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Climate Change and Labor Markets in Rural Mexico: Evidence from Annual Fluctuations in Weather

PRELIMINARY AND INCOMPLETE DRAFT. PLEASE DO NOT CITE OR DISTRIBUTE WITHOUT AUTHORS' PERMISSION

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Abstract

This paper evaluates the effects of annual fluctuations in temperature and precipitation on labor allocation in rural Mexico. We use a 28-year panel of individuals to investigate how people adjust their sector and location of work in response to year-to-year variation in weather. Controlling for state-year and individual fixed effects, we find that individuals are less likely to work locally in years with a high occurrence of extreme heat. This reduction in labor occurs for both agricultural and non-agricultural jobs, with larger reductions among wage workers. Extreme heat early in the year or for individuals located close to the U.S. border increases the likelihood that individuals respond by migrating to the United States. Under two medium-emissions climate change scenarios, our results imply that increased temperatures will lead to a 1.2-3% decrease in local employment and a 1-2% increase in domestic migration from rural to urban areas. These results provide an important example of how climate change could impact rural labor markets in developing countries.

Keywords: climate change; weather; rural employment; migration; Mexico

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1 Introduction

Climate change is predicted to bring increased incidence of extreme weather events, rising temperatures, melting ice caps, and changing precipitation patterns (Solomon et al. 2007). A changing climate likely entails substantial economic costs arising from lower agricultural productivity, loss of natural resources, changing disease patterns, and sea-level rise (Tol 2002, IPCC 2013). The magnitude of these costs will depend on how governments, institutions and humans respond and adapt to climate change.

The most recent IPCC report and a growing body of literature suggests that the costs of climate change may be substantial and far-reaching, impacting agriculture, mortality, labor productivity, economic growth, civil conflict and migration (Burke and Emerick 2013, Deschenes and Greenstone 2007, Deschenes and Greenstone 2011, Dell et al. 2012, Feng et al. 2012, Graff Zivin and Neidell 2014, Hsiang et al. 2013, Lobell and Field 2007, Lobell et al. 2011, Mendelsohn et al. 1994, Schlenker et al. 2005, Schlenker et al. 2006, Schlenker and Roberts 2009,). These costs are expected to be particularly acute in developing countries, where households do not have the portfolio of adaptation strategies or avoidance behaviors (Mishra and Goodwin 1997) that are available in the U.S. Weather shocks have been shown to have a more pronounced effect on economic growth, agricultural yields, and mortality for poorer households and in less developed countries (Burgess et al. 2013, Dell et al. 2012, Guiteras 2009, Compean 2013, Hsiang 2010, Lobell et al. 2008, Fishman 2011, Mendelsohn et. al. 2010). While the costs of climate change are expected to be more severe in less developed countries, a detailed understanding of these impacts, particularly the human capital impacts, is far from complete. This paper seeks to improve on our understanding by evaluating the labor market implications of weather shocks in rural Mexico.

We evaluate the effects of annual fluctuations in temperature and precipitation on rural Mexican employment decisions, including individuals' sector of work and whether they work locally or relocate within Mexico or to the U.S., as a potential adaptation strategy.[1] We hypothesize that weather shocks impact labor allocation through multiple channels, the most notable of which is the linkage between climate, agricultural productivity, and labor demand. To measure employment decisions, we exploit rich annual, self-reported data on individual employment from 1762 households between 1980 and 2007. We combine these data with village level weather data collected from stations located throughout Mexico to evaluate the effects of weather on labor decisions.

Our empirical approach exploits year-to-year variation in weather to compare a given individual's employment decision under various temperature and precipitation conditions. As has been widely discussed in the literature (Deschenes and Greenstone 2007), a cross-sectional comparison of employment decisions across different weather zones may suffer from omitted

[1] Closely related work makes use of state-level data (from 1995, 2000 and 2005) to quantify the effect of climate induced changes in agricultural productivity on cross-border migration from Mexico to the U.S. (Feng et al. 2010). Efforts to replicate this study find no evidence of a causal link between crop yield and emigration (Auffhammer and Vincent 2012). This is because the original study did not include a time effect.

variables bias, since average climate may be correlated with other time invariant factors. In our setting, households in locations with greater weather risk may be more likely to have already integrated migration into their activity portfolios. This would be consistent with Rosenzweig and Stark's (1989) finding that in zones with high weather risk, households invest in creating migration networks to reduce that risk. Regional shocks over time such as the changing pattern of rural income sources also may be correlated with temperature.[2] Our empirical approach controls for these potentially spurious correlations. Specifically, our identification strategy relies on presumably random year-to-year variation in weather after controlling for individual and state-year fixed effects.

Given the context, the sector of local rural employment might be sensitive to weather shocks (as in Kochar 1999). Small farmers (with fewer than 5 hectares of land) dominate Mexico's agricultural sector, owning or managing more than 77% of rural property. These farmers are typically traditional or subsistence farmers and rarely have access to improved seeds, fertilizer, irrigation, or financial credit and marketing. Partly because of these constraints, production of maize - the crop used to define both growing seasons and growing conditions - is quite labor intensive.[3] Labor may be the only margin of adjustment available to respond to weather shocks.

Our results show that temperature shocks influence individual labor allocation decisions in rural Mexico, particularly for wage workers. Using our preferred specification that allows for nonlinear impacts of temperature by modeling temperature as growing degree days (GDDs) and heating degree days (HDDs), we find that an additional HDD (e.g., 1 growing season day with a temperature increase from 32.5 C to 33.5 C) decreases the probability of local employment by 0.062%. Disentangling the effects by sector reveals that the reduction in local employment is largely driven by a reduction in non-agricultural employment and wage labor. The reduction in non-agricultural work is consistent with a framework in which agriculture-non-agriculture linkages form as a result of imperfect market integration in rural areas. The decrease in wage labor supports our theoretical prediction that at the margin employers will respond to weather shocks by disproportionately adjusting their demand for hired labor.

Household data collected in two separate years measure maize yields and the value of agricultural output, allowing us to test the hypothesis that one channel through which weather shocks impact local labor markets is agriculture. We find a positive relationship between local employment and weather-driven changes in agricultural output and maize yields, though with only two years of data statistical inference is limited. While not conclusive, this analysis suggests that weather shocks are impacting labor markets through agricultural output.

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[2] Between 1980 and 2007, non-farm employment, became much more common. In 1980, just 10% of individuals worked in non-agricultural jobs. In 2007, this increased to 17%. It may be the case that regions characterized by better growing conditions also experienced a larger increase in non-agricultural labor.

[3] Compared to the U.S. which requires 0.14 or less person days to produce a ton of maize, on average 14 person days are required to produce a ton of maize in Mexico (calculated from Foreman 2001).

As local labor markets experience negative weather shocks, individuals may seek employment at other locations in order to adapt. International migration, a relatively longer-run decision, may be especially likely in the context of Mexico given its history of labor migration and status as the largest migrant-sending country in the world (Camarota 2007). To evaluate the effect of weather shocks on migration, we exploit the timing of weather shocks and the location of individuals under the hypothesis that if individuals are able to migrate in response to negative shocks, this will happen early in the growing season or for individuals located close to the U.S. border. Consistent with the hypothesis that migration is a relatively longer-run decision, we find that an increase in HDDs early in the season leads to a significant increase in the probability of migrating to the U.S. We also find that individuals from Mexican states that are close to the U.S. border respond to an increase in HDDs by migrating to the U.S., while those located further away do not.

We use our econometric estimates to simulate the predicted change in probability of working in a given sector and location in the year 2075, ceteris paribus. Under medium emissions climate change scenarios from two global circulation models, rural Mexico experiences an average temperature increase of 1.45 C and no significant change in annual precipitation. We find that under the medium emissions scenario, the probability of working locally in rural Mexico falls by 1.2-3% and the probability of out-migration to urban areas in Mexico increases by 1-2% in 2075. Our lower bound projections translate into more than 350,000 fewer individuals employed locally, and a 277,500 increase in migration to urban areas of Mexico.

