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

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

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Abstract

We investigate the influence of weather anomalies on net migration in the Eastern United States using a county-level panel for the period from 1970 to 2009. There is a significant weather-migration relationship in the Corn Belt, but not outside of it. We present evidence that weather affects migration through its influence on agricultural productivity using an instrumental variables approach. Our preferred model uses the seasonality of the sensitivity of corn yields to extreme heat over the growing season, which peaks during corn flowering, as instrument. The reduced-form estimate of the migration response to extreme heat closely mirrors the seasonality of corn yield. Our estimated semi-elasticity ranges imply that 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 climate change is predicted to adversely affect US yields, rural areas might see an increase in outmigration. On the other hand, if yield losses from climate change in the US are not offset by other countries, the accompanying price increase would offset the decrease in productivity.

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♣ School of Economics, Shanghai University of Finance and Economics and Department of Economics, Chinese University of Hong Kong. Email: shuaizhang.feng@gmail.com
♠ Department of Geosciences and Woodrow Wilson School, Princeton University. Email: omichael@princeton.edu
♡ School of International and Public Affairs (SIPA) and Earth Institute, Columbia University. Email: wolfram.schlenker@columbia.edu.

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

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

In particular, we examine whether net migration rates over five year intervals between 1970 and 2009, defined as the fraction of people leaving a county net of new arrivals and deaths, are related to contemporaneous observed weather variations for rural counties, i.e., counties with a total population less than 100000. 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 the same time that corn flowers, changes in agricultural productivity rather than some unobserved confounders drive the observed climate-migration relationship. Moreover, we find that the relationship inside the Corn Belt is driven mainly by young adults, while senior citizens, who are often believed to be more responsive to climatic conditions show no responsiveness.

Based on our preferred model specification, we find a statistically significant semi-elasticity of -0.3 to -0.4 between the net outmigration rate and yields for the population aged 15 to 59. 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 (2009) 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 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 structures of the economy, demographic profiles, and government policies. Nevertheless, we

[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).

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 impact global prices. In a 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. In case there is no such offset, we include a specification that not only account 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 offset by the implied price increase.

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

1 Background

Migration is a defining feature in the history of the United States, not just in terms of arrival of immigrants, but also in terms of internal population movements. During the last century, the mean center of the U.S. population moved about 324 miles west and 101 miles south (Hobbs & Stoops 2002) and the fraction of the population living in rural areas decreased significantly. One of the most important determinants of migration flows has been identified as relative economic opportunities in source and destination regions (see e.g., Borjas, Bronars & Trejo (1992)). For example, during the Great Migration 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).

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 been a long history of interventionist policies to manage migration patterns, policy makers may be able to utilize migration forecasts under climate change to enhance local adaptive capabilities to reduce unnecessary outmigration and manage any remaining migration flows (Adger 2006, McLeman & Smit 2006).

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

While the Dust Bowl experience may be unique in American history, the extreme climatic conditions witnessed in the 1930s may become more frequent in the current century as a consequence of global climate change. Recent researches suggests that climate change is expected to have significant negative impacts on crop yields in the United States. Lobell & Asner (2003) report that for each degree increase in growing season temperature, both corn and soybeans yields would decline by roughly 17%. Similarly, Schlenker & Roberts (2009) identify serious nonlinearities in the temperature-yield relationship. Increasing temperatures are beneficial for crop growth up to a point when they switch to becoming highly detrimental. These breakpoints vary by crop: 29°C or 84°F for corn, 30°C of 86°F for soybeans and 32°C or 90°F for cotton. The effect of being 1 degree above the optimal breakpoint is roughly ten times as harmful as being 1 degree below it. Area-weighted average yields are predicted to decrease by 30-46% before the end of this century under the slowest (B1) warming scenario and by 63%-82% under the most rapid warming scenario (A1F1) based on the Hadley III model. These newly available estimates were considerably larger than what previous modeling studies have suggested (Brown & Rosenberg 1997, Reilly 2002, Cline 2007).[2] It should also be noted that these estimates are based on the existing statistical

[2]To assess the impact of climate change on U.S. agriculture, three different approaches have been used in the literature, each with its own merits and shortcomings. The first one is the production function approach, in which the impact of weather/climate on crop yields is derived using controlled laboratory or field experiments. Some sort of CGE (Computed General Equilibrium) model is sometimes used to incorporate price feedbacks. This approach is usually adopted by agronomists, see for example Rosenzweig & Hillel (1998). The second one is the so called Ricardian approach, which estimates a cross-sectional relationship

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

2 Methodology and Data

2.1 Empirical Methodology: Reduced Form Regression

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

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

Our baseline model examines the ratio m_{it} of all people that were aged 15-59 at the beginning of interval t that outmigrated over the next five years, net of any new arrivals. If weather

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.

$\mathbf{W}_{it}$ explains migration, the coefficients π should be jointly significant.[3] A set of unrestricted county dummy variables, represented by c_i, are included to capture time-invariant county factors, such as proximity to urban centers and natural amenities. Time controls $f(t)$ capture all aggregate-level factors that affect migration trends, such as technological progress in agriculture, changes in agricultural policies, as well as changes in overall economic fundamentals in both source and destination counties. We use four time trends $f(t)$: (a) a linear time trend common to all counties; (b) a quadratic time trend common to all counties; (c) state-specific quadratic time trends; and (d) county-specific time trends that allow for the fact that the economic conditions might be trending differently in each location. The error 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.[4] In a sensitivity check, we also present results of an unweighted regression where we use a grouped bootstrap routine and draw entire 5-year intervals with replacement, i.e., all counties that report in a given 5-year interval.

2.2 Empirical Methodology: IV Regression

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

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

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

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

Because x_{it} may be correlated with ϵ_{it}, we only use yield shocks that are due to presumably exogenous variation in weather.[6] In equation (3), we again include county fixed effects

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

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

[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]For comparison, Table 1, we present results from a simple OLS regression, which are strikingly different

k_i to control for baseline differences as well as time trends $g(t)$ as yields have been trending upward over time. The coefficient β is identified by deviations of the weather variables $\mathbf{W}_{it}$ from their time trends, which are presumably exogenous since we use the same time controls in both the first and second stage. Figure A3 in the appendix displays annual corn and soybean yields for the 13 states in the Corn Belt.[7] The figure displays actual yields as well as predicted yields using our preferred instrument, the effect of degree days above 29°C, which is allowed to vary over the growing season.[8]

Yield growth is approximately piecewise linear in temperatures: Moderate heat, as measured by degree days 10-29°C for corn and degree days 10-30°C for soybeans, is beneficial for plant growth. Extreme heat, as measured by degree days above 29°C for corn and degree days above 30°C for soybeans are very harmful for crops. 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 2.3 below). The effect of an extra degree day above 29°C is allowed to vary smoothly over time. As will show 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, this suggest that 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. Since changes in average yields should not be driven by changing compositions of soybean and corn production, we adjust the yields to make them comparable. Regressions that use the log of the adjusted average yield therefore transform soybean yields into corn equivalents by multiplying them

from the IV regression.

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

[8] Degree days are simply truncated daily temperature variables summed over the growing season. 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. The daily measure is summed over all days of the growing season.

with the soybean to corn price ratio.[9] This makes the two crops comparable on a dollar/acre basis. Ultimately, agricultural returns are the difference between revenues and cost. By prorating yields with the average price ratio, we make them comparable on a revenue/acre basis, which would be an exact conversion under the assumption that the revenue/cost rato is comparable for the two crops. After making the yields comparable, we take the area-weighted average of the equivalent yields. Similarly, we take the area-weighted average of the crop-specific weather variables $\mathbf{W}_{it}$.

We estimate the model separately for (i) counties in the Corn Belt; and (ii) counties in the eastern United States outside the Corn Belt and the state of Florida. In both instances we focus on rural counties, which we define to be counties with a total population of less than 100000. Areas in the Corn Belt predominately grow corn and soybeans. Our null hypothesis is that β is negative for the Corn Belt, but approximately equals zero for areas outside the Corn Belt, where corn and soybean production are less important as a fraction of the overall economic activity. Eastern areas outside the Corn Belt serve as a control group in our research design - if changes in climate affect changes in outmigration through channels other than crop yield (i.e., the error term ϵ_{it} is correlated with the instrument $\mathbf{W}_{it}$), then β would also be non-zero for the sample of counties outside the Corn Belt.

If people have a preference for warmer and drier climate as suggested by the establishment 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. On the other hand, 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. If migration is most sensitive to extreme heat when corn yield is most sensitive, the response is most likely driven through the agricultural channel unless humans dislike heat the most when corn flowers, which seems unlikely as the exact flowering time varies year-to-year.

2.3 Data and Summary Statistics

Since there is no accurate count of number of people migrated at the county level for the 40-year time period that we are focusing on, we use the residual approach to derive the

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

outmigration ratio m_{it} for each county for each five-year period between 1970 and 2009.[10] For example, for the 15-59 age group, in the baseline model in our analysis, we use

$m_{it[15,60)}$: net outmigration rate for those aged $[15, 60)$ at time t in county i.

$p_{it[15,60)}$: total population aged $[15, 60)$ in county i at the beginning of the 5-year interval that started in t.

$p_{i[t+5][20,65)}$: total population aged $[20, 65)$ in county i at the end of the 5-year interval that started in t.

$d_{it[15,60)}$: number of people aged $[15, 60)$ in county i at the beginning of the 5-year interval t that died by the end of it.

To construct the net outmigration ratio

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

We use publicly-available population data from U.S. Census Bureau for $p_{it[15,60)}$ and $p_{i[t+5][20,65)}$ and state- and age-group-specific mortality data from National Center for Health Statistics 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 baseline model.[11] 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

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

[11]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.

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.[12] Since there are hardly any degree days above 29°C towards the end point, we allow the effect of extreme heat to vary according to a restricted cubic spline with 5 knots between 0.1 and 0.75 of the growing season.[13]

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.[14] 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.[15] 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.[16] There are 1,336 counties in our sample, 892 in the Corn Belt sample and 746 in the non-Corn Belt sample.[17] For comparison purposes, we have averaged all

[12]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 A6, but none of our main results changes.

[13]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.

[14]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.

[15]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.

[16]We present sensitivity checks where counties with more than 100,000 inhabitants are included in Table A8. The results are unchanged in unweighted regressions, but do change if we weight by the population in a county.

[17]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.

variables over each five-year period during 1970-2009. Panels A and B present sample means and standard deviations for the Corn Belt and non-Corn Belt samples, respectively. There is substantially more net outmigration for the Corn Belt sample than the non-Corn Belt sample as the Midwest has lost population over the last 40 years. Average county-level crop acreages in the Corn Belt states are also larger, especially for corn, as are average crop yields. For example, during the most recent recent 5-year period (2005-2009), both corn and soybean yields are around 30% higher in the Corn Belt sample than in the non-Corn Belt sample. This likely reflects effects of various factors such as geographic/climatic conditions, technology, and policies. Non-Corn Belt areas experience more extreme heat above 29°C and more precipitation.

3 Results

3.1 The 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 includes eight columns: columns (1a)-(1d) give the results for counties in the Corn Belt as shown in blue in Figure 1, while columns (2a)-(2d) give results for Eastern counties outside the Corn Belt as shown in red in Figure 1. Columns (a)-(d) vary the included temporal controls, ranging from the least flexible (one common time trend in columns (a)) to the most flexible (country-specific linear time trends 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 small in magnitude and only a few are significant, but sometimes of opposite signs depending on what crop is used, for example, in column (2d). The big drawback of such an uninstrumented regression is that there is a clear endogeneity problem: if a productive work force leaves a county, yields might decline, leading to a possible positive correlation between yields and outmigration rates. A bias in the opposite direction is also possible: higher oil prices negatively impact agriculture (higher input cost of both fuel and fertilizer prices, which a er 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. Our subsequent analysis therefore relies on an instrumental variable approach where we instrument log corn yields with extreme heat. In either case, government policies that help to stabilize the local economy when yield declines might lead to a migration-yield relationship that is closer towards zero.

