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

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Abstract

We link a county-level panel of net migration in the Eastern United States to weather-induced yield anomalies in 1970-2009. Our model uses the seasonality of the sensitivity of corn yields to extreme heat over the growing season, which peaks during corn flowering, as instrument. Unless people inside the Corn Belt (but not outside the Corn Belt) have a distaste for heat that varies year-to-year with corn flowering, our results are driven by a change in agricultural productivity and not a direct preference for climate. A one percent change in yields leads to an opposite 0.3-0.4 percentage point change in the net migration rate in rural counties of the Corn Belt. Since agricultural demand is highly inelastic, price feedbacks have the potential to more than offset the effect of production declines on migration. A novel model that includes both local as well as the global production shocks allows us to differentiate between the decline in productivity due to climate change and the effect of price feedbacks occurring when US production shocks are not offset somewhere else.

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We investigate the effect of weather variability on migration patterns of the U.S. population 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 (2012) 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. 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 for rural counties, i.e., counties with a total population less than 100,000 in the 2000 Census. 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 dislike climate outcomes that are conducive to agricultural productivity, which will downward bias our migration-yield relationship towards zero. This poses a challenge to using traditional weather variables as instruments, such as degree days and precipitation over the growing season (Schlenker & Roberts 2009). 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 at the same time that corn flowers (and only inside the Corn Belt but outside of it), 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. For every percent average 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 (2012) observed in the Dust Bowl era. 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 also expanding, while years with bad yields coincide with contractions in non-farm employment. The semi-elasticity for non-farm employment is larger than that for farm employment and statistically significant. Farm labor is shielded from agricultural losses as we find an almost one-to-one increase in subsidy payments for weather-induced reduction in agricultural yields. Additionally, 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.

The estimated reduced form climate-migration relationship in this paper is specific to the period of 1970-2009 and may change in the future depending on many factors, such as the

[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).

structures of the economy, demographic profiles, and government policies. Nevertheless, we believe it is an informative exercise 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. We conduct two thought experiments: a partial equilibrium analysis where prices are assumed to remain constant and a specification that also adjusts for global corn prices. Since the US produces 40% of the world's corn, production shocks in the US impact global prices. In the partial equilibrium analysis, predicted yield declines in the Corn Belt will lead to significant migration out of rural areas in the Corn Belt. This scenario requires that US production losses are offset by increases in other countries, e.g., Canada or Northern Russia to keep price levels constant. In case there is no such offset, we include a specification that not only accounts for yield shocks in a county, but global yield shocks that have been shown to be a good instrument for global prices (Roberts & Schlenker 2013). In this specification, the positive effect of a decrease in productivity on net outmigration is more than offset by the implied price increase, resulting in a net inmigration as the large increase in prices makes farming profitable despite lower yields.

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 results are reported in Section 3, followed by our conclusions in section 4.

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 between 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).[2]

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-to-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) were 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

[2] One exception is the Great Depression, during which urban people returned to agricultural areas to become subsistence farmers (Boone & Wilse-Samson 2014).

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 2012). 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 2012). 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 the current century as a consequence of global climate change. Recent researches suggest 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).[3] 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 already embodied 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-yield 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 Methodology and Data

2.1 Empirical Methodology: IV Regression

To investigate our hypothesis that the migration relationship is driven by changes in agricultural productivity, we use an instrumental variable approach. We link the net outmigration rate m_{it}, defined as the fraction of people leaving a county net of new arrivals and deaths,

[3]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.

in county i during the five-year interval started with year t to observed yield outcomes.[4] Consecutive observations in our panel are five years apart as some of the population data is reported every five years.

$$\begin{aligned} m_{it} &= \beta x_{it} + f(t) + c_i + \epsilon_{it} && (1) \\ x_{it} &= \gamma \mathbf{W}_{it} + g(t) + k_i + \nu_{it} && (2) \end{aligned}$$

We regress the net migration ratio m_{it} 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. 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 quadratic time trends that allow for the fact that the economic conditions might be trending differently in each location. The error term ϵ_{it} might be spatially and serially correlated, and we cluster it at the state level in the baseline regressions, which adjusts for arbitrary within-state correlations along both the cross-sectional and time-series dimensions.[6] All baseline regressions are weighted by county population. In a sensitivity check, we also present results of an unweighted regression where we use a grouped bootstrap routine and draw entire 5-year intervals with replacement, i.e., all counties that report in a given 5-year interval.

Because x_{it} may be correlated with ϵ_{it}, we only use yield shocks that are due to presumably exogenous variation in weather.[7] In equation (2), 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

[4] In our baseline regression we use the difference of the population aged $[20, 65)$ at time $t + 5$ minus the population aged $[15, 60)$ at time t plus deaths of the population subgroup between t and $t + 5$, normalized by the population aged $[15, 60)$ at time t.

[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 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).

[7] For comparison, Table 1 presents results from a simple OLS regression, which are strikingly different from the IV regression.

in both the first and second stage. Figure A3 in the appendix displays annual corn and soybean yields for the 13 states in the Corn Belt.[8] The figure displays actual yields as well as predicted yields using our preferred instrument, the effect of degree days above 29°C, which is allowed to vary over the growing season.[9]

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. The best single predictor of yield is extreme heat. The effect of extreme heat varies over the growing season for corn, as corn is most damaged by heat during flowering (Berry, Roberts & Schlenker 2013). Our baseline model therefore uses a model that only relies on extreme heat (degree days above 29°C for corn), interacted 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 2.2 below). The effect of an extra degree day above 29°C is allowed to vary smoothly over time. As will be shown below, the seasonality in the effect of extreme heat on corn yields is closely mirrored in the reduced form relationship between migration and extreme heat. In other words, people only seem to care about extreme heat when it is detrimental to corn, but not otherwise. Unless people's preference align with corn flowering, which varies year-to-year, migration is not driven by a direct preference for climate.

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 soybean yields are measured in bushels/acre, with corn yields on average roughly three times as high as soybean yields. 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.[10] 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

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

[9]Degree days are simply truncated daily temperature variables summed over the growing season. For example, degree days above 29°C measure temperatures above 29°C (84°F), i.e., a temperature of 32°C would give 3 degree days.

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

revenue/cost ratio 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 excluding the state of Florida. In both instances we focus on rural counties, which we define as counties with a total population of less than 100,000 in the 2000 Census. 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 productions are less important as a fraction of the overall economic activity. Eastern areas outside the Corn Belt thus serve as a control group in our research design - if changes in climate affect 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 of retirement communities in the South, our estimate for β would be biased as people might migrate for reasons that are detrimental/beneficial to crop growth. This poses a serious challenge to the exogeneity assumption of the instruments. Fortunately, for the instruments used in our baseline 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. Recall that we only observe the reduced form relationship over 5-year intervals. If individuals dislike heat in a particular phase of the year, e.g., the fall, they can still move at a different time within the same 5-year interval. For example, if a family dislikes heat at any point in a year, they can still move after the school year is over, and our model would capture this. While people might dislike heat more during the summer for personal reasons, e.g., kids are off from school and want to play outside, the corn-growing season varies year-to-year. We use this year-to-year variation in our identification. If we fix the growing season at the average start and end date, the coefficient on migration is cut by more than half, but should remain unchanged if the driving force was a personal distaste for a heat in the summer. In summary, we observe that 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.

2.2 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.[11] 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

$$m_{it[15,60)} = \frac{p_{it[15,60)} - p_{i[t+5][20,65)} - d_{it[15,60)}}{p_{it[15,60)}} \tag{3}$$

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 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. We calculate total growing-season degree days instead of mean temperatures to capture the nonlinear effect of temperature on crop yields. 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 in our

[11] 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.

baseline model.[12] 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.[13] Since there are hardly any degree days above 29°C at the beginning or the end of the growing season, 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.[14]

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.[15] 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.[16] Counties outside these states that lie east of the 100 degree meridian except Florida are labeled the non-Corn Belt areas.

Table A1 presents sample summary statistics for the counties with planting and harvest dates for corn. 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.[17] There are 1,638 counties in our sample, 892 in the Corn Belt sample and 746

[12] We use the four weather variables of Schlenker & Roberts (2009) as and instrument in the appendix. The reduced form regression between migration and moderate heat suggests that people have a direct preference for moderate heat that would bias our results towards zero.

[13] 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. Yearly planting dates are reported for major corn producing states, which by definition fall almost exclusively within the Corn Belt. Most Eastern states outside the Corn Belt therefore do not report annual planting and harvest dates. Our baseline specification fixes the growing season for Eastern counties outside the Corn Belt and Florida to equal the average planting and harvest dates for Eastern states outside the Corn Belt and Florida that report it. A sensitivity analysis of how the definition of the growing season impacts the results is given in Table A7, but none of our main results changes.

[14] The average exposure to extreme heat over the growing season is shown in Figure A2. 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.

[15] Figure A1 gives the results for soybeans. Our baseline model requires that yields are reported for at least half the years, i.e., there are at least 21 yield observation in our 40-year period. The sensitivity of our results to what counties are included is give in Table A9.

[16] 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.

[17] We present sensitivity checks where counties with more than 100,000 inhabitants are included in Ta-

in the non-Corn Belt sample.[18] 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 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 Yield-Migration Relationship

We start with a panel of net outmigration rates and yields that are *not* instrumented with weather in Table 1. This should be seen as a comparison table to motivate the importance of our IV strategy. The table presents the results for counties in the Corn Belt as shown in blue in Figure 1. Columns (a)-(d) vary in the included temporal controls, ranging from the least flexible, a common linear time trend in columns (a), to the most flexible, a country-specific quadratic time trend in column (d). Panel A uses corn yields, while panel B uses soybean yields, and Panel C uses the average of the two as described in the data section. The estimated semi-elasticities are generally negative, but small in magnitude and only a few are significant. The big drawback of such an uninstrumented regression is that there is a clear endogeneity problem. First, the direction of causality might be reversed: if a productive work force leaves a county, yields might decline. Second, there might be omitted variable bias, for example, higher oil prices negatively impact agriculture (higher input cost of both fuel and fertilizer prices, which are linked to oil prices) and also negatively effects the overall economy, which could speed up the rural-urban migration trends, leading to negative correlation between yield shocks and outmigration rates. Yield declines may also

ble A8. The results are unchanged in unweighted regressions, but do change if we weight by the population in a county.

[18] 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.

be accompanied by subsidies from the government offsetting possible migration responses. Our subsequent analysis therefore relies on an instrumental variable approach where we instrument log corn yields with extreme heat.

3.2 The Weather-Migration Relationship

One potential concern for any IV set up the exclusion restriction, i.e., people migrate as a response to observed weather due to a direct preference for weather, and not changes in agricultural productivity. While this cannot be tested directly, we provide some evidence that suggests that this is unlikely to be the case. Our baseline model uses only extreme heat as measured by temperatures above 29°C (84°F) and how the sensitivity varies over the growing season. Figure 2 shows the reduced form relationship between migration and extreme heat in the top row, where the four columns again vary in the included time trend.[19] Regressions are population-weighted by the total population in a county in 2000 and our sample includes all rural counties in the Corn Belt that reported corn yields for more than half of the years in 1970-2009.

Recall that our migration data is reported in 5-year intervals. Each graph shows how net-outmigration in a county responded to observed amount of extreme heat during the same five year interval. The black line shows the results for a model where the effect is allowed to vary over the truncated growing season and the 95% confidence band is given in grey. Point estimates of models that force the effect to be the same throughout the growing season are shown as red and blue horizontal lines. In the time-varying model, a county with a higher than usual amount of heat early or late during the corn-growing season had no significant increase in outmigration rates. A higher amount of extreme heat around 40% of the time between planting and harvest of corn resulted in people leaving the county more frequently than usual. This is the mirror image of the relationship between corn yields and extreme heat, as shown in the next section, i.e., people are most sensitive to extreme heat when corn is most sensitive.

We replicate the analysis for counties outside the Corn Belt in the top row of Figure 3. The reduced form relationship between migration and extreme heat shows no significant relationship: the grey 95% confidence band includes zero throughout the season. This provides strong support to our exclusion restriction. While there might be reasons that individuals are more sensitive to extreme heat during part of the year, e.g., summer break when kids

[19] We estimate equation (1) by regressing it on the weather variables $\mathbf{W}_{it}$ of equation (2) and dropping yields x_{it}.

play outside, it seems odd why this would only be the case in areas where corn is grown but not outside these areas. Moreover, corn flowering varies year-to-year. We believe the only likely explanation is that the effect of weather (varying extreme heat in growing season) works through the channel of changes in agricultural productivity.

3.3 First Stage: The Weather-Yield Relationship

The bottom row of Figure 2 shows the corresponding relationship between corn yields and the seasonality of extreme heat that has been observed in previous studies (Berry, Roberts & Schlenker 2013). Note the mirror image in timing to the migration-heat relationship in the top row: corn is most sensitive to extreme heat around 40% of the time between planting and harvest. Corn outside the Corn Belt shows the same seasonality in the bottom row of Figure 3.

The seasonality of extreme heat over the truncated growing season is a strong instrument. Table 2 gives the first-stage F-statistics both inside the Corn Belt in columns (1a)-(1d) as well as outside the Corn Belt in column (2a)-(2b). We present two sets of results. Panel A follows previous studies examining the yield-weather relationship that ran unweighted annual regressions of log corn yields on the seasonality of extreme heat, specifically, it's interaction with a restricted cubic spline with 5 knots on $[0.1, 0.75]$ of the growing season. It gives the F-statistics from annual regressions covering our sample period 1970-2009. On the other hand, our migration regressions use 5-year intervals, and hence the number of periods collapses from forty years to eight 5-year intervals. The migration regressions are population-weighted to obtain the most efficient estimator for the overall population. Panel B therefore gives the F-statics for the population-weighted regressions using 5-year intervals. The F-statistics generally decrease as the number of observations is smaller and the 5-year averages have less variations than annual data, but they are still at least 10, the usual cutoff value for weak instruments, in all cases.

