# Too Hot to Handle?
# Weather as a driving force of labour market fluctuations in Mexico

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**Abstract**

We study the effect of temperature and precipitation fluctuations on labour markets of Mexican municipalities. Paying explicit attention non-linearities in the weather effect, we study responses of wages and working times to weekly weather changes. As such, this paper is novel in as much as it focuses on a developing country with very little labour market protection and a large informal employment sector. This article sheds new light on the relationship between temperatures and working time. Our findings provide further evidence for a sensitivity of labour markets to weather. Contrary to findings on the US we find cold temperatures on average to have a stronger impact on working times than heat days. Days with temperatures falling below 10°C on average reduce working times by 22 minutes. Moreover, we predict working hours to drop by 47 minutes during heavy rainfall days (exceeding 30 mm). A further contribution of this paper is the identification of heterogeneity in the estimated weather effects across different segments of the labour market. Especially informal workers are significantly affected by extreme heat and rainfall. Working times of informal workers fall by more than 80 minutes on days with extreme rainfall. Furthermore, we predict gender and age differences in the effect of temperature on hourly wages and working time.

**JEL Classification: J22, J23, Q54 Keywords: Time Allocation and Labor Supply, Labor Demand, Climate**

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# 1 Introduction

We study the effect of temperature and precipitation fluctuations on labour markets of Mexican municipalities. As a middle-income country with a large agricultural sector and a relatively harsh climate, Mexico provides an intriguing study region. The middle-income country is frequently struck by extreme weather events. Tropical cyclones such as Hurricane Wilma in October 2005 and Hurricane Patricia in October 2015 often bring along severe rainfall. Between 2003 and 2007 Mexico experienced a series of regional floods causing severe flash floods, landslides, and high death tolls. The floods of 2007 Mexico became the worst natural disaster on record, leaving as much as 80% of the state under water. Triggered by storms, massive floods named the 'Tabasco Flood' destroyed the houses of half a million people and caused severe destruction of the industry. Starting in 2009 Mexico faced a dry spell over four years. By September 2009 the north-west and central Mexico was already facing the worst drought in 70 years, with about 3.5 million farmers being affected and more than 15 million acres of crop-land destroyed. In 2011 more than 1.7 million cattle died due to lack of water or forage (Chavez, 2011). Furthermore, blizzards affecting the northern hemisphere in the beginning of the years 2010, 2011, 2014, 2016 and recently in December 2017 brought negative temperatures with frost and snowfall, causing considerable crop loss in affected areas. Climate change models predict the frequency of such extreme weather events to increase (Stocker, 2013).

Despite the former freak events, temperatures in Mexico frequently rise above 32 °C in the summer and fall below 10 °C in the winter. Insufficient isolation of buildings, lack of heating and high costs for air-conditioning implies that these temperature fluctuations significantly affect the Mexican population. Severe weather events such as high temperatures and torrential rainfall can cause a substantial disruption to work activities as well as significantly reduce labour productivity depending on the degree of climate exposure of workers. Variations in weather may be an important factor in driving individual labour supply decisions and thus may affect labour markets. Weather-induced changes in labour markets may have significant welfare implications, especially in countries frequently hit by weather shocks. Growing scientific evidence suggests that weather shocks are becoming a more common phenomenon as a consequence of climate change. According to the IPCC Fifths Assessment Report (Stocker, 2013) weather will become increasingly volatile with more frequent weather shocks such as storms, droughts and floods. In the past research on the economic impact of weather extremes primarily studied costs caused by the destruction of capital. While the direct effects of weather shocks, such as casualties and the damage of infrastructure, are evident, the indirect effects, such as low economic growth or for example the loss of productivity are less easily quantified.

While there is a consensus in the scientific literature on the importance of climate as a determinant of economic performance, there is a significant gap in our understanding of potential behavioural responses of individuals to weather variations. The rising climate change awareness has given rise to growing body of literature on impact of weather on economies. The latter suggests a significant relationship between weather extremes and overall economic performance, agricultural yields, health, mortality, education, human capital, migration, poverty, and civil unrest (Arouri et al., 2015; Barrios et al., 2010; Cavallo et al., 2013; Dell et al., 2012; Deschênes and Greenstone, 2007; Fafchamps et al., 1998; Feng et al., 2010; Graff Zivin et al., 2015; Groppo and Kraehnert, 2015; Guerrero Compeán, 2013; Guiteras, 2009; Hidalgo et al., 2010; Hsiang et al., 2014; Mueller and Osgood, 2009a; Reardon et al., 2007; Rodriguez-Oreggia et al., 2013; Schlenker and Roberts, 2009; Wolpin, 1982; Yamano et al., 2007).[1]

This paper relates closely to a new branch of literature analysing the role of weather fluctuations in shaping labour markets (Belasen and Polachek, 2009; Belasen et al., 2016; Boutin, 2014; Cameron and Worswick, 2003; Colmer, 2015; Connolly, 2008; Fafchamps, 1993; Graff Zivin and Neidell, 2014; Jayachandran, 2006; Jessoe et al., 2016; Kochar, 1999; Mueller and Quisumbing, 2010; Mueller and Osgood, 2009b; Rose, 2001; Zander et al., 2015). While most papers utilise event type analysis, recently studies have focused on day-to-day changes in weather. The important study by Graff Zivin and Neidell (2014) estimates the impact of daily temperature shocks on time allocation choices in the US. The authors find high temperatures to considerably reduce working hours for weather exposed sectors in the US. The epidemiological literature provides substantial evidence for a clear link between temperatures and human mortality. Extreme temperatures can result in health issues and lower labour productivity (Kjellstrom et al., 2008). Thermoregulatory control mechanisms such as "shivering, arteriovenous shunt vasoconstriction, sweating and precapillary vasodilation" (Guerrero Compeán, 2013, p. 2) are natural response mechanism of the body to prevent mortal damages to the body such as brain and heart damage. With higher external temperature the transfer of body temperature to the external environment is diminished, and the body is at risk of developing heat stress or a heat stroke. To prevent these life-threatening outcomes the body reacts by reducing physical activity; this includes brain activity and thus implies diminished mental ability. The heat-related reduction in 'work capacity" decreases labour productivity, with ambiguous implications for medium and long-term productivity. Sectors relying on outdoor labour activity are more likely to suffer from temperature related losses in productivity. Studies such as for example the paper by Zander et al. (2015), suggest a clear link between heat stress and labour productivity loss. Besides temperatures rainfall potentially my alter labour productivity by rendering outdoor activities difficult, interruption supply chains due to delays in transportation, as well as potentially destruction of infrastructure in response to extreme rainfall shocks. Less attention has been paid to this indirect effect of temperature and precipitation extremes on labour productivity.

Following poineerig Graff Zivin and Neidell (2014) work, this papers studies the impact of weather fluctuations on labour markets at the municipal level in Mexico. Paying explicit attention non-linearities in the weather effect we study responses of wages and working times to weekly weather changes. As such, this paper is novel in as much as it focuses on a developing country with very little labour market protection and a large informal employment sector. We begin our analysis by estimating the effect of weather shocks on labour market characteristics based on the Encuesta Nacional de Ocupacíon y Empleo (ENOE) provided by Instituto Nacional de Estadística y Geografía (INEGI, 2011) and climate data from the North American Regional Reanalysis (NARR) model (NOAA, OAR and ESRL PSD, 2017) developed by the National Centers for Environmental Prediction (NCEP). Exploiting the panel structure of ENOE this paper employs a difference-in-difference estimation technique (DiD) to identify changes in individuals labour market participation.

The paper sheds new light on the relationship between temperatures and working time. Our findings provide further evidence for a sensitivity of labour markets to weather. Contrary to findings on the US we find cold on average to have a stronger impact than heat days. Moreover, we predict working hours to drop significantly during heavy rainfall days. A further contribution of this paper is the identification of heterogeneity in the estimated weather effects

[1]For a comprehensive review of the current literature see Cavallo and Noy (2009) and Dell et al. (2014).

across different segments of the labour market. Especially informal workers are significantly affected by extreme heat and rainfall. Furthermore, we predict gender and age differences in the effect of temperature on hourly wages. Consistent with Graff Zivin and Neidell (2014) we predict a negative impact of heat for weather exposed sectors. Our results are robust to several specification test.

Studying the labour market in a micro setting as done in this paper brings us closer towards understanding the extent of weather fluctuations as a driving factor of changes in labour demand and supply. Furthermore, our findings have relevant implications for the macroeconomic literature studying the relationship between climate change on economic growth and welfare. Understanding the micro-level relationship between climate and economic factors is crucial for modelling the macroeconomic relationship between weather and economic growth. Moreover, our paper provides a direct test of exogeneity of labour supply concerning climate, the latter being an underlying assumption of Integrated Assessment Models. It further sheds light on possible adaptation mechanisms already in place in society today, potentially mitigating future costs of climate change. Labour responses to weather shocks, such as reducing working times during extreme weather periods to prevent negative health effects could potentially work as short-term protection mechanisms to the adverse effects of climate. These behavioural responses conceivably could cause severe long-term consequences for economic growth and welfare. It is crucial to deepen our understanding of these short- and long-term outcomes to allow policymakers to design successful climate change policies.

The rest of the paper is organised as follows. Section 2 provides an overview of the relevant literature followed by a description of the analytical models. The third section discusses the different datasets employed in the regression analysis. Special attention is paid to the methods used in construction of the weather variables. We present our findings in Section 5, followed by a discussion of several implemented robustness checks. Part 7 closes with a summary of the key findings and a short note on policy implications.

## 2 Literature Review

This research relates closely to several important strands of research. Firstly, it builds upon a large body of literature examining the relationship between climate and various variables of interest such as economic performance, migration, health, education, and development. Moreover, it is closely linked to the rapidly growing field of research studying the effect of random short-term fluctuations in weather on various economic outcomes.[2] Natural disasters are often associated with physical damages such as destruction of land, infrastructure, assets, or more dramatically the loss of human capital, among others. However, disasters also involve indirect costs with potentially far-reaching consequences for affected regions. The latter refers to disruptions of economic activity following an environmental catastrophe. For example, the damage to infrastructure can disrupt supply chains. Other indirect costs are diverse and often result from long-term environmental degradation causing food-security issues as well as potential adverse health effects.

A growing number of macroeconomic studies reflect upon the role of natural disasters for economic growth and performance. Empirical research provides some evidence on a neg-

[2]Dell et al. (2014) provide a comprehensive overview on the current level of research for both strands of literature, while the literature reviews by Cavallo and Noy (2009) and Kousky (2014) concentrate on the scientific literature on the economic costs of natural disasters.

ative association between climate and economic growth in the developing country context. Raddatz (2007) concludes that disasters significantly contribute to short-term growth fluctuations in developing countries. Especially smaller and less developed states are vulnerable to climatic events, with most economic losses occurring within the first year after a disaster. Interestingly Raddatz (2007) results suggest that foreign aid has done little to alleviate the damages from climate shocks.Dell et al. (2012) exploit year-to-year variations in temperature and precipitation to study the impact of temperature and rainfall on worldwide economic activity. They show that a temperature increase of 1°C per year reduces per capita income in developing countries by more than one percent, with suggestive evidence of a permanent effect on growth rates. Exploiting a rich dataset on worldwide cyclones, Hsiang et al. (2014) estimate a negative and persistent decline in post-disaster national income growth, with no post-disaster recovery and a cumulative effect of around seven percent growth reduction for the 90th percentile of sample events. The results underline that the storm intensity matters for impact assessment. Past research shows that different disaster types have contrasting effects on distinct sectors for both developed and developing countries, with the latter being more affected both regarding the magnitude of the impact as well as the diversity of the experience. Moreover, the economic impact of disasters depends on event size with large disasters always involving severe negative costs for the local economy, whereas small events on average have a positive influence due to disaster relief efforts (Loayza et al., 2012). A study by Hsiang (2010) highlights that output losses caused by increasing temperatures in the Caribbean peninsula for nonagricultural production (-2.4% per 1 °C) considerably exceed those experienced by the agricultural sector (-0.1% per 1 °C). Concerning rainfall, reduction in annual precipitation levels is found to be a critical determinant of poor economic performance of African countries during the second half of the 20th century (Barrios et al., 2010). Some authors have looked more deeply into the heterogeneity in disaster resilience. Noy (2009), for example, finds a clear link between disaster recovery and the quality of government policies and economic institutions, education and income levels, as well as trade openness. A shortcoming of the literature is the rather Most macroeconomic studies are limited to a short period of observation. Cavallo et al. (2013) exploit the comparative event study approach using a synthetic control group as the counterfactual to study long-term consequences of natural disasters. The authors find no significant long-run impacts even for very large events except if the latter were directly followed by civil unrest such as the Islamic Iranian Revolution (1979).

In summary, aforementioned findings highlight the merging consensus of a short-term negative effect primarily felt by developing regions, while evidence on long-term consequences is limited. The lack of consensus can partially be explained by differences in the applied methods and data quality. Dell et al. (2014) provides a comprehensive overview of existing literature, with a detailed discussion of the advantages and disadvantages of the implemented methodologies and datasets. Yet, the channels that are responsible for this economic slowdown have not been described methodically at all.

Macroeconomic studies are useful in providing an order of magnitude of severe weather shocks. They stress the importance of weather as a determinant of macroeconomic performance. It is commonly believed that climate change will not only increase average temperatures but also shift the distribution of daily peak temperatures and humidity, along with an increase in the frequency of extreme weather events (Stocker, 2013). The intensity and impact of climate-related shocks strongly depend on the socio-economic environment. A growing body of literature focuses on disentangling these channels within a micro-economic setting. Micro event-studies benefit from a unique identification strategy that enables a rigorous examination of different transmission channels. Much attention is paid to explaining different levels of resilience and coping capacity at the local and household level.

A growing body of literature investigates the potential of local weather shocks as a driver of economic and human development. Baez et al. (2017) examine the impact of tropical storm Agatha on Guatemalan households. The authors find per capita consumption to drop by 12.6 percent, along with an 18 percent increase in poverty, with a subsequent rise in adult and child labour supply in the aftermath of the storm. Similarly, Rodriguez-Oreggia et al. (2013) study the impact of natural disasters on poverty and human development in Mexico. The paper argues that natural disasters, especially floods, significantly worsen poverty, with poverty levels increasing between 1.5 and 3.7 percent in affected communities with a simultaneous fall in human development. Porter (2012) explores non-linearities in the impact of rainfall variations on consumption and income in rural Ethiopia. While less extreme rainfall events have no significant bearing on consumption, rare drought events result in a 10 to 20 percent reduction in consumption.

One explanation for the negative impact of weather shocks on development and poverty is the adverse effects on factor productivity, such as declines in crop yields resulting from drought. Studying historical data from Britain, France and Germany during the late nineteenth century, Solomou and Wu (1999) find weather fluctuations to account for between one- and two-thirds of variations in agricultural production. a more recent study by Guiteras (2009) suggests a reduction in agricultural yields as a response to cumulative degree-days with temperatures above 32 °C during the growing season, with wages dropping by almost 2 % in response to a one-degree temperature increase. Studying mortality, Guerrero Compeán (2013) shows a significant relationship between extreme weather and mortality rate increases and decreases in agricultural income and productivity. In a similar study on India, Burgess et al. (2014) estimate an increase in the number of high-temperature days by one standard deviation to decrease yield and wages in the agricultural sector by 12.6% and 9.8% respectively, while urban incomes remain vastly unaffected. In a further study on India, Jayachandran (2006) predicts a reduction in wages for agricultural subsistence workers following climate-induced weather shocks. The estimated effect size is bigger for poorer districts with worse access to credit institutions and higher migration costs. Mueller and Osgood (2009a) research the long-term consequences of draughts for the Brazilian labour market and note persistent rural wage losses over five years. Similarly, research on the floods of 1998 and 2004 in Bangladesh reveals long-term adverse effects on agricultural casual wages in Bangladesh. Few studies have looked at weather effects on the manufacturing sector. Cachon et al. (2012) test for plant-level productivity losses related to heat finding a significant productivity loss for automobile factories in the US during periods of sustained heat. Evidence from the Indian manufacturing plants further estimates productivity losses in labour-intensive settings of roughly 3 % per 1 °C (Somanathan et al., 2014).

The link between adverse weather and poor mental and physical performance is nothing new. Prolonged heat exposure has been identified as an occupational health problem for considerable time (Kjellstrom et al., 2008). The epidemiological literature provides plentiful evidence on the negative link between temperatures and human health. Exposure to extreme heat can cause major health issues and significantly affect labour productivity (Kjellstrom et al., 2008). Before temperature causes severe health damages, the human body employs different thermoregulatory control mechanisms such as "shivering, arteriovenous shunt vasoconstriction, sweating and precapillary vasodilation" (Guerrero Compeán, 2013, p. 2). For instance, high temperatures reduce the capacity of the body to transfer body heat to the external environment, which increases the risk of the body developing heat stress or a heat stroke. A natural reaction of the body to such life-threatening external temperatures is a reduction in physical activity, which includes a slow down of brain activity resulting in diminished mental ability. As a consequence, labour productivity will decline, with ambiguous implications for medium and long-term productivity. Sectors relying on outdoor labour activity are more likely to suffer from temperature related losses in productivity. The extent of individual productivity loss depends on a combination of climate factors as well as several body functions such as the sweat rate (Kjellstrom et al., 2008). Controlled experiments have shown a significant reduction in labour productivity, with diminished work-capacity, reduced mental task ability, and a higher risk of accidents. In the experimental context, studies by Seppanen et al. (2006) and Wargocki and Wyon (2007) identify productivity losses in different cognitive tasks in higher temperature environments. Zander et al. (2015) estimated that the annual cost of heat-induced work absenteeism and working time reductions for Australia during the years 2013 and 2014 summed up to around US$6.2 billion. In addition to temperature, rainfall can affect labour productivity by interrupting supply chains, destroying infrastructure, or causing environmental degradation. Furthermore, in weather exposed sectors may have to come to a temporary halt as the rain endangers workers, renders their work extremely physical intense, or prohibits certain undertakings.

Less attention has been paid to this indirect effect of temperature and precipitation extremes on labour productivity. While various studies test the importance of labour supply responses as a potential coping mechanism for consumption smoothing and income diversification Cameron and Miller (2015); Colmer (2015); Fafchamps (1993); Ito and Kurosaki (2009); Kochar (1999), few studies have looked directly at working hour responses. A small number of studies have looked explicitly into the influence of weather fluctuations on labour markets and more in particular labour supply responses. Exploiting the American Time Use Survey Connolly (2008) tests for workers responsiveness and ability to substitute leisure over time with respect to daily weather fluctuations in the form of rain. She finds that rainy days are associated with lower enjoyment of recreational activities, increasing wages and effectively resulting in extended working hours of about 30 minutes per day for men. Connolly finds evidence for a substitution effect where time spent on leisure is increasing following a rainy spell. Connolly does note, however, that the result is reverse for those sectors in which workers are exposed to the elements during working hours such as farming and that different parts of the population seem to have varying responsiveness to weather shocks. A more recent study by Graff Zivin and Neidell (2014) examines the relationship between daily temperature fluctuations and time allocation between leisure and work. Using the same data as Connolly and the authors find labour supply in weather exposed sectors to drop by as much as one hour per day for temperatures above 100°F. Using lagged-climate variables the authors find no evidence for substitution between work activities over time. However, the authors find evidence for accommodation to heat by controlling for historical climate. Both papers highlight the importance of heterogeneity in the responsiveness of individuals to weather extremes as well as differences according to the exposure to the elements.

These two influential studies stress the importance of weather as an explanatory variable of individual-level labour market participation as well as worker productivity. However, the geographical focus of both papers on the US limits generalisation of the findings to other areas, in particular to the developing country context. The impact of climate change is predicted to be particularly severe for developing countries. On the one hand, given the geographical location of developing countries, most of the projected changes in climate will disproportionately affect developing countries (Stocker, 2013) implying considerable costs for these regions. On the other hand, households in developing countries are particularly vulnerable to detrimental weather effects due to their limitation in exploiting some of the adaptation and mitigation mechanisms available to less deprived households. Besides, developing countries primarily specialise in industries exposed to climate (e.g. agriculture), thus rendering their economic performance more volatile.

Motivated by the lack of evidence for developing regions, a more recent paper by Jessoe et al. (2016) sheds light on the potential impact on labour market responses in less developed regions. To identify weather-related changes in employment patterns in rural Mexico, the authors exploit self-reported retrospective employment information for rural households in Mexico[3]) in a panel data approach controlling for time-invariant and state-year fixed effects. Using harmful-degree days (HDD)[4], the authors identify annual increases in heat degrees to be responsible for small reductions in rural employment, with presently experienced temperature deviations reducing the local probability of employment by not more than 5.5%. Interestingly, the estimated effect is strongest for age workers as well as off-farm workers. In addition, Jessoe et al. (2016) provide evidence for a link between increases in HDD and rural to urban and international migration to the US.

The main limitation of the former study is retrospective nature and the annual frequency of the employment data, both potential sources for measurement error. Besides, the degree-days approach used in the study may be inappropriate, as it misses the complexity of the temperature behaviour nexus found in non-parametric studies(Burgess et al., 2014; Dell et al., 2014; Graff Zivin and Neidell, 2014; Guerrero Compeán, 2013; Guiteras, 2009). The correct specification of the climate variables is essential for the estimation of effect sizes. A further drawback is the limited scope of the analysis with a focus purely on the rural agricultural labour market. While the latter is arguably affected by weather fluctuations, it is imperative to examine also the implications of weather fluctuations for urban as well as non-agricultural labour markets. The adverse effects of weather are likely to extend beyond rural labour markets. Urban heat sink-effects, for example, may have severe implications for working conditions in cities (Stocker, 2013). The lack of substantive evidence for nonagricultural productivity declines underlines the necessity for further research in this field. Disregarding weather effects on labour markets outside the rural sector might substantially underestimate total impact of weather.

This study contributes to the earlier work by evaluating the influence of weather fluctuations on both wages and working hours. We pay particular attention to non-linearity in the temperature and precipitation impacts in both rural and urban contexts. Furthermore, our study sheds new light on heterogeneous differences in weather effects, in particular with regard to job characteristics. Studying the impact of weather changes on responses to weather shocks in a micro setting as done in this paper brings us a step towards providing evidence on the underlying mechanisms at play.

[3]Jessoe et al. (2016) combined employment information from the Mexican National Rural Household Survey (Encuesta Nacional a Hogares Rurales de Mexico) collected by the Mexican Statistical Office (INEGI) in 2003 and 2008 with data from various other sources.

[4]Annual temperatures during growing season exceeding 32°C.

## 3 Identification and Estimation

Our identification strategy of the impact of weather changes on local labour markets exploits the temporal and spatial variation of weather. In the following we outline the econometric methodology to examine the effect of weather fluctuations on, firstly, the labour demand side (wages), and secondly, the labour supply side (working hours).

To the extent that random changes in the weather affect local labour demand, we analyse the impact of weather shocks on labour markets. Exploiting the panel structure of the labour force survey, we study cross-time variations in wages and working hours caused by weather fluctuations. One concern when working with weather observations is the natural clustering of weather and location-specific characteristics potentially generating biased estimates due to unobserved confounding factors. Our identification strategy exploits within municipality temporal and spatial exogenous variations in weather. Such weather fluctuations are plausibly random and therefore orthogonal to any unobservable confounding factor. Our analysis considers both changes in temperature and precipitation.

Our weather-deviation approach provides a strong causal inference. In order to isolate short-term fluctuations in weather, our empirical strategy relies upon a two-way fixed effect identification with regional and time fixed effects. Furthermore, following the advice of Cameron and Miller (2015), Wooldridge (2003) and Abadie et al. (2017) we cluster our standard errors on the municipality level.

We evaluate different model specifications with the intention to isolate the effect of weather variations on labour market outcomes. A potential methodological issue when studying weather effects is the problem of 'over-controlling', which becomes problematic when control variables are directly or indirectly influenced by weather. While including other time-varying characteristics will increase the precision of the estimates the ceteris-paribus assumption of the coefficient interpretation may not be valid. Therefore, careful choices have to be made about including further controls in our regression. We follow Dell et al. (2014) advise an estimate separate models with and without control variables.

Our baseline model is estimated with the following specification:

$$Y_{it} = \alpha + \Theta T_{mt} + \delta_i + \gamma_t + \epsilon_{imt} \tag{1}$$

where $Y$ denotes the outcome of interest, in our case log hourly wages, and weekly working hours, for individual $i$ at time $t$. $T$ is a vector of weather bins for municipality $m$. The vector $\Theta$ measures the effect of weather on the outcome variable $Y$. We further include individual $\delta_m$ and quarter year fixed effects $\gamma_t$. Including individual fixed effects controls for observable and potential unobservable confounding variables such as age and health. The fixed effects further account for historical climate at the location. Similarly, the time fixed effects $\gamma_t$ control for time-varying changes in our dependent variables which are common across Mexico. Our time fixed effects include year and quarter fixed effects. The quarterly dummies capture seasonal changes in labour markets and weather. Given this two-way fixed effect structure, time-invariant individual specific confounding factors and time-specific cross-regional macroeconomic shocks will not bias our estimates, albeit possibly being correlated with the explanatory variables.[5] If we consider weather realisations to be randomly distributed

[5] A further decision concerning the empirical specification relates to the inclusion of lagged dependent variable. Considering the short time span of the panel structure with $t = 5$ (five quarters per individual) we decided not to include a lagged depended variable as this is likely to result in biased coefficient estimates

over time then equation [1] yields unbiased estimates of the $\Theta$ $\delta_i$, and $\gamma_t$ vectors (Burgess et al., 2014; Deschênes and Greenstone, 2007; Guerrero Compeán, 2013).

In our second model, we include a vector of municipality characteristics $M$ (geographical, socio-economic, institutional and financial), which are not expected to be affected by the shock but are likely to influence the outcome variable. $X$ is a vector of individual characteristics, which include age, age squared, education, marriage status, and gender as well as job-specific characteristics such as the sector, the firm size, and whether the individual works informally. In contrast to the baseline model, Model [2] includes municipality $\delta_m$ fixed effects. The latter control for observable and potential unobservable confounding variables such as demographic and socioeconomic differences across municipalities. They further account for average climatic conditions at the geographical level. The time fixed effects $\gamma_t$ control for time-varying changes in our dependent variables which are common across municipalities. Again, if we assume weather realisations to be randomly distributed across space and over time, then equation [2] yields unbiased estimates of the $\Theta$ vector.

$$Y_{it} = \alpha + \Theta T_{mt} + \Omega M_{mt} + \Phi X_{it} + \delta_m + \gamma_t + \epsilon_{imt} \tag{2}$$

### 3.1 Heterogeneous Effects

The above models do not allow for heterogeneous differences in the adaptation to weather changes. We estimate several alternative models to explore potential heterogeneity in sensitivity of wages and labour supply to weather fluctuations. The impact of weather fluctuations on our outcome variables is likely to be influenced by individual attributes, such as age, gender, and education. Furthermore, we explore differences in the impact by individual job-characteristics, for example job formality, contract type, and employment sector. We exploit the individual information of the labour force survey to run a model with complex interaction terms:

$$Y_{it} = \alpha + \Theta_1 T_m t + \Theta_2 T \times H_{imt} + \Omega M_{mt} + \Phi X_{it} + \delta_m + \gamma_t + \epsilon_{imt} \tag{3}$$

where $T \times H$ here is the interaction effect between weather and different individual characteristics such as education, the firm sector, as well as employment type, i.e. formal or informal employment. As before all interactive models include municipality and time fixed effects to control for seasonality and overall changes in labour markets and the economy over the study period.

Of potential concern are shifts in the local labour force composition due to out- or in-migration. While migration caused by the shock could bias our results, previous studies have found no significant correlation between weather shocks and migration. According to Macías (2010) migration in Mexico is influenced by local pre-shock characteristics rather than weather shocks. While we acknowledge the importance of studying weather-related migration patterns and their implications for regional labour market dynamics, doing so is beyond the scope of this paper given the restrictions given data limitations.

(Nickell, 1981).

# 4 Description of the Data

In this section, we describe the different data sources used to construct our final dataset. The discussion of the climate data will pay particular attention to the construction method for our weather variables.

## 4.1 Labour market observations

Our labour market data consists of the Encuesta Nacional de Ocupacíon y Empleo (Mexican Labour Force Survey) (ENOE) carried out by Instituto Nacional de Estadística y Geografía (INEGI) from 2005 till 2016. ENOE is a nationally representative labour force survey consisting of a rotating panel of five consecutive quarters. The sampling follows a two-stage procedure, where during the first stage geographical areas are stratified, followed by a random selection of households into the survey sample. During each survey round one-fifth of the sample households are dropped from the study and a new cohort is added. The rolling panel structure implies that each quarterly release of the survey contains information on five different survey cohorts. ENOE provides a rich dataset of information on individuals employment situation, their job characteristics, as well as the socio-demographic characteristics of the household. For this paper, we focus on information regarding the current employment status, current wages, working hours, the job characteristics, such as the employment sector and job formality, information on the number of jobs taken up, as well as individual characteristics of the worker, such as level of education, age and gender.

Throughout our analysis, we have matched the labour force survey with the weather variables using the survey completion date as a reference point. The ENOE questionnaire asks participants about their day by day working hours during the previous week. Taking into account start- and end-date of the survey we can use this information to match reported working hours of the previous week with the correct weather data. Of potential concern could be long delays in survey completion, causing a miss-match between weather and our outcome variables, which would result in a measurement error of our coefficients. To limit the potential for attenuation bias, we restrict our sample to respondents with survey completion within the same calendar week.[6]

The final sample consists of 2,681,991 individuals located in 1,261,558 households spread over 1,676 municipalities.[7] Figure A.1 in Appendix A shows a map of all municipalities included in the sample. The map further illustrates the geographical distribution in our data, which is important for our identification strategy. The analysis was further confined to the working population between the age 14 and 98.

Table 1 presents summary statistics of baseline characteristics of our regression sample.[8] Our sample is relatively equally split between men and women, with an average age of about 37 years. Two thirds of our sample individuals have completed secondary education. The average hourly wage is about 3,800 Mexican Pesos (in 2010 prices), with top 5% of earners

[6] We relax this sample restriction to responses within seven days as well as all responses in the robustness section and find no significant differences in our estimates.

[7] The ENOE stratification process excluded 780 of Mexico's 2,456 municipalities. This process implies that ENOE is nationally representative at the state level. We will consider the implications of the survey stratification in the discussion section.

[8] In view of the labour force survey being a rotating panel the summary statistics are generated using the first interview round for each surveyed individual.

in the sample earning almost four times as much. Employment is highest in the trade sector. Most individuals are employed in the formal sector with permanent contracts and work in micro firms with less than 10 employees.

Table 1: Summary Statistics Labour Market Survey

| Variable | Mean | Standard Deviation | 95 % Confidence Interval | |
|---|---|---|---|---|
| *individual char.* | | | | |
| age | 36.73 | 14.66 | 17.00 | 64.00 |
| female | 0.42 | 0.49 | 0.00 | 1.00 |
| married | 0.49 | 0.50 | 0.00 | 1.00 |
| rural | 0.15 | 0.36 | 0.00 | 1.00 |
| *education* | | | | |
| primary | 0.25 | 0.43 | 0.00 | 1.00 |
| secondary | 0.28 | 0.45 | 0.00 | 1.00 |
| preparatory | 0.18 | 0.38 | 0.00 | 1.00 |
| university | 0.25 | 0.43 | 0.00 | 1.00 |
| postgraduate | 0.01 | 0.12 | 0.00 | 0.00 |
| *labour market char.* | | | | |
| wage in 2010 prices | 3,829.22 | 5,713.24 | 0.00 | 11,345.80 |
| weekly working hours (h) | 39.81 | 19.25 | 4.00 | 72.00 |
| weekly working hours (min) | 2,388.55 | 1,155.13 | 240.00 | 4,320.00 |
| unemployment rate (municipality) | 0.04 | 0.02 | 0.00 | 0.08 |
| informal | 0.28 | 0.45 | 0.00 | 1.00 |
| permanent | 0.27 | 0.45 | 0.00 | 1.00 |
| *firm size* | | | | |
| micro | 0.64 | 0.48 | 0.00 | 1.00 |
| small | 0.14 | 0.35 | 0.00 | 1.00 |
| medium | 0.09 | 0.29 | 0.00 | 1.00 |
| large | 0.13 | 0.34 | 0.00 | 1.00 |
| *sector* | | | | |
| agriculture | 0.10 | 0.30 | 0.00 | 1.00 |
| extractive industry | 0.01 | 0.10 | 0.00 | 0.00 |
| manufacturing | 0.15 | 0.36 | 0.00 | 1.00 |
| construction | 0.08 | 0.27 | 0.00 | 1.00 |
| trade | 0.21 | 0.41 | 0.00 | 1.00 |
| restaurants | 0.08 | 0.27 | 0.00 | 1.00 |
| transport & communication | 0.05 | 0.21 | 0.00 | 0.00 |
| professional financial services | 0.07 | 0.25 | 0.00 | 1.00 |
| social services | 0.09 | 0.28 | 0.00 | 1.00 |
| diverse services | 0.11 | 0.32 | 0.00 | 1.00 |
| government | 0.05 | 0.23 | 0.00 | 1.00 |

### 4.2 Weather data

Our weather data consist of the North American Regional Reanalysis (NARR) model (NOAA, OAR and ESRL PSD, 2017) developed by the National Centers for Environmental Prediction (NCEP) and is an extension of the NCEP Global Reanalysis project. Reanalysis weather data is modelled from information collected from ground stations, satellites, and other sources such as rawinsondes. For the research aim of this paper, reanalysis data provides a reliable source of temperature and precipitation data. For our preferred specification of the weather variables, we requires high-resolution high-frequency weather data. NARR has the advantage of being a balanced panel potentially overcoming data issues such as missing station data, irregularities due to unaccounted elevation, and biases caused by urban heat islands. The NARR dataset consists of a long-term, high frequency, dynamically consistent meteorological and land surface hydrology data set. It covers climate data from 1979 to 2017, with weather data provided eight times daily in the form of a 0.3°resolution grid (32 km at the lowest latitude). The final data of NARR is combined using the high-resolution NCEP Eta Model together with the Regional Data Assimilation System (RDAS). Both climate models aim to assimilate and improve the accuracy of the raw weather data. As with any modelled dataset, one has to be cautious when using reanalysis data. The accuracy of the results depends highly on the spatial distribution of underlying weather observations. This observation is particularly important when working with precipitation, as it naturally has a vaster spatial variation than for example temperature. Nonetheless, NARR has a good track record of accurately measuring extreme weather events for Mexico (Mesinger et al., 2006). We will address potential biases resulting from the weather data in the robustness section by using an alternative dataset.

Considering the research aim of this paper, one key element of the analysis is defining the weather variables. Several methodological decisions arise when working with weather shocks. One major concern is the choice of the appropriate functional form of weather variables. Studies often employ simple measures such as a 'levels' definition (Dell et al., 2012; Feng et al., 2010; Hsiang, 2010; Hsiang et al., 2014; Yang and Choi, 2007), anomalies (Anderson et al., 2013; Barrios et al., 2010; Fishman et al., 2015; Hidalgo et al., 2010; Theisen, 2012), and degree-days definitions (Aroonruengsawat and Auffhammer, 2011; Burke and Emerick, 2016; Deschênes and Greenstone, 2007; Graff Zivin and Neidell, 2014; Graff Zivin et al., 2015; Guerrero Compeán, 2013; Guiteras, 2009; Jessoe et al., 2016). Averaging over weather across the working week provides a straightforward measure of weather. However, weekly averages may mask daily fluctuations and extremes. Similarly, degree-days potentially miss the complexity of the impact of weather. Recently the literature highlighted the importance of accounting for non-linearities in the impact of weather (Dell et al., 2014; Deschênes and Greenstone, 2007; Graff Zivin and Neidell, 2014; Guerrero Compeán, 2013; Guiteras, 2009; Schlenker and Roberts, 2009). Non-linearities may be crucial in the context of human behavioural responses to weather due to the non-linear sensitivity of the human body to weather (Burke et al., 2015; Cachon et al., 2012; Colmer, 2015; Dell et al., 2014; Graff Zivin and Neidell, 2014; Graff Zivin et al., 2015; Hsiang, 2010; Kjellstrom et al., 2008; Seppanen et al., 2006; Somanathan et al., 2014; Wargocki and Wyon, 2007).

