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ABSTRACT

We investigate the link between agricultural productivity and net migration in the United States using a county-level panel for the most recent period of 1970-2009. In rural counties of the Corn Belt, we find a statistically significant relationship between changes in net outmigration and climate-driven changes in crop yields, with an estimated semi-elasticity of about -0.17, i.e., a 1% decrease in yields leads to a 0.17% net reduction of the population through migration. This effect is primarily driven by young adults. We do not detect a response for senior citizens, nor for the general population in eastern counties outside the Corn Belt. Applying this semi-elasticity to predicted yield changes under the B2 scenario of the Hadley III model, we project that, holding other factors constant, climate change would on average induce 3.7% of the adult population (ages 15-59) to leave rural counties of the Corn Belt in the medium term (2020-2049) compared to the 1960-1989 baseline, with the possibility of a much larger migration response in the long term (2077-2099). Since there is uncertainty about future warming, we also present projections for a range of uniform climate change scenarios in temperature or precipitation.

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

Such changes will inevitably bring substantial challenges to the U.S. economy and society. In this paper, we investigate one such effect - how climate change might alter economic conditions through changes in agricultural productivity and ultimately mobility of individuals in rural agricultural areas of the Corn Belt. We focus on the agricultural linkage because, unlike sudden events such as hurricanes and flooding, changes in agricultural productivity are expected to have an enduring effect on the geographic distribution of the U.S. population. We utilize an instrumental variables approach where average 5-year county-level crop yields are instrumented with observed weather shocks to estimate the effect of changes in agricultural productivity (crop yields) on migration patterns. One potential concern of such an approach is that weather might directly impact migration patterns. When we replicate the analysis for areas where agriculture is a smaller fraction of the local economy, i.e., urban areas or rural areas in the eastern United States outside the Corn Belt, we find no significant migration response to yield changes. Moreover, we find the largest migration response for young people, and none for retired people, despite the fact that there is a sizable retirement community in the southern United States due to a preference for climate. This suggests to us that the response to *changes* in 5-year weather averages is driven by economic opportunities and not the result of a direct preference for climate, e.g., a preference to live in areas with cool summer and less precipitation.

Recent research has suggested that climate change might have a significant adverse impact on U.S. agriculture, specifically due to an increase in extremely warm temperatures (Lobell & Asner 2003, Schlenker & Roberts 2009). There are two possible responses to changes in agricultural productivity: Individuals can either engage in beneficial adaptive responses or vote with their feet by leaving a county. Large-scale migration resulting from agricultural failures not only impacts people that move away and those who stay put. Some recent studies have also shown that the influx of migrants adversely affects economic prospects of local residents in destination areas and could stimulate further outmigration, thus producing a ripple effect (McIntosh 2008, Boustan, Fishback & Kantor 2010).

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.

Specifically, we draw on U.S. county-level data for 1970-2009, a period characterized by highly mechanized agriculture, to estimate the semi-elasticity of net outmigration to crop yields. We find that for areas where corn and soybeans are the major crop (hereafter referred to as "counties in the Corn Belt," which include all Midwestern states and Kentucky), the estimated semi-elasticity of outmigration with respect to climate-induced crop yields is about -0.17, i.e., holding everything else constant, a 1% decline in crop yields would induce approximately 0.17% of the adult population to out-migrate. To circumvent the possible endogeneity of crop yields, we instrument crop yields with observed weather patterns and hence only use deviations from yield trends that are due to observable weather patterns. This is crucial, as a simple OLS regression that does *not* instrument yields with observed weather finds a much smaller and generally insignificant relationship.

In view of the relatively small proportion of people directly employed in agriculture,[1] our estimated elasticity of migration with respect to yield may seem large. However, there might be considerable spillover effects from agriculture to other sectors of the economy, similar to what Hornbeck (2009) observed for "Dust Bowl" migrants. To shed further light on this issue we examine the responsiveness of overall employment to crop yields using state-level data for the period of 1970-2009. Consistent with the literature on the "DustBowl," we find that weather-induced yield shocks significantly impact non-farm employment. During years when agriculture is doing well, non-farm employment is expanding, while years with bad yields imply contractions in non-farm employment. The semi-elasticity for non-fram employment is larger than for farm employment.

Our estimated semi-elasticities are specific to the period of 1970-2009 and may change in the future depending on many factors, such as the structures of the economy, demographic profiles, and government policies. Nevertheless, we believe it is an informative exercise to use the best estimate available to make projections, in order to illustrate the possible magnitudes of future outmigration flows for counties of the Corn Belt, as further warming is expected to directly affect these agricultural areas in the United States. Our projections are ceteris paribus in nature and should not be regarded as predictions of what will actually happen in the future. Based on the Hadley III model B2 scenario, with other factors held constant, we find that climate change would on average induce around 3.7 percentage points of the adult (15-59) population in non-urban counties (less than 100,000 inhabitants) to migrate out of Corn Belt counties in the medium term (2020-2049) compared to a baseline of 1960-1989. The estimated outmigration effect increases to 11% in the long-term (2070-2099) as extreme heat is predicted to significantly increase under continued warming and adversely impact crop yields. Of course, long run projections should be interpreted with greater caution as

[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).

people's migration responses in the longer term might be considerably different from short-term responses.

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

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

1 Background

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

Agriculture has traditionally been an important driver of U.S. domestic migration flows.

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

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

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

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

While the "Dust Bowl" experience may be unique in American history, the extreme climatic conditions witnessed in the 1930s may become more frequent in current century as a consequence of global climate change. Recent researches suggests that climate change is expected to have significant negative impacts on crop yields in the United States. Lobell & Asner (2003) report that for each degree increase in growing season temperature, both corn and soybeans yields would decline by roughly 17%. Similarly, Schlenker & Roberts (2009) identify serious nonlinearities in the temperature-yield relationship. Increasing temperatures are beneficial for crop growth up to a point when they switch to becoming highly detrimental. These breakpoints vary by crop: 29°C or 84°F for corn, 30°C of 86°F for soybeans and 32°C or 90°F for cotton. The effect of being 1 degree above the optimal breakpoint is roughly ten times as bad 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 between land values and climate while controlling for other factors. The underlying assumption is that the

relationship between yield and climate/weather, and have not incorporated CO_2 fertilization effects and adaptation possibilities beyond what is found in the historic time series. At the same time, recent evidence suggests that the actual CO_2 effect on crop yield is still uncertain and may be considerably less significant than previously thought (Long et al. 2006). Assuming no breakthroughs in technology, potential gains from adaptation may also be limited and may require considerable financial investments.

The magnitudes of the possible impact of changing climate conditions on yields warrants careful examination of the 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

We model the relationship between net outmigration rate m_{it} in county i during the five-year interval started with year t as follows (consecutive observations in our panel are five years apart as the population data is reported every five years).

$$m_{it} = \alpha + \beta x_{it} + f(t) + c_i + \epsilon_{it} \tag{1}$$

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. Our key parameter of interest is β, the semi-elasticity of net outmigration with respect to the aver-

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.

age log yield during the 5-year period x_{it}.[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. Our baseline regression use quadratic time trends, i.e., $f(t) = \gamma_1 t + \gamma_2 t^2$. Finally, ϵ_{it} is the error term. Since ϵ_{it} might be spatially correlated, we cluster at the state level, which adjusts for arbitrary within-state correlations along both the cross-sectional and time-series dimensions.[4] In a sensitivity check, we also present results of an unweighted regression where we use a grouped bootstrap routine and draw all data for a 5-year interval with replacement, i.e., all counties that report in a given 5-year interval.

Because x_{it} may be correlated with ϵ_{it}, we only use corn and/or soybean yield shocks that are due to presumably exogenous variation in weather. In a sensitivity check, we present results from a simple OLS regression for comparison. The results are different from the IV regression. Yields have been trending upward over time, and we hence include again time controls $f(t)$. For example, Figure A1 in the appendix displays annual corn and soybean yields for the 13 states in the Corn Belt.[5] The figure displays actual yields as well as predicted yields using the four weather variables $\mathbf{W}_{it}$ of Schlenker & Roberts (2009): two degree days variables as well as a quadratic in total precipitation.[6] 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.

Formally, our IV regression is

$$x_{it} = \delta + \pi \mathbf{W}_{it} + f(t) + k_i + \nu_{it} \tag{2}$$

As stated above, x_{it} are log crop yields for county i during the 5-year interval starting in t. We again include county fixed effects k_i to control for baseline differences and cluster the

[3]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.

[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. Forthcoming).

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

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

error term ν_{it} at the state level. Since we use the same time controls $f(t)$ in both the first and second stage, the coefficient β is identified by deviations of the four weather variables $\mathbf{W}_{it}$ from their time trends, which are presumably exogenous.

In our empirical analysis below we use three yield shocks: log corn yields, log soybean yields, and the log of the adjusted average of the two. Both corn and soybeans yields are measured in bushels/acre, yet average productivity is significantly different. Corn yields are on average roughly three times as high. Since changes in average yields should not be driven by changing compositions of soybean and corn production, we need to adjust the yields to make them comparable. Regressions that use the log of the adjusted average yield therefore transform soybean yields into corn equivalents by multiplying them with the soybean to corn price ratio.[7] 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 $\mathbf{W}_{it}$. However, in case there is concern about the weighting of the two, we also present results using only corn yields (and the temperature thresholds specific to corn) as well as only soybean yields (and the temperature thresholds specific to soybeans), and consistently get comparable results.

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

2.2 Data and Summary Statistics

Since there is no reliable county-level migration data for the 40-year time period that we are focusing on, we use the residual approach to derive the outmigration ratio m_{it} for each

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

county for each five-year period between 1970 and 2009.[8] For example, for the 15-59 age group, the baseline model in our analysis, we use

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

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

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

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

To construct the net outmigration ratio

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

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

Annual yields for corn and soybeans between 1970 and 2009 are from the U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS), where yields equal county-level production divided by harvested acres. For our main analysis, we use the log of the adjusted average of corn and soybeans yields. Climate variables are constructed over the growing season of corn and soybeans (March-August). We calculate total growing-season degree days instead of mean temperatures to capture the nonlinear effect of temperature on crop yields, as well as total precipitation in the growing period. More details on the sources and reliabilities of yield and climate data can be found in Schlenker & Roberts (2009).

