly nonlinear as all temperature below 29°C are discarded. We use restricted cubic splines in time between one-tenth and three-quarters of the growing season that is normalize to length one. The first-stage results are shown in columns (2a)-(2d) of Table 2.

Columns (a)-(d) again vary the included temporal controls. The third row of the footer lists the p-value for the test that all spline polynomials, i.e., excluding the constant term, are significantly different from zero. This is not a test whether extreme heat is a significant predictor as it excluded the constant term, but only whether it varies significantly over the season, and it is significant at the 10% level in most regressions.

Since 5-year averages have less variation than annual data, measurement error might be amplified, we also replicate the analysis using annual data on yields and weather in Table A3. We find comparable relationships between weather and yield to what is reported in Table 2. Moreover, the test whether the effect of extreme heat is constant throughout the season in columns (2a)-(2d) can now be rejected at any significance level. Limiting the number of observations from 40 to 8 when we aggregate the annual data to 5-year intervals does not seem to impact the point estimates, but reduces significance somewhat.[19] This is especially true for the coefficient on extreme heat in columns (1a)-(1d), which explains most of the year-to-year variation in yields, and the joint significance of the spline polynomials in columns (2a)-(2d).

We plot the spline coefficient as black solid line in the bottom row of Figure 2. The 95% confidence interval is added in grey. The four columns correspond to the regression results of columns (2a)-(2d) in Table A3, respectively.[20] The chosen time control has very little effect on the shape of the seasonality: Extreme heat is most damaging around a third into the growing season. We also add reference points for models where the effect of extreme heat is forced to be uniform across the season (i.e., a horizontal line): A red line shows the constant marginal effect if the extreme heat measure is summed over all days between March 1st and August 31st. The blue line sums extreme heat over the variable growing season as defined by state-level planting and harvest dates.

For comparison, we also display the seasonality of a reduced-form regression of the net out-migration rate on the seasonality of extreme heat in the top row of Figure 2. The four columns again use the four time controls used in columns (a)-(d) of our tables. Note the clear mirror image: migration responds most strongly during time periods of the growing season when corn is most susceptible.

[19]The other difference is that the first-stage regression in Table 2 are population-weighted as are the migration regression in the second stage, while the annual results in the appendix are unweighted regression.

[20]The results are similar if we use the results of columns (2a)-(2d) in Table 2, but the confidence bands are wider since we have fewer observations. We choose to display the more efficient estimates.

3.3 Second Stage: Yield Shocks and Net Outmigration

We estimate equation (2) by two-stage-least-squares (2SLS) and show the second-stage results in Panel A of Table 3. Columns differ by included time controls to capture overall trends in migration as well as yields. Columns (a) use a common linear trend (one variable), columns (b) a common quadratic time trend (two variables), columns (c) a state-specific quadratic time trend (26 variables, 13 states $\times$ two variables per state), columns (d) use county-specific trends (892 variables, one for each county). We choose not to control for year fixed effects, which would absorb most of the variation as 5-year weather averages are highly correlated within the Corn Belt, more so than annual data. The reason is that the 5-year averages are driven by large-scale phenomena like El Nino / La Nina as idiosyncratic annual weather shocks average out. If a half-decade is hotter than usual, it is so for most of the Corn Belt. For example, the seven year (i.e., 5-year interval) fixed effects absorb more variation than the 26 state-specific quadratic trends. Year fixed effects absorb variation that we would like to use in our identification and amplify measurement error in the weather data as most of the common signal is removed (Fisher et al. 2012). If weather is truly exogenous, it should be orthogonal to other measures and hence not require period fixed effects.

Column (1a)-(1d) reports results for the Corn Belt sample when the net migration ratio is regressed on instrumented log corn yield using the standard four weather measures that have been shown to influence corn yields. The estimated semi-elasticity of outmigration with respect to log yield ranges from -0.125 to -0.175, all of which are statistically significant at the 1% level based on clustered standard error. Recall that the first stage F-statistics are 23-46 in Table 2, much higher than the usual cutoff point of 10 to rule out concerns about weak instruments. The semi-elasticity implies that a one percent reduction below trend in corn yields during a 5-year induces an additional 0.125 to 0.175 percent of the adult population to leave the county. As mentioned earlier, this semi-elasticity might be biased towards zero as people show a distaste for moderate heat that is beneficial for corn. Columns (2a)-(2d) therefore only use the seasonality of extreme heat over the growing season, that is closely mirrored between corn and the reduced form migration regression. The estimated semi-elasticity increases to -0.3 to -0.4 accordingly.

Table A6 replicates the analysis using corn yields in Panel A, but also presents results when we instrument log soybeans yields in Panel B, or the weighted average of the two in Panel C. Results in columns (1a)-(1d) are broadly comparable irrespective of which crop we use. Note, however, how the results in columns (2a)-(2d) are much lower for soybeans, which is not surprising as soybeans do not exhibit the same seasonality in the sensitivity to extreme heat as corn does. The revised weather measures that allow for heterogeneity of the effect of extreme heat over the growing season hence do not give different results in the case of soybeans. Therefore, instrumenting corn yields with the seasonality of extreme heat avoids some of the bias that is due to a direct preference for climate. If we take the weighted average of corn on soybeans to make them comparable on revenue-per-acre terms in Panel C, the results lie in the middle.[21]

Table A7 reports the results of the OLS version of columns (a)-(d) of Table 3 where migration rate, both inside and outside the Corn Belt, are regressed on yields that are *not* instrumented on weather to illustrate the importance of instrumenting yields. The estimated semi-elasticity are smaller (closer to zero) by an order of magnitude and generally not significantly different from zero. It is consistent with a story where government policies (or other factors like cheap energy) help to stabilize local economy when yield declines.

One might expect different demographic groups to have different migration responses with respect to yield changes. For example, McLeman (2006) found that young people had a larger migration response following the Dust Bowl. Panels B1 and B2 of Table 3 therefore separate the migration response by sex, while Panels C1-C4 separate it by age, using the same specifications as in Panel A. Males and females have quite similar migration elasticities, suggesting that the relationship is not gender-specific. However, people in different age groups have quite different migration elasticities. The youngest age group, those between 15 and 29, are most sensitive to yield shocks in their migration decisions. The estimated elasticity ranges between -0.41 and -0.53 when we use the seasonality of the sensitivity to extreme heat in columns (2a)-(2d). The semi-elasticities get progressively smaller as we look at older age groups. The 30-44 age group has a semi-elasticity of -0.31 to -0.41, which is still significant at the 1% level. The age group between 45 and 59 has a semi-elasticity is only -0.09 to -0.12, which is only about a fourth of that for the 15-29 group. People aged 60 and above do not have a significant semi-elasticity. Our finding is consistent with the general observation that younger people are more mobile. The results also lend additional support to the exclusion restriction in our instrumental variable setup. If weather fluctuations directly impact migration decisions, one might expect larger responses for the older age group as they care most about weather and climatic conditions, as shown by a sizable retirement community in the Southern United States (McLeman & Hunter 2010).

[21]The weights are constant over time and hence end not endogenous to yield fluctuations.

3.4 Sensitivity Checks

Our baseline regressions only include counties with a total population of less than 100,000 in the 2000 Census for which yield information are observed for more than half of the years of our sample period 1970-2009 (at least 21 out of the 40 years). Regressions are weighted using the total population in a county to get a more efficient estimate. To explore the sensitivity of our results to these restrictions, we conduct a set of robustness checks in the appendix.

Table A8 first addresses population cutoffs and weighting. Panel A of the Table shows the baseline results for comparison, i.e., Panel A of Table 3. Panel B1 and B2 use the same data set and specification except that the regressions are no longer weighted. The point estimates change very little in the unweighted regressions. Panel B1 continues to cluster the error terms at the state level, which adjusts for arbitrary within-state correlations along both the cross-sectional (counties within a state) and time-series dimensions. One possible concern stems from the fact that we are not using annual data, but 5-year averages. Idiosyncratic weather shocks are averaged out, and the remaining variation is driven more strongly by global phenomena like El Nino / La Nina. If a half-decade is hotter than usual, it is likely hotter than usual for most of the Corn Belt. Panel B2 uses a grouped bootstrap procedure where we resample entire 5-year intervals with replacement. While the error terms go up significantly, our preferred estimates using the spline in extreme heat in columns (2a)-(2d) remain significant at least at the 5% level.[22] Since we only have eight intervals, using a clustered bootstrap has its own drawbacks, and our baseline regression therefore clusters by state.[23] Finally, Panel C uses the same specification and clustered errors as B1, but extends the data to also include urban counties. The point estimates again remain basically unchanged.[24]

Table A9 examines the sensitivity of our results to the minimum number of observation we require to have in a county before it is included in the analysis. Panel A again shows the baseline results (Panel A of Table 3) for comparison. Panel B and C are the extreme endpoints of the possible cutoffs: Panel B includes all counties if they have at least one

[22]Cameron, Gelbach & Miller (2008) call this procedure the pairs cluster bootstrap, the "standard method for resampling that preserves the within-cluster features of the error." While this procedure can lead to inestimable model if regressors take on a limited range of values, it works in our case as there is enough variation in climate. We are not aware of a study that tests the performance of the Wild-t bootstrap, their preferred model, in an instrumental variables setting with clustered errors.

[23]Recall that we have 13 states in the Corn Belt sample, which is larger, but still a limited number of clusters.

[24]Include urban counties in a population-weighted regression does make the point estimates smaller in magnitude (closer to zero), as urban places like the counties comprising Chicago get weighted very heavily, yet these places should be less dependent on agriculture.

observation in the years 1970-2009, while Panel C requires a perfectly balanced panel, i.e., observations for all 40 years. The number of counties included in the study is hence highest in Panel B with 935 counties, and lowest in Panel C with 701 counties. The point estimates remain very robust irrespective of what cutoff we use and hence are not driven by a particular sample selection.

3.5 Further Results on Farm Size and Employment

Our estimated semi-elasticity may seem large as the population share directly employed in the agriculture sector is small. One possibility is that there is considerable spillover from agriculture to other sectors of the economy, as was observed for Dust Bowl migrants (Hornbeck 2009). To shed further light on this issue, we regress comparable measures of farm size and employment on instrumented yield shocks. The regressions are similar to the previous IV regression except that we replace the dependent variable, net outmigration, with other measures.

Panels A1 and A2 of Table 4 use data from the Agricultural Census. Since the Census of Agriculture was not published exactly very five years, the time intervals now vary in length as given by the time between consecutive Census years.[25] Panel A1 use the rate of change in the number of farms as dependent variable. The coefficients are all positive and statistically significant, implying that during times when yields decreases, there is a contraction in the number of farms. Such a contraction could be caused by mergers of farms that leave the overall area unchanged, or by a retirement of farmland as farms go out of business. Panel A2 uses the relative change in the farmland area as dependent variable and finds no significant effect. Taken together, these results show that there is consolidation in the farm business when conditions are difficult, but the overall farmland area remains unchanged, it simply changes hand.

Panel B1 and B2 analyzes farm and non-farm employment, respectively, using data from the Bureau of Economic Analysis (BEA). The effect on farm employment is sometimes marginally significant, but the sign of the coefficient flips between models.[26] On the other hand, the coefficients on non-farm employment are consistently positive and statistically significant: If yields are going down, so is non-farm employment in the county. The estimated

[25]The eight intervals are between the nine Census years 1969, 1974, 1978, 1982, 1987, 1992, 1997, 2002, and 2007.

[26]If we use a grouped bootstrap in Table A10, none of the coefficients in the farm employment regression are significant. They are marginally significant for our preferred model (2a)-(2d) for number of farms and non-farm employment.

elasticity of 0.33-0.44 in columns (2a)-(2d) is quite large.

Our results suggest that although a negative weather-induced yield shock does not statistically significantly effect farm employment, it reduced yields in the agricultural sector and negatively affects local economic conditions, thereby triggering relatively large employment contractions in non-farm sectors. One possible explanation for such a finding is that government programs insure farm income (e.g., disaster payments, price floors, and crop insurance) and hence farmers receive enough income that keeps them farming. For example, Key & Roberts (2007) have shown that larger government transfers increase the probability of farm survival using Micro-level Census Data that links individual farms between three Censuses. If government payments insure against yield losses, they will dampen responses in farm labor. Especially since many of them are conditional on the farm remaining in operation. At the same time, yield losses might induce farmers to purchase less outside goods and result in fewer investments. Roberts & Key (2008) have shown that larger government payments result in consolidation in the farm sector, thereby increasing average farm size, which is consistent with our finding in Panel A1.