### 4.2.1 Simple Weather Variables

Considering the controversy around the correct specification, prior to implementing a more flexible functional form approach, we estimate several initial regressions using non-complex specifications of weather variables. These more simplistic regressions serve the purpose of comparability of our estimates with other studies, as well as serving as a reference point for the more complex structural regressions in the second part of the analysis. We employ five different weather indicators in our analysis: (1) average daily temperatures (in °C), (2) average daily total precipitation (in mm), (3) total weekly precipitation (in mm), (4) total harmful degree-days (in °C), (5) and lastly we construct the Heat Index (in °C). Harmful degree-days capture the harmful impact of extreme heat, taking into account the duration of the heat wave by summing excessive degrees over an upper threshold over time. This heat indicator is constructed as the sum of the difference in temperatures above 35 °C and the threshold. An alternative measure suggested by the literature is the Heat Index (Heyes and Saberian, 2017; Kim et al., 2006), which measures the perceived temperature by factoring relative humidity with actual air temperature. The human body adapts to harmful levels of external temperatures by exercising thermoregulatory control mechanisms, sweating and precapillary vasodilation, which prevents overheating. At higher humidity levels, diminished vaporisation of sweat reduces the capacity of the body to cope with the external heat. The formula for calculation of the Heat Index is provided in Appendix C. During the study period, each municipality experienced on average 124 days a year with temperatures deviating from the monthly average by more than one standard deviation and 13 days deviating by more than two standard deviations. Rainfall fluctuates less. Over the period municipalities on average experienced only 27 days per year with daily total precipitation being exceeding average monthly precipitation by one standard deviation, and 12 days by two standard deviations. Summary statistics for our weather variables are presented in Table 2 below. Over the period from 2004 to 2016 average temperatures in Mexico were 22 °C, while average total daily precipitation was 2 mm. In line with the literature, we test for non-linearities by including different combinations of linear, quadratic and higher polynomials of our weather variables.

Table 2: Summary Statistics NOAA Weather Variables

| | Mean | Std. Deviation | 95 % Confidence Interval | |
|---|---|---|---|---|
| avg. temperature | 22.20 | 5.76 | 12.75 | 31.40 |
| avg. daily total percip. | 2.07 | 3.34 | 0.00 | 8.94 |
| total precipitation | 14.47 | 23.41 | 0.00 | 62.60 |
| harmful degree days | 1.92 | 20.10 | 0.00 | 0.00 |
| avg. daily heat index | 25.49 | 6.39 | 17.61 | 37.99 |

### 4.2.2 Weather Bins

To address the issue of non-linearity in labour market responses to weather we follow a similar approach to Barreca et al. (2016); Burgess et al. (2014); Graff Zivin and Neidell (2014); Guerrero Compeán (2013); Guiteras (2009); Schlenker and Roberts (2009) by binning our weather data using the following formulae:

$$D(T) = \left\{ \begin{array}{lll} \sum D & if & \overline{T} \leq 10^\circ C \\ \sum D & if & 10^\circ C < \overline{T} \leq 12^\circ C \\ & \vdots & \\ \sum D & if & 40^\circ C < \overline{T} \end{array} \right\} \quad D(P) = \left\{ \begin{array}{lll} \sum D & if & P = 0\,mm \\ \sum D & if & 0\,mm < P \leq 2\,mm \\ & \vdots & \\ \sum D & if & 30\,mm < P \end{array} \right\} \quad D(HI) = \left\{ \begin{array}{lll} \sum D & if & \overline{HI} \leq 10^\circ C \\ \sum D & if & 10^\circ C < \overline{HI} \leq 12^\circ C \\ & \vdots & \\ \sum D & if & 40^\circ C < \overline{HI} \end{array} \right\} . \tag{4}$$

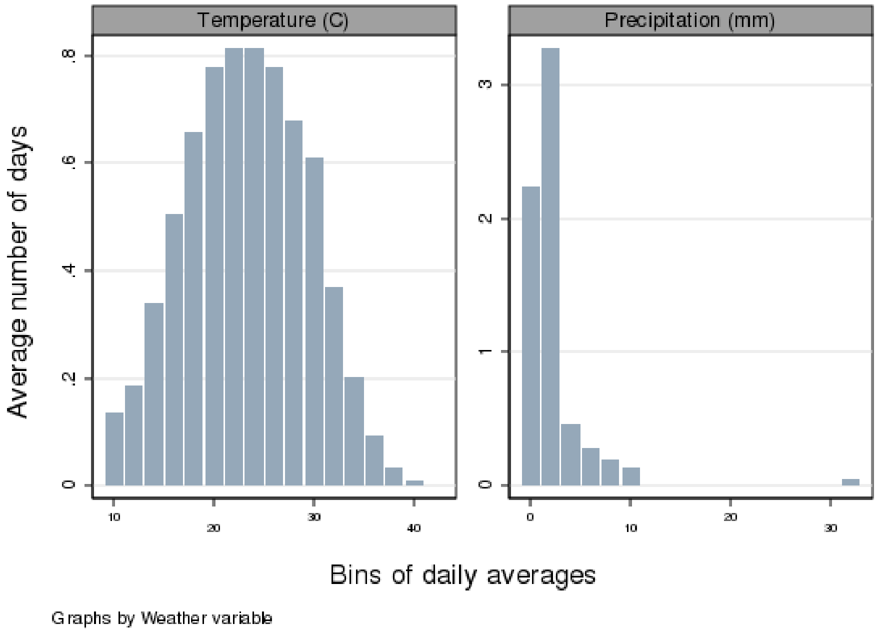
Our approach avoids specifying the functional form due to the non-parametric structure of the weather variables. Weather-bins are the weekly sum of days in which the observed weather falls into the corresponding bin. Daily average temperatures are distributed over 16 bins defined as follows: temperatures below 10°C and above 40°C. Temperatures between these two extreme are distributed over 14 two-degree-wide bins (i.e. 10°C-12°C, 12°C-14°C, ..., 38°C-40°C). For rainfall, we follow the literature by dividing the range of daily accumulated precipitation into 14 bins: 12 two-millimetre-wide bins from 0-30 mm (i.e. 0-2 mm, 2-4 mm, ..., 28-30 mm) and two further bins for days without any precipitation and days with accumulated rainfall exceeding 30 mm. Figure 1 illustrates the distribution of temperature and precipitation over the defined bins for the period from 2005-2016. The bar hight captures the average number of days for which the observed weather falls into the respective bin across municipalities per week. We can deduce from the figure that on average districts experience only a small number of days with temperatures above 34 °C. Due to the scarcity of observations in this temperature range we will collapse observations of these bins to days above 34 °C. For rainfall the distribution over bins is highly skewed towards days with no or little rainfall. The lack of variation in rainfall may render estimation of the impact difficult. Similarly, as with temperature, we have decided to collapse bins of precipitation of 10 mm-20 mm-30 mm, and 30 mm and above. The trade-off between including bins with low frequency and collapsing the bins into greater units is between the precision of the estimation and estimation of non-linearities at extreme levels of the distribution. Appendix B provides further figures on the weekly distribution over quarters and regions. Both graphs further emphasise the decision to collapse the temperature and precipitations bins as discussed with reference to the fixed-effects structure of the model.

Besides the functional form, two further decisions concerning the construction of our weather variables are firstly the level and secondly the method of regional aggregation of the reanalysis data. With regard to the first decision, the appropriate geographical unit for the empirical analysis of weather impacts on labour markets in the context of Mexico is municipalities. Aggregation on a higher regional level could potentially introduce measurement error in our weather variables as climate may vary substantially within the unit of geographical area. Considering the average size of municipalities of around $800km^2$, about the size of New York City, it is reasonable to assume that municipalities experience fairly homogeneous weather. Furthermore, municipalities present useful geographic units of local economic characteristics, providing uniform measures of for example domestic labour and housing market conditions. Treating place characteristics of states such as Chihuahua as uniform is inadequate, given the vast variation in within-state topography, climate, and industrial structure. Municipalities provide a useful level of analysis as they can be considered as an economic entity.

With regard to the geographical aggregation of the reanalysis data, the construction of the weather bins followed a two-step procedure, whereby we first generated weekly bins for every grid point which were then averaged over municipality polygons[9]. The weights used

[9]Note that 2011 municipality Othón P. Blanco in the South-Eastern state Quintana Roo lost 40% of its territory to the newly founded municipality Bacalar. We kept original municipality boundaries from 2005

Figure 1: Distribution of daily avg. temperature and total precipitation over bins per week




to calculate the geometric-averages were generated using the *extract* command of the *raster* package in R. This sequence is essential to account for non-linear effects of weather. Averaging over the geographic area before binning the observations could lead to a misrepresentation of the extreme weather days due to smoothing over extreme observations (Dell et al., 2014). To better understand the reasoning behind the aggregation steps, consider this simplified example where municipality $i$ includes only two grid points with temperatures of 27°and 34°C with equal weights respectively. Assume that labour supply drops significantly for temperatures above 32°C. The mean temperature for the municipality is 30.5°C. However, binning the temperature would assign half a day for each of the corresponding bins for the municipality. Therefore, binning the data by grid point accounts more accurately for the variation in within municipality weather. Note that the sequential aggregation method results in fractional days in bins, while the total days per week and municipality sum to seven days.[10]

Besides geographical aggregation, also the temporal aggregation of our daily weather data needs to considered carefully. Given the various channels through which temperature and precipitation affect labour supply and demand as well as the temporal flexibility of our outcome variables we expect that the size and significance of our estimated weather impacts may be influenced by the temporal aggregation of the weather variables. To address the latter concern, we will check the robustness of our preferred model specifications to different temporal aggregation of our weather variables in Section 6.

A further concern raised in the literature is doubts in the accuracy of reanalysis data. We will address the matter by re-estimating our main estimation results using the CRU TS3.21

throughout the study to ensure consistency in the geographic boundaries and characteristics of municipalities over time.

[10]Conventionally, week 52 in a non-leap year has eight days and nine days in a leap year with a total of 366 days.

dataset produced by the Climatic Research Unit (CRU) at the University of East Anglia (Jones, 2014) as an alternative data source. The CRU time-series dataset provides monthly, homogenised, high-resolution grids $(0.5 \times 0.5°)$[11] created from historical climate observations of more than 4000 weather stations. Similar to the NOAA dataset we construct our weather variables by generating weighted averages per municipality polygon. The lower frequency of weather observations implies that we can only study monthly and quarterly averages rather than weekly observations. The lower data frequency likely introduces measurement error into our analysis and therefore our CRU estimates should be considered as a lower bound estimate.

### 4.3 Residual Variation

Given the spatiotemporal fixed-effects structure of our main regressions, it is important to analyse how much variation in our weather variables will be stripped away from the fixed effects. Following Guiteras (2009) and Jessoe et al. (2016) we regress each weather measure on various definitions of fixed effects and time trends (none, municipality, municipality and year trend, municipality and higher polynomial year trends, quarter and year municipality and region×year, municipality and state×year). We use the residual variation to assess the remaining variation left to identify the impact of weather. Table 3 summarises the number of residuals for weekly average temperatures, precipitation and harmful-degree days, where the absolute value lies above the indicated cut-off levels.

Ideally one would like to have a significant residual variation above reasonable cut-off points. As becomes evident from Table 3, the remaining variation declines substantially with more complex time fixed-effects. Results differ only a little between time trends and year fixed effects, with year fixed effects removing slightly more variation in the weather variables. Given the short period over which data was collected this could suggest that weather has been abnormal for one or more years compared to the overall trend. Year dummies will remove some of this abnormal variation. However, in light off the modest difference in residual variation between year trends and year fixed effects, we prefer to include year fixed effects as the latter are more appropriate controls of any exogenous shocks to labour markets. The last columns of Table 3 show that the introduction of quarterly fixed effects reduce the residual variation in our climate variables substantially, while adding further region and state time-specific trends causes no significant change. The drop in variation is most distinct for average temperatures. This observation is unsurprising considering the smaller seasonal correlation in rainfall compared to precipitation for Mexico. Despite the notable loss of variation, we decide to include year and quarterly fixed effects in our regression. The Robustness Section 6 discusses the robustness of results to different fixed effects structures.

For our bin-variables we follow Guiteras (2009) approach and run separate regressions for each bin $b$ on the various fixed effects specifications. We then calculate the absolute value of the residuals from each regression. Each entry in Table 4 depicts the mean across municipalities over time. The mean value times the number of municipality-by-quarter observations yields the number of observations available to identify the effect for the specific interval. The final numbers in Table 4 can be interpreted as the mean number of days per district-year-quarter available for the identification of the impact of each bin after controlling for the particular spatial/temporal error structure. The larger the number of observations

[11] The CRU grid corresponds approximately to a geographic area of about $56 \times 52km^2$ to $56 \times 42km^2$.

Table 3: Residual Variation of Weekly Weather Variables

Panel 1: Mean Temperatures (°C)

*Municipality Week. Year Observations with Weather Residual >than*

| Mean: 22.2 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 5.76 | 5,554,866 | 0.70 | 3,402,751 | 0.43 | 1,659,302 | 0.21 | 581,662 | 0.07 | 142,268 | 0.02 |
| municipality fe | 4.48 | 4,664,232 | 0.59 | 2,194,312 | 0.28 | 716,362 | 0.09 | 178,910 | 0.02 | 40,584 | 0.01 |
| mun. fe, linear year | 4.48 | 4,657,793 | 0.58 | 2,195,011 | 0.28 | 715,868 | 0.09 | 180,250 | 0.02 | 39,903 | 0.01 |
| mun. fe, quadratic year | 4.47 | 4,647,630 | 0.58 | 2,187,752 | 0.27 | 705,324 | 0.09 | 178,059 | 0.02 | 38,892 | 0.00 |
| mun. fe, cubic year | 4.47 | 4,646,672 | 0.58 | 2,189,797 | 0.27 | 706,258 | 0.09 | 179,436 | 0.02 | 39,432 | 0.00 |
| mun. & year fe | 4.46 | 4,631,686 | 0.58 | 2,172,516 | 0.27 | 692,611 | 0.09 | 175,474 | 0.02 | 41,831 | 0.01 |
| mun. year & qtr. fe | 3.06 | 3,116,173 | 0.39 | 770,939 | 0.10 | 170,763 | 0.02 | 31,586 | 0.00 | 2,350 | 0.00 |
| mun., region× year & qtr. fe | 3.04 | 3,087,373 | 0.39 | 758,189 | 0.10 | 164,931 | 0.02 | 30,895 | 0.00 | 2,284 | 0.00 |
| mun., state× year & qtr. fe | 3.04 | 3,068,016 | 0.39 | 751,129 | 0.09 | 163,637 | 0.02 | 29,797 | 0.00 | 2,291 | 0.00 |

Panel 2: Mean Precipitation (mm)

| Mean: 2.07 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 3.34 | 6,667,056 | 0.84 | 5,853,872 | 0.73 | 4,278,537 | 0.54 | 1,312,430 | 0.16 | 1,146,513 | 0.14 |
| municipality fe | 3.19 | 5,796,185 | 0.73 | 4,412,512 | 0.55 | 3,231,932 | 0.41 | 2,163,881 | 0.27 | 1,517,216 | 0.19 |
| mun. fe, linear year | 3.19 | 5,769,906 | 0.72 | 4,430,664 | 0.56 | 3,171,259 | 0.40 | 2,188,929 | 0.27 | 1,532,657 | 0.19 |
| mun. fe, quadratic year | 3.19 | 5,776,445 | 0.73 | 4,437,040 | 0.56 | 3,176,144 | 0.40 | 2,182,025 | 0.27 | 1,540,473 | 0.19 |
| mun. fe, cubic year | 3.19 | 5,774,313 | 0.72 | 4,436,735 | 0.56 | 3,173,831 | 0.40 | 2,180,663 | 0.27 | 1,543,280 | 0.19 |
| mun. & year fe | 3.18 | 5,746,589 | 0.72 | 4,406,311 | 0.55 | 3,166,993 | 0.40 | 2,220,564 | 0.28 | 1,532,827 | 0.19 |
| mun. year & qtr. fe | 2.78 | 4,480,639 | 0.56 | 3,230,819 | 0.41 | 2,372,422 | 0.30 | 1,753,303 | 0.22 | 1,276,449 | 0.16 |
| mun., region× year & qtr. fe | 2.77 | 4,483,245 | 0.56 | 3,229,829 | 0.41 | 2,359,109 | 0.30 | 1,760,767 | 0.22 | 1,280,933 | 0.16 |
| mun., state× year & qtr. fe | 2.76 | 4,498,927 | 0.56 | 3,224,954 | 0.40 | 2,374,675 | 0.30 | 1,774,554 | 0.22 | 1,296,316 | 0.16 |

Panel 3: Total Precipitation (mm)

| Mean: 14.47 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 23.41 | 7,793,955 | 0.98 | 7,712,222 | 0.97 | 7,628,434 | 0.96 | 7,540,097 | 0.95 | 7,446,738 | 0.93 |
| municipality fe | 22.36 | 7,732,675 | 0.97 | 7,596,855 | 0.95 | 7,422,596 | 0.93 | 7,310,515 | 0.92 | 7,178,825 | 0.90 |
| mun. fe, linear year | 22.32 | 7,694,647 | 0.97 | 7,560,769 | 0.95 | 7,412,658 | 0.93 | 7,259,901 | 0.91 | 7,119,299 | 0.89 |
| mun. fe, quadratic year | 22.32 | 7,692,561 | 0.97 | 7,553,399 | 0.95 | 7,410,829 | 0.93 | 7,265,505 | 0.91 | 7,115,607 | 0.89 |
| mun. fe, cubic year | 22.32 | 7,691,639 | 0.97 | 7,551,910 | 0.95 | 7,409,788 | 0.93 | 7,263,643 | 0.91 | 7,114,447 | 0.89 |
| mun. & year fe | 22.30 | 7,684,155 | 0.96 | 7,539,754 | 0.95 | 7,377,476 | 0.93 | 7,240,151 | 0.91 | 7,103,716 | 0.89 |
| mun. year & qtr. fe | 19.46 | 7,428,775 | 0.93 | 7,166,408 | 0.90 | 6,896,863 | 0.87 | 6,605,979 | 0.83 | 6,339,894 | 0.80 |
| mun., region× year & qtr. fe | 19.38 | 7,405,226 | 0.93 | 7,131,795 | 0.90 | 6,841,671 | 0.86 | 6,567,574 | 0.82 | 6,309,160 | 0.79 |
| mun., state× year & qtr. fe | 19.33 | 7,407,267 | 0.93 | 7,113,686 | 0.89 | 6,841,153 | 0.86 | 6,569,589 | 0.82 | 6,288,176 | 0.79 |

Panel 4: Harmful Degree-Days (°C)

| Mean: 1.92 N: 7964917 | | 2 hd days (°C) | | 10 hd days (°C) | | 20 hd days (°C) | | 30 hd days (°C) | | 40 hd days (°C) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 20.10 | 244,143 | 0.03 | 173,027 | 0.02 | 134,026 | 0.02 | 110,458 | 0.01 | 89,341 | 0.01 |
| municipality fe | 18.45 | 1,202,494 | 0.15 | 416,648 | 0.05 | 207,252 | 0.03 | 153,594 | 0.02 | 134,100 | 0.02 |
| mun. fe, linear year | 18.44 | 1,223,779 | 0.15 | 417,935 | 0.05 | 206,978 | 0.03 | 153,022 | 0.02 | 133,701 | 0.02 |
| mun. fe, quadratic year | 18.44 | 1,222,036 | 0.15 | 417,855 | 0.05 | 207,028 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. fe, cubic year | 18.44 | 1,223,501 | 0.15 | 417,626 | 0.05 | 207,010 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. & year fe | 18.44 | 1,230,230 | 0.15 | 418,576 | 0.05 | 207,236 | 0.03 | 153,026 | 0.02 | 133,437 | 0.02 |
| mun. year & qtr. fe | 18.31 | 4,228,573 | 0.53 | 445,997 | 0.06 | 210,257 | 0.03 | 148,686 | 0.02 | 130,259 | 0.02 |
| mun., region× year & qtr. fe | 18.29 | 3,433,494 | 0.43 | 441,446 | 0.06 | 212,065 | 0.03 | 147,538 | 0.02 | 130,640 | 0.02 |
| mun., state× year & qtr. fe | 18.25 | 3,326,858 | 0.42 | 476,900 | 0.06 | 214,958 | 0.03 | 150,806 | 0.02 | 129,679 | 0.02 |

Panel 5: Mean Heat Index (°C)

| Mean: 25.49 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 6.39 | 5,634,088 | 0.71 | 3,500,996 | 0.44 | 1,630,990 | 0.20 | 779,294 | 0.10 | 416,153 | 0.05 |
| municipality fe | 5.23 | 5,095,219 | 0.64 | 2,583,680 | 0.32 | 1,086,461 | 0.14 | 404,266 | 0.05 | 148,092 | 0.02 |
| mun. fe, linear year | 5.23 | 5,099,815 | 0.64 | 2,584,953 | 0.32 | 1,083,116 | 0.14 | 403,219 | 0.05 | 147,868 | 0.02 |
| mun. fe, quadratic year | 5.23 | 5,101,171 | 0.64 | 2,583,010 | 0.32 | 1,081,566 | 0.14 | 402,945 | 0.05 | 148,404 | 0.02 |
| mun. fe, cubic year | 5.23 | 5,100,664 | 0.64 | 2,581,785 | 0.32 | 1,080,718 | 0.14 | 403,107 | 0.05 | 149,049 | 0.02 |
| mun. & year fe | 5.22 | 5,089,251 | 0.64 | 2,577,217 | 0.32 | 1,079,641 | 0.14 | 404,176 | 0.05 | 147,435 | 0.02 |
| mun. year & qtr. fe | 4.98 | 4,702,560 | 0.59 | 2,222,341 | 0.28 | 928,983 | 0.12 | 366,601 | 0.05 | 144,295 | 0.02 |
| mun., region× year & qtr. fe | 4.96 | 4,670,849 | 0.59 | 2,213,284 | 0.28 | 915,676 | 0.11 | 359,051 | 0.05 | 141,420 | 0.02 |
| mun., state× year & qtr. fe | 4.94 | 4,660,882 | 0.59 | 2,196,160 | 0.28 | 921,645 | 0.12 | 355,354 | 0.04 | 136,994 | 0.02 |

Notes: Table counts residuals from regressions of municipality × qtr × year observations on regressors listed in row headings. Cell entries are number of residuals of absolute value greater than or equal to the cut-offs given in the column headings. Years: 2005-2016 Sample: 2456 municipalities

the better and more precise will be the identification of the impact of our weather bins.

Similar to the findings from Table 3, the number of observations remaining for identification drops significantly if controlling for quarter fixed effects. Consequently, only a few observations are left to identify the impact of weather fluctuations. While reducing the precision of our results, including quarter fixed effects is essential to our identification strategy. Due to seasonality both in climate and in sectoral productivity, dropping quarterly fixed effects from our regression could generate substantial bias in our estimates. In light of the loss in the variation given our preferred fixed-effects strategy, the interpretation of large weather fluctuations should be done with caution.

Table 4: Residual Variation of Weekly Weather Bins

Panel 1: Temperature Bins

| Regressors | ≤ 10 | (10-12] | (12-14] | (14-16] | (16-18] | (18-20] | (20-22] | (22-24] | (24-26] | (26-28] | (28-30] | (30-32] | (32-34] | (34-36] | (36-38] | (38-40] | (>40] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| constant | 0.25 | 0.33 | 0.55 | 0.74 | 0.87 | 0.96 | 0.98 | 0.99 | 0.98 | 0.90 | 0.88 | 0.60 | 0.35 | 0.18 | 0.07 | 0.02 | 0.00 |
| municipality fe | 0.21 | 0.28 | 0.46 | 0.62 | 0.74 | 0.84 | 0.90 | 0.94 | 0.91 | 0.78 | 0.70 | 0.49 | 0.29 | 0.15 | 0.06 | 0.01 | 0.00 |
| mun. fe, linear year | 0.22 | 0.29 | 0.47 | 0.62 | 0.74 | 0.84 | 0.90 | 0.94 | 0.91 | 0.78 | 0.70 | 0.49 | 0.30 | 0.15 | 0.06 | 0.02 | 0.00 |
| mun. fe, quadratic year | 0.22 | 0.29 | 0.47 | 0.63 | 0.74 | 0.84 | 0.90 | 0.94 | 0.91 | 0.78 | 0.71 | 0.49 | 0.30 | 0.15 | 0.06 | 0.02 | 0.00 |
| mun. fe, cubic year | 0.22 | 0.29 | 0.47 | 0.63 | 0.74 | 0.84 | 0.90 | 0.94 | 0.91 | 0.78 | 0.71 | 0.49 | 0.30 | 0.15 | 0.06 | 0.02 | 0.00 |
| mun. & year fe | 0.23 | 0.29 | 0.47 | 0.63 | 0.74 | 0.84 | 0.90 | 0.94 | 0.90 | 0.78 | 0.71 | 0.50 | 0.30 | 0.16 | 0.07 | 0.02 | 0.00 |
| mun. year & qtr. fe | 0.28 | 0.33 | 0.50 | 0.62 | 0.72 | 0.83 | 0.89 | 0.93 | 0.87 | 0.73 | 0.72 | 0.54 | 0.36 | 0.20 | 0.08 | 0.02 | 0.01 |
| mun., region× year & qtr. fe | 0.28 | 0.33 | 0.50 | 0.62 | 0.72 | 0.83 | 0.89 | 0.93 | 0.87 | 0.73 | 0.72 | 0.54 | 0.36 | 0.20 | 0.08 | 0.02 | 0.01 |
| mun., state× year & qtr. fe | 0.28 | 0.33 | 0.50 | 0.62 | 0.72 | 0.82 | 0.89 | 0.93 | 0.86 | 0.73 | 0.71 | 0.53 | 0.36 | 0.20 | 0.08 | 0.02 | 0.01 |

Panel 2: Precipitation Bins

| Regressors | = 0 | (0-2] | (2-4] | (4-6] | (6-8] | (8-10] | (10-12] | (12-14] | (14-16] | (16-18] | (18-20] | (20-22] | (22-24] | (24-26] | (26-28] | (28-30] | (>30] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| constant | 1.71 | 1.31 | 0.55 | 0.38 | 0.28 | 0.21 | 0.16 | 0.12 | 0.09 | 0.07 | 0.06 | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 | 0.09 |
| municipality fe | 1.57 | 1.26 | 0.52 | 0.36 | 0.27 | 0.20 | 0.15 | 0.12 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.09 |
| mun. fe, linear year | 1.56 | 1.26 | 0.52 | 0.36 | 0.27 | 0.20 | 0.15 | 0.12 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.09 |
| mun. fe, quadratic year | 1.56 | 1.26 | 0.52 | 0.36 | 0.27 | 0.20 | 0.15 | 0.12 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.09 |
| mun. fe, cubic year | 1.56 | 1.26 | 0.52 | 0.36 | 0.27 | 0.20 | 0.15 | 0.12 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.09 |
| mun. & year fe | 1.55 | 1.26 | 0.52 | 0.36 | 0.27 | 0.20 | 0.15 | 0.12 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 | 0.09 |
| mun. year & qtr. fe | 1.27 | 1.24 | 0.44 | 0.31 | 0.24 | 0.18 | 0.14 | 0.11 | 0.08 | 0.07 | 0.05 | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 | 0.09 |
| mun., region× year & qtr. fe | 1.27 | 1.24 | 0.44 | 0.31 | 0.23 | 0.18 | 0.14 | 0.11 | 0.08 | 0.07 | 0.05 | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 | 0.09 |
| mun., state× year & qtr. fe | 1.26 | 1.23 | 0.44 | 0.31 | 0.23 | 0.18 | 0.14 | 0.11 | 0.09 | 0.07 | 0.05 | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 | 0.09 |

Panel 3: Heat Index Bins

| Regressors | ≤ 10 | (10-12] | (12-14] | (14-16] | (16-18] | (18-20] | (20-22] | (22-24] | (24-26] | (26-28] | (28-30] | (30-32] | (32-34] | (34-36] | (36-38] | (38-40] | (>40] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| constant | 0.04 | 0.06 | 0.18 | 0.44 | 0.80 | 0.90 | 0.91 | 0.91 | 0.90 | 0.79 | 0.73 | 0.58 | 0.48 | 0.41 | 0.33 | 0.24 | 0.57 |
| municipality fe | 0.04 | 0.06 | 0.16 | 0.37 | 0.68 | 0.79 | 0.83 | 0.86 | 0.84 | 0.77 | 0.71 | 0.54 | 0.42 | 0.34 | 0.27 | 0.20 | 0.48 |
| mun. fe, linear year | 0.04 | 0.06 | 0.16 | 0.38 | 0.68 | 0.79 | 0.83 | 0.86 | 0.84 | 0.77 | 0.71 | 0.54 | 0.42 | 0.34 | 0.27 | 0.20 | 0.48 |
| mun. fe, quadratic year | 0.04 | 0.06 | 0.16 | 0.38 | 0.68 | 0.79 | 0.83 | 0.86 | 0.84 | 0.77 | 0.71 | 0.54 | 0.42 | 0.34 | 0.27 | 0.20 | 0.49 |
| mun. fe, cubic year | 0.04 | 0.06 | 0.16 | 0.38 | 0.68 | 0.79 | 0.83 | 0.86 | 0.84 | 0.77 | 0.71 | 0.54 | 0.42 | 0.34 | 0.27 | 0.20 | 0.49 |
| mun. & year fe | 0.05 | 0.06 | 0.16 | 0.38 | 0.69 | 0.79 | 0.83 | 0.86 | 0.84 | 0.77 | 0.71 | 0.53 | 0.42 | 0.34 | 0.27 | 0.20 | 0.49 |
| mun. year & qtr. fe | 0.05 | 0.07 | 0.18 | 0.38 | 0.67 | 0.78 | 0.83 | 0.85 | 0.81 | 0.74 | 0.68 | 0.53 | 0.42 | 0.35 | 0.28 | 0.22 | 0.54 |
| mun., region× year & qtr. fe | 0.05 | 0.07 | 0.18 | 0.38 | 0.67 | 0.78 | 0.83 | 0.84 | 0.81 | 0.73 | 0.68 | 0.53 | 0.42 | 0.35 | 0.28 | 0.22 | 0.54 |
| mun., state× year & qtr. fe | 0.05 | 0.07 | 0.18 | 0.38 | 0.67 | 0.78 | 0.82 | 0.84 | 0.81 | 0.73 | 0.68 | 0.53 | 0.42 | 0.35 | 0.28 | 0.22 | 0.54 |

Notes: This table assesses the extent of residual variation available after removing district fixed effects and other controls. For each bin, the number of days in that bin is regressed on the controls given in the row heading. The absolute value of the residual is then averaged over all district × year observations. The result can be interpreted as the mean number of days per district × year available to identify the effect of that bin. Years: 2005-2016; Sample: 2456 districts (8720 total year × district observations)

# 5 Results

Regression analysis was used to predict the effect of weather on labour markets in Mexico. As pointed out in the methodology section, our regression analysis involves the estimation of different fixed effect models with different weather variable specification. We will start the analysis based on simple linear weather variables, followed by a more complex specification using weather bins. Subsequently, we will test for heterogeneity in our estimated weather effects by including complex interaction terms between our weather bins and different individual characteristics. Throughout all regression models, we include a set of quarter and year fixed effects, with the baseline being quarter 4 in year 2010. Furthermore, owing to the stratification method of ENOE and to control for geographical clustering in our climate variable we decided to cluster our standard errors at the municipality level (Abadie et al., 2017; Cameron and Miller, 2015).

## 5.1 Baseline Regressions

### 5.1.1 Individual Fixed Effects Regressions

We begin by examining the effect of local weather shocks on within district wages. Following Dell et al. (2014) suggestion, we start by using a simplistic individual fixed effects model. Under the assumption of random fluctuations of weather our model correctly identifies the impact of weather on hourly-wages, having controlled for any time and individual-specific confounding factors, including location-specific labour market characteristics. Table [5] presents the results from individual fixed effects regression including different weather variables. Due to natural collinearity in temperatures and precipitation, including both weather variables simultaneously in the regression would limit identification of the weather parameters. Therefore, we run separate regressions for each weather variable. Our results indicate no significant relationship between daily mean temperatures and hourly wages. This result is further supported by the insignificant harmful degree days (HDD) and the Heat Index (HI) coefficients in in column four and five respectively. Interestingly, precipitation has a small significant negative effect on wages. Our result suggest that a 1 $mm$ increase in average weekly precipitation reduces hourly wages by roughly 0.1%.[12] Considering total weekly precipitation, the effect on wages remains negative and significant, albeit naturally smaller due to the change in the size of the regressor. An increase in total weekly precipitation by 1 $mm$ reduces hourly wages by 0.01%.

[12] As discussed in the robustness section this effect increases by 0.1% if we consider the average precipitation during the previous (three) month(s).

Table 5: Baseline Wage Regression - Individual FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. | 0.0002 | | | | |
| (week) | (0.0002) | | | | |
| avg. precip | | -0.0010*** | | | |
| (week) | | (0.0001) | | | |
| tot. precip | | | -0.0001*** | | |
| (week) | | | (0.0000) | | |
| hdd (week) | | | | -0.0000 | |
| | | | | (0.0000) | |
| heat index | | | | | 0.0001 |
| (week) | | | | | (0.0001) |
| Constant | 8.2342*** | 8.2392*** | 8.2392*** | 8.2376*** | 8.2355*** |
| | (0.0042) | (0.0035) | (0.0035) | (0.0035) | (0.0039) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Table 6: Baseline Working Time Regression - Individual FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. | 4.883*** | | | | |
| (week) | (0.680) | | | | |
| avg. precip | | 0.084 | | | |
| (week) | | (0.485) | | | |
| tot. precip | | | 0.003 | | |
| (week) | | | (0.069) | | |
| hdd (week) | | | | -0.047 | |
| | | | | (0.102) | |
| heat index | | | | | -0.815* |
| (week) | | | | | (0.372) |
| Constant | 2405.031*** | 2497.343*** | 2497.450*** | 2497.480*** | 2516.577*** |
| | (12.784) | (3.842) | (3.843) | (4.067) | (10.159) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Turning now to our main outcome variable of interest weekly working time, Table 6 presents the estimates of our baseline regression specification including individual fixed effects with minutes worked per week. In contrast to our earlier findings regarding wages, we find a significant positive relationship between weekly avg. temperature and minutes worked. The estimated effect is, however, is small in size with a 1 °C increase in the weekly temperature increase working hours in the week by just about five minutes. This implies that an increase of average temperatures from 20 to 32 °C is predicted increase weekly working time in the context of Mexico by just about one hour, on average and ceteris paribus. Interestingly, contrary to avg. temperature the estimated coefficient for HI is negatively correlated with minutes worked. This implies that whereas changes in actual temperature increases working times, changes in apparent temperature have the opposite effect. As discussed earlier, discomfort felt at high temperatures is strongly related to humidity. Accordingly, HI might be a better predictor of displeasure caused by temperatures, while actual temperatures may be a better predictor of discomfort at low temperatures. The results in Table 6 further suggest no statistically significant impact of total and avg. precipitation on weekly working time, nor of HDD.

#### 5.1.2 Municipality Fixed Effects Regressions

Inasmuch as individuals show a different sensitivity to weather extremes, the individuals fixed effect regression possibly underestimates the effect of weather on our outcome variables by removing any individual specific differences variations in the impact of weather. Therefore, we re-estimate the regression using municipality fixed effects and introducing further controls for individual characteristics, including gender age and education as well as job-specific characteristics such as contract type, job-formality, firm size and employment sector. The municipality fixed effects allow for individual heterogeneity in weather impacts. We provide full regression tables including all controls in Appendix E. Our control variables are all significant with the correct sign and expected size. A noteworthy observation from the tables in the Appendix is that earnings in Mexico are lowest in the agricultural sector, while they are highest in the construction industry, followed closely by the extractive industry. Further, wages are substantially lower for women and are convex in age. We will come back to these findings during our discussion of potential heterogeneous impacts. Table 7 summarises our key predictions for the weather variables. Comparing the results with the earlier individual fixed effects regressions, several noticeable changes in the coefficient estimates can be observed. Firstly, the impact of avg. precipitation becomes smaller and looses some of its significance. Similarly, total precipitation is less significant. Allowing for individual heterogeneity in the impact of temperatures we predict a significant negative negative relation between avg. temperature and hourly wages of just about 0.05% per 1 °C. The effect is only significant at the 10 % significance level. Likewise, HDDs have a small significant negative effect on wages. An increase of 1 °C in HDD decreases hourly wages by approximately 0.01 %.

These changes in the size and significance of our estimates suggests heterogeneity in the individual sensitivity to temperature changes in contrast to rather homogeneous impacts of precipitation.