3.2 The Weather-Migration Relationship

One potential concern might be the exclusion restriction, i.e., don't people migrate as a response to observed weather due to a direct preference for weather, and not changes in agricultural productivity. While we can't test this directly, we can provide some evidence that suggests that this is likely not 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 the included time trend. 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 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 season ar 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 country 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 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. For the exclusion restriction to be violated, we would have individuals to be sensitive to extreme in rural counties within the Corn Belt in the middle of the growing season when corn is sensitive to extreme heat, yet people in rural area outside the Corn Belt never exhibit any sensitivity to extreme heat during the entire growing season. While there might be reasons that individuals are more sensitive to extreme heat during part of the year, e.g., summer break when kids play outside, it seems odd why this would only be the case in areas where corn is grown but not outside the area where it is grown. We believe the likely explanation why the migration-weather relationship mirrors the one for corn inside the Corn Belt but not outside is that it 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 shoes 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 and outside the Corn Belt. 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 40 years to eight 5-year intervals. The migration regression are population-weighted to obtain the most efficient estimator for the overal population. Since 5-year averages have less variation than annual data, measurement error might be amplified. 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 lower, but is still larger than 10 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 results 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.[18]

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.[19] 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 0.43-0.79% 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 - Al F-statistics are agin 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 moerdate 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 poses a serious challenge to the instrument variables approach we use and motivates our solution to exclusively rely on the seasonality of the effect of extreme heat as an instrument when we examine the yield-migration relationship.

[18]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.

[19]Table A4 gives the results for soybeans.

3.4 Second Stage: Yield Shocks and Net Outmigration

We estimate equations (2) and (3) by two-stage-least-squares (2SLS) and show the second stage results in Panel A of Table 3. Columns follow the same layout as previous tables: columns (1a)-(1d) show the results for counties inside the Corn Belt, while columns (2a)-(2d) give the results outside the Corn Belt. Columns (a)-(d) differ by included time controls to capture overall trends in migration as well as yields. Columns (a) use a common linear trend (one variable), columns (b) a common quadratic time trend (two variables), columns (c) a state-specific quadratic time trend (26 variables in the Corn Belt, 13 states × two variables per state), columns (d) use county-specific trends (892 variables in the Corn Belt, one for each county). We choose not to control for year fixed effects, which would absorb most of the variation as 5-year weather averages are highly correlated within the Corn Belt, more so than annual data. The reason is that the 5-year averages are in large part driven by large-scale phenomena like El Nino / La Nina whereas 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 variation than the 26 state-specific quadratic trends. Time period fixed effects absorb variation that we would like to use in our identification and amplify measurement error in the weather data as most of the common signal is removed (Fisher et al. 2012). If weather is truly exogenous, it should be orthogonal to other measures and hence time period fixed effects are not required.

Column (1a)-(1d) of Panel A report results for the Corn Belt sample when the net migration ratio is regressed on instrumented log corn yield using 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 are 13-2 in Panel B of Table 2, above than the usual cutoff point of 10 to rule out concerns about weak instruments. The semi-elasticity implies that a one percent reduction below trend in corn yields during a 5-year 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 migration in columns (2a)-(2d) even though the first-stage F-statistics where again above 10.

One might expect different demographic groups to have different migration responses with respect to yield changes. For example, McLeman (2006) found that young people had a larger migration response following the Dust Bowl. Panels B1 and B2 of Table 3 therefore separate the migration response by sex, while Panels C1-C4 separate it by age, using the same specifications as in Panel A. Males and females have quite similar migration elasticities, suggesting that the relationship is not gender-specific. However, people in different age groups have quite different migration elasticities. The youngest age group, those between 15 and 29, are most sensitive to yield shocks in their migration decisions. The estimated elasticity ranges between -0.42 and -0.53 cor the Corn Belt sample in columns (1a)-(1d). The semi-elasticities get progressively smaller as we look at older age groups. The 30-44 age group has a semi-elasticity of -0.31 to -0.41, which is still significant at the 1% level. The age group between 45 and 59 has a semi-elasticity that is -0.10 to -0.12, which is only about a fourth of that for the 15-29 group. People aged 60 and above do not have a significant semi-elasticity. Our finding is consistent with the general observation that younger people are more mobile. The results also lend additional support to the exclusion restriction in our instrumental variable setup. If weather fluctuations directly impact migration decisions, one might expect larger responses for the older age group as they care most about weather and climatic conditions, as shown by a sizable retirement community in the Southern United States (McLeman & Hunter 2010).

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 of our sample period 1970-2009 (at least 21 out of the 40 years). Regressions are weighted using the total population in a county to get a more efficient estimate. To explore the sensitivity of our results to these restrictions, we conduct a set of robustness checks in the appendix.

Table A6 in the appendix varies how the growing season is defined. Fixing it to the average level for all counties in the Eastern United States still gives a significant semi-elasticities of -0.19 to -0.26, which is lower than before. Using the accurate year-to-year variation in planting in harvest dates is crucial to get the exact flowering period correct. On the other hand, it speaks again the possibility that there might be a confounding preference for climate during the summer break when kids are at home, which usually varies not at all between years and should not have been impacted by fixing the growing season at the average level.

Table A7 furthermore replicates the analysis for our Corn Belt sample using two different specifications. Panel A still presents the results instrumenting 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 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. Noet 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. The revised weather measures that allow for heterogeneity of the effect of extreme heat over the growing season hence do not give different results in the case of soybeans. Therefore, instrumenting corn yields with the seasonality of extreme heat avoids some of the bias that is due to a direct preference for climate. If we take the weighted average of corn and soybeans to make them comparable on revenue-per-acre terms in Panel C, the results lie in the middle.[20]

Table A8 first 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. If a half-decade is hotter than usual, it is likely hotter than usual for most of the Corn Belt. Panel B2 uses a grouped bootstrap procedure where we resample entire 5-year intervals with replacement. While the estimated standard errors go up significantly, our preferred estimates using the spline in extreme heat in columns (2a)-(2d) remain significant at least at the 5% level.[21] Since we only have eight intervals, using a clustered bootstrap has its own drawbacks, and our baseline regression therefore clusters by state.[22] 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

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

[21] 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.

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

than 100,000 in the 2000 Census. The point estimates again remain basically unchanged.[23]

Table A9 examines the sensitivity of our results to the minimum number of observation we require to have in a county before it is included in the analysis. Panel A again shows the baseline results (Panel A of Table 3) for comparison. Panel B and C are the extreme endpoints of the possible cutoffs: Panel B includes all counties if they have at least one observation in the years 1970-2009, while Panel C requires a perfectly balanced panel, i.e., observations for all 40 years. The number of counties included in the study is hence highest in Panel B with 935 counties, and lowest in Panel C with 701 counties. The point estimates remain very robust irrespective of what cutoff we use and hence are not driven by a particular sample selection. Finally, Panel D and E exclude the first and second half of the 1908s. 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 2009). To shed further light on this issue, we regress comparable measures of farm size and employment on instrumented yield shocks. The regressions are similar to the regression model specified in equations (2) and (3) except that we replace the dependent variable, net outmigration, with other measures.

Table 4 use data from the Agricultural Census. Since the Census of Agriculture was not published exactly every five years, the time intervals now vary in length as given by the time between consecutive Census years.[24] Panel A uses the rate of change in the number of farms as dependent variable. The coefficients are all positive and statistically significant, implying that during times when yields decreases, there is a contraction in the number of farms. Such a contraction could be caused by mergers of farms that leave the overall area unchanged, or

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

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

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 5 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 varies between models. The errors are so large than we cannot reject that the effect is zero, but also cannot rule out that it is quiet large.[25] For example, our preferred and most flexible specification in column (1d) has a 95% confidence interval that extends to 0.53. 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 0.33-0.44 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 larger government transfers increase the probability of farm survival using micro-level Census data that links individual farms between three Censuses. If government payments insure against yield losses, they will dampen responses in farm labor, especially since many of them are conditional on the farm remaining in operation. At the same time, yield losses might induce farmers to purchase less outside goods and result in fewer investments. Roberts & Key (2008) have shown that larger government payments result in consolidation in the farm sector, thereby increasing average farm size, which is consistent with our finding in Panel A1. An increase in farm size might lead to efficiency gains and hence reduce the demand for services and goods outside the agricultural sector. This would explain why we detect larger employment effects outside of agriculture. At the same time, the U.S. agriculture sector is already highly capital-intensive with a minimum level of farm workforce, thus it is difficult to displace farm labor even at times with negative yield shocks.

We examine the effect of weather-induced yield shocks on government payments in Table 6. The National Agricultural Statistics Service reports state-level annual data on gov-

[25] 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.

ernment transfers. We regress the log of government transfer in each year on agricultural yields.[26] We switch from a regression of 5-year intervals to an annual regression. 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 shows that there is an almost one-to-one relationship between yield shortfalls and increases in government transfers. For example, using our preferred instrument (Panel C) and the most flexible time controls (column 1c), a 1 percent decrease in yields will increase government transfers by 0.92 percent. While these government payments constitute highly subsidized insurance, there seems to be no evidence of moral hazard: simply using observed yield shocks in Panel A does not impact government transfers, while yields shocks that are caused by weather shocks (and hence are not the result of moral hazard) do.

4 Projecting Future Net Outmigration

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

We 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. 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.[27] The revised degree days variables are calculated by adding the predicted changes in temperature to the historic baseline and recalculating the

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

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

nonlinear transformation of the new temperatures series.[28] In a second step, we project changes in yields by multiplying the predicted changes in the four weather variables in each county times the estimated coefficients of column (1d) in Table A3. Table A10 presents the summary of the results for individual counties. The first column displays the mean impact among counties, while the second through fourth column give the standard deviation, minimum, and maximum of the impacts for the 892 counties in the Corn Belt. The last four columns summarize how many counties will have increased yields (displayed in blue in Figure A7) as well as how many counties have decreased outmigration rates (shown in green, yellow, and red).[29]

To complement our use of the Hadley III model, which is just one of roughly 20 GCMs (General Circulation Model, or Global Climate Model) and has above average predicted warming, we also provide migration projections under uniform climate change scenarios, assuming temperature or precipitation changes are the same across all the Corn Belt 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.[30] We predict outmigration rates corresponding to each Celsius degree rise in temperatures up to 5°C (holding precipitation constant) and between -50% and +50% change in precipitation (holding temperature constant) in 20% intervals. Figure A8 and A9 show the results for uniform temperature and precipitation scenarios. While the exact predicted change in yields varies between climate change scenarios, three features stand out: impacts have the potential to be quiet sever 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.

Next, we conduct two thought-experiments about the effect of climate-induced changes in yields on outmigration rates. First, we follow a partial equilibrium approach that assumes there are no price feedbacks, which would be appropriate if other parts of the globe can compensate for the reduced US production by increasing their own. Given our preferred semi-elasticity of -0.4 from the most flexible time trend (column (1d) in Panel A of Table 3),

[28]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.

[29]The standard errors are for a given climate scenario and hence do not incorporate uncertainty about the climate forecast.

[30]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.

predicted changes in corn yield simply have to be multiplied by -0.4 to derive predicted changes in net outmigration rates. 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. Also, we are using the reduced form relationship between weather and migration of Table A5 to predict future migration flows, which captures both responses to changes in agricultural productivity as well as other channels such as people's direct preference for climate.