An increase in farm size might lead to efficiency gains and hence reduce the demand for services and goods outside the agricultural sector. This would explain why we detect larger employment effects outside of agriculture. At the same time, the U.S. agriculture sector is already highly capital-intensive with a minimum level of farm workforce, thus it is difficult to displace farm labor even at times with negative yield shocks.

We examine the effect of weather-induced yield shocks on government payments in Table 5. The National Agricultural Statistics Service reports state-level annual data on government transfers. We regress the log of government transfer in each year on agricultural yields.[27] Panel A reports the results using OLS, while Panel B instruments corn yields with temperature and precipitation (columns (1a)-(1c) in previous tables) and Panel C uses the seasonality of the sensitivity to extreme heat as instrument (columns (2a)-(2c) in previous tables). Panels B and C show that there is an almost 1:1 relationship between yield shortfalls and increases in government transfers. For example, using our preferred instrument (Panel C) and the most flexible time controls (column 1c), a 1 percent decrease in yields will increase government transfers by 0.97 percent. While these governments constitute highly subsidized insurance, there seems to be no evidence of moral hazard: simply using observed yield shocks in Panel A does not impact government transfers, while yields shocks that are

[27]Since the analysis is done at the more aggregate state level, model (d) in previous tables where we include county-specific time trends is no longer feasible.

caused by weather shocks (and hence are not the result of moral hazard) due.

4 Projecting Future Net Outmigration

Like the rest of the world, the United States has already experienced climate change. Over the past 50 years, U.S. average temperature has risen more than 1°C and precipitation has increased an average of about 5 percent (Karl, Melillo & Peterson 2009). Human-induced emissions of heat-trapping gases have been largely responsible for such changes on a worldwide basis, and will lead to additional warming in the future (Solomon et al. 2007). By the end of the century, the average U.S. temperature is projected to increase by approximately 2.2 to 6°C under a range of emission scenarios. Precipitation patterns are also projected to change, with northern areas becoming wetter and southern areas, particularly in the West, becoming drier. In addition, some extremes of weather and climate, such as droughts, heavy precipitation and heat waves, are expected to increase in frequency or geographic extent (Karl, Melillo & Peterson 2009).

We pair predicted changes in climate with our estimate of the elasticity of migration, which is conditional on many factors specific to the U.S. for the period under study, such as the population share of youths who are more likely to migrate, technology, the relative importance of agriculture in the economy and rural areas in particular, and federal and state farm policies, e.g., responses to droughts and other climatic events that adversely affect crop yields. Keeping in mind that these idiosyncratic factors may change in the future, we find it nevertheless instructive to project the effect of climate change on future migrant flows for the Corn Belt sample to illustrate the magnitude of potential migration flows. Our projection exercise does not depend on whether past climate variability in the United States was caused by greenhouse gas emissions, as long as the migration responses are similar to those that would occur with anthropogenic climatic changes. Also, we are using the reduced form relationship between weather and migration of Table 1 to predict future migration flows, which captures both responses to changes in productivity as well as a possible pure preference for climate.

We first base our projections on the B2 scenario of the Hadley III model and project net outmigration ratios of the adult US population (aged 15 to 59) for the medium term (2020-2049) and for the long term (2070-2099). We follow a two step procedure. First, using average climate during the 1960-1989 period as a baseline, we derive expected changes in weather, which are the *absolute changes* in monthly minimum and maximum temperature as well as *relative changes* in precipitation in the climate model.[28] The revised degree days variables are calculated by adding the predicted changes in temperature to the historic baseline and recalculating the nonlinear transformation of the new temperatures series.[29] In a second step, we project population migration ratios by multiplying the predicted changes in the four weather variables in each county times the estimated coefficients of column (1d) in Table 1. Table 6 presents the summary of the results for individual counties. The first column displays the mean impact among counties, while the second through fourth column give the standard deviation, minimum, and maximum of the impacts for the 892 counties in the Corn Belt. The last four columns summarize how many counties will have increased outmigration (displayed in green, yellow, and red in Figure 3) as well as how many counties have decreased outmigration rates (shown in blue).[30]

The first row reports projections for the medium term. On average, by 2020-2049, 5-year outmigration rates are expected to increase by 13 percentage points for the adult population for rural counties in the Corn Belt, i.e., on average 13 percent of the adult population is predicted to leave the county. For comparison, the standard deviation in migration rates in Table A1 is 7 percent, so the average predicted increase equals two standard deviations of the historic fluctuations. Not all counties are expected to experience similar changes in outmigration as they vary between 4 and 24 percentage points. However, all rural counties in the sample are predicted to experience statistically significant increases in the outmigration rate. The second row of Table 6 reports long term projections. Compared to the medium term, the projected increase in outmigration ratios are on average much larger. By 2070-2099, 5-year outmigration rates of rural counties in the Corn Belt are expected to increase by 30 percentage points. As shown in Panel B of Figure 3, counties in the southwestern part of the Corn Belt are most likely to experience substantial increases in net outmigration, while those in the northeastern part would be affected less.

To complement our use of the Hadley III model, which is just one of roughly 20 GCMs (General Circulation Model, or Global Climate Model) and has above average predicted warming, we also provide migration projections under uniform climate change scenarios, assuming temperature or precipitation changes are the same across all the Corn Belt region. The sensitivity of our results to predicted changes in climatic conditions can then be ap-

[28]It is customary to consider relative changes in precipitation as a constant absolute decrease would cause some dry areas to have negative precipitation.

[29]We merge each 2.5x2.5 mile weather grid with the four surrounding grid points of the coarser Hadley model and take the inverse-distance weighted average of the projections at the Hadley grid.

[30]We use 10,000 bootstrap draws from the joint distribution of the coefficients of the regression results to translate predicted changes in weather variables to a distribution of changes in outmigration rates.

proximated from the uniform changes, especially since there is more variability in predicted changes between models than within runs for the Corn Belt.[31] We predict outmigration rates corresponding to each Celsius degree rise in temperatures up to 5°C (holding precipitation constant) and between -50% and +50% change in precipitation (holding temperature constant) in 20% intervals. Results are summarized in Table 6, and graphically shown in Figures A4 and A5. Consistent with our previous projections, we use 1960-1989 as the baseline to which we compare future scenarios. Our results show that outmigration increases nonlinearly with temperature increases. This is due to the fact that extreme heat as measured by degree days above 29°C is a highly nonlinear function of temperature. If temperature rises by 1°C, on average about 4.7% of each rural county in the Corn Belt would out-migrate, yet a 5°C rise in temperature would on average induce 31.2% of the adult population to leave their county. This nonlinear relationship is in accordance with the general finding of the impact literature that warming is likely to be increasingly harmful for human society in virtually all aspects.

The impacts of precipitation changes on outmigration are relatively small. The projected change in outmigration rates never exceeds 4% although precipitation levels change between a decline of 50% and an increase of 50%. The impact of a precipitation increase will decrease the migration rate in some counties and increase it in others, depending on how much precipitation a county already has at the moment. While future changes in temperature and precipitation are expected to be related, agricultural-related outmigration is much more driven by the former. Our results suggest that focusing on predicted temperature changes will give the bulk of the predicted impact.

5 Conclusions

This paper first establishes a reduced-form relationship between weather deviations and migration rates. The likely mechanism behind the observed weather-migration relationship is the effect of weather on agricultural productivity. Our preferred model uses the seasonality in the sensitivity of corn to extreme heat over the growing season as an instrument. Consistent with previous theoretical studies that link migration decisions to economic opportunities in source and destination counties, we find that county-level outmigration is negatively associ-

[31] One approach is to sample model predictions from different global climate models to approximate climate uncertainty (Burke et al. 2011). Since these models are not stochastic in nature, we prefer to display the range of predicted climate impacts using uniform scenarios as there is limited variation within each model for a geographically confined area like the Corn Belt.

ated with crop yields in the Corn Belt. The effect is largest for young adults, and we observe no response for people 60 years or older. If we do not instrument yield shocks with weather, the estimated relationship becomes much closer to zero, demonstrating the importance of relying on yield shocks that are due to exogenous weather patterns.

Second, we extrapolate this relationship while holding every things else constant; our results suggest a nontrivial effect of climate change on future internal U.S. population movements. Based on the Hadley III model B2 scenario, using the 1960-1989 period as a baseline, climate change is on average expected to induce 13 percent of the rural population aged 15-59 to leave in the medium term (2020-2049). Long-run effects are likely to be considerably greater but also much more uncertain due to growing uncertainty in climate projection with progressively larger climate changes. While there is uncertainty about the exact amount of future warming, the consensus estimates suggest that we will experience at least some warming. We present uniform climate change scenarios to show the possible range of migration responses.

Historically, policy makers have tried to dissuade large-scale migration to preserve rural communities. Our research suggest that climate change will likely put further pressure on outmigration from predominately agricultural rural areas. We believe that future research should explore in more detail the underlying determinants of the yield-migration relationship for the areas we highlighted. Our evidence suggest that adjustments in non-farm employment, rather than farm employment, might be the main mechanism through which weather-related yield shocks generate outmigration. One possible explanation is that farmers themselves are already insured by government programs (e.g., crop insurance). In addition, to accurately forecast future outmigration flows, a range of climate models (in addition to Hadley III) should be used to improve confidence. Nevertheless, short-run projections are likely to be similar because much of the warming under any model is already committed by past emissions, with the inter-model differences due to differing climate sensitivities growing strongly with time.

References

Adger, W. Neil. 2006. "Vulnerability." *Global Environmental Change*, 16(3): 268–281.

Alvarez, Javier, and Pascal Mossay. 2006. "Estimation of a continuous spatio-temporal population model." *Journal of Geographical Systems*, 8(3): 307–316.

Beeson, Patricia E., David N. DeJong, and Werner Troesken. 2001. "Population growth in U.S. counties, 18401990." *Regional Science and Urban Economics*, 31(6): 669–699.

Berry, Steven T., Michael J. Roberts, and Wolfram Schlenker. 2013. "Corn Production Shocks in 2012 and Beyond: Implications for Harvest Volatility." In *The Economics of Food Price Volatility*. University of Chicago Press.

Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo. 1992. "Self-selection and internal migration in the United States." *Journal of Urban Economics*, 32(2): 159–185.

Brown, Robert A., and Normal J. Rosenberg. 1997. "Sensitivity of crop yield and water use to change in a range of climatic factors and CO2 concentrations: a simulation study applying EPIC to the central USA." *Agricultural and Forest Meteorology*, 83(3-4): 171–203.

Burke, Marshall, John Dykema, David Lobell, Edward Miguel, and Shanker Satyanath. 2011. "Incorporating Climate Uncertainty Into Estimates of Climate Change Impacts, With Applications to US and African Agriculture." *NBER Working Paper 17092*.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. "Bootstrap-Based Improvements for Inference with Clustered Errors." *Review of Economics and Statistics*, 90(3): 414–427.

Cline, William. 2007. *Global warming and agriculture: Impact estimates by country.* Washington, DC:Peterson Institute for International Economics.

Conley, Timothy G. 1999. "GMM Estimation with Cross Sectional Dependence." *Journal of Econometrics*, 92(1): 1–45.

Cook, Benjamin I., Ron L. Miller, and Richard Seager. 2009. "Amplification of the North American Dust Bowl drought through human-induced land degradation." *Proceedings of the National Academy of Sciences of the United States of America*, 106(13): 4997–5001.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97(1): 354–385.

Dimitri, Carolyn, Anne Effland, and Neilson Conklin. 2005. *The 20th Century Transformation of U.S. Agriculture and Farm Policy.* United States Department of Agriculture - Economic Research Service: Economic Information Bulletin Number 3.

Duquette, Eric N. 2010. "Dissertation: Choice Difficulty and Risk Perceptions in Environmental Economics." University of Oregon.

Eichenlaub, Suzanne C., Stewart E. Tolnay, and J. Trent Alexander. 2010. "Moving Out but Not Up: Economic Outcomes in the Great Migration." *American Sociological Review*, 75(February): 101–125.