Regarding working time, our weather estimates from the fixed effects regression resemble our earlier findings from the baseline regression. One noteworthy difference is the higher significance of our HI estimate at 5 percent significance level. Studying the detailed regression result in Table 15 provided in Appendix E, we note that working hours are concave in age, with women working on average 7.5 hours less per week. Moreover, those with a only a secondary school degree work the longest, whereas those with a bachelor degree work the shortest hours. Considering job characteristics, working times are longest in the transport and communication industry. Informal workers on average work 8 hours less per week. Permanent contracts increase work times on average by half an hour. Working hours are longest in medium-sized firms, with workers working almost two hours more than those of small and micro establishments and one hour longer than employees of large companies. Increases in municipal unemployment reduce the average time spent working. This negative relationship may be explained by higher competition for temporal and informal employment resulting in a reduction in average working hours.

Table 7: Wage Regression - Municipality FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (week) | -0.0005* (0.0002) | | | | |
| avg. precip (week) | | -0.0006** (0.0002) | | | |
| tot. precip (week) | | | -0.0001** (0.0000) | | |
| hdd (week) | | | | -0.0000 (0.0000) | |
| heat index (week) | | | | | -0.0002* (0.0001) |
| Constant | 7.1161*** (0.0191) | 7.1084*** (0.0185) | 7.1084*** (0.0185) | 7.1074*** (0.0185) | 7.1118*** (0.0186) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 8: Working Time Regression - Municipality FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (week) | 4.276*** (0.525) | | | | |
| avg. precip (week) | | -0.146 (0.396) | | | |
| tot. precip (week) | | | -0.030 (0.056) | | |
| hdd (week) | | | | -0.076 (0.066) | |
| heat index (week) | | | | | -0.749** (0.269) |
| Constant | 1829.897*** (22.782) | 1908.082*** (19.747) | 1908.195*** (19.750) | 1907.807*** (19.809) | 1925.632*** (21.465) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

### 5.1.3 Polynomial Weather Variables

Before moving to our preferred weather variable specification, we run one further set of regressions including squared and cubic forms of our weather variables. Table 9 lists the regression estimates. Interestingly, while the linear effect of precipitation remains negative and significant, none of the squared and cubic parameters, except for HDD, were estimated to be significantly different from zero. Studying column 8 reveals that extreme HDD (i.e. $HDD^3$) have significant negative effect on log hourly wages at 10% significance level.

Overall, these results indicate that precipitation has a significant negative effect on wages. In contrast, accounting for non-linearities using quadratic and cubic variable definitions yields insignificant estimates for our different temperature measures.

For working time, the results are more revealing. For all but model (7) we predict a non-linear relationship between our weather variables and weekly working time. Studying the results for avg. temperatures in column (2) we predict a steep increase in working hours for increases in temperatures up to 18 °C and a flattening of the effect at higher temperatures. More remarkable is the prediction for average rainfall. Precipitation increases prolong working time until a local maximum at 5.7 mm is reached. At precipitation levels above 12 mm working time declines substantially till an average daily rainfall level of 30 mm. At levels higher than 40 mm working time increases rapidly again. A similar association is found for total weekly precipitation. Studying model (9) and (10) the results suggest that the quadratic model seems to be a good fit, with an increase in the HI to temperatures of approximately 40 °C decrease working hours by up to 52 minutes. The sign and significance change if a cubic term is added to the model. However, the estimated impact still implies a decline in working time at Hi between 15 and 50 °C. Our estimates for HDD suggest an positive impact of HDDs until 200 °C (approx 29 °C per day above the threshold of 32 °C) with a sharp decline afterwards.

## 5.2 Weather Bins Regressions

As aforementioned, the correct functional form of the weather variables is unclear. In the previous section we assumed that the association between weather and our outcome variables can be accurately estimated using a linear specification or in Section 5.1.3 with combinations of linear, quadratic and cubic forms. In our main model, we avoid specification of the functional form by including weather bins in the regression. The subsequent regression analysis relies on the weather bins as defined in the data section. Using weather bins allows for a fully flexible association between weather and our outcome variables. Note that throughout our regressions our base temperature and HI bin is 20-22 °C. For precipitation our base bin is 2-4 mm. Hence, our temperature results can be interpreted as the change in $Y$ due to one more day in temperature bin $b$ compared to a day in the 20-22°C bin in Quarter 4 in 2010.

### 5.2.1 Individual Fixed Effects Regressions

We begin initially with a very simple specification including individual as well as our year and quarter fixed effects. In Figure 2 we find no clear evidence between hourly wages and the weather experienced during the survey week. Only three bins for the Heat Index are significantly different from zero with very small effect size. For precipitation, only the zero precipitation bin is estimated to have a significant positive effect on wages of 0.1% per day with zero precipitation. More revealing are our findings regarding weekly working time presented

Table 9: Higher Polynomial Weather Wage Regression - Municipality FE

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 0.0001 | -0.0008 | | | | | | | | |
| | (0.0006) | (0.0019) | | | | | | | | |
| avg. temp. $^2$ (week) | -0.0000 | 0.0000 | | | | | | | | |
| | (0.0000) | (0.0001) | | | | | | | | |
| avg. temp. $^3$ (week) | | -0.0000 | | | | | | | | |
| | | (0.0000) | | | | | | | | |
| avg. precip (week) | | | -0.0009** | -0.0009 | | | | | | |
| | | | (0.0003) | (0.0006) | | | | | | |
| avg. precip $^2$ (week) | | | 0.0000 | 0.0000 | | | | | | |
| | | | (0.0000) | (0.0001) | | | | | | |
| avg. precip $^3$ (week) | | | | -0.0000 | | | | | | |
| | | | | (0.0000) | | | | | | |
| tot. precip (week) | | | | | -0.0001** | -0.0001 | | | | |
| | | | | | (0.0000) | (0.0001) | | | | |
| tot. precip. $^2$ (week) | | | | | 0.0000 | 0.0000 | | | | |
| | | | | | (0.0000) | (0.0000) | | | | |
| tot. precip. $^3$ (week) | | | | | | -0.0000 | | | | |
| | | | | | | (0.0000) | | | | |
| hdd (week) | | | | | | | -0.0000 | -0.0001 | | |
| | | | | | | | (0.0001) | (0.0001) | | |
| hdd $^2$ (week) | | | | | | | 0.0000 | 0.0000* | | |
| | | | | | | | (0.0000) | (0.0000) | | |
| hdd $^3$ (week) | | | | | | | | -0.0000* | | |
| | | | | | | | | (0.0000) | | |
| heat index (week) | | | | | | | | | 0.0004 | 0.0002 |
| | | | | | | | | | (0.0005) | (0.0010) |
| heat index $^2$ (week) | | | | | | | | | -0.0000 | -0.0000 |
| | | | | | | | | | (0.0000) | (0.0000) |
| heat index $^3$ (week) | | | | | | | | | | -0.0000 |
| | | | | | | | | | | (0.0000) |
| Constant | 7.1099*** | 7.1158*** | 7.1086*** | 7.1086*** | 7.1086*** | 7.1086*** | 7.1074*** | 7.1074*** | 7.1039*** | 7.1060*** |
| | (0.0204) | (0.0247) | (0.0185) | (0.0185) | (0.0185) | (0.0185) | (0.0186) | (0.0186) | (0.0197) | (0.0219) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 10: Higher Polynomial Weather Working Time Regression - Municipality FE

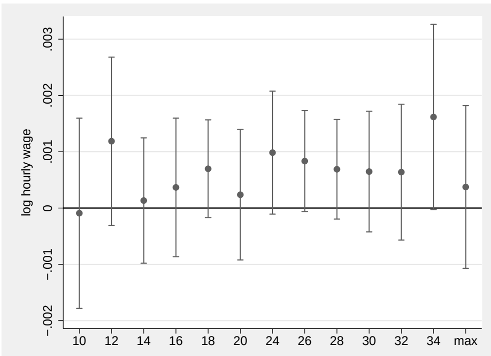
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 11.634*** | 29.913*** | | | | | | | | |
| | (1.546) | (6.119) | | | | | | | | |
| avg. temp. $^2$ (week) | -0.169*** | -1.060*** | | | | | | | | |
| | (0.036) | (0.289) | | | | | | | | |
| avg. temp. $^3$ (week) | | 0.013** | | | | | | | | |
| | | (0.005) | | | | | | | | |
| avg. precip (week) | | | 3.965*** | 8.005*** | | | | | | |
| | | | (0.861) | (1.007) | | | | | | |
| avg. precip $^2$ (week) | | | -0.281*** | -0.835*** | | | | | | |
| | | | (0.048) | (0.091) | | | | | | |
| avg. precip $^3$ (week) | | | | 0.015*** | | | | | | |
| | | | | (0.002) | | | | | | |
| tot. precip (week) | | | | | 0.542*** | 1.105*** | | | | |
| | | | | | (0.122) | (0.143) | | | | |
| tot. precip. $^2$ (week) | | | | | -0.006*** | -0.017*** | | | | |
| | | | | | (0.001) | (0.002) | | | | |
| tot. precip. $^3$ (week) | | | | | | 0.000*** | | | | |
| | | | | | | (0.000) | | | | |
| hdd (week) | | | | | | | 0.079 | 0.309 | | |
| | | | | | | | (0.152) | (0.203) | | |
| hdd $^2$ (week) | | | | | | | -0.000 | -0.002* | | |
| | | | | | | | (0.000) | (0.001) | | |
| hdd $^3$ (week) | | | | | | | | 0.000* | | |
| | | | | | | | | (0.000) | | |
| heat index (week) | | | | | | | | | -2.729** | 1.251 |
| | | | | | | | | | (1.001) | (1.750) |
| heat index $^2$ (week) | | | | | | | | | 0.036 | -0.122 |
| | | | | | | | | | (0.020) | (0.070) |
| heat index $^3$ (week) | | | | | | | | | | 0.002* |
| | | | | | | | | | | (0.001) |
| Constant | 1755.385*** | 1640.028*** | 1905.322*** | 1903.526*** | 1905.507*** | 1903.753*** | 1907.835*** | 1907.824*** | 1951.645*** | 1920.488*** |
| | (26.014) | (43.890) | (19.782) | (19.794) | (19.786) | (19.798) | (19.802) | (19.791) | (25.838) | (22.707) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Standard errors are clustered at the municipality level. ***p<0.01, ** p<0.05, * p<0.10

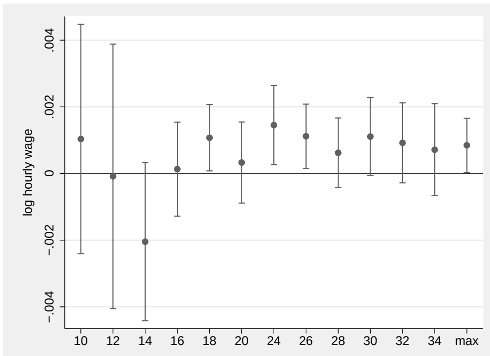
in Figure 3. Most coefficient estimates are negative and statistically significant. Days warmer or colder from the optimal temperature of 20 to 22 °C and below 30 °C reduce working time significantly. Interestingly, the largest temperature effect on hourly wages is predicted for days with temperatures below 10 degrees. Every day with temperatures of only up to 10 °working time declines by over 20 minutes. Consequently, during a week with continuous temperatures below 10 °C average weekly working time declines by more than 2 hours. Similarly, the estimates for Heat Index suggest that the strongest decline in working time is experienced at low temperatures. Again, any deviation from the optimal temperatures reduces working time by a few minutes a day. Regarding precipitation, we find rainfall below and above 4 to 6 mm to decrease working time. The largest estimated reduction of over 40 minutes is for days with extreme precipitation exceeding 30 mm per day.

Figure 2: Weather Bins Coefficeint Plots - Wage Regression

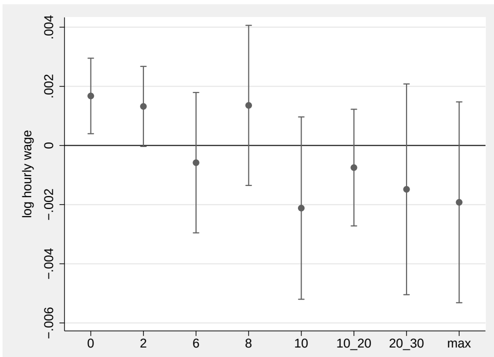
(a) Temperature




(b) Heat Index




(c) Precipitation



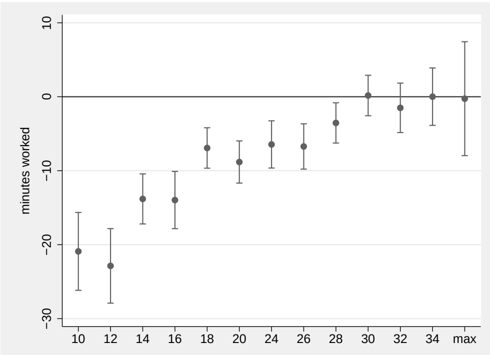

Note: Relationship between hourly wages and weather for all individuals. N=6,131,012 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on hourly wages based on equation 1 in the methodology section. Covariates include individual, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

## 5.3 Municipality Fixed Effects Regressions

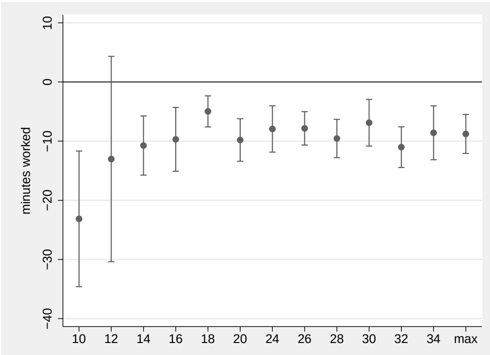
If we change our specification from individual fixed effects and include further controls, we find very similar results for both outcome variables. The coefficient plots in Figure 4 suggest no significant relationship between weather and log. hourly wages. The loss in significance

Figure 3: Weather Bins Coefficient Plots - Working Time Regression

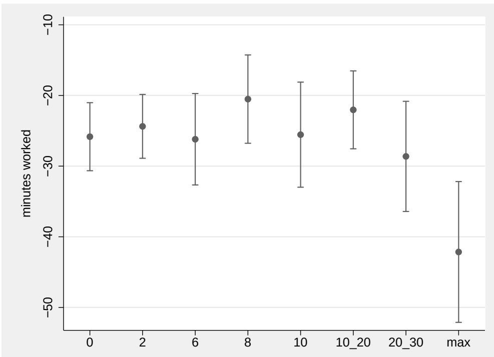
(a) Temperature




(b) Heat Index




(c) Precipitation

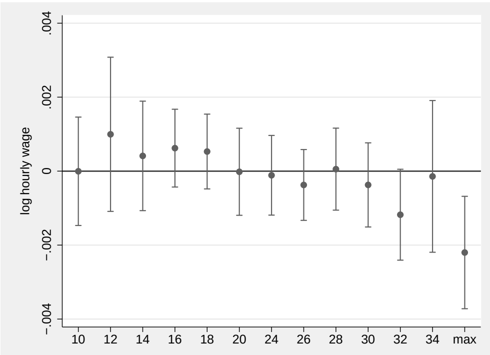



Note: Relationship between weekly working minutes and weather for all individuals. N=7,964,917 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 1 in the methodology section. Covariates include individual, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

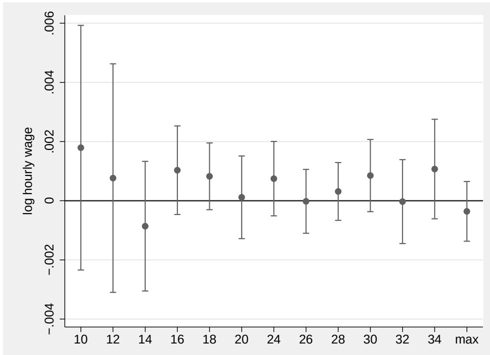
of the zero precipitation coefficient with the municipality fixed effects specification again suggest a homogeneous effect of rainfall on hourly wages across individuals. In contrast, the predicted effects of weather on working times remain significant with similar effect sizes. The strongest estimated effect is for apparent and actual temperatures below 10 °C as well as for extreme rainfall above 30 mm. Contrary to our hypothesis the plots suggest no obvious link between heat and average working hours. In contrast to earlier estimates for the US by Graff Zivin et al. (2015) our results suggest that cold temperatures rather than heat significantly reduces working times in the Mexican context. Besides, our results support the idea of extreme rainfall considerably hindering workers in exercising their job. We will discuss the implications of these findings in the discussion section.

Figure 4: Weather Bins Coefficient Plots - Wage Regression

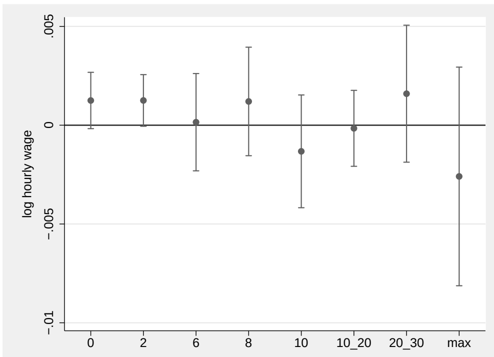
(a) Temperature




(b) Heat Index



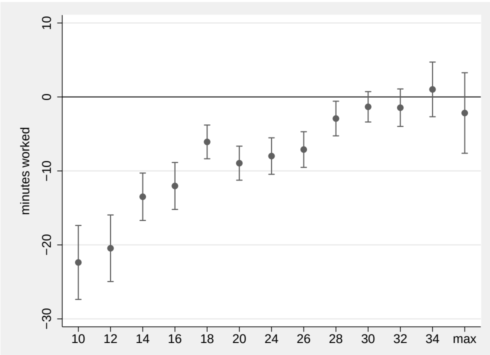

(c) Precipitation



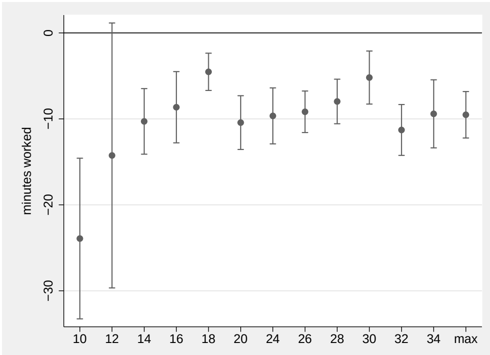

Note: Relationship between log. hourly wage and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

Figure 5: Weather Bins Coefficient Plots - Working Time Regression

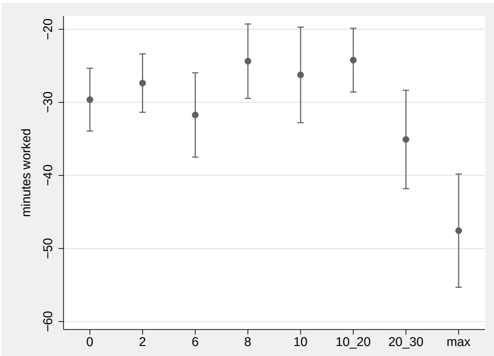
(a) Temperature




(b) Heat Index




(c) Precipitation




Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

### 5.4 Heterogeneous Effects Regressions

While our key regression results suggest only a weak association of weather and wages, we find working time to vary considerably with with precipitation and temperatures fluctuations. An interesting question is whether these weather impacts are homogeneous throughout different segments of the labour force. In the subsequent section, we test for heterogeneous effects of weather by gender, age, and education as well as significant differences in the impact of weather by job formality, contract type, and by employment sector.

Figure 7 depicts the marginal effects of our weather bins for women and men. We observe a distinct gender difference in the impact of weather on earnings, with the effect partly having the opposite sign. Women earn significantly more if apparent temperatures and real temperatures fall below 10 °C. Although cold temperatures reduce male earnings by about 0.3%, they increase female earnings by more than 0.5%. The positive effect on women's earnings if even stronger, if we consider the Heat Index. We find earnings of men to fall by approximately 0.4% in response to extreme heat. However, this effect is not reaffirmed by the Heat Index estimates. The impact of precipitation is not statistically different for men and women.

The general pattern of predicted impacts of apparent and real temperatures as well as rainfall on working hours shows no sharp gender differences. Predicted differences appear to be limited to chilly temperatures. Women on average seem to work 20 minutes more than men when temperatures drop below 10 degrees.

Besides gender differences, one further expects different responsiveness to weather changes depending on the age of workers. The older an individual, the more she might be affected by extreme temperatures. Similarly, the combination of humidity and heat may have different consequences for health depending on the age. The marginal effects per bin by age group in Figure 8 for wages and in Figure 9 for working time reveals that indeed heterogeneous effects by age group are present for both dependent variables. For earnings, predicted age differences with regards to temperature are negligible. However, compelling differences are predicted for the impact of precipitation. Plots (8m) to (8r) suggest that low levels of rainfall increase earnings for workers from the age of 40, while contrarily days with zero rainfall significantly reduce wages for workers under the age of 20. The predicted age differences could potentially be explained by the selectivity of old and young workers into jobs with reverse links between rainfall and worker productivity. Alternatively, the impact of weather on the substitution between leisure and work changes by age.

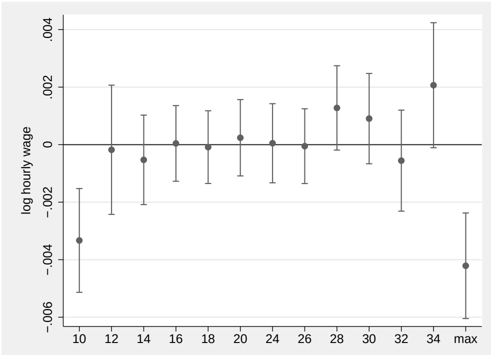
Moving on to working time, we can infer from Figure 9 that working times of young labourers are not sensitive to temperatures changes. Looking in particular over the results of the Heat Index, the responsiveness to temperature seems to follow a u-shaped pattern. Reductions in working time are highest for the age groups 30-39 and 40-49. In line with our earlier results, temperatures below 10 °C cause the largest predicted reduction in working times. Of interest is the notable impact of extreme rainfall both on very young as well as medium-aged (40-59) workers. Working times of these cohorts drop around 55 minutes if precipitation exceeds 30 mm. Unfortunately, our data does not allow us to determine whether the significant difference in the impact of rainfall on working time is due to workers of different age groups being exposed by rain to a varying extent and we, therefore, find them to be more or less sensitive to rain, or whether workers flexibility to adapt their working time to weather fluctuations differs with age.

Beyond potential biological regions for differences in weather sensitivity, also levels of

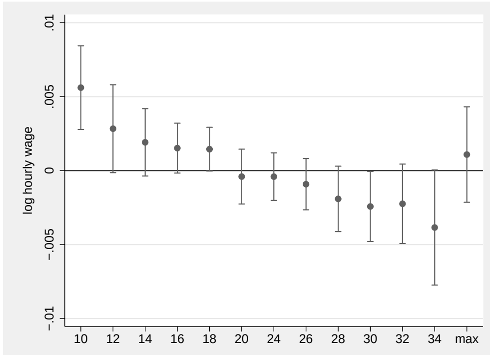
Figure 6: Heterogeneous Effects Wages by Gender

*Temperature*

(a) Male

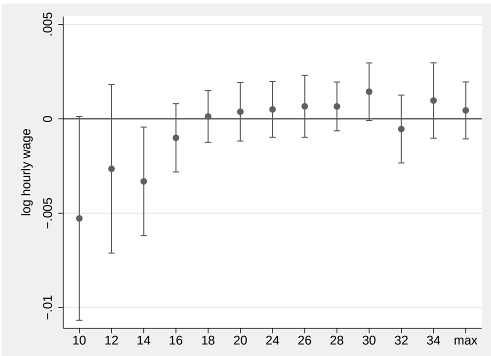



(b) Female

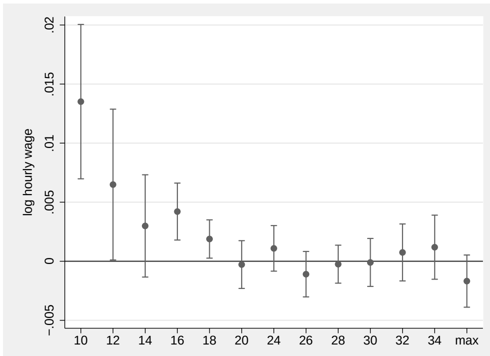



*Heat Index*

(c) Male

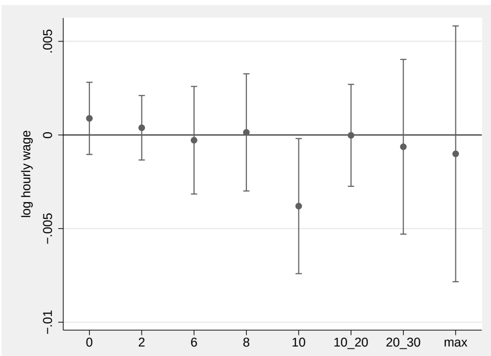



(d) Female

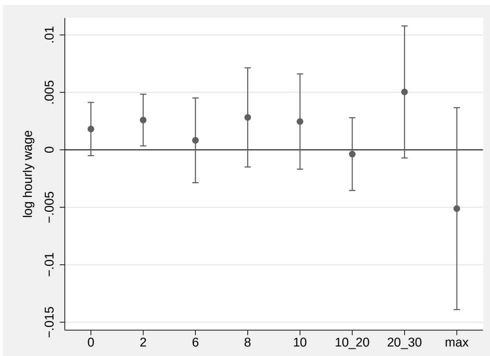



*Precipitation*

(e) Male




(f) Female

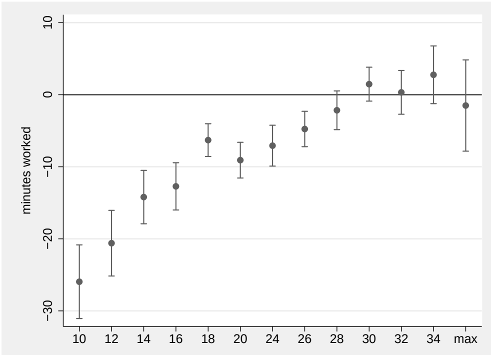



Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

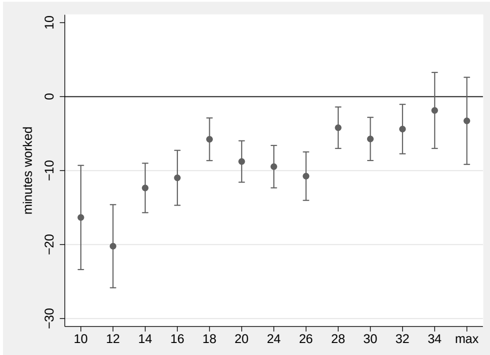
Figure 7: Heterogeneous Effects Work Time by Gender

*Temperature*

(a) Male

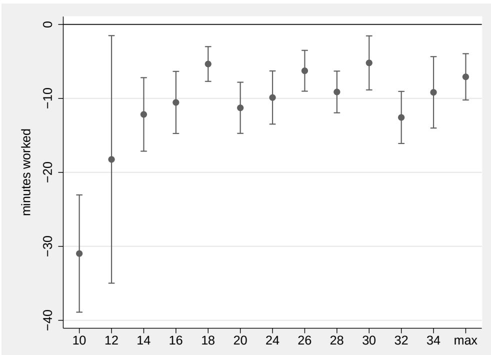



(b) Female

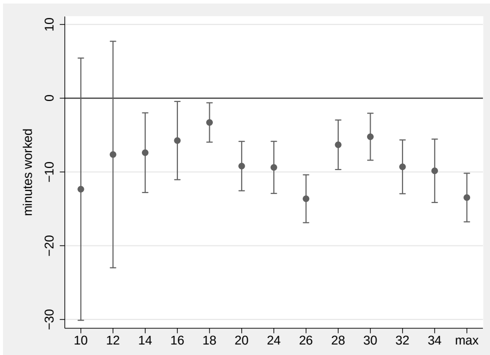



*Heat Index*

(c) Male

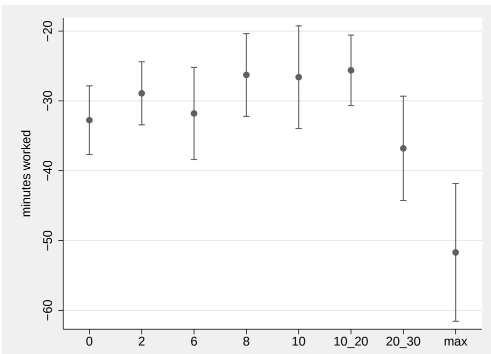



(d) Female

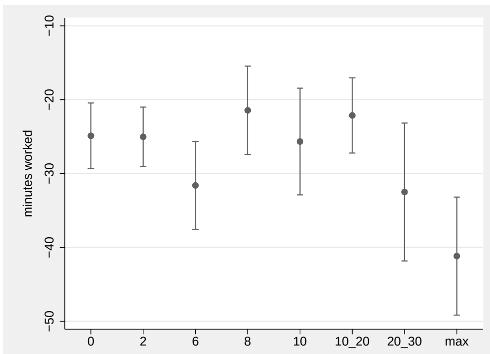



*Precipitation*

(e) Male




(f) Female

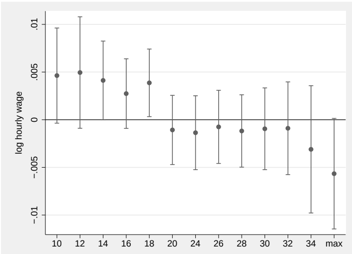



Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^\circ$C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

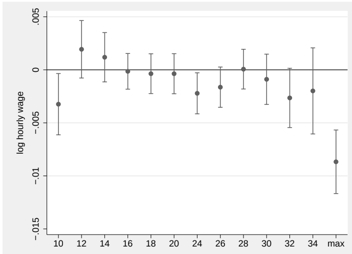
Figure 8: Heterogeneous Effects Wages by Age Group

*Temperature*

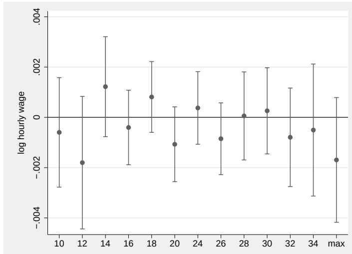
(a) 14-19 yrs



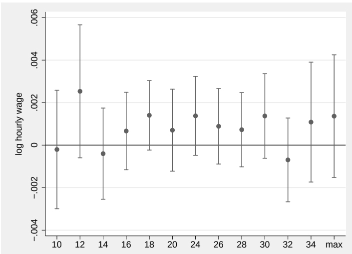

(b) 20-29 yrs



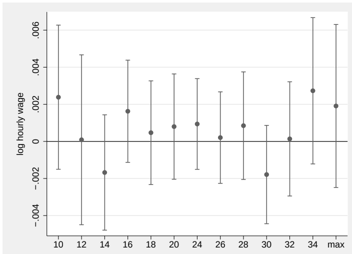

(c) 30-39 yrs



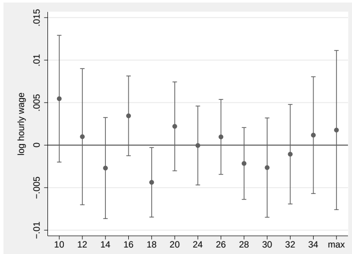

(d) 40-49 yrs




(e) 50-59 yrs

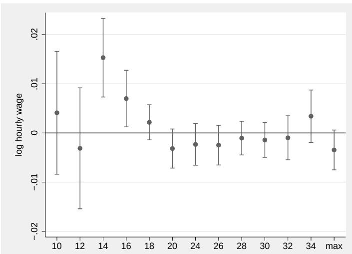



(f) >60 yrs

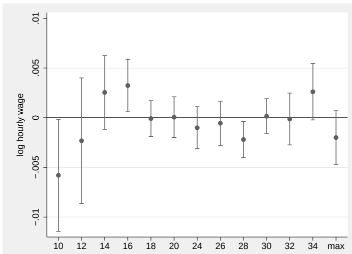



*Heat Index*

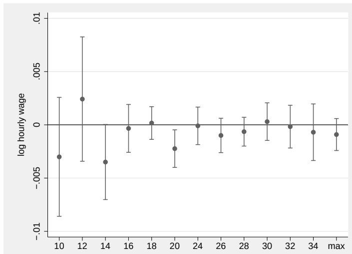
(g) 14-19 yrs



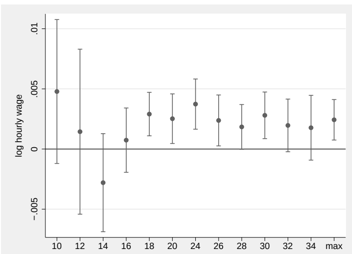

(h) 20-29 yrs



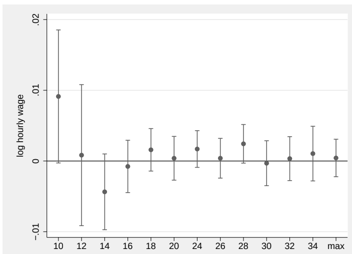

(i) 30-39 yrs



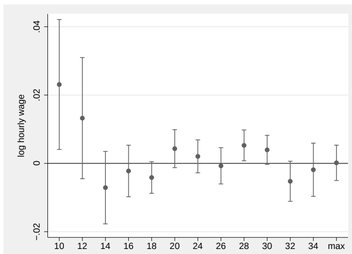

(j) 40-49 yrs



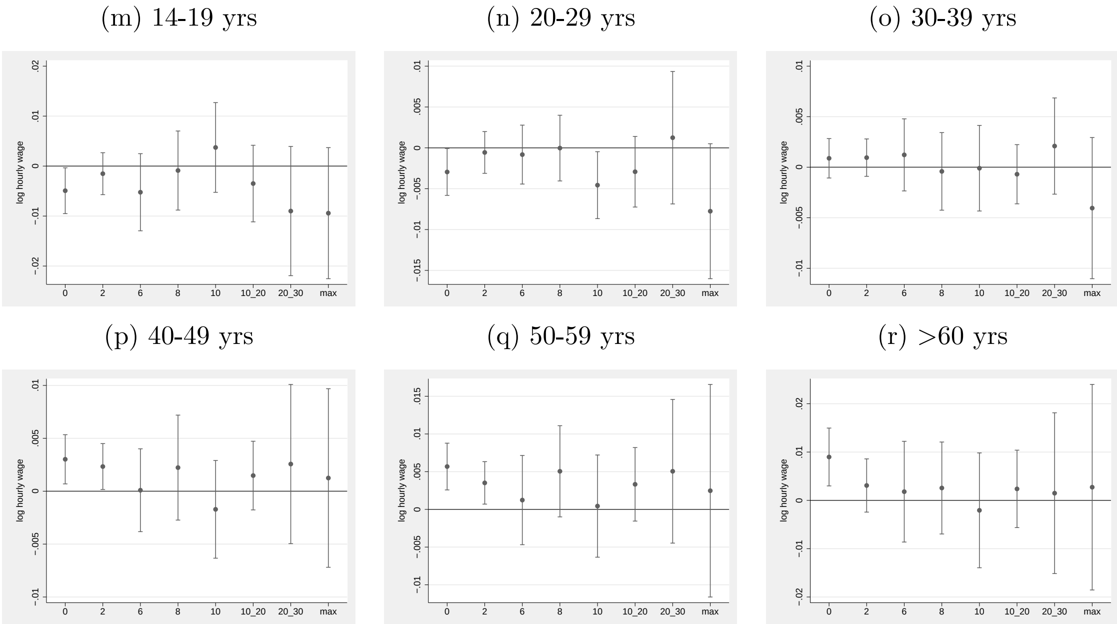

(k) 50-59 yrs




(l) >60 yrs



*Precipitation*




Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

education might alter the extent to which workers react to weather changes. Education levels might capture skill-level differences in jobs characteristics beyond those captured by job formality, contract type and sectoral differences, affecting the influence of weather over wages and working times. We find extreme heat measured by the Heat Index decreases wages for workers with primary education, although the effect size is small. In contrast, wages for workers with a university or postgraduate degree earn more during heat waves. Days with zero precipitation result in a positive increase of wages for workers with primary education, suggesting that low skilled jobs across sectors on average earn more during dry spells. Again, we find the pattern of temperature impacts to be similar across education levels providing support for an underlying biological reason for the responsiveness of working times to weather changes.

Heterogeneous differences in weather impacts may not only relate to individual attributes but also to job characteristics. Informal or temporary employees are likely to be more affected by unfavourable weather, considering the lack of employment security. We further expect to find different impacts across sectors depending on the exposure of workers to weather.

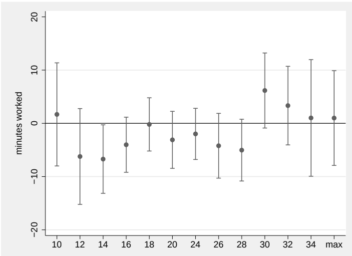
Even though wages of formal workers show no apparent relationship with temperatures, informal workers experience declines in their wages with rising real and apparent temperatures. Furthermore, informal workers experience a significant reduction in their earnings during extreme rainfall periods. These findings imply that informal workers are more vulnerable to income shocks caused by extreme heat and and rainfall.

