Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather

Short Title: Climate Change and Labour in Rural Mexico

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Abstract

This paper evaluates the effects of annual fluctuations in weather on employment in rural Mexico to gain insight into the potential labour market implications of climate change. Using a 28-year panel on individual employment, we find that years with a high occurrence of heat lead to a reduction in local employment, particularly for wage work and non-farm labour. Extreme heat also increases migration domestically from rural to urban areas and internationally to the U.S. A medium emissions scenario implies that increases in extreme heat may decrease local employment by up to 1.4% and climate change may increase migration by 1.4%.

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

JEL Codes: O13, O15, Q1, Q54

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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 growing body of literature suggests that the economic costs of climate change may be substantial and far-reaching, impacting agriculture, mortality, labour productivity, economic growth, civil conflict, and migration (Mendelsohn *et al*., 1994; Schlenker *et al*., 2005; Schlenker *et al*., 2006; Deschenes and Greenstone, 2007; Lobell *et al*., 2008; Schlenker and Roberts, 2009; Deschenes and Greenstone, 2011; Lobell *et al*., 2011; Dell *et al*., 2012; Feng *et al*., 2012; Hsiang *et al*., 2013; IPCC 2013; Graff Zivin and Neidell, 2014; Burke and Emerick, 2015).[1] Ultimately, the magnitude of these costs will depend in part on how humans, governments, and institutions respond and adapt (Oppenheimer, 2013). The costs of climate change are expected to be particularly acute in developing countries, where households do not have access to the portfolio of adaptation strategies or avoidance behaviours available in more developed countries.

The relationship between weather and agricultural volatility has been documented in a number of settings (IPCC, 2014). Rainfall-induced agricultural volatility has a long history of serving as the source of identifying variation to test hypotheses about incomplete insurance, imperfect credit markets, and consumption smoothing (e.g., Rosenzweig and Binswanger, 1994; Foster, 1995; Jacoby and Skoufias, 1997; Jensen, 2000). Until recently, however, the literature has remained relatively silent on the role of temperature in agricultural production and rural incomes. As the science of climate change has evolved, it has become clear that climate change will involve rising temperatures as well as changes in precipitation patterns. Motivated by a desire to understand the costs of climate change, a growing number of studies have examined the relationship between

[1] Dell *et al*. (2014) provide a thorough review of empirical studies that apply panel methods to investigate the relationship between weather and economic outcomes.

temperature and rainfall and health, agricultural production, economic growth, and migration in less-developed countries (Guiteras, 2009; Mendelsohn *et al*., 2010; Dell *et al*., 2012; Burgess *et al*., 2013; Compean, 2013).

This paper investigates the effects of temperature and precipitation on local employment decisions in rural Mexico, including the demand for hired labour, agricultural employment, and non-agricultural employment. Aside from the channel of migration, little is known about the effect of rising temperatures on rural employment in less developed countries, despite the likelihood that labour reallocation will be one of the main mechanisms by which asset-poor households adjust to climate-induced shocks. This is in part driven by a dearth of longitudinal data on individual employment outcomes with the frequency and duration needed to investigate the relationship between weather and local employment. We overcome this hurdle by exploiting rich annual self-reported employment data from 8,107 individuals between 1980 and 2007. We combine these data with village-level weather data collected from 1,334 stations to evaluate the effects of weather on rural Mexicans' sector and location of work.[2]

Our empirical approach uses year-to-year variation in observed weather to compare a given individual's employment decisions under various temperature and precipitation conditions. A cross-sectional comparison of employment decisions across weather zones may suffer from omitted variable bias, inasmuch as average climate is correlated with other time invariant factors

[2] The decision to use weather station data over "gridded" or "reanalysis" data was informed by the rich temporal and spatial coverage of weather stations in Mexico. There are more than 5,000 weather stations located in Mexico. Some of stations began recording temperature and precipitation data in the 1940s, and most have been recording information since 1980, the starting year of our analysis.

(Deschenes and Greenstone, 2007).[3] Time shocks, such as state agricultural policies, also may be correlated with temperature. Our empirical approach controls for these potential confounding factors by utilizing presumably random year-to-year variation in weather after controlling for individual and state-year fixed effects.

Given our empirical setting, local rural employment could be quite sensitive to weather shocks.[4] Small farmers (those with fewer than 5 hectares of land) dominate Mexico's agricultural sector, owning or managing more than 77% of rural property (Juarez, 2013). Typically, these are traditional or subsistence farmers who rarely have access to improved seeds, irrigation, credit, or marketing infrastructure. Partly because of these constraints, production of maize - the basic staple crop used to define both growing seasons and growing conditions - is quite labour intensive.[5] Local nonfarm sectors, linked to agriculture via household demand, are also labour intensive. Labour, both inside and outside of agriculture, may be one of the only margins of adjustment available to respond to weather shocks.

Our results show that temperature shocks influence individual labour opportunities in rural Mexico, particularly for wage workers. They are robust to numerous measures of weather, potential confounding factors, and alternative modelling frameworks, though the effects of extreme events are sensitive to the choice of weather data. Using our preferred specification that allows for

[3] In our setting, households in locations with more variation in climate may already have integrated migration into their portfolio of activities. This would be consistent with Rosenzweig and Stark's (1989) finding that a high variance of profits induces households to diversify their income through migration.

[4] The impact of changing temperatures in Mexico extends beyond our setting. Notably, recent work demonstrates that demand for air conditioning in Mexico is increasing in both temperature and income (Davis and Gertler, 2015).

[5] 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 in Mexico (Turrent Fernandez and Serratos Hernandez, 2004).

nonlinear impacts of temperature by modelling temperature as growing degree days (GDDs) and harmful 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) and a 1 standard deviation increase in HDDs decrease the probability of local employment by 0.05 and 1.90 percentage points, respectively. Consistent with our theoretical predictions, this reduction includes a decline in non-farm labour and wage work. We also provide empirical support for our assumption that one channel through which weather impacts local labour markets is agriculture.

The impacts of negative weather shocks are likely to extend beyond local labour markets and influence an individual's decision to migrate. However, the relationship between migration and environmental change is complex; empirical evidence suggests that environmental shocks may both induce and constrain migration (Munshi, 2003; Barrios *et al*., 2006; Halliday, 2008; Gray and Mueller, 2012; Bazzi, 2016). This is because environmentally-induced migration depends on the permanence of the migration decision, demographics, migration distance and, importantly, the nature of the environmental shock. Recent studies on the migration implications of climate change have focused on the latter consideration, specifically, the link between climatic variation and migration. For the most part, these studies consider either climate induced migration at a macro level or restrict their measure of weather to only rainfall (Munshi, 2003; Barrios *et al*., 2006; Feng *et al*., 2010; Auffhammer and Vincent, 2012; Marchiori *et al*., 2012).[6] Bohra-Mishra *et al*. (2014)

[6] Feng *et al*. (2010) make use of state-level data (from 1995, 2000 and 2005) in Mexico 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, and attribute this to the omission of a time fixed effect in the original study (Auffhammer and Vincent, 2012). In subsequent work, the (original) authors demonstrate the robustness of their main results for rural states in Mexico to the inclusion of time controls (Feng and Oppenheimer, 2012).

and Mueller *et al*. (2014) are exceptions; they provide micro-level examinations of the effect of temperature and rainfall on long-term intra-national migration.

Our work adds a new and critical data point by assessing the effects of temperature and rainfall shocks on both intra-national rural-to-urban and international migration. Our results suggest that an increase in HDDs induces migration to the U.S. and from rural to urban areas in Mexico. Migration to urban areas also increases with positive weather shocks, suggesting that urban migration may be viewed by some as a strategy to mitigate the costs from negative shocks, and by others as a costly but desirable action.

We use our econometric estimates and climate projections to simulate the predicted change in probability of working in a given sector and location in the year 2075, *ceteris paribus*. We find that under medium emissions scenarios, the probability of out-migration to urban areas in Mexico increases by as much as 1.4% by 2075. The increase in HDDs under a medium emissions scenario reduces the probability of working locally in rural Mexico by up to 1.4% and increases the probability of migration to the U.S. by up to 0.25%. These projections translate into 236,094 fewer individuals employed locally, 232,792 migrating to urban areas of Mexico, and 41,275 migrating to the U.S. The decrease in local employment comes from reductions in both agricultural and non-agricultural labour. Projections are sensitive to the climate model used; they are generally lower using the Community Climate System Model 4 Community Earth System Model (CCSM4; Gent *et al*. 2011) than the Hadley Centre Global Environment Model version 2 (HadGEM2; Collins *et al*., 2008).

Our results provide causal confirmation of the longstanding belief that warming temperatures will have local labour market implications in less-developed countries. While well-identified empirical evidence points to the labour market impacts of climate change in the U.S., little is known about the labour market implications outside of this setting (Hornbeck, 2012; Graff Zivin and Neidell, 2014). To our knowledge, our study provides the first such micro-level causal evidence, demonstrating that warming temperatures will meaningfully reduce the probability of local employment, particularly for non-agricultural and hired labour in rural Mexico. Integration with outside markets may partly mitigate the costs of climate change, as individuals respond to warming temperature by migrating to urban areas and internationally in search of employment. This finding is consistent with Bohra-Mishra *et al*. (2014) and Mueller *et al*. (2014), and it adds to the scarce micro-level literature on the impacts of climatic variation on migration. In addition to contributing to our understanding of local labour markets and migration in rural areas, this paper augments our ever-evolving understanding of the costs of climate change. Our results highlight the negative impact of climate change on rural labour markets, particularly for poor wage-labourer households that are most susceptible to local market conditions and may face the greatest response constraints.