In a second step we relax the assumption of constant commodity prices. 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. Table 7 therefore not only includes the yield shock within a county, but also the global world caloric shock during the same time period, which has been shown to be a strong predictor of agricultural prices (Roberts & Schlenker 2013).[31] Including the global shock does not significantly change the semi-elasticities we estimated before, which slightly decrease to a range of -0.27 to 0.37. At the same time, global shocks in corn production impact migration rates through their effect on prices. A reduction in global production will increase prices, which will slow outmigration, hence giving us a positive coefficient on the global yield shocks in the regression equation. If we assume that production shortfalls in te 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 compensates for the decrease in productivity. To see this, note that in our preferred specification in column (1d) of Table 7, a one percent decrease in yields will increase outmigration by 0.37%. At the same time, the 1% decrease in the US implies a global reduction in output of 0.4% all else the same, or a decrease in outmigration by $0.4 \times 0.839 = 0.36\%$. The coefficient on the global shock in the second row of the table are even larger in columns (1a)-(1c), suggesting that the price effect could more than offset the

[31] This variable does not vary from county-to-county but is the same for all counties in a given time period.

productivity effect. Moreover, if a decline in US yields coincidence with global reduction in output, the price feedback will only be multiplied.

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, suggesting that even in case of price feedbacks, there will be heterogenous impacts where population is likely to shift further North within the Corn Belt.

5 Conclusions

This paper first establishes a reduced-form relationship between weather deviations and migration rates. The likely mechanism behind the observed weather-migration relationship is the effect of weather on agricultural productivity. Our 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, which makes it less likely 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 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 patterns.

Second, we extrapolate this relationship while holding every things else constant; our results suggest a nontrivial effect of climate change on future internal U.S. population movements. However, 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 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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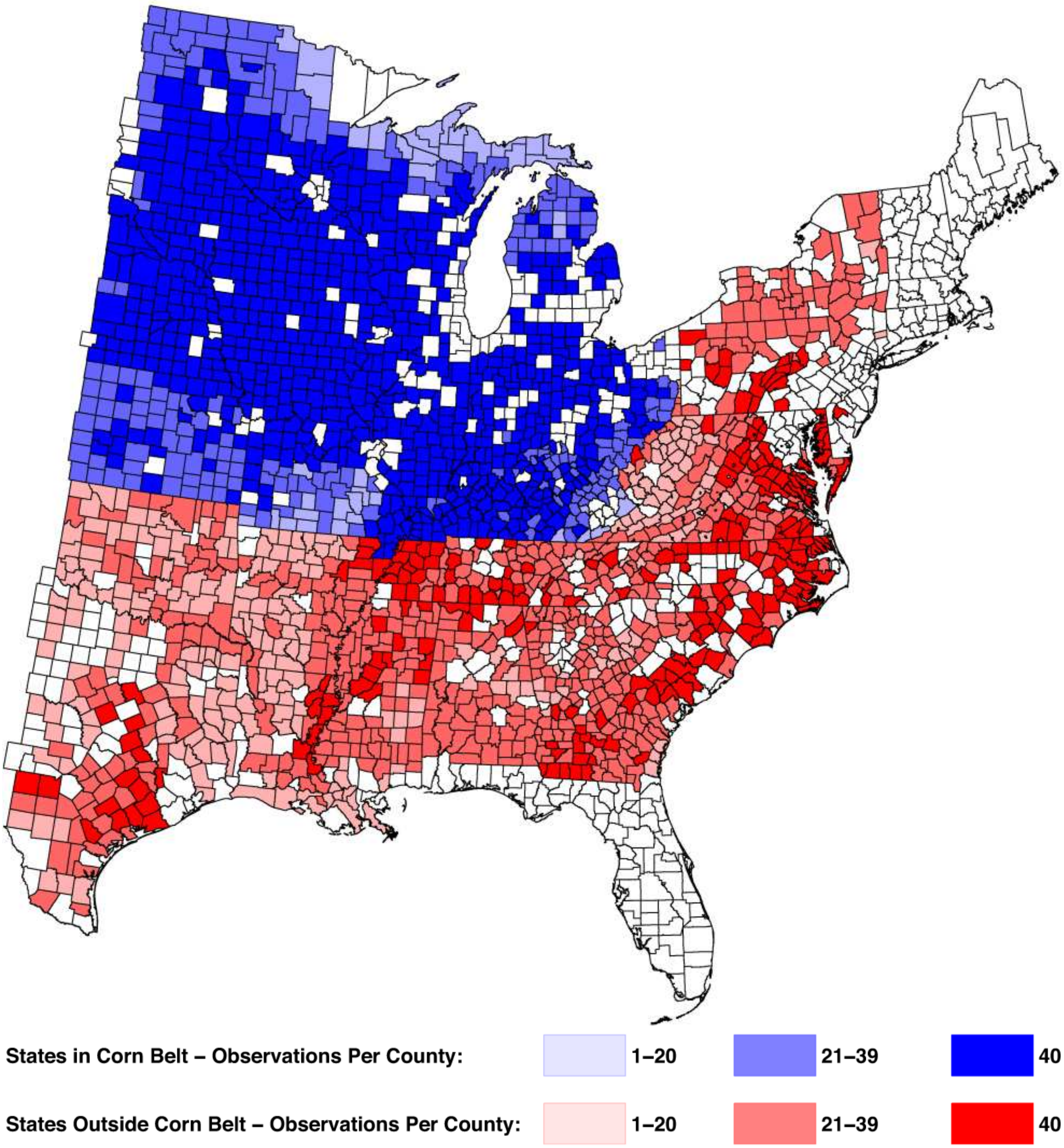
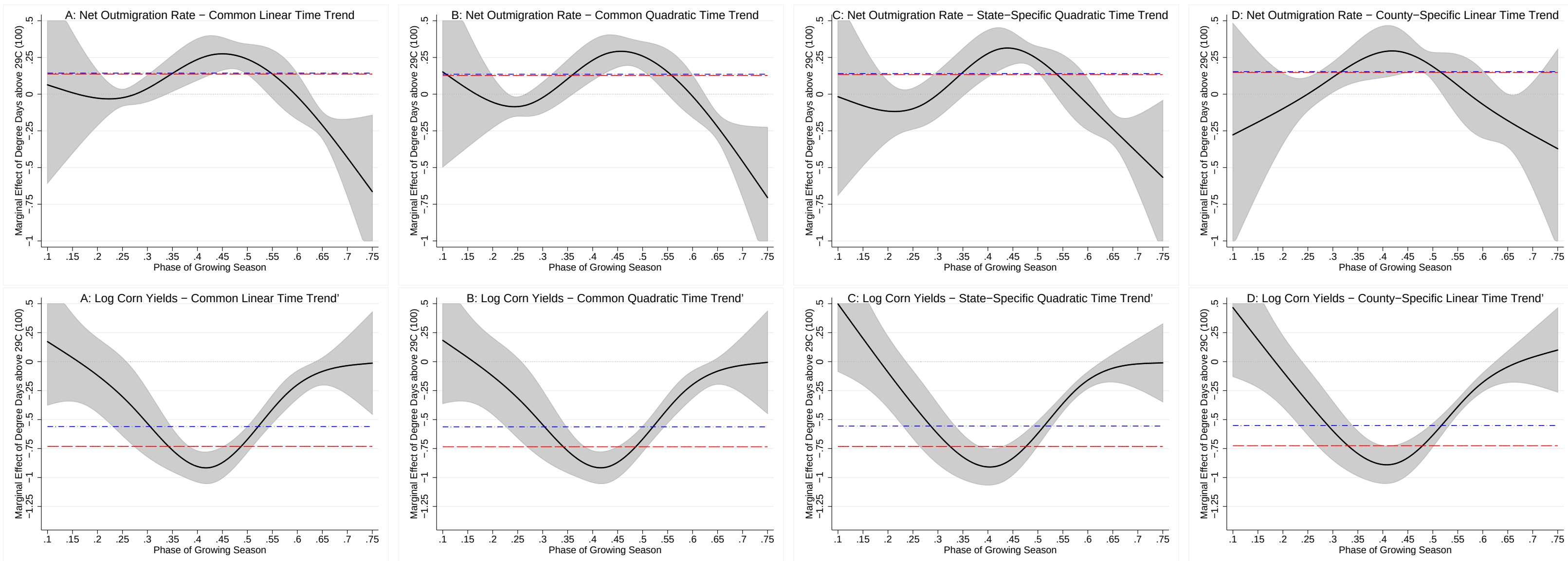
Figure 1: Rural Counties with Migration Data and Corn Yields (1970-2009)



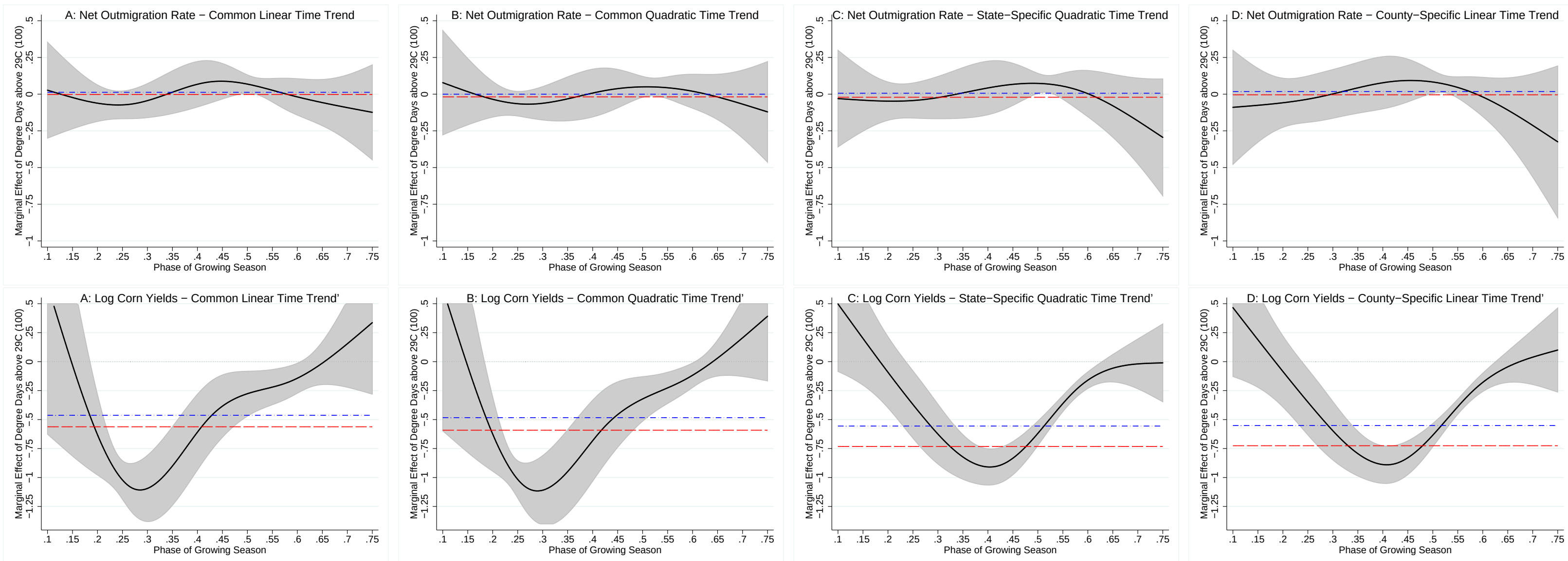
Notes: The left figure displays rural counties (population less than 100000) in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. States covering the corn belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have data.

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. The blue line displays the constant effect from a regression that includes season-total extreme heat over the variable growing season, while the red line uses a fixed growing season March-August and also controls for moderate degree days as well as a quadratic in precipitation. All regressions use counties with at least 21 yield observations in the corn belt. Columns differ by the included time control, which are respectively, a common linear time trend, a common quadratic time trend, state-specific quadratic time trends, and county-specific linear time trends.

Figure 3: 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. 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 linear time trends.