We find distinct differences in the working time responses of formal and informal workers to weather changes. Formal workers are more responsive to cold temperatures than informal workers. While the latter is significantly affected by high temperatures, formal workers are

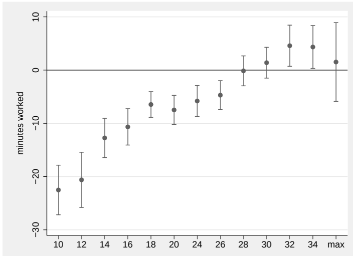
Figure 9: Heterogeneous Effects Work Time by Age Group

*Temperature*

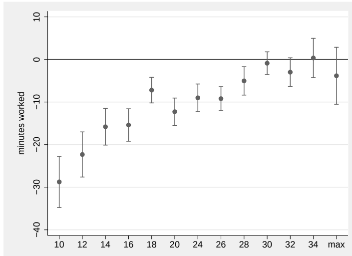
(a) 14-19 yrs



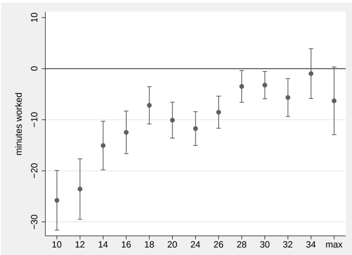

(b) 20-29 yrs



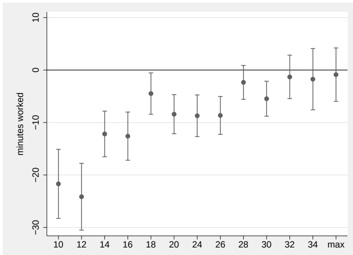

(c) 30-39 yrs



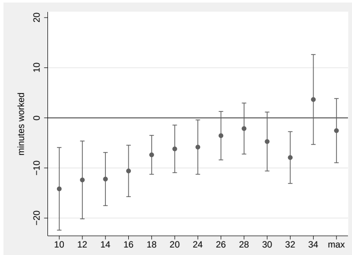

(d) 40-49 yrs




(e) 50-59 yrs

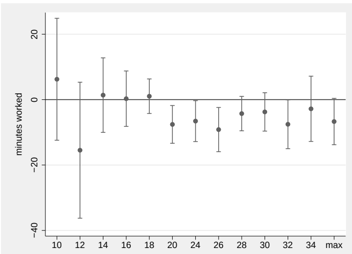



(f) >60 yrs

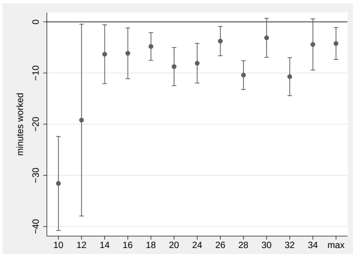



*Heat Index*

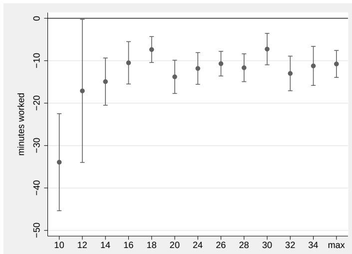
(g) 14-19 yrs



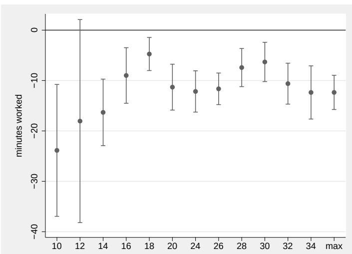

(h) 20-29 yrs



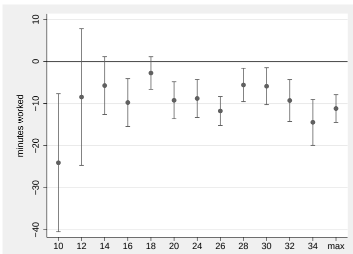

(i) 30-39 yrs



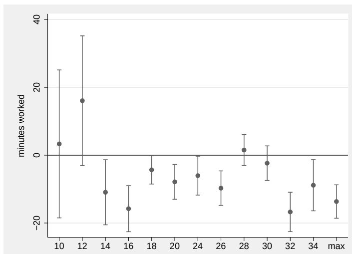

(j) 40-49 yrs



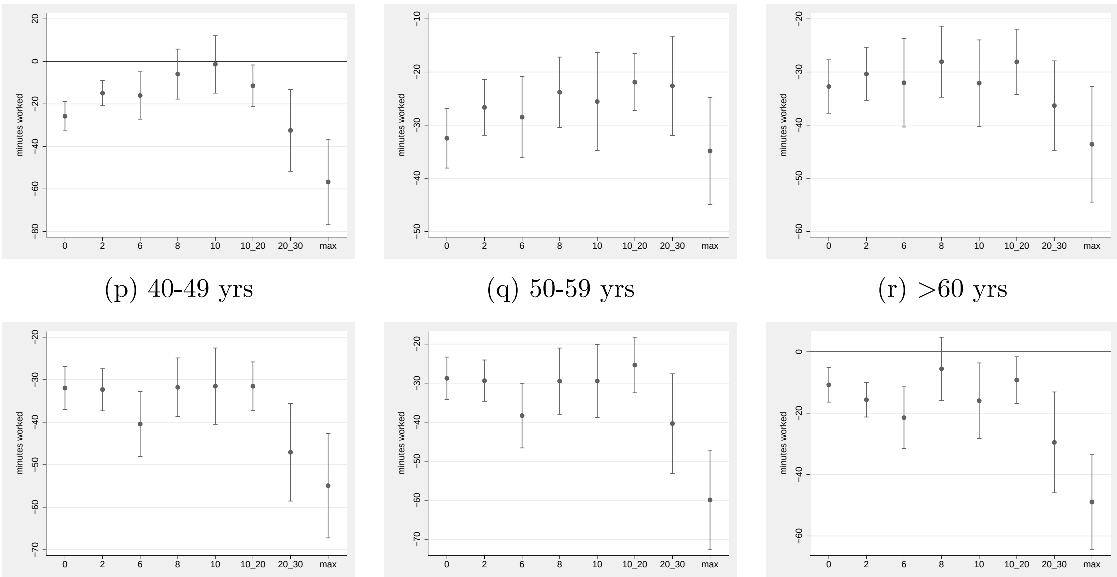

(k) 50-59 yrs




(l) >60 yrs



*Precipitation*




(m) 14-19 yrs (n) 20-29 yrs (o) 30-39 yrs

(p) 40-49 yrs (q) 50-59 yrs (r) >60 yrs

Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

unaffected by heat. For the Heat Index, days with temperatures above 34 °C are estimated to reduce working times of informal workers by roughly 20 minutes. During a heat wave, weekly working time of informal workers decreases on average by approximately 2h 20min. However, the most compelling difference is between the impact of extreme precipitation on formal and informal workers. Extreme precipitation days result in an estimated reduction of weekly working time of informal workers by more than 80 minutes The coefficient for formal workers is considerably smaller with an average effect of just 26 minutes.

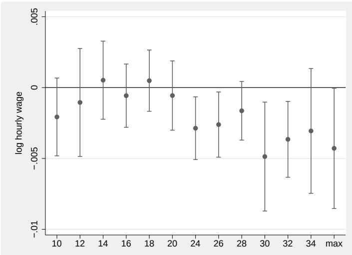
Comparing results of the wage regression for temporary and permanent workers, we find cold to have the opposite effect for the two contract types, with an increase in wages of temporary workers and a decrease for permanent workers. Likewise, the margin plots on precipitation in Figure 14 depicts an opposite effect of zero rainfall on wages of temporary and permanent workers. Differences in the impacts of temperatures on working time between temporary and permanent workers are modest. Only for precipitation, we find noteworthy differences. Matching our earlier finding for informal workers, extreme rainfall considerably reduces minutes worked by temporary workers by over 50 minutes compared to only 18 minutes for permanent workers. Interestingly, the precipitation plot depicts a considerable reduction in working time of permanent workers during days with low levels of precipitations. This suggest a potential substitution effect between leisure and work during low precipitation days.

Figure 16 to 18 summarise our estimated weather effects on wages by sectors. Wages in agriculture, extractive industry, manufacturing and construction are significantly affected by temperature. Workers in the extractive industry earn more during heat waves, while workers in manufacturing and construction see their wages drop. Moderate temperatures

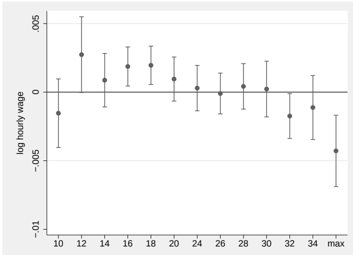
Figure 10: Heterogeneous Effects Wages by Education

*Temperature*

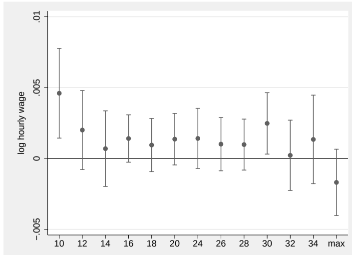
(a) Primary



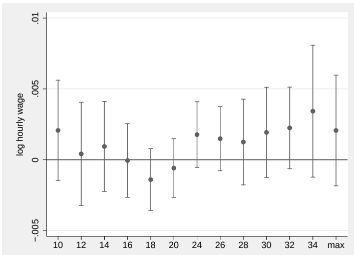

(b) Secondary



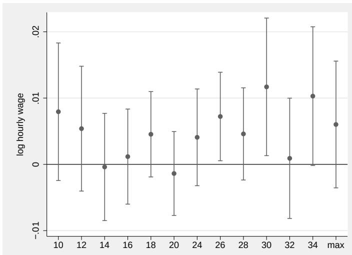

(c) Preparatory




(d) University

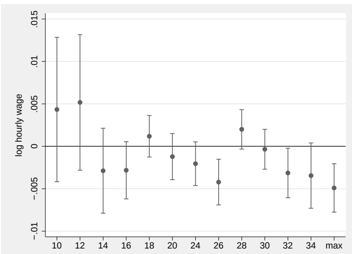



(e) Post Graduate

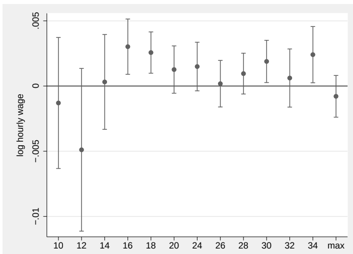



*Heat Index*

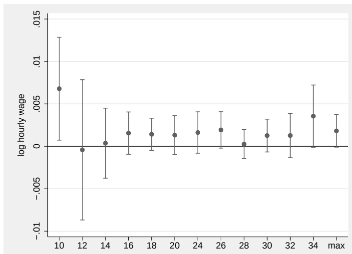
(f) Primary



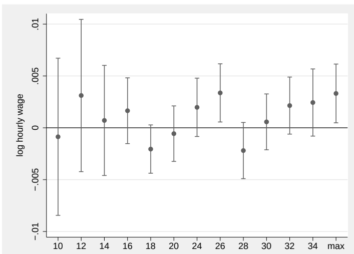

(g) Secondary



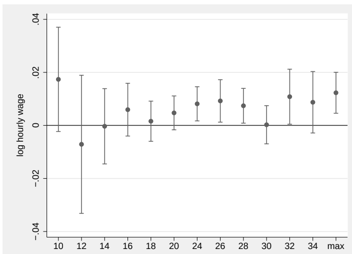

(h) Preparatory




(i) University

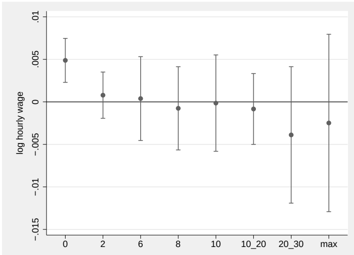



(j) Post Graduate

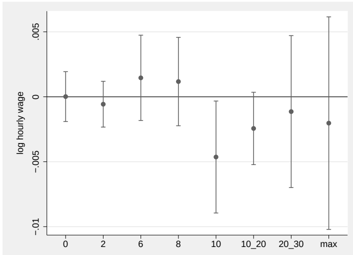


*Precipitation*

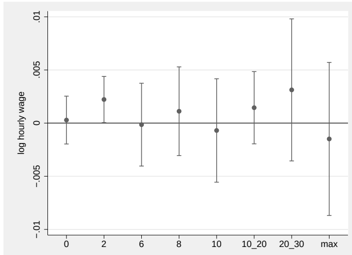
(k) Primary



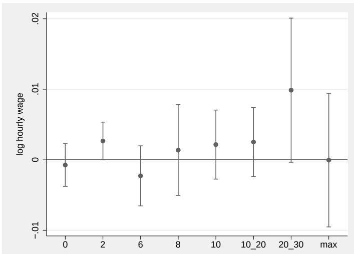

(l) Secondary



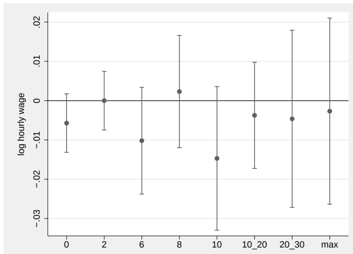

(m) Preparatory




(n) University




(o) Post Graduate




Note: Relationship between log. hourly wages and weather for all individuals. N=5,706,972 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

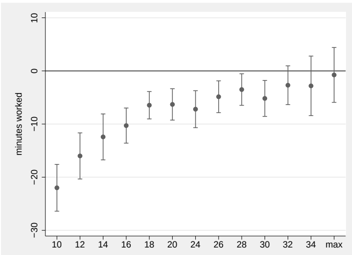
below the optimal temperature of 22 °C but above 10 °C reduce earnings in the agricultural sector. Temperatures below 10 °C significantly reduce earnings in the construction sector. The marginal plots for temperature and Heat Index support the hypothesis that workers in weather exposed sectors are more affected by extreme temperatures. Days without precipitation have a positive effect on agricultural earnings, suggesting that work outdoors is more profitable during dry days. Extreme precipitation increases earning in the extractive industry and reduces wages for the trade and professional service sector. The loss in earnings for the trade sector are likely caused by interruptions to transport, while for the professional service sector the reduction might be caused by a decrease in the number of walk-in customers during heavy rain days.

Sectoral differences in the impact of temperature changes on minutes worked are small and correspond to low temperatures. Extreme rainfall, however, causes severe disruptions for agriculture, manufacturing, construction, and trade.

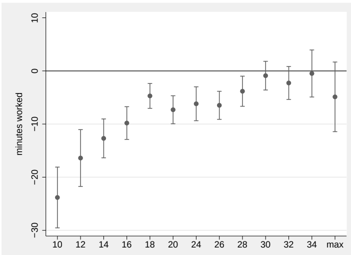
Figure 11: Heterogeneous Effects Working Time by Education

*Temperature*

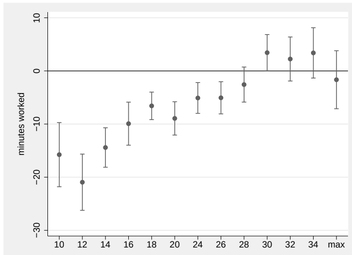
(a) Primary



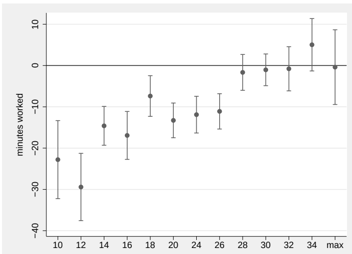

(b) Secondary



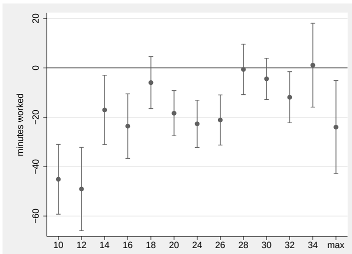

(c) Preparatory




(d) University

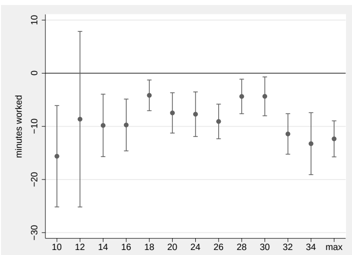



(e) Post Graduate

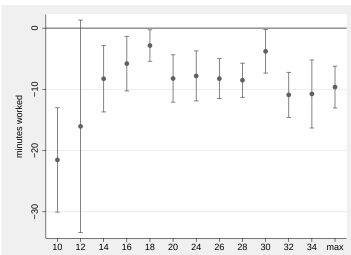



*Heat Index*

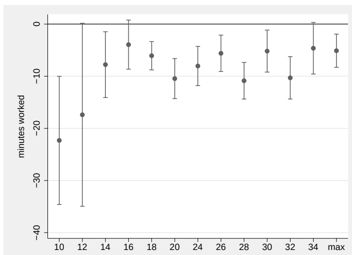
(f) Primary



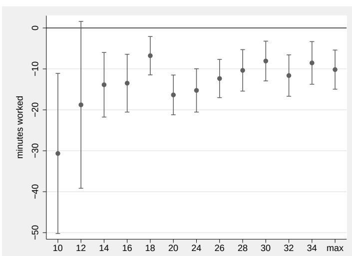

(g) Secondary



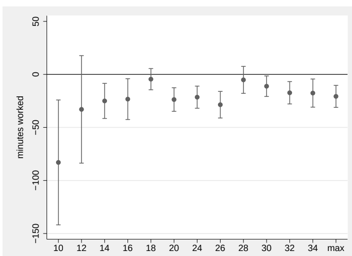

(h) Preparatory




(i) University

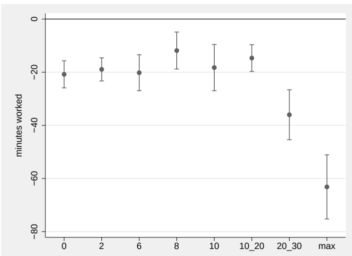



(j) Post Graduate

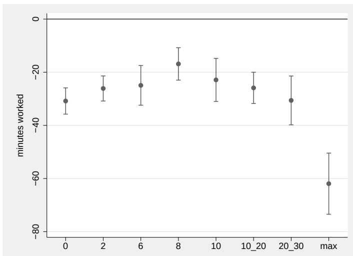


*Precipitation*

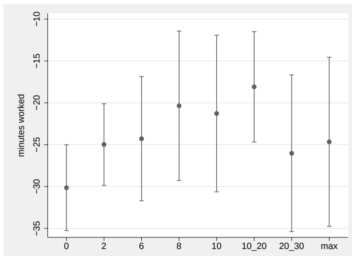
(k) Primary



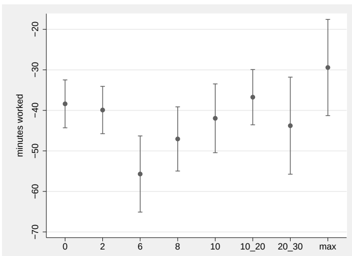

(l) Secondary



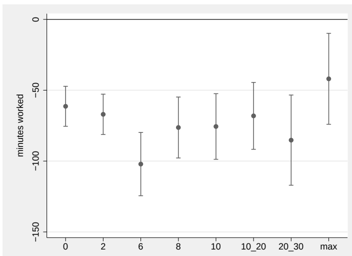

(m) Preparatory




(n) University




(o) Post Graduate

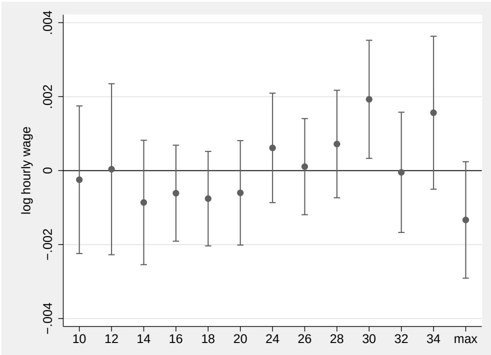



Note: Relationship between weekly working minutes and weather for all individuals. N=7,322,528 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^{\circ}$C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

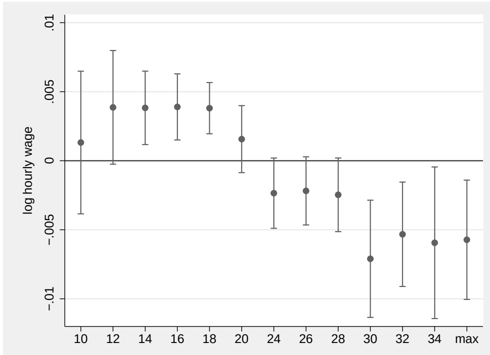
Figure 12: Heterogeneous Effects Wages by Job Formality

*Temperature*

(a) Formal

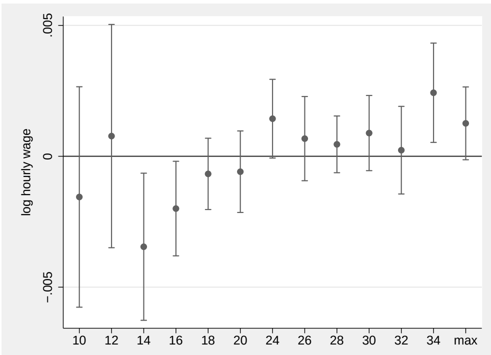



(b) Informal

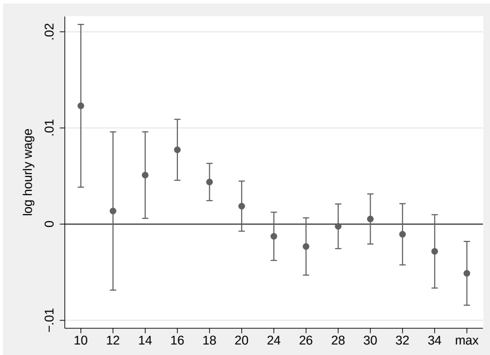



*Heat Index*

(c) Formal

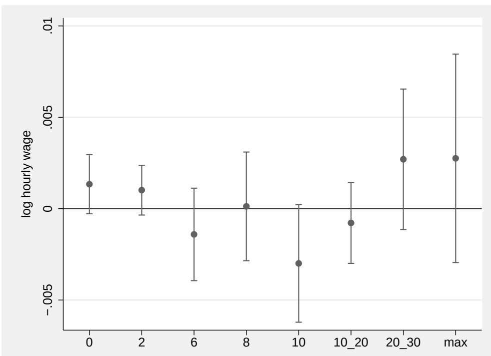



(d) Informal

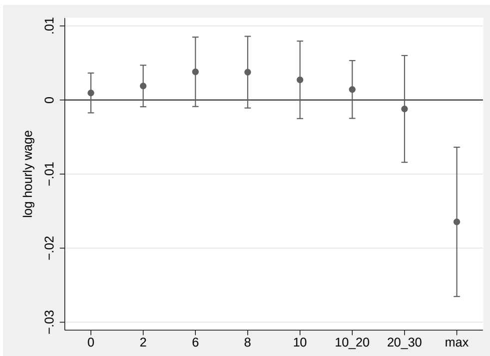



*Precipitation*

(e) Formal




(f) Informal

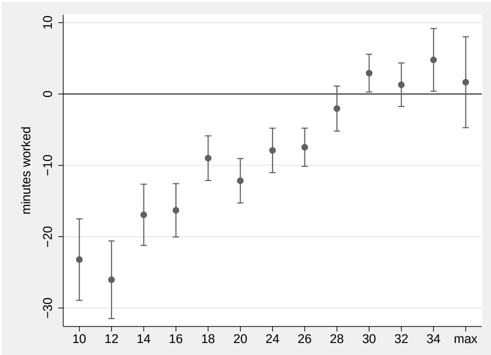



Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section.Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^\circ$C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

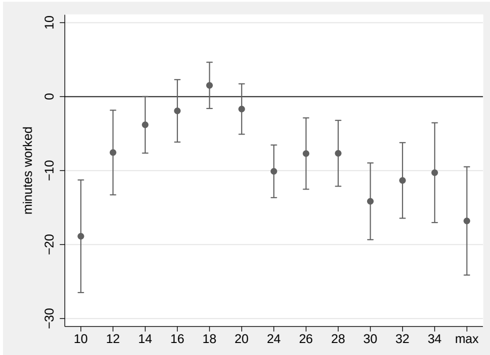
Figure 13: Heterogeneous Effects Work Time by Job Formality

*Temperature*

(a) Formal

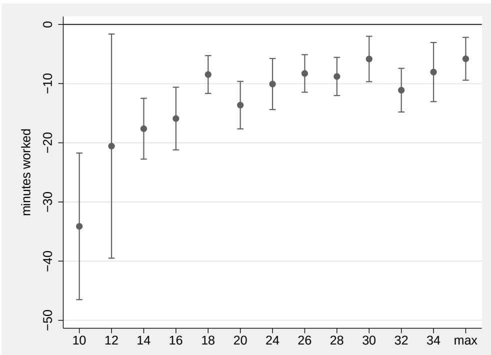



(b) Informal

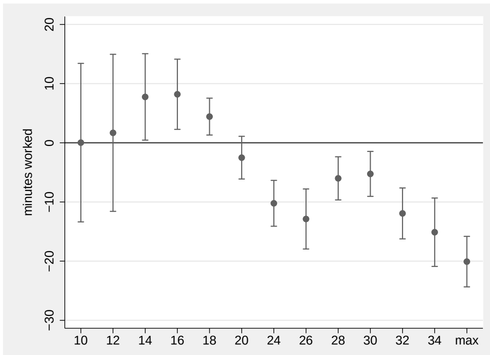



*Heat Index*

(c) Formal

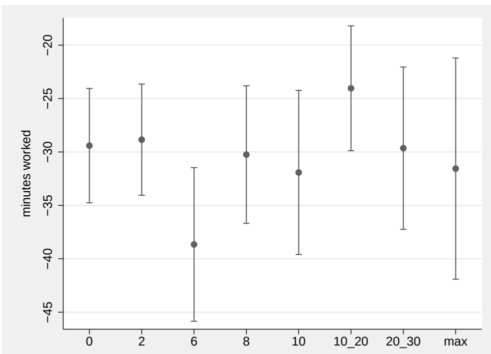



(d) Informal

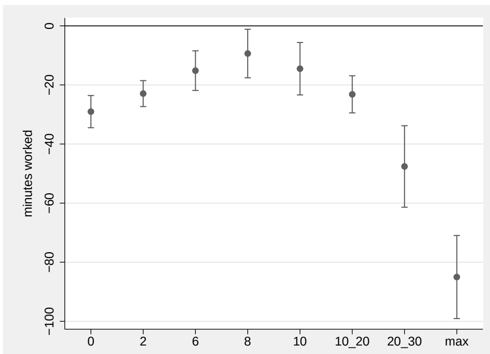



*Precipitation*

(e) Formal




(f) Informal

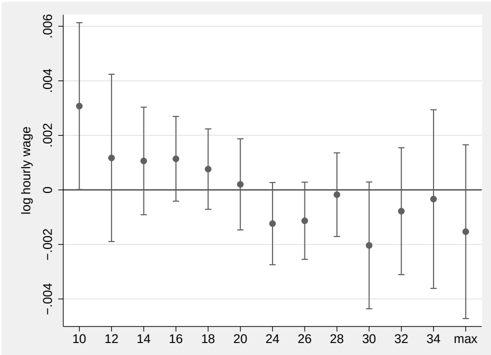



Note: Relationship between weekly working minutes and weather for all individuals. N=7,686,273 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^{\circ}$C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

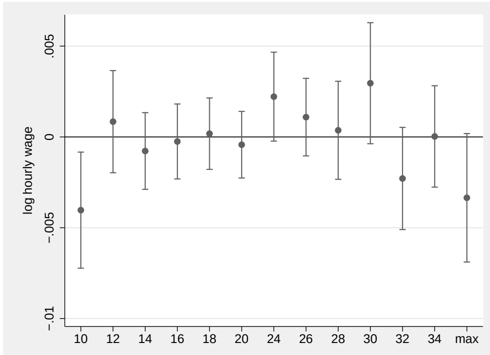
Figure 14: Heterogeneous Effects Wages by Contract Type

*Temperature*

(a) Temporary

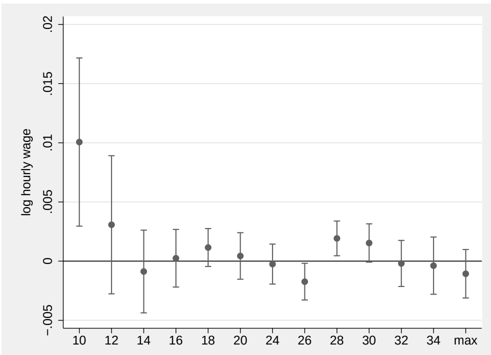



(b) Permanent

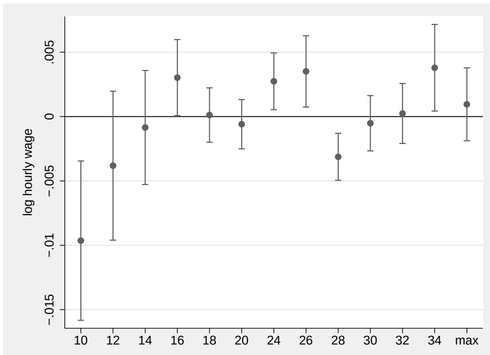



*Heat Index*

(c) Temporary

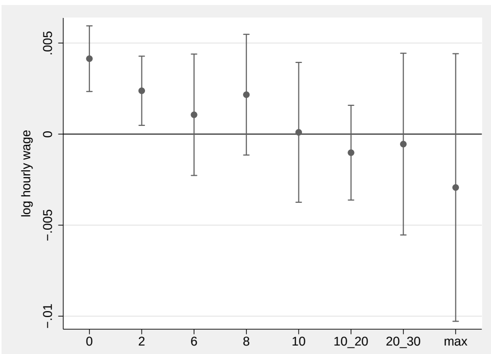



(d) Permanent

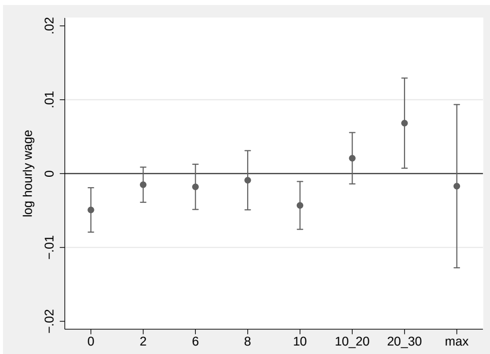



*Precipitation*

(e) Temporary




(f) Permanent

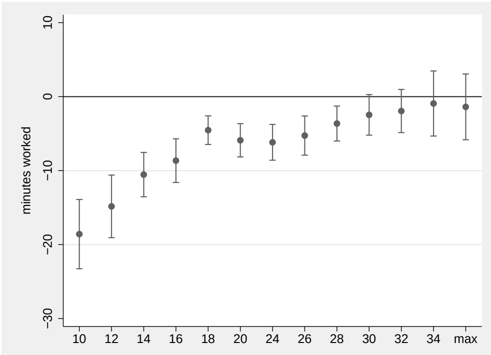



Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^{\circ}$C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

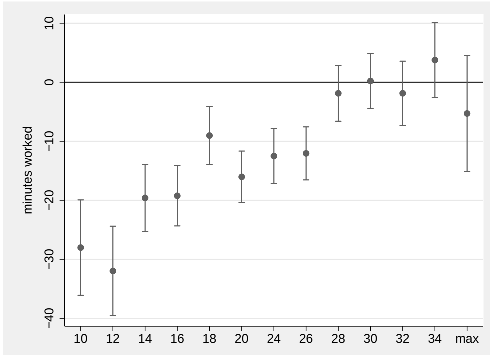
Figure 15: Heterogeneous Effects Work Time by Contract Type

*Temperature*

(a) Temporary

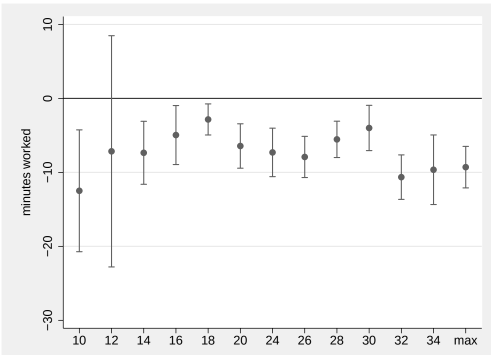



(b) Permanent

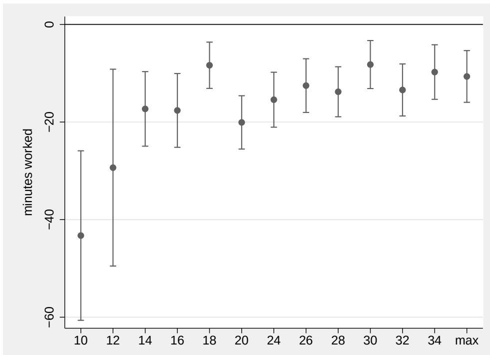



*Heat Index*

(c) Temporary

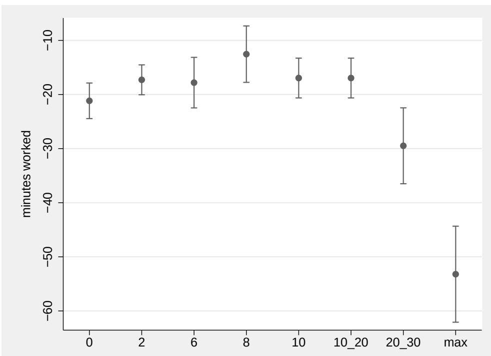



(d) Permanent

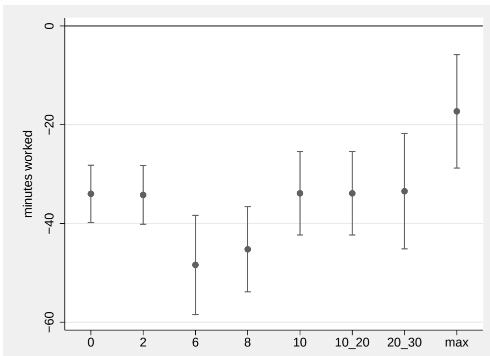



*Precipitation*

(e) Temporary



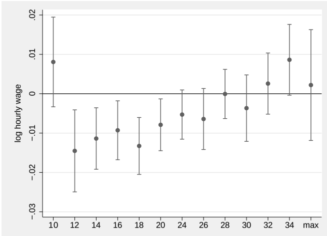

(f) Permanent



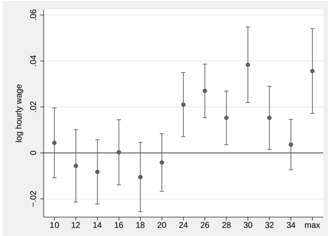

Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

Figure 16: Heterogeneous Effects Wages by Sector - Temperature

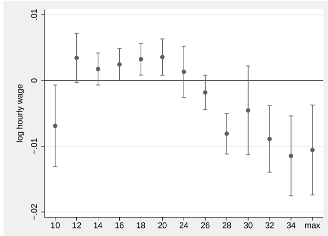
(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing



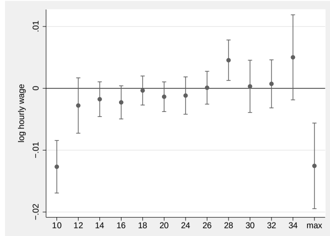

(b) Extractive Industry & Electricity



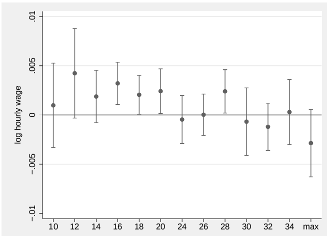

(c) Manufacturing



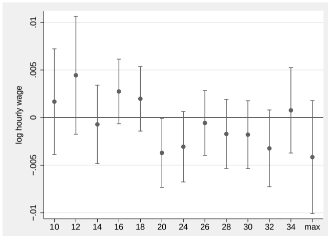

(d) Construction



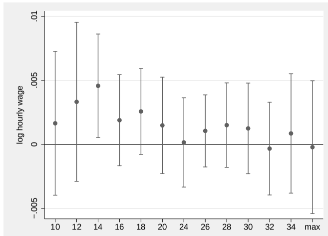

(e) Trade



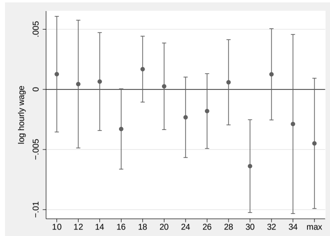

(f) Restaurants & Accommodation Services



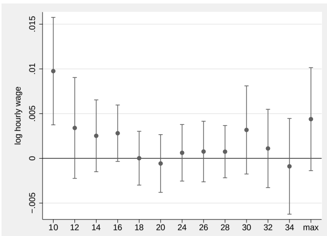

(g) Transport, Communications, Post & Storage



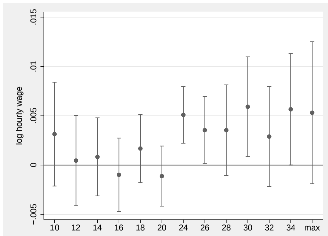

(h) Professional, Financial & Corporate Services



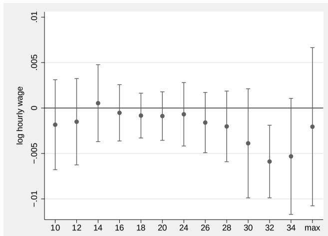

(i) (Diverse Services




(j) Social Services



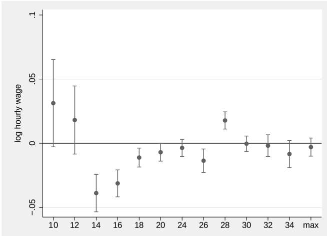

(k) Government & International Organisations



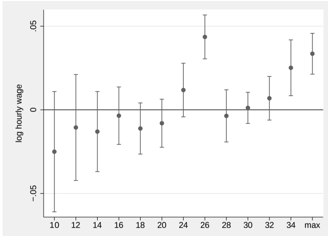

Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

Figure 17: Heterogeneous Effects Wages by Sector - Heat Index

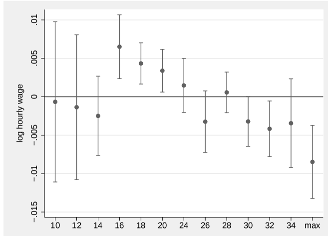
(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing



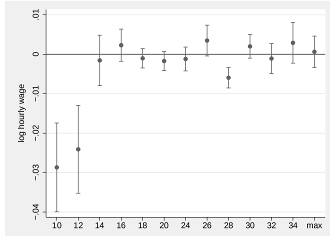

(b) Extractive Industry & Electricity



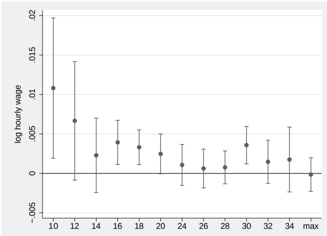

(c) Manufacturing



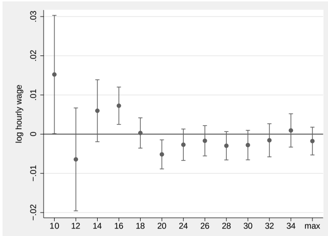

(d) Construction



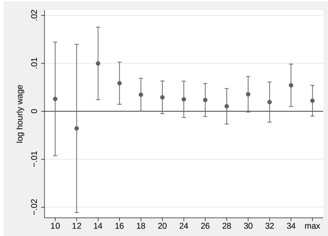

(e) Trade



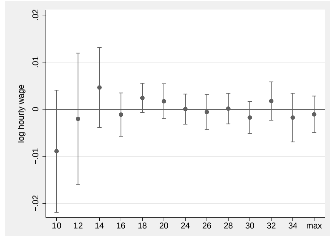

(f) Restaurants & Accommodation Services



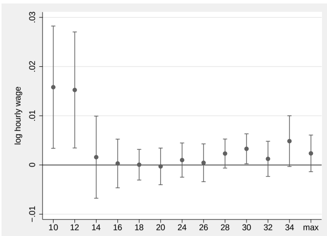

(g) Transport, Communications, Post & Storage



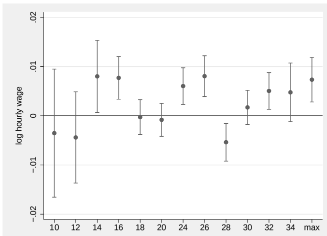

(h) Professional, Financial & Corporate Services



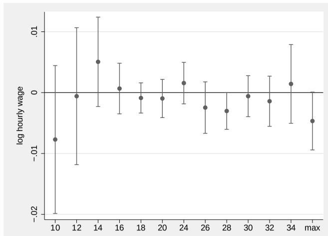

(i) Diverse Services




(j) Social Services



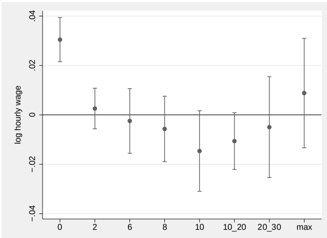

(k) Government & International Organisations



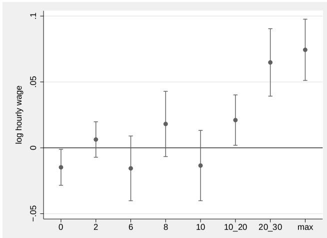

Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

Figure 18: Heterogeneous Effects Wages by Sector - Precipitation

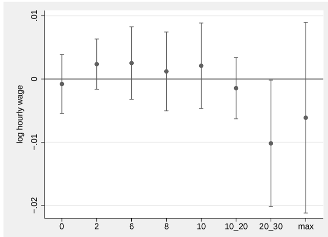
(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing



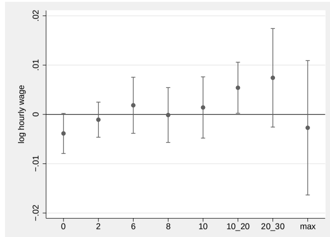

(b) Extractive Industry & Electricity



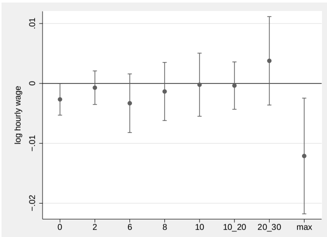

(c) Manufacturing



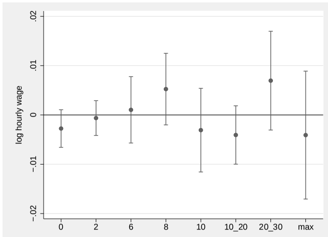

(d) Construction



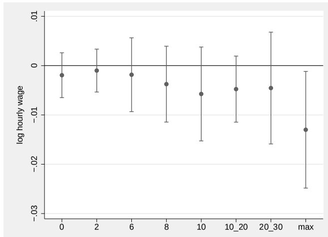

(e) Trade



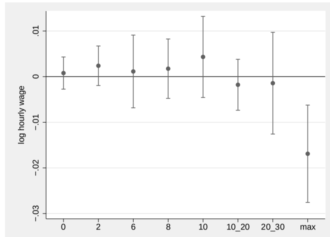

(f) Restaurants & Accommodation Services



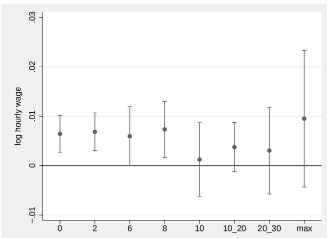

(g) Transport, Communications, Post & Storage



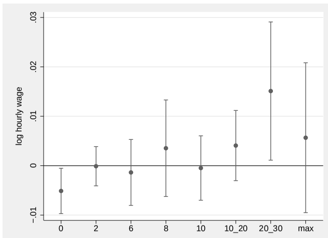

(h) Professional, Financial & Corporate Services



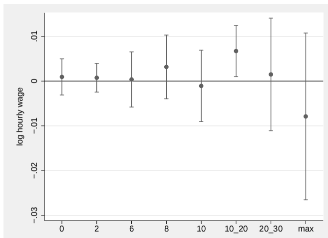

(i) Diverse Services




(j) Social Services

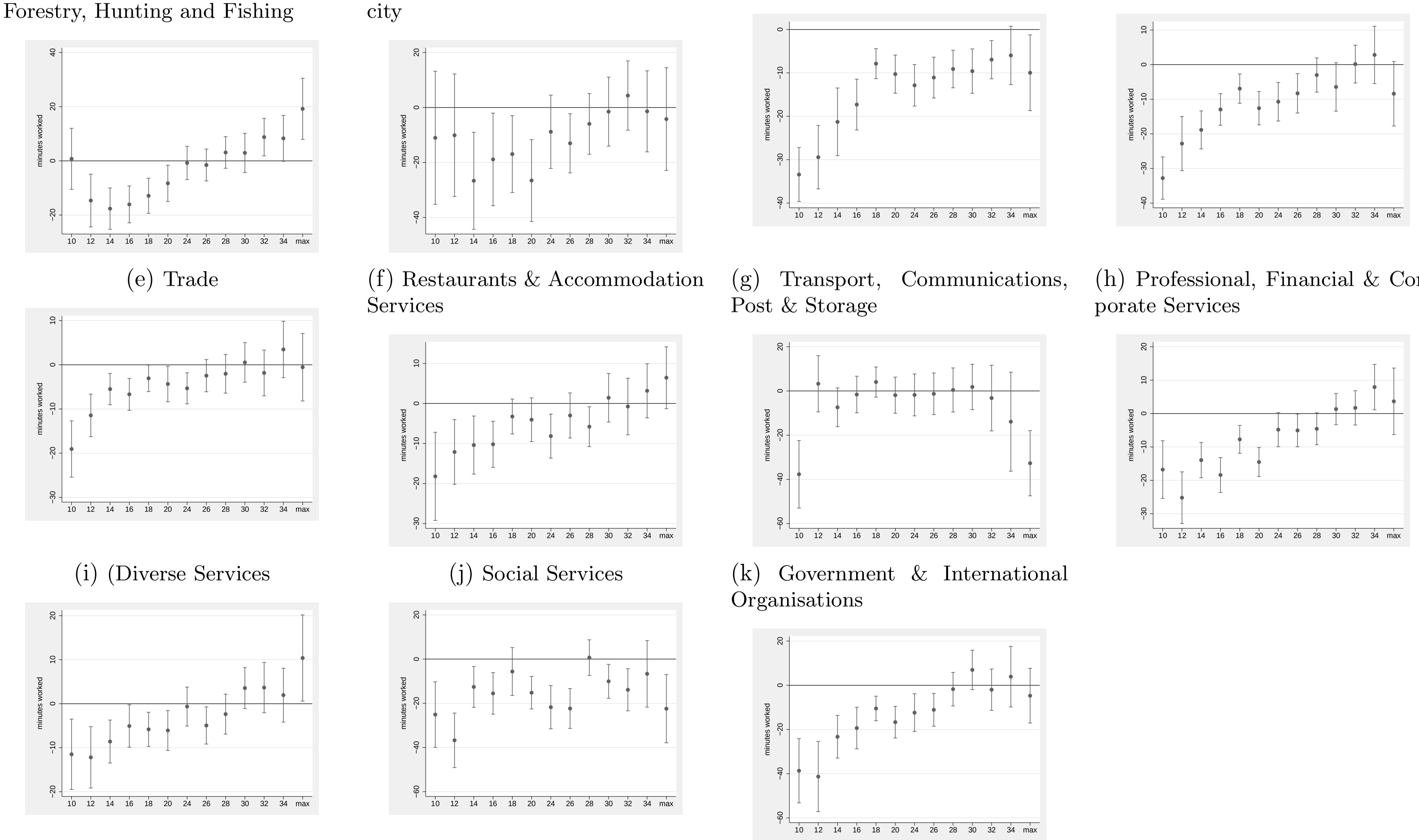



(k) Government & International Organisations




Note: Relationship between log. hourly wages and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on log. hourly wages based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*. Appendix E provides complete regression tables.

Figure 19: Heterogeneous Effects Work Time by Sector - Temperature




(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing

(b) Extractive Industry & Electricity

(c) Manufacturing

(d) Construction

(e) Trade

(f) Restaurants & Accommodation Services

(g) Transport, Communications, Post & Storage

(h) Professional, Financial & Corporate Services

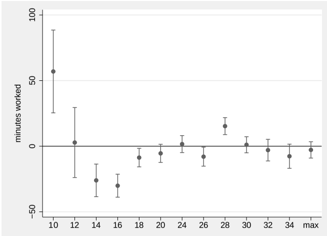
(i) (Diverse Services

(j) Social Services

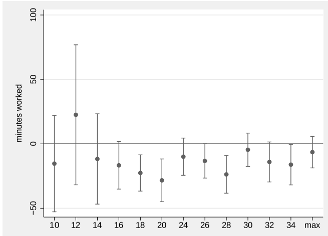
(k) Government & International Organisations

Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

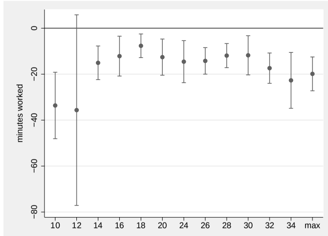
Figure 20: Heterogeneous Effects Work Time by Sector - Heat Index



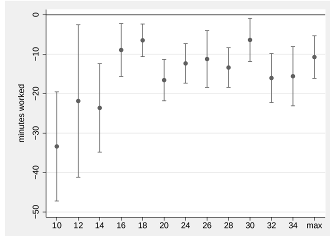

(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing



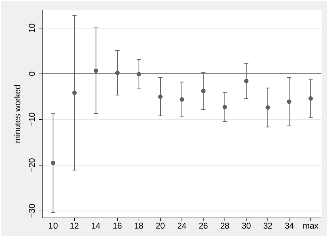

(b) Extractive Industry & Electricity



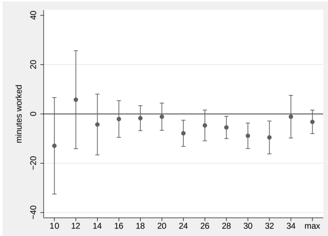

(c) Manufacturing



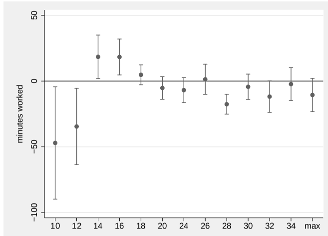

(d) Construction



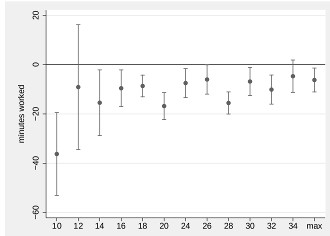

(e) Trade



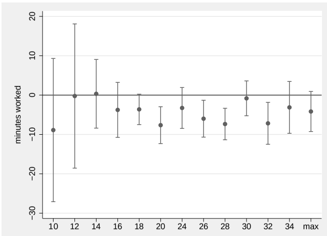

(f) Restaurants & Accommodation Services



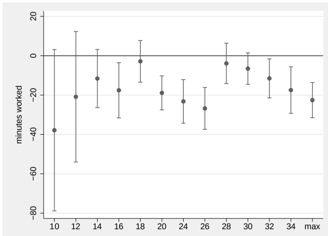

(g) Transport, Communications, Post & Storage



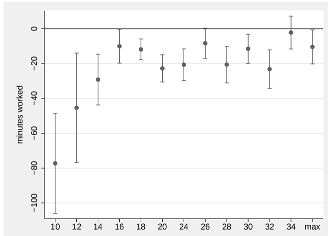

(h) Professional, Financial & Corporate Services




(i) Diverse Services




(j) Social Services

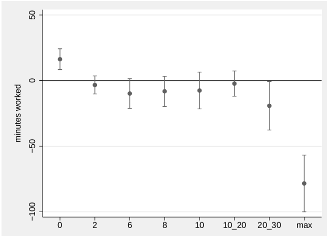



(k) Government & International Organisations

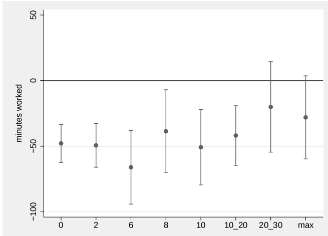
Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

Figure 21: Heterogeneous Effects Work Time by Sector - Precipitation

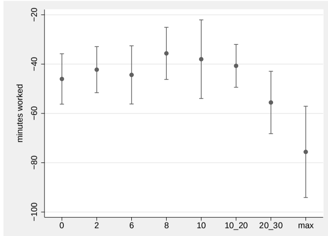
(a) Agriculture, Livestock rearing, Forestry, Hunting and Fishing



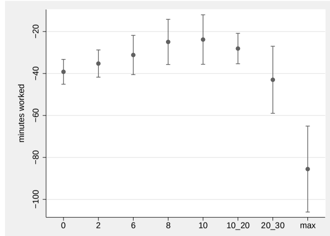

(b) Extractive Industry & Electricity



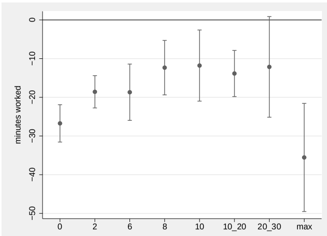

(c) Manufacturing



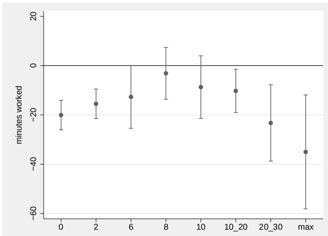

(d) Construction



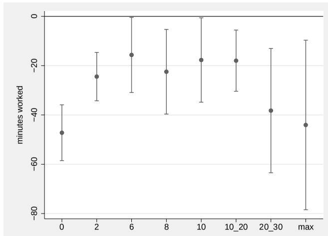

(e) Trade



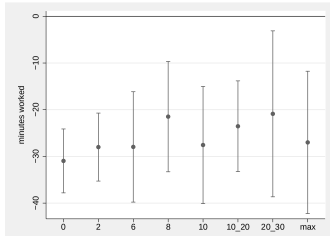

(f) Restaurants & Accommodation Services



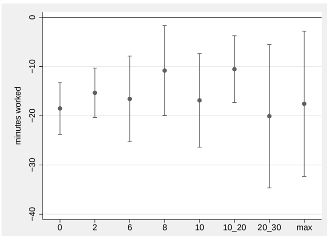

(g) Transport, Communications, Post & Storage



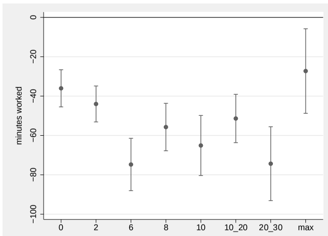

(h) Professional, Financial & Corporate Services



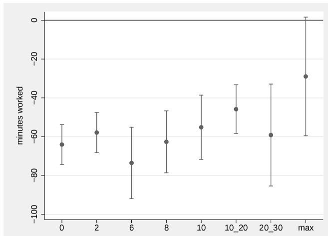

(i) Diverse Services




(j) Social Services




(k) Government & International Organisations




Note: Relationship between weekly working minutes and weather for all individuals. N=7,642,920 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 3 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] $mm$. Appendix E provides complete regression tables.

## 6 Robustness Checks

We implemented several specification checks to test the structural validity of our key findings. Firstly, we tested the robustness of our regressions to the inclusion of different fixed effects and time trends. Note that including time trends will also remove some of the variation in our weather variables as comes apparent if we study our residual variation tables in Section 4.3. Interestingly, if we introduce more complex quarter year time trends, we find average temperatures and our average Heat Index variable to have a significant positive impact on wages, while the estimated effects of precipitation turn insignificant. The impact of total and average precipitation on working time remains insignificant. However, after the introduction of more complex quarterly time trends the coefficient for average temperature reduces drops to one-forth of the initial effect size. Further, the coefficient for Heat Index becomes more negative and strongly significant, suggesting that if controlling for the temporal correlation in our dependent and independent variables, exogenous temperature fluctuations become significant predictors of the variation in wages. With respect to working time, year-quarter time trends reduce the predicted impact of average temperatures, while at the same time the coefficient for apparent temperatures increases in size. The municipality fixed effects results are highly consistent with the individual fixed effects regressions. One noteworthy difference is the insignificant estimate for the impact of the Heat Index on wages.

We run the same specification test for our binned regressions. First, for our individual fixed effect model we find more complex time trends to change our coefficients for higher temperature bins as well as for extreme apparent temperatures to show a significant positive on hourly wages, while the predicted effects of our precipitation bins remain insignificant. The coefficients for the municipality fixed effects specification remain insignificant. Our working time results are very robust to the different fixed effect and time trend specifications. For both the individual and the municipality fixed effects specification we find the predicted coefficients for temperature with quarter-year time trends become highly significant.

As briefly touched upon in the data section, the estimated weather impact might be sensitive to the time period of aggregation of our climate variables. While wages are agreed for a designated period and thus are likely to adjust to temperatures with some delay, we expect working hours to be more flexible in their response to weather changes, and therefore working time adjustments should be instantaneous. Our initial results showed most instantaneous reactions are caused by extreme temperatures as well as torrential rainfall while responses to other weather fluctuations are minimal. However, sustained severe rainfall or prolonged drought could cause medium-term changes in labour productivity, thereby affecting both labour supply and demand. To test for medium-term impacts we re-estimate our regressions based on weather variables calculated for a period of one month, and three months previous to the survey. Interestingly, for both the individual and the municipality fixed effects regressions the predicted impact of average and total precipitation on working time increases with the longest time specification, while the estimated impact of temperature declines. The effect of rainfall on log hourly wages is robust throughout our different specifications. Average temperatures and the Heat Index of the preceding month have a significant negative impact at 5% significance level. The Heat Index coefficient remains significant, if we extend the time period to the previous three months. Considering our higher polynomial regressions, average temperatures over the preceding 12 weeks are estimated to have a strong quadratic relationship with wages. The impact of rainfall seems to disappear between one and three months previous to the survey date. Interestingly the estimated effect of rain on working times seems to be strongest if we consider rainfall over a month period, while the impact of average temperatures declines if we extend the period of observation. This supports the idea of a cumulative effect or lagged effect of rainfall on working time, while temperatures cause an instantaneous working time adaptation.

Applying the same specification test to our weather bin regressions we find no indication of a medium-term effect of temperatures on wages in the individual fixed effects regressions. Rainfall days below our base bin of 2-4 mm precipitation remains a significant positive factor explaining variations in hourly wages, yet the effect size declines with the extended time period. The picture changes slightly if we consider the municipality fixed effects results. Within municipality accumulations of extreme temperature days over the previous three months significantly reduce hourly wages by over 0.5% per day. This cumulative relationship between wages and extreme temperatures might be driven by losses in productivity during sustained heat and cold waves. For example delays in construction due to hot external temperatures may causes wages in the construction sector to drop in the medium-term. For both our individual and municipality fixed effect regressions, the predicted coefficients of our working time regression decline in size and significance. Consequently, our estimates suggest a medium-term effect of extreme temperatures on hourly wages compared to a immediate adaptation of working time to weather changes.

To ensure that our sample restriction does not affect the robustness of our results, we re-estimate our models, firstly, including individuals that completed the survey within seven days,and secondly, all individuals currently in employment. As one would expect from the introduction of measurement error we observe a small drop in the predicted coefficients. However, the direction and significance of the weather coefficients on the whole remains unaffected.

A further concern could be the geographical correlation between our weather variables and some confounding factors, resulting in biased estimates. In order to test this hypothesis, we merge our survey responses with the weather of 15 weeks later (approx 100 days). Assuming that the weather of 100 days later is only weakly correlated with today's weather and the municipality fixed effects control for any geographical correlation, our estimated impacts should decline towards zero. And indeed this is true for all specifications. We are not concerned about the significant coefficients as especially for wages we do expect some anticipation of future weather changes in the negotiation process. The clear trend observed for our coefficient estimates from the earlier regressions has disappeared. On the whole, the placebo results provide support for our identification strategy.

## 7 Discussion and Conclusion

This article examines the impact of weather on hourly wages and working times in Mexico. Concerning hourly wages, we find no general association between weather and observed differences in wage. More revealing are our findings regarding working times. We find a strong relationship between weather and working times. Contrary to earlier findings for the US, we find the strongest impact in the Mexican context to be caused by cold weather and extreme rainfall. Days with average temperatures below 10 °C reduce working times by around 20 minutes. Extreme rainfall of above 30 mm per day decreases working time by over 50 minutes per day. These findings suggest workers being more affected by cold temperatures potentially due to the lack of adequate heating and clothing. These findings are robust to different specification test.

We further test for heterogeneity in the responses to weather for different segments of society and the economy. A significant finding is a distinct gender difference in the estimated impact of weather on earnings. Our findings suggest a reduction in the gender wage gap during cold days and hot days. While women's hourly wages increase by 0.5% during cold spells, men find their wages to drop by 0.3%. The reversed effect by gender suggests a decline in productivity for male jobs with a simultaneous increase in average female productivity. Furthermore, men find their earnings declining during extreme heat periods, with a drop by around 0.4%. Predicted gender differences for working times are limited to freezing temperatures, where women on average are estimated to work 20 minutes more when temperatures drop below 10 degrees. These gender differences both in wages and working times may be explained by the disproportional employment of men for outdoor high intensity manual labour, with the latter being presumably more sensitive to weather changes.

Besides gender differences we test for heterogeneous effects by age. We find zero rainfall days to raise earnings of workers from the age of 40 and at the same time to reduce wages for our youngest age group of 14 to 20 years. The age differences in the sensitivity of earnings to rainfall could be explained by the selectivity of workers into jobs with different forms of rainfall-dependent worker productivity. Interestingly, we find a significant impact of temperatures on working times for all but the youngest age group. Workers with an age of 30 to 49 are most sensitive to temperatures deviating from the optimal temperature of 22 degrees. Of interest is the large predicted effect of extreme rainfall days (more than 30 mm) on working times of both very young as well as medium-aged (40-59) workers. Minutes worked by both age cohorts drop by about 55 minutes for the maximum rainfall bin. Our result further suggest education levels to affect the extent to which earnings fluctuate with weather. Unfortunately, our data does not allow us to determine whether the former set of heterogeneous differences are the result of sample differences in the exposure to rainfall, contractual arrangements beyond formal and permanent employment, such as for example working time flexibility, or biological differences in the sensitivity to weather.

Studying heterogeneous differences related to job characteristics, we find interesting results particular for informal workers. We estimate a significant negative interaction between informal employment and higher temperatures as well as extreme precipitation. In terms of working times adaptation, formal workers are more responsive to cold temperatures. In contrast, we find only informal workers to be significantly affected by geat. If temperatures climb above 34 °C the working time of informal workers declines by roughly 20 minutes. During heat waves, this implies in a reduction of weekly working time of this group on by 2h 20min. Even more extreme is the estimated difference in the response to extreme precipitation. Working times of informal workers drop by more than 80 minutes, compared to just over 25 minutes for formal workers. Taken together with our results on earnings, this finding suggests a potential causal link between extreme rainfall shocks, reduced working times informal workers and consequently lower earnings for this part of the labour force. Resembling our results for informal workers, extreme rainfall substantially reduces minutes worked by temporary workers, however, we do not find a significant impact on earnings for temporary employees.

We finally test the for heterogeneous effects by sector. Temperatures below 10 °C reduce earnings in both the agricultural and the manufacturing sector. Furthermore, zero precipitation days have a positive effect on agricultural earnings, suggesting higher productivity of agricultural workers during dry spells. Extreme rainfall days, on the one hand, reduce wages in both the trade and professional service sector and, on the other hand, increase wages in the extractive industry. The decline in earnings of the trade sector most likely stems from interruptions to transportation, while for the professional service sector it might result from a decrease in the number of customers.

Working times in the agricultural sector increase during extreme heat days by 18 minutes. Cold temperatures consistently reduce working times throughout all sectors. However, the largest declines are estimated for the manufacturing, construction, transport and government sector. Although workers exposure to cold temperatures will be different between outdoor and indoor activity, the significant drop in working times across both types of activities may be explained by the lack of heating and insulation for Mexican buildings. We find the only industries strongly affected by heat are the agriculture and the transport sector. Days with temperatures above 34 °C increase working times of agricultural labour on average by 18 minutes and reduce them for workers in the transport sector by more than 45 minutes. Interestingly, taking into account humidity, the impact of heat changes. We find no significant effect on neither agriculture nor transport, but rather estimate working times to declines in the manufacturing and construction sector as well as social services. Moreover, a Heat Index of below 10 °C results in an increase of working times in the agricultural sector of over 50 minutes. A potential explanation may be prolonged working hours to prevent harvest losses caused by cold, for example through frost. Our results further suggest sectoral differences in the impact of rainfall on working times. During heavy rainfall days weather-exposed sectors such as agriculture, construction, trade and transport, but also sectors with walk-in customers, such as professional and restaurant services, experience a decline in working times. An unusual result is the predicted negative impact of severe rainfall on working times in the manufacturing sector. Since manufacturing largely depends on indoor labour activity, we struggle to explain this result. As expected we find zero rainfall days to increase working times in the agricultural sector, while reducing them for all other sectors. The latter negative impact potentially is explained by a substitution effect away from time spent working to recreational outdoor activities, which become more attractive during days with zero precipitation. On the other hand, agricultural labour is likely to be more productive during dry weather spells.

In conclusion, our results suggest a sensitivity of Mexican labour markets to weather fluctuations. Both cold temperatures and extreme rainfall are predicted to significantly affect working times throughout the economy. The effects of weather on wages are less pronounced Productivity losses due to cold could be prevented by better insulation or installation of heating in offices and plants. Disruption of economic activity due to rainfall may be reduced to investment in better infrastructure. A further important conclusion from our results is that weather impacts on both labour supply and demand are diverse. The direction and size of weather effects vary both by individual attributes as well as job specific characteristics. Our findings particularly highlight the vulnerability of informal and temporary workers to weather shocks. Provision of adequate jobs for the latter group of workers and the development of effective labour market policies, such as job security and risk-management strategies for weather related uncertainties, are needed to protect workers from the negative impacts of weather. An example for such a labour market policy could be weather-based insurance products. Although the Mexican government established a public insurance scheme as part of the Mexican Catastrophic Climate Contingency Insurance Program (CADENA), informal workers are currently not eligible to take part in the program.

A caveat of our study is the limitation in information on the underlying causes for estimated heterogeneity in the wage and working hour responses. More information on the type of jobs exercised, for example outdoor versus indoor activities, would help to better understand the underlying sources for heterogeneity in weather sensitivity levels. Differences, for example caused by age, gender and education, might be explained by biological factors. At the same time, labour selectivity into jobs is influenced by individual characteristics, therefore, potentially resulting in selection of individuals into jobs with different levels of weather exposure. In addition, labour selectivity likely results in distinct differences in contractual agreements, and thus in the labour-leisure substitution flexibility for different labour force groups. The flexibility discrepancies give room to variations in workers responsiveness to weather fluctuations. The total weather effect is likely to be explained by a combination all three channels. Ideally one would like to distinguish between these underlying causes. A better understanding would allow for improved targeting of policies to those vulnerable to weather shocks, rather than those with the flexibility to adapt to weather extremes.

Our findings might not be transferable to the context of other developing countries with dissimilar climatic and labour market conditions. One would like to replicate this study for a wider spectrum of countries to identify similarities and dissimilarities across countries. This would further help to distinguish between biological factors and other potential causes for the observed heterogeneity in the weather impact.

While the evidence on wage and working hour responsiveness to weather extremes cannot be generalised for the expected changes due to global warming, our findings nevertheless shed some insights into potential costs of higher frequency extreme weather events. An increased number in whether shocks would imply more frequent losses in earnings for some workers, therefore rendering the latter more vulnerable to poverty. Furthermore, the total amount of working time lost to the economy due to extreme weather is likely to increase under climate scenarios, if there is no adaptation in the working conditions to weather exposure. Of course adequate investment in heating and air-conditioning, as well as investment in the physical infrastructure, limiting the negative impact of heavy rain, will reduce the scope for responsiveness of our outcome variables to weather extremes. Therefore, any conclusions drawn with respect to climate change should be taken with caution. Nevertheless, our results highlight the important influence of weather on especially labour demand as well as the necessity for further research in the area.

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# A Maps of Mexican Municipalities

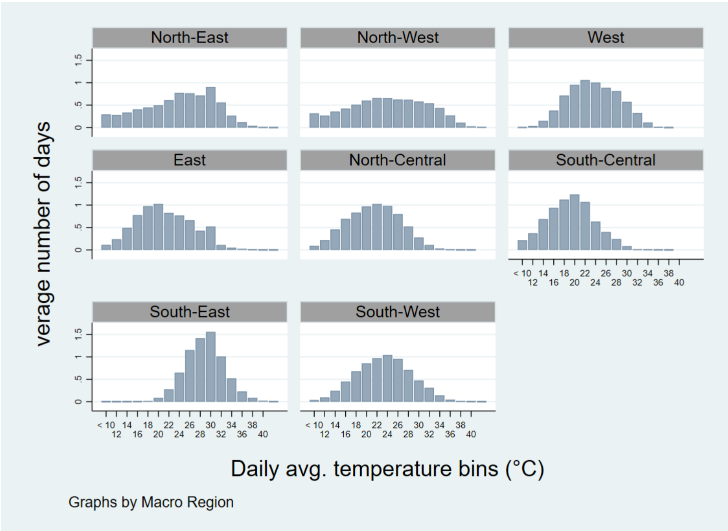
Figure A.1: Map of Mexican Municipality


Note: 780 municipalities coloured in green are not included in the final sample.

# B Distribution of Weather Variables over Bins

Figure B.1: Regional differences in temperatures and precipitation

(a) Temperature (°C)




(b) Precipitation (mm)

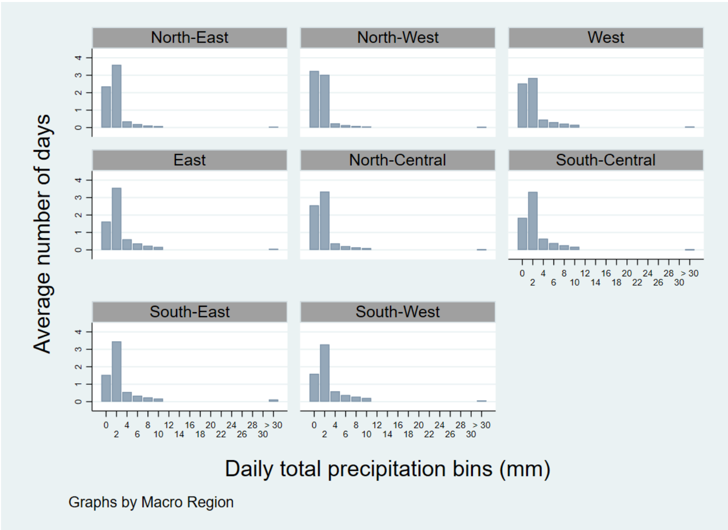
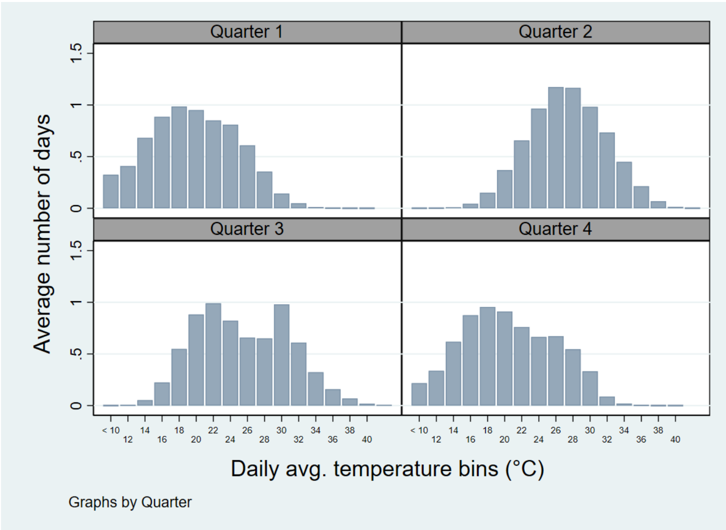
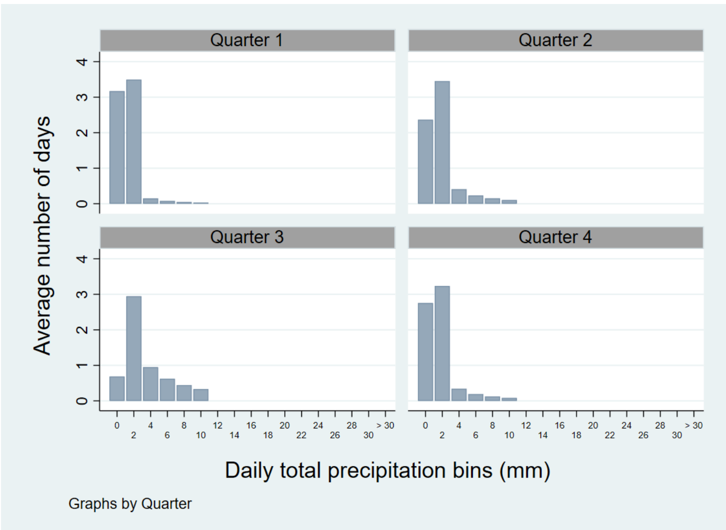


Figure B.2: Quarterly differences in temperatures and precipitation

(a) Temperature (°C)




(b) Precipitation (mm)



# C Construction of the Heat Index

In the construction of the *Heat Index* we follow the US National Weather Service approach (NOAA, National Weather Service, 2017) by using Lans P. Rothfusz (Rothfusz, 1990) equation and applying several adjustments to it. Rothfusz regression is

$$\begin{aligned} HI = & -42.379 + 2.04901523 \times T + 10.14333127 \times RH - 0.22475541 \times T \times RH \\ & - 0.00683783 \times T^2 - 0.05481717 \times RH^2 + 0.00122874 \times T^2 \times RH \\ & + 0.00122874 \times T \times RH^2 - 0.00000199 \times T^2 RH^2 \quad , \end{aligned}$$

where $T$ is temperature in °F and $RH$ is relative humidity in percent. Further adjustments have to be made for the following combinations of $RH$ and $T$.