1. Theoretical Considerations and Testable Hypotheses

Our analysis posits that weather shocks influence labour allocations initially by impacting crop production, and 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 labour (L) and quasi-fixed land and capital ($\overline{K}$). The quantity produced is given by $Q = f(L, \theta; \overline{K})$, and it is assumed that $f_L > 0$, $f_\theta > 0$, $f_{LL} < 0$, and $f_{L\theta} > 0$. As in Ravallion (1988), the random variable θ represents the realization of weather during a given year, where a higher value of θ indicates better weather, which increases production.[7] We further assume that weather and labour are complements.

In the textbook model (Singh, *et al*., 1986) the agricultural household is a price-taker in all markets. The household maximizes utility in a single period subject to a full-income constraint (Y), which includes agricultural profits and the value of the household's time endowment:

$$\max_{L,X_a,X_{na},X_l} U(X_a, X_{na}, X_l) \quad s.t.\ p_a X_a + p_{na} X_{na} + wX_l = y = p_a f(L, \theta; \bar{K}) - wL + wT. \quad (1)$$

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:

$$p_a f_L(L, \theta, \bar{K}) = w. \quad (2)$$

Demand for labour can then be characterized by $L^*(p_a, w, \bar{K}, \theta)$; it is a function of weather outcomes; capital, which is assumed to be fixed in a year; and local prices. Maximizing utility subject to optimal full income $Y^* = p_a f(L^*, \theta; \bar{K}) - wL^* + wT$ yields consumption demands:

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

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

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

[7] In the empirical section of this paper, we precisely define how weather affects agricultural production.

A labour-deficient household will hire labour ($H* > 0$) 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 conventional 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 agricultural labour demand.*

This follows directly from the first-order condition (2).

- HYPOTHESIS 2: *The negative weather shock reduces demand for hired labour*.

Assuming leisure is a normal good, the family labour supply increases as full income falls (4). This as well as the contraction in labour demand in (5) leads to a decrease in H^* .

A decrease in farm incomes also leads to a decrease in demand for non-agricultural goods. In poor rural economies, services that are by nature non-tradable constitute a large part of non-agricultural consumption 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 labour demand. By the same logic as above, service-producing household-firms cut back on hired labour. This motivates a third hypothesis:

- HYPOTHESIS 3: *A negative weather shock will reduce non-farm labour demand.*

If local wages adjust to the shock, they may partially mitigate the impacts on hired labour demand. Integration with outside labour markets likely limits 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). Further, general equilibrium models for rural Mexico reveal that excess labour supply is likely to spill out into migrant labour markets as local wages fall (Levy and van Wijnbergen, 1995; Taylor *et al*., 2005). These stylized observations lead to our last hypothesis,

- HYPOTHESIS 4: *A negative weather shock will increase labour migration.*

Based on this simple theoretical framework, we expect to find that adverse weather shocks decrease local employment for both farm and nonfarm labour, decrease hired labour, and increase labour allocations outside the local economy, through migration.

2. Data and Summary Statistics

Our empirical analysis integrates annual labour-allocation data from household surveys with daily weather station data from rural Mexico.

2.1 Labour Allocation Data

The data on rural Mexican employment come from the Mexico National Rural Household Survey (*Encuesta Nacional a Hogares Rurales de Mexico*—ENHRUM), a nationally representative survey of 1,762 households in 80 rural communities spanning Mexico's five census regions.[8] The survey was carried out in the winters of 2003 and 2008.

The 2008 survey asked respondents retrospectively where and in which sector the household head, spouse, and *all* children of either the household head or spouse worked each year beginning in 1990. The household reported whether each family member worked in an agricultural or non-agricultural job and whether the job involved self-employment or wage work. The question was asked for local work, work elsewhere in Mexico, and work in the United States. For work elsewhere in Mexico, respondents also reported the state in which family members worked. In the 2003 survey, the same format was used to collect employment history retrospective to 1980. One distinction from the 2008 survey is that information was only collected for a randomly chosen *subset* of individuals in each household. Due to this restriction on the sample, we use the 2008 survey as our primary dataset and where possible combine it with the 2003 survey to create a panel of annual data on family members' work histories spanning the period from 1980 to 2007.

Table 1 reports summary statistics on the employment choices of working age individuals (Panel A) between 1980 and 2007 and for four selected years within this period. Information about household size (Panel B) is reported from 1990 onwards. The sample is comprised of 8,107 individuals from 1,514 households; employment data are available in both survey rounds for 3,895 individuals. On average, 48% 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

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[8] 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 but more than 50 inhabitants.

workers.[9] The dominant form of employment is local agricultural work, though the share of individuals working in this sector declined from 47% in 1980 to 23% in 2007. In our sample, 17% of all individuals are employed in local non-agricultural work, and employment in this sector increased from 15% to 17% over the study period.

The probability of relocating within Mexico or to the U.S. increased between 1980 and 2007. In 1980 there was a 9% chance that an individual worked in another state in Mexico and only a 2% chance that s/he worked in the U.S. By 2007, these probabilities had jumped to roughly 11% and 10%, respectively. There is also cross-sectional heterogeneity in migration patterns, with the lowest levels of international migration occurring in the southern states and the highest levels occurring in the northern and central states. This heterogeneity may in part reflect regional differences in migration costs.

Changes in the profile of employment between 1990 and 2007 can be partly attributed to the retrospective nature of the survey. As shown in Panel B of Table 1, the number of working age family members per household increases from 4.4 in 1990 to 7.4 in 2007. The possibility that a change in the employment profile may reflect the changing age structure of an individual (or household) presents an empirical concern if the age of an individual is systematically correlated with weather shocks. Both the science and economics literature have documented a relationship between weather and the timing of conception (Lam and Miron, 1991; Campbell and Wood, 1994; Pitt and Sigle, 1998), suggesting that weather shocks may be systematically related to the timing of

[9] The probability of employment in our sample is 68%. The sample is comprised of all working-age individuals. For comparison, according to the U.S. Bureau of Labour Statistics the 2013-2014 employment-to-population ratio in the U.S., defined as the working-age population that is employed, was 59%.

births. To address the possibility that the changing age profile may confound our results, we later test the robustness of our results to the inclusion of age as a covariate.

Another empirical concern arises from the use of self-reported retrospective data, and in particular the well-known difficulty of recalling the 20-year employment history of each family member (Bond *et al*., 1988; Smith and Thomas, 2003; Song, 2007). Deviations between actual employment and self-reported employment will lead to measurement error in the dependent variable. This may bias our estimates if weather shocks are systematically correlated with one's recollection of past labour outcomes. Given that individuals have been shown to more accurately recall salient events, our results may reflect how weather affects workers' recollection of the past as well as actual weather impacts. Measurement error may also produce a downward bias in the effects of extreme weather on employment if mild or favourable weather leads to an underreporting of unemployment and negative weather shocks are correlated with an over-reporting of unemployment. To investigate these possibilities, we make use of matched retrospective employment data from 1990-2002, which allow us to determine whether respondents consistently recalled the employment history of family members in the two surveys.

A final caveat when using the ENHRUM data is that only households with at least one member in rural Mexico at the time of the 2003 survey had a probability of being surveyed. Entire households that migrated from rural Mexico are excluded from our sample. If households respond to weather shocks by leaving rural areas, then our estimates will understate the true impacts of weather on employment.

[Table 1]

2.2 Weather Data

Daily weather data from 1,437 weather stations were obtained from the Mexican National Water Commission. The data include daily maximum and minimum temperatures and total precipitation between 1980 and 2007. To measure daily weather, W_{ml}, in village m we take a weighted average of readings from the nearest five (or fewer) weather stations, N, located within 50 km of the village centre.[10] The weight (α_n) assigned to each station is the inverse square root of the distance (d) to the center of the village:

$$W_{ml} = \sum_{n=1}^{N} \alpha_n(\omega_{mnl}) \tag{7}$$

where $\alpha_n = \frac{\sum_{n=1}^{N} \sqrt{d_n}}{\sqrt{d_n}}$ and ω_{mnl} is the weather outcome recorded at station *n* of village *m* on day *l*. 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. Missing data introduce measurement error, and this error may have meaningful implications when using both cross-sectional and time fixed effects (Auffhammer *et al*., 2013). 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

[10] The average distance between a village and stations is 33.5 km. On average, a village-day observation uses readings from 3.6 stations.

stations to those in which data are present for at least 75% of the sample days. This reduces the number of weather stations to 1,334.

We predict missing weather data at a given station following Auffhammer and Kellogg (2011), with a few modifications. We regress weather at each station on weather at all other stations assigned to a village and use the predicted values to replace the missing observations. Weather at a given station remains missing if any of the regressors are missing. To predict the remaining missing observations, we drop the most distant station from the village centre 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 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 (and to a lesser extent, temperature) contain some measurement error that could lead to attenuation bias.[11]

Alternatively, we could have chosen to use "reanalysis" data. This would have removed the need to develop a procedure to account for missing observations. As discussed in Auffhammer *et al*. (2013), reanalysis data are particularly valuable in data sparse regions, but they have drawbacks, as

[11] Recall that this procedure relies on weather stations assigned to a given village to predict weather for the station missing data. We find that the normalized error between actual and predicted weather is greater for precipitation than temperature. We attribute this to the fact that there is less variation in temperatures (or more variation in precipitation) across the stations assigned to a given village.

well.[12] Our decision to use weather station data was informed by the observation-rich nature of our setting. Later, we use the North American Regional Reanalysis (NARR) data to measure temperature and precipitation and compare the results to those using weather station data.[13]

2.3 Measures of Weather

Recall that weather, our regressor of interest, is measured daily, while employment, our dependent variable of interest, is measured annually. To analyse 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 May 1 and October 31, since this roughly corresponds to the spring-summer growing season for maize, the dominant crop in rural Mexico (Galarza *et al*., 2011; Juarez, 2013).[14]

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[12] Reanalysis data are produced from weather models that combine output from global climate models with observational data (e.g., weather stations) to generate non-missing weather data across space and time. Reanalysis data are particularly valuable in data sparse regions, because they provide weather measures based on models and observational data from elsewhere. However, they are constrained by structural assumptions that limit the ability to accurately capture weather extremes. This poses a concern given our focus on the relationship between extreme temperatures and labour allocation.