2 Theoretical Considerations and Testable Hypotheses

Our analysis posits that weather shocks influence labor allocations initially by impacting crop production, then through linked local markets. To illustrate this, consider an agricultural household that derives utility from the consumption of non-agricultural goods and services (X_{na}), leisure (X_l), and agricultural goods (X_a). Agricultural goods are produced using labor (L), quasi-fixed land and capital ($\bar{K}$). The quantity produced is given by $Q = \theta f(L;\bar{K})$, and it is assumed that $\theta f'(L;\bar{K}) > 0$, and $\theta f''(L;\bar{K}) < 0$. The random variable θ represents the realization of weather during a given crop year. We treat production as a single period problem in which households choose the amount of labor conditional upon $\bar{K}$ and the realization of θ.[4]

In the textbook model (Singh, Squire and Strauss 1986) the agricultural household is a price taker in all markets. The household maximizes utility subject to a full-income constraint that includes agricultural profits:

$$\max_{L, X_a, X_{na}, X_l} U(X_a, X_{na}, X_l) \text{ s.t. } p_a X_a + p_{na} X_{na} + wX_l = Y = p_a \theta Q(L,\bar{K}) - wL + wT \qquad (1)$$

[4] Capital is assumed fixed within a year and so does not respond to weather shocks.

The prices of the agricultural and non-agricultural goods and the local wage are given by p_a, p_{na} and $p_l = w$, respectively, and T denotes the household's time endowment. Solving the production side of this model gives the familiar result:

$$p_a \theta Q_L(L, \bar{K}) = w \tag{2}$$

Demand for labor can then be characterized by $L^*(p_a, w, \bar{K}, \theta)$. Maximizing utility subject to optimal full income $Y^* = p_a \theta Q(L^*, \bar{K}) - wL^* + wT$ yields consumption demands:

$$X_i^*(p_a, p_{na}, w, Y^*) \tag{3}$$

The family labor supply ($F*$) reflects the difference between the time endowment and leisure demand:

$$F^*(p_a, p_{na}, w, Y^*) = T - X_l^* \tag{4}$$

A labor-deficit household will hire labor ($H* > 0$) at the margin to carry out its crop production:

$$H^*(p_a, p_{na}, w, Y^*) = L^* - F^* = L^* - (T - X_l^*) \tag{5}$$

The only difference between this model and the staple agricultural household model is the inclusion of the weather-shock variable θ. Equations (2) - (5) lead to our first two testable hypotheses:

Hypothesis 1: A negative weather shock decreases the agricultural labor demand. This follows directly from the first-order condition (2).

Hypothesis 2: There is a disproportionately large decrease in hired labor demand. Assuming leisure is a normal good, the family labor supply increases as full income falls (4). The disproportionately large increase in H^* follows from the increase in F^* together with the contraction in labor demand in (5).

We now consider the impacts of weather shocks on the non-agricultural sector. A decrease in farm incomes also leads to a decrease in demand for non-agricultural goods. In poor rural economies, services, which by nature are non-tradable, constitute a large part of non-agricultural demand. A local market-clearing constraint sets the sum of household demands equal to the supply (S) of services:

$$\sum X_{na}^*(p_a, p_{na}, w, Y^*) = S(p_{na}, w, \bar{K}_{na}) \tag{6}$$

This yields a local equilibrium price and quantity. A contraction in the demand for services puts downward pressure on the local price, triggering a decrease in non-farm labor demand. By the same logic as above, service-producing household-firms cut back disproportionately on hired labor. In rural Mexico, services are more hired-labor intensive than crop production.[5] This, together with our expectation of a high income elasticity of demand for services relative to food, will tend to magnify the impact of the weather shock on non-farm hired labor demand. These considerations lead us to:

Hypothesis 3: The weather shock produces a disproportionately large impact on non-farm hired labor demand.

If local wages adjust to the shock, they may partially mitigate the impacts on hired labor demand. Integration with outside labor markets would limit the wage response, however. In 2007, 30% of households in rural Mexico had migrants in the U.S. and 46.5% had migrants elsewhere in Mexico (Arslan and Taylor, 2012). Given close contacts with migrant labor markets, excess labor supply is likely to spill out into outside labor markets as local wages fall. Thus,

Hypothesis 4: The weather shock stimulates labor migration.

In short, based on this simple theoretical framework, we expect to find that adverse weather shocks decrease local employment, both farm and nonfarm; decrease hired labor disproportionately; and increase labor allocations outside the local economy, through migration. We now turn to the data to test these predictions empirically.

3 Data

3.1 Labor Allocation Data

The data on rural Mexican employment come from the *Encuesta Nacional a Hogares Rurales de Mexico* (ENHRUM), a nationally representative survey of 1762 households in 80 rural communities spanning Mexico's five census regions.[6] The survey was carried out in the winters of 2003 and 2008.

In the 2003 survey, households were asked retrospectively where, and in which sector, each member worked starting in 1980. The household reported whether each household member worked in an agricultural or non-agricultural job and whether the job was self-employment or wage work. The question was repeated for local work, work elsewhere in Mexico, and work in the United States. For work elsewhere in Mexico, households also reported the state in which members worked. The same survey format was repeated in 2008, retrospective to 1990. Information from the two surveys was combined to create a panel of annual data on household

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[5] Our data from rural Mexico show hired labor shares of 0.08 in agriculture and 0.16 in services.

[6] A description of the survey is available at: http://precesam.colmex.mx/ENHRUM/PAG%20PRIN_ENHRUM_.htm. We use the official definition of rural as people living in communities with fewer than 2,499 residents. Due to cost and logistics, disperse populations with fewer than 50 inhabitants were not surveyed.

work histories spanning the period from 1980 to 2007, with overlapping work histories from 1990-2002

One limitation in using self-reported retrospective data is the well-known difficulty of recalling the 20-year employment history of each member of the household (Bond et al.1988, Smith and Thomas 2003, Song 2007). Errors in the recollection of employment history will bias our estimates if weather shocks are systematically correlated with one's belief or impression about past labor decisions. Given that individuals have been shown to more accurately recall more salient events, our results may reflect how weather affects workers' recollection of the past as well as actual weather impacts. To evaluate this possibility, we make use of matched retrospective employment data from 1990-2002. These data allow us to validate whether households accurately recollected the employment history of family members in the two surveys. Later, as a robustness test we control for recall bias and test the sensitivity of our main results to this specification.

A second issue is that only households with at least one member still in rural Mexico have a probability of being surveyed. Entire households that migrated from rural Mexico are excluded from the sample. If households respond to weather shocks by leaving rural communities, then our estimates will be biased towards zero, thereby underestimating the true impacts of weather on employment choices.

Table 1 reports summary statistics on the employment choices of individuals (Panel A) and households (Panel B) in our study between 1980 and 2007, and for four separate years. The household sample consists of 1509 of the 1762 households sampled (41,436 household-years and 130,603 individual-years) in ENHRUM; the sample was reduced due to the lack of reliable weather station data for certain villages. Also, prior to 2003, work histories were only collected for a random selection of individuals. For 2003-2007, all individuals are included. On average, 42 percent of individuals work locally, where local employment is defined as the sum of agricultural and non-agricultural employment, both for self-employed and wage earning workers. The dominant form of employment is in local agricultural work, where the share of individuals working in this sector declined from 36% in 1980 to 23% in 2007. In our sample an average of 15% of individuals are employed in local non-agricultural work, where employment in this sector increases from 11% to 17% over the study period. The majority of households have at least one individual earning a local wage[7].

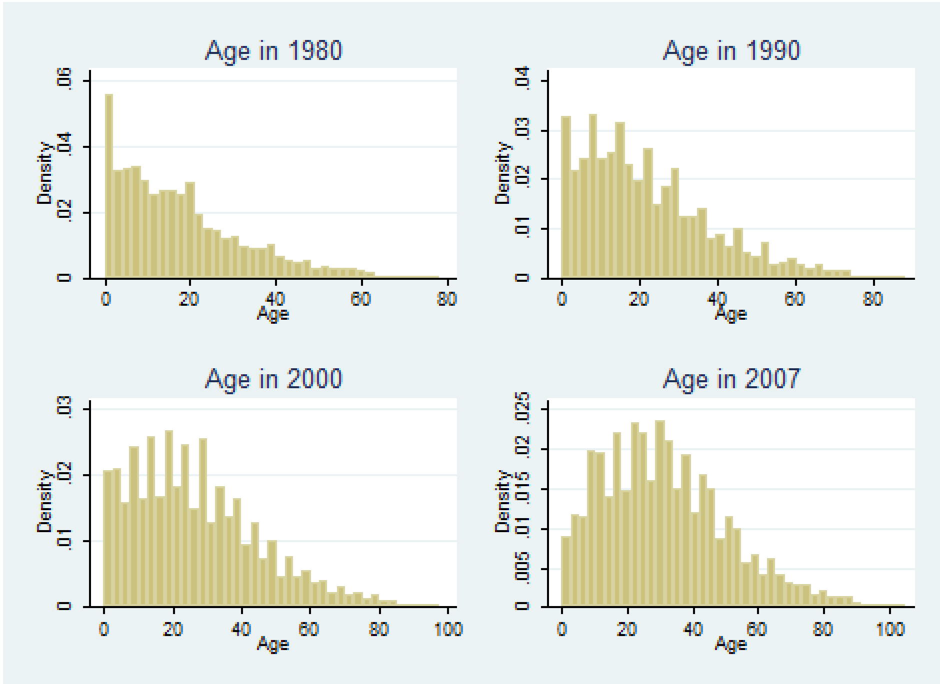
The probability of relocating within Mexico or to the U.S. increased significantly between 1980 and 2007. In 1980 there was an 8.1% chance that an individual worked in another state in Mexico and only a 1.7% chance that s/he worked in the U.S. By 2007, both these probabilities jumped to roughly 10%. Migration patterns differ across Mexico, with the lowest levels of international migration occurring in the southern states and the highest levels occurring in the northern states. This heterogeneity may in part reflect regional differences in migration costs.