Feng, Shuaizhang, Alan B. Krueger, and Michael Oppenheimer. 2010. "Linkages among climate change, crop yields and MexicoUS cross-border migration." *Proceedings of the National Academy of Sciences of the United States*, 107(32): 14257–14262.

Ferrie, Joseph P. 2003. *Internal Migration.* Vol. Historical Statistics of the United States: Millennial Edition, New York:Cambridge University Press.

Fisher, Anthony C., W. Michael Hanemann, Michael J. Roberts, and Wolfram Schlenker. 2012. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment." *American Economic Review*, 102(7): 3749–3760.

Hobbs, Frank, and Nicole Stoops. 2002. *Demographic trends in the 20th century.* U.S. Census Bureau, Census 2000 Special Reports, Series CENSR-4,.

Hornbeck, Richard. 2009. "The Enduring Impact of the American Dust Bowl: Short and Long-run Adjustments to Environmental Catastrophe." *NBER Working Paper No. 15605.*

Karl, Thomas R., Jerry M. Melillo, and Thomas C. Peterson. 2009. *Global Climate Change Impacts in the United States.* New York:Cambridge University Press.

Key, Nigel D., and Michael J. Roberts. 2007. "Do Government Payments Influence Farm Size and Survival?" *Journal of Agricultural and Resource Economics*, 32(2): 330–348.

Leighton, Michelle. 2009. *Migration and Slow-Onset Disasters.* Vol. Migration and Environment: Assessing the Evidence, Geneva, Switzerland:International Organization for Migration.

Lobell, David B., and Gregory P. Asner. 2003. "Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields." *Science*, 299(5609): 1032.

Long, Stephen P., Elizabeth A. Ainsworth, Andrew D. B. Leakey, Josef Nosberger, and Donald R. Ort. 2006. "Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising CO2 Concentrations." *Science*, 312: 1918–1921.

McLeman, Richard, and Barry Smit. 2006. "Migration as an Adaptation to Climate Change." *Climatic Change*, 76(1-2): 31–53.

McLeman, Robert. 2006. "Migration Out of 1930s Rural Eastern Oklahoma: Insights for Climate Change Research." *Great Plains Quarterly*, 26(1): 27–40.

McLeman, Robert A., and Lori M. Hunter. 2010. "Migration in the context of vulnerability and adaptation to climate change: insights from analogues." *Wiley Interdisciplinary Reviews: Climate Change*, 1: 450–461.

McLeman, Robert, Dick Mayo, Earl Strebeck, and Barry Smit. 2008. "Drought adaptation in rural eastern Oklahoma in the 1930s: lessons for climate change adaptation research." *Mitigation and Adaptation Strategies for Global Change*, 13(4): 379–400.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*, 84(4): 753–771.

Rappaport, Jordan. 2007. "Moving to nice weather." *Regional Science and Urban Economics*, 37(3): 375–398.

Reilly, John M. 2002. *Agriculture: the potential consequences of climate variability and change for the United States.* Cambridge University Press.

Reisner, Marc. 1993. *Cadillac Desert: The American West and Its Disappearing Water, Revised Edition.* Penguin.

Roberts, Michael J., and Nigel Key. 2008. "Agricultural Payments and Land Concentration: A Semiparametric Spatial Regression Analysis." *American Journal of Agricultural Economics*, 90(3): 627–643.

Rosenzweig, Cynthia, and Daniel Hillel. 1998. *Climate change and the global harvest.* Oxford University Press.

Rosenzweig, Cynthia, Francesco N. Tubiello, Richard Goldberg, Evan Mills, and Janine Bloomfield. 2002. "Increased crop damage in the US from excess precipitation under climate change." *Global Environmental Change*, 12(3): 197–202.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States*, 106(37): 15594–15598.

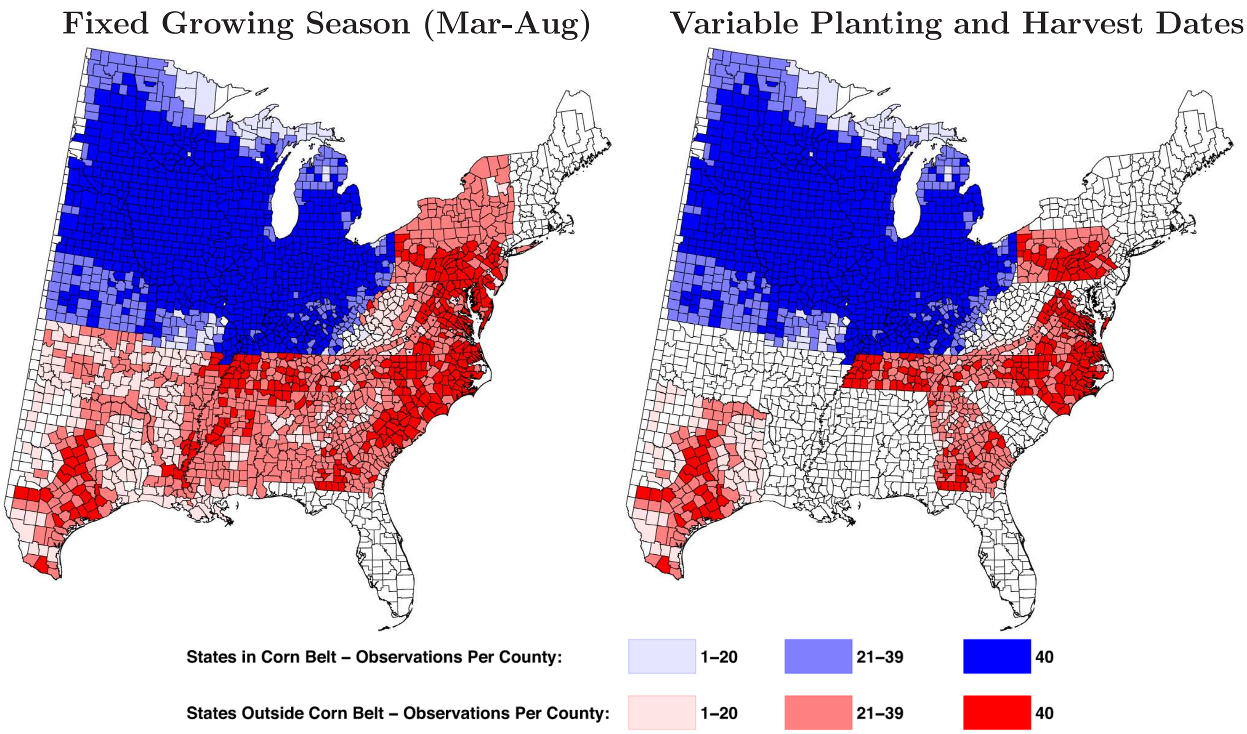
Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. 2005. "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review*, 95(1): 395–406.

Schubert, Siegfried D., Max J. Suarez, Philip J. Pegion, Randal D. Koster, and Julio T. Bacmeister. 2004. "On the Cause of the 1930s Dust Bowl." *Science*, 303(5665): 1855–1859.

Solomon, S., D. Qin, M. Manning, Z. Chen andM. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller, ed. 2007. *Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press.

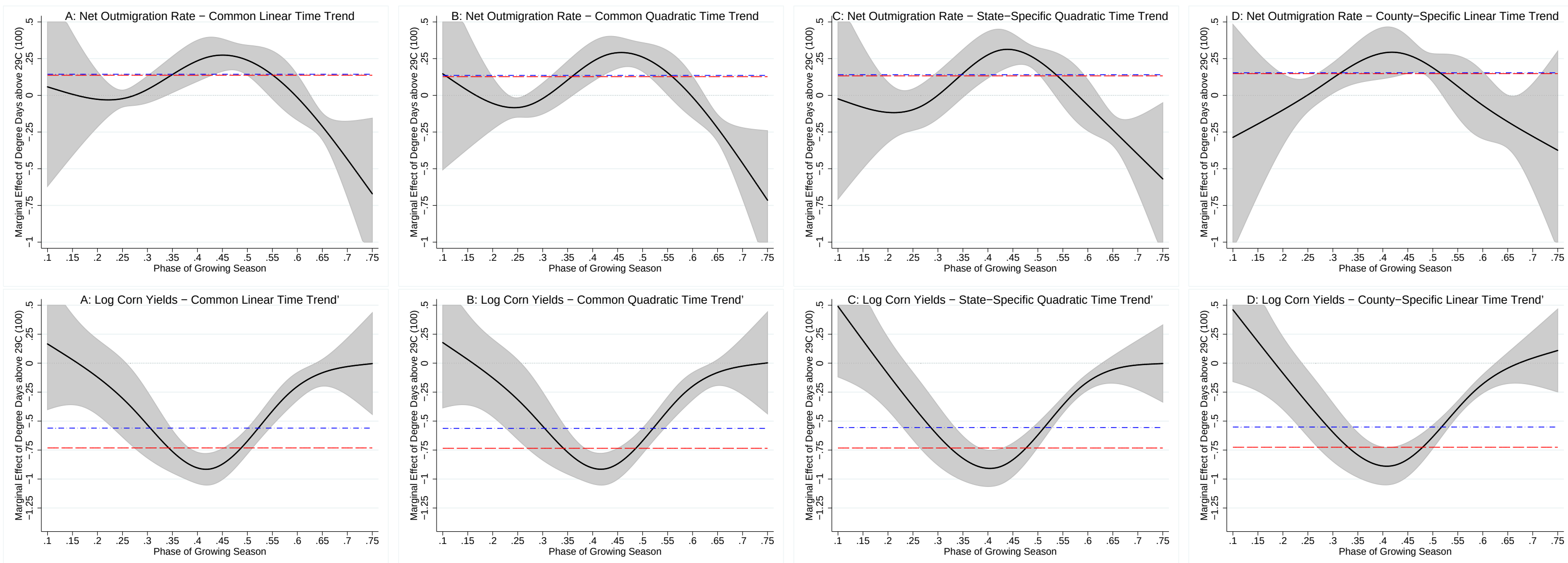
White, Katherine J. Curtis. 2008. "Population change and farm dependence: Temporal and spatial variation in the U.S. great plains,19002000." *Demography*, 45(2): 363–386.

Figure 1: Counties with Corn Yields (1970-2009)



Notes: The left figure displays counties in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. The right column furtherermore requires that state-level planting and harvest dates are available for at least one year. States covering the corn belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have data.

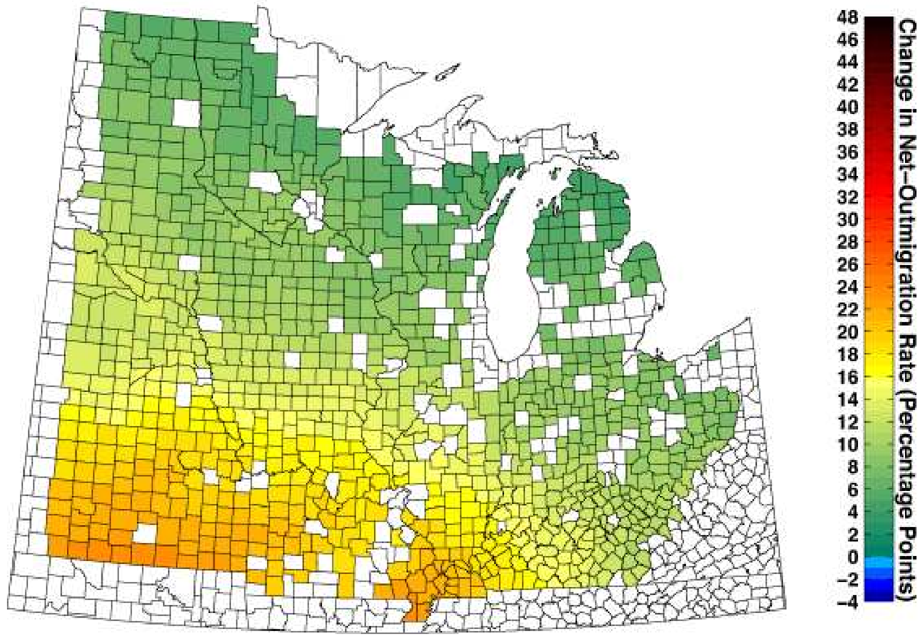
Figure 2: Seasonality in Response to Extreme Heat