We follow Schlenker & Roberts (2009) and 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. We label counties in the following 13 states "Corn Belt" counties: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Mis-

[8]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.

souri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.[9] Counties outside these states as well as Florida that lie east of the 100 degree meridian are labeled the "non-Corn Belt" areas.

Table 1 presents sample summary statistics. 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.[10] There are 1,697 counties in our sample, 892 in the Corn Belt sample and 805 in the non-Corn Belt sample.[11] For comparison purposes, we have averaged all variables over each five-year period during 1970-2009. Panels A and B present sample means and standard deviations for the Corn Belt and non-Corn Belt samples, respectively. There is substantially more net outmigration for the Corn Belt sample than the non-Corn Belt sample as the Midwest has lost population over the last 40 years. Average county-level crop acreages in the Corn Belt states are also larger, especially for corn, as are average crop yields. For example, during the most recent recent 5-year period (2005-2009), both corn and soybean yields are around 30% higher in the Corn Belt sample than in the non-Corn Belt sample. This likely reflects effects of various factors such as geographic/climatic conditions, technology, and policies. Non-Corn Belt areas experience more extreme heat above 29°C or 30°C and more precipitation.

3 Results

3.1 The Weather-Yield Relationship

We first replicate the weather-yield relationship of Schlenker & Roberts (2009), with two notable exceptions: we aggregate the data to 5-year intervals and present separate analyses for the Corn Belt and non-Corn Belt samples. Since year-to-year weather shocks are random, there is considerably more variation in the yearly data than in 5-year averages. Still, Table 2

[9]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.

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

[11]In some alternative specifications we use either corn yields or soybean yields instead of the weighted average of the two, which results in a slightly lower number of counties in our sample as sometimes only one of the two crops is grown.

reports significant results using 5-year averages of log yields and climate data from 1970 to 2009. The first three columns of Table 2 show results for counties in the Corn Belt. The dependent variable in column (1) of Table 2 is the log of adjusted corn and soybean yields. Results for the four climate variables are shown in the Table, while the quadratic time trends as well as county fixed effects are suppressed. The climate variables including two growing season degree days variables: moderate heat and extreme heat, as well as growing season total precipitation and its square term. The results confirm the significant nonlinear relationship between weather/climate and yields (see e.g.: Schlenker & Roberts (2009); Rosenzweig et al. (2002)). An increase of 10 degree days in moderate heat (between 10 and 29°C for corn and between 10 and 30°C for soybeans) during the growing season would increase crop yields by approximately 0.57%. On the other hand, extremely hot temperatures are very harmful - each 10 degree day increase in extreme heat decreases yields by around 6.76%. More rainfall is initially beneficial for crops, but at a decreasing rate, and becomes detrimental when it exceeds some optimum level. The null hypothesis that all coefficients of climate variables are jointly zero is rejected at even the 0.1% significance level. Columns (2) and (3) of Table 2 replicate the analysis of column (1) with different dependent variables: log corn yields and log soybean yields, respectively. Results are similar to those in column (1).

The last three columns of Table 2 display regression results for counties in the non-Corn Belt sample. Although regression coefficients are somewhat different, the relationships between climate and yields are similar to that in the Corn Belt. In all three regressions, we strongly reject the null that climate variables are jointly insignificant. The F-statistic as well as the p-value are shown at the bottom of the table.

Since 5-year averages have less variation than annual data, measurement error might be amplified. We therefore also replicate the analysis using annual data on yields and weather in Table A1 of the appendix. We find comparable relationships between weather and yield to what is reported in Table 2 for both the Corn Belt and non-Corn Belt samples. Limiting the number of observations from 40 to 8 when we aggregate the annual data to 5-year intervals does not seem to impact the results.[12] This is especially true for the coefficient on extreme heat, which explains most of the year-to-year variation in yields.

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

3.2 The Effect of Yield Shocks on Net Outmigration

We estimate equation (1) by two-stage-least-squares (2SLS) and show the results in Table 3. Panels differ by included time controls to capture overall trends in migration as well as yields. Panel A uses a simple linear time trend (one variable), while Panel D uses flexible state-specific restricted cubic splines with 3 knots (26 variables, 13 states $\times$ two spline variables per state). Our baseline regression uses quadratic time trends (Panel B of Table 3) as state-level yield trends in Figure A1 in the appendix apear to be well approximated with quadratic time trends. The results, however, are more or less robust with respect to different time controls. We choose not to control for year fixed effects, which would absorb most of the variation as 5-year weather averages are highly correlated within the Corn Belt, more so than annual data. The reason is that the 5-year averages are driven by large-scale phenomena like El Nino / La Nina as idiosyncratic annual weather shocks average out. If a half-decade is hotter than usual, it is so for most of the Corn Belt. For example, the seven year (i.e., 5-year interval) fixed effects absorb more variation than the 26 state-specific cubic splines. Year fixed effects absorb variation that we would like to use in our identification and amplify measurement error in the weather data as most of the common signal is removed (Fisher et al. Forthcoming). If weather is truly exogenous, it should be orthogonal to other measures and hence not require period fixed effects.

Column (1) reports results for the Corn Belt sample when the net migration ratio is regressed on the log of the yearly average of adjusted corn and soybean yields. The estimated semi-elasticity of outmigration with respect to log yield changes is -0.168, which is statistically significant at the 1% level based on clustered standard error. Recall that the first stage F-statistic is 36.9, much higher than the usual cutoff point of 10 to rule out concerns about weak instruments. To explore the effect of averaging corn and soybean yields on the estimated semi-elasticity, we run the same regressions using either corn or soybean yields, and report the results in columns (2) and (3) of Table 3. The estimated semi-elasticities of outmigration with respect to corn and soybeans yields are -0.165 and -0.160 under quadratic time trends (panel B), respectively. Both are statistically significant at the 1% level and are very close in magnitude to the coefficient estimate in column (1).

We also report results for the non-Corn Belt sample in the last three columns of Table 3. Column (4) presents results using the log of the yearly average yield measure, while columns (5) and (6) use either corn or soybean yields. Note that in all cases the estimated elasticities are small in magnitudes and not statistically significantly different from zero. The negative yield-migration relationship only exists for the Corn Belt sample, consistent with our hypothesis. The fact that we cannot find a significant yield-migration relationship for the non-Corn Belt counties suggests that our results are not driven by other direct channels between climate and migration, such as people's living preferences.

Table A2 in the appendix reports the results of the OLS version of Table 3 where migration rates are regressed on yields that are *not* instrumented on weather. The estimated semi-elasticity are smaller in magnitude (closer to zero) and generally not significantly different from zero. It is consistent with a story where government policies (or other factors like cheap energy) increase both investment in agriculture (yields) and the population in a county. Table A2 demonstrates the importance of our IV approach where we only utilize the variation in yields that is due to exogenous weather fluctuations.

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 explore the sensitivity of our results to these restrictions, we conduct a set of robustness checks in the appendix. Table A3 performs unweighted regression with the same samples as in Table 3. Table A4 again uses unweighted regressions but also includes urban counties with more than 100,000 inhabitants. Table A5 varies the requirement on the minimum number of yield observations in a county, ranging from 1 (i.e., any county that ever had an observation) to 40 (i.e., a balanced panel). In all cases the estimated semi-elasticity for the Corn Belt sample are very close to what is reported in Table 3.[13] The only exceptions are population-weighted regressions including urban counties, which show a lower sensitivity, as there are a few counties with a disproportionately larger population (e.g., Cook County in Illinois that harbors Chicago). We find this reaffirming as it makes it again less likely that our results are driven by direct migration responses to climate. To explain our observed results, the rural population would have to have climate preferences that covary with the nonlinear relationship of crops, while people in urban centers in the same areas do not.

Finally, we check the sensitivity of our estimated standard errors. Our baseline model clusters by state, 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

[13] For the non-Corn Belt we do not find a statistically significant yield-migration relationship.

than usual for most of the Corn Belt. In a sensitivity check in Table A6 we therefore resample 5-year intervals with replacement. The standard errors generally become larger, but all coefficients are still significant except for the model with state-specific restricted cubic splines.[14] Since we only have eight intervals, using a clustered bootstrap has its own drawbacks, and our baseline regression therefore clusters by state.[15]

3.3 Further Results

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." Table 4 therefore presents analyses for various sex and age subgroups for the Corn Belt sample, using the same basic model specifications as in Table 3. Different columns use various crop yields as explanatory variables for migration responses. The first two panels (Panel A and B) show that males and females have quite similar migration elasticities. The next four panels (Panel C-F) analyze different age groups separately. The youngest age group, those between 15 and 29, are most sensitive to yield shocks in their migration decisions. The estimated elasticity is -0.28 when using the log of the average of the adjusted yearly corn and soybean yields. The 30-44 group has a semi-elasticity of -0.154, which is significant at the 1% level. For the relatively older age group between 45 and 59, the estimated semi-elasticity is only -0.022, which is less than one-tenth of that for the 15-29 group, and is not statistically significantly different from zero. In panel F we perform the same analysis for those aged 60 and above, and find a zero 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 are not tied to an area by their job, and there is a sizable retirement community in the Southern United States.

Our estimated semi-elasticity may seem large as the population share directly employed in the agriculture sector is small. One possibility is that there is considerable spillover from agriculture to other sectors of the economy, as was observed for "Dust Bowl" migrants

[14]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.