Our baseline model use annual state-level data on the beginning and end of the growing season for the years in which it is available and the average values for each county for the remaining years for counties of the Corn Belt. One challenge is that USDA only reports state-level planting and harvest dates for major corn producing states, which are primarily confined to states within the Corn Belt. We therefore use the average planting and harvest date among Eastern states outside the Corn Belt and Florida that report it and apply the average planting and harvest dates to all counties and years outside the Corn Belt. However, our results are not driven by the definition of the growing season. If we set the growing season to equal the average of all counties or only use counties outside the Corn Belt that have state-level planting dates, the fact that migration and corn yields exhibit a strong seasonality to extreme heat within the Corn Belt, but only corn yields do so outside the Corn Belt, persists.[20]

Earlier work on the weather-yield relationship of Schlenker & Roberts (2009) used four weather variables: moderate degree days (degree days 10-29°C for corn), extreme heat as measured by degree days above 29°C, and a quadratic in precipitation. We obtain similar results in Table A3 of the appendix both for an unweighted annual regression and a population-weighted regression that uses 5-year intervals.[21] 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 0.43-0.84% in the Corn Belt. On the other hand, extremely hot temperatures are very harmful - each degree day increase in extreme heat decreases yields by 0.50-0.74%, which is 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 can easily be rejected - all F-statistics are again above 10 for the Corn Belt. However, the reduced-form relationship between migration and these four weather variables in Table A5 finds significant coefficients for both moderate and extreme heat, the measure on moderate heat has a counterintuitive sign: moderate heat is good for crop growth as shown in columns (1a)-(1d) of Table A3 and increases outmigration. Since moderate heat improves yields and the economic livelihood of an agricultural area, it would decrease rather than increase the net out-migration rate if weather affects migration only through the agricultural channel. The counter-intuitive sign in the reduced-form migration regression equation suggests otherwise, that is, climate affects migration through non-agricultural channels as well, possibly via a direct preference for cool weather. This observation partly motivates our choice to exclusively rely on the seasonality of the effect of extreme heat as an instrument when we examine the yield-migration relationship.

[20]Figures A4 and A5 replicate the seasonality analysis for counties within and outside the Corn Belt, respectively, if we fix the growing season to equal the average planting and harvest dates within the entire sample (both inside and outside the Corn Belt). Figure A6 replicates the analysis if we only use counties that are in Eastern states outside the Corn Belt and Florida that report planting and harvest dates. The number of counties drops from 746 to 444.

[21]Table A4 gives the results for soybeans.

3.4 Second Stage: Yield Shocks and Net Outmigration

We estimate equations (1) and (2) by two-stage-least-squares (2SLS) and present the second stage results in Panel A of Table 3. Columns follow the same layout as the previous table. Columns (a) use a common linear trend (one variable), columns (b) use a common quadratic time trend (two variables), columns (c) use state-specific quadratic time trends (26 variables in the Corn Belt, 13 states $\times$ two variables per state), columns (d) use county-specific quadratic time trends (1784 variables, 892 counties $\times$ two variable by county). We choose not to control for year fixed effects for two reasons. First, in a sensitivity check below we include the global production shock as a control for price movements, which does not vary among counties within a given time period and hence would be absorbed by the period fixed effect. Second, period fixed effects absorb a lot of the variations as 5-year weather averages are highly correlated within the Corn Belt, more so than annual data 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 time period (i.e., 5-year interval) fixed effects absorb more variations than the 26 state-specific quadratic trends. Including time period fixed effects would absorb variations useful in our identification and amplify measurement errors 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 time period fixed effects are not required.

Panel A reports results for the Corn Belt sample when the net migration ratio is regressed on log corn yield instrumented by the seasonality of extreme heat. The estimated semi-elasticity of outmigration with respect to log yield ranges from -0.31 to -0.40, all of which are statistically significant at the 1% level based on clustered standard errors. Recall that the first stage F-statistics reported in Panel B of Table 2 are all above the usual cutoff point of 10 for concerns of weak instruments. The semi-elasticity implies that a one percent reduction below trend in corn yields during a 5-year period induces an additional 0.3 to 0.4 percent of the adult population to leave the county. On the other hand, counties outside the Corn Belt show no significant response in Panel B even though the first-stage F-statistics suggest a similar relationship between yield and weather variables as in the Corn Belt counties.

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 A1 and A2 of Table 4 therefore separate the migration response by sex, while Panels B1-B4 separate it by age, using the same specifications as in Panel A in Table 3. 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 -0.42 and -0.54. 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 quite large in magnitude and statistically significant at the 1% level. The age group between 45 and 59 has a semi-elasticity that is -0.09 to -0.10, 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 the largest responses from the 60+ age group as they are not tied to a location by a job and tend to care most about climate as shown by a sizable retirement community in the Southern United States (McLeman & Hunter 2010).

Another aspect of the migration decision is the timing between when the shocks are realized and when people migrate. Our baseline model links migration rates over 5-year intervals to the contemporaneous weather-induced yield anomalies. On the one hand, there might be delayed migration patterns that occur afterward the 5-year period, leading to a combined effect that would be larger. On the other hand, there might be a counter-movement in the next period as yield anomalies subside, which would dampen the overall effect. Table 5 regresses migration rates on both the contemporaneous weather-induced yield shock as well as one lag, i.e., the previous five year period, effectively linking it to a decade worth of yield shocks. The table gives the coefficient on both the contemporaneous shock, the lagged shock as well the combined effect. The combined effect is very close to our baseline regression. The dynamic aspects of the migration decisions appear to be sufficiently captured in our baseline regression using only contemporaneous shocks.

Lastly, we use a novel methodology to estimate both the direct productivity effect as well as possible price feedbacks in a reduced-form setting. Agricultural demand is highly inelastic and reductions in supply might drive up commodity prices. While a single US county is small on the global scale, the US as a whole produces roughly 40% of the world's corn and soybeans. Reductions in overall US output have the potential to significantly alter global food prices. For decades the US government has tried to use supply restrictions to help farmers by increasing prices. We examine price feedbacks in a revised regression model that not only includes the local yield shock x_{it} in equation (1) but also the global yield shock z_t, defined as the sum of all yield deviations from a trend (Roberts & Schlenker 2013). Note that this shock is common among all counties in a given period, i.e., it only takes on eight different values for our eight 5-year intervals. While a reduction in *local* yields and the resulting decline in productivity increases outmigration, a reduction in *global* yields should increase food prices, make farming more profitable and thereby decrease outmigration. We therefore expect the coefficient on the global yield shock to be positive.

Table 6 presents the regression results when we not only include the local yield shock in a county (first row) but also the global shock (second row). The coefficient on the local shock is very close to our baseline estimates in Panel A of Table 3, which is not surprising as local yield shocks are uncorrelated with the global shock. The coefficient on the global yield shock is positive and significant as expected. The magnitude is large: given that the US produces 40% of the world's corn, the direct effect of a US decline on outmigration, a coefficient of -0.327 in our preferred most flexible specification (1d) is smaller in magnitude than the offsetting prices feedback on migration $0.4 \times 1.577 = 0.631$. If yield declines from climate change in the US are not offset somewhere else, outmigration out of rural areas is predicted to decline as profitability is increasing. Production losses are more than offset by price increases. Climate change would accomplish what the US government tried for several decades: limit supply to increase profitability. This result crucially hinges on the assumption that the loss of US productivity is not offset somewhere else. If a warming climate were to make higher latitudes more profitable, an expansion of the growing area in these areas might offset US yield declines. We discuss this point in greater length in Section 3.7 below.

3.5 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 in 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.

Table A6 replicates the analysis for our Corn Belt sample using two different specifications. Panel A still presents the results for corn yields, while Panel B instruments log soybean yields, and Panel C the weighted average of the two. Columns (2a)-(2d) now use the four weather variables (moderate and extreme heat as well as a quadratic in precipitation as instruments). As mentioned above, the reduced form weather-migration relationship in Table A5 shows that people have a preference against moderate heat which is good for crop growth. Accordingly, when corn yields are instrumented with moderate heat, the yield-migration relationship is biased towards zero in columns (2a)-(2d) of Panel A. Note that the results in columns (2a)-(2d) are broadly comparable across panels irrespective of which crop we use. The results in columns (1a)-(1d) are much lower for soybeans than for corn, which is not surprising as soybeans do not exhibit the same seasonality in the sensitivity to extreme heat as corn does. Therefore, using weather measures that allow for heterogeneity of the effect of extreme heat over the growing season does not give much different results in the case of soybeans. It highlights the crucial importance of using the time-varying sensitivity of corn yields as an instrument to avoid violation of the exclusion restriction. If we take the weighted average of corn and soybeans to make them comparable on revenue-per-acre terms in Panel C, the results lie in the middle.[22]

Table A7 in the appendix varies how the growing season is defined. Fixing it to the average level for all counties in the Eastern United States gives smaller, although still significant semi-elasticities of -0.18 to -0.22. These are comparable to the estimates we get in columns (2a)-(2b) of Table A6 that do not incorporate the seasonality of extreme heat. It is crucial to use the accurate year-to-year variation in planting in harvest dates to get the exact flowering period correct.

Table A8 addresses population cutoffs and weighting. Panel A of the table reproduces 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. To address this concern, panel B2 uses a grouped bootstrap procedure where we resample entire 5-year intervals with replacement. While the estimated standard errors go up, they remain significant at least at the 10% level within the Corn Belt.[23] Since we only have eight intervals, using a clustered bootstrap has its own

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

[23]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.

drawbacks, and our baseline regression therefore clusters by state.[24] Finally, Panel C uses the same specification and clustered errors as B1, but extends the data to also include urban counties, i.e., those with a total population of more than 100,000 in the 2000 Census. The point estimates again remain basically unchanged.[25]

Table A9 examines the sensitivity of our results to the minimum number of observation for a county to be 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 yield 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 (although this is a highly unbalanced panel with some counties only appearing in one period), 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. Finally, Panel D and E exclude the first and second half of the 1980s. The first half saw a big boom in agricultural activity and the US increased its market share in global caloric production, before the recession in the second half reversed the situation again. For example, farmland prices dropped by almost a third between the 1982 and 1987 Census. Excluding each of the intervals ensures that our results are not driven by the run-up or bust, and the estimated semi-elasticities change very little.

3.6 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 the Dust Bowl (Hornbeck 2012). 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 regression model specified in equations (1) and (2) except that we replace the dependent variable, net outmigration, with other measures.

Table 7 uses data from the Agricultural Census. Since the Census of Agriculture was not

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

[25] Including 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. The fact that urban counties do not show the same sensitivity reinforces our claim that our results are not driven by a direct preference for climate but by changes in agricultural productivity.

published exactly every five years, the time intervals now vary in length as given by the time between consecutive Census years.[26] Panel A uses the rate of change in the number of farms as dependent variable to keep the analysis consistent with our migration regressions that use migration rates. 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. To answer this question, panel B 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.

Table 8 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 significance level varies between models. The errors are so large that we can neither reject the null that the effect is zero, nor rule out the possibility that it is quite large.[27] For example, our preferred and most flexible specification in column (1d) has a 95% confidence interval that extends to 0.36. 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 elasticity of 0.33-0.52 is quite large, suggesting significant spillover effects.

One possible explanation for not finding significant effects in farm employment 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 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. On the other hand, yield losses might induce farmers to purchase less outside goods and result in fewer investments. Roberts & Key (2008) have shown that government payments result in consolidations in the farm sector, thereby increasing average farm size, which is consistent with what we find in Table 7. An increase in farm size might lead to efficiency gains and

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

[27]If we use a grouped bootstrap, none of the coefficients in the farm employment regression are significant. They are marginally significant for the number of farms and non-farm employment.

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 9. 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.[28] Panel A reports the results using OLS, while Panel B instruments corn yields with the sensitivity to extreme heat over the growing season (columns (1a)-(1c) in previous tables). Panel B shows that there is an almost one-to-one relationship between yield shortfalls and increases in government transfers. For example, using our preferred instrument (and the most flexible time controls (column 1c in Panel B), a 1 percent decrease in yields will increase government transfers by 0.92 percent. These government payments therefore constitute highly subsidized insurance for yield variations caused by weather anomalies, but not other types of yield declines, as uninstrumented yield shocks are not correlated with government transfers (Panel A), while yields shocks caused by weather shocks are.

3.7 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 (Intergovernmental Panel on Climate Change 2013*b*). By the end of the century, the average temperature in Central North America is projected to increase by approximately 1 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 (Intergovernmental Panel on Climate Change 2013*a*).

In order to make any projections on future migration, we first derive predicted yield changes under various climate scenarios. We base our projections on the B2 scenario of the Hadley III model and project net changes for corn yields for the medium term (2020-2049) and for the long term (2070-2099), and also present a range of uniform scenarios. These

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

scenarios and model runs predate IPCC 2013 but suffice to provide an indication of the sensitivity of future migration to climate change. In doing so, 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.[29] 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.[30] We obtain predicted changes in yields by multiplying the coefficients in Panel A, column (1d) of Table A3 by the predicted changes in the four weather variables.[31]

In a second step, we project changes in outmigration by multiplying the predicted changes in yields in each county times the estimated coefficients of column (1d) in Table 3. We conduct two thought experiments. Panel A of Table 10 presents the summary of the results for individual counties under a partial equilibrium approach that assumes no price effects, which would be appropriate if other parts of the globe can compensate for the reduction in US production by increasing their own production. Such a forecast not only assumes that there are no price feedbacks, but it is also 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.

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

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

[30] 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.

[31] Although we prefer to use the seasonality of the sensitivity to extreme heat in our IV estimation of the yield-migration semi-elasticity, we opt for using all four weather variables for projecting future yields. We do so as the exclusion restriction should hold for all four weather variables in the yield-weather relationship and we do not only want to measure the effect of extreme heat, but also moderate heat and precipitation.

the 892 counties in the Corn Belt. The last four columns summarize how many counties will have increased yields (displayed in blue in Figure 4) as well as how many counties have decreased yields (shown in green, yellow, and red).[32] 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 yield projections under uniform climate change scenarios, assuming temperature or precipitation changes are the same across all the Corn Belt counties. The sensitivity of our results to predicted changes in climatic conditions can then be approximated from the uniform changes, especially since there is more variability in predicted changes between models than within runs for the Corn Belt.[33] We predict corn yields 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. The left column in Figures A7 - A10 show the results for uniform temperature and precipitation scenarios under the partial equilibrium analysis. While the exact predicted change in yields varies between climate change scenarios, three features stand out: impacts have the potential to be quiet severe due to the nonlinear weather-yield relationship; impacts of precipitation are small compared to temperature effects and there is considerable heterogeneity even within the Corn Belt.