If $RH$ less than 13 per cent and temperature between 80 and 112 °F

$$HI_{adj} = HI - \frac{13 - RH}{4} \times \sqrt{\frac{17 - |T - 95|}{17}} \quad . \tag{5}$$

If $RH$ is greater than 85 per cent and the temperature is between 80 and 87 °F:

$$HI_{adj} = HI + \frac{RH - 85}{10} \times \frac{87 - T}{5} \quad . \tag{6}$$

The use of the Rothfusz regression is not appropriate for temperatures below 80°F. At these temperatures a more simple formula is used

$$HI = 0.5 \times (T + 61 + (T - 68) \times 1.2 + RH * 0.094) \quad . \tag{7}$$

Finally, for the purpose of comparability with our average temperature measurement we transformed the unit of measurement from °F to °C.

Table 11 below shows the implication of different temperature ranges for health.

Table 11: Health effects of different Heat Index bands

| | |
|---|---|
| 27-32 °C | Caution: Fatigue is possible with prolonged exposure and or Physical activity. |
| 32-41 °C | Extreme Caution: Sunstroke, muscle cramps, and/or heat exhaustion possible with prolonged exposure and/or physical activity. |
| 41-54 °C | Danger: Sunstroke, muscle cramps, and/or heat exhaustion likely. Heatstroke possible with prolonged exposure and/or physical activity. |
| over 54 °C | Extreme Danger: Heat stroke likely. |

# D Residual Variation - Alternative time specification

Table 12: Residual Variation of Monthly Weather Variables

Panel 1: Monthly Mean Temperatures (°C)

*Municipality Qtr. Year Observations with Weather Residual >than*

| Mean: 22.2 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 5.61 | 5,497,167 | 0.69 | 3,344,769 | 0.42 | 1,589,667 | 0.20 | 485,731 | 0.06 | 83,602 | 0.01 |
| municipality fe | 4.29 | 4,675,389 | 0.59 | 2,043,571 | 0.26 | 545,849 | 0.07 | 141,329 | 0.02 | 23,355 | 0.00 |
| mun. fe, linear year | 4.29 | 4,674,180 | 0.59 | 2,047,712 | 0.26 | 541,871 | 0.07 | 141,216 | 0.02 | 23,251 | 0.00 |
| mun. fe, quadratic year | 4.28 | 4,656,120 | 0.58 | 2,034,335 | 0.26 | 537,042 | 0.07 | 140,544 | 0.02 | 22,825 | 0.00 |
| mun. fe, cubic year | 4.28 | 4,655,969 | 0.58 | 2,036,404 | 0.26 | 537,479 | 0.07 | 140,045 | 0.02 | 22,991 | 0.00 |
| mun. & year fe | 4.27 | 4,639,091 | 0.58 | 2,009,737 | 0.25 | 535,230 | 0.07 | 137,078 | 0.02 | 23,767 | 0.00 |
| mun. year & qtr. fe | 2.84 | 2,882,895 | 0.36 | 590,715 | 0.07 | 116,299 | 0.01 | 12,028 | 0.00 | 0 | 0.00 |
| mun., region× year & qtr. fe | 2.82 | 2,857,212 | 0.36 | 583,016 | 0.07 | 116,038 | 0.01 | 11,265 | 0.00 | 0 | 0.00 |
| mun., state× year & qtr. fe | 2.81 | 2,845,135 | 0.36 | 573,354 | 0.07 | 113,527 | 0.01 | 10,651 | 0.00 | 0 | 0.00 |

Panel 2: Monthly Mean Precipitation (mm)

| Mean: 2.07 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 3.34 | 6,667,056 | 0.84 | 5,853,872 | 0.73 | 4,278,537 | 0.54 | 1,312,430 | 0.16 | 1,146,513 | 0.14 |
| municipality fe | 3.19 | 5,796,185 | 0.73 | 4,412,512 | 0.55 | 3,231,932 | 0.41 | 2,163,881 | 0.27 | 1,517,216 | 0.19 |
| mun. fe, linear year | 3.19 | 5,769,906 | 0.72 | 4,430,664 | 0.56 | 3,171,259 | 0.40 | 2,188,929 | 0.27 | 1,532,657 | 0.19 |
| mun. fe, quadratic year | 3.19 | 5,776,445 | 0.73 | 4,437,040 | 0.56 | 3,176,144 | 0.40 | 2,182,025 | 0.27 | 1,540,473 | 0.19 |
| mun. fe, cubic year | 3.19 | 5,774,313 | 0.72 | 4,436,735 | 0.56 | 3,173,831 | 0.40 | 2,180,663 | 0.27 | 1,543,280 | 0.19 |
| mun. & year fe | 3.18 | 5,746,589 | 0.72 | 4,406,311 | 0.55 | 3,166,993 | 0.40 | 2,220,564 | 0.28 | 1,532,827 | 0.19 |
| mun. year & qtr. fe | 2.78 | 4,480,639 | 0.56 | 3,230,819 | 0.41 | 2,372,422 | 0.30 | 1,753,303 | 0.22 | 1,276,449 | 0.16 |
| mun., region× year & qtr. fe | 2.77 | 4,483,245 | 0.56 | 3,229,829 | 0.41 | 2,359,109 | 0.30 | 1,760,767 | 0.22 | 1,280,933 | 0.16 |
| mun., state× year & qtr. fe | 2.76 | 4,498,927 | 0.56 | 3,224,954 | 0.40 | 2,374,675 | 0.30 | 1,774,554 | 0.22 | 1,296,316 | 0.16 |

Panel 2: Monthly Total Precipitation (mm)

| Mean: 57.72 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 73.10 | 7,907,697 | 0.99 | 7,878,784 | 0.99 | 7,847,368 | 0.99 | 7,817,813 | 0.98 | 7,787,860 | 0.98 |
| municipality fe | 67.76 | 7,892,410 | 0.99 | 7,855,937 | 0.99 | 7,822,100 | 0.98 | 7,785,272 | 0.98 | 7,746,239 | 0.97 |
| mun. fe, linear year | 67.58 | 7,879,726 | 0.99 | 7,839,690 | 0.98 | 7,800,007 | 0.98 | 7,761,291 | 0.97 | 7,717,000 | 0.97 |
| mun. fe, quadratic year | 67.57 | 7,884,290 | 0.99 | 7,848,672 | 0.99 | 7,807,756 | 0.98 | 7,760,155 | 0.97 | 7,717,283 | 0.97 |
| mun. fe, cubic year | 67.57 | 7,886,276 | 0.99 | 7,847,787 | 0.99 | 7,808,634 | 0.98 | 7,758,376 | 0.97 | 7,717,693 | 0.97 |
| mun. & year fe | 67.43 | 7,877,452 | 0.99 | 7,834,186 | 0.98 | 7,788,604 | 0.98 | 7,749,344 | 0.97 | 7,703,365 | 0.97 |
| mun. year & qtr. fe | 52.35 | 7,809,164 | 0.98 | 7,735,352 | 0.97 | 7,656,798 | 0.96 | 7,576,123 | 0.95 | 7,492,652 | 0.94 |
| mun., region× year & qtr. fe | 51.93 | 7,792,283 | 0.98 | 7,712,013 | 0.97 | 7,635,117 | 0.96 | 7,561,191 | 0.95 | 7,488,700 | 0.94 |
| mun., state× year & qtr. fe | 51.63 | 7,796,081 | 0.98 | 7,716,114 | 0.97 | 7,637,520 | 0.96 | 7,550,610 | 0.95 | 7,467,844 | 0.94 |

Panel 3: Monthly Harmful Degree-Days (°C)

| Mean: 1.92 N: 7964917 | | 2 hd days (°C) | | 10 hd days (°C) | | 20 hd days (°C) | | 30 hd days (°C) | | 40 hd days (°C) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 20.10 | 244,143 | 0.03 | 173,027 | 0.02 | 134,026 | 0.02 | 110,458 | 0.01 | 89,341 | 0.01 |
| municipality fe | 18.45 | 1,202,494 | 0.15 | 416,648 | 0.05 | 207,252 | 0.03 | 153,594 | 0.02 | 134,100 | 0.02 |
| mun. fe, linear year | 18.44 | 1,223,779 | 0.15 | 417,935 | 0.05 | 206,978 | 0.03 | 153,022 | 0.02 | 133,701 | 0.02 |
| mun. fe, quadratic year | 18.44 | 1,222,036 | 0.15 | 417,855 | 0.05 | 207,028 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. fe, cubic year | 18.44 | 1,223,501 | 0.15 | 417,626 | 0.05 | 207,010 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. & year fe | 18.44 | 1,230,230 | 0.15 | 418,576 | 0.05 | 207,236 | 0.03 | 153,026 | 0.02 | 133,437 | 0.02 |
| mun. year & qtr. fe | 18.31 | 4,228,573 | 0.53 | 445,997 | 0.06 | 210,257 | 0.03 | 148,686 | 0.02 | 130,259 | 0.02 |
| mun., region× year & qtr. fe | 18.29 | 3,433,494 | 0.43 | 441,446 | 0.06 | 212,065 | 0.03 | 147,538 | 0.02 | 130,640 | 0.02 |
| mun., state× year & qtr. fe | 18.25 | 3,326,858 | 0.42 | 476,900 | 0.06 | 214,958 | 0.03 | 150,806 | 0.02 | 129,679 | 0.02 |

Panel 4: Monthly Mean Heat Index (°C)

| Mean: 25.54 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 5.94 | 5,504,228 | 0.69 | 3,194,860 | 0.40 | 1,366,085 | 0.17 | 684,619 | 0.09 | 348,777 | 0.04 |
| municipality fe | 4.66 | 4,835,241 | 0.61 | 2,225,964 | 0.28 | 825,547 | 0.10 | 240,034 | 0.03 | 67,140 | 0.01 |
| mun. fe, linear year | 4.66 | 4,834,669 | 0.61 | 2,214,292 | 0.28 | 824,687 | 0.10 | 235,501 | 0.03 | 69,097 | 0.01 |
| mun. fe, quadratic year | 4.65 | 4,831,842 | 0.61 | 2,214,293 | 0.28 | 820,961 | 0.10 | 236,782 | 0.03 | 69,146 | 0.01 |
| mun. fe, cubic year | 4.65 | 4,834,211 | 0.61 | 2,213,178 | 0.28 | 819,256 | 0.10 | 237,999 | 0.03 | 69,103 | 0.01 |
| mun. & year fe | 4.65 | 4,826,991 | 0.61 | 2,207,543 | 0.28 | 823,754 | 0.10 | 235,740 | 0.03 | 68,194 | 0.01 |
| mun. year & qtr. fe | 4.42 | 4,451,353 | 0.56 | 1,935,890 | 0.24 | 702,678 | 0.09 | 227,923 | 0.03 | 61,455 | 0.01 |
| mun., region× year & qtr. fe | 4.40 | 4,435,591 | 0.56 | 1,931,152 | 0.24 | 691,484 | 0.09 | 222,891 | 0.03 | 57,716 | 0.01 |
| mun., state× year & qtr. fe | 4.38 | 4,423,138 | 0.56 | 1,931,718 | 0.24 | 678,792 | 0.09 | 217,056 | 0.03 | 52,500 | 0.01 |

Notes: Table counts residuals from regressions of municipality × qtr × year observations on regressors listed in row headings. Cell entries are number of residuals of absolute value greater than or equal to the cut-offs given in the column headings. Years: 2005-2016 Sample: 2456 municipalities

## Table 13: Residual Variation of Three Monthly Weather Variables

### Panel 1: Three Month Mean Temperatures (°C)

*Municipality Qtr. Year Observations with Weather Residual >than*

| Mean: 22.2 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 5.31 | 5,379,474 | 0.68 | 3,162,740 | 0.40 | 1,362,319 | 0.17 | 322,095 | 0.04 | 37,176 | 0.00 |
| municipality fe | 3.89 | 4,515,566 | 0.57 | 1,540,800 | 0.19 | 341,938 | 0.04 | 74,869 | 0.01 | 3,250 | 0.00 |
| mun. fe, linear year | 3.88 | 4,511,295 | 0.57 | 1,537,744 | 0.19 | 341,348 | 0.04 | 75,071 | 0.01 | 3,676 | 0.00 |
| mun. fe, quadratic year | 3.88 | 4,502,210 | 0.57 | 1,524,482 | 0.19 | 343,412 | 0.04 | 72,642 | 0.01 | 2,984 | 0.00 |
| mun. fe, cubic year | 3.88 | 4,503,582 | 0.57 | 1,527,310 | 0.19 | 344,328 | 0.04 | 72,445 | 0.01 | 3,110 | 0.00 |
| mun. & year fe | 3.86 | 4,503,726 | 0.57 | 1,515,169 | 0.19 | 336,008 | 0.04 | 73,021 | 0.01 | 3,093 | 0.00 |
| mun. year & qtr. fe | 2.53 | 2,417,780 | 0.30 | 392,641 | 0.05 | 63,538 | 0.01 | 6,876 | 0.00 | 0 | 0.00 |
| mun., region× year & qtr. fe | 2.51 | 2,396,014 | 0.30 | 378,242 | 0.05 | 59,139 | 0.01 | 6,450 | 0.00 | 0 | 0.00 |
| mun., state× year & qtr. fe | 2.50 | 2,380,051 | 0.30 | 374,173 | 0.05 | 57,714 | 0.01 | 6,027 | 0.00 | 0 | 0.00 |

### Panel 2: Three Month Mean Precipitation (mm)

| Mean: 2.06 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 2.20 | 5,756,843 | 0.72 | 4,394,955 | 0.55 | 2,094,496 | 0.26 | 1,095,478 | 0.14 | 858,758 | 0.11 |
| municipality fe | 1.97 | 4,976,602 | 0.62 | 3,489,568 | 0.44 | 2,290,037 | 0.29 | 1,384,684 | 0.17 | 805,531 | 0.10 |
| mun. fe, linear year | 1.96 | 4,940,739 | 0.62 | 3,493,368 | 0.44 | 2,245,502 | 0.28 | 1,361,259 | 0.17 | 806,102 | 0.10 |
| mun. fe, quadratic year | 1.96 | 4,940,117 | 0.62 | 3,496,497 | 0.44 | 2,252,045 | 0.28 | 1,360,221 | 0.17 | 813,209 | 0.10 |
| mun. fe, cubic year | 1.96 | 4,940,228 | 0.62 | 3,497,072 | 0.44 | 2,253,415 | 0.28 | 1,360,321 | 0.17 | 813,197 | 0.10 |
| mun. & year fe | 1.95 | 4,930,581 | 0.62 | 3,496,387 | 0.44 | 2,205,775 | 0.28 | 1,359,503 | 0.17 | 807,911 | 0.10 |
| mun. year & qtr. fe | 1.39 | 3,303,192 | 0.41 | 1,880,495 | 0.24 | 976,853 | 0.12 | 506,430 | 0.06 | 290,680 | 0.04 |
| mun., region× year & qtr. fe | 1.38 | 3,285,308 | 0.41 | 1,838,073 | 0.23 | 948,068 | 0.12 | 486,237 | 0.06 | 277,732 | 0.03 |
| mun., state× year & qtr. fe | 1.36 | 3,277,494 | 0.41 | 1,831,880 | 0.23 | 940,562 | 0.12 | 474,032 | 0.06 | 266,705 | 0.03 |

### Panel 2: Three Month Total Precipitation (mm)

| Mean: 173.3 N: 7964917 | | 1.0 mm | | 1.5 mm | | 2.0 mm | | 2.5 mm | | 3.0 mm | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 184.34 | 7,938,322 | 1.00 | 7,925,515 | 1.00 | 7,915,030 | 0.99 | 7,901,185 | 0.99 | 7,889,936 | 0.99 |
| municipality fe | 165.19 | 7,929,501 | 1.00 | 7,912,467 | 0.99 | 7,896,756 | 0.99 | 7,880,348 | 0.99 | 7,865,002 | 0.99 |
| mun. fe, linear year | 164.52 | 7,926,872 | 1.00 | 7,910,992 | 0.99 | 7,893,251 | 0.99 | 7,878,749 | 0.99 | 7,861,780 | 0.99 |
| mun. fe, quadratic year | 164.51 | 7,928,461 | 1.00 | 7,910,696 | 0.99 | 7,891,647 | 0.99 | 7,874,217 | 0.99 | 7,858,792 | 0.99 |
| mun. fe, cubic year | 164.50 | 7,928,481 | 1.00 | 7,909,915 | 0.99 | 7,890,622 | 0.99 | 7,874,354 | 0.99 | 7,856,884 | 0.99 |
| mun. & year fe | 163.93 | 7,931,343 | 1.00 | 7,912,139 | 0.99 | 7,895,441 | 0.99 | 7,872,307 | 0.99 | 7,854,727 | 0.99 |
| mun. year & qtr. fe | 117.05 | 7,902,238 | 0.99 | 7,870,686 | 0.99 | 7,838,874 | 0.98 | 7,805,740 | 0.98 | 7,771,684 | 0.98 |
| mun., region× year & qtr. fe | 115.56 | 7,902,903 | 0.99 | 7,873,519 | 0.99 | 7,843,224 | 0.98 | 7,812,101 | 0.98 | 7,781,731 | 0.98 |
| mun., state× year & qtr. fe | 114.41 | 7,906,876 | 0.99 | 7,874,630 | 0.99 | 7,842,399 | 0.98 | 7,807,430 | 0.98 | 7,777,050 | 0.98 |

### Panel 3: Three Month Harmful Degree-Days (°C)

| Mean: 1.92 N: 7964917 | | 2 hd days (°C) | | 10 hd days (°C) | | 20 hd days (°C) | | 30 hd days (°C) | | 40 hd days (°C) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 20.10 | 244,143 | 0.03 | 173,027 | 0.02 | 134,026 | 0.02 | 110,458 | 0.01 | 89,341 | 0.01 |
| municipality fe | 18.45 | 1,202,494 | 0.15 | 416,648 | 0.05 | 207,252 | 0.03 | 153,594 | 0.02 | 134,100 | 0.02 |
| mun. fe, linear year | 18.44 | 1,223,779 | 0.15 | 417,935 | 0.05 | 206,978 | 0.03 | 153,022 | 0.02 | 133,701 | 0.02 |
| mun. fe, quadratic year | 18.44 | 1,222,036 | 0.15 | 417,855 | 0.05 | 207,028 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. fe, cubic year | 18.44 | 1,223,501 | 0.15 | 417,626 | 0.05 | 207,010 | 0.03 | 153,108 | 0.02 | 133,675 | 0.02 |
| mun. & year fe | 18.44 | 1,230,230 | 0.15 | 418,576 | 0.05 | 207,236 | 0.03 | 153,026 | 0.02 | 133,437 | 0.02 |
| mun. year & qtr. fe | 18.31 | 4,228,573 | 0.53 | 445,997 | 0.06 | 210,257 | 0.03 | 148,686 | 0.02 | 130,259 | 0.02 |
| mun., region× year & qtr. fe | 18.29 | 3,433,494 | 0.43 | 441,446 | 0.06 | 212,065 | 0.03 | 147,538 | 0.02 | 130,640 | 0.02 |
| mun., state× year & qtr. fe | 18.25 | 3,326,858 | 0.42 | 476,900 | 0.06 | 214,958 | 0.03 | 150,806 | 0.02 | 129,679 | 0.02 |

### Panel 4: Three Month Mean Heat Index (°C)

| Mean: 25.56 N: 7964917 | | 2.5 °C | | 5.0 °C | | 7.5 °C | | 10.0 °C | | 12.5 °C | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regressors | RMSE | Number | Share | Number | Share | Number | Share | Number | Share | Number | Share |
| constant | 5.40 | 5,232,320 | 0.66 | 2,565,035 | 0.32 | 1,120,827 | 0.14 | 587,585 | 0.07 | 248,767 | 0.03 |
| municipality fe | 3.96 | 4,142,651 | 0.52 | 1,627,140 | 0.20 | 491,188 | 0.06 | 102,680 | 0.01 | 13,702 | 0.00 |
| mun. fe, linear year | 3.96 | 4,141,797 | 0.52 | 1,620,298 | 0.20 | 483,562 | 0.06 | 101,176 | 0.01 | 13,584 | 0.00 |
| mun. fe, quadratic year | 3.95 | 4,141,600 | 0.52 | 1,614,395 | 0.20 | 479,449 | 0.06 | 102,099 | 0.01 | 14,045 | 0.00 |
| mun. fe, cubic year | 3.95 | 4,144,648 | 0.52 | 1,613,160 | 0.20 | 478,649 | 0.06 | 101,960 | 0.01 | 13,972 | 0.00 |
| mun. & year fe | 3.94 | 4,148,805 | 0.52 | 1,617,551 | 0.20 | 474,276 | 0.06 | 101,791 | 0.01 | 12,621 | 0.00 |
| mun. year & qtr. fe | 3.73 | 3,783,613 | 0.48 | 1,432,382 | 0.18 | 380,285 | 0.05 | 81,101 | 0.01 | 11,926 | 0.00 |
| mun., region× year & qtr. fe | 3.71 | 3,758,608 | 0.47 | 1,415,584 | 0.18 | 379,116 | 0.05 | 77,124 | 0.01 | 9,715 | 0.00 |
| mun., state× year & qtr. fe | 3.68 | 3,763,477 | 0.47 | 1,409,862 | 0.18 | 362,919 | 0.05 | 68,552 | 0.01 | 6,284 | 0.00 |

Notes: Table counts residuals from regressions of municipality × qtr × year observations on regressors listed in row headings. Cell entries are number of residuals of absolute value greater than or equal to the cut-offs given in the column headings. Years: 2005-2016 Sample: 2456 municipalities

# E Regression Tables Including Controls

## E.1 Simple Weather Variables Municipality Fixed Effects Regression

Table 14: Wage Regression - Municipality FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. | -0.0005* | | | | |
| (week) | (0.0002) | | | | |
| avg. precip | | -0.0006** | | | |
| (week) | | (0.0002) | | | |
| tot. precip | | | -0.0001** | | |
| (week) | | | (0.0000) | | |
| hdd (week) | | | | -0.0000 | |
| | | | | (0.0000) | |
| heat index | | | | | -0.0002* |
| (week) | | | | | (0.0001) |
| married | 0.0483*** | 0.0483*** | 0.0483*** | 0.0483*** | 0.0483*** |
| | (0.0024) | (0.0024) | (0.0024) | (0.0024) | (0.0024) |
| female | -0.3819*** | -0.3819*** | -0.3819*** | -0.3819*** | -0.3819*** |
| | (0.0051) | (0.0051) | (0.0051) | (0.0051) | (0.0051) |
| age | 0.0485*** | 0.0485*** | 0.0485*** | 0.0485*** | 0.0485*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| $age^2$ | -0.0006*** | -0.0006*** | -0.0006*** | -0.0006*** | -0.0006*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| secondary | 0.1114*** | 0.1114*** | 0.1114*** | 0.1114*** | 0.1114*** |
| | (0.0028) | (0.0028) | (0.0028) | (0.0028) | (0.0028) |
| preparatory | 0.2208*** | 0.2208*** | 0.2208*** | 0.2208*** | 0.2208*** |
| | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| university | 0.4991*** | 0.4991*** | 0.4991*** | 0.4991*** | 0.4991*** |
| | (0.0077) | (0.0077) | (0.0077) | (0.0077) | (0.0077) |
| postgraduate | 0.4617*** | 0.4617*** | 0.4617*** | 0.4617*** | 0.4617*** |
| | (0.0103) | (0.0103) | (0.0103) | (0.0103) | (0.0103) |
| unemp. rate | -0.4498*** | -0.4500*** | -0.4500*** | -0.4504*** | -0.4490*** |
| | (0.0792) | (0.0794) | (0.0794) | (0.0794) | (0.0794) |
| Rural | -0.1111*** | -0.1111*** | -0.1111*** | -0.1111*** | -0.1111*** |
| | (0.0093) | (0.0093) | (0.0093) | (0.0093) | (0.0093) |
| medium | 0.0357*** | 0.0358*** | 0.0358*** | 0.0358*** | 0.0358*** |
| | (0.0048) | (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| large | 0.0907*** | 0.0907*** | 0.0907*** | 0.0907*** | 0.0907*** |
| | (0.0088) | (0.0088) | (0.0088) | (0.0088) | (0.0088) |
| informal | -0.2797*** | -0.2797*** | -0.2797*** | -0.2797*** | -0.2797*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| permanent | 0.1677*** | 0.1677*** | 0.1677*** | 0.1677*** | 0.1677*** |
| | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| agriculture | -0.3080*** | -0.3080*** | -0.3080*** | -0.3080*** | -0.3080*** |
| | (0.0169) | (0.0169) | (0.0169) | (0.0169) | (0.0169) |
| extractive | 0.4615*** | 0.4615*** | 0.4615*** | 0.4615*** | 0.4615*** |
| industry | (0.0337) | (0.0337) | (0.0337) | (0.0337) | (0.0337) |
| manufacturing | 0.0920*** | 0.0920*** | 0.0920*** | 0.0920*** | 0.0920*** |
| | (0.0094) | (0.0094) | (0.0094) | (0.0094) | (0.0094) |
| construction | 0.4774*** | 0.4774*** | 0.4774*** | 0.4774*** | 0.4774*** |
| | (0.0090) | (0.0090) | (0.0090) | (0.0090) | (0.0090) |
| trade | 0.0796*** | 0.0797*** | 0.0797*** | 0.0796*** | 0.0796*** |
| | (0.0062) | (0.0062) | (0.0062) | (0.0062) | (0.0062) |
| restaurants | 0.1558*** | 0.1558*** | 0.1558*** | 0.1558*** | 0.1558*** |
| | (0.0076) | (0.0076) | (0.0076) | (0.0076) | (0.0076) |
| transport & | 0.3151*** | 0.3151*** | 0.3151*** | 0.3151*** | 0.3151*** |
| communication | (0.0061) | (0.0061) | (0.0061) | (0.0061) | (0.0061) |
| prof. financial | 0.1760*** | 0.1760*** | 0.1760*** | 0.1760*** | 0.1760*** |
| services | (0.0053) | (0.0053) | (0.0053) | (0.0053) | (0.0053) |
| social services | 0.2743*** | 0.2743*** | 0.2743*** | 0.2743*** | 0.2743*** |
| | (0.0102) | (0.0102) | (0.0102) | (0.0102) | (0.0102) |
| government | 0.2596*** | 0.2596*** | 0.2596*** | 0.2596*** | 0.2596*** |
| | (0.0113) | (0.0113) | (0.0113) | (0.0113) | (0.0113) |
| Constant | 7.1161*** | 7.1084*** | 7.1084*** | 7.1074*** | 7.1118*** |
| | (0.0191) | (0.0185) | (0.0185) | (0.0185) | (0.0186) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 15: Working Time Regression - Municipality FE

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. | 4.276*** | | | | |
| (week) | (0.525) | | | | |
| avg. precip | | -0.146 | | | |
| (week) | | (0.396) | | | |
| tot. precip | | | -0.030 | | |
| (week) | | | (0.056) | | |
| hdd (week) | | | | -0.076 | |
| | | | | (0.066) | |
| heat index | | | | | -0.749** |
| (week) | | | | | (0.269) |
| married | -24.462*** | -24.461*** | -24.461*** | -24.459*** | -24.455*** |
| | (2.240) | (2.240) | (2.240) | (2.240) | (2.240) |
| female | -458.107*** | -458.107*** | -458.107*** | -458.111*** | -458.120*** |
| | (6.667) | (6.667) | (6.667) | (6.666) | (6.665) |
| age | 40.477*** | 40.476*** | 40.476*** | 40.476*** | 40.475*** |
| | (0.821) | (0.821) | (0.821) | (0.821) | (0.821) |
| age$^2$ | -0.472*** | -0.472*** | -0.472*** | -0.472*** | -0.472*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| secondary | 4.356 | 4.336 | 4.336 | 4.336 | 4.333 |
| | (3.304) | (3.302) | (3.302) | (3.302) | (3.302) |
| preparatory | -42.742*** | -42.751*** | -42.750*** | -42.751*** | -42.752*** |
| | (5.074) | (5.073) | (5.073) | (5.073) | (5.072) |
| university | -169.669*** | -169.674*** | -169.674*** | -169.673*** | -169.680*** |
| | (7.433) | (7.432) | (7.432) | (7.432) | (7.432) |
| postgraduate | -30.618*** | -30.581*** | -30.580*** | -30.583*** | -30.605*** |
| | (6.697) | (6.694) | (6.694) | (6.694) | (6.693) |
| unemp. rate | -549.811*** | -544.466*** | -544.442*** | -544.430*** | -539.393*** |
| | (53.456) | (52.728) | (52.729) | (52.752) | (52.649) |
| Rural | -45.855*** | -45.843*** | -45.844*** | -45.856*** | -45.855*** |
| | (7.845) | (7.845) | (7.845) | (7.842) | (7.844) |
| medium | 106.315*** | 106.236*** | 106.236*** | 106.230*** | 106.207*** |
| | (6.472) | (6.470) | (6.470) | (6.470) | (6.469) |
| large | 57.855*** | 57.880*** | 57.879*** | 57.880*** | 57.861*** |
| | (9.041) | (9.046) | (9.046) | (9.047) | (9.045) |
| informal | -489.378*** | -489.373*** | -489.374*** | -489.376*** | -489.372*** |
| | (10.640) | (10.637) | (10.637) | (10.637) | (10.637) |
| permanent | 34.310*** | 34.287*** | 34.286*** | 34.287*** | 34.312*** |
| | (5.888) | (5.887) | (5.887) | (5.887) | (5.888) |
| agriculture | -158.358*** | -158.573*** | -158.572*** | -158.587*** | -158.647*** |
| | (16.507) | (16.496) | (16.496) | (16.491) | (16.485) |
| extractive | 170.107*** | 170.129*** | 170.129*** | 170.131*** | 170.125*** |
| industry | (18.449) | (18.438) | (18.438) | (18.439) | (18.433) |
| manufacturing | 253.666*** | 253.706*** | 253.706*** | 253.708*** | 253.706*** |
| | (7.691) | (7.684) | (7.684) | (7.683) | (7.683) |
| construction | 377.024*** | 377.045*** | 377.045*** | 377.049*** | 377.046*** |
| | (11.251) | (11.252) | (11.252) | (11.252) | (11.250) |
| trade | 505.909*** | 505.895*** | 505.895*** | 505.892*** | 505.886*** |
| | (11.184) | (11.180) | (11.180) | (11.179) | (11.180) |
| restaurants | 380.499*** | 380.500*** | 380.500*** | 380.498*** | 380.493*** |
| | (8.478) | (8.474) | (8.474) | (8.474) | (8.473) |
| transport & | 770.749*** | 770.723*** | 770.723*** | 770.720*** | 770.719*** |
| communication | (20.507) | (20.510) | (20.510) | (20.510) | (20.510) |
| prof. financial | 260.558*** | 260.618*** | 260.618*** | 260.612*** | 260.608*** |
| services | (8.169) | (8.168) | (8.168) | (8.167) | (8.168) |
| social services | -385.562*** | -385.550*** | -385.550*** | -385.551*** | -385.551*** |
| | (9.983) | (9.981) | (9.981) | (9.981) | (9.980) |
| government | 99.045*** | 99.051*** | 99.051*** | 99.049*** | 99.056*** |
| | (14.538) | (14.530) | (14.530) | (14.529) | (14.528) |
| Constant | 1829.897*** | 1908.082*** | 1908.195*** | 1907.807*** | 1925.632*** |
| | (22.782) | (19.747) | (19.750) | (19.809) | (21.465) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 16: Binned Weather Wage Regression - Individual FE

| | (1) | (2) | (3) |
|---|---|---|---|
| $\leq$ 10 temp. | -0.0001 | | |
| (week) | (0.0009) | | |
| 10-12 temp. | 0.0012 | | |
| (week) | (0.0008) | | |
| 12-14 temp. | 0.0001 | | |
| (week) | (0.0006) | | |
| 14-16 temp. | 0.0004 | | |
| (week) | (0.0006) | | |
| 16-18 temp. | 0.0007 | | |
| (week) | (0.0004) | | |
| 18-20 temp. | 0.0002 | | |
| (week) | (0.0006) | | |
| 22-24 temp. | 0.0010 | | |
| (week) | (0.0006) | | |
| 24-26 temp. | 0.0008 | | |
| (week) | (0.0005) | | |
| 26-28 temp. | 0.0007 | | |
| (week) | (0.0005) | | |
| 28-30 temp. | 0.0006 | | |
| (week) | (0.0005) | | |
| 30-32 temp. | 0.0006 | | |
| (week) | (0.0006) | | |
| 32-34 temp. | 0.0016 | | |
| (week) | (0.0008) | | |
| >34 | 0.0004 | | |
| temp. (week) | (0.0007) | | |
| = 0 precip. | | 0.0017* | |
| (week) | | (0.0007) | |
| 0-2 precip | | 0.0013 | |
| (week) | | (0.0007) | |
| 4-6 precip | | -0.0006 | |
| (week) | | (0.0012) | |
| 6-8 precip | | 0.0014 | |
| (week) | | (0.0014) | |
| 8-10 precip | | -0.0021 | |
| (week) | | (0.0016) | |
| 10-20 precip. | | -0.0007 | |
| (week) | | (0.0010) | |
| 20-30 precip. | | -0.0015 | |
| (week) | | (0.0018) | |
| >30 | | -0.0019 | |
| precip. (week) | | (0.0017) | |
| $\leq$ 10 HI | | | 0.0010 |
| (week) | | | (0.0018) |
| 10-12 HI (week) | | | -0.0001 |
| | | | (0.0020) |
| 12-14 HI (week) | | | -0.0020 |
| | | | (0.0012) |
| 14-16 HI (week) | | | 0.0001 |
| | | | (0.0007) |
| 16-18 HI (week) | | | 0.0011* |
| | | | (0.0005) |
| 18-20 HI (week) | | | 0.0003 |
| | | | (0.0006) |
| 22-24 HI (week) | | | 0.0015* |
| | | | (0.0006) |
| 24-26 HI (week) | | | 0.0011* |
| | | | (0.0005) |
| 26-28 HI (week) | | | 0.0006 |
| | | | (0.0005) |
| 28-30 HI (week) | | | 0.0011 |
| | | | (0.0006) |
| 30-32 HI (week) | | | 0.0009 |
| | | | (0.0006) |
| 32-34 HI (week) | | | 0.0007 |
| | | | (0.0007) |
| >34 | | | 0.0008* |
| HI (week) | | | (0.0004) |
| Constant | 8.2341*** | 8.2293*** | 8.2328*** |
| | (0.0038) | (0.0058) | (0.0039) |
| Qtr fe | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 |