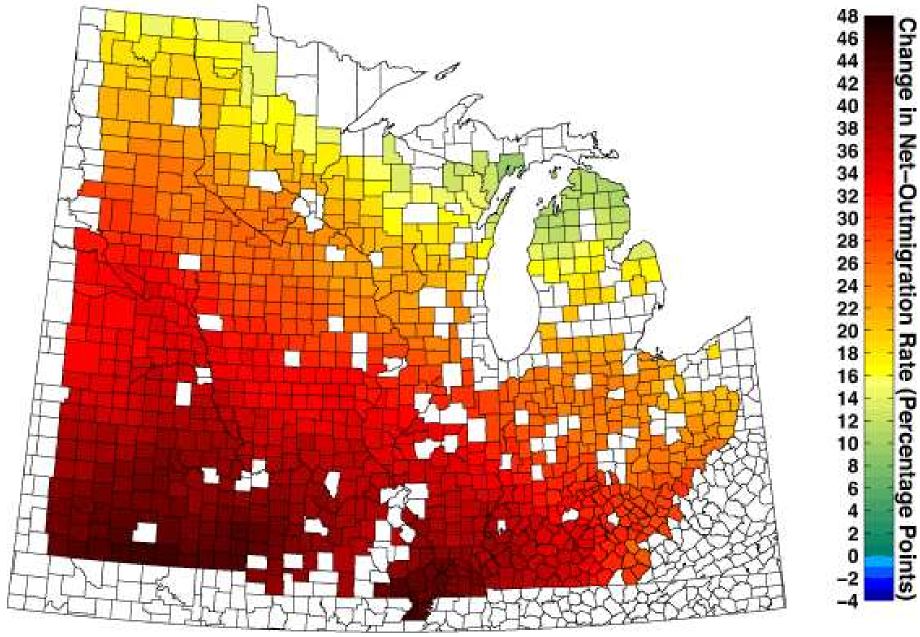
Notes: Panels displays how the sensitivity to extreme heat (degree days above 29°C) vary over the growing season, i.e., the marginal effect of an extra degree day above 29°C. The solid black line shows the point estimate and the 95% confidence band is added in grey. The top row shows the sensitivity of the net outmigration rate to extreme heat over the season, while the bottom row shows the sensitivity of log corn yields. The sensitivity is allowed to vary using a spline with 5 knots in the truncated growing phase. The blue line displays the constant effect from a regression that includes season-total extreme heat over the variable growing season, while the red line uses a fixed growing season March-August and also controls for moderate degree days as well as a quadratic in precipitation. All regressions use counties with at least 21 yield observations in the corn Belt. Columns differ by the included time control, which are respectively, a common linear time trend, a common quadratic time trend, state-specific quadratic time trends, and county-specific linear time trends.

Figure 3: Predicted Changes in Net Outmigration Under Hadley III - B2 Scenario

Panel A: Predicted Impact by Mid-Century (2020-2049)



Panel B: Predicted Impact by End of Century (2070-2099)



Notes: Panels display predicted changes in net outmigration rates under the Hadley III - B2 clmate change scenario for counties in the Corn Belt using the regression results of column (1d) of Table 1. Panel A shows predicted impacts by the middle of the century (2020-2049) compared to a 1960-1989 baseline. The bottom panel shows predicted impacts by the end of the century (2070-2099) compared to 1960-1989. Appendix Figures A4 and A5 show the results for uniform temperature and precipitation scenarios.

Table 1: Weather and Migration

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Extreme Heat (100 degree days)	0.137***	0.127***	0.133***	0.148***	-0.002	-0.016	-0.029	-0.008
	(0.034)	(0.033)	(0.037)	(0.038)	(0.043)	(0.044)	(0.054)	(0.064)
Moderate Heat (1000 degree days)	0.167***	0.167***	0.167***	0.176***	0.195	0.186	0.161	0.228
	(0.053)	(0.050)	(0.047)	(0.056)	(0.146)	(0.149)	(0.148)	(0.205)
Precipitation (m)	0.019	0.018	0.018	0.022*	-0.016	-0.022	-0.030	-0.024
	(0.011)	(0.012)	(0.013)	(0.011)	(0.016)	(0.016)	(0.020)	(0.016)
Precipitation Squared (m^2)	-0.001	-0.001	-0.001	-0.002	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
F-stat (joint significance)	52	42	35	26	2	2	3	4
p-value (joint significance)	1.7e-07	5.6e-07	1.6e-06	7.1e-06	.2808	.286	.1623	.0925
R-squared	0.1039	0.1087	0.1302	0.3141	0.0079	0.0095	0.0236	0.1809
Observations	7078	7078	7078	7078	3371	3371	3371	3371
Counties	892	892	892	892	444	444	444	444
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Table displays reduced form regression of migration rates on weather for 5-year intervals 1970-2009 (using the bounds for the largest crop corn). Columns (1a)-(1d) look at counties in the corn belt, while columns (2a)-(2d) focus on counties outside the corn belt as shown in Figure 1. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively. The F-statistics (p-values) for joint significance of the weather variables is given at the bottom of the Table.

Table 2: Weather and Crop Yields

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Extreme Heat (100 degree days)	-0.569***	-0.584***	-0.525***	-0.498***	0.644	0.715	1.682	1.426
	(0.090)	(0.095)	(0.080)	(0.086)	(1.261)	(1.397)	(1.718)	(1.435)
Extreme Heat x spline 1					-3.282	-3.702	-7.723	-6.295
					(6.027)	(6.845)	(8.332)	(6.856)
Extreme Heat x spline 2					2.430	4.494	12.999	11.724
					(27.477)	(30.958)	(37.684)	(34.019)
Extreme Heat x spline 3					2.211	-3.033	1.549	-16.209
					(85.070)	(91.950)	(105.031)	(106.492)
Extreme Heat x spline 4					-7.976	-3.792	-92.692	-1.703
					(148.756)	(151.046)	(134.254)	(169.408)
Moderate Heat (1000 degree days)	0.640***	0.640***	0.766***	0.791***				
	(0.139)	(0.142)	(0.140)	(0.145)				
Precipitation (m)	0.178***	0.177***	0.152***	0.160***				
	(0.026)	(0.025)	(0.025)	(0.025)				
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.013***	-0.014***				
	(0.002)	(0.002)	(0.002)	(0.002)				
F-stat (1st stage)	24	27	23	46	22	24	13	23
p-value (1st stage)	1.2e-05	6.9e-06	1.6e-05	3.4e-07	1.3e-05	7.5e-06	1.4e-04	9.5e-06
Joint sig. splines (p-value)					.0775	.076	.0763	.1023
R-squared	0.8370	0.8374	0.8623	0.8918	0.8275	0.8275	0.8524	0.8811
Observations	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Table displays first stage results of Table 3. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively. The F-statistics (p-values) for joint significance of the weather variables is given at the bottom of the Table, as well as the p-value for the test whether the seasonality components of the splines are jointly significant.

Table 3: Weather-Induced Yield Shocks and Net Outmigration in Corn Belt

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A - Baseline: Age [15,60)							
Log Yield	-0.175***	-0.156***	-0.125***	-0.135***	-0.320***	-0.305***	-0.337***	-0.396***
	(0.026)	(0.022)	(0.030)	(0.036)	(0.071)	(0.069)	(0.093)	(0.090)
	Panel B1: Males Age [15,60)							
Log Yield	-0.164***	-0.145***	-0.107***	-0.119***	-0.325***	-0.310***	-0.342***	-0.407***
	(0.025)	(0.022)	(0.031)	(0.037)	(0.073)	(0.070)	(0.095)	(0.092)
	Panel B2: Females Age [15,60)							
Log Yield	-0.186***	-0.168***	-0.141***	-0.153***	-0.316***	-0.301***	-0.331***	-0.385***
	(0.027)	(0.023)	(0.029)	(0.037)	(0.071)	(0.069)	(0.091)	(0.089)
	Panel C1: Age [15,30)							
Log Yield	-0.281***	-0.271***	-0.220***	-0.222***	-0.421***	-0.414***	-0.454**	-0.530***
	(0.068)	(0.068)	(0.083)	(0.084)	(0.121)	(0.121)	(0.179)	(0.163)
	Panel C2: Age [30,45)							
Log Yield	-0.171***	-0.146***	-0.130***	-0.139***	-0.336***	-0.314***	-0.351***	-0.412***
	(0.014)	(0.017)	(0.029)	(0.029)	(0.054)	(0.053)	(0.067)	(0.066)
	Panel C3: Age [45,60)							
Log Yield	-0.026	-0.014	0.004	-0.018	-0.101***	-0.092**	-0.097**	-0.120***
	(0.018)	(0.023)	(0.022)	(0.015)	(0.038)	(0.042)	(0.048)	(0.045)
	Panel C4: Age [60,oo)							
Log Yield	-0.009	-0.005	-0.002	-0.008	-0.018	-0.014	-0.008	-0.016
	(0.011)	(0.011)	(0.014)	(0.013)	(0.014)	(0.013)	(0.019)	(0.016)
Observation	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Each panel is from a separate regression and varies which population (sub)group is considered. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 4: Weather-Induced Yield Shocks and the Effect on Farms and Overall Employment

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A1: Number of Farms (USDA)							
Log Yield	0.200***	0.188***	0.272***	0.326***	0.289**	0.293**	0.528***	0.563***
	(0.067)	(0.063)	(0.078)	(0.084)	(0.126)	(0.125)	(0.169)	(0.166)
Observation	7076	7076	7076	7076	7076	7076	7076	7076
Counties	892	892	892	892	892	892	892	892
	Panel A2: Total Farmlad Area (USDA)							
Log Yield	0.060	0.059	0.084	0.084	-0.074	-0.075	-0.103	-0.082
	(0.043)	(0.044)	(0.064)	(0.062)	(0.055)	(0.056)	(0.091)	(0.089)
Observation	7076	7076	7076	7076	7076	7076	7076	7076
Counties	892	892	892	892	892	892	892	892
	Panel B1: Farm Employment (BEA)							
Log Yield	-0.012	-0.129	-0.269*	-0.229	0.272**	0.183*	0.064	0.231
	(0.127)	(0.117)	(0.138)	(0.152)	(0.117)	(0.097)	(0.130)	(0.161)
Observation	7074	7074	7074	7074	7074	7074	7074	7074
Counties	892	892	892	892	892	892	892	892
	Panel B2: Non-Farm Employment (BEA)							
Log Yield	0.160***	0.232***	0.251***	0.153***	0.331***	0.386***	0.435***	0.401***
	(0.057)	(0.042)	(0.047)	(0.049)	(0.083)	(0.083)	(0.124)	(0.113)
Observation	7074	7074	7074	7074	7074	7074	7074	7074
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Table regresses changes in farmland and employment on instrumented yield shocks. Panels A1-A2 use changes between the 1969, 1974, 1978, 1982, 1987, 1992, 1997, 2002, and 2007 Census, while Panles B1-B2 use the same 5-year intervals as the migration regressions. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Regressions in Panels A1-A3 are weighted by the average cropland area in a county, while Panels B1-B2 use again population weights. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 5: Yield Shocks and Government Transfers

	(1a)	(1b)	(1c)
	Panel A: OLS		
Log Yield	0.036	-0.054	0.042
	(0.256)	(0.212)	(0.230)
	Panel B: IV with Temp / Prec		
Log Yield	-0.756**	-0.598**	-0.453*
	(0.328)	(0.254)	(0.259)
	Panel C: Spline in Extreme Heat		
Log Yield	-1.356***	-1.169***	-0.967***
	(0.426)	(0.313)	(0.320)
Observation	520	520	520
States	13	13	13
Time Trend	Linear	Quad.	State