[7] Averages are qualitatively similar when including only the working age population. Average employment decreases by an average of 5% in each sector. For comparison, in 2002 1.6% of US jobs were agricultural wage or self-employed (Bureau of Labor Statistics).

Table 1: Summary Statistics on Employment Choices						
Panel A: Individual Employment						
	All Years		Year			
	Mean	Std. Dev.	1980	1990	2000	2007
Work in US	0.053	0.224	0.017	0.031	0.058	0.100
Work O/S Home State	0.086	0.280	0.081	0.078	0.080	0.108
Work in Same State	0.033	0.179	0.031	0.029	0.029	0.042
Local Work	0.419	0.493	0.470	0.418	0.397	0.399
Local Agriculture	0.272	0.445	0.362	0.287	0.233	0.229
Local Non-agriculture	0.147	0.354	0.108	0.131	0.164	0.169
Local Wage	0.233	0.423	0.238	0.229	0.233	0.241
Observations	130603		2158	3599	5276	7374
Panel B: Household Employment						
	All Years		Year			
	Mean	Std. Dev.	1980	1990	2000	2007
Work in US	0.157	0.581	0.025	0.075	0.201	0.538
Work O/S Home State	0.255	0.677	0.122	0.190	0.280	0.584
Work in Same State	0.099	0.412	0.047	0.070	0.101	0.229
Local Work	1.320	1.401	0.768	1.093	1.474	2.233
Local Agriculture	0.857	1.167	0.591	0.751	0.867	1.285
Local Non-agriculture	0.463	0.931	0.177	0.342	0.608	0.948
Local Wage	0.734	1.125	0.389	0.598	0.863	1.349
Household Size	5.937	3.590	4.162	5.604	6.795	7.599
Observations	41436		1454	1489	1509	1367

The overall increase in employment locally, nationally, and internationally between 1980 and 2007 can be partly attributed to the retrospective nature of the survey. Figure 1 illustrates the age distribution in the sample in 1980 (Panel A), 1990 (Panel B), 2000 (Panel C) and Panel D (2007). Between 1980 and 2007, the mean age increases dramatically from 18 to 32 years reflective of an aging sample, and as shown in Panel B of Table 1, the potential labor force in a household increased from 4 in 1980 to 7.6 in 2007. The descriptive evidence suggests that the increase in employment partly reflects the changing age structure of a household. This will bias our results if the age of an individual is systematically correlated with weather shocks. Both the science and economics literature have documented a strong relationship between weather and the timing of conception (Campbell and Wood 1994, Lam and Miron 1991, Pitt and Sigle 1998) suggesting that weather shocks may be systematically related to the timing of births. To control for this possibility, we later test the robustness of our results to the inclusion of age as a covariate and the restriction of the sample to the working age population.

Figure 1: Distribution of Age 1980-2007



3.2 Weather Data

Daily weather data from 1437 weather stations were obtained from the Mexican National Water Commission. The data include daily maximum and minimum temperatures, and totalprecipitation between 1980 and 2007. To measure daily weather, W_{mt}, in village m we take a weighted average of readings from all weather stations, s, located within 50 km of the village center. The weight (α_s) assigned to each station is the inverse square root of the distance (d) to the center of the village,

$$W_{mt} = \sum_{s=1}^{N} \alpha_s(W_{st}) \quad (1)$$

where $\alpha_s = \frac{\sum_{s=1}^{N}\sqrt{d_s}}{\sqrt{d_s}}$. In calculating village weather, we normalize the weights so that their inverse over all stations in a village sums to 1.

As is common when using data from weather stations, stations enter and exit the sample and daily observations may be missing from existing weather stations. These missing data introduce measurement error, and this error may have meaningful implications when using both cross-sectional and time fixed effects. Many of the stations date back to the 1960s, while others began collecting data more recently. Some stations were taken offline at some point in the past and no longer provide weather information. To account for entry and exit, we restrict our sample of stations to those in which data are present for at least 75% of the sample. This reduces the number of weather stations to 1334.

Following Auffhammer and Kellogg (2011) we then predict missing weather at a given station using the following procedure. We regress weather at each station on weather at all the other stations located within 50 km of a village and use the predicted values to replace the missing observations. Weather at a given station will remain missing if any of the regressors in the regression are also missing. To predict the remaining missing observations, we drop the most distant station from the community center and repeat the above step. We continue to reduce the number of stations used as regressors until the missing values have been filled or there are no remaining stations with which to predict weather. Upon completion of this procedure, less than 0.1% of the station-days are missing. To get a sense of the extent to which this procedure approximates the true data generating process, we compare actual and predicted weather variables. The reported correlation coefficient is 0.92 and 0.91 for maximum and minimum temperature, respectively. The procedure performs less well for precipitation, suggesting that our constructed measures of precipitation likely contain substantial measurement error.

3.3 Measures of Weather

Recall that weather, our regressor of interest, is measured daily, while employment, our dependent variable of interest, is measured annually. To analyze the effect of weather on employment, we construct multiple measures of annual weather, all of which are calculated using daily weather data. We restrict the sample of weather to include precipitation and temperature between April 1 and September 31 since this roughly corresponds to the spring-summer growing season for maize, the dominant crop grown in rural Mexico.[8]

Averaging temperature across the season provides a straightforward approach to create an annual temperature measure. However, as is well-known the use of monthly or annual average temperature attenuates much of the variation in daily weather and masks the importance of extreme temperatures. Further, agronomic studies suggest that accumulated exposure to heat over the growing season determines crop growth, as opposed to a seasonal average.

Therefore, we employ an alternative approach, which follows the standard convention in agronomy of converting daily mean temperatures into growing degree days. This measure of temperature stems from agricultural experiments showing that below (and above) certain

[8] Maize is grown in two seasons, a spring-summer and fall-winter season, with the former responsible for over 75% of maize production. In the spring-summer season, planting primarily occurs in June and July and harvesting mainly occurs in November and December. The ideal growing conditions for corn include temperatures above 20 degrees C (68 degrees F) and rainfall between 600 and 1000 millimeters per year. As corn begins to become reproductive, it is most sensitive to climate. This tends to occur in July for corn that is harvested in November or later (Galarza et. al. 2011).

thresholds, plants cannot absorb (additional) heat, while within the bounds of an upper and lower threshold heat absorption increases linearly in temperature. Based on maize production in the U.S., we use the following formula to convert daily temperatures into growing degree days (GDD),

$$GDD(T) = \begin{cases} 0 & if\ T \leq 8C \\ T-8 & if\ 8C < T \leq 32C \\ 24 & if\ T \geq 32 \end{cases} \qquad (2)$$

and then take the sum of growing degree days to form an annual measure.
GDDs alone may not accurately account for the effect of extremely high temperatures on yields and hence employment choices. This is because the effect of extremely high temperatures levels off at the optimum (e.g., a day on which the average temperature is 35 contributes 24 degree days), whereas studies have shown that temperatures above the optimum are harmful for agricultural yields (Schlenker and Roberts 2009).

In addition to GDDs, we construct a measure of harmful degree days (HDDs), which incorporates the possibility that temperatures above a given threshold may be harmful. A heating degree day (HDD) takes the form of:

$$HDD(T) = T - 32\ if\ T \geq 32C \qquad (3)$$

As with GDDs, we sum HDDs over the growing season to construct an annual measure of weather.