Alternatively, we relax the assumption of unchanging commodity prices and consider possible price feedback effects in Panel B of Table 10 and the right column of Figure 4. The United States produces two-fifths of the world's corn, and significant reduction in productivity hence have the potential to alter overall price levels. If we assume that production shortfalls in the US are *not* offset by other countries at all, the global production shortfall is simply 0.4 times the US shortfall given its market share. The resulting price effect more than compensates for the decrease in productivity. To see this, note that in our preferred specification in column (1d) of Table 6, a one percent decrease in yields will increase outmigration by 0.327%. At the same time, the 1% decrease in the US production implies a global reduction in output of 0.4% all else the same, or a decrease in outmigration by $0.4 \times 1.577 = 0.631\%$.[34] Moreover, if a decline in US yields coincide with global reduction

[32]The standard errors are for a given climate scenario and hence do not incorporate uncertainty about the climate forecast. We use 10,000 bootstrap runs to jointly sample from both the weather-yield and yield-migration response, where the two random draws are assumed to be independent.

[33]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.

[34]We again use 10,000 bootstrap runs to jointly sample from both the weather-yield and yield-migration

in output, the price feedback effect will be even larger.

In summary, whether the US will see increased outmigration from rural areas of the Corn Belt crucially depends on what happens to world supply, which impacts global food prices. While the price feedback is the same for all counties and gives some insurance against declining productivity, the latter varies across counties within the Corn Belt, with larger predicted negative effects in the Southern Corn Belt than the Northern Corn Belt. This suggests that even in case of price feedbacks, there will be heterogenous impacts where population is likely to shift further North within the Corn Belt.

4 Conclusions

This paper establishes a relationship between weather-induced yield anomalies and migration rates during 1970-2009. We show that the most likely mechanism behind the observed weather-migration relationship is the effect of weather on agricultural productivity. Our model uses the seasonality in the sensitivity of corn to extreme heat over the growing season as an instrument, which is closely mirrored in the weather-migration relationship within the Corn Belt, but not outside the Corn Belt. This fact makes it unlikely that we are picking up a direct preference for climate that impacts migration decisions. Moreover, utilizing the year-to-year variation in planting and harvest dates gives a larger elasticity than using the average growing season. For the exclusion restriction to be violated, people in the Corn Belt cannot simply have a distaste for extreme heat during a particular season, but it has to vary year-to-year with corn flowering, and only in the Corn Belt and not outside the Corn Belt.

Consistent with previous theoretical and empirical studies that link migration decisions to economic opportunities in source and destination areas, we find that county-level outmigration is negatively associated 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 fluctuations.

We extrapolate the weather-migration relationship to project future outmigration rates while holding everything else constant. The results suggest a nontrivial effect of climate change on future internal U.S. population movements. We present a novel way to estimate the

response. The US yield shock in each draw is calculated as the total production decline among all counties in the Corn Belt for each draw.

effect of local production shocks as well as possible price feedbacks. If production shortfalls within the United States are not offset by increases in production in other parts of the world, the price feedback effect (reduction in outmigration due to higher corn prices) will more than offset the productivity effect (increase in outmigration due to lower productivity). The global production impact is beyond the scope of this study.

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 unless there are large price feedbacks. 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.

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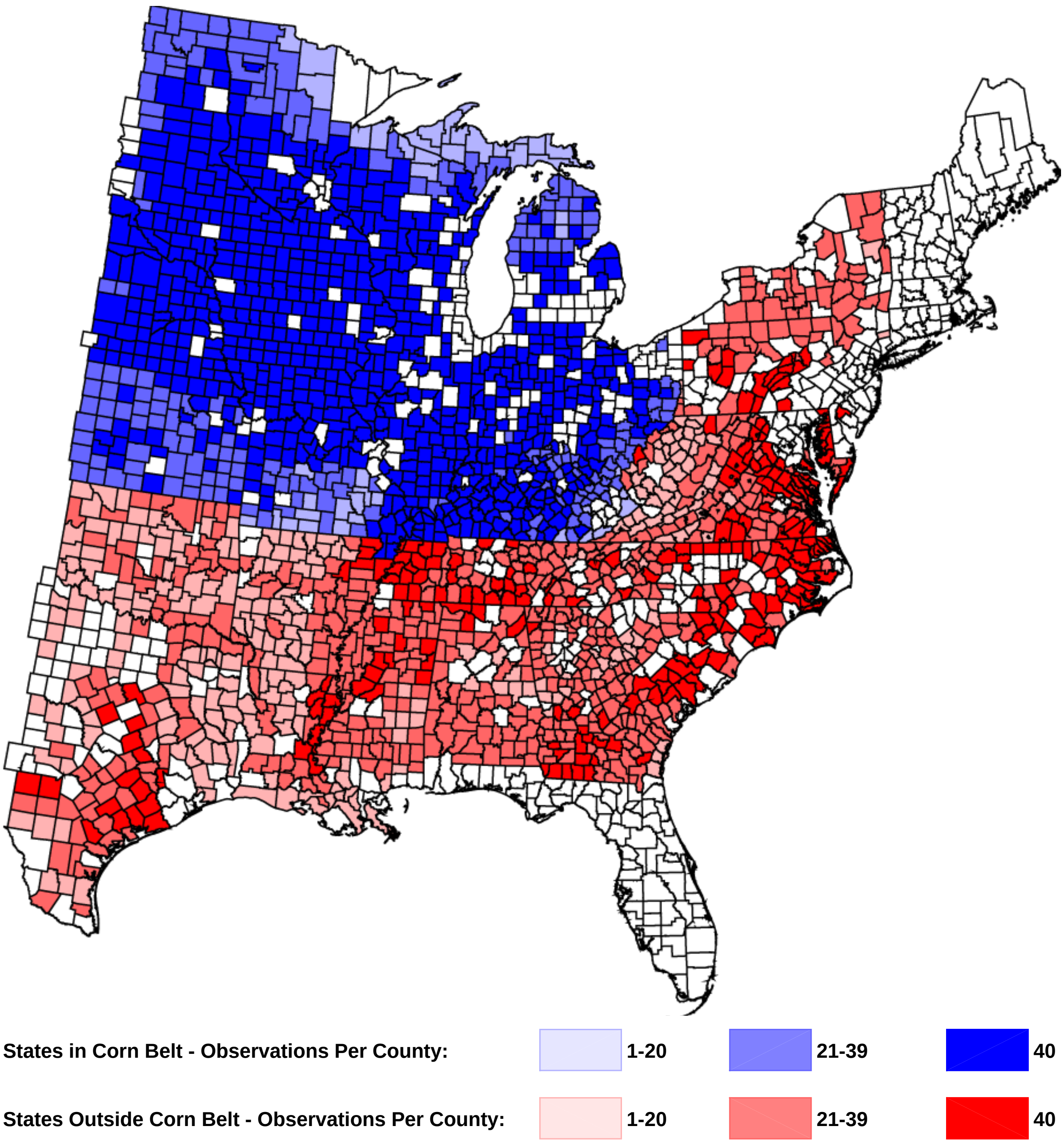
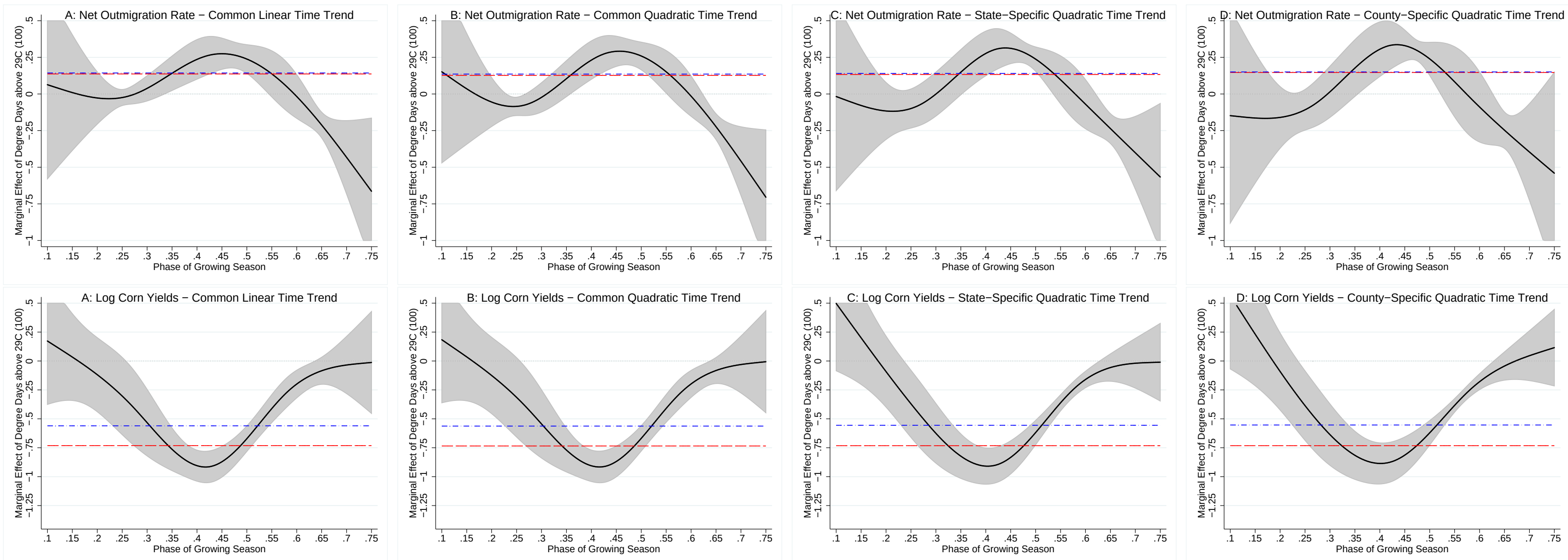
Figure 1: Rural Counties with Migration Data and Corn Yields (1970-2009)



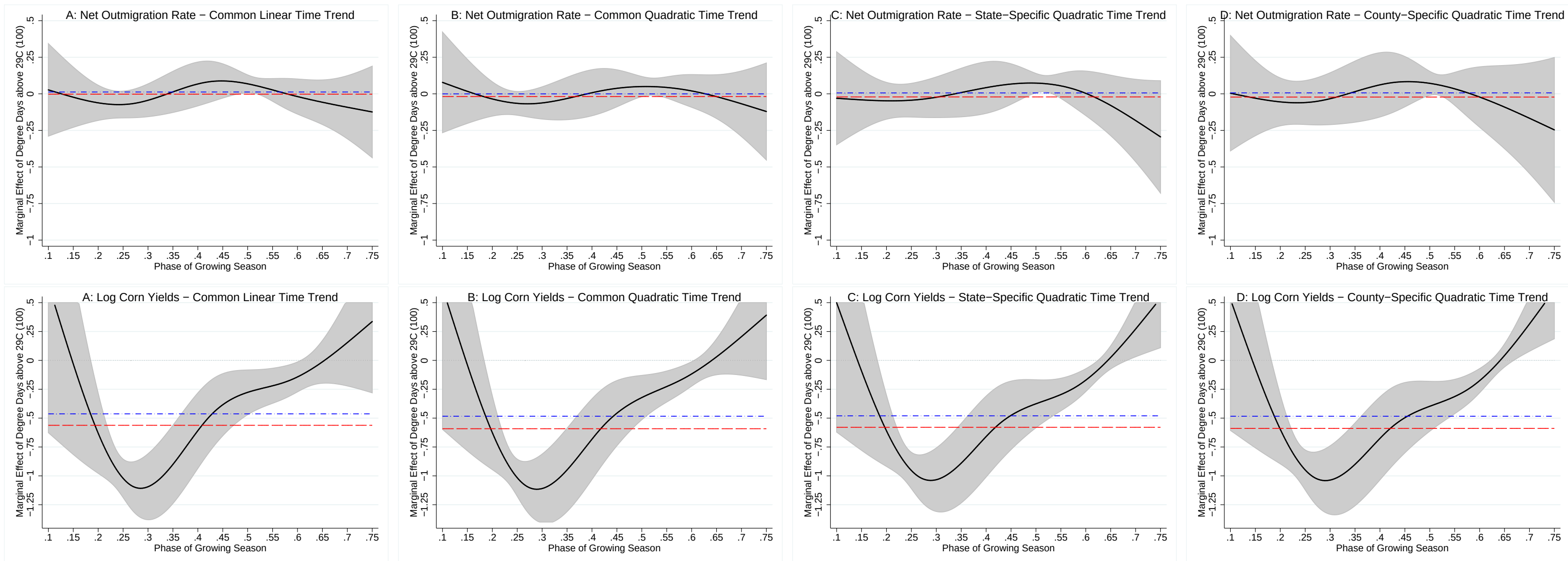
Notes: Figure displays rural counties (population less than 100,000 in 2000) in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. States covering the Corn Belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have yield data in 1970-2009.