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

(Hornbeck 2009). To shed further light on this issue, we regress annual state-level farm and non-farm log employment on weather-instrumented yields and their lagged values for the same time period of 1970-2009. The results are shown in Table 5. We include concurrent weather as well as four lags to make the time frame comparable to our 5-year intervals on which migration data was measured. Note that the cumulative effect (the sum of the individual effects of all five years) is given at the bottom of each panel. Panel A analyzes farm employment using data from the Bureau of Economic Analysis (BEA), and finds no statistically significant relationship. Panel B analyzes non-farm employment data from BEA. We find that non-farm employment is positively related to yield shocks for the Corn Belt sample, but there's no statistically significant relationship for the non-Corn Belt sample. The estimated cumulative elasticity of 0.25 is also quite large. In panel C, we replicate the analysis using non-farm employment data from the Bureau of Labor Statistics, and find even larger impacts (0.375) for the Corn Belt sample.[16] Our results suggest that although a negative weather-induced yield shock does not directly affect farm employment, it dampens profitability and income in the agricultural sector and negatively affects local economic conditions, thereby triggering relatively large employment contractions in non-farm sectors. One possible explanation for such a finding is that government programs insure farm income (e.g., disaster payments, price floors, and crop insurance) and hence farmers receive enough income that keeps them farming. For example, Key & Roberts (2007) have shown that larger government transfers increase the probability of farm survival using Micro-level Census Data that links individual farms between three Censuses. If government payments insure against yield losses, they will dampen responses in farm labor. Especially since many of them are conditional on the farm remaining in operation. At the same time, yield losses might induce farmers to purchase less outside goods and result in fewer investments. Roberts & Key (2008) have also shown that larger government payments result in consolidation in the farm sector, thereby increasing average farm size. 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 pick up 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.

[16]Employment data from BEA and BLS differ in their coverage and a number of other issues. BEA covers more workers: the average employment numbers reported by BLS are only around 80% of those reported by BEA. More detailed explanations on the differences between BEA and BLS employment data can be found from the BEA website.

4 Projecting Future Net Outmigration

Our estimate of the elasticity of migration is conditional on many factors specific to U.S. for the period under study, such as the population share of youths who are more likely to migrate, farming technology, the relative importance of agriculture in the economy, 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.

We first base our projections on the B2 scenario of the Hadley III model and project net outmigration ratios of the adult US population (aged 15 to 59) that are attributable to predicted changes in crop yields for the medium term (2020-2049) and for the long term (2070-2099). We follow a two step procedure. First, using average climate during the 1960-1989 period as a baseline, we derive expected changes in log crop yields using the estimated climate-yield relationship. Specifically, the predicted change in crop yields is the difference in predicted yields under the observed weather record for 1960-1989 and a counterfactual one, where we add predicted *absolute changes* in monthly minimum and maximum temperature as well as *relative changes* in precipitation to the historic baseline. In a second step, we project population migration ratios using the semi-elasticity of -0.168. Table 6 presents the summary of the results for individual counties. The first column displays the mean impact among counties, while the second through fourth column give the standard deviation, minimum, and maximum of the impacts for the 892 counties in the Corn Belt. The last four columns summarize how many counties will have increased outmigration (displayed in green, yellow, and red in Figure 2) as well as how many counties have decreased outmigration rates (shown in blue).[17]

The first row reports projections for the medium term. On average, by 2020-2049, 5-year outmigration rates are expected to increase by 3.67 percentage points for the adult population for rural counties in the Corn Belt. Not all counties are expected to experience similar changes in outmigration. At the 5% significance level, we can project that 761

[17] We use 10,000 bootstrap draws from the first and second stage coefficients of the baseline regression (errors are clustered by state) to translate predicted changes in weather variables to a distribution of changes in outmigration rates.

counties would experience increased net outmigration due to climate change. On the other hand, 37 counties would witness less outmigration, mostly those in the north as shown in panel A of Figure 2.

The second row of Table 6 reports long term projections. Compared to the medium term, the projected increase in outmigration ratios are on average much larger. By 2070-2099, 5-year outmigration rates of rural counties in the Corn Belt are expected to increase by 11.3 percentage points. This reflects much more severe declines of crop yields as continued warming significantly increases the occurrence of extremely warm days that are detrimental to crop growth. At the same time, the long-term projections are also associated with more variability of the predicted impacts among counties. Some cold places continue to benefit from warming, and the minimum predicted impact - the biggest *decline* in outmigration - is larger in the second row. As shown in Panel B of Figure 2, counties in the southwestern part of the Corn Belt are most likely to experience substantial increases in net outmigration, while those in the northeastern part would be affected less. Only 2 counties are projected to have less outmigration in the long term.

To complement our use of the Hadley III model, which is just one of roughly 20 GCMs (General Circulation Model, or Global Climate Model), we also provide migration projections under uniform climate change scenarios, assuming temperature or precipitation changes are the same across all the Corn Belt region. The sensitivity of our results to predicted changes in climatic conditions can then be approximated from the uniform changes, especially since there is more variability in predicted changes between models than within runs for the Corn Belt.[18] We predict outmigration rates corresponding to each Celsius degree rise in temperatures up to 5°C (holding precipitation constant) and between -50% and +50% change in precipitation (holding temperature constant) in 20% intervals. Results are summarized in Table 6, and graphically shown in Figures A2 and A3 in the appendix. Consistent with our previous projections, we use 1960-1989 as the baseline to which we compare future scenarios. Our results show that outmigration increases nonlinearly with temperature increases. This is due to the fact that predicted yield impacts are highly nonlinear in temperature. If temperature rises by 1°C, on average about 0.6% of each rural county in the Corn Belt would out-migrate, yet a 5°C rise in temperature would on average induce 9.3% of the adult population to leave their county. This nonlinear relationship is in accordance with the general

[18] 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.

finding of the impact literature that warming is likely to be increasingly harmful for human society in virtually all aspects.

The impacts of precipitation changes on outmigration are relatively small. The projected change in outmigration rates never exceeds 2% although precipitation levels change between a decline of 50% and an increase of 50%. Although future changes in temperature and precipitation are expected to be related, agricultural-related outmigration is much more driven by the former. Our results suggest that focusing on predicted temperature changes will give the bulk of the predicted impact.

5 Conclusions

We have examined the sensitivity of U.S. internal migration to weather-induced changes in crop yields using data for the most recent period of 1970-2009. Consistent with previous theoretical studies that link migration decisions to economic opportunities in source and destination counties, we find that county-level outmigration is negatively 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.

Our results suggest a nontrivial effect of climate change on future internal U.S. population movements. Based on the Hadley III model B2 scenario, with other factors held constant and using the 1960-1989 period as a baseline, climate change is expected to increase 5-year net outmigration rates on average by 3.7 percentage points for the population aged 15-59 in the medium term (2020-2049). Long run effects are likely to be considerably greater but also much more uncertain due to growing uncertainty in climate projection with progressively larger climate changes. While there is uncertainty about the exact amount of future warming, the consensus estimate suggest that we will experience at least some warming. We present uniform climate change scenarios to show the possible range of migration responses.

Historically, policy makers have tried to disuade large scale migration to preserve rural communities. Our research suggest that climate change will likely put further pressure on outmigration from predominately agricultural rural areas. We believe that future research should explore in more detail the underlying determinants of the yield-migration relationship for the areas we highlighted. Our tentative 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, and the inter-model differences due to differing climate sensitivities grow strongly with time.

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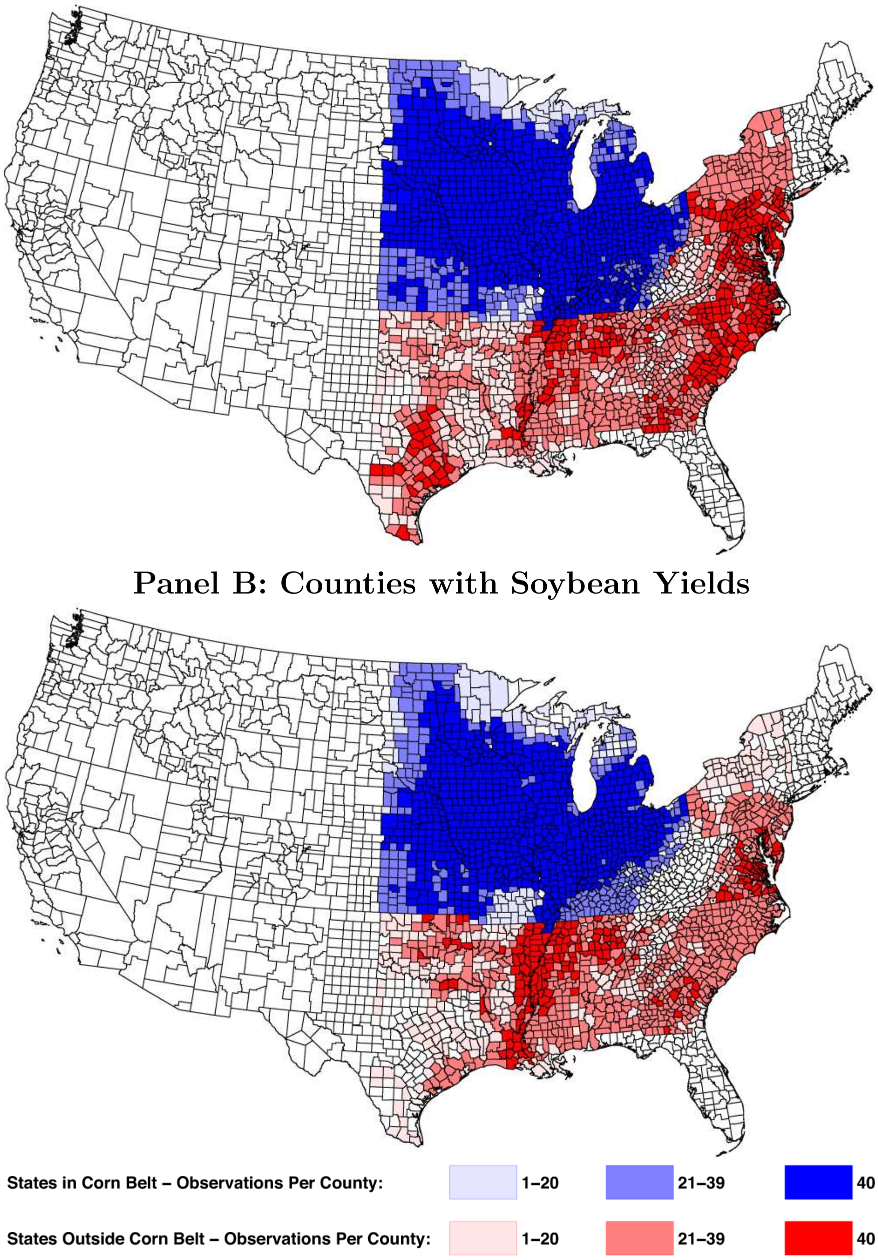
Figure 1: Counties Used in Regressions