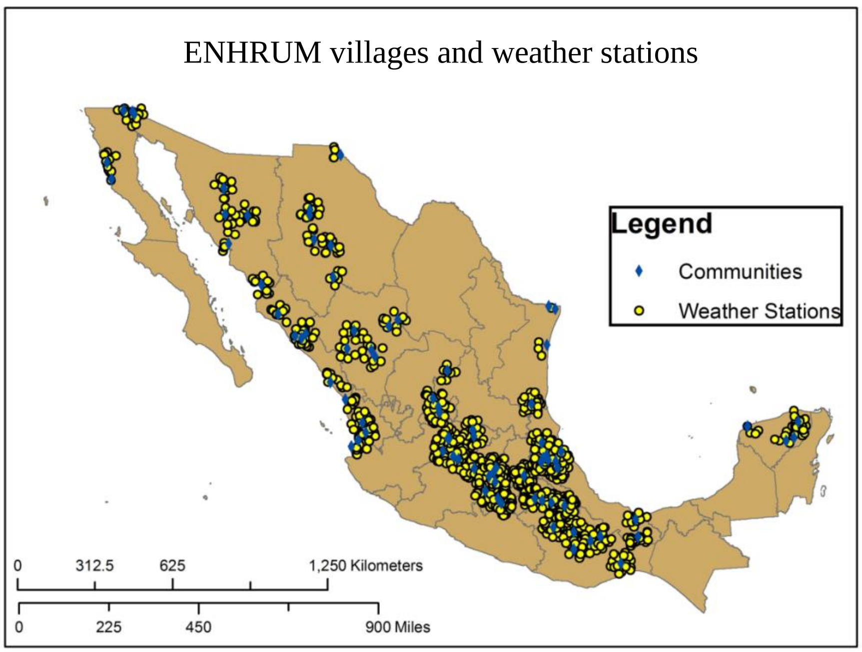
3.4 Variation in weather data

One consideration when including individual fixed effects and state-year fixed effects is that these controls may soak up most of the variation in weather. It is therefore important to evaluate the residual variation that remains after accounting for these controls. This will inform the extent to which the residual variation in weather is as large as the weather changes predicted in the climate change models, and ensure we can identify the effects of climate change on employment from variation in the weather data

Before presenting these results, we visually examine the cross-sectional variation in community weather. A map illustrating the location of each rural community and weather station in the sample (Figure 2) highlights that both communities and weather stations are spread throughout Mexico. This map also indicates that there is substantial overlap in the weather stations used to measure community weather, implying that weather is likely to be spatially correlated across villages within a region.

Table 3 reports results on the residual variation in average temperature, GDDs, total precipitation, and HDDs after controlling for various fixed effects. Given that cross-sectional variation in weather occurs at the village, we define an observation as a village-year, thereby reducing the sample to approximately 1900 village-years. We then regress each weather variable on either village fixed effects, village and year fixed effects, village and year fixed effects and state-year trends, and village and state-year fixed effects. Each column in the table presents the count of observations for which the absolute value of predicted weather exceeds actual weather by a certain threshold. For example, in column 1 of the panel labeled Mean Temperature, there are 837 village-years or roughly 43% of total observations in which the predicted temperature exceeds the actual temperature by 0.5 C, after conditioning on village fixed effects.

Figure 2: Map of surveyed villages and weather stations within 50 km



As is apparent from Table 3, time and location explain much of the variation in mean temperature and GDDs. This is especially true of our preferred empirical approach, shown in the last row of each panel, which controls for village and state-year fixed effects. Under a medium emissions scenario, GDDs and HDDs are predicted to increase by 253 and 6 degrees C. Table 3, Panel B shows that actual GDDs exceeded predicted GDDs by at least 200 in 110 observations. Omitting all time controls increases the number of village-years that exceed 200 GDDs to 224.

Table 2: Residual Variation in Weather					
Mean Temperature (N=1928)	Mean (sd) = 23.05 (4.80)				
Panel A: Number of Municipality-years when Actual Mean Temp Differs from Predicted by more than					
Regressors	0.5 deg C	1.0 deg C	1.5 deg C	2.0 deg C	2.5 deg C
Village FE	837	276	88	29	17
Village FE, Yr FE	725	214	73	25	15
Village FE, State Trends	660	172	65	24	14
Village FE, State-yr FE	538	122	41	15	8
Growing Degree Days (N= 1903)	Mean (sd) = 2738 (859)				
Panel B: Number of Municipality-years when Actual GDDs Differ from Predicted by more than					
Regressors	100 dd	200 dd	300 dd	400 dd	500 dd
Village FE	768	224	86	45	36
Village FE, Yr FE	652	196	79	45	37
Village FE, State Trends	598	173	69	44	36
Village FE, State-yr FE	485	110	57	38	32
Harmful Degree Days (N = 1903)	Mean (sd) = 10.25 (36.28)				
Panel C: Number of Municipality-years when Actual HDDs Differ from Predicted by more than					
Regressors	1 HDD	10 HDDs	20 HDDs	30 HDDs	40 HDDs
Village FE	741	230	126	96	76
Village FE, Yr FE	1640	201	120	92	70
Village FE, State Trends	1428	248	145	100	64
Village FE, State-yr FE	911	221	130	89	65
Total Precipitation (N= 1903)	Mean (sd) = 652 (433)				
Panel D: Number of Municipality-years when Total Precipitation Differs from Predicted by more than					
Regressors	1.0 mm	1.5 mm	2.0 mm	2.5 mm	3.0 mm
Village FE	1911	1905	1893	1882	1879
Village FE, Yr FE	1921	1911	1906	1900	1896
Village FE, State Trends	1911	1902	1894	1889	1878
Village FE, State-yr FE	1894	1878	1870	1845	1830

4 Empirical Approach and Results

In order to identify the impacts of weather on labor allocation, we use a panel data approach (Deschenes and Greenstone 2007, Guiteras 2008, Schlenker and Roberts 2009) which controls for time-invariant individual and state-year fixed effects. We estimate the following:

$$E_{it}^{s} = f(W_{mt}; \beta^{s}) + \gamma_{jt} + \lambda_i + \epsilon_{it} \qquad (4)$$

where E_{it}^{s} is a binary variable indicating whether individual i chooses to be employed in sector s in year t. The local employment choices in this study are agricultural employment, non-agricultural employment, and wage work. The employment decisions related to migration are whether an individual chooses to work outside of the village but within the state, out of the state, or in the US. The regressors of interest, W_{mt}, are functions of weather in year t and village m. Controls include both state-year (γ_{jt}) and individual (λ_i) fixed effects. Estimation is carried out using a linear probability model, so coefficients (β_i) can be interpreted as the change in probability that an individual is employed in a given sector with a one unit increase in temperature or precipitation.

Identification of the effect of weather on the location and sector of employment comes from deviations in municipality weather, controlling for annual shocks to a state. Our estimating equation further controls for fixed individual characteristics that may impact employment decisions. The key assumption behind this approach is that, conditional on individual fixed effects and state-year shocks, variation in weather is orthogonal to unobserved determinants of the choice of employment.

To account for correlation within a village over time and across space within a year, we use the procedure developed by Cameron et. al. (2011) to compute standard errors that are robust to contemporaneous correlation within a state-year and across time within a village.

4.1 Local Labor Allocation and Weather

We begin by estimating the effects of GDDs, HDDs, precipitation and precipitation-squared on individual employment outcomes,

$$E_{it}^{s} = \beta_1^s HDD_{mt} + \beta_2^s GDD_{mt} + \beta_3^s P_{mt} + \beta_4^s P_{mt}^2 + \gamma_{jt} + \lambda_i + \epsilon_{it} \qquad (5)$$

where P_{mt} denotes annual precipitation. This specification allows for heterogeneous impacts across temperatures by modeling temperature as GDDs and HDDs.

Table 3 reports results for the probability that an individual works locally (col. 1), works locally in agriculture (col. 2), works locally in a non-agricultural job (col. 3), and/or works locally for a wage (col. 4). Four central results emerge from this table. First, as shown in column 1, HDDs lead to a meaningful decrease in the probability of being employed locally, with an additional HDD (say from 32.5 to 33.5 C) reducing the probability of local work by 0.062%.