Figure 2: Seasonality in Response to Extreme Heat - Counties In Corn Belt



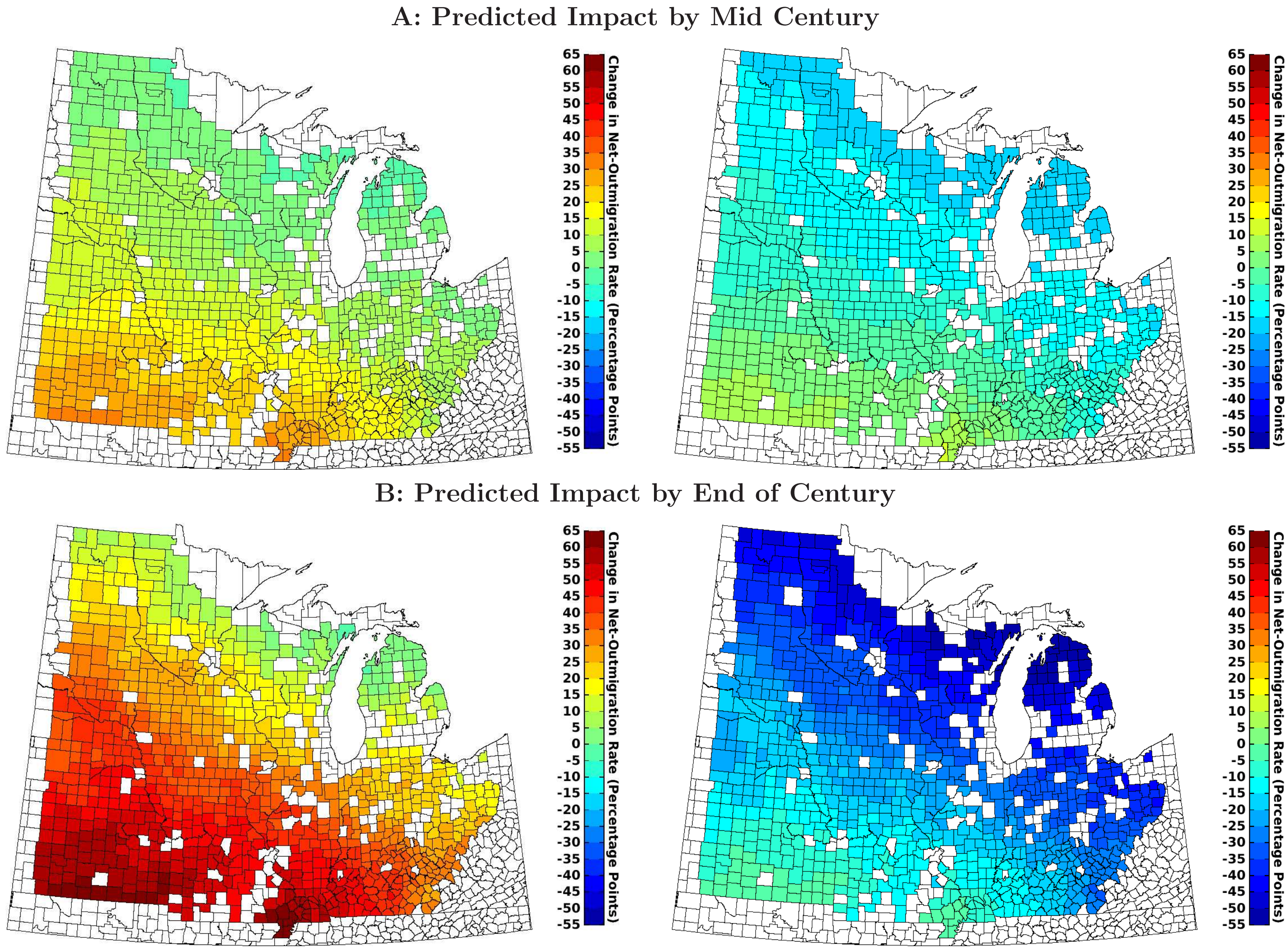
Notes: Panels displays how the sensitivity to extreme heat (degree days above 29°C) varies over the growing season, i.e., the marginal effect of an extra 100 degree days above 29°C. The solid black line shows the point estimate and the 95% confidence band is added in grey. The top row shows the sensitivity of the net outmigration rate over 5-year intervals to realized extreme heat over the season during the same five years. The bottom row shows the sensitivity of annual log corn yields over the same time period. The sensitivity is allowed to vary using a spline with 5 knots in the truncated growing phase (planting date is 0 and harvest is 1). 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 quadratic time trends.

Figure 3: Seasonality in Response to Extreme Heat - Counties Outside Corn Belt



Notes: Panels displays how the sensitivity to extreme heat (degree days above 29°C) varies over the growing season, i.e., the marginal effect of an extra 100 degree days 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 over 5-year intervals to realized extreme heat over the season during the same five years. The bottom row shows the sensitivity of annual log corn yields over the same time period. The sensitivity is allowed to vary using a spline with 5 knots in the truncated growing phase (planting date is 0 and harvest is 1). 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 outside 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 quadratic time trends.

Figure 4: Predicted Changes in Migration Patterns (Hadley III - B2 Scenario)



Notes: Panels display predicted changes in migration rates under the Hadley III - B2 clmate change scenario for counties in the Corn Belt. The left column uses yield changes in a county (column (1d) in Panel A of Table 3) while the right column uses both local yield changes as well as price feedbacks from overall production changes in the United States (column (1d) in Table 6). The top row gives results by mid-century (2020-2049) while the bottom row gives results by the end of the century (2070-2099).

Table 1: Yield Shocks and Net Outmigration in Eastern United States - OLS Regressions

	(1a)	(1b)	(1c)	(1d)
		A: Corn Yields		
Log Yield	-0.018	-0.016	0.000	-0.013
	(0.015)	(0.013)	(0.016)	(0.023)
Observations	7078	7078	7078	7078
Counties	892	892	892	892
		B: Soybean Yields		
Log Yield	-0.012	-0.024	-0.019	-0.031
	(0.018)	(0.016)	(0.018)	(0.022)
Observations	6413	6413	6413	6413
Counties	810	810	810	810
		C: Avg of Corn and Soybeans		
Log Yield	-0.028*	-0.030**	-0.014	-0.030
	(0.015)	(0.013)	(0.016)	(0.023)
Observations	7086	7086	7086	7086
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables regresses net outmigration on uninstrumented log yield shocks as well as county fixed effects for counties in the Corn Belt that are shown in blue in Figure 1. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 2: First Stage: Corn Yields and the Seasonality of Extreme Heat

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
				A: Annual Data				
$F_{\text{1st-stage}}$	152.0	172.6	292.7	184.0	151.6	134.8	51.4	46.9
$p_{\text{1st-stage}}$	2.0e-10	9.6e-11	4.2e-12	6.6e-11	2.7e-12	6.4e-12	6.6e-09	1.2e-08
Observations	34788	34788	34788	34788	26124	26124	26124	26124
Counties	892	892	892	892	746	746	746	746
				B: 5 Year Intervals				
$F_{\text{1st-stage}}$	20.5	22.4	13.2	10.0	17.4	27.1	38.7	14.2
$p_{\text{1st-stage}}$	1.7e-05	1.0e-05	1.5e-04	5.9e-04	8.9e-06	5.2e-07	4.8e-08	3.1e-05
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table displays regression of log corn yields on the seasonality of extreme heat. F-statistic and p-value are for the joint significance of the weather variables, but not the time trend. Panel A replicates an annual unweighted regression of log corn yields on the seasonality of extreme heat for our sample, i.e., counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Results are given for counties inside the Corn Belt in columns (1a)-(1d) and outside the Corn Belt in columns (2a)-(2d). The variation of the sensitivity over the growing season is plotted in the bottom row of Figure 2 and Figure 3, respectively. Panel B represents the corresponding first-stage results of migration regressions, which are population-weighted and aggregates to 5-year intervals at which the migration data is available. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 3: Weather-Induced Yield Shocks and Net Outmigration

	(1a)	(1b)	(1c)	(1d)
	A: Counties Inside Corn Belt			
Log Yield	-0.320***	-0.305***	-0.337***	-0.393***
	(0.071)	(0.069)	(0.093)	(0.108)
Observations	7078	7078	7078	7078
Counties	892	892	892	892
	B: Counties Outside Corn Belt			
Log Yield	0.022	0.038	-0.004	-0.042
	(0.055)	(0.048)	(0.098)	(0.135)
Observations	5628	5628	5628	5628
Counties	746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables regresses net outmigration on weather-instrumented log yield shocks in the same county. Panel A uses counties inside the Corn Belt, while panel B uses counties outside the Corn Belt. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 Net Outmigration - Population Subsets

	(1a)	(1b)	(1c)	(1d)
	A1: Males Age [15,60)			
Log Yield	-0.325***	-0.310***	-0.342***	-0.401***
	(0.073)	(0.070)	(0.095)	(0.110)
	A2: Females Age [15,60)			
Log Yield	-0.316***	-0.301***	-0.332***	-0.386***
	(0.071)	(0.069)	(0.091)	(0.107)
	B1: Age [15,30)			
Log Yield	-0.423***	-0.416***	-0.456**	-0.537***
	(0.122)	(0.122)	(0.180)	(0.203)
	B2: Age [30,45)			
Log Yield	-0.335***	-0.313***	-0.351***	-0.410***
	(0.054)	(0.053)	(0.066)	(0.076)
	B3: Age [45,60)			
Log Yield	-0.100***	-0.091**	-0.095**	-0.105*
	(0.038)	(0.042)	(0.049)	(0.055)
	B4: Age [60,oo)			
Log Yield	-0.017	-0.014	-0.007	-0.011
	(0.014)	(0.013)	(0.019)	(0.017)
Observations	7078	7078	7078	7078
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables replicates the results of Panel A in Table 3 for various subgroups. Panels A1 and A2 run separate regression for males and females, while Panels B1-B4 look at different age groups. Panels regresses net outmigration on weather-instrumented log yield shocks in the same county. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 5: Weather-Induced Yield Shocks and Net Outmigration - Lags

	(1a)	(1b)	(1c)	(1d)
Log Yield$_t$	-0.270***	-0.246***	-0.257***	-0.213***
	(0.063)	(0.059)	(0.071)	(0.077)
Log Yield$_{t-5}$	-0.181***	-0.142**	-0.160***	-0.161**
	(0.053)	(0.062)	(0.059)	(0.067)
Combined Effect	-0.452***	-0.388***	-0.417***	-0.375***
	(0.089)	(0.092)	(0.106)	(0.123)
Observations	7060	7060	7060	7060
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables replicates the results of Panel A in Table 3 but includes both the contemporaneous weather-instrumented yield shocks as well as one lag. The combined effect is listed as well. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 6: Weather-Induced Yield Shocks and Net Outmigration - Global Production Shock

	(1a)	(1b)	(1c)	(1d)
$\text{Shock}_{\text{county}}$	-0.305***	-0.258***	-0.277***	-0.327***
	(0.066)	(0.059)	(0.069)	(0.082)
$\text{Shock}_{\text{global}}$	0.875***	1.571***	1.584***	1.577***
	(0.231)	(0.311)	(0.326)	(0.367)
Observations	7078	7078	7078	7078
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables replicates the results of Panel A in Table 3 but also includes the global production shock for corn for the same 5-year interval, which is the same for all counties. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 7: Weather-Induced Yield Shocks and the Effect on Farms

	(1a)	(1b)	(1c)	(1d)
A: Number of Farms (USDA)				
Log Yield	0.286**	0.290**	0.537***	0.562***
	(0.124)	(0.124)	(0.171)	(0.186)
B: Total Farmland Area (USDA)				
Log Yield	-0.073	-0.073	-0.104	-0.061
	(0.054)	(0.055)	(0.092)	(0.088)
Observations	7076	7076	7076	7076
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Tables regresses changes in farm characteristics on weather-instrumented log yield shocks in the same county. Panels use changes between the 1969, 1974, 1978, 1982, 1987, 1992, 1997, 2002, and 2007 Census. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Regressions are weighted by the average cropland area in a county. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 8: Weather-Induced Yield Shocks and the Effect on Employment

	(1a)	(1b)	(1c)	(1d)
	A: Farm Employment			
Log Yield	0.266^{**}	0.179^{*}	0.057	0.073
	(0.116)	(0.096)	(0.130)	(0.146)
	B: Non-Farm Employment			
Log Yield	0.330^{***}	0.384^{***}	0.435^{***}	0.523^{***}
	(0.082)	(0.083)	(0.123)	(0.149)
Observations	7074	7074	7074	7074
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table regresses changes in employment on weather-instrumented log yield shocks in the same county. Panels use the same 5-year intervals as the migration regressions in Panel A of Table 3. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 9: Yield Shocks and Government Transfers

	(1a)	(1b)	(1c)
A: OLS			
Log Yield	0.075	0.064	0.186
	(0.270)	(0.219)	(0.238)
B: Spline in Extreme Heat			
Log Yield	-1.402***	-1.117***	-0.917***
	(0.329)	(0.258)	(0.253)
Observations	520	520	520
States	13	13	13
Time Trend	Linear	Quad.	St-Qu.

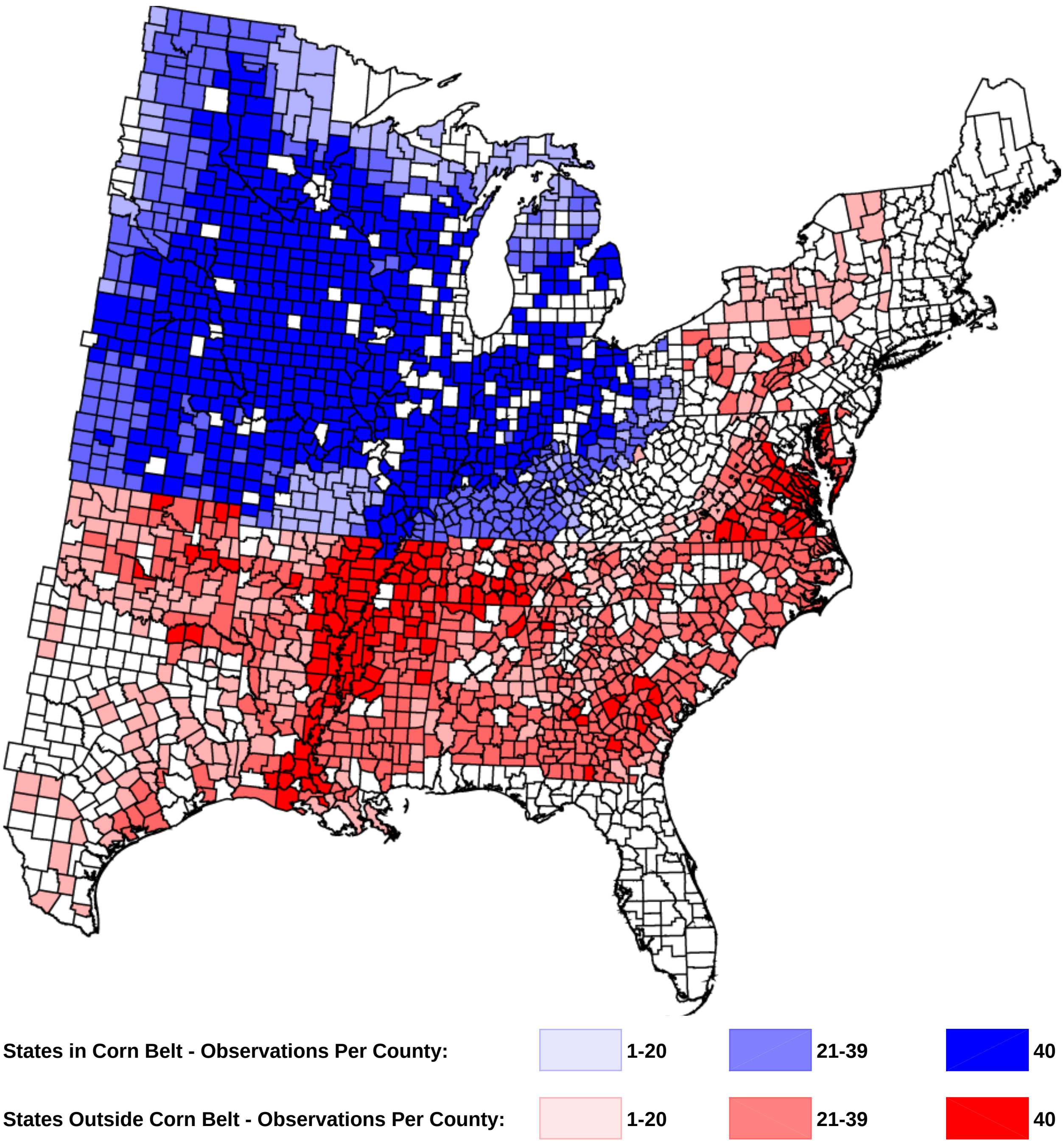
Notes: Table regresses annual state-level log government transfers on log corn yield shocks in the same county. Panel A uses uninstrumented yield shocks while Panel B instruments yield shocks with the time-varying sensitivity to extreme heat of columns (1a)-(1c) in Panel A of Table A3. All columns include county fixed effects. Columns (a)-(c) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(c) include a common and state-specific quadratic time trends, respectively. All regression are unweighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 10: Predicted Changes in Migration Rates Under Climate Change