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

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A: Corn Yields							
Log Yield	-0.018	-0.016	0.000	-0.013	0.010	0.004	0.012	0.029*
	(0.015)	(0.013)	(0.016)	(0.022)	(0.014)	(0.013)	(0.013)	(0.015)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
	Panel B: Soybean Yields							
Log Yield	-0.012	-0.024	-0.019	-0.017	-0.036***	-0.024	-0.021	-0.051**
	(0.018)	(0.016)	(0.018)	(0.022)	(0.014)	(0.016)	(0.019)	(0.021)
Observations	6413	6413	6413	6413	4442	4442	4442	4442
Counties	810	810	810	810	595	595	595	595
	Panel C: Weighted Average of Corn and Soybean Yields							
Log Yield	-0.028*	-0.030**	-0.014	-0.026	-0.011	-0.008	0.002	-0.010
	(0.015)	(0.013)	(0.016)	(0.024)	(0.016)	(0.014)	(0.015)	(0.019)
Observations	7086	7086	7086	7086	6102	6102	6102	6102
Counties	892	892	892	892	805	805	805	805
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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

Table 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)
				Panel A: Annual Data				
$F_{\text{1st-stage}}$	152.0	172.6	292.7	154.2	151.6	134.8	51.4	73.6
$p_{\text{1st-stage}}$	2.0e-10	9.6e-11	4.2e-12	1.9e-10	2.7e-12	6.4e-12	6.6e-09	5.1e-10
Observations	34788	34788	34788	34788	26124	26124	26124	26124
Counties	892	892	892	892	746	746	746	746
				Panel B: 5 Year Intervals				
$F_{\text{1st-stage}}$	20.5	22.4	13.2	22.2	17.4	27.1	38.7	23.6
$p_{\text{1st-stage}}$	1.7e-05	1.0e-05	1.5e-04	1.1e-05	8.9e-06	5.2e-07	4.8e-08	1.3e-06
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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). Coefficients are 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 for which migration data is available. Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. 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

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
				Panel A - Baseline: Age [15,60)				
Log Yield	-0.320***	-0.305***	-0.337***	-0.397***	0.022	0.038	-0.004	-0.054
	(0.071)	(0.069)	(0.093)	(0.090)	(0.055)	(0.048)	(0.098)	(0.113)
				Panel B1: Males Age [15,60)				
Log Yield	-0.325***	-0.310***	-0.342***	-0.408***	0.041	0.053	0.018	-0.026
	(0.073)	(0.070)	(0.095)	(0.092)	(0.056)	(0.052)	(0.108)	(0.118)
				Panel B2: Females Age [15,60)				
Log Yield	-0.316***	-0.301***	-0.332***	-0.386***	0.006	0.025	-0.023	-0.080
	(0.071)	(0.069)	(0.091)	(0.089)	(0.055)	(0.045)	(0.089)	(0.109)
				Panel C1: Age [15,30)				
Log Yield	-0.423***	-0.416***	-0.456**	-0.534***	-0.055	-0.063	-0.227	-0.202
	(0.122)	(0.122)	(0.180)	(0.165)	(0.038)	(0.046)	(0.142)	(0.127)
				Panel C2: Age [30,45)				
Log Yield	-0.335***	-0.313***	-0.351***	-0.411***	0.076	0.094	0.081	0.036
	(0.054)	(0.053)	(0.066)	(0.065)	(0.075)	(0.063)	(0.096)	(0.124)
				Panel C3: Age [45,60)				
Log Yield	-0.100***	-0.091**	-0.095**	-0.118***	0.049	0.086*	0.149***	0.041
	(0.038)	(0.042)	(0.049)	(0.045)	(0.073)	(0.048)	(0.055)	(0.091)
				Panel C4: Age [60,oo)				
Log Yield	-0.017	-0.014	-0.007	-0.015	-0.006	0.014	0.025	-0.029
	(0.014)	(0.013)	(0.019)	(0.016)	(0.033)	(0.019)	(0.019)	(0.045)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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

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

	(1a)	(1b)	(1c)	(1d)
Panel A: Number of Farms (USDA)				
Log Yield	0.286**	0.290**	0.537***	0.574***
	(0.124)	(0.124)	(0.171)	(0.169)
Panel B: Total Farmland Area (USDA)				
Log Yield	-0.073	-0.073	-0.104	-0.081
	(0.054)	(0.055)	(0.092)	(0.090)
Observations	7076	7076	7076	7076
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Quad.	County

Notes: Table regresses changes in farm characteristics on instrumented log yield shocks. Panels use changes between the 1969, 1974, 1978, 1982, 1987, 1992, 1997, 2002, and 2007 Census fir counties inside the corn belt. Columns (a)-(d) differ by the included time controls: column (a) includes a common linear time trend, column (b) includes a common quadratic time trend, column (c) includes state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Regressions 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 5: Weather-Induced Yield Shocks and the Effect on Employment

	(1a)	(1b)	(1c)	(1d)
Panel A: Farm Employment (BEA)				
Log Yield	0.266**	0.179*	0.057	0.221
	(0.116)	(0.096)	(0.130)	(0.158)
Panel B: Non-Farm Employment (BEA)				
Log Yield	0.330***	0.384***	0.435***	0.403***
	(0.082)	(0.083)	(0.123)	(0.112)
Observations	7074	7074	7074	7074
Counties	892	892	892	892
Time Trend	Linear	Quad.	St-Quad.	County

Notes: Table regresses changes in employment on instrumented log yield shocks. Panels use the same 5-year intervals as the migration regressions in Table 3. Columns (a)-(d) differ by the included time controls: column (a) includes a common linear time trend, column (b) includes a common quadratic time trend, column (c) includes state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 6: Yield Shocks and Government Transfers

	(1a)	(1b)	(1c)
Panel A: OLS			
Log Yield	0.071	0.064	0.184
	(0.271)	(0.219)	(0.238)
Panel B: Spline in Extreme Heat			
Log Yield	-1.402***	-1.118***	-0.918***
	(0.329)	(0.258)	(0.253)
Observations	520	520	520
States	13	13	13
Time Trend	Linear	Quad.	St-Quad.

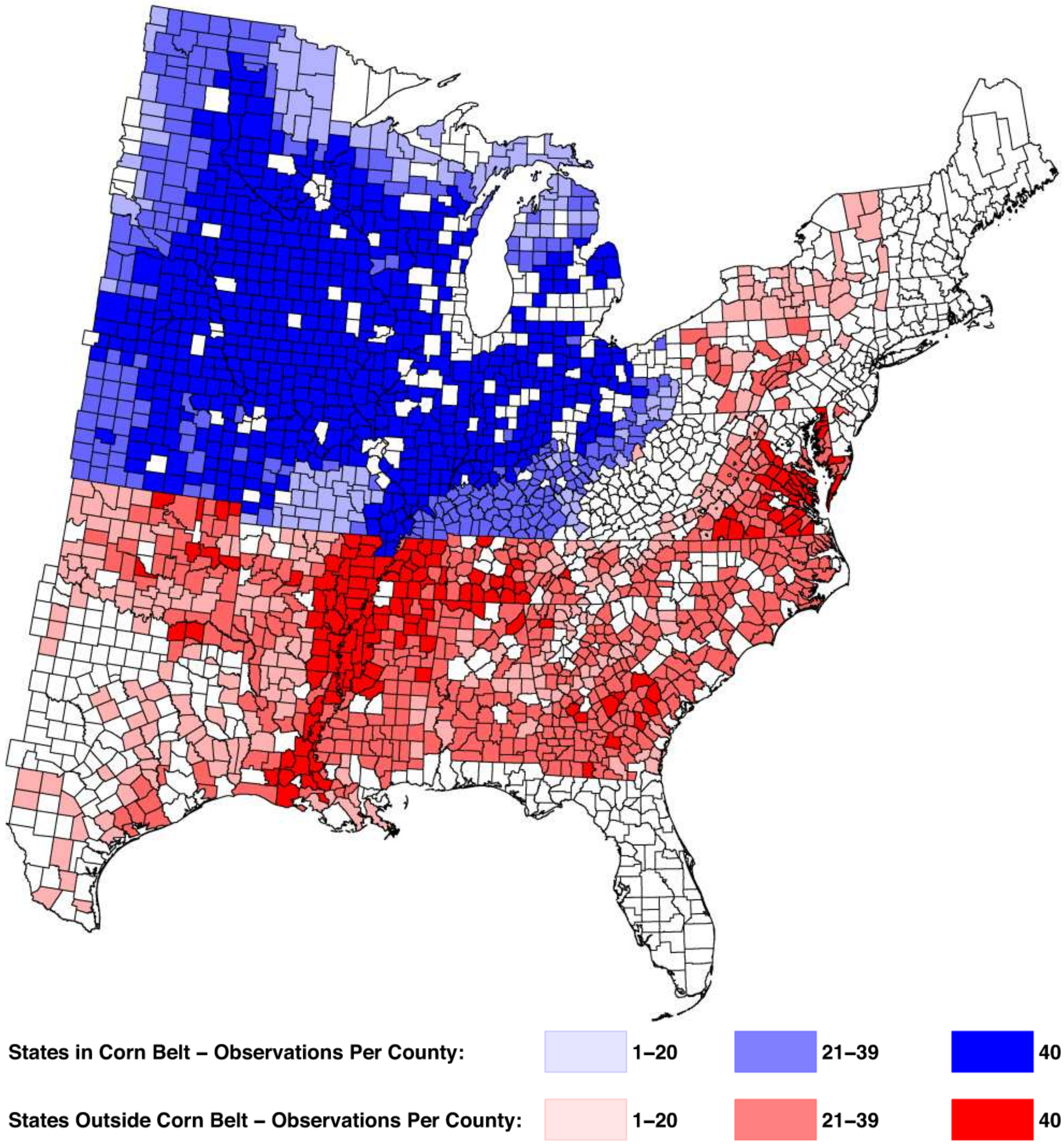
Notes: Table regresses annual state-level log government transfers on log corn yield shocks. Panel A uses uninstrumented yield shocks while Panel B instruments yield shocks with the time-varying sensitivity to extreme heat of columns (1a)-(1c) in Table 3. Columns (a)-(c) differ by the included time controls: column (a) includes a common linear time trend, column (b) includes a common quadratic time trend, and column (c) includes state-specific quadratic time trends. 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 7: Weather-Induced Yield Shocks and Net Outmigration - Price Feedbacks

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Log Yield	-0.308***	-0.266***	-0.288***	-0.370***	0.022	0.041	0.002	-0.057
	(0.067)	(0.060)	(0.073)	(0.078)	(0.054)	(0.046)	(0.093)	(0.114)
Global Shock	0.848***	1.437***	1.441***	0.839***	-0.073	0.150	0.139	-0.164
	(0.190)	(0.258)	(0.271)	(0.248)	(0.121)	(0.158)	(0.143)	(0.171)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

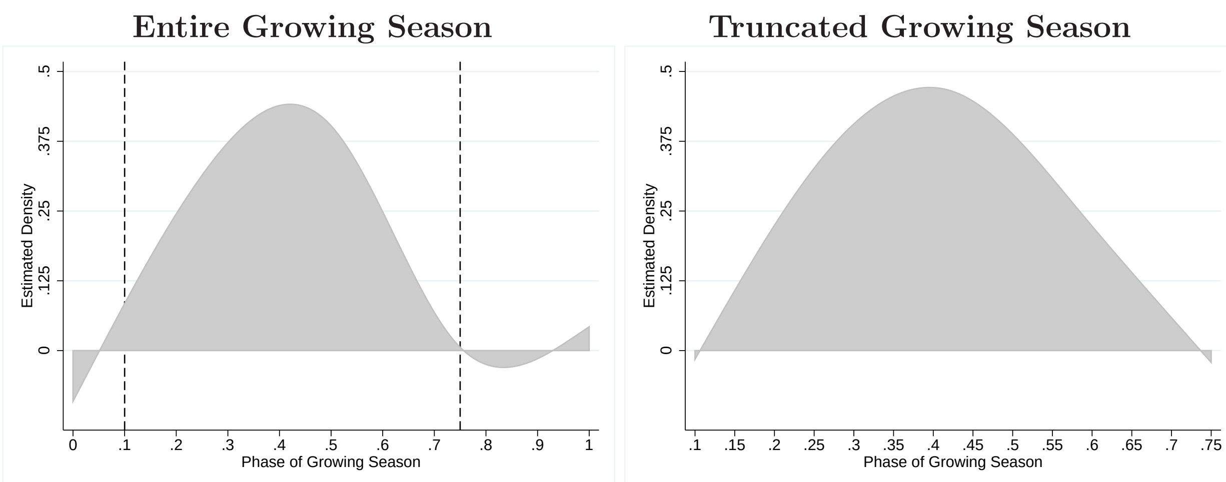
Notes: Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Regressions additionally include the global log corn yield shock as a control, which has been shown to impact global food prices. Results are given for counties inside the corn belt in columns (1a)-(1d) and outside the corn belt in columns (2a)-(2d). Columns (a)-(d) differ by the included time controls: columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