Second, the reduction in local employment is largely driven by a reduction in local wage work (which includes both agricultural and non-agricultural work). This is consistent with the prediction generated from the theoretical model that hired labor is more sensitive to weather shocks. In the presence of these shocks, employers respond at the margin by hiring or firing wage workers.

Table 3: Effect of Cumulative HDD and GDD on Local Employment				
	(1)	(2)	(3)	(4)
	Local Work	Local Ag	Local Non-ag	Local Wage
Harmful Deg Days	-0.000623***	-0.000171	-0.000452***	-0.000433***
	(0.000171)	(0.000122)	(0.000165)	(0.000163)
Growing Deg Days	-3.27e-05	-2.53e-05	-7.42e-06	-5.05e-06
	(2.97e-05)	(1.90e-05)	(1.97e-05)	(2.40e-05)
Tot Precip (mm)	-4.91e-05	-3.53e-05	-1.38e-05	-7.32e-07
	(3.89e-05)	(3.28e-05)	(1.84e-05)	(2.55e-05)
Tot Precip^2	1.31e-08	1.09e-08	2.18e-09	2.50e-09
	(1.29e-08)	(1.13e-08)	(5.69e-09)	(8.69e-09)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	128,823	128,823	128,823	128,823
R^2	0.648	0.692	0.617	0.627
Number of Ind.	7,790	7,790	7,790	7,790

Notes: The dependent variable is whether an individual is employed in a given sector. Columns 1-4 report results from a linear probability model with standard errors clustered at the village level and the state-year. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1

Third, most of the reduction in local employment occurs in the non-agricultural sector. The finding that non-agricultural labor is responsive to weather shocks is consistent with a theoretical framework in which there are strong linkages between agricultural income, demand for non-agricultural goods and demand for non-agricultural labor. Relative to the agricultural market, the non-agricultural market is comprised of a higher proportion of wage workers and demand for non-agricultural services is likely to be more income elastic. These two features would lead non-farm labor to be disproportionately more responsive to price shocks. This finding is also consistent with recent work in the U.S. that finds a more elastic off-farm response to weather shocks (Feng et al. 2012).

Lastly, Table 3 highlights the nonlinearity of temperature impacts. By separately evaluating the effects of GDDs and HDDs, we find that an additional growing degree day has little impact on labor markets, while an increase in extreme temperatures causes a real and significant impact. In contrast, results (available upon request) that model weather using average temperature or only GDDs mask the nonlinear effects of temperature on labor market outcomes. Interestingly, point estimates for the impact of a GDD are negative. This likely occurs because of nonlinear impacts within the range of 0-24 degrees C. This possibility is explored as a robustness check using 2-degree bins for temperature.

The measurement error present in our measure of precipitation makes us cautious in interpreting the impacts of precipitation on labor markets. Perhaps for this reason we find that annual measures of precipitation have no significant impact on labor markets in rural Mexico. We leave a more detailed analysis of extreme precipitation impacts for future work[9].

To investigate how the timing of weather shocks affects labor markets in rural Mexico, we allow HDDs and GDDs at different times of the year to have differing impacts. Specifically, we investigate three time periods: April-May, which coincides with planting; June-July, when most of the plant growth occurs for maize; and August-September. Table 5 demonstrates that the most detrimental HDDs occur in the middle of the agricultural season, when corn yields are most sensitive to temperature. An additional HDD in the June/July period leads to a significant decrease in local employment in all sectors and types of work with the exception of agricultural labor.

Table 4: Effect of HDD and GDD Timing on Local Employment

	(1)	(2)	(3)	(4)
	Local Work	Local Ag	Local Non-ag	Local Wage
HDD April/May	-0.00196**	-0.00129*	-0.000664	-0.000519
	(0.000922)	(0.000686)	(0.000712)	(0.000664)
Tot Precip April/May	-0.000134	-6.52e-05	-6.87e-05	-5.21e-05
	(0.000115)	(9.86e-05)	(7.14e-05)	(9.74e-05)
HDD June/July	-0.000849**	-0.000122	-0.000727**	-0.000652**
	(0.000364)	(0.000171)	(0.000293)	(0.000314)
Tot Precip June/July	2.04e-05	1.80e-05	2.46e-06	4.27e-05
	(4.56e-05)	(5.18e-05)	(2.99e-05)	(3.74e-05)
HDD Aug/Sept	-0.000189	-8.84e-05	-0.000100	-0.000163
	(0.000184)	(0.000149)	(0.000223)	(0.000190)
Tot Precip Aug/Sept	-8.60e-05**	-7.71e-05*	-8.87e-06	-1.49e-05
	(4.25e-05)	(4.56e-05)	(3.24e-05)	(3.15e-05)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	128,823	128,823	128,823	128,823
R^2	0.648	0.692	0.617	0.627
Number of Ind.	7,790	7,790	7,790	7,790

Notes: The dependent variable is whether an individual is employed in a given sector. Columns 1-4 report results from a linear probability model with standard errors clustered at the village level and the state-year. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, p<0.1

4.2 Agricultural Production and Weather

[9] In the case of rural Mexico, temperature is predicted to increase significantly while changes in precipitation are less important.

Our operating assumption is that a primary channel through which weather shocks impact labor is agricultural production. However, while data on employment and weather are available over a 28 year panel, information on agricultural output and agricultural yields are only available for 2 years in the panel. Therefore, we make use of the limited sample on agricultural production to examine the extent to which weather shocks impact labor market outcomes through agricultural production. We do this by modeling two stages separately. First, agricultural production is a function of the weather (6b). In the second stages, agricultural production influences the demand for a labor in the sector.

The impact of weather shocks on local employment is estimated using standard 2SLS,

$$E_{it}^{s} = \beta_1^S \hat{Y}_{ht} + \gamma_{jt} + \lambda_i + \epsilon_{it} \tag{6a}$$

$$Y_{ht} = f(W_{mt}, \alpha^s) + \gamma_{jt} + \lambda_i + \mu_{it} \tag{6b}$$

where Y_{ht} denotes annual corn yields or the value of agricultural output in year t for household h and weather is modeled using the number of heating degree days, growing degree days, total precipitation and total precipitation-squared. The validity of weather as instruments for agricultural output and yields rests on the assumption that weather only impacts local employment through the channel of agricultural production. However, it is likely that weather may impact the probability of working through other channels, such as fatigue or health, as well. As such we view this empirical exercise as support for the assumption that weather impacts labor market outcomes through the conduit of agriculture. Results from 2SLS are reported in Table 5.

As expected, we generally find a positive relationship between local employment and weather induced changes in corn yields and the value of agricultural output, though with only two years of data statistical inference is limited. The F-statistics for the joint significance of the weather instruments are 23 and 42, indicating that the instruments are strong in predicting yields and the value of agricultural output, respectively. Our main results suggest that an increase in weather-driven maize yields leads to a weakly significant increase in the probability of being employed locally, while an increase in the weather-driven value of agricultural output increases the probability of local employment and local non-agricultural employment. While not definitive, these results support the hypothesis that weather shocks are impacting labor markets through the channel of agricultural production.

Table 5. 2SLS Model of Probability of Local Employment				
	(1)	(2)	(3)	(4)
VARIABLES	Local Work	Local Agriculture	Local Non-agriculture	Local Wage Work
PANEL A				
Corn Harvest (Kilos)	1.82e-05	2.19e-05*	-3.72e-06	9.13e-06
	(1.19e-05)	(1.14e-05)	(7.69e-06)	(9.04e-06)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
First Stage F-stat	41.89	41.89	41.89	41.89
Individuals	3,609	3,609	3,609	3,609
Observations	5,857	5,857	5,857	5,857
PANEL B				
Value of Agricultural Output	3.46e-06*	1.48e-06	1.98e-06*	1.08e-06
	(1.80e-06)	(1.66e-06)	(1.17e-06)	(1.36e-06)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
First Stage F-stat	22.97	22.97	22.97	22.97
Individuals	3,608	3,608	3,608	3,608
Observations	5,857	5,857	5,857	5,857

Notes: The dependent variable is whether an individual is employed in a given sector. Columns 1-4 report results from 2SLS. Instruments are the number of HDDs, GDDs, total precipitation and total precipitation squared in the agricultural season. Standard errors are clustered at the village level and the state-year. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, p<0.1

4.3 Migration

We have shown that negative weather shocks impact local labor markets, reducing the demand for local labor. These negative shocks likely extend beyond local labor markets, and in the long-run may influence migration decisions. One drawback of our empirical strategy is that short-run fluctuations are not well-suited to capture longer-run decisions such as the choice to migrate to other states within Mexico or to the United States. While migration often occurs as the result of a long-run decision, some households may have lower migration costs than others and can use migration as a risk management strategy to cope with weather shocks in the short-run. We posit that if households are able to migrate in the short-run, this will happen early in the growing season or for individuals located closer to the U.S. border.