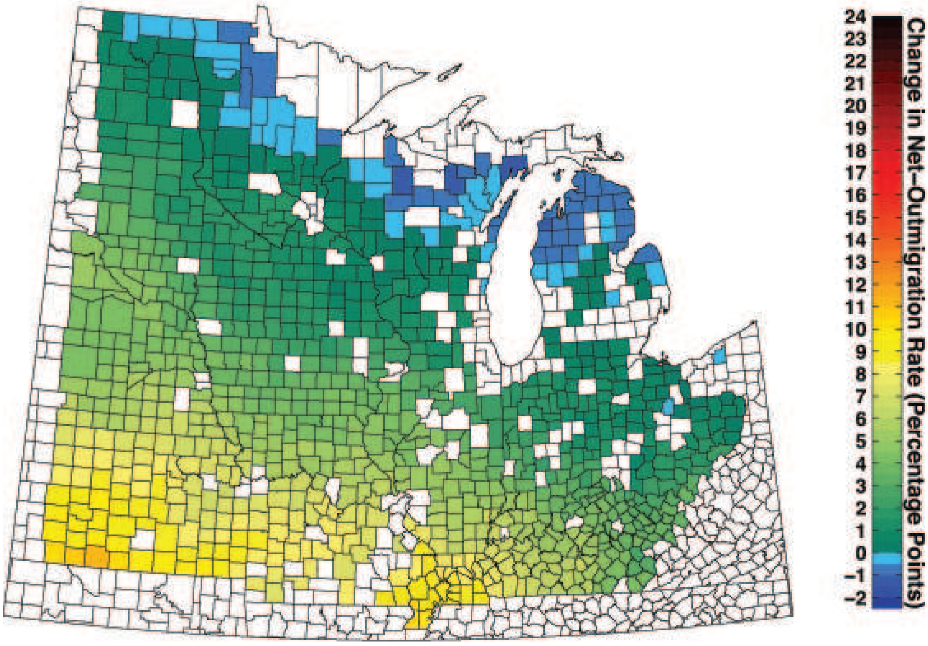
Panel A: Counties with Corn Yields



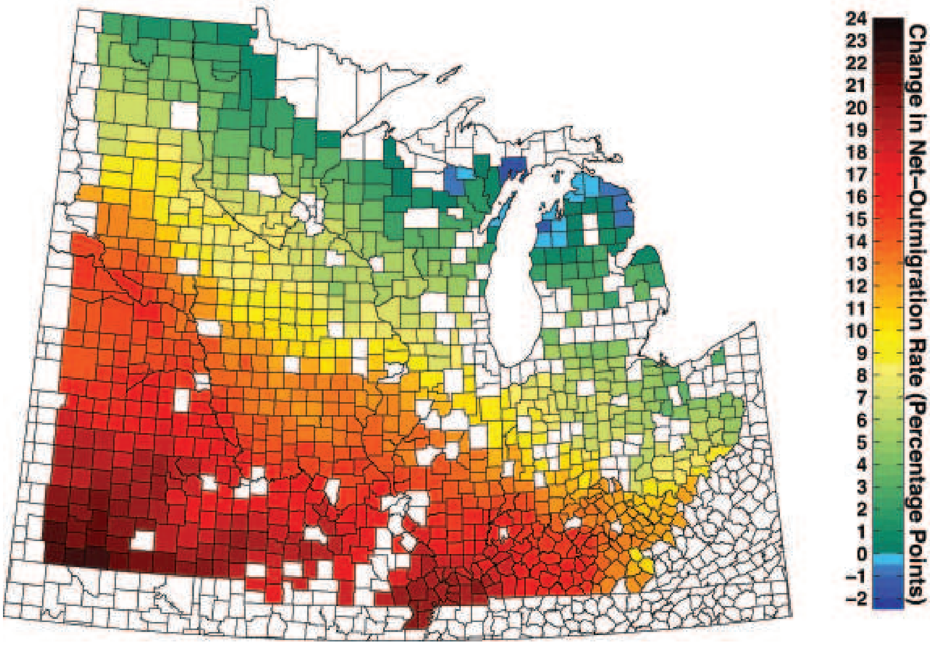
Notes: Figure displays counties in the eastern United States (east of the 100 degree meridian) where migration and yield data are available. States covering the Corn Belt are shown in blue, while other states are shown in red. Different shading indicate the number of yield observations in the county for corn in the top panel and soybeans in the bottom panel.

Figure 2: Predicted Changes in Net Outmigration Under Climate Change (Hadley III - B2 Scenario)

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



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



Notes: Figure displays predicted changes in net outmigration rates for counties in the Corn Belt with at least 21 yield observations in 1970-2009 that had less than 100,000 inhabitants in 2000 (colored blue in Figure 1) under the Hadley III - B2 scenario. 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.

Table 1: Descriptive Statistics

	Data Over 5-Year Periods							
	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-2009
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	1462	1434	1515	1417	1422	1453	1464
(s.d.)	(250)	(248)	(240)	(243)	(262)	(241)	(265)	(256)
Degree Days Above 29° C	35.0	35.7	44.8	42.1	27.1	31.5	32.3	32.3
(s.d.)	(27.0)	(26.1)	(33.6)	(21.8)	(22.6)	(22.5)	(29.2)	(24.9)
Soybean Area (1000 acres)	33.9	38.8	44.5	44.9	47.8	58.4	65.6	63.4
(s.d.)	(40.2)	(44.7)	(46.6)	(45.4)	(46.3)	(51.0)	(53.2)	(50.7)
Soybean Yield (bushel/acre)	25.5	28.8	29.0	32.1	35.5	37.3	37.8	41.6
(s.d.)	(5.2)	(5.8)	(6.3)	(5.8)	(6.9)	(6.7)	(7.2)	(7.8)
Degree Days 10-30° C	1460	1485	1455	1533	1434	1443	1472	1483
(s.d.)	(251)	(249)	(245)	(247)	(263)	(241)	(266)	(256)
Degree Days Above 30° C	23.1	23.5	32.2	28.6	17.6	20.6	21.6	21.2
(s.d.)	(21.0)	(20.3)	(27.7)	(16.2)	(16.8)	(16.7)	(23.0)	(18.6)
Precipitation (cm)	54.6	55.5	55.4	49.5	57.7	58.6	55.5	56.4
(s.d.)	(11.0)	(9.6)	(10.1)	(8.1)	(8.3)	(10.4)	(9.9)	(10.9)
Panel B: 805 Counties Outside Corn Belt								
Migration Rate Age [15,60) (%)	-3.22	-2.72	0.37	1.94	-2.02	-5.46	-0.81	-0.99
(s.d.)	(8.56)	(14.90)	(7.00)	(8.35)	(6.96)	(8.81)	(6.85)	(7.05)
Migration Rate Males [15,60) (%)	-3.47	-2.23	0.54	2.22	-1.96	-6.86	-0.73	-1.00
(s.d.)	(9.11)	(15.14)	(7.67)	(8.78)	(8.37)	(12.07)	(7.39)	(8.73)
Migration Rate Females [15,60) (%)	-3.06	-3.24	0.19	1.70	-2.06	-4.14	-0.82	-0.98
(s.d.)	(8.30)	(14.83)	(6.66)	(8.10)	(6.52)	(8.17)	(6.79)	(6.76)
Migration Rate Age [15,30) (%)	-0.21	2.37	4.58	6.82	2.58	-0.79	-3.14	10.13
(s.d.)	(11.94)	(16.52)	(9.37)	(11.91)	(10.43)	(14.07)	(14.08)	(11.33)
Migration Rate Age [30,45) (%)	-6.52	-7.51	-2.03	-1.41	-5.48	-8.34	-0.69	-5.34
(s.d.)	(8.13)	(17.49)	(7.09)	(6.79)	(6.86)	(9.02)	(5.94)	(8.05)
Migration Rate Age [45,59) (%)	-4.61	-6.45	-4.22	-1.77	-4.10	-7.57	0.69	-7.93
(s.d.)	(6.35)	(12.34)	(6.21)	(6.80)	(6.61)	(8.56)	(3.36)	(8.12)
Migration Rate Age [60,oo) (%)	0.65	0.36	2.46	2.62	1.93	-0.07	2.53	-0.53
(s.d.)	(4.35)	(9.03)	(3.96)	(4.33)	(4.05)	(5.21)	(3.83)	(5.44)
Corn Area (1000 acres)	7.4	8.3	7.5	6.6	6.3	6.9	7.3	8.6
(s.d.)	(10.5)	(11.9)	(10.8)	(9.5)	(9.0)	(9.5)	(10.1)	(11.7)
Corn Yield (bushel/acre)	52.9	59.9	67.9	76.4	84.4	88.5	105.5	108.5
(s.d.)	(16.4)	(17.7)	(16.7)	(16.8)	(17.3)	(18.8)	(23.1)	(27.1)
Degree Days 10-29° C	1888	1917	1894	1948	1917	1926	1944	1944
(s.d.)	(387)	(382)	(389)	(380)	(378)	(395)	(401)	(392)
Degree Days Above 29° C	61.9	69.7	85.5	81.1	69.7	84.1	71.5	85.4
(s.d.)	(43.9)	(43.6)	(54.7)	(46.4)	(43.7)	(56.7)	(51.1)	(53.7)
Soybean Area (1000 acres)	21.1	28.1	28.8	19.8	17.1	18.6	16.7	18.4
(s.d.)	(39.2)	(46.0)	(43.5)	(34.2)	(32.3)	(34.4)	(30.2)	(32.7)
Soybean Yield (bushel/acre)	21.9	22.9	21.3	23.5	26.3	25.7	30.6	31.4
(s.d.)	(2.7)	(2.9)	(3.8)	(3.9)	(5.0)	(4.4)	(6.1)	(6.7)
Degree Days 10-30° C	2012	2045	1990	2047	2020	2025	1975	1989
(s.d.)	(253)	(260)	(295)	(281)	(280)	(287)	(360)	(343)
Degree Days Above 30° C	42.2	52.2	63.8	57.3	49.8	59.8	46.0	57.1
(s.d.)	(25.8)	(28.3)	(34.7)	(25.8)	(23.3)	(31.2)	(30.2)	(31.6)
Precipitation (cm)	71.0	70.2	67.7	60.5	69.5	63.6	65.3	61.3
(s.d.)	(9.4)	(10.8)	(10.3)	(8.1)	(8.5)	(9.8)	(9.3)	(10.1)

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 either corn or soybeans are included.