[13] We use the National Centre for Environmental Protection (NCEP) NARR dataset available at http://www.esrl.noaa.gov/psd/ (Mesinger *et al*. 2006). Daily average temperature and precipitation from 1980 to 2007 are obtained at a resolution of 32 km x 32 km. Bilinear interpolation is used to calculate a weather variable for the centre of each ENHRUM village.

[14] In Mexico, 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 May and June and harvesting mainly occurs between September and October, though there is some regional variation in the growing season. The ideal growing conditions for corn include temperatures above 20 degrees C (68 degrees F) and rainfall between 600 and 1000 millimetres 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 October or later.

Averaging temperature across the season provides a straightforward approach to create an annual temperature measure. However, the use of monthly or less frequent average temperature attenuates much of the variation in daily weather and masks the importance of extreme temperatures. Furthermore, 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 (Herrero and Johnson, 1980; Wilson and Barnett, 1983; Bassetti and Westgate, 1993). This measure of temperature stems from agricultural experiments showing that below (and above) certain thresholds, plants cannot absorb (additional) heat, while within the bounds of an upper and lower threshold heat absorption increases linearly with temperature. We construct daily temperatures as the average of daily minimum and maximum temperature. Then, based on maize production in the U.S., we use the following formula to convert daily temperatures into growing degree days (GDD):

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

We take the sum of growing degree days in an agricultural season to form an annual measure.

GDDs alone may not accurately account for the effect of extremely high temperatures on yields and hence employment choices. The effect of extremely high temperatures in (8) levels off at the optimum, whereas research has 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. For a day at temperature T,

$$HDD(T) = T - 32 \; if \; T \geq 32C \tag{9}$$

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

We later test the sensitivity of our results to our choice of growing season, temperature thresholds, and more flexible models of weather.

2.4 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. This will inform the extent to which the residual variation in weather is as large as the weather changes predicted by climate change models, and ensure that we can identify the effects of climate change on employment from observed variation in weather data.

A map illustrating the location of each rural village and weather station in the sample (Figure 1) highlights that both villages and weather stations are spread throughout Mexico. This map also indicates that there is overlap in the weather stations used to measure village weather, implying that weather is likely to be spatially correlated across villages within a region.

Table 2 reports variable averages as well as results on the residual variation in mean temperature, GDDs, HDDs, and total precipitation after controlling for various fixed effects. Given that cross-sectional variation in weather occurs at the village level, we define a weather observation as a village-year, thereby reducing the sample to 1,900 village-years. The average temperature across the sample is 22.98 degrees C. This translates into an average of 2,741 GDDs and 10.24 HDDs. Precipitation averages 708 mm per growing season.

We regress each weather variable on village fixed effects, village and year fixed effects, village and year fixed effects and state-year trends, or village and state-year fixed effects. Each cell in Table 2 presents the count of observations for which the absolute value of predicted weather exceeds actual weather by the threshold indicated in the column title of each panel. For example, column 1 of Panel A reports that in 789 village-years, or roughly 42% of total observations, the predicted temperature exceeds the actual temperature by 0.5 C, after conditioning on village fixed effects.

[Figure 1]

As evident in Table 2, time and location explain much of the variation in mean temperature, GDDs and HDDs. 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 226 and 6 degree days. Panel B (C) of Table 2 shows that actual GDDs (HDDs) exceed predicted GDDs (HDDs) by at least 200 (10) in 115 (216) observations, implying that there is modest overlap between the weather variation in our sample and the increase in HDDs and GDDs predicted under a medium emissions scenario.

[Table 2]

3. Empirical Approach and Results

To identify the impacts of weather on labour allocation, we use a panel data approach that controls for time-invariant individual and state-year fixed effects (Deschenes and Greenstone, 2007; Guiteras, 2009; Schlenker and Roberts, 2009). We estimate the following model:

$$E_{it}^{s} = f(W_{mt}; \beta^{s}) + \gamma_{jt} + \lambda_i + \epsilon_{it} \tag{10}$$

where E_{it}^{s} is a binary variable indicating whether individual i is employed in sector s in year t. The local employment choices in this study are agricultural employment, non-agricultural employment, and wage work (which includes agricultural and non-agricultural employment). The employment decisions related to migration include work outside the village but within the same state, out of the state but within Mexico, or in the U.S. 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^{s} can be interpreted as the change in probability that an individual is employed in a given sector resulting from a one-unit increase in the corresponding weather variable.[15] Using the procedure developed by Cameron *et al*. (2011), we compute standard errors that are robust to contemporaneous correlation within a state-year and serial correlation within a village.[16]

Identification of the effect of weather on the location and sector of employment comes from deviations in village weather, controlling for annual state weather shocks. Our estimating equation

[15] In reality, an individual faces a set of employment opportunities in a given year, so a choice model such as a multinomial logit may better approximate the decision-making process. We later show that our results are robust to the use of this modelling framework.

[16] We also compute standard errors using the procedure developed in Hsiang (2010) that allows for contemporaneous spatial correlation between villages located within 100 km of each other. Our results are robust to Hsiang standard errors.

further controls for fixed individual characteristics that may impact employment decisions. The key assumption behind this approach, which we later explore, is that conditional on individual fixed effects and state-year shocks, variation in weather is orthogonal to unobserved determinants of the choice of employment.

3.1 Local Labour Allocation and Weather

We begin by estimating the effects of GDDs, HDDs, precipitation (P_{mt}) and precipitation-squared on individual employment outcomes:

$$E_{it}^{s} = \beta_1^s HDD_{mt} + \beta_2^s GDD_{mt} + \beta_3^s P_{mt} + \beta_4^s P_{mt}^2 + \gamma_{jt} + \lambda_i + \epsilon_{it} \tag{11}$$

Our choice to capture the non-linear impacts of temperature by separately including HDDs and GDDs, and to allow for nonlinear precipitation effects by including precipitation and precipitation squared, is rooted in the existing literature (Deschenes and Greenstone, 2007; Guiteras, 2009; Schlenker and Roberts, 2009; Burke and Emerick, 2015). We later test the robustness of our results to our assumptions about the relationship between weather and labour.

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), or works locally for a wage (col. 4). Note that coefficients on HDDs and GDDs are the change in the probability of work in response to a 10 degree day increase. Four central results emerge from these models.

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 0.05%. To provide some context, this implies that a one standard deviation increase in HDDs, which translates into an additional 36.5 HDDs, would decrease the probability of local employment from roughly 47.8 to 45.9%, or 4%. Framed slightly differently, a one standard deviation increase in the growing season share characterized by HDDs (from 7 to 33) would decrease the probability of local employment by 1.5 percentage points. An extreme increase in HDDs, say from the mean to the 95th percentile, would lead to a roughly 48 degree increase in HDDs and a 2.5 percentage point reduction in the probability of local employment. This suggests that for a large range of observed weather, on average the local labour market effects of short-run negative increases in temperature are unlikely to exceed 5.5%.

Second, the reduction in local employment is largely driven by a reduction in local wage work. This is consistent with the theoretical prediction that hired labour is sensitive to weather shocks. It also aligns with a hypothesis in which employers respond to negative shocks at the margin by hiring or firing wage workers.

[Table 3]

Third, most of the reduction in local employment occurs in the non-agricultural sector. The result that non-agricultural labour decreases with an increase in HDDs is consistent with our theoretical framework, in which there are strong linkages between agricultural income, demand for non-agricultural goods, and demand for non-agricultural labour. To explain why the local non-agricultural sector would be more responsive than the agricultural sector, we frame our results within three key observational features of our setting. First, relative to the agricultural market, the non-agricultural market is comprised of a high proportion of wage workers. Our data show hired labour shares in value added of 0.08 in agriculture and 0.16 in services. Second, in rural Mexico there is a high income elasticity of demand for services relative to food. Third the presence of agricultural support programs may dampen the effect of weather shocks on local agricultural labour. This third possibility is consistent with recent work in the U.S. that finds the non-farm response to weather shocks to be more elastic than the agricultural response (Feng *et al*., 2012).

Finally, the results highlight 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 labour markets, while an increase in extreme temperatures causes a real and significant impact. In contrast, results from a model using average temperature or only GDDs mask the nonlinear effects of temperature on labour market outcomes.

The measurement error in our measure of village precipitation makes us cautious in interpreting the impacts of precipitation on labour markets. Annual measures of precipitation do not significantly impact labour markets in rural Mexico, but we cannot discern to what extent measurement error biases these estimates towards zero.[17] We do not expect this to influence our projections about the labour market implications of climate change, inasmuch as climate change models indicate that Mexico will experience relatively small changes in total precipitation under medium and high emissions scenarios.

To investigate how the timing of weather shocks affects labour markets in rural Mexico, we disaggregate our measure of weather into specific periods within the agricultural season and evaluate the impact of these weather shocks on local employment. As shown in Table 4, negative shocks early in the agricultural season, when planting occurs, lead to a reduction in local work, including agricultural work. These results are consistent with bad weather early in the season reducing land planted and the demand for agricultural labour across the year. Additional HDDs in

[17] To investigate this concern, we later rely on weather measures obtained from the North American Regional Reanalysis data and estimate equation (11). As a preview to these results, we find that contemporaneous precipitation increases the probability of local work at a decreasing rate, though with the exception of local agriculture this effect is not statistically significant.

the middle of the agricultural season, when corn yields are most sensitive to temperature, also lead to a reduction in local work; however, we do not find that agricultural labour is statistically sensitive to mid-season shocks. This may be because our dependent variable is measured annually and employment may have happened earlier in the agricultural season, or farmers may compensate for a negative shock in the growing season by increasing family labour and decreasing hired labour.