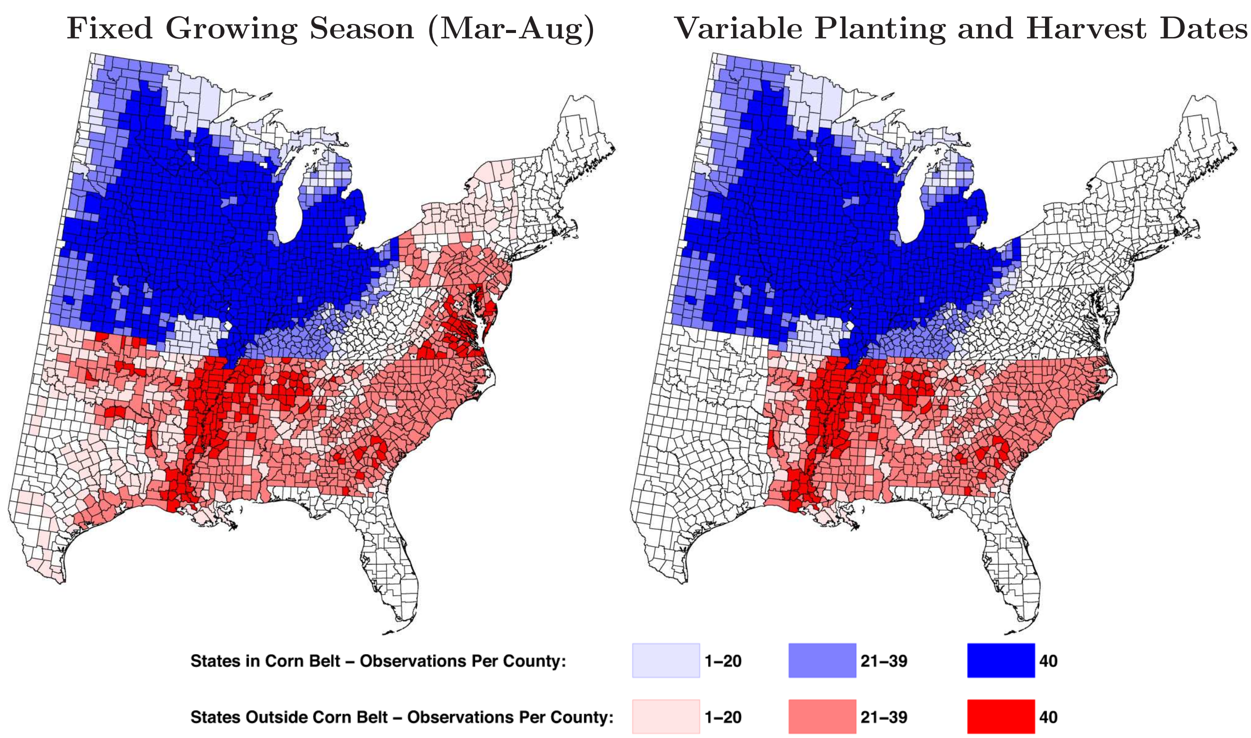
Notes: Table regresses annual state-level log government transfers on yield shocks. Panel A uses uninstrumented yield shocks, panel B instruments yield shocks with the temperature and precipitaion variables of columns (1a)-(1c) in Table 3, respectively, and Panel C instruments yield shocks with the time-varying sensitivity to extreme heat of columns (2a)-(2c) in Table 3. Columns (a)-(c) differ by the included time controls. Column (a) includes a common linear time trend, column (b) includes a common quadratic time trend, and column (c) includes state-specific quadratic time trends. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 6: Predicted Changes in Net Outmigration Under Climate Change

	Predicted Outmigration Rate				Increased Outmigration		Decreased Outmigration	
	Mean	SDev	Min	Max	Total N	Sign. N	Total N	Sign. N
Hadley III-B2 (2020-2049)	12.69	(4.50)	4.24	23.63	892	892	0	0
Hadley III-B2 (2070-2099)	29.73	(7.84)	9.74	44.46	892	892	0	0
Uniform +1° C	4.67	(1.18)	2.12	7.61	892	892	0	0
Uniform +2° C	10.07	(2.48)	4.52	16.03	892	892	0	0
Uniform +3° C	16.26	(3.90)	7.26	25.32	892	892	0	0
Uniform +4° C	23.29	(5.42)	10.45	35.69	892	892	0	0
Uniform +5° C	31.19	(7.04)	14.17	47.20	892	892	0	0
Uniform -50% Precipitation	-1.87	(0.29)	-2.27	-0.83	0	0	892	461
Uniform -30% Precipitation	-0.80	(0.27)	-1.18	0.08	2	0	890	256
Uniform -10% Precipitation	-0.16	(0.12)	-0.35	0.22	114	0	778	147
Uniform +10% Precipitation	0.05	(0.16)	-0.41	0.31	561	50	331	0
Uniform +30% Precipitation	-0.17	(0.57)	-1.80	0.84	373	27	519	0
Uniform +50% Precipitation	-0.81	(1.11)	-3.96	1.22	243	12	649	0

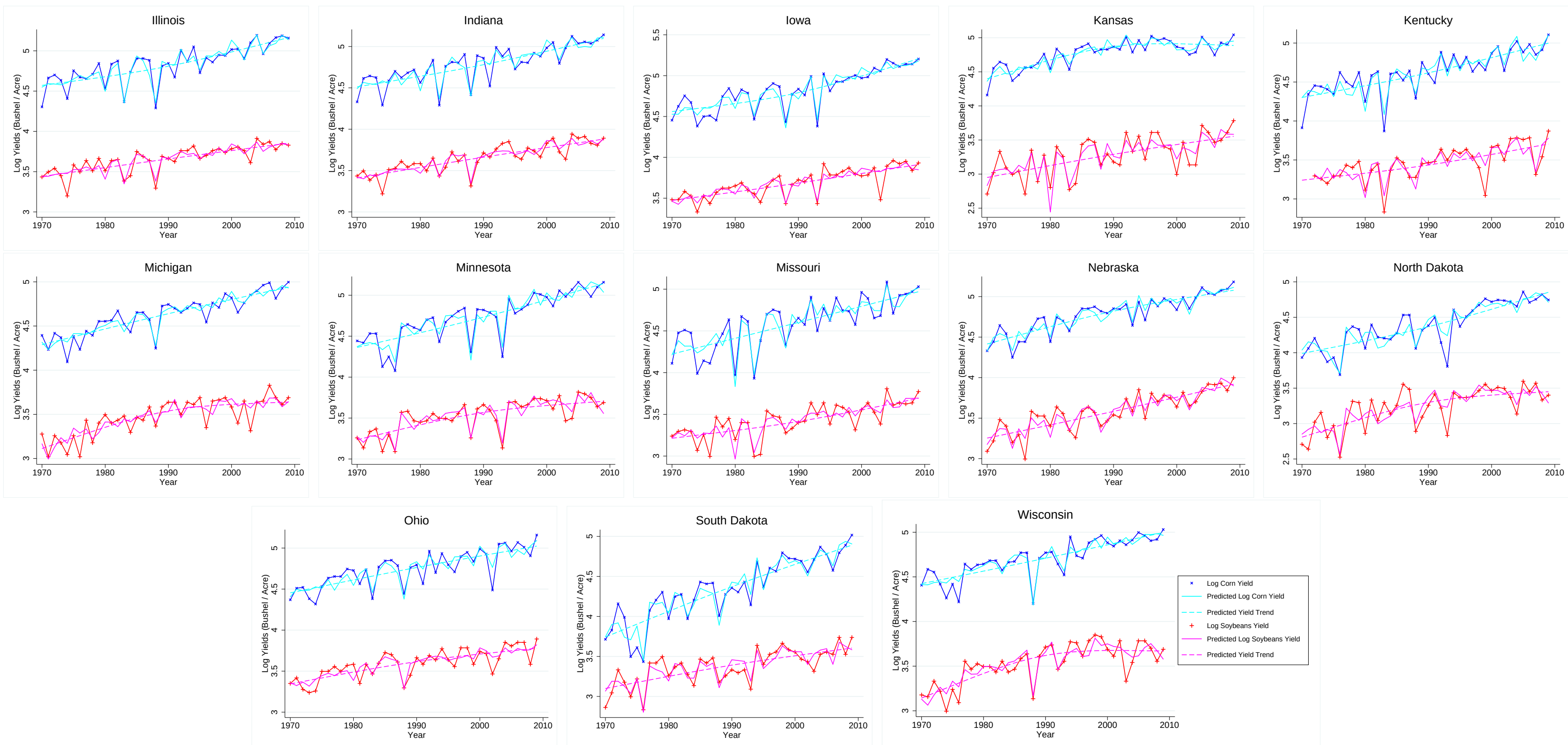
Notes: Tables displays predicted increases in net outmigration under various climate change scenarios for the regression model in column (1d) of Table 3. The first two rows use medium and long-term projections under the Hadley III - B2 scenario. The remaining columns display predicted changes under uniform climate change scenarios. The first four columns summarize the predicted change in net outmigration rates. The last four columns give the number of counties that are predicted to have an increase or a decrease in net outmigration rates. For each category we give the total number of counties as well as the number of counties that have a statistically significant increase or decrease. The spatial distribution of impacts is given in Figures 3 for the first two rows and Figures A4 and A5 in the appendix for the remaining uniform scenarios.

Figure A1: Counties with Soybean Yields (1970-2009)



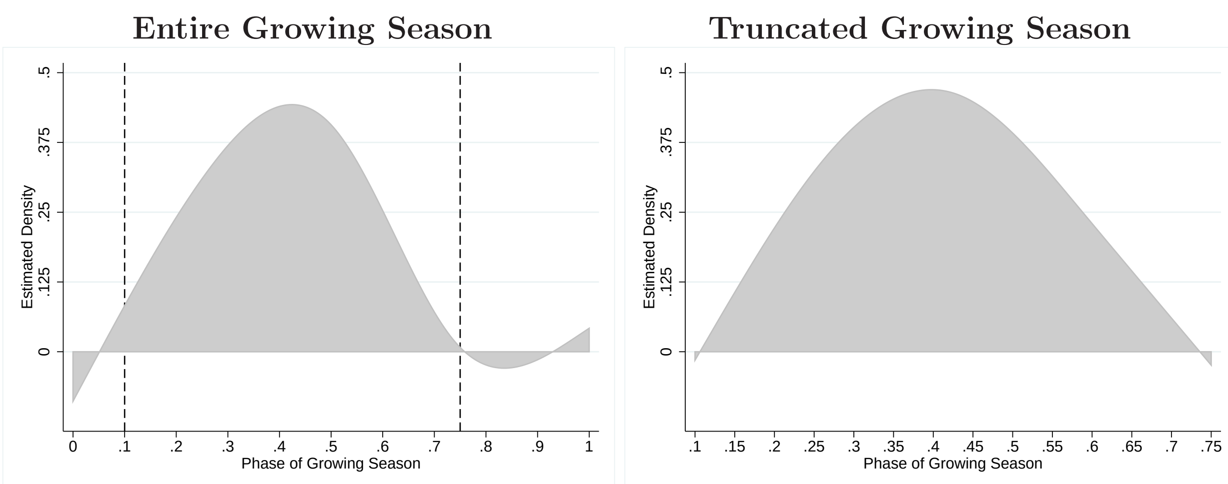
Notes: The left figure displays counties in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. The right column furtherermore requires that state-level planting and harvest dates are available for at least one year. States covering the corn belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have data.

Figure A2: State-Level Log Yields and Weather



Notes: State-level yields, yield trends, and predicted yields for the 13 states in the Corn Belt. Predicted yields are derived from the baseline model using moderate degree days, extreme degree days as well as a quadratic in season-total precipitation for the fixed growing seaosn March-August.