	Predicted Changes in Net Out-Migration				Counties With Pop. Loss		Counties with Pop. Increase	
	Mean	SDev	Min	Max	N	Sig N	N	Sig N
A: Partial Equilibrium - Yield Shock in County								
Hadley III-B2 (2020-2049)	12.04	(7.96)	-2.08	33.23	859	835	33	2
Hadley III-B2 (2070-2099)	33.99	(14.93)	-1.71	63.83	890	880	2	0
Uniform +1° C	2.79	(2.10)	-1.33	8.69	822	735	70	9
Uniform +2° C	7.06	(4.50)	-2.36	19.08	850	806	42	3
Uniform +3° C	12.95	(7.17)	-2.90	31.28	876	840	16	1
Uniform +4° C	20.57	(10.09)	-2.72	45.41	888	869	4	0
Uniform +5° C	30.05	(13.26)	-1.57	61.81	891	886	1	0
Uniform -50% Precipitation	3.62	(1.27)	-0.47	5.42	890	847	2	0
Uniform -30% Precipitation	1.16	(1.07)	-2.09	2.84	745	591	147	28
Uniform -10% Precipitation	0.05	(0.46)	-1.30	0.83	480	364	412	203
Uniform +10% Precipitation	0.29	(0.56)	-0.73	1.90	591	465	301	212
Uniform +30% Precipitation	1.88	(2.00)	-1.86	7.52	704	612	188	124
Uniform +50% Precipitation	4.82	(3.85)	-2.57	15.56	781	709	111	50
B: Including Price Feedback from US Yield Changes								
Hadley III-B2 (2020-2049)	-7.14	(6.66)	-18.94	10.57	157	0	735	413
Hadley III-B2 (2070-2099)	-25.05	(12.48)	-54.90	-0.11	0	0	892	392
Uniform +1° C	-1.57	(1.76)	-5.02	3.37	180	0	712	387
Uniform +2° C	-4.22	(3.76)	-12.10	5.83	127	0	765	378
Uniform +3° C	-8.10	(5.99)	-21.35	7.23	82	0	810	371
Uniform +4° C	-13.30	(8.43)	-32.77	7.46	58	0	834	370
Uniform +5° C	-19.90	(11.08)	-46.33	6.64	30	0	862	365
Uniform -50% Precipitation	-3.22	(1.06)	-6.63	-1.71	0	0	892	366
Uniform -30% Precipitation	-1.22	(0.90)	-3.93	0.19	60	0	832	440
Uniform -10% Precipitation	-0.17	(0.38)	-1.30	0.49	338	37	554	446
Uniform +10% Precipitation	-0.07	(0.47)	-0.92	1.28	399	149	493	359
Uniform +30% Precipitation	-0.92	(1.67)	-4.05	3.79	255	3	637	364
Uniform +50% Precipitation	-2.73	(3.22)	-8.90	6.24	181	0	711	360

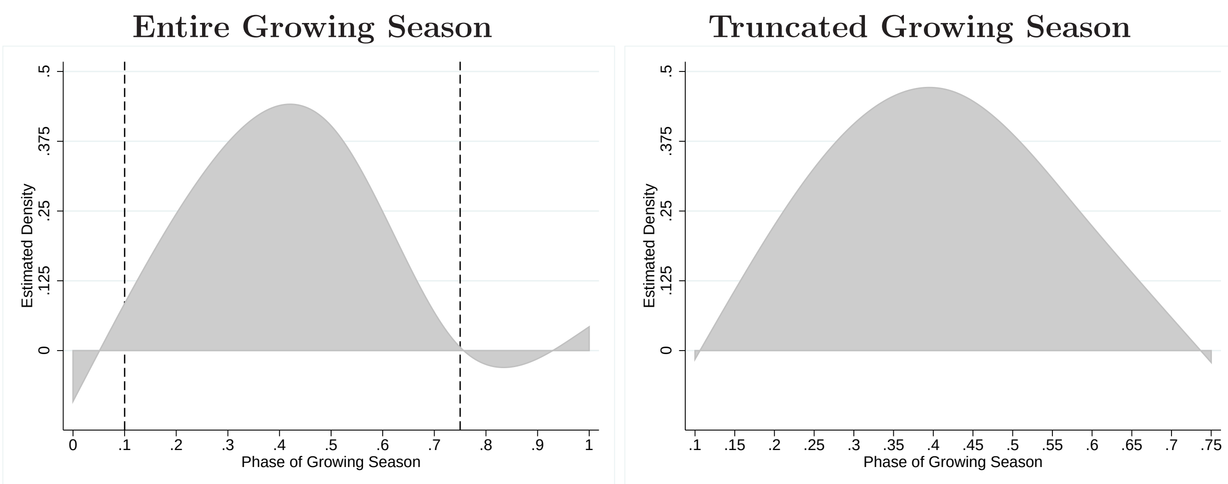
Notes: Tables displays predicted changes in net outmigration ratios under various climate change scenarios. Panel A considers only the local productivity effects in column (1d) of Table 3, while Panel B also includes the price feedback of a decrease in US production in column (1d) of Table 6. Predicted changes in yields come from column (1d) of Table A5. The first two rows of each panel 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 4 for the first two rows and Figures A7-A10 in the appendix for the remaining uniform scenarios.

Figure A1: Rural Counties with Migration Data and Soybean Yields (1970-2009)



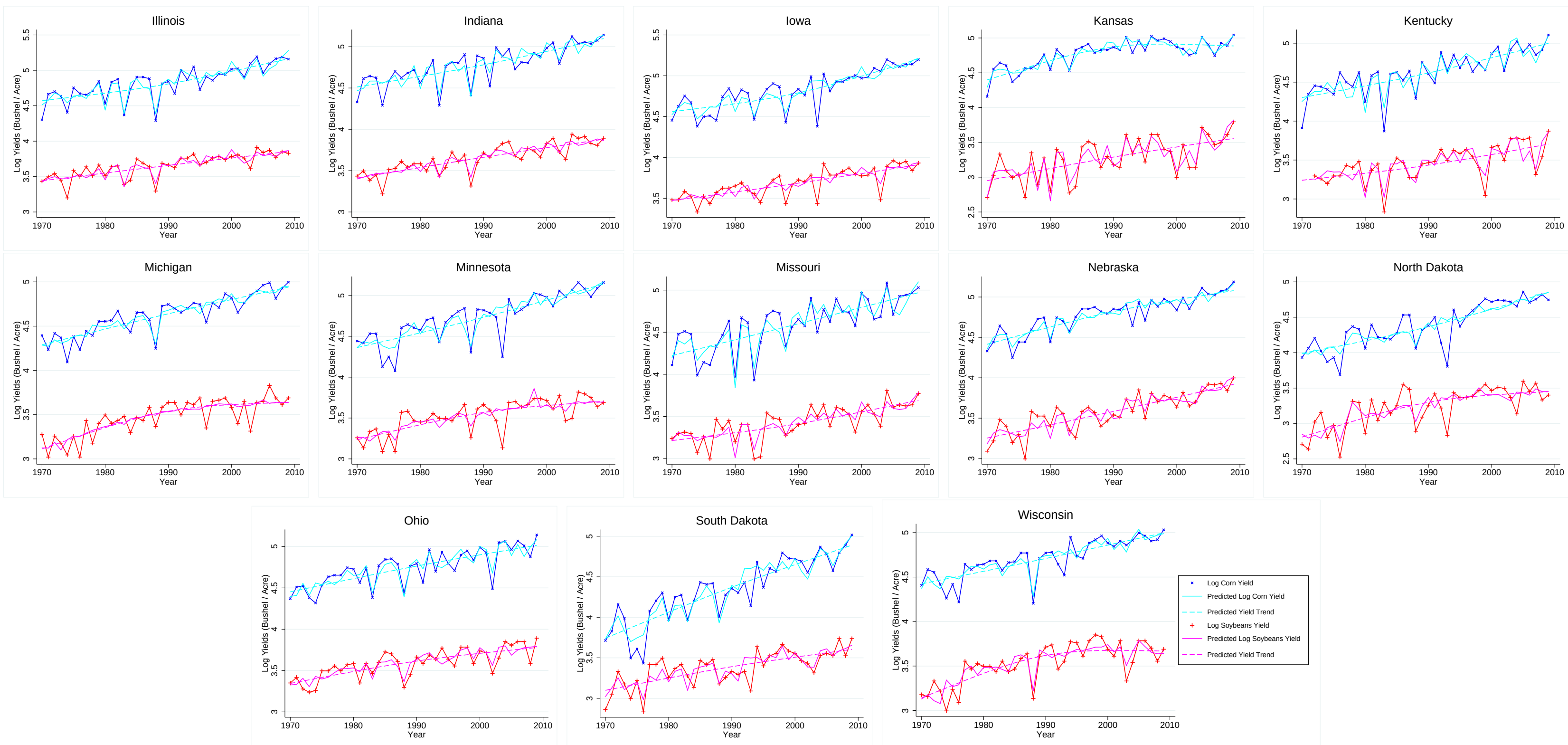
Notes: Figure displays rural counties (population less than 100,000 in 2000) in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. States covering the Corn Belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have yield data in 1970-2009.

Figure A2: Average Exposure to Degree Days above 29°C Over the Growing Season



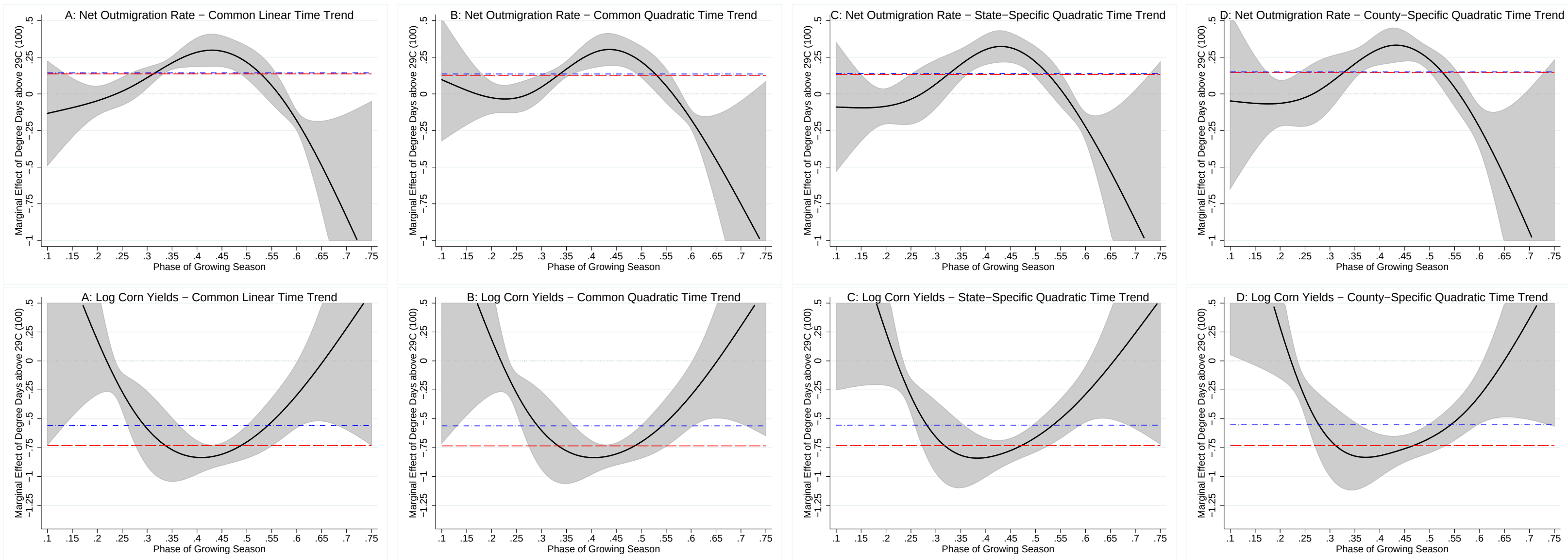
Notes: Both graphs display the average exposure to degree days above 29°C over the growing season for counties of the Corn Belt, where 0 corresponds to planting and 1 to harvest. The density is approximated using a restricted cubic spline with 5 knots. The left graph uses the entire growing season $[0, 1]$, 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 A3: State-Level Log Yields and Weather



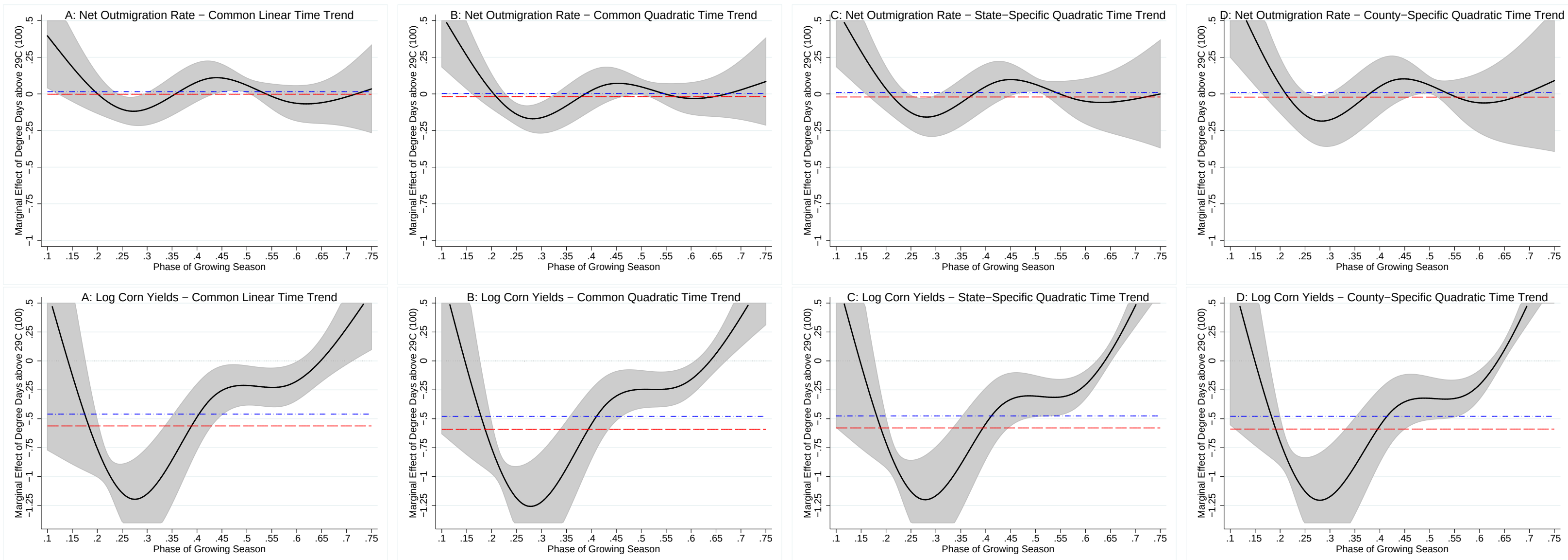
Notes: State-level yields, quadratic yield trends, and predicted yields for the 13 states in the Corn Belt. Predicted yields are derived from the baseline model using the seasonality of extreme heat over the truncated growing season.