[Table 4]

3.2 Migration

The impacts of negative weather shocks likely extend beyond local labour markets and in the long-run may influence migration, both within Mexico and to the U.S. One limitation of our empirical approach is that short-run weather fluctuations may not be well-suited to capture these longer-run decisions. Nevertheless, insights into the migration implications of weather shocks are critical in order to understand the labour market impacts of climate change in less-developed countries. We now evaluate the effect of weather shocks on migration, recognizing that the results are likely to provide a lower bound estimate.

Table 5 shows that migration both to the U.S. and within Mexico occurs in response to weather shocks. When weather is measured across the entire agricultural season (columns 1-3), negative shocks increase U.S. migration, and positive shocks, as measured by an increase in GDDs, induce relocation within Mexico from rural to urban areas. These results suggest that migration may be viewed by some individuals as a strategy to mitigate costs of negative shocks, and by others as a costly but desirable opportunity. The finding that U.S. migration increases with HDDs is consistent with previous work in Mexico demonstrating that higher temperatures increase international migration rates through decreased crop yields (Feng *et al*., 2010).

The remaining columns in Table 5 confirm that the timing of weather shocks within the agricultural season meaningfully impacts whether and where households migrate in response to shocks. In columns 4-6, we restrict our measure of weather to the early agricultural season (May and June), and in columns 7-9, weather is measured in the months of July and August, when most plant growth for maize occurs. Negative shocks early in the agricultural season increase the probability of U.S. migration, and negative shocks in the growth season induce migration to urban areas within Mexico. These findings are consistent with the hypothesis that, if individuals are able to migrate in response to negative weather shocks, this will happen relatively early in the growing season, when there is more time to cope and respond. Early season shocks may also align better with the demand for labour at migrant destinations.

[Table 5]

3.3 Robustness

Our primary results are predicated on a number of assumptions about the relationship between weather and labour outcomes. We now explore the sensitivity of our local labour employment results to various constructions of the weather variables, examine the possibility that confounding factors may bias our coefficient estimates, and test the robustness of our results to alternative modelling frameworks. Our primary results are robust to an array of considerations, and we interpret this as strong evidence that extreme heat shocks reduce the probability of local employment in rural Mexico.

3.3.1 Weather considerations

Table 6 explores the sensitivity of our results to a number of judgments about the relationship between weather and local labour market outcomes. It highlights the robustness of our main qualitative result that an increase in the number of harmful degree days reduces the probability of local employment. Incorporating within-day variation in temperature using the process used in Schlenker and Roberts (2009) and proposed in Snyder (1985) (col. 1), decreasing the harmful degree threshold to 30C (col. 2), increasing the harmful degree day threshold to 34C (col. 3), redefining the agricultural season to span May to November (col. 4), or excluding the precipitation variables from the estimating equation (col. 5) does not alter the primary finding that negative weather shocks reduce the probability of being locally employed.[18] As reported in column 6, we also find that weather shocks occurring outside of the agricultural season do not impact local rural employment opportunities. In addition to serving as a robustness check, this result suggests that weather shocks operate through the channel of agriculture.

[Table 6]

While modelling temperature using HDDs and GDDs allows for some nonlinearity in impacts of temperature on employment, previous work suggests that a more flexible approach to modelling weather could better reflect the relationship between weather and agricultural yields (Schlenker and Roberts, 2009). To test the robustness of our results to this consideration, we constructed two-degree C bins and measured weather as the number of days that the average temperature falls

[18] In alternative specifications, we evaluate the effect of precipitation exclusively, interactions between temperature and precipitation, and lagged weather on local labour outcomes. When we exclude temperature from the estimating equation, we continue to find no statistically significant effect of precipitation on local labour; the inclusion of interaction terms does not alter the interpretation of our results; and in specifications with lagged weather variables, we find only contemporaneous weather variables to be significant in impacting local work.

within each bin.[19] Figure 2 illustrates marginal effects relative to a growing condition base bin of 26-28 degrees. This figure confirms our earlier finding that a day above 32 degrees C decreases the probability of an individual working locally (by 0.1% per day relative to a day between 26 and 28 degrees C).

[Figure 2]

In developing countries where weather station data are often sparse, economists have relied on reanalysis data to study the impacts of weather (e.g., Guiteras, 2009; Hsiang *et al*., 2011; Kudamatsu, *et al*., 2012). We have a setting characterized by a rich network of weather stations, thus affording us the opportunity to explore the sensitivity of our results to our choice of weather data. We replicate Figure 2 using the North American Regional Reanalysis data to measure weather; results appear in Appendix Figure 1. A comparison across the two sets of results highlights the consistency in the qualitative finding that an increase in the days characterized by optimal growing temperatures increases the probability of local employment, and that estimates are noisy. There is, however, a divergence in the impact of an increase in harmful degree days across the two data sets. Using the reanalysis data we cannot reject the hypothesis that extremely hot days have no impact on local employment. We are not the first to document the sensitivity of coefficient estimates to the choice of weather data. Auffhammer *et al*. (2013) compare annual deviations in mean weather across two gridded data sets and one reanalysis data set and find that substantive differences exist, particularly between the gridded and reanalysis data.

[19] Specifically, we constructed two-degree C temperature bins for all temperatures ranging between 14-32C (e.g., 14-16, 16-18, etc.), a bin for all days on which the average temperature is less than 14C, and a bin indicating the number of days that the average temperature is greater than 32C. It should be noted that to construct these bins we take a weighted average over all weather station temperature bins assigned to a village. Simply averaging temperature across all stations and then constructing bins would attenuate the variation in weather that we seek to capture.

We believe that these differences are largely driven by temperature extremes. The correlation coefficients between HDDs, GDDs, and precipitation using weather station and reanalysis data are 0.81, 0.84, and 0.73 respectively, indicating that while there is a strong relationship between the two weather measures, there are also some differences. One limitation of reanalysis data sets is that the restrictions imposed on the model may prevent the model from capturing strong deviations in weather (Auffhammer *et al*., 2013). For this reason, as well as the presence of a rich set of weather stations, an interpolation procedure that has been relied upon by others, and the robustness of our results to numerous specifications, we choose to lean on the results produced using weather station data. We view the reanalysis results, and in particular the discrepancy in statistical significance across the two data sets, as adding another data point to the growing suite of studies that highlights the sensitivity of results to the choice of weather data. The discrepancy in the estimated effect of extreme weather across the two data sets reiterates the need to better understand why and under what conditions observational and reanalysis weather data sets diverge.

3.3.2 Potentially confounding factors

The retrospective nature of the survey causes the sample size to increase and the age distribution to change over time. These features of the data confound the interpretation of our results if birth rates, and hence the age of an individual, are systematically correlated with weather and meaningfully impact employment. To control for this possibility, we estimate a slight variation of equation (11) that includes the age of an individual as a covariate. Results, reported in column 1 of Table 7, make it clear that the coefficient estimates on weather are not sensitive to the inclusion or exclusion of this variable.

[Table 7]

Measurement error introduced from the self-reported and retrospective nature of the survey may bias the estimated effects of weather on employment. This can occur if an individual's ability to correctly recall past employment decisions is systematically correlated with weather shocks. Recall bias is a relevant consideration in our setting given existing studies that find that individuals more accurately recall salient events. A related concern is that mild weather might be systematically correlated with an underreporting of true unemployment, and extreme heat might be correlated with an over-reporting of unemployment. To assess the possibility that extreme weather at the time of employment is systematically correlated with measurement error in the dependent variable, we take advantage of a unique feature of our employment data – the collection of 1990 to 2002 employment histories in two separate surveys. For these overlapping years we include a dummy variable indicating whether (= 0) or not an individual's reported employment history in a given year is identical across the two surveys. We assume that if the reported histories for an individual-year are identical across the two surveys there is no measurement error in the dependent variable. The results, reported in column 2 of Table 7, suggest that while a discrepancy in recollection is systematically correlated with a lower probability of employment, our coefficient estimates on weather are robust to the inclusion of this control.[20]

3.3.3. Decision making process

Traditionally, labour allocation decisions in Mexico have been modelled as the result of a household decision-making process as opposed to an individual one (Stark and Taylor, 1991; McKenzie and Rapoport, 2011). In this framework, a household coordinates the sector and location

[20] It is also conceivable that cognitive issues are related to extreme heat or rainfall at the time of the survey. We are not aware of any extreme heat or rainfall events at the time of the ENHRUM surveys; such events would be unlikely given the time of year in which the surveys were carried out (winter, which is the cool and dry season in Mexico).

of work for each individual. To test whether our results are sensitive to this alternative decision making structure, we estimate equation (11) at the household level, where the dependent variable is the number of household members in a given year who work in a given sector, and condition on household size. The results, reported in column 3 of Table 7, are qualitatively similar to those reported in column 1 of Table 3.

A choice model in which an individual simultaneously chooses one employment opportunity amongst an array of possibilities may better reflect the decision-making process. We estimated a multinomial logit model in which an individual faces the following choices in a given year: local agricultural work, local non-agricultural work, migration, or no employment. Marginal effects from a multinomial logit model with village and state-year fixed effects are reported for each employment opportunity relative to no employment in columns 4-6 of Table 7. Consistent with our earlier results, an increase in harmful degree days significantly decreases the probability that an individual is locally employed, and this holds for both agricultural and non-agricultural labour. In line with the results reported in Table 5, we continue to find that the probability of migration increases in response to an increase in extremely hot days.