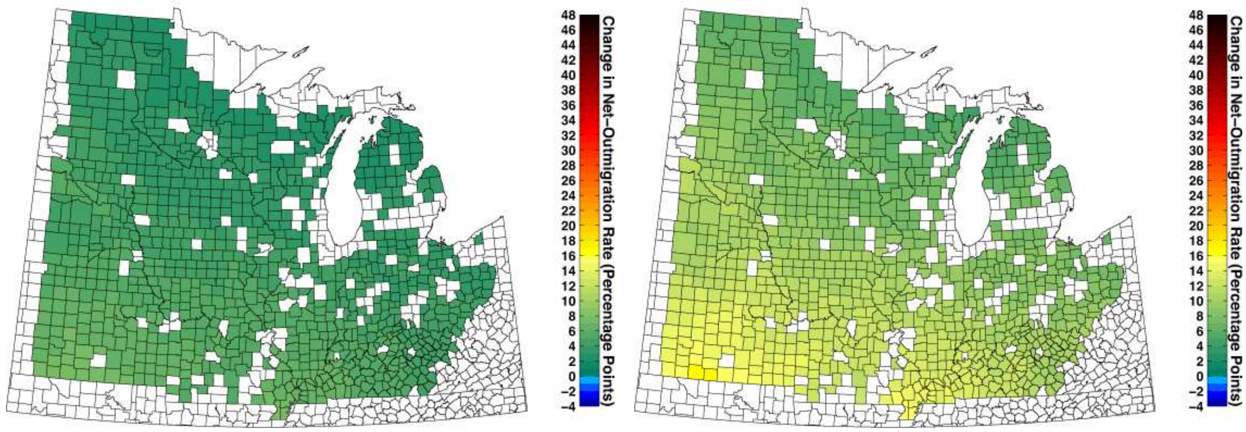
Figure A3: Average Exposure to Degree Days above 29°C Over Growing Season



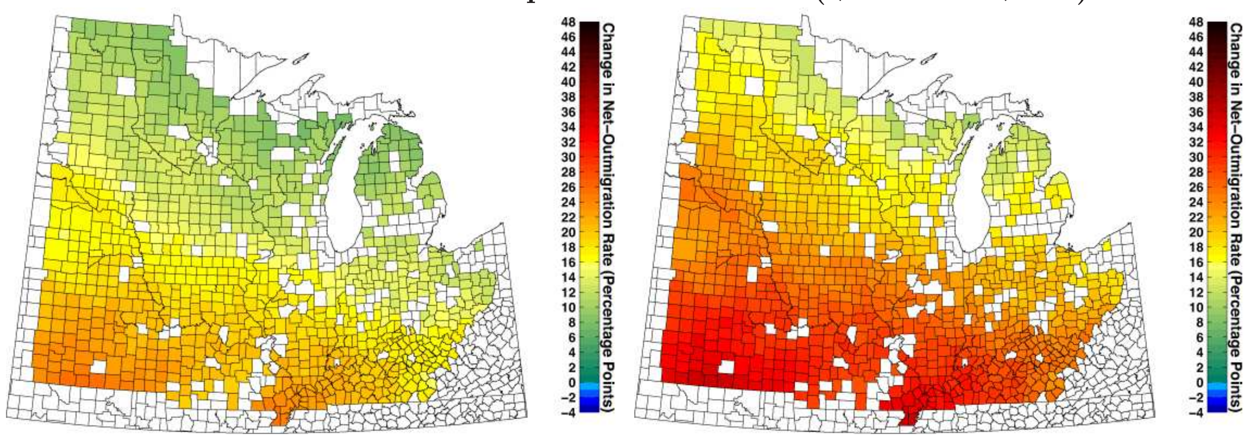
Notes: Both graphs display the average exposure to degree days above 29°C over the growing season, where 0 corresponds to planting and 1 to harvest. The density is approximated using a restricted cubic spline with 5 knots. The left graph uses the entire growing season $[0, 1]$, while the right graph uses a truncated season $[0.1, 0.75]$ as there is hardly any exposure to extremely hot temperatures outside this interval.

Figure A4: Predicted Changes in Net Outmigration (Uniform Temperature Scenarios)

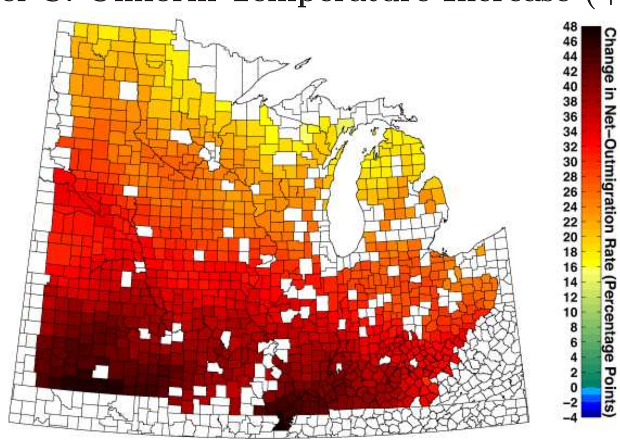
Panel A: Uniform Temperature Increase (+1°C and +2°C)



Panel B: Uniform Temperature Increase (+3°C and +4°C)



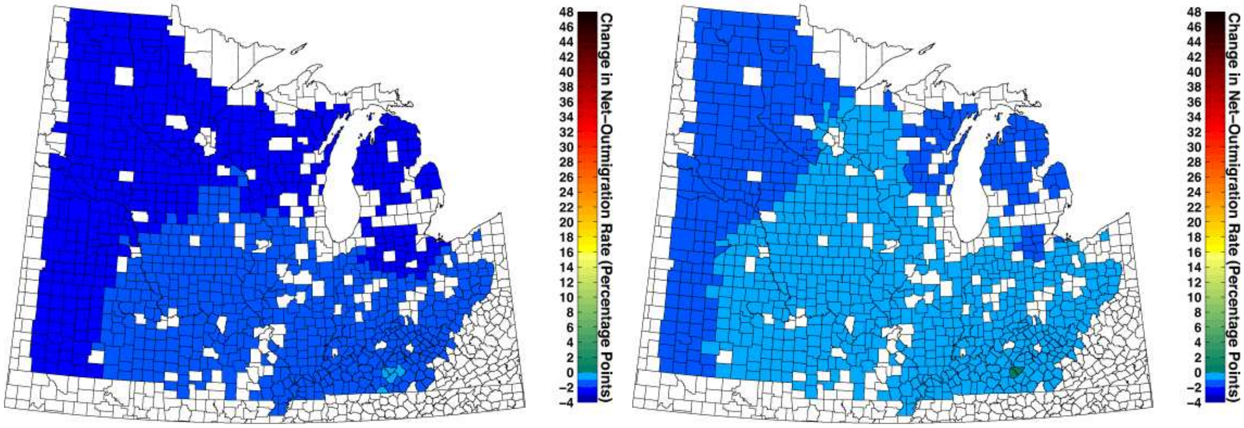
Panel C: Uniform Temperature Increase (+5°C)



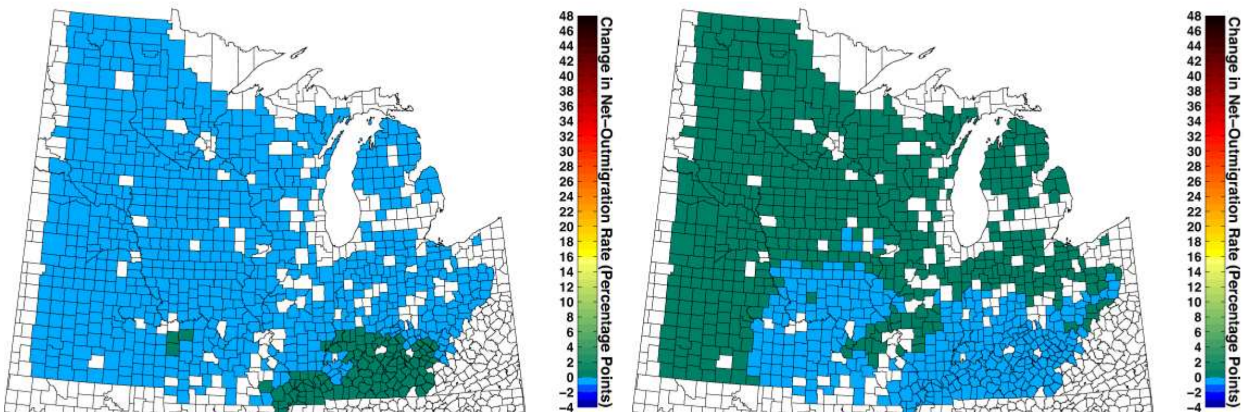
Notes: Panels display predicted changes in net outmigration rates under uniform temperature increases ranging from +1°C to +5°C for counties in the Corn Belt using the regression results of column (1d) of Table 1.

Figure A5: Predicted Changes in Net Outmigration (Uniform Precipitation Scenarios)

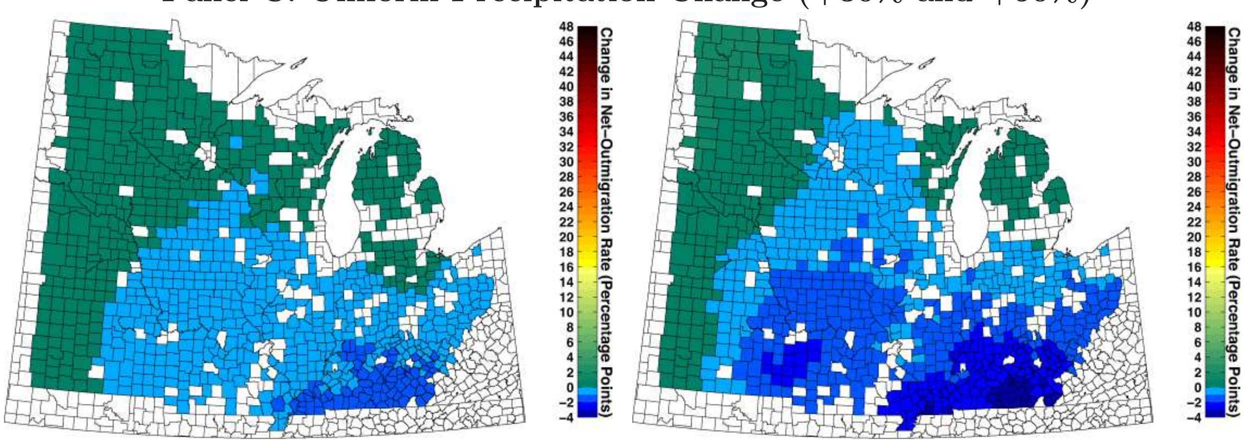
Panel A: Uniform Precipitation Change (-50% and -30%)



Panel B: Uniform Precipitation Change (-10% and +10%)



Panel C: Uniform Precipitation Change (+30% and +50%)



Notes: Panels display predicted changes in net outmigration rates under uniform precipitation changes ranging from -50% to +50% for counties in the Corn Belt using the regression results of column (1d) of Table 1.