First, we exploit the timing of weather shocks, and hypothesize that if individuals are able to migrate in response to negative shocks this will happen relatively early in the growing season. To test this, we disaggregate HDDs and GDDs into the three time periods previously described in section 4.1. The first 3 columns of Table 6 show that annual changes in HDDs, GDDs, and precipitation do not cause an increase in domestic or U.S. migration. In contrast, an additional HDD early in the season (April/May) makes an individual 0.06% more likely to migrate to the U.S. If the HDDs occur later in the season, they do not have a significant impact on the probability of migrating to the U.S. These results suggest that labor market implications of negative weather shocks extend beyond local markets.

Table 6: Effect of GDD and HDD Timing on Migration

	(1)	(2)	(3)	(4)	(5)	(6)
	US Work	Mexico Work	Within State Work	US Work	Mexico Work	Within State Work
Harmful Deg Days	6.17e-05	9.94e-05	4.41e-05			
	(5.65e-05)	(6.61e-05)	(5.11e-05)			
Growing Deg Days	-5.97e-06	3.81e-05***	4.18e-06			
	(1.13e-05)	(1.47e-05)	(5.91e-06)			
Tot Precip (mm)	1.21e-05	-4.78e-06	-3.46e-06			
	(1.75e-05)	(1.79e-05)	(8.64e-06)			
HDD April/May				0.000627**	0.000422	-0.000131
				(0.000303)	(0.000430)	(0.000154)
Tot Precip April/May				-3.03e-05	2.41e-05	1.53e-05
				(6.16e-05)	(6.81e-05)	(2.93e-05)
HDD June/July				-5.70e-05	0.000141	4.98e-05
				(0.000160)	(0.000105)	(5.46e-05)
Tot Precip June/July				-3.53e-05	1.21e-05	-2.73e-05*
				(2.84e-05)	(3.20e-05)	(1.44e-05)
HDD Aug/Sept				0.000129	4.04e-06	6.07e-05
				(0.000153)	(0.000129)	(7.94e-05)
Tot Precip Aug/Sept				4.86e-05**	-1.48e-05	1.17e-05
				(2.21e-05)	(2.79e-05)	(1.31e-05)
Fixed Effects	Individual	Individual	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year	State-year	State-year
R^2	0.544	0.535	0.490	0.544	0.535	0.490
Number of Ind.	7,651	7,664	7,830	7,651	7,664	7,830

Notes: The dependent variable is whether an individual migrates. Columns 1-6 report results from a linear probability model with standard errors clustered at the village and state-year. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Next, we use regional heterogeneity in migration costs to test whether individuals living close to the U.S. border (i.e. Northern States) are more likely to migrate to the U.S. in response to negative weather shocks. This would occur because both the planning horizon and the costs to migrate to the U.S. are increasing in the distance to the U.S. border. To empirically examine this possibility, we divide Mexico into 5 regions – Central, Central-West, Northeast, Northwest, and South – and interact each regional dummy variables with the weather variables (HDD, GDD, precipitation and precipitation-squared). We find weather shocks differentially increase the probability of migration for individuals residing in the Northeast, an area that borders the U.S., and the Center region of Mexico. Historically, these two regions have had the highest occurrence of U.S. migration, suggesting that perhaps migration costs are disproportionately low in these two regions. It has been shown that the existence of migrant networks lowers migration costs, so for this reason migration costs may be lower in these two regions (McKenzie and Rapoport 2010 and Munshi 2003). These results suggest that households with lower migration costs may have the opportunity to use migration as a short-run response to weather shocks. They also provide another piece of evidence that negative weather shocks extend beyond local labor markets, and can increase migration to the U.S.

Table 7: Regional Effects of Cumulative HDD and GDD on Migration

	(1) Local Work	(2) US work	(3) Mexico work	(4) Within state work
Harmful Deg Days	-0.000252	-1.61e-06	-0.000243	-2.75e-05
	(0.000211)	(7.66e-05)	(0.000208)	(7.03e-05)
Harmful Deg Days*Center Region	-0.00239	0.000337**	0.00108**	-0.000128
	(0.00179)	(0.000169)	(0.000476)	(0.000200)
Harmful Deg Days*Center West	0.00501**	-0.00268**	0.000125	-0.000117
	(0.00228)	(0.00129)	(0.000953)	(0.000485)
Harmful Deg Days*North West	-0.000307	5.69e-05	0.000315	6.93e-05
	(0.000265)	(9.77e-05)	(0.000218)	(9.03e-05)
Harmful Deg Days*North East	-0.00404**	0.00141**	0.00144***	-0.000200
	(0.00170)	(0.000655)	(0.000391)	(0.000187)
Growing Deg Days	4.64e-05	-2.25e-06	6.36e-05	7.79e-06
	(3.94e-05)	(1.02e-05)	(4.85e-05)	(5.78e-06)
Growing Deg Days*Center Region	-5.81e-05	-2.41e-05	-2.60e-05	-2.00e-05
	(7.02e-05)	(2.77e-05)	(5.53e-05)	(1.79e-05)
Growing Deg Days*Center West	-0.000150*	3.87e-05	-5.68e-05	-7.01e-06
	(8.64e-05)	(3.61e-05)	(5.08e-05)	(1.17e-05)
Growing Deg Days*North West	-9.95e-05	-1.27e-05	-9.58e-06	6.15e-06
	(7.88e-05)	(1.98e-05)	(5.42e-05)	(1.40e-05)
Growing Deg Days*North East	-0.000128	9.96e-06	-7.22e-05	-2.94e-07
	(7.95e-05)	(3.87e-05)	(5.75e-05)	(1.22e-05)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	128,823	120,944	121,532	141,158
R^2	0.6481	0.544	0.535	0.490
Number of ind.	7,790	7,651	7,664	7,830

Notes: The dependent variable is whether an individual migrates in a given year. Columns 1-3 report results from a linear probability model with standard errors clustered at the village and state-year. ***p<0.01, **p<0.05, *p<0.1.

4.3 Robustness Checks

While modeling temperature using HDDs and GDDs allows for some nonlinearity in the impacts of temperature on employment, our estimates still rely on the assumption of linearity within the specified ranges. To address this issue, we construct two-degree C temperature bins for all temperatures ranging between 12-32C (e.g. 12-14C, 14-16, etc.), a bin for all days on which the average temperature is less than 12C, and a bin indicating the number of days that the average temperature is greater than 32C.[10] Our reason for using temperature bins is based on earlier work that shows temperature to have nonlinear effects on agricultural yields (Schlenker and Roberts 2009). This flexible form makes minimal assumptions about the functional form relating weather to employment outcomes. Results (available upon request) confirm that a day above 32 degrees C decreases the probability of an individual working locally (by 0.09% per day) while beneficial temperatures appear to increase the probability of working locally.

Traditionally, labor allocation decisions in Mexico have been modeled as a household decision-making process as opposed to an individual decision. In this framework, a household coordinates the sector and location of work for each individual. To test whether our results are sensitive to this alternative decision making structure, we estimate equation (5) at the household level, where the dependent variable is the number of household members in a given year who work in a given sector. In this specification, we also control for household size. Results are qualitatively similar to those reported in Table 3.

Due to the retrospective nature of the survey, the sample is aging and increasing over time. This feature of the data will confound the interpretation of our results if birth rates, and hence the age of an individual, are systematically correlated with weather. To control for this possibility, we perform two empirical extensions: we estimate a slight variation of equation (5) in which we include the age of an individual as a covariate. Results which are reported in Table 8 make clear that the coefficient estimates on weather are not sensitive to the inclusion or exclusion of this covariate.

[10] It should be noted that to construct these bins we take a weighted average over all weather station temperature bins assigned to a municipality. Simply averaging temperature across all stations and then constructing bins would attenuate the variation in weather that we seek to capture.