3.4 Extensions

Thus far, we have assumed that a primary channel through which weather shocks impact labour markets is agricultural production. Self-reported information on corn yields and the value of agricultural output can be used to test the plausibility of this assumption using instrumental variables, as in Feng *et al*. (2010). Unlike data on employment and weather, which are available over the 28-year panel, the aforementioned variables are only provided for two years in the panel (those immediately preceding each survey). In what follows, we make use of the limited household sample on agricultural production to examine the extent to which weather shocks impact labour market outcomes through agricultural production. We implement this using 2SLS, where in the first stage weather variables serve as instruments for agricultural production:

$$Y_{ht} = f(W_{mt}, \alpha^{s}) + \gamma_{jt} + \lambda_{i} + \mu_{it} \tag{12}$$

Y_{ht} denotes annual corn yields or the value of agricultural output in year t for household h, and weather is modelled using the number of harmful degree days, growing degree days, total precipitation and total precipitation-squared. The validity of these weather instruments rests on the assumption that weather impacts local employment only through agricultural production. It is likely that weather impacts the probability of working through other channels, such as health, as well. Therefore, we view this empirical exercise as a tentative test for the assumption that weather impacts labour market outcomes through agriculture.

Results from 2SLS are reported in Table 8. Our results suggest that an increase in weather-driven maize yields (Panel A) leads to a significant increase in the probability of being employed locally in agriculture, while an increase in the weather-driven value of agricultural output (Panel B) increases the probability of local non-agricultural employment. The finding that yields mainly affect agricultural labour, while the value of output impacts local non-agricultural employment, is consistent with our hypothesis that income serves as the link between agricultural and non-agricultural markets. These results, particularly when combined with the finding that weather shocks outside of the agricultural season do not impact local employment, support our assumption that weather shocks impact labour markets through the channel of agricultural production.

[Table 8]

4. Climate Change and Labour Allocation in Rural Mexico

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*. 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. Because our projections include only short-run responses, results should not be viewed as predictions. Instead, they provide insights into the potential magnitude of impacts of changing weather realizations on labour market outcomes for rural Mexicans. The results can be interpreted as the impact of climate change conditional on current long-run labour allocations.

We use two global climate models–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)—to obtain estimates of daily temperature and rainfall over the period 1980 to 2075. 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.[21] We consider two different global emissions scenarios: medium (rcp4.5) and high (rcp6.0).

To construct village weather projections, we first take the village centre latitude and longitude and interpolate weather variables using the four nearest grid-points from each model.[22] We then calculate the projected change in weather that will occur between 1995 and 2075 under medium and high global emission scenarios. We use these projected changes, together with the coefficient

[21] Historical and projected daily weather data from CCSM4 and HadGEM2 can be downloaded using the Earth System Grid Federation website.

[22] To interpolate, we use general bilinear remapping interpolation.

estimates reported in Table 3 and Table 5 (columns 1-3), to simulate the impacts of climate change on labour allocation in rural Mexico.[23]

Appendix Table 1 reports the predicted changes in annual precipitation, average temperature, growing degree days, and harmful degree days from 1995 to 2075 from each climate model and for each region in Mexico, under medium and high emissions scenarios. Under all emissions scenarios, average temperatures increase in 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 (107) 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.[24] Both models predict an overall increase in agricultural season precipitation of around one percent. Of course, if the timing of precipitation changes, this could impact labour markets in ways we are unable to capture.

Using coefficient estimates from our preferred econometric model specifications, we project how climate change will affect employment under various climate change scenarios, *ceteris paribus*. Table 9 reports the results nationally and by region. In odd columns the projected changes in climate are restricted to HDDs, and in the even columns climate change is measured as the collective change in temperature and precipitation.

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[23] We tested the sensitivity of our results to the choice of base year and terminal years and found that they are robust to these choices. An alternative approach to modelling the terminal year would be to average across a five- or ten-year span. However, this would attenuate much of the variation in weather, particularly extremely hot and cold days, that we seek to capture.

[24] The HadGEM2 projects a higher average temperature under the medium emissions scenario than under the high emissions scenario. This is due to our choice of using 2075 as the terminal year. When 2074 is used as the terminal year, this pattern is reversed.

Consistent with our econometric results, decreases in local labour come from a reduction in agricultural and non-agricultural labour, including wage workers. These results are statistically meaningful when we restrict our climate change projections to HDDs only, but they become noisy once climate change projections include precipitation and GDDs, likely because of the large standards errors on GDDs and large projected changes in GDDs. Using the CCSM4 model, a medium emissions scenario and restricting the change in climate to HDDs only, climate change is projected to decrease the probability that a rural Mexican works in his/her home village by 0.31%, implying that, by 2075, 51,181 fewer individuals will be employed locally. We project a larger but qualitatively similar impact of climate change using the HadGEM2 model. Under a medium-emissions scenario, the probability of working locally decreases by 1.4% (or 236,094 fewer individuals).[25]

All climate change scenarios in both models suggest that individuals will out-migrate, relocating to more urban areas in Mexico. Under a medium-emissions scenario, out-migration to other areas in Mexico increases by 0.67% (CCSM4 with all measures of weather), which translates into 110,618 individuals. Using the HadGEM2 model, the increase doubles to 1.4%, or 232,792 individuals. There is no statistically meaningful impact of climate change on migration to the U.S. when climate change projections include GDDs, HDDs and precipitation. When we restrict the climate change projections to HDDs only, a medium-emissions scenario leads to a 0.05% (8,750-person) to 0.25% (41,275-person) increase in migration to the U.S. using the CCSM4 and HadGEM2 models, respectively. This migration response is smaller than the one reported in Feng *et al*. (2010), both in

[25] The World Bank World Development Indicator Database provides an estimated rural Mexican population of 26,208,586 in 2010. According to the survey data used in the analysis, 63% of individuals are of working age on average. This translates into a potential rural labour force of 16,510,112 individuals. If the probability of local employment decreases by 0.55%, this translates into approximately 90,806 fewer people employed in local jobs.

percentage and absolute terms. This can partly be explained by differences in the sample, since our analysis restricts its attention to the rural population as opposed to the national population. It suggests that urban Mexicans may be better positioned to respond to climate change by migrating internationally.

[Table 9]

5. Conclusion

This paper investigates the impact of annual fluctuations in temperature on labour markets in rural Mexico. We find that an increased occurrence of extreme heat decreases the probability that an individual works locally. Weather shocks disproportionately affect local wage work and non-agricultural labour, consistent with a rural general-equilibrium 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. Given that migration is likely to be a longer-run decision and our empirical approach is equipped to identify short-run responses to weather shocks, our study might provide a lower bound estimate of migration impacts. Even in the short-run, we find that extreme heat shocks early in the growing season increase the probability that individuals migrate to the U.S. and from rural to urban areas within Mexico.

Extrapolating these results under a medium emissions scenario, we project that the probability of migrating from rural to urban areas within Mexico will increase by 0.7% to 1.4% as a result of climate change. The probability of working locally will decrease by 0.3% to 1.4%, and the probability of U.S. migration will rise by 0.05% to 0.25%. These percentage changes imply up to 236,094 fewer people employed locally, 232,792 additional rural-urban migrants, and 41,275 more Mexico-U.S. migrants. Our results illustrate the sensitivity of impacts to both climate projections and behavioural responses.

A caveat when interpreting these 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 potentially to understate or overstate the impacts of climate change on local employment. We underestimate labour market effects if employers maintain labour demand in response to short-run negative shocks. We overestimate them if, in the long-run, households adapt and mitigate the impacts of climate change on agricultural production and hence employment. Recent evidence from the U.S. suggests that adaptation will play a limited role in mitigating the impacts of climate change on agricultural yields (Burke and Emerick, 2015). Given that most Mexican farmers do not have access to the same portfolio of adaptation strategies as U.S. farmers, it is likely that they will be less favourably positioned to adjust to climate change.

Our results suggest that climate change will have an economically significant impact on rural labour markets in less developed countries. Extreme temperatures will affect local earnings opportunities negatively. Poor wage-labourer households will be most vulnerable to these shocks, as their local employment opportunities are most sensitive to extreme heat.

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Appendix Material

[Appendix Table 1]

[Appendix Figure 1]

Table 1: Summary Statistics on Employment Choices						
	All Years		Year			
Panel A: Individual Employment	Mean	Std. Dev.	1980	1990	2000	2007
Work in US	0.068	0.251	0.019	0.050	0.081	0.100
Work O/S Home State	0.103	0.303	0.092	0.095	0.112	0.109
Work in Same State	0.040	0.196	0.036	0.035	0.042	0.043
Local Work	0.478	0.500	0.622	0.482	0.448	0.400
Local Agriculture	0.309	0.462	0.468	0.331	0.264	0.230
Local Non-agriculture	0.169	0.375	0.153	0.151	0.184	0.171
Local Wage	0.267	0.442	0.315	0.266	0.263	0.242
Age	32.922	12.465	30.837	31.116	33.155	35.119
Observations	137162		1885	4684	6784	7531
Panel B: Household Characteristics						
Household Members In Survey	5.820	3.620	2.102	5.389	6.638	7.379
Observations	38065					

Notes: Means of the probability of employment in each category are reported for all years and by year for individuals in Panel A. Panel B reports the average number of members of working age included in the survey for all years and by year.