Table A1: Descriptive Statistics: Counties with Corn Yields

	Data Over 5-Year Periods							
	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09
Panel A: 892 Counties in Corn Belt								
Migration Rate Age [15,60) (%)	-1.34	0.69	4.96	4.75	-1.22	-0.60	1.35	2.53
(s.d.)	(7.75)	(6.97)	(4.72)	(5.97)	(5.63)	(6.70)	(5.75)	(4.59)
Migration Rate Males [15,60) (%)	-1.90	0.88	5.16	4.98	-1.09	-1.33	1.34	2.56
(s.d.)	(8.10)	(7.06)	(5.21)	(6.37)	(6.02)	(7.62)	(5.94)	(5.50)
Migration Rate Females [15,60) (%)	-0.88	0.46	4.74	4.53	-1.35	0.15	1.34	2.46
(s.d.)	(7.57)	(7.04)	(4.60)	(5.74)	(5.48)	(6.41)	(5.78)	(4.59)
Migration Rate Age [15,30) (%)	0.10	4.84	10.25	11.08	4.25	5.68	3.09	15.17
(s.d.)	(10.81)	(9.81)	(7.11)	(9.12)	(8.23)	(11.30)	(13.93)	(9.64)
Migration Rate Age [30,45) (%)	-3.48	-2.56	2.37	1.36	-4.24	-5.30	-0.12	-3.99
(s.d.)	(6.94)	(6.84)	(4.42)	(4.95)	(6.41)	(7.15)	(3.93)	(6.28)
Migration Rate Age [45,59) (%)	-1.49	-2.49	-0.77	-0.49	-4.18	-1.17	1.24	-3.44
(s.d.)	(6.78)	(6.49)	(5.39)	(5.82)	(6.36)	(7.96)	(2.70)	(5.79)
Migration Rate Age [60,oo) (%)	2.80	1.52	2.29	3.01	2.72	1.14	2.78	1.22
(s.d.)	(3.65)	(3.14)	(2.59)	(2.93)	(3.00)	(3.63)	(2.94)	(3.98)
Corn Area (1000 acres)	48.8	55.2	54.0	52.5	56.0	57.7	60.1	65.9
(s.d.)	(49.4)	(56.0)	(54.2)	(52.1)	(56.4)	(56.9)	(56.5)	(61.2)
Corn Yield (bushel/acre)	77.0	86.9	89.7	101.7	107.7	114.5	128.8	139.9
(s.d.)	(18.1)	(19.7)	(20.4)	(21.0)	(22.1)	(20.5)	(24.6)	(27.0)
Degree Days 10-29° C	1432	1463	1435	1517	1418	1422	1453	1465
(s.d.)	(250)	(248)	(240)	(242)	(262)	(240)	(265)	(256)
Degree Days Above 29° C	34.8	35.5	44.8	42.2	27.0	31.4	32.0	32.1
(s.d.)	(26.9)	(26.0)	(33.8)	(21.7)	(22.6)	(22.4)	(29.1)	(24.8)
Precipitation (mm)	538.3	557.0	552.4	497.6	575.2	588.4	558.8	556.4
(s.d.)	(112.2)	(103.0)	(96.8)	(76.7)	(84.8)	(103.3)	(101.4)	(100.8)
Panel B: 444 Counties Outside Corn Belt								
Migration Rate Age [15,60) (%)	-4.32	-3.92	-0.97	0.39	-4.01	-7.99	-2.58	-2.26
(s.d.)	(7.92)	(18.33)	(7.23)	(8.30)	(7.12)	(9.18)	(7.20)	(6.99)
Migration Rate Males [15,60) (%)	-4.59	-3.46	-0.87	0.63	-4.01	-9.59	-2.47	-2.17
(s.d.)	(8.46)	(18.58)	(7.93)	(8.58)	(8.99)	(13.22)	(8.01)	(8.93)
Migration Rate Females [15,60) (%)	-4.17	-4.43	-1.09	0.16	-3.99	-6.46	-2.60	-2.36
(s.d.)	(7.77)	(18.24)	(6.87)	(8.22)	(6.54)	(8.56)	(7.06)	(6.52)
Migration Rate Age [15,30) (%)	-1.76	0.91	2.97	4.68	0.41	-5.19	-6.87	9.52
(s.d.)	(11.34)	(19.35)	(9.30)	(11.74)	(11.05)	(14.68)	(14.97)	(11.79)
Migration Rate Age [30,45) (%)	-7.31	-8.55	-3.07	-2.29	-7.40	-9.49	-2.01	-6.17
(s.d.)	(7.22)	(22.14)	(7.89)	(6.88)	(6.87)	(9.67)	(6.55)	(8.22)
Migration Rate Age [45,59) (%)	-5.18	-7.23	-5.33	-2.98	-5.73	-9.04	0.30	-9.99
(s.d.)	(6.04)	(15.36)	(6.72)	(7.14)	(6.87)	(9.21)	(3.62)	(8.64)
Migration Rate Age [60,oo) (%)	0.39	-0.32	1.69	2.14	1.19	-0.98	1.88	-1.94
(s.d.)	(4.71)	(11.65)	(3.91)	(4.57)	(4.16)	(5.19)	(3.96)	(5.66)
Corn Area (1000 acres)	9.3	10.5	9.3	7.8	6.9	6.7	6.9	7.5
(s.d.)	(11.3)	(12.5)	(11.1)	(9.9)	(9.3)	(9.3)	(9.9)	(10.8)
Corn Yield (bushel/acre)	57.4	62.4	69.3	74.9	83.4	85.9	104.4	105.9
(s.d.)	(15.7)	(17.8)	(15.5)	(15.6)	(16.7)	(17.9)	(21.6)	(25.1)
Degree Days 10-29° C	1856	1892	1872	1927	1909	1907	1944	1943
(s.d.)	(389)	(382)	(388)	(374)	(379)	(397)	(403)	(391)
Degree Days Above 29° C	54.5	64.3	80.2	79.2	68.8	79.6	68.1	82.7
(s.d.)	(46.5)	(46.5)	(58.3)	(52.3)	(49.5)	(62.7)	(57.1)	(59.2)
Precipitation (mm)	675.8	654.6	631.0	567.0	649.6	605.9	657.9	561.6
(s.d.)	(111.5)	(97.6)	(106.1)	(80.3)	(90.3)	(107.6)	(102.8)	(87.5)

Notes: Sample means and standard deviations by 5-year periods for which we have migration data (1970-2009). Counties with less than 100,000 people in 2000 that have at least 21 yield observations for corn yields with time-varying planting dates are included.

Table A2: Descriptive Statistics: Counties with Soybean Yields

	Data Over 5-Year Periods							
	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09
Panel A: 810 Counties in Corn Belt								
Migration Rate Age [15,60) (%)	-0.97	0.89	5.12	5.02	-0.95	-0.22	1.47	2.54
(s.d.)	(6.99)	(6.23)	(4.51)	(5.72)	(5.35)	(6.28)	(5.72)	(4.59)
Migration Rate Males [15,60) (%)	-1.55	1.04	5.31	5.25	-0.81	-0.93	1.45	2.59
(s.d.)	(7.31)	(6.33)	(5.03)	(6.13)	(5.69)	(7.08)	(5.90)	(5.52)
Migration Rate Females [15,60) (%)	-0.47	0.72	4.93	4.80	-1.09	0.50	1.47	2.45
(s.d.)	(6.91)	(6.33)	(4.38)	(5.47)	(5.25)	(6.03)	(5.77)	(4.60)
Migration Rate Age [15,30) (%)	0.37	4.82	10.29	11.30	4.45	5.94	3.36	14.99
(s.d.)	(10.03)	(9.16)	(6.97)	(8.97)	(8.08)	(10.93)	(13.73)	(9.50)
Migration Rate Age [30,45) (%)	-3.09	-2.21	2.53	1.53	-3.97	-5.03	-0.06	-4.11
(s.d.)	(6.35)	(6.24)	(4.29)	(4.80)	(6.15)	(7.08)	(3.92)	(6.24)
Migration Rate Age [45,59) (%)	-0.98	-2.06	-0.39	-0.03	-3.83	-0.52	1.26	-3.13
(s.d.)	(5.79)	(5.61)	(4.93)	(5.26)	(6.09)	(7.00)	(2.73)	(5.23)
Migration Rate Age [60,oo) (%)	2.87	1.59	2.29	3.01	2.71	1.40	2.78	1.25
(s.d.)	(3.39)	(2.96)	(2.42)	(2.85)	(2.80)	(3.37)	(2.85)	(3.51)
Soybean Area (1000 acres)	54.5	61.5	59.4	57.9	61.6	63.4	64.8	70.6
(s.d.)	(49.7)	(56.1)	(54.3)	(52.0)	(56.4)	(56.9)	(56.3)	(61.0)
Soybean Yield (bushel/acre)	80.3	89.1	91.4	103.9	110.0	116.9	131.1	142.3
(s.d.)	(16.8)	(18.8)	(20.3)	(20.7)	(21.6)	(19.9)	(23.7)	(26.2)
Degree Days 10-30° C	1456	1481	1450	1533	1432	1434	1464	1478
(s.d.)	(237)	(234)	(229)	(229)	(251)	(232)	(257)	(248)
Degree Days Above 30° C	36.3	37.0	46.6	43.8	28.1	32.5	33.2	33.1
(s.d.)	(27.3)	(26.6)	(34.1)	(21.7)	(23.0)	(22.8)	(29.7)	(25.5)
Precipitation (mm)	548.2	561.1	558.0	499.0	578.7	591.5	559.6	560.9
(s.d.)	(112.3)	(96.5)	(95.9)	(77.0)	(81.5)	(99.0)	(98.4)	(97.5)
Panel B: 459 Counties Outside Corn Belt								
Migration Rate Age [15,60) (%)	-2.03	-1.05	1.56	3.13	-1.14	-5.59	0.24	-1.17
(s.d.)	(8.56)	(7.21)	(5.76)	(6.94)	(6.35)	(8.40)	(6.29)	(7.56)
Migration Rate Males [15,60) (%)	-2.11	-0.43	1.90	3.57	-0.76	-7.61	0.41	-1.25
(s.d.)	(9.14)	(7.53)	(6.31)	(7.37)	(7.14)	(12.09)	(6.59)	(8.85)
Migration Rate Females [15,60) (%)	-1.98	-1.66	1.25	2.75	-1.47	-3.69	0.16	-1.08
(s.d.)	(8.12)	(7.10)	(5.50)	(6.68)	(6.03)	(7.28)	(6.47)	(7.52)
Migration Rate Age [15,30) (%)	1.54	4.31	5.63	8.37	3.52	-1.98	-0.31	8.28
(s.d.)	(11.87)	(10.00)	(8.34)	(9.94)	(9.14)	(13.64)	(12.03)	(10.75)
Migration Rate Age [30,45) (%)	-5.70	-6.05	-0.85	-0.76	-4.70	-8.25	0.17	-4.92
(s.d.)	(8.04)	(7.07)	(5.36)	(5.81)	(6.45)	(8.70)	(5.16)	(7.90)
Migration Rate Age [45,59) (%)	-4.02	-5.19	-3.07	-0.78	-3.38	-7.16	0.48	-7.10
(s.d.)	(6.07)	(5.66)	(4.74)	(5.54)	(5.61)	(7.68)	(3.47)	(8.38)
Migration Rate Age [60,oo) (%)	0.80	1.03	3.04	3.10	2.38	0.56	2.89	-0.31
(s.d.)	(3.90)	(3.58)	(3.85)	(3.84)	(3.85)	(4.23)	(3.65)	(5.99)
Soybean Area (1000 acres)	9.0	9.7	7.8	6.7	6.5	7.6	8.2	10.0
(s.d.)	(11.9)	(13.2)	(11.1)	(9.3)	(8.8)	(9.5)	(10.8)	(12.5)
Soybean Yield (bushel/acre)	48.9	54.0	62.8	74.8	84.0	90.2	111.1	116.4
(s.d.)	(14.5)	(13.6)	(14.4)	(18.1)	(18.3)	(20.1)	(23.3)	(27.4)
Degree Days 10-30° C	2040	2066	2046	2098	2064	2066	2077	2079
(s.d.)	(198)	(191)	(195)	(180)	(189)	(203)	(193)	(173)
Degree Days Above 30° C	67.1	78.1	95.0	91.1	77.6	88.7	73.7	91.8
(s.d.)	(26.8)	(24.5)	(28.6)	(26.3)	(26.0)	(34.3)	(30.6)	(29.0)
Precipitation (mm)	746.8	736.7	705.6	615.2	712.7	673.3	683.0	615.5
(s.d.)	(62.3)	(84.9)	(84.7)	(72.9)	(72.4)	(86.3)	(72.4)	(104.5)

Notes: Sample means and standard deviations by 5-year periods for which we have migration data (1970-2009). Counties with less than 100,000 people in 2000 that have at least 21 yield observations for soybean yields with time-varying planting dates are included.