Table 17: Binned Weather Wage Regression - Municipality FE

| | (1) | (2) | (3) |
|---|---|---|---|
| $\leq$ 10 temp. | -0.0000 | | |
| (week) | (0.0007) | | |
| 10-12 temp. | 0.0010 | | |
| (week) | (0.0011) | | |
| 12-14 temp. | 0.0004 | | |
| (week) | (0.0008) | | |
| 14-16 temp. | 0.0006 | | |
| (week) | (0.0005) | | |
| 16-18 temp. | 0.0005 | | |
| (week) | (0.0005) | | |
| 18-20 temp. | -0.0000 | | |
| (week) | (0.0006) | | |
| 22-24 temp. | -0.0001 | | |
| (week) | (0.0005) | | |
| 24-26 temp. | -0.0004 | | |
| (week) | (0.0005) | | |
| 26-28 temp. | 0.0001 | | |
| (week) | (0.0006) | | |
| 28-30 temp. | -0.0004 | | |
| (week) | (0.0006) | | |
| 30-32 temp. | -0.0012 | | |
| (week) | (0.0006) | | |
| 32-34 temp. | -0.0001 | | |
| (week) | (0.0010) | | |
| >34 | -0.0022** | | |
| temp. (week) | (0.0008) | | |
| = 0 precip. | | 0.0013 | |
| (week) | | (0.0007) | |
| 0-2 precip | | 0.0013 | |
| (week) | | (0.0007) | |
| 4-6 precip | | 0.0002 | |
| (week) | | (0.0013) | |
| 6-8 precip | | 0.0012 | |
| (week) | | (0.0014) | |
| 8-10 precip | | -0.0013 | |
| (week) | | (0.0015) | |
| 10-20 precip. | | -0.0002 | |
| (week) | | (0.0010) | |
| 20-30 precip. | | 0.0016 | |
| (week) | | (0.0018) | |
| >30 | | -0.0026 | |
| precip. (week) | | (0.0028) | |
| $\leq$ 10 HI | | | 0.0018 |
| (week) | | | (0.0021) |
| 10-12 HI (week) | | | 0.0008 |
| | | | (0.0020) |
| 12-14 HI (week) | | | -0.0009 |
| | | | (0.0011) |
| 14-16 HI (week) | | | 0.0010 |
| | | | (0.0008) |
| 16-18 HI (week) | | | 0.0008 |
| | | | (0.0006) |
| 18-20 HI (week) | | | 0.0001 |
| | | | (0.0007) |
| 22-24 HI (week) | | | 0.0007 |
| | | | (0.0006) |
| 24-26 HI (week) | | | -0.0000 |
| | | | (0.0006) |
| 26-28 HI (week) | | | 0.0003 |
| | | | (0.0005) |
| 28-30 HI (week) | | | 0.0009 |
| | | | (0.0006) |
| 30-32 HI (week) | | | -0.0000 |
| | | | (0.0007) |
| 32-34 HI (week) | | | 0.0011 |
| | | | (0.0009) |
| >34 | | | -0.0004 |
| HI (week) | | | (0.0005) |
| Constant | 7.1059*** | 7.1000*** | 7.1047*** |
| | (0.0185) | (0.0191) | (0.0183) |
| Controls | × | × | × |
| Sector fe | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 |

## E.2 Weather Bins Municipality Fixed Effects Regression

Table 18: Binned Weather Working Time Regression - Individual FE

| | (1) | (2) | (3) |
|---|---|---|---|
| ≤ 10 temp. | -20.905*** | | |
| (week) | (2.683) | | |
| 10-12 temp. | -22.863*** | | |
| (week) | (2.569) | | |
| 12-14 temp. | -13.812*** | | |
| (week) | (1.725) | | |
| 14-16 temp. | -13.965*** | | |
| (week) | (1.970) | | |
| 16-18 temp. | -6.925*** | | |
| (week) | (1.393) | | |
| 18-20 temp. | -8.822*** | | |
| (week) | (1.454) | | |
| 22-24 temp. | -6.445*** | | |
| (week) | (1.628) | | |
| 24-26 temp. | -6.721*** | | |
| (week) | (1.561) | | |
| 26-28 temp. | -3.538* | | |
| (week) | (1.388) | | |
| 28-30 temp. | 0.167 | | |
| (week) | (1.394) | | |
| 30-32 temp. | -1.498 | | |
| (week) | (1.703) | | |
| 32-34 temp. | 0.012 | | |
| (week) | (1.980) | | |
| >34 | -0.257 | | |
| temp. (week) | (3.925) | | |
| = 0 precip. | | -25.836*** | |
| (week) | | (2.455) | |
| 0-2 precip | | -24.373*** | |
| (week) | | (2.303) | |
| 4-6 precip | | -26.198*** | |
| (week) | | (3.297) | |
| 6-8 precip | | -20.517*** | |
| (week) | | (3.187) | |
| 8-10 precip | | -25.549*** | |
| (week) | | (3.792) | |
| 10-20 precip. | | -22.035*** | |
| (week) | | (2.810) | |
| 20-30 precip. | | -28.624*** | |
| (week) | | (3.974) | |
| >30 | | -42.149*** | |
| precip. (week) | | (5.080) | |
| ≤ 10 HI | | | -23.134*** |
| (week) | | | (5.841) |
| 10-12 HI (week) | | | -13.022 |
| | | | (8.845) |
| 12-14 HI (week) | | | -10.745*** |
| | | | (2.552) |
| 14-16 HI (week) | | | -9.699*** |
| | | | (2.750) |
| 16-18 HI (week) | | | -4.971*** |
| | | | (1.340) |
| 18-20 HI (week) | | | -9.810*** |
| | | | (1.835) |
| 22-24 HI (week) | | | -7.939*** |
| | | | (1.998) |
| 24-26 HI (week) | | | -7.835*** |
| | | | (1.439) |
| 26-28 HI (week) | | | -9.554*** |
| | | | (1.649) |
| 28-30 HI (week) | | | -6.884*** |
| | | | (2.011) |
| 30-32 HI (week) | | | -11.017*** |
| | | | (1.753) |
| 32-34 HI (week) | | | -8.590*** |
| | | | (2.320) |
| >34 | | | -8.780*** |
| HI (week) | | | (1.680) |
| Constant | 2558.758*** | 2664.339*** | 2552.037*** |
| | (8.408) | (17.462) | (10.273) |
| Qtr fe | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 |
| N | 7,964,917 | 7,964,917 | 7,964,917 |

Table 19: Binned Weather Working Time Regression - Municipality FE

| | (1) | (2) | (3) |
|---|---|---|---|
| $\leq$ 10 temp. | -22.374*** | | |
| (week) | (2.549) | | |
| 10-12 temp. | -20.454*** | | |
| (week) | (2.294) | | |
| 12-14 temp. | -13.492*** | | |
| (week) | (1.634) | | |
| 14-16 temp. | -12.033*** | | |
| (week) | (1.618) | | |
| 16-18 temp. | -6.077*** | | |
| (week) | (1.162) | | |
| 18-20 temp. | -8.954*** | | |
| (week) | (1.173) | | |
| 22-24 temp. | -7.990*** | | |
| (week) | (1.258) | | |
| 24-26 temp. | -7.111*** | | |
| (week) | (1.229) | | |
| 26-28 temp. | -2.918* | | |
| (week) | (1.193) | | |
| 28-30 temp. | -1.333 | | |
| (week) | (1.047) | | |
| 30-32 temp. | -1.452 | | |
| (week) | (1.292) | | |
| 32-34 temp. | 1.020 | | |
| (week) | (1.884) | | |
| >34 | -2.169 | | |
| temp. (week) | (2.776) | | |
| = 0 precip. | | -29.633*** | |
| (week) | | (2.192) | |
| 0-2 precip | | -27.363*** | |
| (week) | | (2.039) | |
| 4-6 precip | | -31.726*** | |
| (week) | | (2.943) | |
| 6-8 precip | | -24.365*** | |
| (week) | | (2.594) | |
| 8-10 precip | | -26.243*** | |
| (week) | | (3.332) | |
| 10-20 precip. | | -24.225*** | |
| (week) | | (2.223) | |
| 20-30 precip. | | -35.078*** | |
| (week) | | (3.430) | |
| >30 | | -47.561*** | |
| precip. (week) | | (3.949) | |
| $\leq$ 10 HI | | | -23.922*** |
| (week) | | | (4.764) |
| 10-12 HI (week) | | | -14.256 |
| | | | (7.857) |
| 12-14 HI (week) | | | -10.293*** |
| | | | (1.946) |
| 14-16 HI (week) | | | -8.646*** |
| | | | (2.113) |
| 16-18 HI (week) | | | -4.528*** |
| | | | (1.105) |
| 18-20 HI (week) | | | -10.434*** |
| | | | (1.595) |
| 22-24 HI (week) | | | -9.653*** |
| | | | (1.660) |
| 24-26 HI (week) | | | -9.175*** |
| | | | (1.232) |
| 26-28 HI (week) | | | -7.976*** |
| | | | (1.322) |
| 28-30 HI (week) | | | -5.193*** |
| | | | (1.573) |
| 30-32 HI (week) | | | -11.291*** |
| | | | (1.508) |
| 32-34 HI (week) | | | -9.414*** |
| | | | (2.018) |
| >34 | | | -9.524*** |
| HI (week) | | | (1.378) |
| Constant | 1971.578*** | 2098.253*** | 1961.824*** |
| | (21.020) | (24.046) | (22.170) |
| Controls | × | × | × |
| Sector fe | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 |

# F Alternative Fixed Effects Specifications – Simple Weather Variables

The following tables show re-estimations of our key models using different fixed effects specifications and alternatively time trends.

## F.1 Individual Fixed Effects Regressions

Table 20: Baseline Regression - Wages

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0007*** | 0.0007*** | 0.0007*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0001) | (0.0001) | (0.0001) |
| Constant | 8.2342*** | 8.1991*** | 8.2047*** | 8.1827*** | 8.1914*** | 8.1859*** | 8.1745*** |
| | (0.0042) | (0.0097) | (0.0113) | (0.0116) | (0.0095) | (0.0115) | (0.0116) |
| heat index (week) | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0003*** | 0.0003*** | 0.0004*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Constant | 8.2355*** | 8.2003*** | 8.2059*** | 8.1844*** | 8.1987*** | 8.1934*** | 8.1815*** |
| | (0.0039) | (0.0087) | (0.0104) | (0.0108) | (0.0088) | (0.0110) | (0.0111) |
| hdd (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 8.2376*** | 8.2026*** | 8.2082*** | 8.1867*** | 8.2078*** | 8.2025*** | 8.1908*** |
| | (0.0035) | (0.0086) | (0.0103) | (0.0107) | (0.0086) | (0.0107) | (0.0109) |
| tot. precip (week) | -0.0001*** | -0.0001*** | -0.0001*** | -0.0001*** | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 8.2392*** | 8.2042*** | 8.2094*** | 8.1880*** | 8.2081*** | 8.2028*** | 8.1911*** |
| | (0.0035) | (0.0086) | (0.0103) | (0.0107) | (0.0086) | (0.0107) | (0.0109) |
| avg. precip (week) | -0.0010*** | -0.0009*** | -0.0009*** | -0.0009*** | -0.0002 | -0.0002 | -0.0003 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Constant | 8.2392*** | 8.2042*** | 8.2094*** | 8.1880*** | 8.2081*** | 8.2028*** | 8.1911*** |
| | (0.0035) | (0.0086) | (0.0103) | (0.0107) | (0.0086) | (0.0107) | (0.0109) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.10

## F.2 Municipality Fixed Effects Regressions

## F.3 Higher Polynomial Regressions

Table 21: Baseline Regression - Working Time

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. | 4.8835*** | 4.8571*** | 4.8575*** | 4.8430*** | 1.1528*** | 1.1509*** | 1.1504*** |
| (week) | (0.6799) | (0.6697) | (0.6715) | (0.6705) | (0.3049) | (0.3050) | (0.3050) |
| Constant | 2405.0306*** | 2408.3447*** | 2445.7607*** | 2458.9535*** | 2417.0918*** | 2435.8928*** | 2432.9461*** |
| | (12.7842) | (18.2882) | (18.8842) | (19.6309) | (15.6607) | (17.8142) | (18.3748) |
| heat index | -0.8152* | -0.7938* | -0.8186* | -0.8170* | -1.1197*** | -1.1196*** | -1.1176*** |
| (week) | (0.3716) | (0.3696) | (0.3715) | (0.3711) | (0.3342) | (0.3342) | (0.3338) |
| Constant | 2516.5767*** | 2522.7388*** | 2561.9866*** | 2576.6021*** | 2471.8166*** | 2490.8281*** | 2487.9282*** |
| | (10.1593) | (12.6313) | (14.4224) | (14.9677) | (12.8688) | (15.2784) | (15.9264) |
| hdd (week) | -0.0469 | -0.0465 | -0.0468 | -0.0463 | -0.0703 | -0.0703 | -0.0706 |
| | (0.1024) | (0.1024) | (0.1020) | (0.1023) | (0.0850) | (0.0849) | (0.0847) |
| Constant | 2497.4798*** | 2503.0810*** | 2540.4628*** | 2555.1862*** | 2442.7122*** | 2461.7311*** | 2458.7410*** |
| | (4.0668) | (11.1570) | (12.7802) | (13.3914) | (12.3375) | (15.0112) | (15.6193) |
| avg. precip | 0.0844 | 0.1308 | 0.1464 | 0.1434 | 0.4664 | 0.4684 | 0.4653 |
| (week) | (0.4851) | (0.4884) | (0.4876) | (0.4882) | (0.5068) | (0.5069) | (0.5067) |
| Constant | 2497.3428*** | 2502.8563*** | 2540.2439*** | 2554.9803*** | 2442.0499*** | 2461.1227*** | 2458.1767*** |
| | (3.8419) | (11.3694) | (12.9700) | (13.5689) | (12.5692) | (15.1982) | (15.7812) |
| tot. precip | 0.0035 | 0.0101 | 0.0123 | 0.0118 | 0.0601 | 0.0603 | 0.0599 |
| (week) | (0.0688) | (0.0693) | (0.0692) | (0.0693) | (0.0720) | (0.0720) | (0.0719) |
| Constant | 2497.4500*** | 2502.9497*** | 2540.3198*** | 2555.0594*** | 2442.1016*** | 2461.1698*** | 2458.2207*** |
| | (3.8427) | (11.3708) | (12.9709) | (13.5709) | (12.5683) | (15.1980) | (15.7815) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Standard errors are clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.10

Table 22: Municipality FE Regression - Wages

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. (week) | -0.0005* | -0.0003 | -0.0003 | -0.0003 | 0.0005*** | 0.0005*** | 0.0004*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0001) | (0.0001) | (0.0001) |
| Constant | 7.0943*** | 7.1796*** | 7.1833*** | 7.1157*** | 7.1666*** | 7.1685*** | 7.1188*** |
| | (0.0190) | (0.0212) | (0.0231) | (0.0231) | (0.0210) | (0.0224) | (0.0223) |
| hdd (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0857*** | 7.1738*** | 7.1766*** | 7.1096*** | 7.1775*** | 7.1793*** | 7.1289*** |
| | (0.0184) | (0.0207) | (0.0222) | (0.0223) | (0.0209) | (0.0221) | (0.0220) |
| heat index (week) | -0.0002 | -0.0001 | -0.0001 | -0.0002 | 0.0001 | 0.0001 | 0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Constant | 7.0899*** | 7.1767*** | 7.1797*** | 7.1140*** | 7.1743*** | 7.1761*** | 7.1268*** |
| | (0.0184) | (0.0204) | (0.0220) | (0.0222) | (0.0208) | (0.0221) | (0.0221) |
| avg. precip (week) | -0.0006** | -0.0007** | -0.0007** | -0.0006** | 0.0001 | 0.0001 | 0.0000 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Constant | 7.0867*** | 7.1745*** | 7.1773*** | 7.1104*** | 7.1775*** | 7.1793*** | 7.1290*** |
| | (0.0184) | (0.0207) | (0.0222) | (0.0223) | (0.0208) | (0.0220) | (0.0220) |
| tot. precip (week) | -0.0001* | -0.0001** | -0.0001** | -0.0001** | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0867*** | 7.1745*** | 7.1773*** | 7.1104*** | 7.1775*** | 7.1793*** | 7.1290*** |
| | (0.0184) | (0.0207) | (0.0222) | (0.0223) | (0.0208) | (0.0220) | (0.0220) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 23: Municipality FE Regression - Working Time

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 4.2754*** | 4.3544*** | 4.2322*** | 4.2129*** | 1.1813*** | 1.1169*** | 1.1186*** |
| | (0.5242) | (0.5209) | (0.5240) | (0.5201) | (0.2550) | (0.2563) | (0.2559) |
| Constant | 1820.5601*** | 1825.5147*** | 1838.5584*** | 1862.9397*** | 1856.5073*** | 1866.3028*** | 1873.8352*** |
| | (22.7872) | (23.6565) | (25.2000) | (26.4298) | (21.1861) | (22.2818) | (23.0497) |
| hdd (week) | -0.0748 | -0.0724 | -0.0751 | -0.0737 | -0.0785 | -0.0813 | -0.0803 |
| | (0.0669) | (0.0687) | (0.0673) | (0.0677) | (0.0566) | (0.0553) | (0.0555) |
| Constant | 1898.4536*** | 1911.7171*** | 1925.0494*** | 1949.6637*** | 1883.0275*** | 1892.0203*** | 1899.5022*** |
| | (19.8180) | (20.1469) | (21.3080) | (22.5688) | (20.1845) | (21.1309) | (21.9388) |
| heat index (week) | -0.7472** | -0.7428** | -0.7647** | -0.7468** | -1.0240*** | -1.0354*** | -1.0308*** |
| | (0.2691) | (0.2705) | (0.2666) | (0.2670) | (0.2526) | (0.2492) | (0.2501) |
| Constant | 1916.2298*** | 1929.8993*** | 1943.9187*** | 1967.8404*** | 1909.2639*** | 1918.6363*** | 1925.8630*** |
| | (21.4946) | (21.4745) | (22.5090) | (23.9288) | (21.4770) | (22.2689) | (23.1650) |
| avg. precip (week) | -0.1408 | -0.1935 | -0.1741 | -0.1916 | 0.5530 | 0.5490 | 0.5645 |
| | (0.3965) | (0.3871) | (0.3875) | (0.3909) | (0.3709) | (0.3709) | (0.3729) |
| Constant | 1898.7225*** | 1911.8784*** | 1925.1477*** | 1949.8299*** | 1882.1296*** | 1891.0826*** | 1898.7000*** |
| | (19.7517) | (20.1379) | (21.3130) | (22.5623) | (20.1411) | (21.1001) | (21.8967) |
| tot. precip (week) | -0.0296 | -0.0371 | -0.0344 | -0.0369 | 0.0715 | 0.0709 | 0.0731 |
| | (0.0562) | (0.0549) | (0.0550) | (0.0555) | (0.0526) | (0.0526) | (0.0529) |
| Constant | 1898.8346*** | 1911.9497*** | 1925.2147*** | 1949.9056*** | 1882.1994*** | 1891.1533*** | 1898.7588*** |
| | (19.7550) | (20.1405) | (21.3158) | (22.5667) | (20.1431) | (21.1023) | (21.8998) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 24: Higher Polynomial Regression - Wages

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 0.0001 | -0.0000 | -0.0000 | 0.0005 | 0.0007 | 0.0007 | 0.0011 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| avg. temp. $^2$ (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0883*** | 7.1768*** | 7.1805*** | 7.1071*** | 7.1646*** | 7.1665*** | 7.1121*** |
| | (0.0204) | (0.0232) | (0.0249) | (0.0249) | (0.0232) | (0.0245) | (0.0243) |
| avg. temp. (week) | -0.0007 | -0.0018 | -0.0018 | -0.0008 | -0.0026 | -0.0027 | -0.0022 |
| | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0020) |
| avg. temp. $^2$ (week) | 0.0000 | 0.0001 | 0.0001 | 0.0000 | 0.0002 | 0.0002 | 0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| avg. temp. $^3$ (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0938*** | 7.1882*** | 7.1915*** | 7.1153*** | 7.1858*** | 7.1878*** | 7.1332*** |
| | (0.0248) | (0.0272) | (0.0289) | (0.0292) | (0.0275) | (0.0289) | (0.0292) |
| hdd (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| hdd $^2$ (week) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0857*** | 7.1738*** | 7.1766*** | 7.1097*** | 7.1775*** | 7.1793*** | 7.1289*** |
| | (0.0184) | (0.0207) | (0.0222) | (0.0223) | (0.0209) | (0.0221) | (0.0220) |
| hdd (week) | -0.0001 | -0.0001 | -0.0001 | -0.0001 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| hdd $^2$ (week) | 0.0000 | 0.0000* | 0.0000* | 0.0000* | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| hdd $^3$ (week) | -0.0000* | -0.0000* | -0.0000* | -0.0000* | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0857*** | 7.1738*** | 7.1766*** | 7.1097*** | 7.1775*** | 7.1794*** | 7.1290*** |
| | (0.0184) | (0.0207) | (0.0223) | (0.0223) | (0.0209) | (0.0221) | (0.0220) |
| heat index (week) | 0.0004 | -0.0002 | -0.0001 | 0.0005 | -0.0006 | -0.0006 | 0.0004 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| heat index $^2$ (week) | -0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0824*** | 7.1774*** | 7.1797*** | 7.1048*** | 7.1839*** | 7.1851*** | 7.1229*** |
| | (0.0196) | (0.0226) | (0.0237) | (0.0232) | (0.0229) | (0.0236) | (0.0231) |
| heat index (week) | 0.0003 | -0.0019 | -0.0017 | 0.0004 | -0.0031** | -0.0030** | -0.0002 |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0009) |
| heat index $^2$ (week) | -0.0000 | 0.0001 | 0.0001 | -0.0000 | 0.0001** | 0.0001** | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| heat index $^3$ (week) | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000* | -0.0000* | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0828*** | 7.1910*** | 7.1922*** | 7.1053*** | 7.2040*** | 7.2043*** | 7.1277*** |
| | (0.0218) | (0.0251) | (0.0258) | (0.0253) | (0.0251) | (0.0253) | (0.0247) |
| avg. precip (week) | -0.0009** | -0.0010** | -0.0010** | -0.0010** | 0.0007* | 0.0007* | 0.0004 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| avg. precip $^2$ (week) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0869*** | 7.1747*** | 7.1775*** | 7.1106*** | 7.1771*** | 7.1788*** | 7.1288*** |
| | (0.0183) | (0.0206) | (0.0222) | (0.0222) | (0.0208) | (0.0220) | (0.0220) |
| avg. precip (week) | -0.0009 | -0.0010 | -0.0010 | -0.0010 | 0.0013** | 0.0012** | 0.0008 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| avg. precip $^2$ (week) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0001* | -0.0001* | -0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| avg. precip $^3$ (week) | 0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0869*** | 7.1747*** | 7.1775*** | 7.1106*** | 7.1768*** | 7.1785*** | 7.1285*** |
| | (0.0183) | (0.0206) | (0.0222) | (0.0222) | (0.0208) | (0.0220) | (0.0219) |
| tot. precip (week) | -0.0001** | -0.0001** | -0.0001** | -0.0001** | 0.0001* | 0.0001* | 0.0001 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| tot. precip. $^2$ (week) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0868*** | 7.1747*** | 7.1775*** | 7.1106*** | 7.1771*** | 7.1788*** | 7.1287*** |
| | (0.0183) | (0.0206) | (0.0222) | (0.0222) | (0.0208) | (0.0220) | (0.0220) |
| tot. precip (week) | -0.0001 | -0.0001 | -0.0001 | -0.0001 | 0.0002** | 0.0002** | 0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| tot. precip. $^2$ (week) | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -0.0000* | -0.0000* | -0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| tot. precip. $^3$ (week) | 0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 7.0868*** | 7.1747*** | 7.1775*** | 7.1106*** | 7.1768*** | 7.1785*** | 7.1285*** |
| | (0.0183) | (0.0206) | (0.0222) | (0.0222) | (0.0208) | (0.0220) | (0.0219) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 25: Higher Polynomial Regression - Working Time

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| avg. temp. (week) | 11.6232*** | 11.6914*** | 11.5740*** | 11.3604*** | 9.3648*** | 9.2854*** | 9.2223*** |
| | (1.5470) | (1.5548) | (1.5460) | (1.5389) | (1.3626) | (1.3637) | (1.3612) |
| avg. temp. $^2$ (week) | -0.1684*** | -0.1683*** | -0.1684*** | -0.1639*** | -0.1869*** | -0.1865*** | -0.1851*** |
| | (0.0356) | (0.0356) | (0.0353) | (0.0352) | (0.0307) | (0.0306) | (0.0306) |
| Constant | 1746.1461*** | 1751.1406*** | 1764.1509*** | 1789.6308*** | 1773.4408*** | 1783.3500*** | 1791.0187*** |
| | (25.9416) | (26.6624) | (27.9308) | (28.8409) | (24.4794) | (25.4840) | (26.0585) |
| avg. temp. (week) | 29.9149*** | 29.4027*** | 29.4949*** | 29.1337*** | 41.6409*** | 41.4505*** | 41.3903*** |
| | (6.1251) | (6.1195) | (6.0880) | (6.0649) | (6.0705) | (6.0528) | (6.0514) |
| avg. temp. $^2$ (week) | -1.0599*** | -1.0315*** | -1.0419*** | -1.0302*** | -1.7472*** | -1.7414*** | -1.7401*** |
| | (0.2898) | (0.2895) | (0.2879) | (0.2874) | (0.2846) | (0.2836) | (0.2837) |
| avg. temp. $^3$ (week) | 0.0135** | 0.0131** | 0.0132** | 0.0131** | 0.0236*** | 0.0236*** | 0.0236*** |
| | (0.0045) | (0.0045) | (0.0045) | (0.0045) | (0.0043) | (0.0043) | (0.0043) |
| Constant | 1630.7114*** | 1639.4680*** | 1651.2618*** | 1677.5630*** | 1567.0153*** | 1577.5555*** | 1585.2121*** |
| | (43.9950) | (45.0063) | (45.4514) | (45.0741) | (44.5621) | (45.2659) | (45.1992) |
| hdd (week) | 0.0821 | 0.0893 | 0.0827 | 0.0849 | 0.0342 | 0.0274 | 0.0287 |
| | (0.1534) | (0.1566) | (0.1543) | (0.1543) | (0.1332) | (0.1315) | (0.1314) |
| hdd $^2$ (week) | -0.0004 | -0.0004 | -0.0004 | -0.0004 | -0.0003 | -0.0003 | -0.0003 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0002) | (0.0002) | (0.0002) |
| Constant | 1898.4834*** | 1911.6962*** | 1925.0029*** | 1949.6282*** | 1882.9311*** | 1891.9106*** | 1899.3968*** |
| | (19.8107) | (20.1380) | (21.2982) | (22.5587) | (20.1680) | (21.1141) | (21.9230) |
| hdd (week) | 0.3153 | 0.3325 | 0.3189 | 0.3201 | 0.1947 | 0.1813 | 0.1821 |
| | (0.2042) | (0.2057) | (0.2048) | (0.2038) | (0.1839) | (0.1834) | (0.1829) |
| hdd $^2$ (week) | -0.0020* | -0.0020* | -0.0020* | -0.0020* | -0.0014 | -0.0013 | -0.0013 |
| | (0.0009) | (0.0009) | (0.0009) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| hdd $^3$ (week) | 0.0000* | 0.0000* | 0.0000* | 0.0000* | 0.0000 | 0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 1898.4745*** | 1911.6516*** | 1924.9266*** | 1949.5434*** | 1882.8307*** | 1891.7961*** | 1899.2775*** |
| | (19.8001) | (20.1232) | (21.2810) | (22.5424) | (20.1432) | (21.0882) | (21.8995) |
| heat index (week) | -2.7360** | -2.8044** | -2.5823** | -2.8102** | -3.7740*** | -3.5364*** | -3.6796*** |
| | (1.0023) | (0.9913) | (0.9909) | (0.9905) | (1.0503) | (1.0531) | (1.0517) |
| heat index $^2$ (week) | 0.0359 | 0.0372 | 0.0328 | 0.0373 | 0.0495* | 0.0450* | 0.0477* |
| | (0.0202) | (0.0200) | (0.0200) | (0.0200) | (0.0199) | (0.0200) | (0.0199) |
| Constant | 1942.3687*** | 1957.0414*** | 1967.6470*** | 1995.2019*** | 1945.4497*** | 1951.2847*** | 1960.9652*** |
| | (25.8132) | (25.9204) | (26.5807) | (27.7040) | (26.8666) | (27.2468) | (28.0147) |
| heat index (week) | 1.3381 | 0.7402 | 1.5374 | 0.7832 | -0.7025 | 0.0596 | -0.3382 |
| | (1.7468) | (1.7386) | (1.7828) | (1.7538) | (1.6633) | (1.7171) | (1.6893) |
| heat index $^2$ (week) | -0.1259 | -0.1037 | -0.1309 | -0.1055 | -0.0727 | -0.0980 | -0.0851 |
| | (0.0701) | (0.0695) | (0.0709) | (0.0701) | (0.0662) | (0.0678) | (0.0670) |
| heat index $^3$ (week) | 0.0020* | 0.0017 | 0.0020* | 0.0018 | 0.0015 | 0.0018* | 0.0016 |
| | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) |
| Constant | 1910.4769*** | 1929.2977*** | 1935.5894*** | 1966.9100*** | 1921.4168*** | 1923.2755*** | 1934.6881*** |
| | (22.6865) | (22.6631) | (22.9084) | (23.7324) | (23.4347) | (23.5318) | (24.1509) |
| avg. precip (week) | 3.9597*** | 3.8106*** | 3.7607*** | 3.7647*** | 4.3327*** | 4.2653*** | 4.3115*** |
| | (0.8620) | (0.8440) | (0.8408) | (0.8429) | (0.7499) | (0.7493) | (0.7493) |
| avg. precip $^2$ (week) | -0.2804*** | -0.2739*** | -0.2692*** | -0.2707*** | -0.2867*** | -0.2819*** | -0.2841*** |
| | (0.0487) | (0.0481) | (0.0478) | (0.0475) | (0.0460) | (0.0459) | (0.0457) |
| Constant | 1895.9606*** | 1909.4455*** | 1922.4307*** | 1947.2887*** | 1879.4730*** | 1888.1166*** | 1896.2206*** |
| | (19.7823) | (20.1855) | (21.3809) | (22.6644) | (20.1430) | (21.1238) | (21.9338) |
| avg. precip (week) | 8.0098*** | 7.8016*** | 7.6032*** | 7.5909*** | 8.2332*** | 8.0500*** | 8.1162*** |
| | (1.0072) | (0.9994) | (1.0134) | (1.0073) | (0.9495) | (0.9604) | (0.9542) |
| avg. precip $^2$ (week) | -0.8359*** | -0.8219*** | -0.7968*** | -0.7960*** | -0.8583*** | -0.8363*** | -0.8414*** |
| | (0.0914) | (0.0920) | (0.0935) | (0.0925) | (0.0923) | (0.0935) | (0.0927) |
| avg. precip $^3$ (week) | 0.0155*** | 0.0153*** | 0.0147*** | 0.0147*** | 0.0163*** | 0.0158*** | 0.0159*** |
| | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| Constant | 1894.1646*** | 1907.6159*** | 1920.2706*** | 1945.0605*** | 1877.7794*** | 1886.1209*** | 1894.3787*** |
| | (19.7981) | (20.1970) | (21.4012) | (22.7199) | (20.1289) | (21.1166) | (21.9417) |
| tot. precip (week) | 0.5409*** | 0.5196*** | 0.5125*** | 0.5130*** | 0.6012*** | 0.5916*** | 0.5981*** |
| | (0.1220) | (0.1195) | (0.1191) | (0.1194) | (0.1064) | (0.1064) | (0.1063) |
| tot. precip. $^2$ (week) | -0.0056*** | -0.0054*** | -0.0053*** | -0.0054*** | -0.0057*** | -0.0056*** | -0.0057*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0009) | (0.0009) | (0.0009) |
| Constant | 1896.1458*** | 1909.5847*** | 1922.5743*** | 1947.4317*** | 1879.5938*** | 1888.2456*** | 1896.3249*** |
| | (19.7865) | (20.1888) | (21.3845) | (22.6690) | (20.1467) | (21.1277) | (21.9383) |
| tot. precip (week) | 1.1062*** | 1.0766*** | 1.0483*** | 1.0464*** | 1.1496*** | 1.1234*** | 1.1328*** |
| | (0.1431) | (0.1420) | (0.1440) | (0.1432) | (0.1352) | (0.1368) | (0.1359) |
| tot. precip. $^2$ (week) | -0.0167*** | -0.0164*** | -0.0159*** | -0.0158*** | -0.0172*** | -0.0168*** | -0.0169*** |
| | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) |
| tot. precip. $^3$ (week) | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Constant | 1894.3914*** | 1907.7991*** | 1920.4678*** | 1945.2579*** | 1877.9272*** | 1886.2832*** | 1894.5131*** |
| | (19.8025) | (20.2010) | (21.4057) | (22.7252) | (20.1336) | (21.1217) | (21.9475) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

# G Alternative Fixed Effect Specification – Weather Bins

## G.1 Individual Fixed Effects Regressions

Table 26: Individual Fixed Effect Regression Wages - Temperature

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 temp. | -0.0001 | -0.0001 | -0.0001 | -0.0002 | -0.0007 | -0.0007 | -0.0007 |
| (week) | (0.0009) | (0.0008) | (0.0008) | (0.0009) | (0.0008) | (0.0008) | (0.0009) |
| 10-12 temp. | 0.0012 | 0.0013 | 0.0013 | 0.0011 | 0.0004 | 0.0004 | 0.0004 |
| (week) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| 12-14 temp. | 0.0001 | 0.0001 | 0.0001 | 0.0001 | -0.0007 | -0.0007 | -0.0007 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 14-16 temp. | 0.0004 | 0.0004 | 0.0004 | 0.0003 | -0.0004 | -0.0004 | -0.0004 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 16-18 temp. | 0.0007 | 0.0007 | 0.0007 | 0.0007 | 0.0002 | 0.0002 | 0.0002 |
| (week) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| 18-20 temp. | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0000 | 0.0000 | 0.0001 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 22-24 temp. | 0.0010 | 0.0009 | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0011 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 24-26 temp. | 0.0008 | 0.0008 | 0.0008 | 0.0008 | 0.0009* | 0.0009* | 0.0010* |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 26-28 temp. | 0.0007 | 0.0007 | 0.0007 | 0.0007 | 0.0010* | 0.0010* | 0.0010* |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0004) | (0.0004) | (0.0004) |
| 28-30 temp. | 0.0006 | 0.0006 | 0.0006 | 0.0007 | 0.0014** | 0.0014** | 0.0014** |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 30-32 temp. | 0.0006 | 0.0006 | 0.0006 | 0.0006 | 0.0015* | 0.0015* | 0.0015* |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 32-34 temp. | 0.0016 | 0.0017* | 0.0017* | 0.0017* | 0.0025** | 0.0025** | 0.0026*** |
| (week) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| >34 | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0012 | 0.0012 | 0.0012 |
| temp. (week) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Constant | 8.2341*** | 8.1990*** | 8.2046*** | 8.1832*** | 8.2037*** | 8.1983*** | 8.1865*** |
| | (0.0038) | (0.0090) | (0.0108) | (0.0112) | (0.0092) | (0.0114) | (0.0115) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

## G.2 Municipality Fixed Effects Regressions

Table 27: Individual Fixed Effect Regression Wages - Heat Index

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 HI | 0.0010 | 0.0014 | 0.0015 | 0.0007 | -0.0007 | -0.0007 | -0.0009 |
| (week) | (0.0018) | (0.0017) | (0.0017) | (0.0018) | (0.0017) | (0.0018) | (0.0018) |
| 10-12 HI (week) | -0.0001 | 0.0001 | 0.0001 | 0.0002 | -0.0014 | -0.0014 | -0.0018 |
| | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| 12-14 HI (week) | -0.0020 | -0.0022 | -0.0021 | -0.0021 | -0.0035** | -0.0035** | -0.0036** |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| 14-16 HI (week) | 0.0001 | 0.0001 | 0.0001 | 0.0001 | -0.0006 | -0.0006 | -0.0006 |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| 16-18 HI (week) | 0.0011* | 0.0011* | 0.0011* | 0.0011* | 0.0003 | 0.0003 | 0.0004 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 18-20 HI (week) | 0.0003 | 0.0003 | 0.0003 | 0.0004 | 0.0001 | 0.0001 | 0.0002 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 22-24 HI (week) | 0.0015* | 0.0014* | 0.0014* | 0.0015* | 0.0014* | 0.0014* | 0.0015* |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 24-26 HI (week) | 0.0011* | 0.0011* | 0.0011* | 0.0011* | 0.0014** | 0.0014** | 0.0014** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 26-28 HI (week) | 0.0006 | 0.0007 | 0.0006 | 0.0006 | 0.0005 | 0.0005 | 0.0006 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0006) | (0.0005) | (0.0005) |
| 28-30 HI (week) | 0.0011 | 0.0011 | 0.0011 | 0.0011 | 0.0008 | 0.0008 | 0.0008 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 30-32 HI (week) | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0007 | 0.0007 | 0.0008 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 32-34 HI (week) | 0.0007 | 0.0008 | 0.0008 | 0.0008 | 0.0008 | 0.0008 | 0.0009 |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| >34 | 0.0008* | 0.0009* | 0.0008* | 0.0008* | 0.0014*** | 0.0014*** | 0.0014** |
| HI (week) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Constant | 8.2328*** | 8.1978*** | 8.2030*** | 8.1815*** | 8.2034*** | 8.1977*** | 8.1858*** |
| | (0.0039) | (0.0091) | (0.0108) | (0.0112) | (0.0091) | (0.0113) | (0.0115) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Table 28: Individual Fixed Effect Regression Wages - Precipitation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| = 0 precip. | 0.0017* | 0.0017* | 0.0017* | 0.0016* | -0.0008 | -0.0008 | -0.0006 |
| (week) | (0.0007) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 0-2 precip | 0.0013 | 0.0014* | 0.0014* | 0.0014* | -0.0003 | -0.0003 | -0.0002 |
| (week) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| 4-6 precip | -0.0006 | -0.0006 | -0.0006 | -0.0006 | -0.0011 | -0.0011 | -0.0010 |
| (week) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| 6-8 precip | 0.0014 | 0.0013 | 0.0013 | 0.0013 | 0.0008 | 0.0008 | 0.0009 |
| (week) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) |
| 8-10 precip | -0.0021 | -0.0020 | -0.0020 | -0.0021 | -0.0022 | -0.0022 | -0.0022 |
| (week) | (0.0016) | (0.0016) | (0.0016) | (0.0016) | (0.0016) | (0.0016) | (0.0016) |
| 10-20 precip. | -0.0007 | -0.0006 | -0.0006 | -0.0007 | -0.0011 | -0.0011 | -0.0010 |
| (week) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| 20-30 precip. | -0.0015 | -0.0015 | -0.0015 | -0.0015 | -0.0020 | -0.0020 | -0.0018 |
| (week) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) |
| >30 | -0.0019 | -0.0018 | -0.0018 | -0.0016 | -0.0033 | -0.0033 | -0.0031 |
| precip. (week) | (0.0017) | (0.0017) | (0.0017) | (0.0017) | (0.0018) | (0.0018) | (0.0018) |
| Constant | 8.2293*** | 8.1940*** | 8.1991*** | 8.1779*** | 8.2118*** | 8.2064*** | 8.1941*** |
| | (0.0058) | (0.0095) | (0.0112) | (0.0117) | (0.0089) | (0.0113) | (0.0114) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Table 29: Individual Fixed Effect Regression Working Time - Temperature