Table 2: Residual Variation in Weather

Mean Temperature (N=1928)	Mean (sd) = 22.98 (4.99)				
Panel A: Number of Municipality-years when Predicted Mean Temp Differs from Observed 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	789	257	89	33	14
Village FE, Yr FE	675	204	66	27	14
Village FE, State Trends	604	157	63	26	12
Village FE, State-yr FE	532	122	44	15	9

Growing Degree Days (N= 1900)	Mean (sd) = 2741.52 (899.34)				
Panel B: Number of Municipality-years when Predicted GDD Differs from Observed by more than					
Regressors	100 dd	200 dd	300 dd	400 dd	500 dd
Village FE	717	219	83	49	40
Village FE, Yr FE	607	185	72	51	38
Village FE, State Trends	554	150	75	48	36
Village FE, State-yr FE	482	115	57	39	33

Harmful Degree Days (N = 1900)	Mean (sd) = 10.24 (36.54)				
Panel C: Number of Municipality-years when Predicted HDD Differs from Observed by more than					
Regressors	1 HDD	10 HDDs	20 HDDs	30 HDDs	40 HDDs
Village FE	738	227	127	99	78
Village FE, Yr FE	1658	197	120	92	72
Village FE, State Trends	1439	244	145	92	64
Village FE, State-yr FE	905	216	128	88	67

Total Precipitation (N= 1900)	Mean (sd) = 708.52 (482.79)				
Panel D: Number of Municipality-years when Predicted Precipitation Differs from Observed by more than					
Regressors	1.0 mm	1.5 mm	2.0 mm	2.5 mm	3.0 mm
Village FE	1905	1881	1869	1859	1844
Village FE, Yr FE	1916	1900	1884	1874	1859
Village FE, State Trends	1916	1900	1888	1874	1861
Village FE, State-yr FE	1907	1884	1852	1830	1800

Notes: This table reports residual variation in annual village weather from a regression of weather on village fixed effects and various time controls. Each row lists the controls included. Each cell displays the count of observations for which the absolute value of predicted weather exceeds the actual weather by the threshold listed in the column heading.

Table 3: Effect of HDD and GDD on Local Employment				
	(1)	(2)	(3)	(4)
	Local Work	Local Ag	Local Non-ag	Local Wage
Harmful Deg Days	-0.00509***	-0.00112	-0.00397***	-0.0028**
	(0.00141)	(0.000831)	(0.0015)	(0.00132)
Growing Deg Days	-0.0001	-0.0000401	-0.0000599	-0.0000299
	(0.000251)	(0.000162)	(0.000176)	(0.000192)
Tot Precip (cm)	-0.000137	-0.0000501	-0.0000867	0.0000988
	(0.000281)	(0.000251)	(0.000133)	(0.00019)
Tot Precip^2	0.000000	0.000000	0.000000	0.000000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
Observations	136,926	136,926	136,926	136,926
R^2	0.688	0.735	0.688	0.683
Number of Ind.	8,107	8,107	8,107	8,107

Notes: Coefficients on HDDs and GDDs are the change in probability of work in response to a 10 degree increase in the variable. The dependent variable is whether an individual is employed in the sector indicated in the column heading in a given year. Columns 1-8 report results from a linear probability model with standard errors clustered at the village and state-year. Additional controls include growing degree days and precipitation squared for each of the two time intervals. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Table 4: Effect of HDD and GDD on Local Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Local Work	Local Ag	Local Non-ag	Local Wage	Local Work	Local Ag	Local Non-ag	Local Wage
HDD May/June	-0.0121***	-0.00425**	-0.00786***	-0.00522**				
	(0.00326)	(0.00186)	(0.00286)	(0.00238)				
Tot Precip May/June	0.00057	0.000681	-0.000111	0.000725*				
	(0.0007)	(0.000545)	(0.000314)	(0.000448)				
HDD July/Aug					-0.00847***	-0.00122	-0.00725***	-0.00499*
					(0.00274)	(0.00149)	(0.00279)	(0.00272)
Tot Precip July/Aug					-0.000508	-0.000228	-0.00028	-0.00014
					(0.000431)	(0.000381)	(0.000283)	(0.000333)
Fixed Effects	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
Observations	136,926	136,926	136,926	136,926	136,926	136,926	136,926	136,926
R^2	0.688	0.735	0.688	0.683	0.688	0.735	0.688	0.683
Number of Ind.	8,107	8,107	8,107	8,107	8,107	8,107	8,107	8,107

Notes: Coefficients on HDDs and GDDs are the change in probability of work in response to a 10 degree increase in the variable. The dependent variable is whether an individual is employed in the sector indicated in the column heading in a given year. Columns 1-8 report results from a linear probability model with standard errors clustered at the village and state-year. Additional controls include growing degree days and precipitation squared for each of the two time intervals. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Table 5: Effect of HDD and GDD on Migration

	(1) US Work	(2) Mexico Work	(3) Within State Work	(4) US Work	(5) Mexico Work	(6) Within State Work	(7) US Work	(8) Mexico Work	(9) Within State Work
Harmful Deg Days	0.000862*	0.00092	0.000348						
	(0.000446)	(0.000588)	(0.000548)						
Growing Deg Days	-0.000133	0.00028**	0.00000637						
	(0.000105)	(0.000126)	(0.0000761)						
Tot Precip (cm)	0.000006	-0.0000803	-0.0000678						
	(0.000119)	(0.00016)	(0.0000888)						
HDD May/June				0.00317**	0.00224	0.000192			
				(0.00151)	(0.00178)	(0.00129)			
Tot Precip May/June				-0.000497*	0.000108	-0.000175			
				(0.000263)	(0.000337)	(0.000192)			
HDD July/Aug							0.00084	0.00194**	0.00081
							(0.000671)	(0.000883)	(0.000786)
Tot Precip July/Aug							0.000181	-0.000195	-0.000277*
							(0.000189)	(0.000277)	(0.000168)
Fixed Effects	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
Observations	124,895	125,772	125,772	125,808	126,697	126,697	125,673	126,559	126,559
R^2	0.669	0.666	0.633	0.669	0.665	0.632	0.669	0.666	0.632
Number of Ind.	7,762	7,799	7,799	7,769	7,804	7,804	7,763	7,799	7,799

Notes: Coefficients on HDDs and GDDs are the change in probability of work in response to a 10 degree increase in the variable. The dependent variable is whether an individual migrates to the destination indicated in the column heading in a given year. Columns 1-9 report results from a linear probability model with standard errors clustered at the village and state-year. Additional controls in columns 1-3 include precipitation squared. Columns 4-9 contain controls for growing degree days and precipitation-squared for each of two time intervals. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Table 6: Effect of the Weather on Local Employment in Rural Mexico, Sensitivity to Weather Definitions						
	(1)	(2)	(3)	(4)	(5)	(6)
	Sinusoidal Daily Weather	HDD Cut-off at 30 C	HDD Cut-off at 34 C	Weather from May to December	Only Temperature	Including Non-ag Weather
Harmful Deg Days	-0.00238**	-0.003***	-0.00959***	-0.00484***	-0.00511***	-0.00489***
	(0.0011)	(0.00109)	(0.00217)	(0.00146)	(0.00141)	(0.00136)
Growing Deg Days	0.0000352	-0.0000309	-0.000148	-0.000126	-0.0000855	0.000113
	(0.000189)	(0.000258)	(0.000253)	(0.000242)	(0.000251)	(0.000197)
Tot Precip (cm)	-0.000172	-0.000145	-0.000151	-0.000204		-0.000166
	(0.000284)	(0.000283)	(0.000279)	(0.000239)		(0.000299)
Tot Precip^2	0.0000	0.0000	0.0000	0.0000		0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
Harmful Deg Days Non-Ag Season						-0.0163
						(0.0298)
Growing Deg Days Non-Ag Season						-0.000477
						(0.000431)
Tot Precip Non-Ag Season (mm)						-0.00042
						(0.000621)
Tot Precip^2 Non-Ag Season						0.00000
						(0.0000)
	Individual	Individual	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year	State-year	State-year
Observations	136,926	136,926	136,926	136,141	136,926	135,618
R^2	0.688	0.688	0.688	0.689	0.688	0.689
Number of Ind.	8,107	8,107	8,107	8,100	8,107	8,095

Notes: Coefficients on HDDs and GDDs are the change in probability of work in response to a 10 degree increase in the variable. The dependent variable is whether an individual is employed locally in rural Mexico in a given year. Columns 1-6 report results from a linear probability model with standard errors clustered at the village level and the state-year. Variations on the definition of weather include the use of sinusoidal functions to get hourly temperature from daily minimum and maximum temperature (1), defining HDDs as occuring when daily average exceeds 30 (2) and 34 (3), defining the agricultural season as May to December (4), only including temperature (5), and a test that includes weather both in the growing season and non-agricultural season (6). Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Table 7: Effect of Weather on Local Employment, Robustness to Confounding Factors

	Linear Probability Model			Multinomial Logit (Marginal Effects)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Work	Local Work	Local Work	Local Ag	Local Non-ag	Migration
Harmful Deg Days	-0.00526***	-0.00512***	-0.0213*	-0.001795*	-0.002867**	0.002616***
	(0.0014)	(0.00138)	(0.0114)	(0.001008)	(0.001295)	(0.000999)
Growing Deg Days	-0.000105	-0.000108	-0.00129	-0.000134	0.0000704	0.000105
	(0.000243)	(0.000253)	(0.000816)	(0.000177)	(0.000192)	(0.000182)
Tot Precip (cm)	-0.000149	-0.000131	-0.0000178	-0.0000703	-0.000133	0.000166
	(0.000264)	(0.000279)	(0.00118)	(0.000268)	(0.000164)	(0.000182)
Tot Precip^2	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Age	0.00393***					
	(0.00114)					
Mismatched Response		-0.0559**				
		(0.0241)				
Household Size			0.140***			
			(0.0161)			
Fixed Effects	Individual	Individual	Individual	Village	Village	Village
	State-year	State-year	State-year	State-year	State-year	State-year
Observations	133,456	136,926	40,817	138,453	138,453	138,453
R^2	0.679	0.690	0.681			
Number of Ind.	8,049	8,107	1,514			

Notes: Coefficients on HDDs and GDDs are the change in probability of work in response to a 10 degree increase in the variable. Results from a linear probability model in which the dependent variable is an indicator variable denoting whether or not an individual is employed in local employment are reported in columns 1-3. Column 1 conditions on the age of an individual; column 2 includes a dummy set equal to 1 if employment histories are not identical across the two surveys; and the unit of observation in column 3 is a household-year. Household size is the number of working age individuals in the household. Standard errors clustered at the village level and the state-year. Colums 4-6 report the output from a multinomial logit model where the base outcome is not-employed. Standard errors are clustered at the village. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Table 8: 2SLS Model of Probability of Local Employment

	(1)	(2)	(3)	(4)
	Local Work	Local Agriculture	Local Non-agriculture	Local Wage Work
Panel A				
Corn Harvest (Kilos)	0.0000241	0.0000409**	-0.0000168	0.0000227
	(0.0000178)	(0.0000186)	(0.0000114)	(0.0000142)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
First Stage F-stat	9.04	9.04	9.04	9.04
Individuals	1,896	1,896	1,896	1,896
Observations	3,792	3792	3792	3792
Panel B				
Value of Agricultural Output	0.00000057	-0.0000004	0.00000102*	0.0000006
	(0.000000662)	(0.000000569)	(0.000000551)	(0.000000611)
Fixed Effects	Individual	Individual	Individual	Individual
	State-year	State-year	State-year	State-year
First Stage F-stat	17.26	17.26	17.26	17.26
Individuals	6,621	6,621	6,621	6,621
Observations	13,242	13,242	13,242	13,242

Notes: The dependent variable is whether an individual is employed in the sector indicated by the column heading in a given year. Columns 1-4 report results from 2SLS. Instruments for maize yields (Panel A) and the value of agricultural output (Panel B) are the number of HDDs, GDDs, total precipitation and total precipitation squared in the agricultural season. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, p<0.1.