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



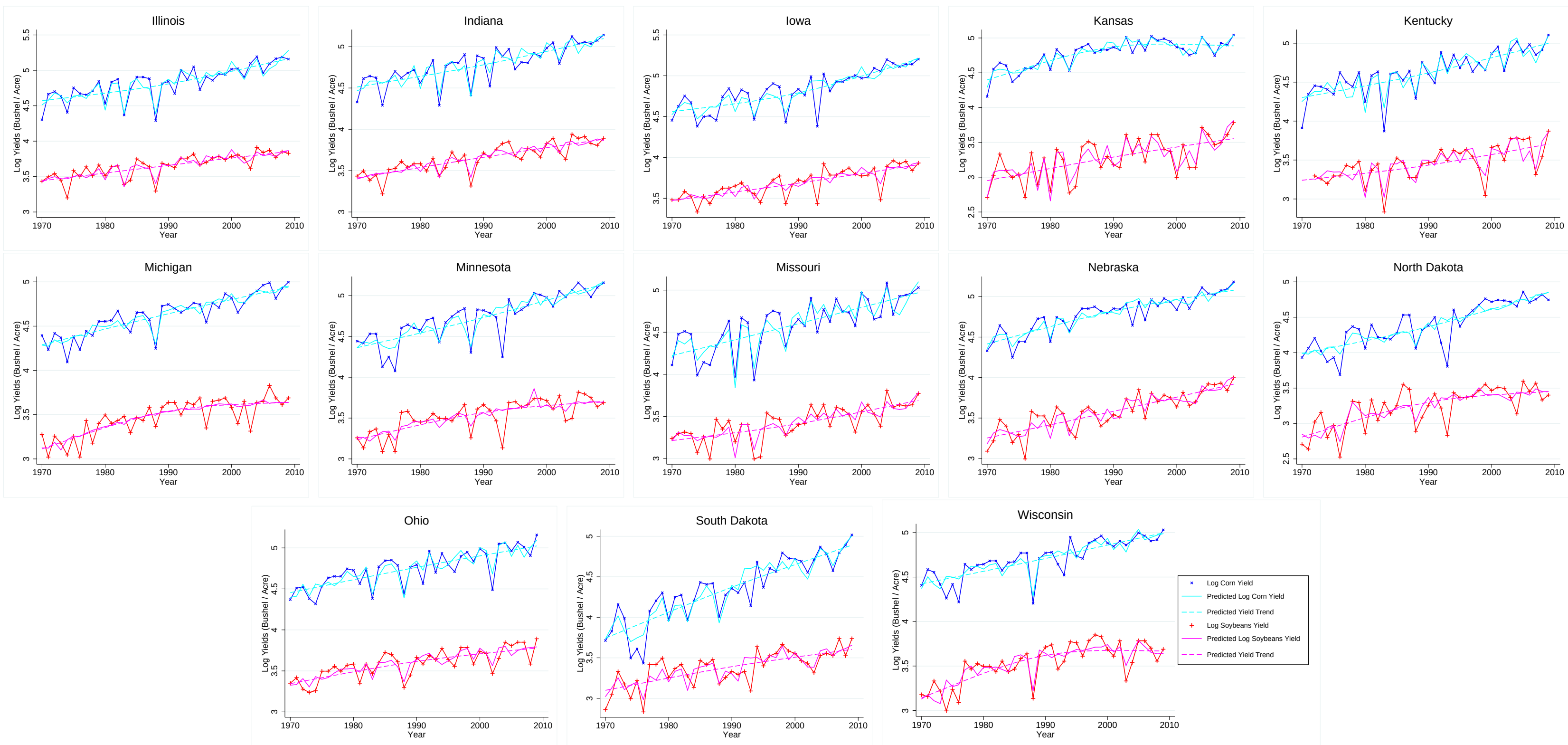
Notes: The left figure displays rural counties (population less than 100000) in the eastern United States (east of the 100 degree meridian except for Florida) where migration and yield data are available. States covering the corn belt are shown in blue, while other states are shown in red. Different shading indicate the number of observations in the county for which we have data.

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



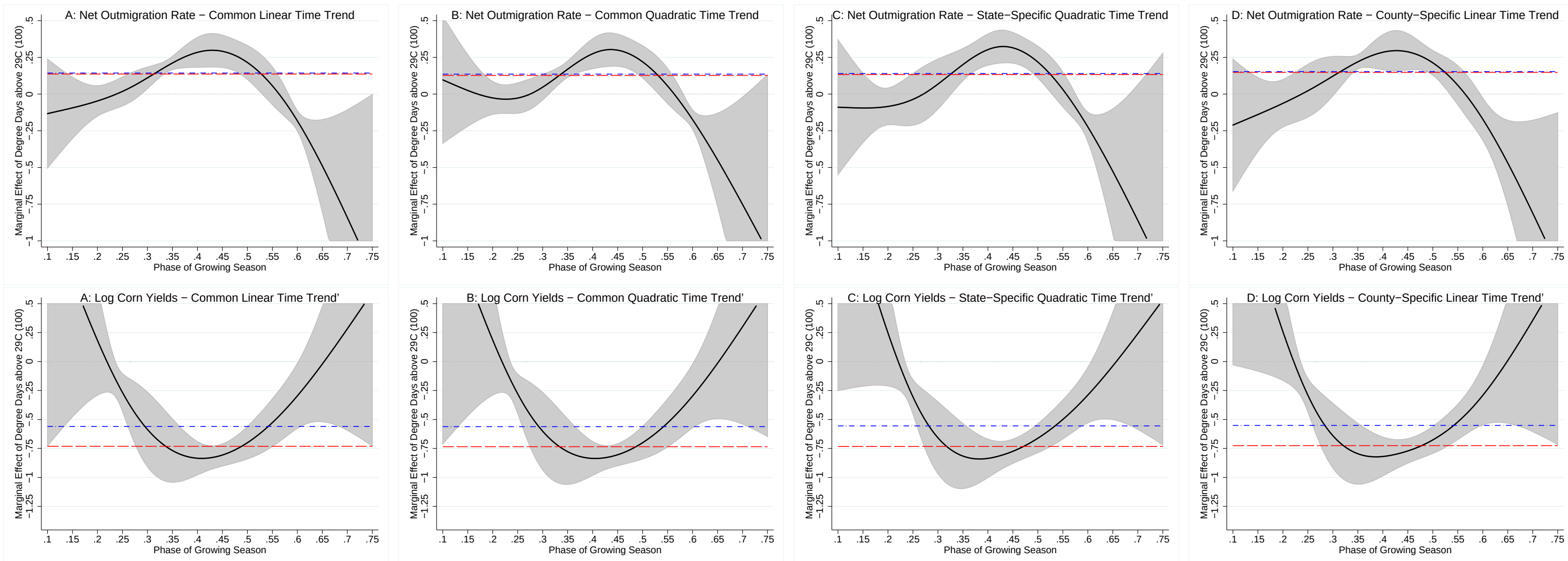
Notes: Both graphs display the average exposure to degree days above 29°C over the growing season in counties of the corn belt, where 0 corresponds to planting and 1 to harvest. The density is approximated using a restricted cubic spline with 5 knots. The left graph uses the entire growing season $[0, 1]$, 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



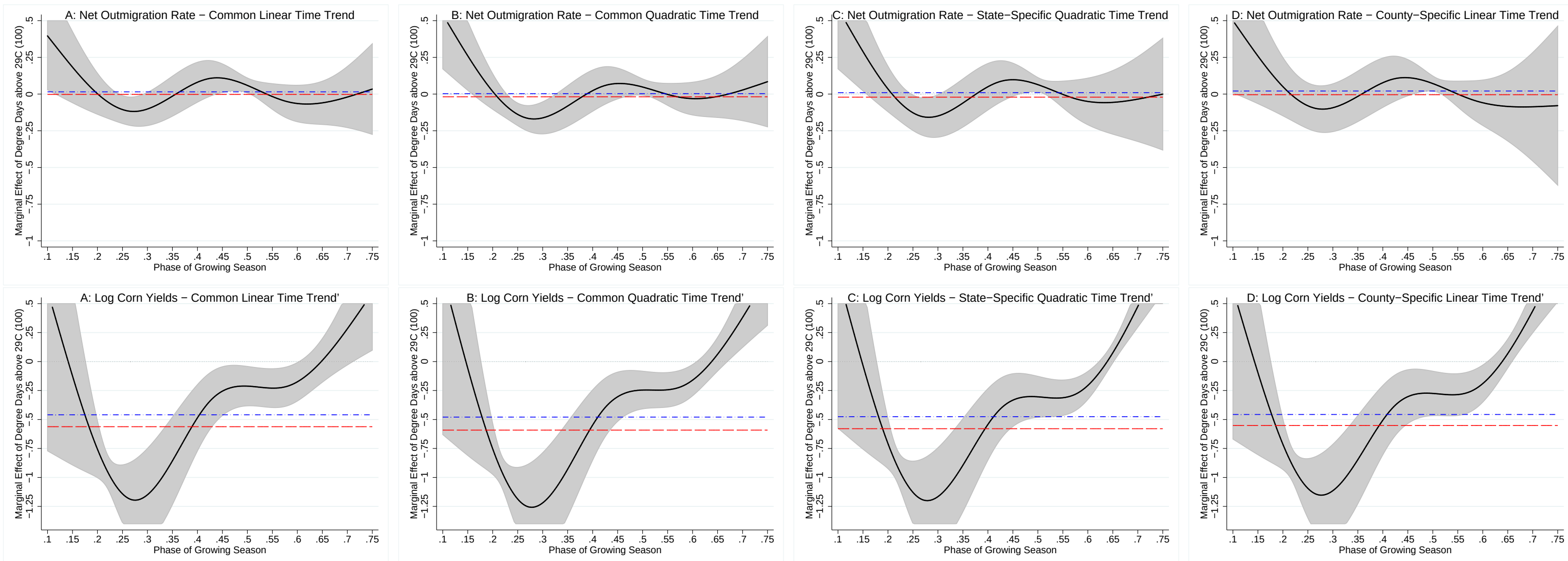
Notes: State-level yields, yield trends, and predicted yields for the 13 states in the Corn Belt. Predicted yields are derived from the baseline model using the seasonality of extreme heat over the truncated growing season.