Table 8: Effect of Weather on Local Employment Controlling for Age				
	(1)	(2)	(3)	(4)
	Local Work	Local Ag	Local Non-ag	Local Wage
Harmful Deg Days	-0.000623***	-0.000169	-0.000453***	-0.000432**
	(0.000165)	(0.000126)	(0.000171)	(0.000164)
Growing Deg Days	-3.28e-05	-2.52e-05	-7.67e-06	-5.22e-06
	(2.83e-05)	(1.80e-05)	(1.91e-05)	(2.33e-05)
Tot Precip (mm)	-4.91e-05	-3.46e-05	-1.45e-05	-1.62e-06
	(3.70e-05)	(2.94e-05)	(1.76e-05)	(2.48e-05)
Tot Precip^2	1.31e-08	1.08e-08	2.30e-09	2.69e-09
	(1.19e-08)	(9.73e-09)	(5.14e-09)	(8.38e-09)
Age	-0.00812***	-0.00555	-0.00257	-0.00548**
	(0.00280)	(0.00462)	(0.00184)	(0.00213)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	128,825	128,825	128,825	128,825
R^2	0.647	0.6914	0.6155	0.6254
Number of Ind.	7,988	7,988	7,988	7,988

Notes: The dependent variable is whether an individual is employed in a given sector. Columns 1-4 report results from a linear probability model with standard errors clustered at the village level and the state-year. Additional controls include a dummy variable indicating if employment histories were identical across the two surveys. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1

The retrospective nature of the survey also introduces the well-known possibility of recall bias. If an individual's ability to correctly recall past employment decisions is systematically correlated with weather shocks, this will bias our results. This is a relevant consideration in our setting given existing studies that find individuals more accurately recall more salient events. To address the general concerns about measurement error in self-reported data, we include a dummy variable indicating if an individual's employment history was identical across the two surveys. Results which are reported in Table 9 suggest that while accurate recollection is systematically correlated with a higher probability of employment, our coefficient estimates on weather are robust to the inclusion of this control.

Table 9: Effect of Weather on Local Employment Controlling for Survey Recollection				
	(1)	(2)	(3)	(4)
	Local Work	Local Ag	Local Non-ag	Local Wage
Harmful Deg Days	-0.000636***	-0.000186	-0.000450***	-0.000437***
	(0.000176)	(0.000132)	(0.000164)	(0.000165)
Growing Deg Days	-3.12e-05	-2.40e-05	-7.19e-06	-4.44e-06
	(2.94e-05)	(1.91e-05)	(1.97e-05)	(2.39e-05)
Tot Precip (mm)	-4.81e-05	-3.42e-05	-1.39e-05	-4.70e-07
	(3.89e-05)	(3.26e-05)	(1.83e-05)	(2.57e-05)
Tot Precip^2	1.35e-08	1.09e-08	2.61e-09	2.83e-09
	(1.29e-08)	(1.13e-08)	(5.77e-09)	(8.72e-09)
Recall Bias	-0.0576**	-0.0795***	0.0220	-0.00924
	(0.0238)	(0.0152)	(0.0163)	(0.0191)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	128,823	128,823	128,823	128,823
R^2	0.6508	0.6935	0.6189	0.6282
Number of Ind.	7,790	7,790	7,790	7,790

Notes: The dependent variable is whether an individual is employed in a given sector. Columns 1-4 report results from a linear probability model with standard errors clustered at the village level and the state-year. Additional controls include a dummy variable indicating if employment histories were identical across the two surveys. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1

Overall, our base results are robust to many specifications. We take this as strong evidence that extreme heat causes a reduction in local employment in rural Mexico.

5 Climate Change and Labor Allocation in Rural Mexico

We use our econometric estimates to simulate the predicted change in the probability of working in a given sector and location in the year 2075, ceteris paribus. Our estimates are specific to the time period 1980-2007, and may change depending on future agricultural policies and local demographic trends. They also capture only the set of short-run responses to weather shocks which may deviate from the long-run response to changes in weather patterns.[11] Because our projections include only short-run responses, results should not be viewed as predictions. Instead, they provide important insights on the potential magnitude of the impacts of changing weather realizations on labor market outcomes for rural Mexicans. The results can be interpreted as the impact of climate change conditional on current long-run labor allocations.

[11] Identification of long-run responses requires variation in climate. For example, Hornbeck (2012) uses longer-run changes in climate to identify impacts of the American Dust Bowl. No similar change in climate occurs over our sample timeframe.

We use two global circulation models to obtain estimates for daily temperature and rainfall over the period of 1980 to 2075. The models include the Community Climate System Model 4 Community Earth System Model (CCSM4; Gent et al. 2011) and the Hadley Centre Global Environment Model version 2 (HadGEM2; Collins et. al. 2008) which are from the Coupled Model Inter-comparison Project Phase 5 (CMIP5). Both models provide daily measures of historical and projected daily temperature and precipitation across the globe at a resolution of approximately 1 degree by 1 degree.[12] We consider two different global emissions scenarios: medium (rcp4.5[13]) and high (rcp6.0).

We use projections from both models to construct village weather projections. To do this, we take the village center latitude and longitude and interpolate weather variables using the four nearest grid-points from each model.[14] We then calibrate the model data to the observed weather station data by using the average difference between historical model output and station data from 1990-2005. Differences between station and model data are used to adjust CCSM4 and HadGEM2 projections based on medium and high global emission scenarios.

We project the change in weather that will occur between 1995 and 2075. We test sensitivity to the base year and find that simulation results are robust to the choice of base and future years.

Table 10 reports the predicted changes in annual precipitation, average temperature, growing degree days, and heating degree days in from 1995-2075 for each region in Mexico under medium and high emissions scenarios for each model. Under all emissions scenarios, average temperatures increase in all regions of Mexico. This leads to an increase in GDDs and HDDs. The increase in HDDs is concentrated in the Northwest region of the country, where HDDs increase by 32 (104) degrees C under the medium emissions scenario using the CCSM4 (HadGEM2) model. For a given emissions scenario, the HadGEM2 model projects a larger temperature increase than the CCSM4 model.[15]

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[12] Historical and projected daily weather data from CCSM4 can be downloaded using the Earth System Grid Federation website (http://pcmdi9.llnl.gov/esgf-web-fe/.

[13] RCP is representative concentration pathways and are standard emissions scenarios with different levels of climate forcing.

[14] To interpolate, we use general bilinear remapping interpolation. See http://www.cerfacs.fr/~daget/TECHREPORT/TR_CMGC_03_79_html/node14.html

[15] HadGEM2 shows a higher average temperature under the medium emissions scenario than under high emissions. This is a result of using only 1 year (2075) of model data. Using 2074, the pattern is reversed but simulation results do not change qualitatively. Using one year weather instead of averaging allows us to capture weather extremes that do not show up in averages. Simulation results are not sensitive to the choice of year and so we present the impact of a change from 1995 weather realizations to those predicted for 2075.

Table 10: Predicted Change in Annual Weather, 1995 to 2075, CCSM4								
	Precipitation (mm)		Average Temp		GDDs		HDDs	
	CCSM4	HadGEM2	CCSM4	HadGEM2	CCSM4	HadGEM2	CCSM4	HadGEM2
RCP4.5								
National	-0.047552	-0.047555	1.45	2.65	253.21	444.06	6.47	30.76
S-SE Region	-0.187201	-0.187210	1.14	2.74	211.98	472.73	-3.03	28.32
Center	-0.163528	-0.163536	1.56	2.86	277.52	514.56	-0.10	-0.07
Center-west	-0.173732	-0.173720	1.52	2.38	278.17	435.12	-0.67	-0.21
NW	0.208898	0.208891	1.61	2.76	243.25	368.58	32.17	104.12
NE	0.235706	0.235708	1.34	2.34	245.80	418.55	-1.94	9.21
RCP6.0								
National	-0.047559	-0.047553	1.50	2.46	253.93	418.82	13.76	21.95
S-SE Region	-0.187214	-0.187206	1.22	1.95	220.51	353.37	3.34	4.05
Center	-0.163542	-0.163531	1.49	2.11	265.08	378.12	-0.10	-0.10
Center-west	-0.173721	-0.173725	1.23	2.42	224.75	442.09	-0.17	0.37
NW	0.208889	0.208895	2.06	3.33	296.53	478.95	56.12	90.18
NE	0.235695	0.235706	1.46	2.48	264.66	452.12	1.35	1.54

Notes: Entries indicate the predicted annual change in weather variables under the 2 emissions scenarios. Regional and national changes are constructed from village weather averages.