Table 9: Projected Regional Impacts of Climate Change, 1995-2075

	CCSM4				Hadley GEM2			
	RCP4.5		RCP6.0		RCP4.5		RCP6.0	
National	HDDs Only	All Weather	HDDs Only	All Weather	HDDs Only	All Weather	HDDs Only	All Weather
Local Work	-0.0031***	-0.0055	-0.0072***	-0.0102	-0.0143***	-0.0186	-0.0112***	-0.0155
	(0.00085)	(0.006)	(0.002)	(0.0078)	(0.004)	(0.0117)	(0.0031)	(0.0114)
Local Agriculture	-0.0007	-0.0016	-0.0016	-0.0028	-0.0032	-0.0049	-0.0025	-0.0042
	(0.00051)	(0.0037)	(0.0012)	(0.0047)	(0.0024)	(0.007)	(0.0019)	(0.0068)
Local Non-agriculture	-0.0024***	-0.0039	-0.0057***	-0.0075	-0.0113***	-0.0139*	-0.0089***	-0.0115
	(0.00092)	(0.0041)	(0.0022)	(0.0054)	(0.0043)	(0.0084)	(0.0034)	(0.008)
Local Wage	-0.0017**	-0.0022	-0.004**	-0.0048	-0.008**	-0.0091	-0.0063**	-0.0074
	(0.00080)	(0.0045)	(0.0019)	(0.0058)	(0.0038)	(0.0089)	(0.003)	(0.0086)
US Migration	0.00053*	-0.0024	0.0012*	-0.0025	0.0025*	-0.003	0.0019	-0.0036
	(0.00027)	(0.0023)	(0.00064)	(0.0028)	(0.0013)	(0.0041)	(0.0010)	(0.0041)
Domestic Migration	0.00056	0.0067**	0.0013	0.0091**	0.0026	0.0141***	0.0021	0.0135***
	(0.00036)	(0.0029)	(0.00085)	(0.0035)	(0.0017)	(0.0052)	(0.0013)	(0.0051)
S-SE								
Local Work	0.00017	0.00450	-0.00013	0.0065	-0.00054	0.0112	-5.28E-05	0.0097
	(0.00090)	(0.0055)	(0.00069)	(0.0077)	(0.0028)	(0.0133)	(0.000270)	(0.0114)
US Migration	0.0001	0.0003	-0.0001	0.0000	-0.0003	-0.0005	0.0000	-0.0001
	(0.00031)	(0.0019)	(0.00024)	(0.0021)	(0.00098)	(0.003)	(0.000095)	(0.0034)
Domestic Migration	-0.00026	0.0076	0.00020	0.0123*	0.00081	0.0223**	0.000079	0.018*
	(0.00078)	(0.0049)	(0.00060)	(0.0065)	(0.0024)	(0.011)	(0.00024)	(0.0101)
Center								
Local Work	0.0002	0.0088	0.0002	0.0114	0.0002	0.0163	0.0002	0.0142
	(0.00024)	(0.0122)	(0.00024)	(0.0159)	(0.00016)	(0.023)	(0.00024)	(0.0198)
US Migration	0.0000	-0.0137***	0.0000	-0.0179***	0.0000	-0.026***	0.0000	-0.0225***
	(0.000046)	(0.0049)	(0.000046)	(0.0064)	(0.000030)	(0.0093)	(0.000046)	(0.008)
Domestic Migration	-0.000086**	0.0029	-0.000086**	0.0039	-0.000057**	0.0059	-0.000086**	0.005
	(0.000036)	(0.0053)	(0.000036)	(0.0069)	(0.000023)	(0.0099)	(0.000036)	(0.0085)
Center-West								
Local Work	-0.0023**	-0.0183	-0.00048**	-0.0184	-0.00062**	-0.0259	0.0023**	-0.0268
	(0.0011)	(0.0161)	(0.00023)	(0.0177)	(0.00030)	(0.0251)	(0.0011)	(0.0286)
US Migration	0.0010	0.0070	0.0002	0.0070	0.0003	0.0101	-0.0010	0.0104
	(0.00065)	(0.007)	(0.00014)	(0.0077)	(0.00018)	(0.0109)	(0.00066)	(0.0124)
Domestic Migration	0.00042	0.0021	0.0001	0.0019	0.0001	0.0027	-0.00042	0.0025
	(0.00049)	(0.0035)\	(0.00010)	(0.0038)	(0.00013)	(0.0054)	(0.00049)	(0.0061)
NW								
Local Work	-0.0082	-0.0201	-0.0148	-0.0276*	-0.0272	-0.0456*	-0.024	-0.0436*
	(0.0056)	(0.014)	(0.01)	(0.0159)	(0.0184)	(0.0241)	(0.0162)	(0.0242)
US Migration	0.0023	0.0024	0.0042	0.0044	0.0077	0.0084	0.0068	0.0075
	(0.0016)	(0.003)	(0.0029)	(0.0038)	(0.0053)	(0.006)	(0.0047)	(0.0057)
Domestic Migration	-0.0015	0.0087*	-0.0027	0.0082*	-0.0050	0.0106	-0.0044	0.0122
	(0.0023)	(0.0048)	(0.0041)	(0.005)	(0.0076)	(0.0073)	(0.0067)	(0.0075)
NE								
Local Work	0.0084***	0.0097	-0.0066***	-0.0078	-0.0262***	-0.0286	-0.0029***	-0.0069
	(0.003)	0.0084	(0.0024)	(0.0142)	(0.0094)	(0.0198)	(0.001)	(0.0201)
US Migration	-0.0014	-0.0152	0.0011	-0.0144	0.0045	-0.0119	0.0005	-0.0171
	(0.00094)	0.0104	(0.00074)	(0.0138)	(0.0029)	(0.0149)	(0.00033)	(0.0186)
Domestic Migration	-0.0014**	-0.0025	0.0011**	-0.0001	0.0044**	0.0031	0.00048**	-0.00088
	(0.00064)	0.0069	(0.00051)	(0.0095)	(0.002)	(0.0104)	(0.00022)	(0.0132)

Note: Each cell displays the predicted change in probability of working in each sector and location under emissions scenarios RCP4.5 and RCP 6.0. CCSM4 presents predicted changes based on output from the Community Climate System Model 4. Hadley GEM2 is the Hadley Center Global Environment Model, version 2. Asterisks indicate statistical significance; ***p<0.01, **p<0.05, *p<0.1.