Figure A4: Seasonality in Response to Extreme Heat - Counties In Corn Belt (Average Planting Date)



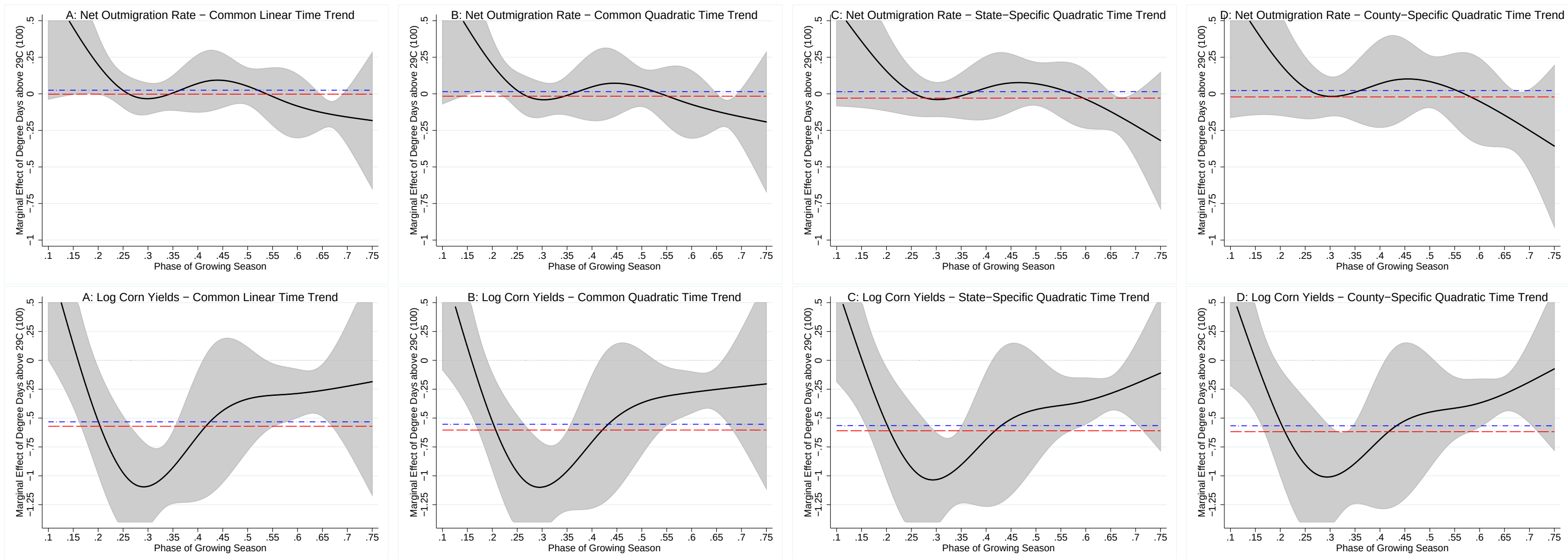
Notes: Figure replicates Figure 2 except that the growing season is the same for all counties and set to equal the average of all counties in the Eastern United States. Panels displays how the sensitivity to extreme heat (degree days above 29°C) vary over the growing season, i.e., the marginal effect 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 quadratic time trends.

Figure A5: Seasonality in Response to Extreme Heat - Counties Outside Corn Belt (Average Planting Date)



Notes: Figure replicates Figure 3 except that the growing season is the same for all counties and set to equal the average of all counties in the Eastern United States. 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 outside 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 quadratic time trends.

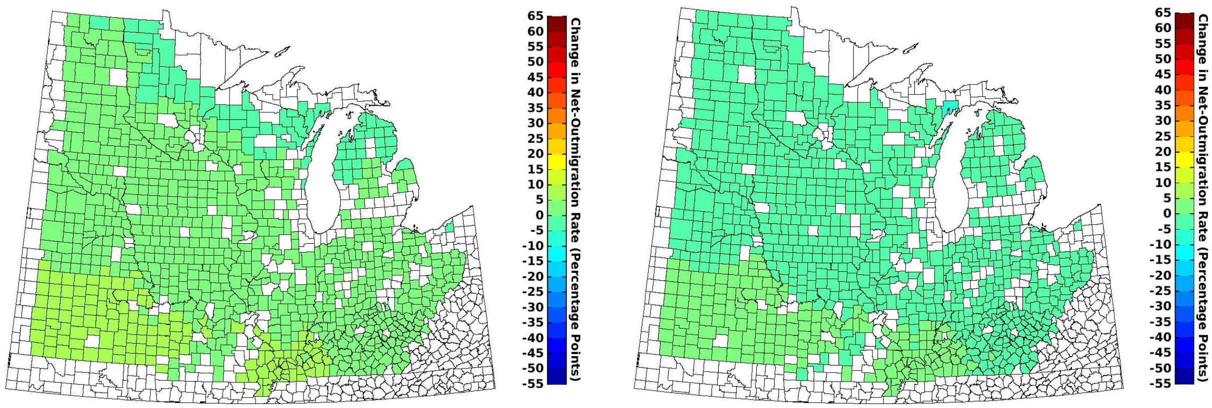
Figure A6: Seasonality in Response to Extreme Heat - Counties Outside Corn Belt in States with Planting Dates



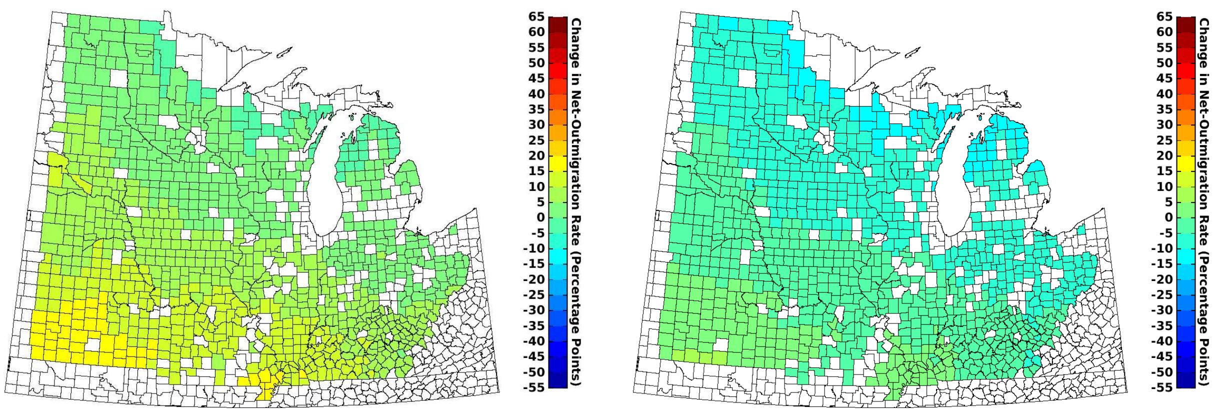
Notes: Figure replicates Figure 3 except that only counties in states that have planting dates are used in the analysis. The number of counties decreases from 746 to 444. Panels displays how the sensitivity to extreme heat (degree days above 29°C) vary over the growing season, i.e., the marginal effect 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 quadratic time trends.

Figure A7: Predicted Changes in Corn Yields (Uniform Temperature Scenarios 1-3°C)

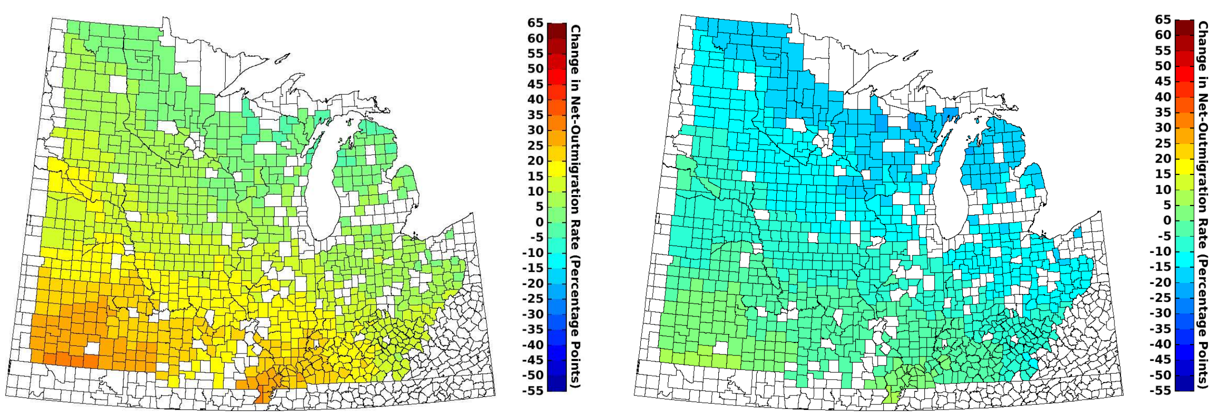
A: Uniform Temperature Increase (+1°C)



B: Uniform Temperature Increase (+2°C)



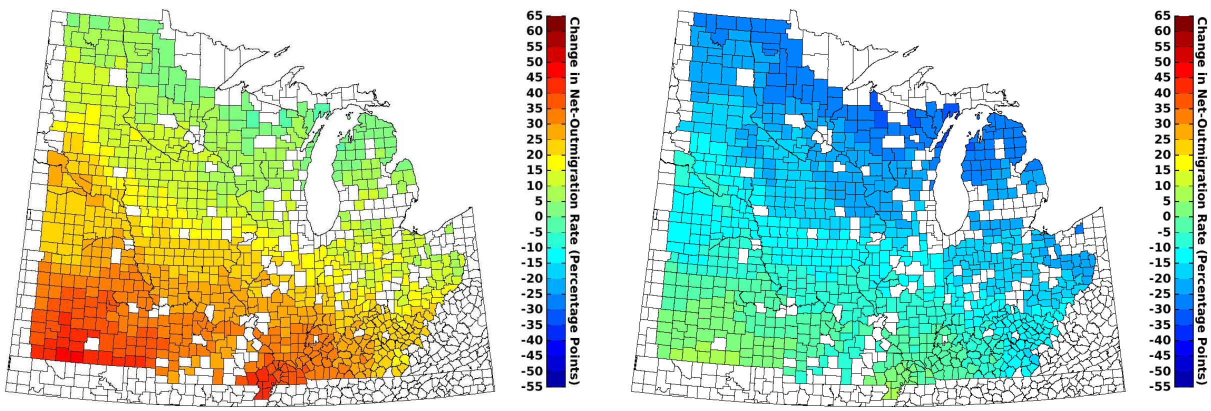
C: Uniform Temperature Increase (+3°C)



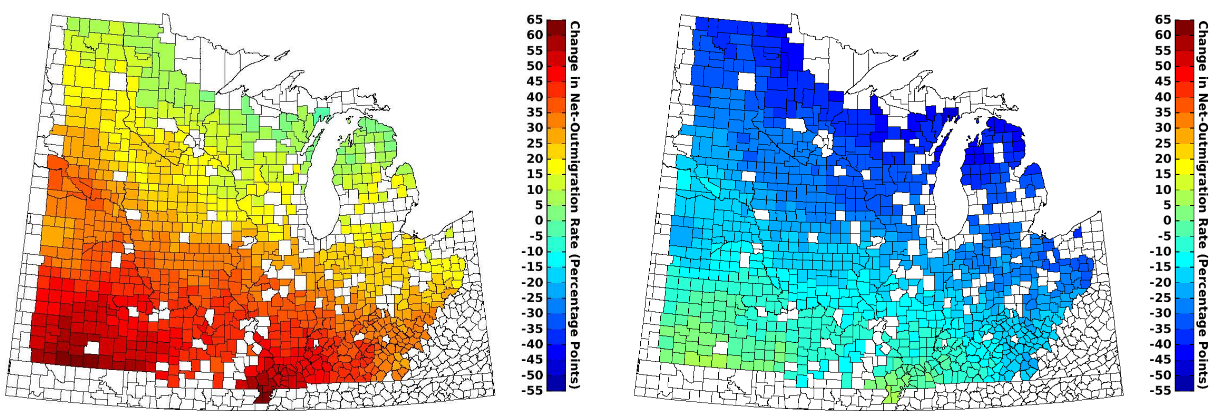
Notes: Panels display predicted changes in migration rates under uniform temperature scenarios ranging from +1°C to +3°C for counties in the Corn Belt. The left column uses yield changes in a county (column (1d) in Panel A of Table 3) while the right column uses both local yield changes as well as price feedbacks from overall production changes in the United States (column (1d) in Table 6).