Table 2: Weather and Crop Yields

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
Moderate Heat (1000 degree days)	0.572***	0.613***	0.483***	-0.044	-0.133	0.618***
	(0.085)	(0.133)	(0.099)	(0.179)	(0.251)	(0.114)
Extreme Heat (100 degree days)	-0.676***	-0.589***	-0.747***	-0.099	-0.286***	-0.483***
	(0.069)	(0.093)	(0.049)	(0.067)	(0.074)	(0.082)
Precipitation (m)	1.325***	1.664***	1.357***	0.651	0.452	0.525
	(0.301)	(0.277)	(0.225)	(0.461)	(0.754)	(0.464)
Precipitation Squared (m^2)	-1.182***	-1.465***	-1.187***	-0.366	-0.558	-0.245
	(0.249)	(0.250)	(0.202)	(0.306)	(0.545)	(0.310)
F-stat (1st stage)	36.98	24.52	169.98	6.93	9.97	18.14
p-value (1st stage)	1.2e-06	1.1e-05	1.9e-10	.0023	3.9e-04	3.1e-05
R-squared	0.8205	0.8376	0.7849	0.5999	0.6636	0.5233
Observations	7086	7078	6413	6102	5628	4442
Counties	892	892	810	805	746	595
Min. Yield Obs. per County	21	21	21	21	21	21
Maximum Population	100000	100000	100000	100000	100000	100000

Notes: Table displays first stage results of Panel B in Table 3, i.e., log yields are regressed on four weather variables as well as a quadratic time trend and county fixed effects. Counties in and outside the Corn Belt are shown in Figure 1. Regressions include all 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 3: Weather-Induced Yield Shocks and Net Outmigration in Eastern United States

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
	Panel A: Linear Time Trend					
Log Yield	-0.184***	-0.182***	-0.186***	-0.074	-0.014	-0.038
	(0.046)	(0.027)	(0.065)	(0.134)	(0.070)	(0.057)
F-stat (1st stage)	36.90	23.43	35.90	5.66	10.12	28.48
	Panel B: Quadratic Time Trend					
Log Yield	-0.168***	-0.165***	-0.160***	-0.010	0.007	0.004
	(0.037)	(0.023)	(0.050)	(0.141)	(0.060)	(0.073)
F-stat (1st stage)	36.98	24.52	169.98	6.93	9.97	18.14
	Panel C: Restricted Cubic Splines (3 knots)					
Log Yield	-0.167***	-0.165***	-0.160***	-0.001	0.007	0.007
	(0.036)	(0.022)	(0.048)	(0.142)	(0.061)	(0.072)
F-stat (1st stage)	35.62	24.59	146.93	6.96	9.97	17.83
	Panel D: State-specific Restricted Cubic Splines (3 knots)					
Log Yield	-0.155***	-0.137***	-0.149***	-0.032	-0.033	-0.035
	(0.043)	(0.028)	(0.049)	(0.081)	(0.099)	(0.058)
F-stat (1st stage)	155.33	24.20	276.92	18.02	9.17	22.71
Observations	7086	7078	6413	6102	5628	4442
Counties	892	892	810	805	746	595

Notes: Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panels differ by included time controls. Counties in and outside the Corn Belt are shown in Figure 1. Regressions include counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009 and are population weighted. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 4: Weather-Induced Yield Shocks and Net Outmigration - Heterogeneity between Subgroups

	Counties in Corn Belt		
	Corn+Soy	Corn	Soybeans
	Panel A: Females Only		
Log Yield	-0.173***	-0.177***	-0.167***
	(0.039)	(0.024)	(0.052)
	Panel B: Males Only		
Log Yield	-0.161***	-0.154***	-0.155***
	(0.035)	(0.023)	(0.049)
	Panel C: Ages [15,30)		
Log Yield	-0.283***	-0.284***	-0.268**
	(0.091)	(0.069)	(0.107)
	Panel D: Ages [30,45)		
Log Yield	-0.154***	-0.152***	-0.152***
	(0.020)	(0.016)	(0.034)
	Panel E: Ages [45,60)		
Log Yield	-0.022	-0.017	-0.006
	(0.024)	(0.023)	(0.021)
	Panel F: Ages [60,oo)		
Log Yield	-0.004	-0.002	0.001
	(0.011)	(0.011)	(0.009)
Observations	7086	7078	6413
Counties	892	892	810

Notes: Tables regresses net outmigration on weather-instrumented yield shocks as well as a quadratic time trend and county fixed effects (Panel B in Table 3). Columns correspond to first three columns of Table 3, but panels limit the data set to population subgroups. Panels A and B look separately at the migration decisions of males and females, while Panels C-F look at different age ranges (both sexes combined). 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 5: Weather-Induced Yield Shocks and Employment: Annual State-Level Regression

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
	Panel A: Farm Employment BEA					
Log Yield$_t$	-0.048**	-0.037	-0.042	-0.038	-0.040	-0.130**
	(0.024)	(0.024)	(0.029)	(0.087)	(0.038)	(0.050)
Log Yield$_{t-1}$	-0.023	-0.015	-0.019	-0.025	-0.041	-0.113*
	(0.024)	(0.024)	(0.034)	(0.085)	(0.036)	(0.058)
Log Yield$_{t-2}$	-0.006	-0.002	0.004	-0.013	-0.070	-0.094*
	(0.016)	(0.017)	(0.027)	(0.076)	(0.046)	(0.053)
Log Yield$_{t-3}$	-0.020	-0.013	-0.013	-0.003	-0.062	-0.064**
	(0.019)	(0.017)	(0.027)	(0.050)	(0.048)	(0.032)
Log Yield$_{t-4}$	0.009	0.012	0.009	0.043	-0.004	0.005
	(0.014)	(0.013)	(0.021)	(0.042)	(0.036)	(0.027)
Cumulative Effect	-0.088	-0.055	-0.061	-0.036	-0.217	-0.396*
(s.e.)	(0.090)	(0.088)	(0.131)	(0.334)	(0.187)	(0.206)
Observations	520	520	514	672	672	563
	Panel B: Non-Farm Employment BEA					
Log Yield$_t$	0.055**	0.046**	0.044	-0.100**	-0.085***	-0.077***
	(0.026)	(0.022)	(0.031)	(0.050)	(0.021)	(0.025)
Log Yield$_{t-1}$	0.057***	0.048***	0.056**	-0.083	-0.060***	-0.072**
	(0.020)	(0.016)	(0.025)	(0.051)	(0.020)	(0.030)
Log Yield$_{t-2}$	0.056***	0.051***	0.050***	-0.041	-0.037	-0.037
	(0.017)	(0.013)	(0.018)	(0.047)	(0.030)	(0.031)
Log Yield$_{t-3}$	0.048***	0.040***	0.051***	0.014	-0.000	0.021
	(0.013)	(0.009)	(0.017)	(0.028)	(0.024)	(0.021)
Log Yield$_{t-4}$	0.035***	0.028***	0.037**	-0.006	-0.021	0.019
	(0.013)	(0.007)	(0.016)	(0.022)	(0.020)	(0.015)
Cumulative Effect	0.251***	0.213***	0.239**	-0.217	-0.204*	-0.146
(s.e.)	(0.082)	(0.059)	(0.101)	(0.190)	(0.104)	(0.113)
Observations	520	520	514	672	672	563
	Panel C: Non-Farm Employment BLS					
Log Yield$_t$	0.083**	0.067**	0.080*	-0.091*	-0.086***	-0.079***
	(0.034)	(0.028)	(0.045)	(0.051)	(0.023)	(0.030)
Log Yield$_{t-1}$	0.079***	0.066***	0.086***	-0.076	-0.064***	-0.078**
	(0.026)	(0.021)	(0.033)	(0.052)	(0.022)	(0.037)
Log Yield$_{t-2}$	0.087***	0.075***	0.086***	-0.027	-0.035	-0.033
	(0.024)	(0.018)	(0.025)	(0.048)	(0.034)	(0.038)
Log Yield$_{t-3}$	0.074***	0.061***	0.084***	0.025	0.002	0.025
	(0.019)	(0.015)	(0.024)	(0.029)	(0.027)	(0.025)
Log Yield$_{t-4}$	0.051***	0.042***	0.055***	0.003	-0.019	0.026
	(0.016)	(0.011)	(0.019)	(0.021)	(0.023)	(0.017)
Cumulative Effect	0.375***	0.311***	0.390***	-0.165	-0.201*	-0.140
(s.e.)	(0.113)	(0.083)	(0.139)	(0.191)	(0.117)	(0.137)
Observations	520	520	514	672	672	563