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



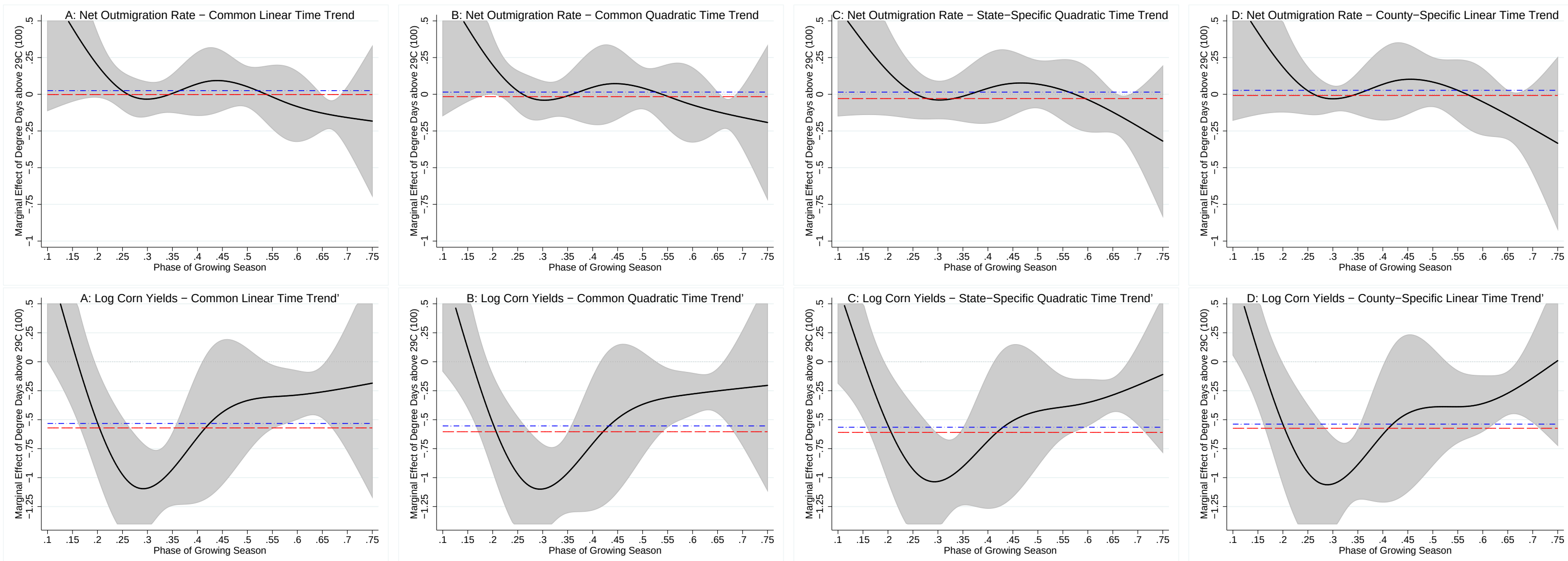
Notes: Figure replicates Figure 2 except that the growing season is the same for all counties and set to equal the average of all counties in the Eastern United States. Panels displays how the sensitivity to extreme heat (degree days above 29°C) vary over the growing season, i.e., the marginal effect 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 linear 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 in the corn Belt. Columns differ by the included time control, which are respectively, a common linear time trend, a common quadratic time trend, state-specific quadratic time trends, and county-specific linear time trends.

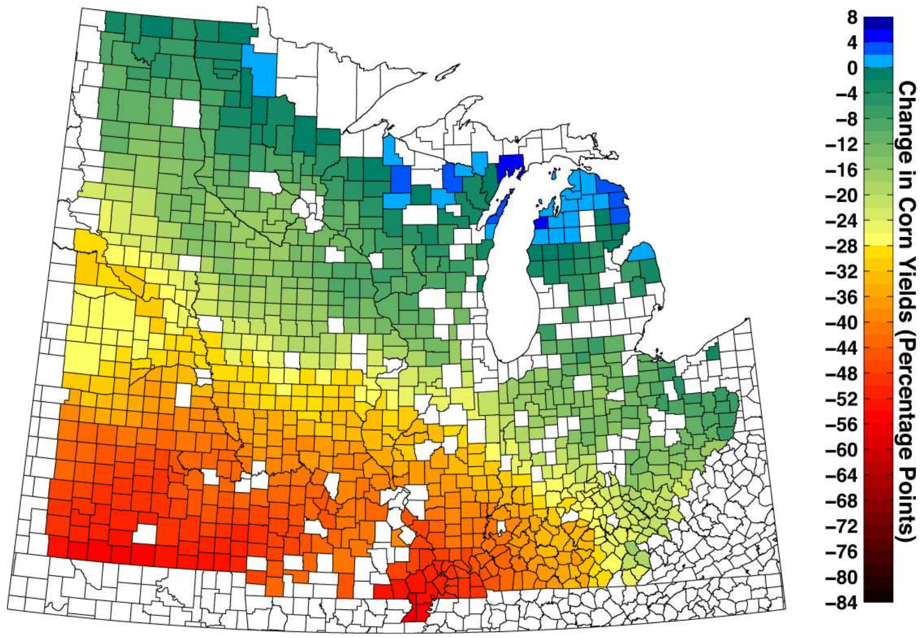
Figure A6: Seasonality in Response to Extreme Heat - Counties Outside Corn Belt (Counties in States with Planting Dates)



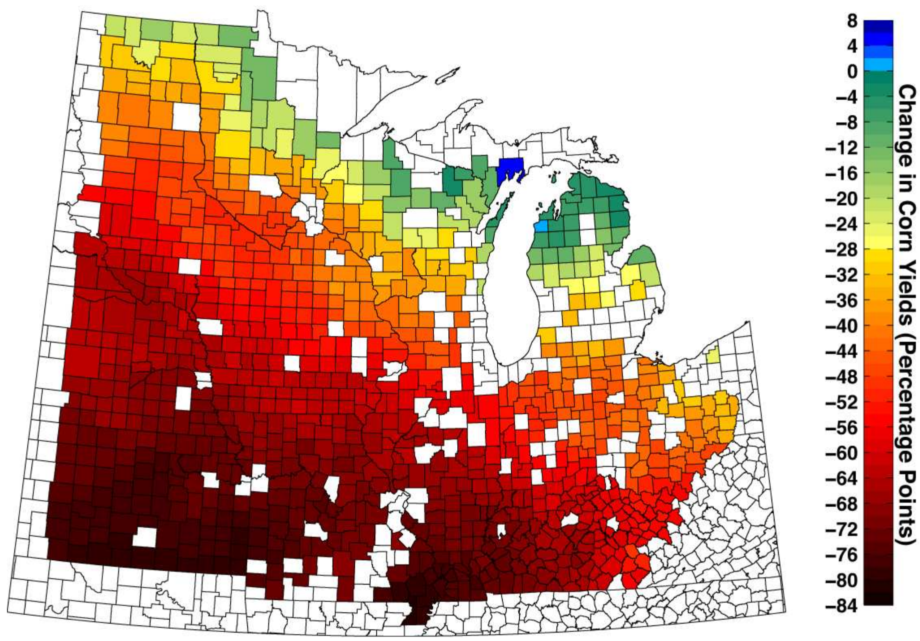
Notes: Figure replicates Figure 2 except that only counties in states that have planting dates are used in the analysis. The number of counties decreases from 746 to 444. Panels displays how the sensitivity to extreme heat (degree days above 29°C) vary over the growing season, i.e., the marginal effect 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 linear time trends.

Figure A7: Predicted Changes in Corn Yields Under Hadley III - B2 Scenario

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



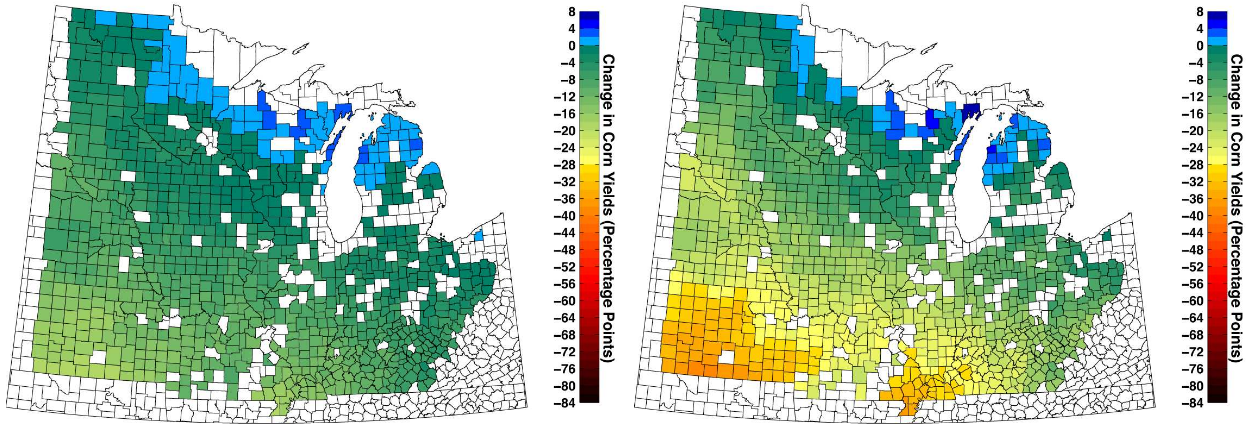
Panel B: Predicted Impact by End of Century (2070-2099)



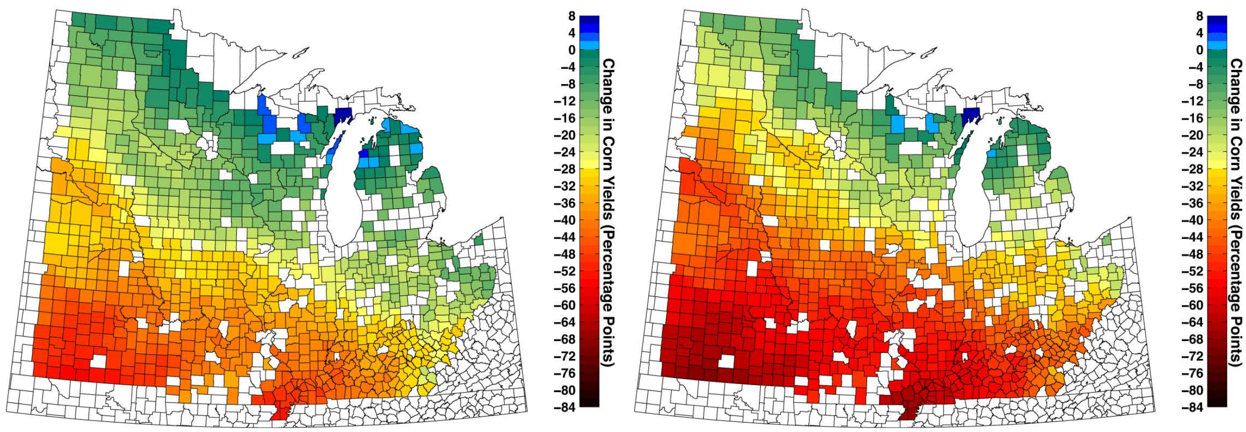
Notes: Panels display predicted changes in corn yields under the Hadley III - B2 clmate change scenario for counties in the Corn Belt using the regression results of column (1d) in Panel A of Table A3. Panel A shows predicted impacts by the middle of the century (2020-2049) compared to a 1960-1989 baseline. The bottom panel shows predicted impacts by the end of the century (2070-2099) compared to 1960-1989. Figures A8 and A9 show the results for uniform temperature and precipitation scenarios.