Figure A8: Predicted Changes in Corn Yields (Uniform Temperature Scenarios 4-5°C)

A: Uniform Temperature Increase (+4°C)



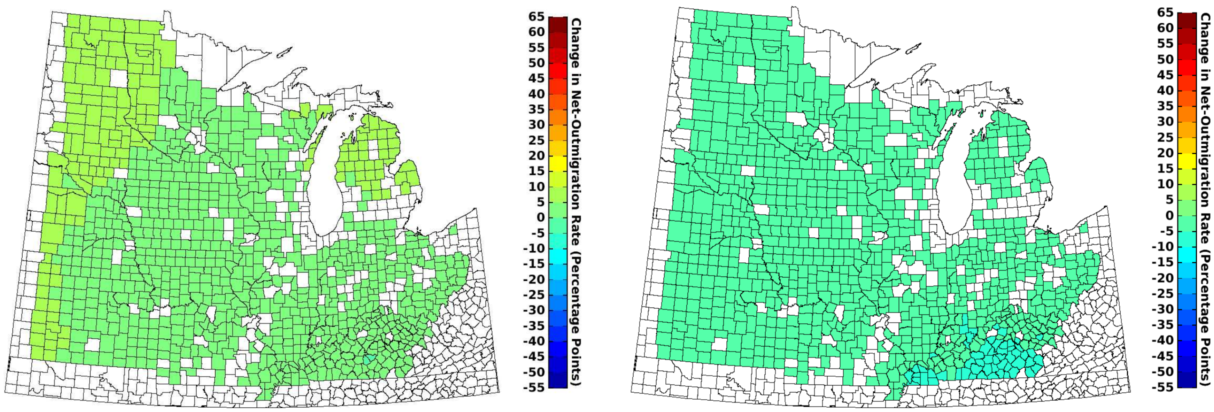
B: Uniform Temperature Increase (+5°C)



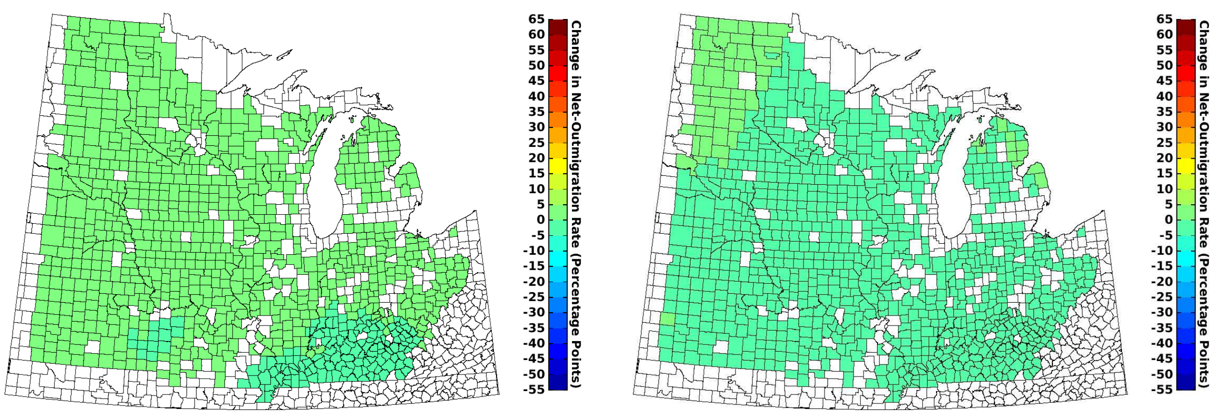
Notes: Panels display predicted changes in migration rates under uniform temperature scenarios ranging from +4°C to +5°C for counties in the Corn Belt. The left column uses yield changes in a county (column (1d) in Panel A of Table 3) while the right column uses both local yield changes as well as price feedbacks from overall production changes in the United States (column (1d) in Table 6).

Figure A9: Predicted Changes in Corn Yields (Uniform Decrease in Precipitation)

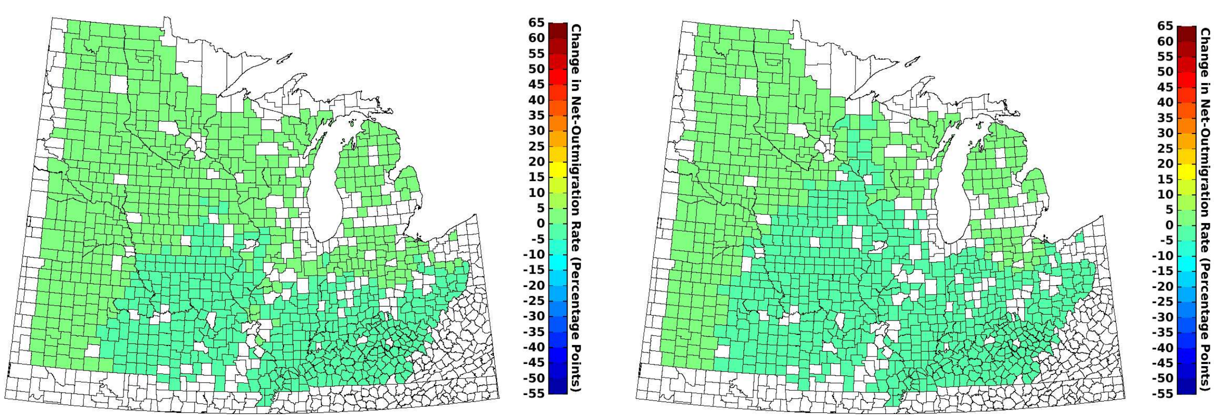
Panel A: Uniform Precipitation Change (-50%)



Panel B: Uniform Precipitation Change (-30%)

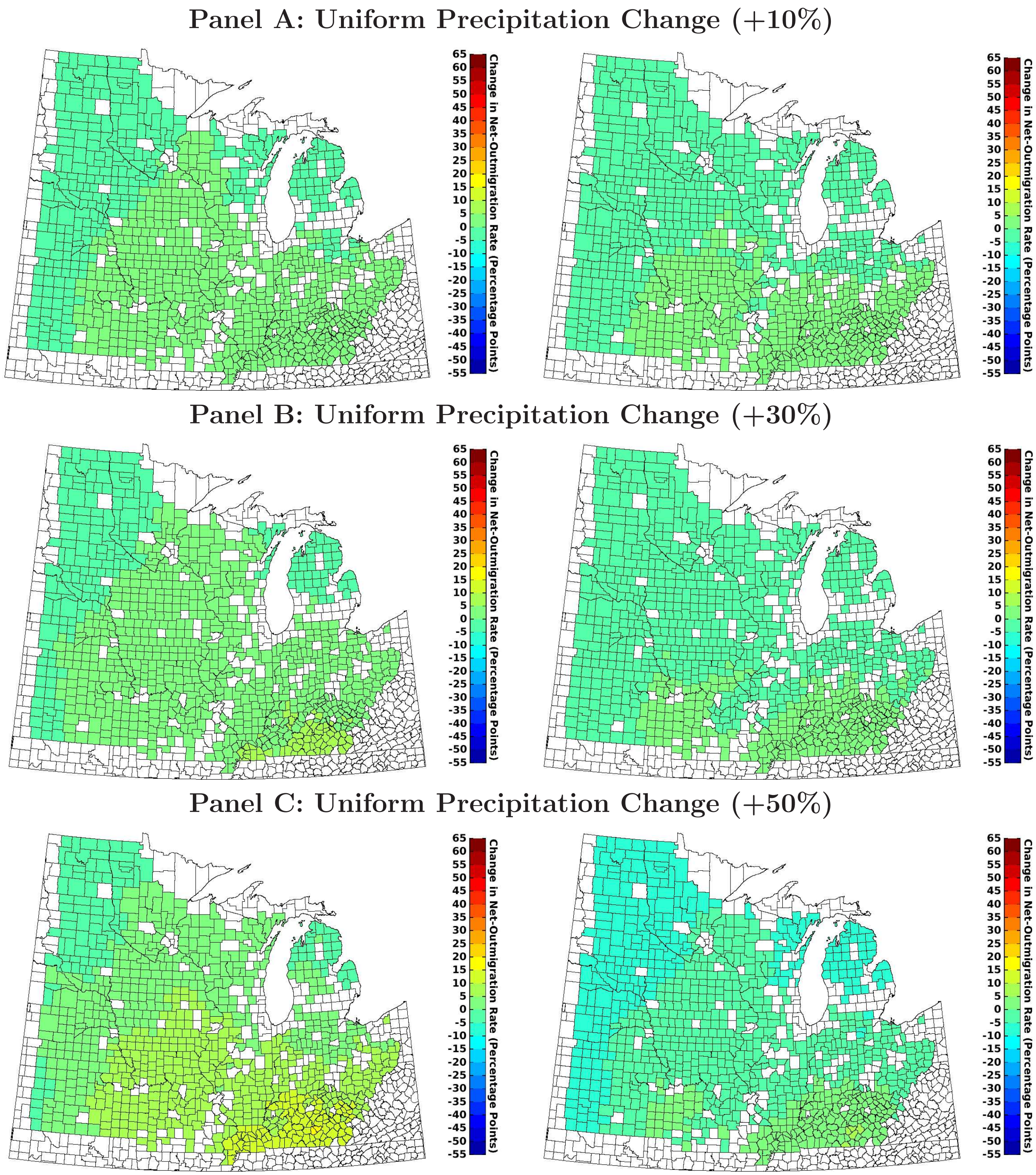


Panel C: Uniform Precipitation Change (-10%)



Notes: Panels display predicted changes in migration rates under uniform precipitation scenarios ranging from -50% to -10% for counties in the Corn Belt. The left column uses yield changes in a county (column (1d) in Panel A of Table 3) while the right column uses both local yield changes as well as price feedbacks from overall production changes in the United States (column (1d) in Table 6).

Figure A10: Predicted Changes in Corn Yields (Uniform Increase in Precipitation)



Notes: Panels display predicted changes in migration rates under uniform precipitation scenarios ranging from +10% to +50% for counties in the Corn Belt. The left column uses yield changes in a county (column (1d) in Panel A of Table 3) while the right column uses both local yield changes as well as price feedbacks from overall production changes in the United States (column (1d) in Table 6).

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)
Global Log Yield Residual (%)	0.42	1.35	0.72	-0.38	-0.67	-0.02	-0.96	0.98
(s.d.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: 746 Counties Outside Corn Belt								
Migration Rate Age [15,60) (%)	-2.93	-2.33	0.53	1.94	-1.99	-5.48	-0.83	-0.98
(s.d.)	(8.27)	(15.06)	(6.75)	(8.00)	(6.92)	(8.84)	(6.90)	(7.06)
Migration Rate Males [15,60) (%)	-3.16	-1.84	0.70	2.22	-1.92	-6.93	-0.75	-0.96
(s.d.)	(8.84)	(15.31)	(7.39)	(8.40)	(8.33)	(12.17)	(7.45)	(8.63)
Migration Rate Females [15,60) (%)	-2.80	-2.84	0.36	1.70	-2.04	-4.11	-0.84	-1.01
(s.d.)	(8.01)	(14.98)	(6.45)	(7.79)	(6.49)	(8.11)	(6.84)	(6.82)
Migration Rate Age [15,30) (%)	0.11	2.80	4.78	6.89	2.63	-0.85	-3.18	10.17
(s.d.)	(11.87)	(16.57)	(8.97)	(11.40)	(10.35)	(14.14)	(14.17)	(11.32)
Migration Rate Age [30,45) (%)	-6.22	-7.11	-1.90	-1.46	-5.45	-8.28	-0.72	-5.31
(s.d.)	(7.63)	(17.80)	(6.92)	(6.48)	(6.86)	(9.06)	(5.99)	(8.04)
Migration Rate Age [45,59) (%)	-4.42	-6.21	-4.12	-1.86	-4.12	-7.65	0.68	-7.98
(s.d.)	(5.91)	(12.43)	(6.12)	(6.72)	(6.62)	(8.56)	(3.38)	(8.17)
Migration Rate Age [60,oo) (%)	0.73	0.40	2.49	2.62	1.92	-0.08	2.52	-0.58
(s.d.)	(4.29)	(9.28)	(3.76)	(4.15)	(4.03)	(4.92)	(3.83)	(5.46)
Corn Area (1000 acres)	7.9	8.9	7.9	6.9	6.4	7.0	7.4	8.8
(s.d.)	(10.7)	(12.1)	(11.0)	(9.6)	(9.1)	(9.6)	(10.2)	(11.8)
Corn Yield (bushel/acre)	53.9	60.8	68.6	76.8	84.6	88.7	105.7	108.9
(s.d.)	(16.4)	(17.7)	(16.5)	(16.6)	(17.2)	(18.6)	(23.0)	(27.0)
Degree Days 10-29° C	1875	1903	1883	1938	1915	1922	1941	1942
(s.d.)	(393)	(387)	(392)	(383)	(381)	(398)	(403)	(393)
Degree Days Above 29° C	60.0	67.7	83.8	80.4	69.3	82.4	70.1	84.4
(s.d.)	(43.8)	(43.5)	(54.2)	(47.0)	(43.9)	(55.9)	(50.5)	(53.4)
Precipitation (mm)	686.0	676.9	649.3	582.2	666.8	623.8	659.3	580.6
(s.d.)	(111.6)	(113.5)	(115.4)	(83.6)	(98.1)	(108.4)	(97.8)	(91.4)
Global Log Yield Residual (%)	0.42	1.35	0.72	-0.38	-0.67	-0.02	-0.96	0.98
(s.d.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

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)
Global Log Yield Residual (%)	0.67	2.14	-4.21	-1.13	1.18	2.55	0.04	-1.89
(s.d.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: 595 Counties Outside Corn Belt								
Migration Rate Age [15,60) (%)	-2.94	-2.44	1.00	2.39	-1.71	-5.49	-0.76	-1.12
(s.d.)	(9.09)	(16.75)	(6.09)	(7.77)	(6.66)	(8.03)	(6.63)	(6.88)
Migration Rate Males [15,60) (%)	-3.03	-1.83	1.28	2.76	-1.56	-7.15	-0.64	-1.09
(s.d.)	(9.62)	(16.93)	(6.60)	(8.16)	(8.31)	(11.56)	(6.81)	(7.94)
Migration Rate Females [15,60) (%)	-2.91	-3.06	0.74	2.06	-1.82	-3.90	-0.80	-1.15
(s.d.)	(8.71)	(16.70)	(5.89)	(7.57)	(6.06)	(7.07)	(6.83)	(6.90)
Migration Rate Age [15,30) (%)	0.47	2.90	5.17	7.35	2.67	-1.30	-3.05	9.37
(s.d.)	(12.58)	(18.25)	(8.67)	(11.09)	(10.29)	(12.90)	(13.93)	(10.34)
Migration Rate Age [30,45) (%)	-6.58	-7.57	-1.46	-1.26	-5.17	-8.34	-0.53	-5.19
(s.d.)	(8.51)	(19.98)	(5.75)	(6.39)	(6.68)	(8.51)	(5.29)	(7.50)
Migration Rate Age [45,59) (%)	-4.66	-6.28	-3.53	-1.23	-3.55	-7.15	0.60	-7.58
(s.d.)	(6.42)	(13.78)	(5.24)	(6.21)	(5.69)	(7.74)	(3.33)	(8.16)
Migration Rate Age [60,oo) (%)	0.72	0.45	2.69	2.85	2.21	0.40	2.65	-0.37
(s.d.)	(4.17)	(10.38)	(3.90)	(4.20)	(3.87)	(4.62)	(3.74)	(5.57)
Soybean Area (1000 acres)	8.7	9.5	8.3	7.3	6.9	7.8	8.5	10.1
(s.d.)	(11.6)	(12.9)	(11.4)	(10.0)	(9.2)	(9.7)	(10.6)	(12.2)
Soybean Yield (bushel/acre)	51.3	56.2	65.9	76.2	84.8	90.3	109.8	112.0
(s.d.)	(16.4)	(15.4)	(15.8)	(17.2)	(17.7)	(19.2)	(21.8)	(27.0)
Degree Days 10-30° C	1998	2029	1975	2033	1998	1994	2001	2007
(s.d.)	(227)	(221)	(270)	(257)	(256)	(276)	(274)	(260)
Degree Days Above 30° C	66.6	76.7	89.9	86.0	74.0	85.4	70.6	86.3
(s.d.)	(31.9)	(29.0)	(37.4)	(31.4)	(29.7)	(39.8)	(35.8)	(36.8)
Precipitation (mm)	715.9	709.3	680.6	603.9	690.4	648.2	671.6	597.6
(s.d.)	(90.4)	(97.3)	(93.7)	(72.5)	(80.1)	(91.6)	(76.8)	(99.9)
Global Log Yield Residual (%)	0.67	2.14	-4.21	-1.13	1.18	2.55	0.04	-1.89
(s.d.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