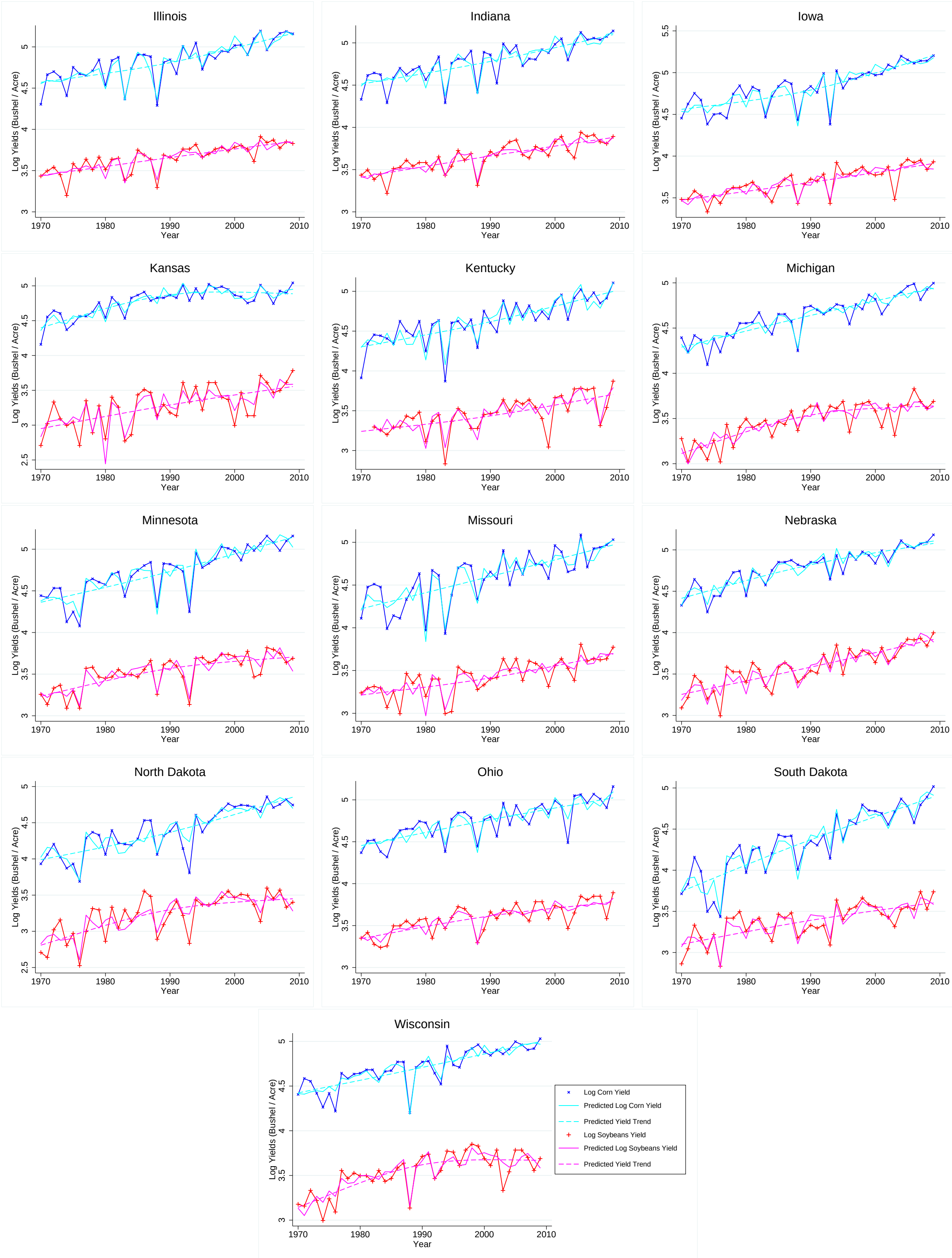
Notes: Tables regresses annual state-level employment on weather-instrumented yield shocks as well as a quadratic time trend and state fixed effects. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table 6: Predicted Changes in Net Outmigration Under Climate Change

	Predicted Outmigration Rate				Increased Outmigration		Decreased Outmigration	
	Mean	SDev	Min	Max	Total N	Sign. N	Total N	Sign. N
Hadley III-B2 (2020-2049)	3.67	(2.85)	-1.38	11.02	820	761	72	37
Hadley III-B2 (2070-2099)	11.32	(5.50)	-1.81	22.38	877	854	15	2
Uniform +1° C	0.61	(0.74)	-0.80	2.92	655	530	237	87
Uniform +2° C	1.79	(1.60)	-1.48	6.51	761	608	131	49
Uniform +3° C	3.60	(2.56)	-1.98	10.81	829	736	63	20
Uniform +4° C	6.08	(3.62)	-2.19	15.87	862	809	30	4
Uniform +5° C	9.30	(4.78)	-2.02	21.73	884	846	8	1
Uniform -50% Precipitation	1.43	(0.43)	-0.01	2.04	891	813	1	0
Uniform -30% Precipitation	0.50	(0.36)	-0.65	1.07	796	543	96	6
Uniform -10% Precipitation	0.05	(0.16)	-0.43	0.31	551	317	341	146
Uniform +10% Precipitation	0.07	(0.19)	-0.28	0.65	542	383	350	184
Uniform +30% Precipitation	0.58	(0.69)	-0.73	2.60	680	559	212	102
Uniform +50% Precipitation	1.56	(1.34)	-1.05	5.41	744	679	148	49

Notes: Tables displays predicted increases in net outmigration under various climate change scenarios for the baseline model (First column of Panel B in Table 3). The first two rows use medium and long-term projections under the Hadley III - B2 scenario. The remaining columns display predicted changes under uniform climate change scenarios. The first four columns summarize the predicted change in net outmigration rates. The last four columns give the number of counties that are predicted to have an increase or a decrease in net outmigration rates. For each category we give the total number of counties as well as the number of counties that have a statistically significant increase or decrease. The spatial distribution of impacts is given in Figures 2 for the first two rows and Figures A2 and A3 in the appendix for the remaining uniform scenarios.

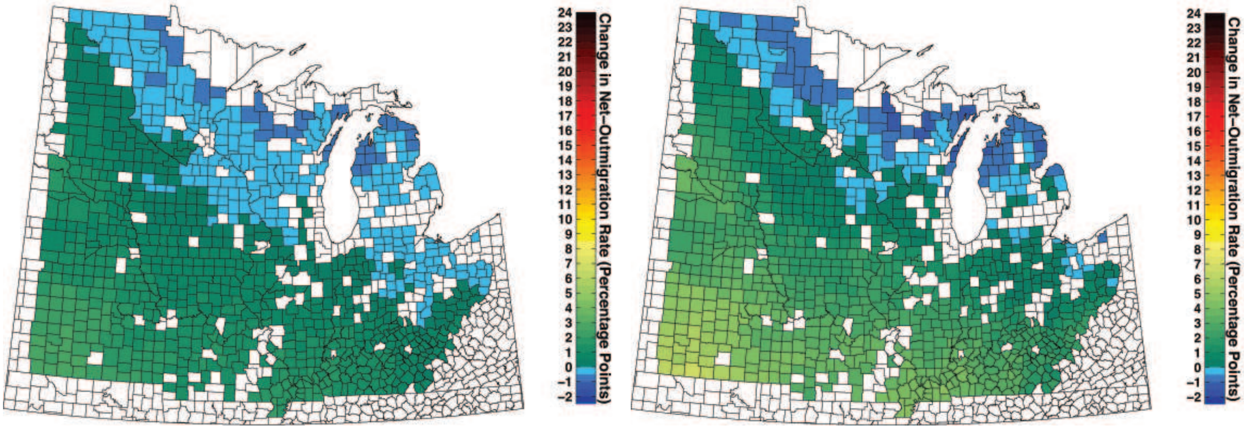
Figure A1: State-level Log Yields and Weather



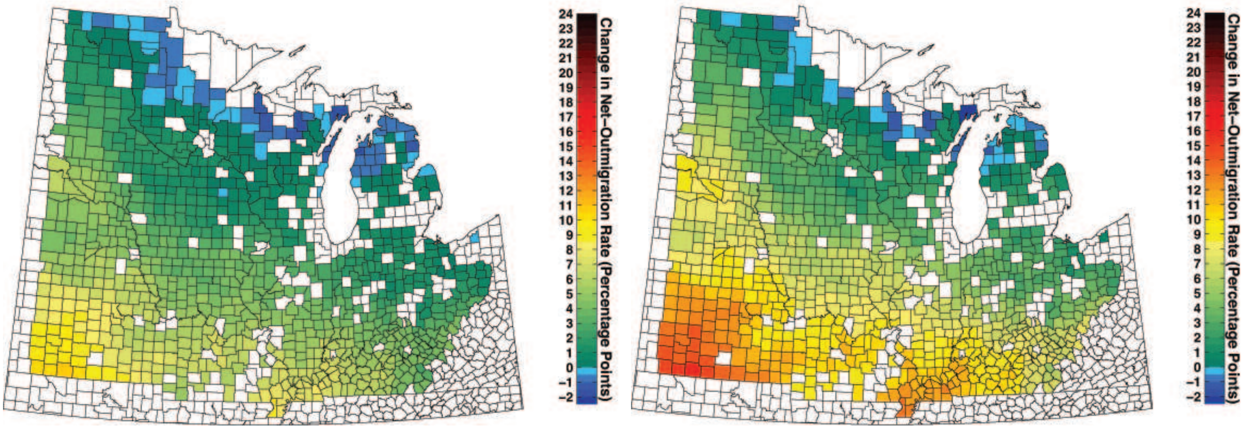
Notes: State-level yields, yield trend, and predicted yields for states in the Corn Belt.