Figure 1: Map of Surveyed Villages and Weather Stations within 50 Km

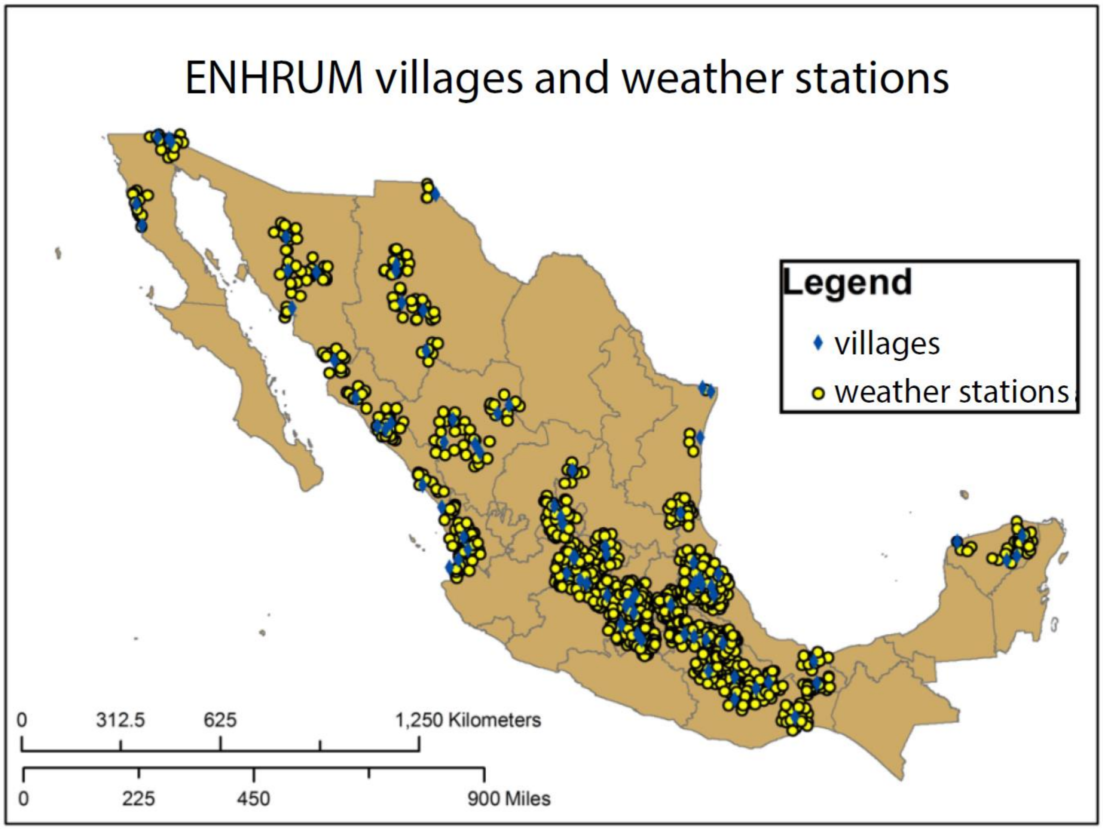
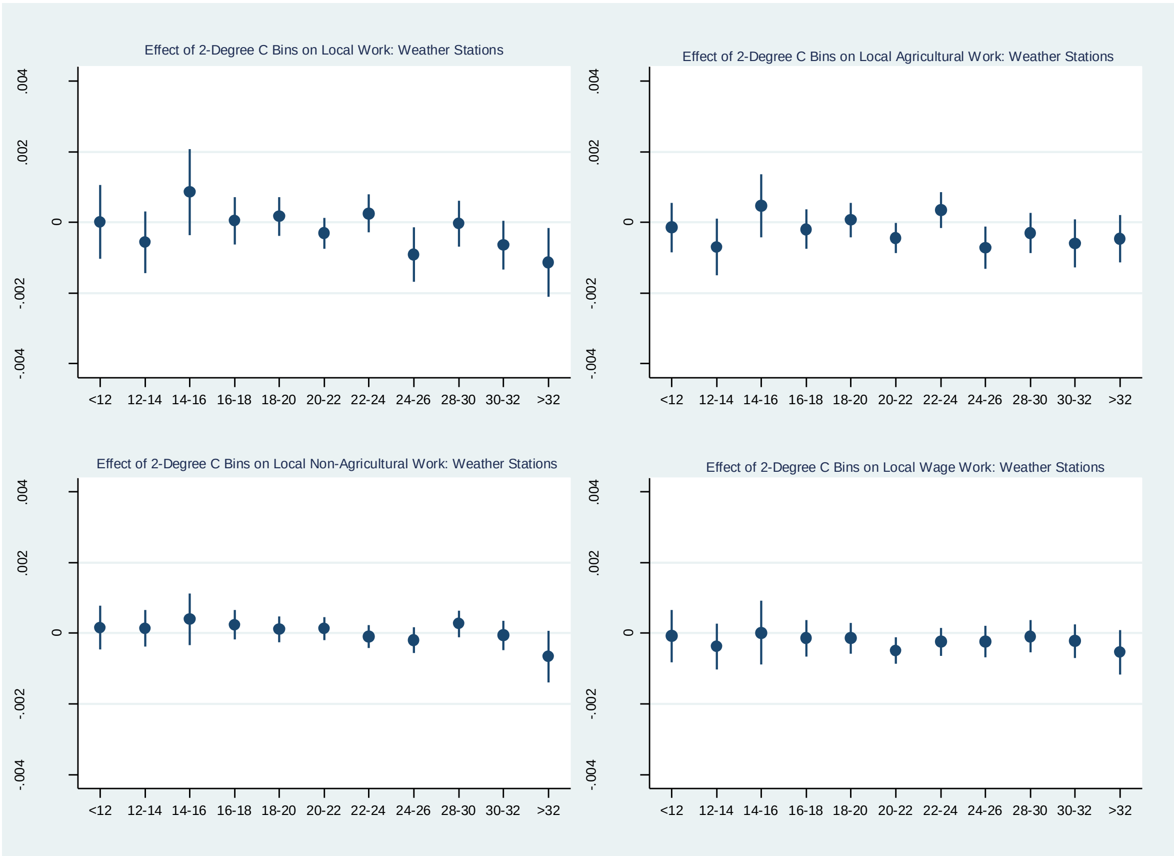


Figure 2: Effect of 2-Degree C Bins on Employment Using Weather Station Data



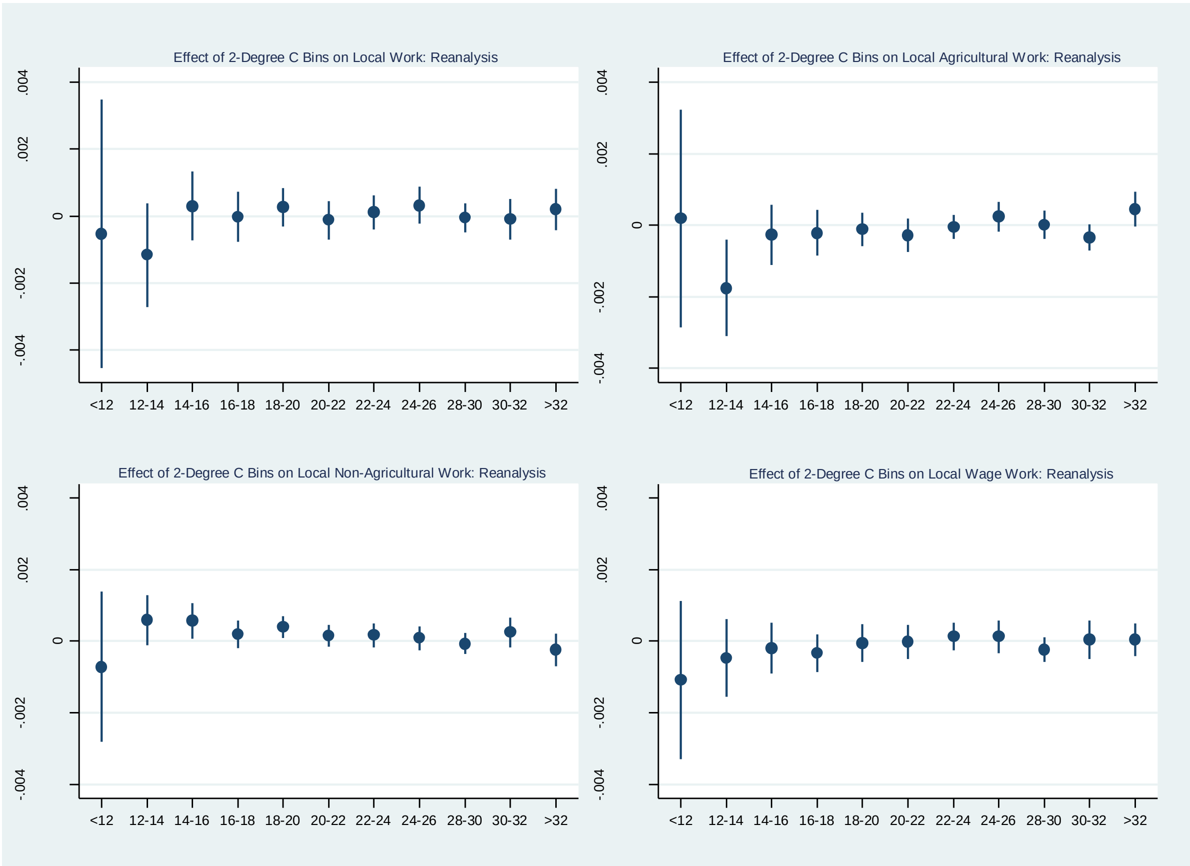
Notes: Points indicate the estimated impact on an additional day in each 2-degree temperature bin on employment in the indicated sector, relative to a base of 26-28 degrees C. Ninety percent confidence intervals are included.

Appendix Table A1: Predicted Change in Annual Weather, 1995 to 2075

	Average Temp		GDDs		HDDs		Precipitation (mm)	
	CCSM4	HadGEM2	CCSM4	HadGEM2	CCSM4	HadGEM2	CCSM4	HadGEM2
RCP4.5								
National	1.30	2.48	226.41	416.97	6.09	28.55	9.54	9.54
S-SE Region	0.90	2.54	171.37	451.54	-5.10	15.98	-63.95	-63.95
Center	1.40	2.60	245.39	464.60	-0.09	-0.06	-9.95	-9.95
Center-west	1.31	2.13	242.61	391.37	-0.68	-0.19	16.80	16.81
NW	1.67	2.92	254.89	394.99	32.32	106.85	61.07	61.07
NE	1.03	1.92	191.04	347.68	-1.85	5.82	66.69	66.69
RCP6.0								
National	1.66	2.43	284.01	414.93	14.39	22.37	9.54	9.54
S-SE Region	1.43	2.06	258.68	378.39	3.90	1.55	-63.95	-63.95
Center	1.81	2.25	320.45	400.63	-0.09	-0.09	-9.95	-9.95
Center-west	1.48	2.47	272.48	452.86	-0.15	0.69	16.80	16.80
NW	1.93	3.00	274.46	421.42	58.25	94.22	61.07	61.07
NE	1.64	2.28	299.60	419.14	1.47	0.64	66.69	66.69

Notes: Entries indicate the predicted annual change in weather variable under 2 emissions scenarios. RCP4.5 is a medium emissions scenario and RCP6.0 is a high emissions scenario. Changes are based on output from the Community Climate System Model 4 (CCSM4) and the Hadley Center Global Environmental Model version 2 (HadGEM2). Regional and national changes are constructed from village weather averages.

Appendix Figure A1: Effect of 2-degree C Bins on Employment using Modelled Reanalysis Data



Notes: Points indicate the estimated impact on an additional day in each 2-degree temperature bin on employment in the indicated sector, relative to a base of 26-28 degrees C. Ninety percent confidence intervals are included.