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

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
				A: Annual Data				
Degree Days 10-29°C (1000)	0.427***	0.427***	0.449***	0.453***	-0.003	0.014	0.057	0.052
	(0.104)	(0.104)	(0.103)	(0.107)	(0.098)	(0.100)	(0.086)	(0.086)
Degree Days 29°C (100)	-0.731***	-0.735***	-0.732***	-0.732***	-0.562***	-0.592***	-0.579***	-0.589***
	(0.112)	(0.112)	(0.109)	(0.116)	(0.092)	(0.093)	(0.090)	(0.096)
Precipitation (m)	0.167***	0.166***	0.154***	0.153***	0.043	0.035	0.042	0.039
	(0.037)	(0.038)	(0.035)	(0.036)	(0.036)	(0.038)	(0.038)	(0.042)
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.014***	-0.014***	-0.004	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$F_{\text{1st-stage}}$	18.5	18.3	19.5	18.9	15.7	14.2	12.2	11.8
R-squared	0.6126	0.6130	0.6325	0.6649	0.5040	0.5195	0.5842	0.6317
Observations	34788	34788	34788	34788	26124	26124	26124	26124
Counties	892	892	892	892	746	746	746	746
				B: 5 Year Intervals				
Degree Days 10-29°C (1000)	0.640***	0.640***	0.766***	0.836***	-0.178	-0.180	0.233	0.237
	(0.139)	(0.142)	(0.140)	(0.180)	(0.242)	(0.261)	(0.192)	(0.236)
Degree Days 29°C (100)	-0.569***	-0.584***	-0.525***	-0.504***	-0.220***	-0.294***	-0.262***	-0.254***
	(0.090)	(0.095)	(0.080)	(0.109)	(0.071)	(0.076)	(0.055)	(0.077)
Precipitation (m)	0.178***	0.177***	0.152***	0.154***	0.089	0.061	0.040	0.028
	(0.026)	(0.025)	(0.025)	(0.039)	(0.072)	(0.072)	(0.044)	(0.075)
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.013***	-0.013***	-0.009	-0.007	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)
F-stat (1st stage)	24	27	23	21	12	11	9	3
R-squared	0.1933	0.1947	0.1814	0.2408	0.0334	0.0457	0.0488	0.0566
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table replicates Table 2 using the weather variables of Schlenker & Roberts (2009). 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. The F-statistic for joint significance of the weather variables is given at the top of the footer. Columns (a)-(d) differ by the included time controls: ccolumns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 Soybean Yields

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
A: Annual Data								
Degree Days 10-30°C (1000)	0.501***	0.500***	0.513***	0.516***	0.287***	0.278***	0.269***	0.283***
	(0.050)	(0.048)	(0.049)	(0.050)	(0.071)	(0.073)	(0.073)	(0.074)
Degree Days 30°C (100)	-0.644***	-0.656***	-0.662***	-0.664***	-0.572***	-0.558***	-0.558***	-0.562***
	(0.037)	(0.040)	(0.041)	(0.042)	(0.028)	(0.029)	(0.031)	(0.034)
Precipitation (m)	0.171***	0.168***	0.161***	0.160***	0.120***	0.124***	0.124***	0.128***
	(0.026)	(0.025)	(0.023)	(0.024)	(0.028)	(0.027)	(0.026)	(0.027)
Precipitation Squared (m^2)	-0.014***	-0.014***	-0.013***	-0.013***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$F_{\text{1st-stage}}$	94.1	91.7	84.4	85.0	185.8	171.3	189.5	156.8
R-squared	0.5334	0.5386	0.5603	0.5960	0.4056	0.4104	0.4304	0.4860
Observations	31154	31154	31154	31154	20492	20492	20492	20492
Counties	810	810	810	810	595	595	595	595
B: 5 Year Intervals								
Degree Days 10-30°C (1000)	0.480***	0.489***	0.535***	0.568***	0.585***	0.591***	0.419***	0.672***
	(0.103)	(0.109)	(0.097)	(0.107)	(0.113)	(0.121)	(0.124)	(0.166)
Degree Days 30°C (100)	-0.646***	-0.743***	-0.778***	-0.791***	-0.547***	-0.493***	-0.511***	-0.480***
	(0.067)	(0.048)	(0.041)	(0.045)	(0.055)	(0.081)	(0.072)	(0.102)
Precipitation (m)	0.140***	0.135***	0.114***	0.117**	0.020	0.036	0.025	0.052
	(0.032)	(0.022)	(0.032)	(0.040)	(0.052)	(0.047)	(0.043)	(0.051)
Precipitation Squared (m^2)	-0.012***	-0.012***	-0.010***	-0.010**	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
F-stat (1st stage)	34	162	265	256	30	18	22	20
R-squared	0.1662	0.2111	0.2371	0.3125	0.1908	0.1582	0.1796	0.2637
Observations	6413	6413	6413	6413	4442	4442	4442	4442
Counties	810	810	810	810	595	595	595	595
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table replicates Table A3 for soybeans. 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 A1. The F-statistic for joint significance of the weather variables is given at the top of the footer. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Degree Days 10-29°C (100)	0.167***	0.167***	0.167***	0.200***	0.134*	0.134	0.147*	0.159
	(0.051)	(0.048)	(0.045)	(0.047)	(0.079)	(0.083)	(0.089)	(0.134)
Degree Days 29°C (1000)	0.137***	0.127***	0.133***	0.147***	-0.002	-0.018	-0.021	-0.022
	(0.033)	(0.031)	(0.036)	(0.035)	(0.022)	(0.022)	(0.028)	(0.032)
Precipitation (m)	0.019*	0.018	0.018	0.036***	-0.000	-0.006	-0.017	-0.023**
	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.010)
Precipitation Squared (m^2)	-0.001	-0.001	-0.001	-0.003***	-0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$F_{\text{1st-stage}}$	52.2	42.3	35.0	37.7	2.8	1.7	3.7	3.7
R-squared	0.1031	0.0932	0.0900	0.1400	0.0054	0.0047	0.0092	0.0117
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table displays reduced form regression of migration rates on the four weather variables of Schlenker & Roberts (2009) 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. The F-statistic for joint significance of the weather variables is given at the top of the footer. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 - Weather Instruments and Crops

	Spline in Extreme Heat				**Temperature and Precipitation**			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	A: Instrumenting Corn Yields							
Log Yield	-0.320***	-0.305***	-0.337***	-0.393***	-0.175***	-0.156***	-0.125***	-0.094***
	(0.071)	(0.069)	(0.093)	(0.108)	(0.026)	(0.022)	(0.030)	(0.036)
Observations	7078	7078	7078	7078	7078	7078	7078	7078
Counties	892	892	892	892	892	892	892	892
	B: Instrumenting Soybean Yields							
Log Yield	-0.175**	-0.191**	-0.195**	-0.197**	-0.183***	-0.155***	-0.144***	-0.148***
	(0.087)	(0.084)	(0.091)	(0.087)	(0.064)	(0.049)	(0.049)	(0.049)
Observations	6413	6413	6413	6413	6413	6413	6413	6413
Counties	810	810	810	810	810	810	810	810
	C: Instrumenting Weighted Average of Corn and Soybean Yields							
Log Yield	-0.281***	-0.262***	-0.272***	-0.284***	-0.176***	-0.158***	-0.145***	-0.130***
	(0.093)	(0.081)	(0.105)	(0.109)	(0.045)	(0.036)	(0.043)	(0.041)
Observations	7086	7086	7086	7086	7086	7086	7086	7086
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table regresses log yields on different sets of weather instruments: columns (1a)-(1d) continue to use the seasonality in the sensitivity to extreme heat of columns (1a)-(1d) in Panel A of Table 3, while columns (2a)-(2d) use the four weather variables of Schlenker & Roberts (2009). Panel A use log corn yields, Panel B uses log soybean yields, and Panel C uses the log of the weighted average of corn and soybean yields. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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: Weather-Induced Yield Shocks and Net Outmigration - Sensitivity to Definition of Growing Season

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	A: Annual State-level Planting Dates							
Log Yield	-0.320***	-0.305***	-0.337***	-0.393***	-0.126	-0.082	-0.094	-0.144
	(0.071)	(0.069)	(0.093)	(0.108)	(0.144)	(0.115)	(0.157)	(0.157)
Observations	7078	7078	7078	7078	3371	3371	3371	3371
Counties	892	892	892	892	444	444	444	444
	B: Average Planting Dates							
Log Yield	-0.238***	-0.222***	-0.193***	-0.184***	0.018	0.049	0.025	0.050
	(0.048)	(0.047)	(0.045)	(0.046)	(0.059)	(0.050)	(0.098)	(0.132)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
	C: Average Planting Date Outside Corn Belt							
Log Yield					0.022	0.038	-0.004	-0.042
					(0.055)	(0.048)	(0.098)	(0.135)
Observations					5628	5628	5628	5628
Counties					746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Table varies how the growing season is defined. Columns (1a)-(1d) in Panel A and columns (2a)-(2d) in Panel C are the baseline estimates of Table 3. Panel A uses only counties that are in states that report the start and end of the growing season. Panel B fixes the growing season to equal the average growing season for all counties in the entire data set. Panel C fixes the growing season to equal the average growing season for counties outside the Corn Belt. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
A: Weighted Regression - Less than 100,000 Inhabitants								
Log Yield	-0.320***	-0.305***	-0.337***	-0.393***	0.022	0.038	-0.004	-0.042
	(0.071)	(0.069)	(0.093)	(0.108)	(0.055)	(0.048)	(0.098)	(0.135)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
B1: Unweighted Regression - Less than 100,000 Inhabitants								
Log Yield	-0.310***	-0.309***	-0.360***	-0.451***	0.040	0.051	0.011	-0.021
	(0.069)	(0.066)	(0.103)	(0.119)	(0.054)	(0.049)	(0.094)	(0.128)
B2: Same as B1 with Bootstrapped Errors								
Log Yield	-0.310***	-0.309***	-0.360**	-0.451*	0.040	0.051	0.011	-0.021
	(0.090)	(0.104)	(0.148)	(0.236)	(0.053)	(0.051)	(0.091)	(0.166)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
C: Unweighted Regression - All Counties								
Log Yield	-0.301***	-0.298***	-0.349***	-0.427***	0.044	0.057	0.036	0.019
	(0.064)	(0.061)	(0.099)	(0.111)	(0.052)	(0.047)	(0.086)	(0.124)
Observations	8069	8069	8069	8069	6986	6986	6986	6986
Counties	1016	1016	1016	1016	921	921	921	921

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 - the errors are again clustered by state. 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 while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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 - Subsets of Data

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	A: Baseline Age [15,60)							
Log Yield	-0.320***	-0.305***	-0.337***	-0.393***	0.022	0.038	-0.004	-0.042
	(0.071)	(0.069)	(0.093)	(0.108)	(0.055)	(0.048)	(0.098)	(0.135)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
	B: Counties With At Least 1 Yield Observations							
Log Yield	-0.316***	-0.300***	-0.333***	-0.387***	0.034	0.049	0.015	-0.026
	(0.071)	(0.069)	(0.092)	(0.108)	(0.043)	(0.038)	(0.068)	(0.101)
Observations	7244	7244	7244	7244	6468	6468	6468	6468
Counties	935	935	935	935	973	973	973	973
	C: Counties with All 40 Yield Observations							
Log Yield	-0.392***	-0.377***	-0.428***	-0.446***	-0.092	-0.047	-0.094	-0.096
	(0.084)	(0.082)	(0.103)	(0.122)	(0.104)	(0.094)	(0.157)	(0.132)
Observations	5608	5608	5608	5608	1808	1808	1808	1808
Counties	701	701	701	701	226	226	226	226
	D: Excluding Years 1980-1984							
Log Yield	-0.301***	-0.301***	-0.271***	-0.338***	0.027	0.037	0.011	-0.008
	(0.095)	(0.094)	(0.091)	(0.113)	(0.049)	(0.046)	(0.081)	(0.089)
Observations	6186	6186	6186	6186	4894	4894	4894	4894
Counties	892	892	892	892	746	746	746	746
	E: Excluding Years 1985-1989							
Log Yield	-0.280***	-0.284***	-0.333***	-0.348***	0.020	0.018	-0.006	0.025
	(0.057)	(0.059)	(0.076)	(0.076)	(0.034)	(0.036)	(0.060)	(0.057)
Observations	6186	6186	6186	6186	4890	4890	4890	4890
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Qu.	Co-Qu.	Linear	Quad.	St-Qu.	Co-Qu.

Notes: Panel A is the same as Table 3, i.e., it uses all counties that reported at east 21 yield observations in 1970-2009. Remaining panels using different subsets of the data: Panels B and C, respectively use counties that have at least 1 yield observation or are a balanced panel with data for all 40 years. Panel D excludes 1980-1984 when agriculture was booming, panel E excludes 1985-1989 when US agriculture fell into a big depression. All columns include county fixed effects. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend while columns (b)-(d) include a common, state-specific, and county-specific quadratic time trend, respectively. 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.