Figure A2: Predicted Changes in Net Outmigration (Uniform Temperature Scenarios)

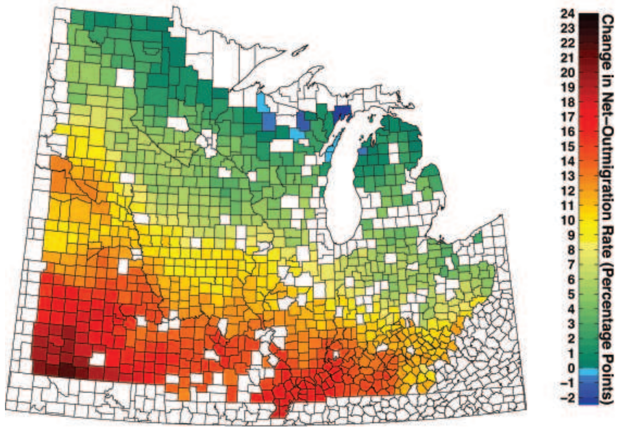
Panel A: Uniform Temperature Increase (+1°C and +2°C)



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



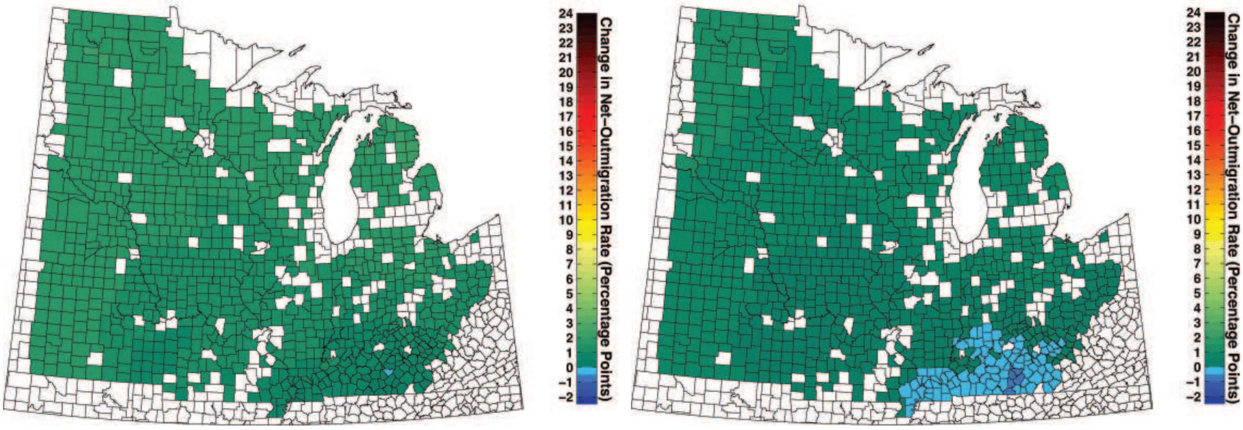
Panel C: Uniform Temperature Increase (+5°C)



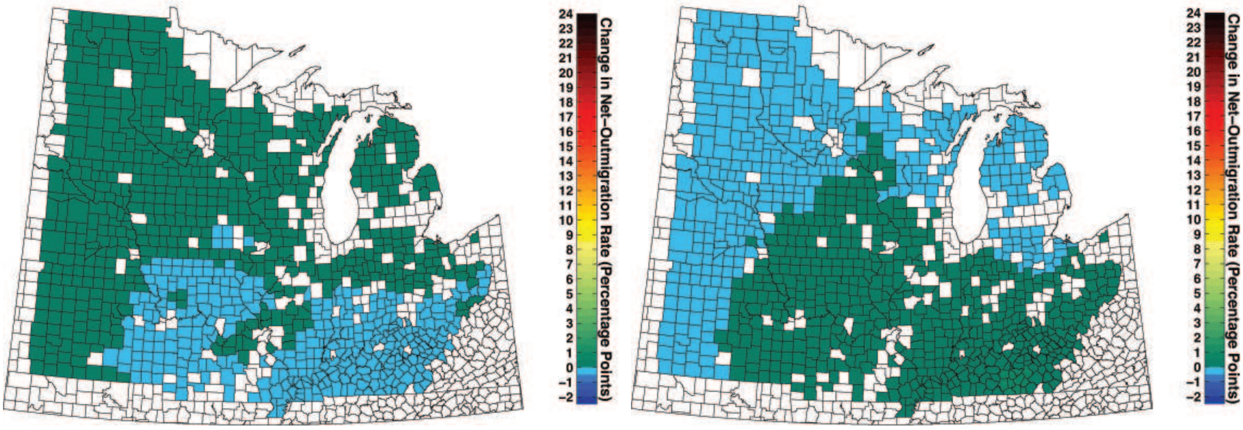
Notes: Figure displays predicted changes in net outmigration rates for counties in Corn Belt that had less than 100,000 inhabitants in 2000 and at least 21 yield observations in 1970-2009 (colored blue in Figure 1) under uniform temperature increases ranging from +1°C to +5°C.

Figure A3: Predicted Changes in Net Outmigration (Uniform Precipitation Scenarios)

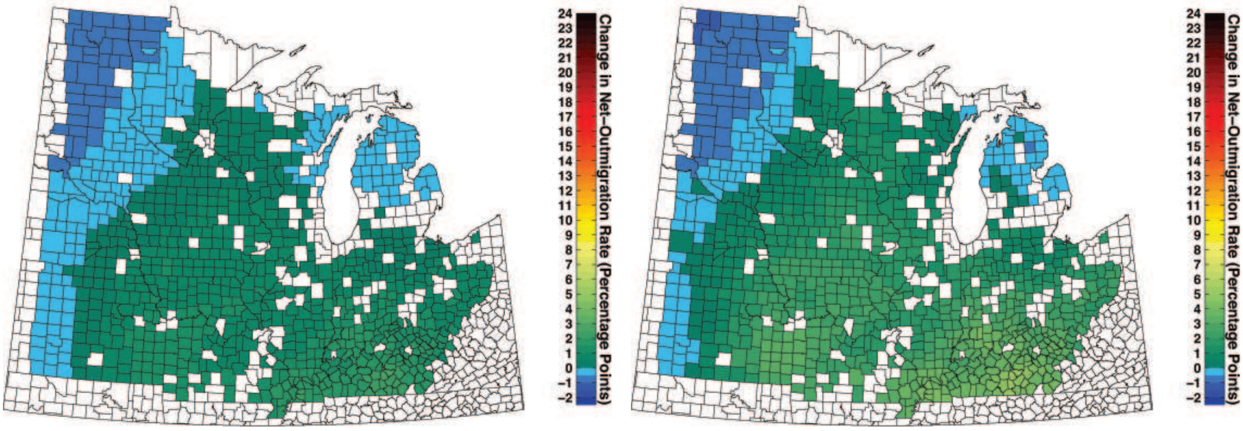
Panel A: Uniform Precipitation Change (-50% and -30%)



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



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



Notes: Figure displays predicted changes in net outmigration rates for counties in Corn Belt that had less than 100,000 inhabitants in 2000 and at least 21 yield observations in 1970-2009 (colored blue in Figure 1) under uniform precipitation changes ranging from -50% to +50%.

Table A1: Weather and Crop Yields - Panel of Annual Yields

	Counties in Corn Belt		Counties Outside Corn Belt	
Log Yield	Corn	Soybeans	Corn	Soybeans
Moderate Heat (1000 degree days)	0.421***	0.497***	0.024	0.278***
	(0.101)	(0.048)	(0.099)	(0.072)
Extreme Heat (100 degree days)	-0.738***	-0.659***	-0.592***	-0.557***
	(0.110)	(0.039)	(0.094)	(0.030)
Precipitation (m)	1.636***	1.627***	0.329	1.302***
	(0.381)	(0.247)	(0.389)	(0.267)
Precipitation Squared (m^2)	-1.477***	-1.315***	-0.323	-0.860***
	(0.346)	(0.220)	(0.278)	(0.158)
R-squared	0.6139	0.5379	0.5186	0.4094
Observations	34788	31154	26124	20492
Counties	892	810	746	595

Notes: Table replicates Table 2 except that it uses *annual* log yields and the regressions are unweighted. Moderate heat is measured by degree days 10-29°C for corn and 10-30°C for soybeans, extreme heat by degree days above 29°C for corn and 30°C for soybeans. Regressions include all counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Counties in the Corn Belt sample are shown in Figure 1. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A2: Yield Shocks and Net Outmigration in Eastern United States - OLS Regressions

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
	Panel A: Linear Time Trend					
Log Yield	-0.028*	-0.018	-0.012	-0.011	0.010	-0.037***
	(0.015)	(0.015)	(0.018)	(0.016)	(0.014)	(0.014)
	Panel B: Quadratic Time Trend					
Log Yield	-0.030**	-0.016	-0.024	-0.008	0.004	-0.024
	(0.013)	(0.013)	(0.016)	(0.014)	(0.013)	(0.017)
	Panel C: Restricted Cubic Splines (3 knots)					
Log Yield	-0.030**	-0.016	-0.024	-0.007	0.004	-0.024
	(0.013)	(0.013)	(0.016)	(0.014)	(0.013)	(0.016)
	Panel D: State-specific Restricted Cubic Splines (3 knots)					
Log Yield	-0.014	0.001	-0.019	0.001	0.011	-0.023
	(0.016)	(0.016)	(0.018)	(0.015)	(0.013)	(0.019)
Observations	7086	7078	6413	6102	5628	4442
Counties	892	892	810	805	746	595

Notes: Table replicates Table 3 except that yields are *not* instrumented with observed weather shocks. Panels differ by included time controls. Counties in and outside the Corn Belt are shown in Figure 1. 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 A3: Weather-Induced Yield Shocks and Net Outmigration in Eastern United States - Unweighted Regressions