Figure A8: Predicted Changes in Corn Yields (Uniform Temperature Scenarios)

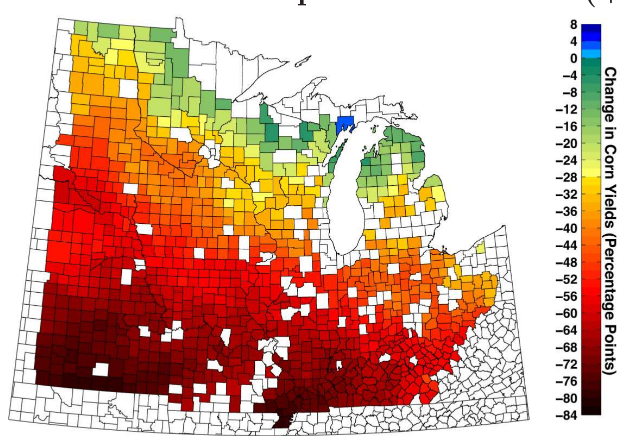
Panel A: Uniform Temperature Increase (+1°C and +2°C)



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

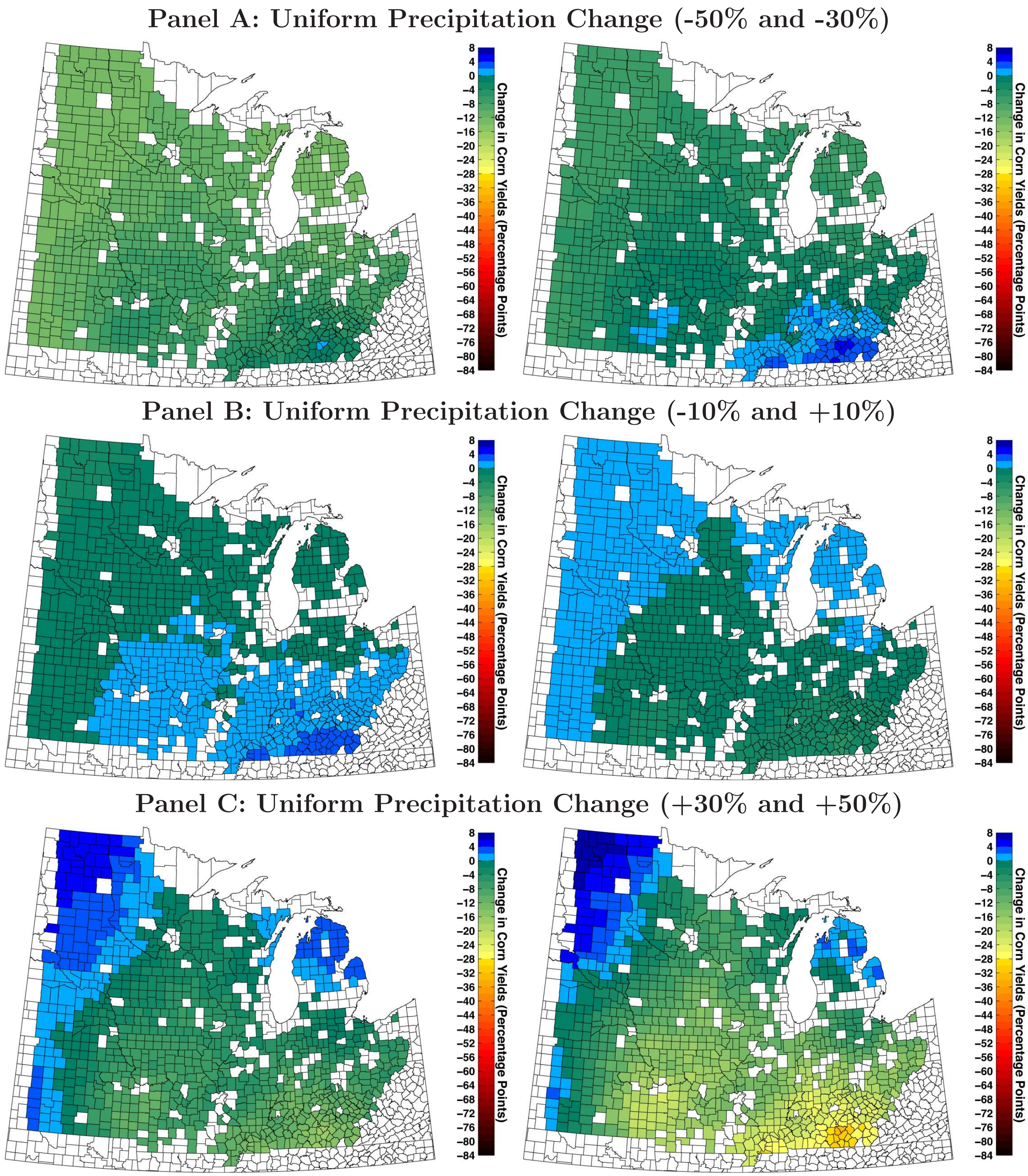


Panel C: Uniform Temperature Increase (+5°C)



Notes: Panels display predicted changes in corn yields under uniform temperature increases ranging from +1°C to +5°C for counties in the Corn Belt using the regression results of column (1d) in Panel A of Table A3.

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



Notes: Panels display predicted changes in corn yields under uniform precipitation changes ranging from -50% to +50% for counties in the Corn Belt using the regression results of column (1d) in Panel A of Table A3.

Table A1: Descriptive Statistics: Counties with Corn Yields

	Data Over 5-Year Periods							
	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09
Panel A: 892 Counties in Corn Belt								
Migration Rate Age [15,60) (%)	-1.34	0.69	4.96	4.75	-1.22	-0.60	1.35	2.53
(s.d.)	(7.75)	(6.97)	(4.72)	(5.97)	(5.63)	(6.70)	(5.75)	(4.59)
Migration Rate Males [15,60) (%)	-1.90	0.88	5.16	4.98	-1.09	-1.33	1.34	2.56
(s.d.)	(8.10)	(7.06)	(5.21)	(6.37)	(6.02)	(7.62)	(5.94)	(5.50)
Migration Rate Females [15,60) (%)	-0.88	0.46	4.74	4.53	-1.35	0.15	1.34	2.46
(s.d.)	(7.57)	(7.04)	(4.60)	(5.74)	(5.48)	(6.41)	(5.78)	(4.59)
Migration Rate Age [15,30) (%)	0.10	4.84	10.25	11.08	4.25	5.68	3.09	15.17
(s.d.)	(10.81)	(9.81)	(7.11)	(9.12)	(8.23)	(11.30)	(13.93)	(9.64)
Migration Rate Age [30,45) (%)	-3.48	-2.56	2.37	1.36	-4.24	-5.30	-0.12	-3.99
(s.d.)	(6.94)	(6.84)	(4.42)	(4.95)	(6.41)	(7.15)	(3.93)	(6.28)
Migration Rate Age [45,59) (%)	-1.49	-2.49	-0.77	-0.49	-4.18	-1.17	1.24	-3.44
(s.d.)	(6.78)	(6.49)	(5.39)	(5.82)	(6.36)	(7.96)	(2.70)	(5.79)
Migration Rate Age [60,oo) (%)	2.80	1.52	2.29	3.01	2.72	1.14	2.78	1.22
(s.d.)	(3.65)	(3.14)	(2.59)	(2.93)	(3.00)	(3.63)	(2.94)	(3.98)
Corn Area (1000 acres)	48.8	55.2	54.0	52.5	56.0	57.7	60.1	65.9
(s.d.)	(49.4)	(56.0)	(54.2)	(52.1)	(56.4)	(56.9)	(56.5)	(61.2)
Corn Yield (bushel/acre)	77.0	86.9	89.7	101.7	107.7	114.5	128.8	139.9
(s.d.)	(18.1)	(19.7)	(20.4)	(21.0)	(22.1)	(20.5)	(24.6)	(27.0)
Degree Days 10-29° C	1432	1463	1435	1517	1418	1422	1453	1465
(s.d.)	(250)	(248)	(240)	(242)	(262)	(240)	(265)	(256)
Degree Days Above 29° C	34.8	35.5	44.8	42.2	27.0	31.4	32.0	32.1
(s.d.)	(26.9)	(26.0)	(33.8)	(21.7)	(22.6)	(22.4)	(29.1)	(24.8)
Precipitation (mm)	538.3	557.0	552.4	497.6	575.2	588.4	558.8	556.4
(s.d.)	(112.2)	(103.0)	(96.8)	(76.7)	(84.8)	(103.3)	(101.4)	(100.8)
Panel B: 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)

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

Table A2: Descriptive Statistics: Counties with Soybean Yields

	Data Over 5-Year Periods							
	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09
	Panel A: 810 Counties in Corn Belt							
Migration Rate Age [15,60) (%)	-0.97	0.89	5.12	5.02	-0.95	-0.22	1.47	2.54
(s.d.)	(6.99)	(6.23)	(4.51)	(5.72)	(5.35)	(6.28)	(5.72)	(4.59)
Migration Rate Males [15,60) (%)	-1.55	1.04	5.31	5.25	-0.81	-0.93	1.45	2.59
(s.d.)	(7.31)	(6.33)	(5.03)	(6.13)	(5.69)	(7.08)	(5.90)	(5.52)
Migration Rate Females [15,60) (%)	-0.47	0.72	4.93	4.80	-1.09	0.50	1.47	2.45
(s.d.)	(6.91)	(6.33)	(4.38)	(5.47)	(5.25)	(6.03)	(5.77)	(4.60)
Migration Rate Age [15,30) (%)	0.37	4.82	10.29	11.30	4.45	5.94	3.36	14.99
(s.d.)	(10.03)	(9.16)	(6.97)	(8.97)	(8.08)	(10.93)	(13.73)	(9.50)
Migration Rate Age [30,45) (%)	-3.09	-2.21	2.53	1.53	-3.97	-5.03	-0.06	-4.11
(s.d.)	(6.35)	(6.24)	(4.29)	(4.80)	(6.15)	(7.08)	(3.92)	(6.24)
Migration Rate Age [45,59) (%)	-0.98	-2.06	-0.39	-0.03	-3.83	-0.52	1.26	-3.13
(s.d.)	(5.79)	(5.61)	(4.93)	(5.26)	(6.09)	(7.00)	(2.73)	(5.23)
Migration Rate Age [60,oo) (%)	2.87	1.59	2.29	3.01	2.71	1.40	2.78	1.25
(s.d.)	(3.39)	(2.96)	(2.42)	(2.85)	(2.80)	(3.37)	(2.85)	(3.51)
Soybean Area (1000 acres)	54.5	61.5	59.4	57.9	61.6	63.4	64.8	70.6
(s.d.)	(49.7)	(56.1)	(54.3)	(52.0)	(56.4)	(56.9)	(56.3)	(61.0)
Soybean Yield (bushel/acre)	80.3	89.1	91.4	103.9	110.0	116.9	131.1	142.3
(s.d.)	(16.8)	(18.8)	(20.3)	(20.7)	(21.6)	(19.9)	(23.7)	(26.2)
Degree Days 10-30° C	1456	1481	1450	1533	1432	1434	1464	1478
(s.d.)	(237)	(234)	(229)	(229)	(251)	(232)	(257)	(248)
Degree Days Above 30° C	36.3	37.0	46.6	43.8	28.1	32.5	33.2	33.1
(s.d.)	(27.3)	(26.6)	(34.1)	(21.7)	(23.0)	(22.8)	(29.7)	(25.5)
Precipitation (mm)	548.2	561.1	558.0	499.0	578.7	591.5	559.6	560.9
(s.d.)	(112.3)	(96.5)	(95.9)	(77.0)	(81.5)	(99.0)	(98.4)	(97.5)
	Panel B: 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)