Using coefficient estimates from our preferred specifications, we project how climate change will affect employment under various climate change scenarios, ceteris paribus. Table 11 reports results using both national and regional estimates, where results using the CCSM4 are our primary results, and results based on the Hadley model serve as a robustness check.[16] Under a medium-emissions scenario, we find that climate change will decrease the probability that a rural Mexican works in his/her home village by 1.2%, implying that 367,500 fewer individuals will be employed locally. At the 5% significance level, we can project that this decline occurs for both agricultural and non-agricultural jobs. (See Appendix I for a description of how standard errors of predicted changes are calculated.) We project a larger, but qualitatively similar, impact of climate change using the HadGEM2 model. Under a medium-emissions scenario, the probability that an individual works locally decreases by over 3%.

All climate change scenarios in both models suggest that individuals will out-migrate, relocating to more urban areas in Mexico. A medium-emissions scenario will increase out-migration to other areas in Mexico by 1.0% which translates into 277,500 individuals. Using the HadGEM2 model, this percent doubles to 2.0%. In contrast, there is no economically or statistically meaningful impact of climate change on migration to the U.S.. This can be explained by the regional variation in the HDD projections. The Center and Northeast regions of Mexico which have the highest prevalence of international migration and were estimated to be most responsive to weather shocks are projected to experience a decline in HDD under medium emissions climate change scenarios.

In the remainder of Table 11, we explore how responses are likely to vary across regions. While regional regressions are imprecise, point estimates using both climate models suggest that all regions except the south-southeast will experience a decrease in local employment. Everywhere except the northeast, domestic migration will provide other job opportunities for rural Mexicans.

[16] We choose the CCSM4 as our base model since it presents a conservative estimate of the temperature increases.

Table 11: Projected Regional Impacts of Climate Change, 1995-2075

	CCSM4		Hadley GEM2-ES	
	RCP4.5	RCP6.0	RCP4.5	RCP6.0
National				
Local Work	-0.0123	-0.0169**	-0.0337**	-0.0274**
	0.0078	(0.0082)	(0.0149)	(0.0135)
Local Agriculture	-0.0075**	-0.0088**	-0.0165**	-0.0143**
	0.0048	(0.005)	(0.0091)	(0.0083)
Local Non-agriculture	-0.0048**	-0.0081**	-0.0172**	-0.013**
	0.005	(0.0052)	(0.0095)	(0.0086)
Local Wage	-0.0041**	-0.0072**	-0.0156**	-0.0116**
	0.0062	(0.0066)	(0.012)	(0.0108)
US Migration	-0.0011	-6.67E-04	-7.54E-04	-0.0011
	0.0028	(0.0028)	(0.0049)	(0.0046)
Domestic Migration	0.0103**	0.011**	0.02**	0.0181**
	0.0014	(0.0015)	(0.0026)	(0.0024)
S-SE				
Local Work	0.0106	0.0094	0.0148	0.0154
	(0.0412)	(0.0397)	(0.1182)	(0.0632)
US Migration	-0.000474	-0.000503	-0.0011	-8.03E-04
	(0.0159)	(0.0143)	(0.0451)	(0.0228)
Domestic Migration	0.0142	0.0132	0.0232	0.0215
	(0.0339)	(0.0329)	(0.0705)	(0.053)
Center				
Local Work	-0.003	-0.0028	-0.0058	-0.0041
	(0.0502)	(0.048)	(0.0931)	(0.0684)
US Migration	-0.0074	-0.007	-0.0136	-0.01
	(0.0186)	(0.0178)	(0.0345)	(0.0253)
Domestic Migration	0.0104	0.0099	0.0193	0.0141
	(0.0427)	(0.0408)	(0.0791)	(0.0582)
Center-West				
Local Work	-0.032	-0.024	-0.046	-0.044
	(0.0507)	(0.0407)	(0.0788)	(0.0797)
US Migration	0.0119	0.0087	0.0164	0.0151
	(0.0189)	(0.0151)	(0.0292)	(0.0294)
Domestic Migration	0.002	0.0015	0.003	0.003
	(0.043)	(0.0346)	(0.0670	(0.0678)
NW				
Local Work	-0.0309	-0.0471	-0.0778	-0.0759
	(0.1113)	(0.19)	(0.35)	(0.3054)
US Migration	-0.0019	-0.0013	2.29E-04	-0.0022
	(0.0457)	(0.0795)	(0.1483)	(0.1277)
Domestic Migration	0.0155	0.0201	0.0274	0.0324
	(0.0458)	(0.071)	(0.1248)	(0.1141)
NE				
Local Work	-0.0118	-0.0274	-0.0737	-0.0435
	(0.0459)	(0.0473)	(0.0772)	(0.0811)
US Migration	-0.000852	0.0039	0.0162	0.0056
	(0.0174)	(0.0173)	(0.0277)	(0.0298)
Domestic Migration	-0.0044	-0.000647	0.0075	-0.002
	(0.0386)	(0.0402)	(0.0619)	(0.069)

**p<0.05

6 Conclusion

In this paper we investigate the impact of annual fluctuations in temperature on labor decisions in rural Mexico. We find that an increased occurrence of extreme heat decreases the probability that an individual works locally. This impact likely occurs through the channel of agriculture. These weather shocks disproportionately affect local wage work and non-agricultural labor, and are consistent with a rural agricultural model in which non-agricultural sectors are comprised mainly of non-tradable services.

In response to negative weather shocks, individuals may migrate to other areas in search of employment. While migration is a longer-run decision, we evaluate if migration both within Mexico and to the U.S. occurs in the short-run for individuals with lower migration costs. Our proxies for lower migration costs are shocks that occur early in an agricultural season or in regions adjacent to the U.S. border. We find that extreme heat shocks increase the probability of international migration for these individuals.

Extrapolating these results, under a medium emissions scenario we project a 1.2-3% decrease in local rural agricultural labor and a 1.-2% increase in migration within Mexico. However, a main caveat when interpreting our results is that our empirical approach only captures the set of short-run responses to weather shocks. These may deviate from the set of long-run responses to climate change, leading us to potentially understate or overstate the impacts of climate change on local employment. We will underestimate the labor market effects if employers maintain labor demand in response to short-run negative shocks and overestimate them if, in the long-run, households adapt and mitigate the impacts of climate change on agricultural production and hence employment. Recent evidence in the U.S. suggests that adaptation will play a limited role in mitigating the impacts of climate change on agricultural yields (Burke and Emerick 2013). Given that Mexican farmers do not have access to the same portfolio of adaptation strategies, they will likely be less well-positioned to adjust to climate change.

Our results indicate that climate change will have an economically significant impact on rural labor markets. Extreme temperatures will negatively affect earnings opportunities and poor agricultural laborer households will be most vulnerable to these shocks, as their alternative employment opportunities decrease. Policy may play a role in offsetting the negative impacts of climate change in rural communities but before implementing a specific policy, a more comprehensive understanding of individual behavior in response to longer-run temperature and precipitation changes is needed.

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Appendix I

In year t, the predicted probability that individual i in village v works in a given sector is equal to:

$$y_{it}{}^{p} = x_{tv}\beta^{p} + \gamma_{jt}^{p} + \lambda_{i}^{p}$$

x_{tv} represents a vector of weather variables. We simulate climate change as a change in the distribution of expected weather in a village. The change in predicted probability that results from this change in weather is:

$$dy_{it}{}^{p} = dx_{vt}\beta^{p}$$

$$\Delta\, y_{it}{}^{p} \approx \Delta\, x_{vt}\beta^{p}$$

Therefore, we can approximate the change in predicted probability of working in a given sector by multiplying the discrete change in weather variables by the estimated coefficients. We treat climate model output as deterministic (despite large levels of uncertainty in reality) and use the standard errors of estimated coefficients to construct standard errors around the change in predicted probabilities. Specifically,

$$var(dy_{it}{}^{p}) = dx_{vt}var(\beta^{p})dx'_{vt}$$

$$s.e.(dy_{it}{}^{p}) = (dx_{vt}var(\beta^{p})dx'_{vt})^{\frac{1}{2}}$$

Because we have village-level weather, we calculate weather changes at the village level. For ease of interpretation, village-level weather changes are aggregated to the national or regional level by averaging. Therefore, we multiply the national average change in weather variables by our coefficient estimates in the following way

$$d\bar{y}^{p} = d\bar{x}\beta^{p}$$

$$var(d\bar{y}^{p}) = d\bar{x}var(\beta^{p})d\bar{x}'$$

where bars represent national average changes in 5-year weather averages.