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
	Panel A: Linear Time Trend					
Log Yield	-0.193***	-0.195***	-0.192***	-0.120	-0.047	-0.055
	(0.042)	(0.027)	(0.063)	(0.119)	(0.065)	(0.049)
F-stat (1st stage)	13.67	9.10	85.82	12.54	20.06	29.82
	Panel B: Quadratic Time Trend					
Log Yield	-0.186***	-0.185***	-0.178***	-0.082	-0.023	-0.023
	(0.036)	(0.025)	(0.055)	(0.131)	(0.055)	(0.064)
F-stat (1st stage)	13.21	9.33	86.29	18.79	13.87	19.63
	Panel C: Restricted Cubic Splines (3 knots)					
Log Yield	-0.186***	-0.185***	-0.179***	-0.075	-0.023	-0.019
	(0.035)	(0.025)	(0.054)	(0.132)	(0.056)	(0.064)
F-stat (1st stage)	13.04	9.23	79.50	19.07	13.95	19.12
	Panel D: State-specific Restricted Cubic Splines (3 knots)					
Log Yield	-0.169***	-0.143***	-0.167***	-0.052	-0.046	-0.067
	(0.045)	(0.027)	(0.054)	(0.083)	(0.094)	(0.056)
F-stat (1st stage)	76.18	16.91	66.89	17.87	7.27	25.28
Observations	7086	7078	6413	6102	5628	4442
Counties	892	892	810	805	746	595

Notes: Table replicates Table 3 except that regressions are unweighted. Table regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panels differ by included time controls. Regressions include all counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Counties in and outside the Corn Belt are shown in Figure 1. 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-Induced Yield Shocks and Net Outmigration in Eastern United States - Unweighted Regressions Including Urban Counties

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
	Panel A: Linear Time Trend					
Log Yield	-0.179***	-0.183***	-0.179***	-0.050	-0.032	-0.042
	(0.037)	(0.025)	(0.057)	(0.108)	(0.065)	(0.044)
F-stat (1st stage)	13.83	9.62	90.79	19.99	20.28	35.41
	Panel B: Quadratic Time Trend					
Log Yield	-0.172***	-0.173***	-0.166***	-0.002	-0.007	-0.004
	(0.032)	(0.023)	(0.049)	(0.112)	(0.056)	(0.057)
F-stat (1st stage)	13.47	9.72	95.66	17.29	16.01	24.65
	Panel C: Restricted Cubic Splines (3 knots)					
Log Yield	-0.172***	-0.173***	-0.166***	0.004	-0.007	-0.002
	(0.031)	(0.023)	(0.048)	(0.111)	(0.056)	(0.056)
F-stat (1st stage)	13.30	9.68	87.01	17.28	16.04	24.10
	Panel D: State-specific Restricted Cubic Splines (3 knots)					
Log Yield	-0.160***	-0.140***	-0.157***	0.011	0.003	-0.043
	(0.042)	(0.026)	(0.049)	(0.079)	(0.094)	(0.051)
F-stat (1st stage)	76.46	17.17	75.26	26.85	12.43	34.60
Observations	8077	8069	7397	7571	6986	5440
Counties	1016	1016	933	995	921	732

Notes: Table replicates Table 3 except that regressions are unweighted and also include counties with more than 100,000 inhabitants. Counties still had to have at least 21 yield observations in 1970-2009 to be included. Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panels differ by included time controls. Counties in and outside the Corn Belt are shown in Figure 1. 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-Induced Yield Shocks and Net Outmigration in Eastern United States - Sensitivity to Minimum Number of Yield Observations

	Counties in Corn Belt			Counties Outside Corn Belt		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Panel A: Using Average of Corn and Soybean Yield					
Log Yield	-0.167***	-0.168***	-0.142***	-0.009	-0.010	-0.129
	(0.036)	(0.037)	(0.033)	(0.093)	(0.141)	(0.128)
F-stat (1st stage)	40.90	36.98	41.37	13.76	6.93	8.67
Observations	7258	7086	5976	6771	6102	2696
Counties	935	892	747	985	805	337
	Panel B: Using Corn Yield					
Log Yield	-0.163***	-0.165***	-0.146***	0.015	0.007	-0.112
	(0.023)	(0.023)	(0.025)	(0.054)	(0.060)	(0.068)
F-stat (1st stage)	25.82	24.52	43.76	14.67	9.97	7.14
Observations	7244	7078	5608	6468	5628	1808
Counties	935	892	701	973	746	226
	Panel C: Using Soybean Yield					
Log Yield	-0.156***	-0.160***	-0.184***	0.016	0.004	-0.046
	(0.044)	(0.050)	(0.056)	(0.060)	(0.073)	(0.080)
F-stat (1st stage)	135.47	169.98	47.68	19.71	18.14	6.10
Observations	6732	6413	4728	5173	4442	1232
Counties	892	810	591	806	595	154
Min. Yield Obs.	1	21	40	1	21	40

Notes: Table replicates Panel B of Table 3 but changes the cutoff when counties are included. Columns (a)-(c) limit the analysis to counties that have progressively larger numbers of yield observations per county in 1970-2009. Counties were only included if they had at most 100,000 inhabitants in 2000. Tables regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panels differ by crop yield measures used and all regressions include quadratic time controls. Counties in and outside the Corn Belt are shown in Figure 1. 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 in Eastern United States - Unweighted Regressions with Bootstrapped Errors

	Counties in Corn Belt			Counties Outside Corn Belt		
	Corn+Soy	Corn	Soybeans	Corn+Soy	Corn	Soybeans
			Panel A: Linear Time Trend			
Log Yield	-0.193**	-0.195**	-0.192**	-0.120	-0.047	-0.055
	(0.084)	(0.085)	(0.079)	(0.204)	(0.106)	(0.112)
			Panel B: Quadratic Time Trend			
Log Yield	-0.186**	-0.185**	-0.178**	-0.082	-0.023	-0.023
	(0.090)	(0.084)	(0.077)	(0.216)	(0.096)	(0.110)
			Panel C: Restricted Cubic Splines (3 knots)			
Log Yield	-0.186**	-0.185**	-0.179**	-0.075	-0.023	-0.019
	(0.089)	(0.085)	(0.078)	(0.219)	(0.096)	(0.108)
			Panel D: State-specific Restricted Cubic Splines (3 knots)			
Log Yield	-0.169	-0.143	-0.167*	-0.052	-0.046	-0.067
	(0.114)	(0.128)	(0.087)	(0.182)	(0.146)	(0.127)
Observations	7086	7078	6413	6102	5628	4442
Counties	892	892	810	805	746	595

Notes: Table replicates Table 3 except that regressions are unweighted and standard errors are obtained using 100 clustered bootstrap runs where we randomly draw entire 5-year intervals with replacement. Table regresses net outmigration on weather-instrumented yield shocks as well as county fixed effects. Panels differ by included time controls. Regressions include all counties with at most 100,000 inhabitants in 2000 that had at least 21 yield observations in 1970-2009. Counties in and outside the Corn Belt are shown in Figure 1. Errors are clustered at the state level. Stars indicate significance: ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

Table A7: Predicted Changes in Net Outmigration Under Climate Change

	Predicted Outmigration Rate				Increased Outmigration		Decreased Outmigration	
	Mean	SDev	Min	Max	Total N	Sign. N	Total N	Sign. N
	Panel A: Log Yields Instrumented with Corn Yields							
Hadley III-B2 (2020-2049)	3.14	(2.66)	-1.57	10.19	794	680	98	39
Hadley III-B2 (2070-2099)	9.78	(5.10)	-2.26	20.05	860	828	32	3
Uniform +1° C	0.45	(0.70)	-0.89	2.48	605	417	287	89
Uniform +2° C	1.41	(1.51)	-1.68	5.54	717	524	175	52
Uniform +3° C	2.93	(2.41)	-2.32	9.24	791	620	101	27
Uniform +4° C	5.05	(3.40)	-2.71	13.60	828	720	64	8
Uniform +5° C	7.80	(4.48)	-2.78	18.74	860	798	32	1
Uniform -50% Precipitation	1.84	(0.51)	0.12	2.55	892	874	0	0
Uniform -30% Precipitation	0.67	(0.44)	-0.72	1.33	819	681	73	5
Uniform -10% Precipitation	0.08	(0.19)	-0.50	0.40	583	394	309	119
Uniform +10% Precipitation	0.07	(0.23)	-0.35	0.77	526	345	366	243
Uniform +30% Precipitation	0.65	(0.84)	-0.91	3.09	663	531	229	160
Uniform +50% Precipitation	1.81	(1.62)	-1.29	6.47	735	663	157	75
	Panel B: Log Yields Instrumented with Soybean Yields							
Hadley III-B2 (2020-2049)	3.59	(2.88)	-0.98	11.31	754	669	56	14
Hadley III-B2 (2070-2099)	11.26	(5.49)	-1.01	22.51	803	789	7	0
Uniform +1° C	0.61	(0.75)	-0.63	2.90	610	452	200	48
Uniform +2° C	1.76	(1.61)	-1.12	6.47	689	537	121	21
Uniform +3° C	3.54	(2.59)	-1.37	10.76	759	655	51	7
Uniform +4° C	6.00	(3.68)	-1.29	15.80	788	726	22	0
Uniform +5° C	9.20	(4.86)	-0.77	21.65	803	768	7	0
Uniform -50% Precipitation	1.48	(0.39)	0.15	2.03	810	778	0	0
Uniform -30% Precipitation	0.54	(0.33)	-0.53	1.06	756	578	54	0
Uniform -10% Precipitation	0.07	(0.14)	-0.39	0.31	556	332	254	54
Uniform +10% Precipitation	0.05	(0.18)	-0.28	0.59	475	229	335	184
Uniform +30% Precipitation	0.49	(0.64)	-0.72	2.40	610	449	200	121
Uniform +50% Precipitation	1.40	(1.23)	-1.02	5.04	676	576	134	47

Notes: Table replicates Table 6 if migration is instrumented by corn yields or soybean yields only. Tables displays predicted increases in net outmigration under various climate change scenarios for the baseline model (Columns 2 and 3 of Panel B in Table 3). The first two rows use medium and long-term projections under the Hadley III - B2 scenario. The remaining columns display predicted changes under uniform climate change scenarios. The first four columns summarize the predicted change in net outmigration rates. The last four columns give the number of counties that are predicted to have an increase or a decrease in net outmigration rates. For each category we give the total number of counties as well as the number of counties that have a statistically significant increase or decrease.