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)
Panel A: Annual Data								
Degree Days 10-29°C (1000)	0.427***	0.427***	0.449***	0.443***	-0.003	0.014	0.057	0.024
	(0.104)	(0.104)	(0.103)	(0.104)	(0.098)	(0.100)	(0.086)	(0.093)
Degree Days 29°C (100)	-0.731***	-0.735***	-0.732***	-0.726***	-0.562***	-0.592***	-0.579***	-0.552***
	(0.112)	(0.112)	(0.109)	(0.112)	(0.092)	(0.093)	(0.090)	(0.096)
Precipitation (m)	0.167***	0.166***	0.154***	0.156***	0.043	0.035	0.042	0.055
	(0.037)	(0.038)	(0.035)	(0.034)	(0.036)	(0.038)	(0.038)	(0.037)
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.014***	-0.014***	-0.004	-0.003	-0.003	-0.004
	(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	21.2	15.7	14.2	12.2	13.8
R-squared	0.6126	0.6130	0.6325	0.6525	0.5040	0.5195	0.5842	0.5908
Observations	34788	34788	34788	34788	26124	26124	26124	26124
Counties	892	892	892	892	746	746	746	746
Panel B: 5 Year Intervals								
Degree Days 10-29°C (1000)	0.640***	0.640***	0.766***	0.791***	-0.178	-0.180	0.233	0.018
	(0.139)	(0.142)	(0.140)	(0.145)	(0.242)	(0.261)	(0.192)	(0.239)
Degree Days 29°C (100)	-0.569***	-0.584***	-0.525***	-0.498***	-0.220***	-0.294***	-0.262***	-0.179*
	(0.090)	(0.095)	(0.080)	(0.086)	(0.071)	(0.076)	(0.055)	(0.086)
Precipitation (m)	0.178***	0.177***	0.152***	0.160***	0.089	0.061	0.040	0.094
	(0.026)	(0.025)	(0.025)	(0.025)	(0.072)	(0.072)	(0.044)	(0.057)
Precipitation Squared (m^2)	-0.015***	-0.015***	-0.013***	-0.014***	-0.009	-0.007	-0.003	-0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.004)
F-stat (1st stage)	24	27	23	46	12	11	9	3
R-squared	0.8370	0.8374	0.8623	0.8918	0.0334	0.0457	0.0488	0.0363
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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: columns (a) include a common linear time trend, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A4: Weather and Crop Yields - Panel of Annual Soybean Yields

	Counties Inside Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A: Annual Data								
Degree Days 10-30°C (1000)	0.501***	0.500***	0.513***	0.524***	0.287***	0.278***	0.269***	0.279***
	(0.050)	(0.048)	(0.049)	(0.054)	(0.071)	(0.073)	(0.073)	(0.069)
Degree Days 30°C (100)	-0.644***	-0.656***	-0.662***	-0.657***	-0.572***	-0.558***	-0.558***	-0.564***
	(0.037)	(0.040)	(0.041)	(0.039)	(0.028)	(0.029)	(0.031)	(0.031)
Precipitation (m)	0.171***	0.168***	0.161***	0.161***	0.120***	0.124***	0.124***	0.128***
	(0.026)	(0.025)	(0.023)	(0.025)	(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	86.6	185.8	171.3	189.5	175.8
R-squared	0.5334	0.5386	0.5603	0.5671	0.4056	0.4104	0.4304	0.4542
Observations	31154	31154	31154	31154	20492	20492	20492	20492
Counties	810	810	810	810	595	595	595	595
Panel B: 5 Year Intervals								
Degree Days 10-30°C (1000)	0.480***	0.489***	0.535***	0.637***	0.585***	0.591***	0.419***	0.672***
	(0.103)	(0.109)	(0.097)	(0.125)	(0.113)	(0.121)	(0.124)	(0.108)
Degree Days 30°C (100)	-0.646***	-0.743***	-0.778***	-0.702***	-0.547***	-0.493***	-0.511***	-0.490***
	(0.067)	(0.048)	(0.041)	(0.056)	(0.055)	(0.081)	(0.072)	(0.063)
Precipitation (m)	0.140***	0.135***	0.114***	0.125**	0.020	0.036	0.025	0.055
	(0.032)	(0.022)	(0.032)	(0.044)	(0.052)	(0.047)	(0.043)	(0.053)
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)	(0.004)
F-stat (1st stage)	34	162	265	42	30	18	22	36
R-squared	0.7638	0.7842	0.8180	0.8203	0.1908	0.1582	0.1796	0.2306
Observations	6413	6413	6413	6413	4442	4442	4442	4442
Counties	810	810	810	810	595	595	595	595
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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 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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A5: Weather and Migration

	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***	0.176***	0.134	0.134	0.147	0.161
	(0.053)	(0.050)	(0.047)	(0.056)	(0.082)	(0.086)	(0.092)	(0.120)
Degree Days 29°C (1000)	0.137***	0.127***	0.133***	0.148***	-0.002	-0.018	-0.021	-0.004
	(0.034)	(0.033)	(0.037)	(0.038)	(0.023)	(0.023)	(0.029)	(0.033)
Precipitation (m)	0.019	0.018	0.018	0.022*	-0.000	-0.006	-0.017	-0.008
	(0.011)	(0.012)	(0.013)	(0.011)	(0.013)	(0.011)	(0.012)	(0.014)
Precipitation Squared (m^2)	-0.001	-0.001	-0.001	-0.002	-0.000	0.000	0.001	-0.000
	(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	26.5	2.8	1.7	3.7	4.6
R-squared	0.1039	0.1087	0.1302	0.3141	0.0062	0.0131	0.0380	0.1863
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A6: Weather-Induced Yield Shocks and Net Outmigration - Growing Season

	Counties in 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***	-0.397***	-0.126	-0.082	-0.094	-0.197
	(0.071)	(0.069)	(0.093)	(0.090)	(0.144)	(0.115)	(0.157)	(0.163)
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***	-0.256***	0.018	0.049	0.025	-0.073
	(0.048)	(0.047)	(0.045)	(0.047)	(0.059)	(0.050)	(0.098)	(0.131)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
				C: Average Planting Dates outside Corn Belt				
Log Yield					0.022	0.038	-0.004	-0.054
					(0.055)	(0.048)	(0.098)	(0.113)
Observations					5628	5628	5628	5628
Counties					746	746	746	746
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A7: 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)
	Panel A: Instrumenting Corn Yields							
	Panel A - Baseline: Age [15,60)							
Log Yield	-0.320***	-0.305***	-0.337***	-0.397***	-0.175***	-0.156***	-0.125***	-0.135***
	(0.071)	(0.069)	(0.093)	(0.090)	(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
	Panel B: Instrumenting Soybean Yields							
Log Yield	-0.175**	-0.191**	-0.195**	-0.175**	-0.183***	-0.155***	-0.144***	-0.164***
	(0.087)	(0.084)	(0.091)	(0.088)	(0.064)	(0.049)	(0.049)	(0.060)
Observations	6413	6413	6413	6413	6413	6413	6413	6413
Counties	810	810	810	810	810	810	810	810
	Panel C: Instrumenting Weighted Average of Corn and Soybean Yields							
Log Yield	-0.281***	-0.262***	-0.272***	-0.296**	-0.176***	-0.158***	-0.145***	-0.147***
	(0.093)	(0.081)	(0.105)	(0.116)	(0.045)	(0.036)	(0.043)	(0.050)
Observations	7086	7086	7086	7086	7086	7086	7086	7086
Counties	892	892	892	892	892	892	892	892
Time Trend	Linear	Quad.	St-Quad.	County	Linear	Quad.	St-Quad.	County

Notes: Table regresses log yields on different set of weather instruments: columns (2a)-(2d) continue to use the seasonality in the sensitivity to extreme heat, while columns (1a)-(1d) use the four weather variables of Schlenker & Roberts (2009). Panel A use log corn yields, Panel B uses log soybean yields, and 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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

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

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A: Baseline: Weighted Regression - Less than 100,000 Inhabitants								
Log Yield	-0.320***	-0.305***	-0.337***	-0.397***	0.022	0.038	-0.004	-0.054
	(0.071)	(0.069)	(0.093)	(0.090)	(0.055)	(0.048)	(0.098)	(0.113)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Panel B1: Unweighted Regression - Less than 100,000 Inhabitants								
Log Yield	-0.310***	-0.309***	-0.360***	-0.431***	0.040	0.051	0.011	-0.035
	(0.069)	(0.066)	(0.103)	(0.092)	(0.054)	(0.049)	(0.094)	(0.112)
Panel B2: Same as B1 with Bootstrapped Errors								
Log Yield	-0.310***	-0.309***	-0.360**	-0.431**	0.040	0.051	0.011	-0.035
	(0.090)	(0.104)	(0.148)	(0.184)	(0.052)	(0.051)	(0.093)	(0.180)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
Panel C: Unweighted Regression - All Counties								
Log Yield	-0.301***	-0.298***	-0.349***	-0.415***	0.044	0.057	0.036	-0.006
	(0.064)	(0.061)	(0.099)	(0.087)	(0.052)	(0.047)	(0.086)	(0.104)
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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties that had at least 21 yield observations in 1970-2009. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A9: Weather-Induced Yield Shocks and Net Outmigration - Subsets of Data

	Counties in Corn Belt				Counties Outside Corn Belt			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	Panel A - Baseline: Age [15,60)							
Log Yield	-0.320***	-0.305***	-0.337***	-0.397***	0.022	0.038	-0.004	-0.054
	(0.071)	(0.069)	(0.093)	(0.090)	(0.055)	(0.048)	(0.098)	(0.113)
Observations	7078	7078	7078	7078	5628	5628	5628	5628
Counties	892	892	892	892	746	746	746	746
	Panel B: Counties With At Least 1 Yield Observations							
Log Yield	-0.316***	-0.300***	-0.333***	-0.391***	0.034	0.049	0.015	-0.028
	(0.071)	(0.069)	(0.092)	(0.089)	(0.043)	(0.038)	(0.068)	(0.086)
Observations	7244	7244	7244	7244	6468	6468	6468	6468
Counties	935	935	935	935	973	973	973	973
	Panel C: Counties with All 40 Yield Observations							
Log Yield	-0.392***	-0.377***	-0.428***	-0.463***	-0.092	-0.047	-0.094	-0.150
	(0.084)	(0.082)	(0.103)	(0.105)	(0.104)	(0.094)	(0.157)	(0.136)
Observations	5608	5608	5608	5608	1808	1808	1808	1808
Counties	701	701	701	701	226	226	226	226
	Panel 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
	Panel 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-Quad.	County	Linear	Quad.	St-Quad.	County

Notes: Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panel A is the same as in 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 and E exclude sub-periods of the 1980s when agriculture when through a large boom and bust cycle. 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, columns (b) include a common quadratic time trend, columns (c) include state-specific quadratic time trends, and columns (d) include county-specific linear trends. Regressions include counties with at most 100,000 inhabitants in 2000 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A10: Predicted Changes in Corn Yields Under Climate Change

	Predicted Changes in Corn Yields				Counties With Increased Yields		Counties with Decreased Yields	
	Mean	SDev	Min	Max	Total N	Sign. N	Total N	Sign. N
Hadley III-B2 (2020-2049)	-24.92	(14.52)	-56.94	5.28	28	5	864	842
Hadley III-B2 (2070-2099)	-54.64	(17.87)	-80.17	4.18	2	0	890	885
Uniform +1° C	-6.77	(4.91)	-19.81	3.37	69	21	823	759
Uniform +2° C	-15.95	(9.44)	-38.39	6.03	41	6	851	818
Uniform +3° C	-26.91	(13.09)	-54.79	7.41	14	1	878	848
Uniform +4° C	-38.82	(15.50)	-68.40	6.84	4	1	888	877
Uniform +5° C	-50.76	(16.51)	-79.15	3.71	1	0	891	888
Uniform -50% Precipitation	-9.03	(3.00)	-13.17	0.97	2	0	890	868
Uniform -30% Precipitation	-3.01	(2.68)	-7.14	5.40	144	42	748	674
Uniform -10% Precipitation	-0.15	(1.18)	-2.15	3.37	396	237	496	395
Uniform +10% Precipitation	-0.70	(1.44)	-4.75	1.92	313	243	579	488
Uniform +30% Precipitation	-4.51	(4.89)	-17.54	4.99	193	157	699	632
Uniform +50% Precipitation	-11.10	(8.74)	-32.92	6.98	115	74	777	719

Notes: Tables displays predicted changes in corn yields under various climate change scenarios for the regression model in column (1d) of Table A5. The first two rows use medium and long-term projections under the Hadley III - B2 scenario. The remaining columns display predicted changes under uniform climate change scenarios. The first four columns summarize the predicted change in net outmigration rates. The last four columns give the number of counties that are predicted to have an increase or a decrease in net outmigration rates. For each category we give the total number of counties as well as the number of counties that have a statistically significant increase or decrease. The spatial distribution of impacts is given in Figures A7 for the first two rows and Figures A8 and A9 in the appendix for the remaining uniform scenarios.