Table A3: Weather and Crop Yields - Panel of Annual Corn Yields For Counties of Corn Belt

	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Extreme Heat (100 degree days)	-0.731***	-0.735***	-0.732***	-0.726***	0.436	0.468	1.081*	1.013*
	(0.112)	(0.112)	(0.109)	(0.112)	(0.531)	(0.525)	(0.543)	(0.550)
Extreme Heat x spline 1					-2.704	-2.903	-5.905**	-5.519**
					(2.700)	(2.671)	(2.529)	(2.532)
Extreme Heat x spline 2					-9.644	-8.602	3.857	2.707
					(13.373)	(13.322)	(11.189)	(11.091)
Extreme Heat x spline 3					56.548	53.801	24.128	24.869
					(37.746)	(37.668)	(29.765)	(29.516)
Extreme Heat x spline 4					-103.322**	-100.682**	-79.254**	-72.739**
					(45.244)	(45.245)	(31.165)	(31.399)
Moderate Heat (1000 degree days)	0.427***	0.427***	0.449***	0.443***				
	(0.104)	(0.104)	(0.103)	(0.104)				
Precipitation (m)	0.167***	0.166***	0.154***	0.156***				
	(0.037)	(0.038)	(0.035)	(0.034)				
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.014***	-0.014***				
	(0.003)	(0.003)	(0.003)	(0.003)				
Joint sig. splines (p-value)					8.5e-05	8.7e-05	4.6e-05	1.2e-04
R-squared	0.6126	0.6130	0.6325	0.6525	0.5931	0.5934	0.6164	0.6358
Observation	34788	34788	34788	34788	34788	34788	34788	34788
Counties	892	892	892	892	892	892	892	892

Notes: Table replicates Table 2 except that it uses *annual* log yields of counties in the Corn Belt and the regressions are unweighted. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. The spline coefficients are shown in the bottom row of Figure 2. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A4: Weather and Crop Yields - Panel of Annual Corn Yields For Eastern Counties Outside Corn Belt

	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Extreme Heat (100 degree days)	-0.571**	-0.604**	-0.610***	-0.574**	2.397*	2.290*	1.908*	2.227**
	(0.159)	(0.160)	(0.150)	(0.163)	(0.940)	(1.009)	(0.925)	(0.848)
Extreme Heat x spline 1					-15.171**	-14.607**	-12.742*	-14.376**
					(5.144)	(5.574)	(5.320)	(5.060)
Extreme Heat x spline 2					64.222*	60.154	53.304	62.278
					(30.760)	(32.417)	(32.740)	(33.001)
Extreme Heat x spline 3					-152.684	-139.573	-126.621	-153.036
					(94.368)	(97.935)	(100.207)	(101.948)
Extreme Heat x spline 4					115.309	98.036	99.076	131.923
					(124.602)	(125.947)	(127.865)	(131.093)
Moderate Heat (1000 degree days)	-0.160	-0.146	-0.075	-0.108				
	(0.152)	(0.156)	(0.126)	(0.134)				
Precipitation (m)	0.017	0.005	0.020	0.035				
	(0.040)	(0.043)	(0.048)	(0.046)				
Precipitation Squared (m^2)	-0.001	-0.000	-0.001	-0.002				
	(0.003)	(0.003)	(0.003)	(0.003)				
Joint sig. splines (p-value)					5.0e-03	1.5e-03	3.1e-05	2.4e-04
R-squared	0.4651	0.4760	0.5234	0.5409	0.4852	0.4972	0.5372	0.5536
Observation	15946	15946	15946	15946	15946	15946	15946	15946
Counties	444	444	444	444	444	444	444	444

Notes: Table replicates Table 2 except that it uses *annual* log yields of Eastern counties oustide the Corn Belt and the regressions are unweighted. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A5: Weather and Migration - Northern versus Southern Counties Outside Corn Belt

	North-Eastern Counties				**South-Eastern Counties**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Extreme Heat (100 degree days)	0.136	0.089	0.066	0.118	-0.007	-0.019	-0.035	-0.015
	(0.112)	(0.082)	(0.099)	(0.110)	(0.045)	(0.048)	(0.063)	(0.072)
Moderate Heat (1000 degree days)	-0.251*	-0.251*	-0.201**	-0.291	0.352**	0.347*	0.315*	0.432*
	(0.026)	(0.020)	(0.014)	(0.150)	(0.110)	(0.118)	(0.126)	(0.136)
Precipitation (m)	0.064	0.061	0.071	0.060	-0.023	-0.029	-0.035	-0.026
	(0.034)	(0.036)	(0.040)	(0.068)	(0.021)	(0.021)	(0.021)	(0.013)
Precipitation Squared (m^2)	-0.006	-0.006	-0.007	-0.006	0.001	0.002	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
F-stat (joint significance)	1	1	0	4	90	131	16	16
p-value (joint significance)	.4395	.4761	.6247	.3032	.002	.0011	.0228	.0235
R-squared	0.0123	0.0129	0.0171	0.1643	0.0484	0.0525	0.0683	0.2643
Observations	860	860	860	860	2511	2511	2511	2511
Counties	109	109	109	109	335	335	335	335
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Table displays reduced form regression of migration rates on weather (using the bounds for the largest crop corn). Columns (1a)-(1d) look at northern-eastern counties outside the corn belt (east and north of corn belt), while columns (2a)-(2d) focus on south-eastern counties outside the corn belt as shown in Figure 1. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A6: Weather-Induced Yield Shocks and Net Outmigration - Corn Verus Soybean Yields

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A: Instrumenting Corn Yields							
Log Yield	-0.175***	-0.156***	-0.125***	-0.135***	-0.320***	-0.305***	-0.337***	-0.396***
	(0.026)	(0.022)	(0.030)	(0.036)	(0.071)	(0.069)	(0.093)	(0.090)
Observation	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
	Panel B: Instrumenting Soybean Yields							
Log Yield	-0.183***	-0.155***	-0.144***	-0.164***	-0.176**	-0.192**	-0.196**	-0.176**
	(0.064)	(0.049)	(0.049)	(0.060)	(0.088)	(0.084)	(0.091)	(0.088)
Observation	6413	6413	6413	6413	6413	6413	6413	6413
Counties	810	810	810	810	810	810	810	810
	Panel C: Instrumenting Weighted Average of Corn and Soybean Yields							
Log Yield	-0.176***	-0.158***	-0.145***	-0.147***	-0.281***	-0.261***	-0.272***	-0.295**
	(0.045)	(0.036)	(0.043)	(0.050)	(0.093)	(0.081)	(0.105)	(0.116)
Observation	7086	7086	7086	7086	7086	7086	7086	7086
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Panel A is the same as in Table 3. Panels B and C instead use log soybean yields, and the log of the weighted average of corn and soybean yields, respectively. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A7: Yield Shocks and Net Outmigration in Eastern United States - OLS Regressions

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A: Corn Yields							
Log Yield	-0.018	-0.016	0.000	-0.013	-0.007	-0.009	0.008	0.004
	(0.015)	(0.013)	(0.016)	(0.022)	(0.022)	(0.021)	(0.020)	(0.014)
Observation	7078	7078	7078	7078	3371	3371	3371	3371
Counties	892	892	892	892	444	444	444	444
	Panel B: Soybean Yields							
Log Yield	-0.012	-0.024	-0.019	-0.017	-0.032**	-0.015	-0.020	-0.065***
	(0.018)	(0.016)	(0.018)	(0.022)	(0.016)	(0.016)	(0.018)	(0.022)
Observation	6413	6413	6413	6413	3413	3413	3413	3413
Counties	810	810	810	810	459	459	459	459
	Panel C: Weighted Average of Corn and Soybean Yields							
Log Yield	-0.028*	-0.030**	-0.014	-0.026	-0.015	-0.011	-0.002	-0.025
	(0.015)	(0.013)	(0.016)	(0.024)	(0.021)	(0.018)	(0.019)	(0.022)
Observation	7086	7086	7086	7086	5151	5151	5151	5151
Counties	892	892	892	892	693	693	693	693
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Tables regresses net outmigration on uninstrumented yield shocks as well as county fixed effects. Columns (1a)-(1d) look at counties in the corn belt, while columns (2a)-(2d) focus on counties outside the corn belt as shown in Figure 1. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A8: Weather-Induced Yield Shocks and Net Outmigration - Unweighted Regressions and Population Cutoffs

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A: Weighted Regression - Less than 100,000 Inhabitants							
Log Yield	-0.175***	-0.156***	-0.125***	-0.135***	-0.320***	-0.305***	-0.337***	-0.396***
	(0.026)	(0.022)	(0.030)	(0.036)	(0.071)	(0.069)	(0.093)	(0.090)
Observation	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
	Panel B1: Unweighted Regression - Less than 100,000 Inhabitants							
Log Yield	-0.193***	-0.181***	-0.133***	-0.129***	-0.311***	-0.310***	-0.360***	-0.431***
	(0.013)	(0.013)	(0.015)	(0.014)	(0.017)	(0.017)	(0.022)	(0.023)
	Panel B2: Same as B1 with Bootstrapped Errors							
Log Yield	-0.193**	-0.181**	-0.133	-0.129	-0.311***	-0.310***	-0.360**	-0.431**
	(0.091)	(0.088)	(0.131)	(0.173)	(0.090)	(0.104)	(0.148)	(0.184)
Observation	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
	Panel C: Unweighted Regression - All Counties							
Log Yield	-0.182***	-0.170***	-0.131***	-0.128***	-0.301***	-0.299***	-0.350***	-0.415***
	(0.013)	(0.012)	(0.014)	(0.013)	(0.016)	(0.016)	(0.020)	(0.021)
Observation	8069	8069	8069	8069	8069	8069	8069	8069
Counties	1016	1016	1016	1016	1016	1016	1016	1016

Notes: Panel A is the same as Table 3. Panels B1 and B2 use unweighted regression instead of population weighted regression. B1 continues to cluster by state, while B2 uses 1000 grouped bootstrap draws where entire 5-year intervals are drawn with replacement. Panel C uses an unweighted regression for all counties in the corn belt - the errors are again clustered by state. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties that had at least 21 yield observations in 1970-2009. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A9: Weather-Induced Yield Shocks and Net Outmigration - Minimum Number of Yield Observations

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A: Baseline Results - At Least 21 Yield Observations							
Log Yield	-0.175***	-0.156***	-0.125***	-0.135***	-0.320***	-0.305***	-0.337***	-0.396***
	(0.026)	(0.022)	(0.030)	(0.036)	(0.071)	(0.069)	(0.093)	(0.090)
Observation	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
	Panel B: At Least 1 Yield Observations							
Log Yield	-0.175***	-0.155***	-0.126***	-0.140***	-0.316***	-0.300***	-0.333***	-0.391***
	(0.026)	(0.022)	(0.029)	(0.035)	(0.071)	(0.069)	(0.092)	(0.089)
Observation	7244	7244	7244	7244	7244	7244	7244	7244
Counties	935	935	935	935	935	935	935	935
	Panel C: At Least 40 Yield Observations							
Log Yield	-0.157***	-0.137***	-0.103***	-0.120***	-0.392***	-0.377***	-0.429***	-0.464***
	(0.029)	(0.026)	(0.037)	(0.043)	(0.084)	(0.082)	(0.103)	(0.105)
Observation	5608	5608	5608	5608	5608	5608	5608	5608
Counties	701	701	701	701	701	701	701	701

Notes: Panel A is the same as Table 3. Panels B and C vary the required minimum number of yield observations in a county to be included in the regression. Panel B uses all counties that have any observation, while Panel C requires a balanced panel with 40 yield observations. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A10: Weather-Induced Yield Shocks and the Effect on Farms and Overall Employment - Unweighted Regression with Bootstrapped Errors

	Temperature and Precipitation				**Spline in Extreme Heat**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
				Panel A1: Number of Farms (USDA)				
Log Yield	0.265	0.257	0.416	0.429	0.396	0.395*	0.708*	0.741
	(0.202)	(0.173)	(0.270)	(0.447)	(0.243)	(0.209)	(0.402)	(0.455)
Observation	7076	7076	7076	7076	7076	7076	7076	7076
Counties	892	892	892	892	892	892	892	892
				Panel A2: Total Farmlad Area (USDA)				
Log Yield	0.067	0.075	0.152	0.137	-0.094	-0.089	-0.077	-0.055
	(0.090)	(0.078)	(0.104)	(0.138)	(0.099)	(0.094)	(0.136)	(0.201)
Observation	7076	7076	7076	7076	7076	7076	7076	7076
Counties	892	892	892	892	892	892	892	892
				Panel B1: Farm Employment (BEA)				
Log Yield	0.015	-0.044	-0.247	-0.233	0.231	0.232	0.058	0.187
	(0.203)	(0.185)	(0.298)	(0.212)	(0.173)	(0.180)	(0.233)	(0.415)
Observation	7074	7074	7074	7074	7074	7074	7074	7074
Counties	892	892	892	892	892	892	892	892
				Panel B2: Non-Farm Employment (BEA)				
Log Yield	0.171	0.200	0.184	0.111	0.334*	0.329*	0.439*	0.460
	(0.184)	(0.183)	(0.268)	(0.294)	(0.200)	(0.182)	(0.264)	(0.410)
Observation	7074	7074	7074	7074	7074	7074	7074	7074
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	State	County	Linear	Quad.	State	County

Notes: Table replicates Table 4 except that regressions are unweighted and standard errors are constructed by using a grouped bootstrap by resampling entire years with replacement. Columns (1a)-(1d) use temperature and precipitation as instruments, while columns (2a)-(2d) only uses the seasonal variation in the sensitivity to extreme heat. Columns (a)-(d) differ by the included time controls. Columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.