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 temp. | -20.905*** | -20.926*** | -20.883*** | -20.826*** | -18.021*** | -17.999*** | -17.994*** |
| (week) | (2.683) | (2.641) | (2.647) | (2.646) | (2.527) | (2.525) | (2.525) |
| 10-12 temp. | -22.863*** | -22.732*** | -22.811*** | -22.744*** | -17.269*** | -17.262*** | -17.258*** |
| (week) | (2.569) | (2.530) | (2.547) | (2.545) | (2.566) | (2.565) | (2.564) |
| 12-14 temp. | -13.812*** | -13.749*** | -13.727*** | -13.720*** | -8.644*** | -8.648*** | -8.644*** |
| (week) | (1.725) | (1.718) | (1.725) | (1.726) | (1.833) | (1.833) | (1.833) |
| 14-16 temp. | -13.965*** | -14.060*** | -14.014*** | -13.989*** | -9.165*** | -9.158*** | -9.158*** |
| (week) | (1.970) | (1.976) | (1.976) | (1.972) | (1.965) | (1.964) | (1.964) |
| 16-18 temp. | -6.925*** | -6.994*** | -6.931*** | -6.919*** | -3.732* | -3.735* | -3.732* |
| (week) | (1.393) | (1.399) | (1.397) | (1.397) | (1.529) | (1.530) | (1.529) |
| 18-20 temp. | -8.822*** | -8.866*** | -8.838*** | -8.838*** | -7.421*** | -7.413*** | -7.408*** |
| (week) | (1.454) | (1.473) | (1.469) | (1.468) | (1.516) | (1.515) | (1.515) |
| 22-24 temp. | -6.445*** | -6.507*** | -6.486*** | -6.485*** | -8.428*** | -8.417*** | -8.409*** |
| (week) | (1.628) | (1.642) | (1.631) | (1.630) | (1.649) | (1.648) | (1.648) |
| 24-26 temp. | -6.721*** | -6.894*** | -6.844*** | -6.827*** | -8.708*** | -8.700*** | -8.698*** |
| (week) | (1.561) | (1.574) | (1.568) | (1.567) | (1.423) | (1.421) | (1.422) |
| 26-28 temp. | -3.538* | -3.560* | -3.543* | -3.541* | -6.376*** | -6.381*** | -6.379*** |
| (week) | (1.388) | (1.404) | (1.401) | (1.400) | (1.364) | (1.362) | (1.362) |
| 28-30 temp. | 0.167 | 0.160 | 0.190 | 0.177 | -4.424*** | -4.425*** | -4.423*** |
| (week) | (1.394) | (1.405) | (1.397) | (1.396) | (1.332) | (1.332) | (1.332) |
| 30-32 temp. | -1.498 | -1.700 | -1.720 | -1.722 | -8.464*** | -8.468*** | -8.472*** |
| (week) | (1.703) | (1.711) | (1.710) | (1.711) | (1.612) | (1.612) | (1.612) |
| 32-34 temp. | 0.012 | -0.089 | -0.059 | -0.049 | -7.381*** | -7.369*** | -7.364*** |
| (week) | (1.980) | (1.978) | (1.972) | (1.971) | (1.841) | (1.840) | (1.839) |
| >34 | -0.257 | -0.334 | -0.318 | -0.319 | -6.624* | -6.624* | -6.622* |
| temp. (week) | (3.925) | (3.931) | (3.922) | (3.919) | (3.160) | (3.160) | (3.160) |
| Constant | 2558.758*** | 2563.040*** | 2600.865*** | 2611.562*** | 2493.334*** | 2511.349*** | 2508.402*** |
| | (8.408) | (13.040) | (14.621) | (15.310) | (13.439) | (16.451) | (17.036) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Table 30: Individual Fixed Effect Regression Working Time - Heat Index

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 HI | -23.134*** | -24.628*** | -24.000*** | -23.522*** | -24.182*** | -24.053*** | -24.101*** |
| (week) | (5.841) | (5.880) | (5.827) | (5.812) | (5.938) | (5.937) | (5.940) |
| 10-12 HI (week) | -13.022 | -12.635 | -12.352 | -12.408 | -16.381 | -16.291 | -16.359 |
| | (8.845) | (8.844) | (8.840) | (8.810) | (9.191) | (9.190) | (9.203) |
| 12-14 HI (week) | -10.745*** | -10.990*** | -10.728*** | -10.733*** | -8.414** | -8.417** | -8.436** |
| | (2.552) | (2.589) | (2.590) | (2.590) | (2.874) | (2.872) | (2.868) |
| 14-16 HI (week) | -9.699*** | -9.853*** | -9.710*** | -9.724*** | -6.782* | -6.786* | -6.790* |
| | (2.750) | (2.779) | (2.767) | (2.767) | (2.682) | (2.682) | (2.682) |
| 16-18 HI (week) | -4.971*** | -5.077*** | -5.029*** | -5.029*** | -4.218** | -4.212** | -4.201** |
| | (1.340) | (1.350) | (1.347) | (1.345) | (1.481) | (1.481) | (1.479) |
| 18-20 HI (week) | -9.810*** | -9.846*** | -9.807*** | -9.832*** | -9.595*** | -9.592*** | -9.579*** |
| | (1.835) | (1.838) | (1.842) | (1.843) | (1.874) | (1.875) | (1.874) |
| 22-24 HI (week) | -7.939*** | -7.928*** | -7.939*** | -7.951*** | -8.826*** | -8.819*** | -8.805*** |
| | (1.998) | (2.015) | (2.010) | (2.008) | (2.065) | (2.065) | (2.063) |
| 24-26 HI (week) | -7.835*** | -8.002*** | -7.942*** | -7.936*** | -8.967*** | -8.966*** | -8.967*** |
| | (1.439) | (1.443) | (1.437) | (1.436) | (1.437) | (1.437) | (1.437) |
| 26-28 HI (week) | -9.554*** | -9.560*** | -9.567*** | -9.555*** | -10.715*** | -10.721*** | -10.700*** |
| | (1.649) | (1.650) | (1.652) | (1.655) | (1.785) | (1.784) | (1.786) |
| 28-30 HI (week) | -6.884*** | -6.898*** | -6.930*** | -6.916*** | -6.279** | -6.279** | -6.275** |
| | (2.011) | (2.012) | (2.012) | (2.010) | (1.961) | (1.961) | (1.961) |
| 30-32 HI (week) | -11.017*** | -11.090*** | -11.085*** | -11.092*** | -11.243*** | -11.249*** | -11.230*** |
| | (1.753) | (1.760) | (1.757) | (1.759) | (1.734) | (1.734) | (1.733) |
| 32-34 HI (week) | -8.590*** | -8.478*** | -8.471*** | -8.481*** | -8.012*** | -7.996*** | -7.972*** |
| | (2.320) | (2.325) | (2.333) | (2.331) | (2.294) | (2.294) | (2.291) |
| >34 | -8.780*** | -8.794*** | -8.838*** | -8.834*** | -9.900*** | -9.930*** | -9.947*** |
| HI (week) | (1.680) | (1.683) | (1.682) | (1.682) | (1.552) | (1.554) | (1.555) |
| Constant | 2552.037*** | 2557.441*** | 2593.206*** | 2606.649*** | 2498.184*** | 2517.862*** | 2514.578*** |
| | (10.273) | (12.495) | (14.332) | (14.912) | (12.479) | (15.516) | (16.034) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.486 | 0.486 | 0.486 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Table 31: Individual Fixed Effect Regression Working Time - Precipitation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| = 0 precip. | -25.836*** | -26.139*** | -26.138*** | -26.094*** | -23.620*** | -23.614*** | -23.596*** |
| (week) | (2.455) | (2.470) | (2.470) | (2.469) | (2.491) | (2.491) | (2.491) |
| 0-2 precip | -24.373*** | -24.380*** | -24.417*** | -24.425*** | -23.847*** | -23.862*** | -23.855*** |
| (week) | (2.303) | (2.299) | (2.298) | (2.296) | (2.487) | (2.487) | (2.487) |
| 4-6 precip | -26.198*** | -26.451*** | -26.397*** | -26.379*** | -27.410*** | -27.402*** | -27.390*** |
| (week) | (3.297) | (3.296) | (3.299) | (3.294) | (3.472) | (3.472) | (3.473) |
| 6-8 precip | -20.517*** | -20.738*** | -20.724*** | -20.700*** | -21.815*** | -21.821*** | -21.814*** |
| (week) | (3.187) | (3.202) | (3.195) | (3.195) | (3.283) | (3.281) | (3.279) |
| 8-10 precip | -25.549*** | -25.709*** | -25.669*** | -25.623*** | -27.437*** | -27.422*** | -27.423*** |
| (week) | (3.792) | (3.801) | (3.807) | (3.802) | (3.805) | (3.808) | (3.811) |
| 10-20 precip. | -22.035*** | -22.210*** | -22.156*** | -22.096*** | -23.237*** | -23.223*** | -23.221*** |
| (week) | (2.810) | (2.796) | (2.799) | (2.802) | (2.923) | (2.925) | (2.925) |
| 20-30 precip. | -28.624*** | -28.790*** | -28.792*** | -28.782*** | -29.287*** | -29.291*** | -29.269*** |
| (week) | (3.974) | (3.968) | (3.978) | (3.980) | (4.006) | (4.005) | (4.005) |
| >30 | -42.149*** | -41.510*** | -41.577*** | -41.676*** | -38.681*** | -38.707*** | -38.680*** |
| precip. (week) | (5.080) | (5.059) | (5.043) | (5.051) | (5.004) | (5.008) | (5.003) |
| Constant | 2664.339*** | 2673.340*** | 2711.560*** | 2725.471*** | 2605.811*** | 2625.003*** | 2622.455*** |
| | (17.462) | (17.661) | (18.656) | (19.039) | (16.901) | (18.476) | (18.848) |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.486 | 0.486 | 0.486 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Table 32: Municipality Fixed Effect Regression Wages - Temperature

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 temp. | -0.0000 | -0.0000 | 0.0000 | -0.0003 | -0.0011 | -0.0010 | -0.0010 |
| (week) | (0.0007) | (0.0007) | (0.0007) | (0.0008) | (0.0007) | (0.0007) | (0.0007) |
| 10-12 temp. | 0.0010 | 0.0008 | 0.0008 | 0.0005 | -0.0005 | -0.0005 | -0.0005 |
| (week) | (0.0011) | (0.0010) | (0.0010) | (0.0011) | (0.0010) | (0.0010) | (0.0010) |
| 12-14 temp. | 0.0004 | 0.0001 | 0.0001 | 0.0001 | -0.0012 | -0.0011 | -0.0011 |
| (week) | (0.0008) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| 14-16 temp. | 0.0006 | 0.0004 | 0.0004 | 0.0005 | -0.0007 | -0.0007 | -0.0005 |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 16-18 temp. | 0.0005 | 0.0004 | 0.0004 | 0.0005 | -0.0003 | -0.0003 | -0.0002 |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 18-20 temp. | -0.0000 | -0.0003 | -0.0003 | -0.0000 | -0.0006 | -0.0006 | -0.0003 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 22-24 temp. | -0.0001 | -0.0002 | -0.0002 | -0.0002 | -0.0002 | -0.0002 | 0.0000 |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 24-26 temp. | -0.0004 | -0.0003 | -0.0003 | -0.0003 | -0.0002 | -0.0002 | -0.0001 |
| (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 26-28 temp. | 0.0001 | 0.0002 | 0.0002 | 0.0003 | 0.0004 | 0.0004 | 0.0007 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 28-30 temp. | -0.0004 | -0.0002 | -0.0003 | -0.0001 | 0.0008 | 0.0008 | 0.0009 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| 30-32 temp. | -0.0012 | -0.0010 | -0.0010 | -0.0011 | 0.0001 | 0.0001 | -0.0000 |
| (week) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 32-34 temp. | -0.0001 | 0.0005 | 0.0005 | 0.0002 | 0.0016 | 0.0016 | 0.0014 |
| (week) | (0.0010) | (0.0011) | (0.0011) | (0.0011) | (0.0010) | (0.0010) | (0.0010) |
| >34 | -0.0022** | -0.0020** | -0.0021** | -0.0020** | -0.0009 | -0.0009 | -0.0008 |
| temp. (week) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| Constant | 7.1059*** | 7.1942*** | 7.1961*** | 7.1287*** | 7.1990*** | 7.1998*** | 7.1485*** |
| | (0.0185) | (0.0205) | (0.0220) | (0.0220) | (0.0208) | (0.0219) | (0.0218) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 33: Municipality Fixed Effect Regression Wages - Heat Index

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\leq$ 10 HI | 0.0018 | 0.0019 | 0.0020 | 0.0021 | -0.0003 | -0.0003 | 0.0006 |
| (week) | (0.0021) | (0.0021) | (0.0021) | (0.0022) | (0.0020) | (0.0020) | (0.0021) |
| 10-12 HI (week) | 0.0008 | 0.0010 | 0.0010 | 0.0006 | -0.0009 | -0.0008 | -0.0013 |
| | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) | (0.0020) |
| 12-14 HI (week) | -0.0009 | -0.0015 | -0.0014 | -0.0013 | -0.0029** | -0.0029** | -0.0029** |
| | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| 14-16 HI (week) | 0.0010 | 0.0006 | 0.0006 | 0.0008 | -0.0000 | -0.0000 | -0.0000 |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| 16-18 HI (week) | 0.0008 | 0.0006 | 0.0006 | 0.0008 | -0.0002 | -0.0002 | 0.0001 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| 18-20 HI (week) | 0.0001 | -0.0002 | -0.0002 | 0.0002 | -0.0004 | -0.0004 | 0.0000 |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| 22-24 HI (week) | 0.0007 | 0.0005 | 0.0005 | 0.0006 | 0.0004 | 0.0004 | 0.0006 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 24-26 HI (week) | -0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0003 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| 26-28 HI (week) | 0.0003 | 0.0002 | 0.0002 | 0.0004 | -0.0003 | -0.0003 | 0.0002 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| 28-30 HI (week) | 0.0009 | 0.0010 | 0.0010 | 0.0009 | 0.0005 | 0.0005 | 0.0005 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| 30-32 HI (week) | -0.0000 | -0.0004 | -0.0004 | -0.0002 | -0.0007 | -0.0007 | -0.0003 |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| 32-34 HI (week) | 0.0011 | 0.0008 | 0.0008 | 0.0012 | 0.0008 | 0.0008 | 0.0013 |
| | (0.0009) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0009) |
| >34 | -0.0004 | 0.0001 | 0.0000 | -0.0004 | 0.0007 | 0.0007 | 0.0001 |
| HI (week) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Constant | 7.1047*** | 7.1926*** | 7.1944*** | 7.1265*** | 7.1978*** | 7.1986*** | 7.1472*** |
| | (0.0183) | (0.0203) | (0.0218) | (0.0218) | (0.0206) | (0.0218) | (0.0217) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 34: Municipality Fixed Effect Regression Wages - Precipitation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| = 0 precip. | 0.0013 | 0.0012 | 0.0012 | 0.0014 | -0.0011 | -0.0011 | -0.0004 |
| (week) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0006) | (0.0006) | (0.0006) |
| 0-2 precip | 0.0013 | 0.0014* | 0.0015* | 0.0016* | -0.0002 | -0.0002 | 0.0003 |
| (week) | (0.0007) | (0.0006) | (0.0007) | (0.0007) | (0.0006) | (0.0006) | (0.0006) |
| 4-6 precip | 0.0002 | -0.0003 | -0.0003 | 0.0001 | -0.0006 | -0.0006 | 0.0000 |
| (week) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) |
| 6-8 precip | 0.0012 | 0.0011 | 0.0011 | 0.0013 | 0.0007 | 0.0007 | 0.0013 |
| (week) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0013) | (0.0013) | (0.0014) |
| 8-10 precip | -0.0013 | -0.0010 | -0.0009 | -0.0011 | -0.0010 | -0.0010 | -0.0010 |
| (week) | (0.0015) | (0.0015) | (0.0015) | (0.0015) | (0.0015) | (0.0015) | (0.0015) |
| 10-20 precip. | -0.0002 | -0.0001 | -0.0001 | -0.0003 | -0.0003 | -0.0003 | -0.0002 |
| (week) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| 20-30 precip. | 0.0016 | 0.0007 | 0.0007 | 0.0017 | 0.0004 | 0.0005 | 0.0017 |
| (week) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) | (0.0018) |
| >30 | -0.0026 | -0.0027 | -0.0026 | -0.0017 | -0.0041 | -0.0040 | -0.0030 |
| precip. (week) | (0.0028) | (0.0029) | (0.0029) | (0.0028) | (0.0030) | (0.0030) | (0.0029) |
| Constant | 7.1000*** | 7.1862*** | 7.1878*** | 7.1199*** | 7.2024*** | 7.2032*** | 7.1489*** |
| | (0.0191) | (0.0211) | (0.0224) | (0.0227) | (0.0211) | (0.0220) | (0.0223) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 35: Municipality Fixed Effect Regression Working Time - Temperature

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| ≤ 10 temp. | -22.374*** | -22.321*** | -22.106*** | -21.990*** | -19.992*** | -19.833*** | -19.835*** |
| (week) | (2.549) | (2.573) | (2.551) | (2.535) | (2.489) | (2.474) | (2.471) |
| 10-12 temp. | -20.454*** | -20.515*** | -20.390*** | -20.285*** | -16.205*** | -16.129*** | -16.126*** |
| (week) | (2.294) | (2.293) | (2.299) | (2.289) | (2.311) | (2.310) | (2.309) |
| 12-14 temp. | -13.492*** | -13.529*** | -13.392*** | -13.355*** | -9.456*** | -9.399*** | -9.402*** |
| (week) | (1.634) | (1.650) | (1.653) | (1.646) | (1.692) | (1.691) | (1.686) |
| 14-16 temp. | -12.033*** | -12.106*** | -11.959*** | -11.963*** | -8.209*** | -8.127*** | -8.145*** |
| (week) | (1.618) | (1.631) | (1.632) | (1.626) | (1.639) | (1.636) | (1.635) |
| 16-18 temp. | -6.077*** | -6.128*** | -6.021*** | -6.043*** | -3.497** | -3.453** | -3.474** |
| (week) | (1.162) | (1.174) | (1.171) | (1.162) | (1.227) | (1.226) | (1.222) |
| 18-20 temp. | -8.954*** | -8.886*** | -8.855*** | -8.929*** | -7.689*** | -7.686*** | -7.726*** |
| (week) | (1.173) | (1.185) | (1.189) | (1.186) | (1.213) | (1.217) | (1.215) |
| 22-24 temp. | -7.990*** | -7.960*** | -7.979*** | -7.991*** | -9.816*** | -9.819*** | -9.846*** |
| (week) | (1.258) | (1.267) | (1.267) | (1.264) | (1.274) | (1.272) | (1.270) |
| 24-26 temp. | -7.111*** | -7.143*** | -7.165*** | -7.186*** | -9.160*** | -9.151*** | -9.176*** |
| (week) | (1.229) | (1.229) | (1.232) | (1.233) | (1.153) | (1.156) | (1.156) |
| 26-28 temp. | -2.918* | -2.735* | -2.828* | -2.874* | -5.706*** | -5.751*** | -5.782*** |
| (week) | (1.193) | (1.210) | (1.210) | (1.207) | (1.203) | (1.200) | (1.199) |
| 28-30 temp. | -1.333 | -1.185 | -1.307 | -1.366 | -5.192*** | -5.253*** | -5.268*** |
| (week) | (1.047) | (1.047) | (1.061) | (1.060) | (0.918) | (0.927) | (0.926) |
| 30-32 temp. | -1.452 | -1.345 | -1.566 | -1.522 | -7.300*** | -7.429*** | -7.414*** |
| (week) | (1.292) | (1.285) | (1.298) | (1.296) | (1.138) | (1.148) | (1.147) |
| 32-34 temp. | 1.020 | 0.958 | 0.822 | 0.929 | -5.593** | -5.625** | -5.593** |
| (week) | (1.884) | (1.868) | (1.863) | (1.851) | (1.733) | (1.728) | (1.723) |
| >34 | -2.169 | -2.005 | -2.177 | -2.199 | -7.715*** | -7.806*** | -7.821*** |
| temp. (week) | (2.776) | (2.780) | (2.768) | (2.771) | (2.111) | (2.108) | (2.107) |
| Constant | 1971.578*** | 1976.389*** | 1985.836*** | 2008.476*** | 1941.133*** | 1948.728*** | 1956.055*** |
| | (21.020) | (21.587) | (22.860) | (24.115) | (21.770) | (22.791) | (23.578) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 36: Municipality Fixed Effect Regression Working Time - Heat Index

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| ≤ 10 HI | -23.922*** | -23.472*** | -22.768*** | -22.748*** | -23.994*** | -23.529*** | -23.638*** |
| (week) | (4.764) | (4.760) | (4.771) | (4.756) | (4.773) | (4.794) | (4.798) |
| 10-12 HI (week) | -14.256 | -14.243 | -13.867 | -13.731 | -17.557* | -17.314* | -17.252* |
| | (7.857) | (7.767) | (7.814) | (7.829) | (8.057) | (8.094) | (8.109) |
| 12-14 HI (week) | -10.293*** | -10.536*** | -10.371*** | -10.413*** | -8.920*** | -8.888*** | -8.877*** |
| | (1.946) | (1.954) | (1.935) | (1.942) | (2.109) | (2.095) | (2.098) |
| 14-16 HI (week) | -8.646*** | -8.928*** | -8.752*** | -8.802*** | -6.532** | -6.439** | -6.430** |
| | (2.113) | (2.156) | (2.149) | (2.135) | (2.159) | (2.156) | (2.152) |
| 16-18 HI (week) | -4.528*** | -4.634*** | -4.498*** | -4.582*** | -4.169*** | -4.081*** | -4.123*** |
| | (1.105) | (1.121) | (1.117) | (1.108) | (1.155) | (1.151) | (1.147) |
| 18-20 HI (week) | -10.434*** | -10.426*** | -10.363*** | -10.482*** | -10.295*** | -10.262*** | -10.312*** |
| | (1.595) | (1.592) | (1.606) | (1.595) | (1.629) | (1.641) | (1.634) |
| 22-24 HI (week) | -9.653*** | -9.714*** | -9.678*** | -9.699*** | -10.584*** | -10.543*** | -10.568*** |
| | (1.660) | (1.673) | (1.672) | (1.664) | (1.723) | (1.721) | (1.716) |
| 24-26 HI (week) | -9.175*** | -9.166*** | -9.206*** | -9.226*** | -10.049*** | -10.091*** | -10.109*** |
| | (1.232) | (1.225) | (1.227) | (1.228) | (1.227) | (1.232) | (1.231) |
| 26-28 HI (week) | -7.976*** | -7.787*** | -7.760*** | -7.843*** | -9.388*** | -9.354*** | -9.424*** |
| | (1.322) | (1.339) | (1.335) | (1.327) | (1.401) | (1.396) | (1.393) |
| 28-30 HI (week) | -5.193*** | -5.302*** | -5.257*** | -5.232*** | -5.178** | -5.135** | -5.136** |
| | (1.573) | (1.584) | (1.589) | (1.579) | (1.581) | (1.585) | (1.580) |
| 30-32 HI (week) | -11.291*** | -11.279*** | -11.232*** | -11.290*** | -11.696*** | -11.665*** | -11.706*** |
| | (1.508) | (1.521) | (1.515) | (1.514) | (1.524) | (1.524) | (1.522) |
| 32-34 HI (week) | -9.414*** | -9.454*** | -9.292*** | -9.427*** | -9.180*** | -9.026*** | -9.092*** |
| | (2.018) | (2.028) | (2.029) | (2.024) | (1.982) | (1.985) | (1.978) |
| >34 | -9.524*** | -9.429*** | -9.635*** | -9.466*** | -10.038*** | -10.219*** | -10.143*** |
| HI (week) | (1.378) | (1.379) | (1.383) | (1.377) | (1.292) | (1.299) | (1.297) |
| Constant | 1961.824*** | 1974.630*** | 1987.407*** | 2011.244*** | 1948.675*** | 1957.582*** | 1964.634*** |
| | (22.170) | (22.597) | (23.871) | (24.839) | (22.776) | (23.790) | (24.351) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 37: Municipality Fixed Effect Regression Working Time - Precipitation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| = 0 precip. | -29.633*** | -29.365*** | -29.190*** | -29.217*** | -27.500*** | -27.343*** | -27.459*** |
| (week) | (2.192) | (2.189) | (2.193) | (2.194) | (2.210) | (2.213) | (2.210) |
| 0-2 precip | -27.363*** | -27.069*** | -26.912*** | -26.943*** | -26.584*** | -26.455*** | -26.534*** |
| (week) | (2.039) | (2.041) | (2.035) | (2.029) | (2.157) | (2.152) | (2.149) |
| 4-6 precip | -31.726*** | -31.710*** | -31.535*** | -31.649*** | -32.323*** | -32.201*** | -32.307*** |
| (week) | (2.943) | (2.940) | (2.943) | (2.937) | (3.038) | (3.042) | (3.039) |
| 6-8 precip | -24.365*** | -24.390*** | -24.325*** | -24.388*** | -25.133*** | -25.095*** | -25.175*** |
| (week) | (2.594) | (2.623) | (2.609) | (2.607) | (2.685) | (2.676) | (2.674) |
| 8-10 precip | -26.243*** | -26.551*** | -26.348*** | -26.274*** | -27.630*** | -27.479*** | -27.482*** |
| (week) | (3.332) | (3.370) | (3.370) | (3.347) | (3.370) | (3.373) | (3.361) |
| 10-20 precip. | -24.225*** | -24.358*** | -24.117*** | -24.000*** | -24.949*** | -24.775*** | -24.763*** |
| (week) | (2.223) | (2.238) | (2.255) | (2.243) | (2.325) | (2.342) | (2.337) |
| 20-30 precip. | -35.078*** | -34.542*** | -34.209*** | -34.541*** | -34.711*** | -34.446*** | -34.661*** |
| (week) | (3.430) | (3.422) | (3.422) | (3.416) | (3.444) | (3.441) | (3.438) |
| >30 | -47.561*** | -46.636*** | -46.266*** | -46.539*** | -44.342*** | -44.029*** | -44.181*** |
| precip. (week) | (3.949) | (3.976) | (3.954) | (3.948) | (3.908) | (3.890) | (3.879) |
| Constant | 2098.253*** | 2111.057*** | 2121.645*** | 2147.033*** | 2073.916*** | 2080.495*** | 2090.655*** |
| | (24.046) | (24.276) | (24.996) | (26.026) | (24.636) | (25.205) | (25.819) |
| Controls | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | No | No | No |
| Year fe | Yes | No | No | No | No | No | No |
| Year trend | No | Yes | Yes | Yes | No | No | No |
| Year trend$^2$ | No | No | Yes | Yes | No | No | No |
| Year trend$^3$ | No | No | No | Yes | No | No | No |
| Qtr trend | No | No | No | No | Yes | Yes | Yes |
| Qtr trend$^2$ | No | No | No | No | No | Yes | Yes |
| Qtr trend$^3$ | No | No | No | No | No | No | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

## G.3 Alternative Time Specification Simple Weather Variables

## G.4 Individual Fixed Effects Regressions

Table 38: Baseline Wage Regression - Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (month) | 0.0001 | | | | |
| | (0.0002) | | | | |
| avg. precip (month) | | -0.0018*** | | | |
| | | (0.0002) | | | |
| tot. precip (month) | | | -0.0001*** | | |
| | | | (0.0000) | | |
| hdd (month) | | | | -0.0000 | |
| | | | | (0.0000) | |
| heat index (month) | | | | | -0.0000 |
| | | | | | (0.0001) |
| Constant | 8.2347*** | 8.2414*** | 8.2414*** | 8.2376*** | 8.2379*** |
| | (0.0044) | (0.0036) | (0.0036) | (0.0035) | (0.0039) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.709 | 0.709 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Table 39: Baseline Wage Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (3 mths) | 0.0003 | | | | |
| | (0.0002) | | | | |
| avg. precip (3 mths) | | -0.0024*** | | | |
| | | (0.0003) | | | |
| tot. precip (3 mths) | | | -0.0000*** | | |
| | | | (0.0000) | | |
| hdd (3 mths) | | | | -0.0000 | |
| | | | | (0.0000) | |
| heat index (3 mths) | | | | | -0.0002 |
| | | | | | (0.0001) |
| Constant | 8.2311*** | 8.2460*** | 8.2460*** | 8.2376*** | 8.2431*** |
| | (0.0051) | (0.0039) | (0.0039) | (0.0035) | (0.0046) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.709 | 0.710 | 0.710 | 0.709 | 0.709 |
| N | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 | 6,131,012 |

Table 40: Baseline Working Time Regression - Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (month) | 4.988*** (0.759) | | | | |
| avg. precip (month) | | 1.238 (0.938) | | | |
| tot. precip (month) | | | 0.043 (0.033) | | |
| hdd (month) | | | | -0.047 (0.102) | |
| heat index (month) | | | | | -0.268 (0.390) |
| Constant | 2399.439*** (14.647) | 2494.601*** (4.034) | 2494.669*** (4.031) | 2497.480*** (4.067) | 2503.790*** (10.083) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

Table 41: Baseline Working Time Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (3 mths) | 4.612*** (0.751) | | | | |
| avg. precip (3 mths) | | -1.830* (0.852) | | | |
| tot. precip (3 mths) | | | -0.022* (0.010) | | |
| hdd (3 mths) | | | | -0.047 (0.102) | |
| heat index (3 mths) | | | | | 0.554 (0.395) |
| Constant | 2398.788*** (15.510) | 2503.805*** (4.312) | 2503.772*** (4.309) | 2497.480*** (4.067) | 2483.966*** (9.514) |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | ind. fe | ind. fe | ind. fe | ind. fe | ind. fe |
| Adjusted $R^2$ | 0.487 | 0.487 | 0.487 | 0.487 | 0.487 |
| N | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 | 7,964,917 |

## G.5 Municipality Fixed Effects Regressions

Table 42: Municipality FE Wage Regression - Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (month) | -0.0006** (0.0002) | | | | |
| avg. precip (month) | | -0.0012*** (0.0004) | | | |
| tot. precip (month) | | | -0.0000*** (0.0000) | | |
| hdd (month) | | | | -0.0000 (0.0000) | |
| heat index (month) | | | | | -0.0003** (0.0001) |
| Constant | 7.1190*** (0.0193) | 7.1101*** (0.0184) | 7.1101*** (0.0184) | 7.1074*** (0.0185) | 7.1151*** (0.0188) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

## G.6 Higher Polynomial Regressions

Table 43: Municipality FE Wage Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (3 mths) | -0.0005<br>(0.0003) | | | | |
| avg. precip (3 mths) | | -0.0017**<br>(0.0006) | | | |
| tot. precip (3 mths) | | | -0.0000**<br>(0.0000) | | |
| hdd (3 mths) | | | | -0.0000<br>(0.0000) | |
| heat index (3 mths) | | | | | -0.0006***<br>(0.0001) |
| Constant | 7.1186***<br>(0.0203) | 7.1133***<br>(0.0181) | 7.1132***<br>(0.0181) | 7.1074***<br>(0.0185) | 7.1224***<br>(0.0194) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 44: Municipality FE Working Time Regression - Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (month) | 4.354***<br>(0.585) | | | | |
| avg. precip (month) | | -0.346<br>(0.637) | | | |
| tot. precip (month) | | | -0.014<br>(0.023) | | |
| hdd (month) | | | | -0.076<br>(0.066) | |
| heat index (month) | | | | | -0.224<br>(0.298) |
| Constant | 1825.165***<br>(23.307) | 1908.604***<br>(19.599) | 1908.695***<br>(19.602) | 1907.807***<br>(19.809) | 1913.122***<br>(21.529) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 45: Municipality FE Working Time Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| avg. temp. (3 mths) | 3.624*** | | | | |
| | (0.556) | | | | |
| avg. precip (3 mths) | | -1.581* | | | |
| | | (0.683) | | | |
| tot. precip (3 mths) | | | -0.019* | | |
| | | | (0.008) | | |
| hdd (3 mths) | | | | -0.076 | |
| | | | | (0.066) | |
| heat index (3 mths) | | | | | 0.490 |
| | | | | | (0.304) |
| Constant | 1832.187*** | 1913.309*** | 1913.270*** | 1907.807*** | 1895.978*** |
| | (21.999) | (20.185) | (20.185) | (19.809) | (20.567) |
| Controls | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Table 46: Higher Polynomial Wage Regression - Month

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (month) | 0.0007 | 0.0003 | | | | | | | | |
| | (0.0007) | (0.0024) | | | | | | | | |
| avg. temp. $^2$ (month) | -0.0000* | -0.0000 | | | | | | | | |
| | (0.0000) | (0.0001) | | | | | | | | |
| avg. temp. $^3$ (month) | | -0.0000 | | | | | | | | |
| | | (0.0000) | | | | | | | | |
| avg. precip (month) | | | -0.0014* | -0.0030* | | | | | | |
| | | | (0.0006) | (0.0012) | | | | | | |
| avg. precip $^2$ (month) | | | 0.0000 | 0.0004 | | | | | | |
| | | | (0.0001) | (0.0002) | | | | | | |
| avg. precip $^3$ (month) | | | | -0.0000* | | | | | | |
| | | | | (0.0000) | | | | | | |
| tot. precip (month) | | | | | -0.0000* | -0.0001* | | | | |
| | | | | | (0.0000) | (0.0000) | | | | |
| tot. precip. $^2$ (month) | | | | | 0.0000 | 0.0000 | | | | |
| | | | | | (0.0000) | (0.0000) | | | | |
| tot. precip. $^3$ (month) | | | | | | -0.0000* | | | | |
| | | | | | | (0.0000) | | | | |
| hdd (month) | | | | | | | -0.0000 | -0.0001 | | |
| | | | | | | | (0.0001) | (0.0001) | | |
| hdd $^2$ (month) | | | | | | | 0.0000 | 0.0000* | | |
| | | | | | | | (0.0000) | (0.0000) | | |
| hdd $^3$ (month) | | | | | | | | -0.0000* | | |
| | | | | | | | | (0.0000) | | |
| heat index (month) | | | | | | | | | 0.0016 | 0.0014 |
| | | | | | | | | | (0.0009) | (0.0039) |
| heat index $^2$ (month) | | | | | | | | | -0.0000 | -0.0000 |
| | | | | | | | | | (0.0000) | (0.0001) |
| heat index $^3$ (month) | | | | | | | | | | -0.0000 |
| | | | | | | | | | | (0.0000) |
| Constant | 7.1054*** | 7.1081*** | 7.1103*** | 7.1112*** | 7.1102*** | 7.1111*** | 7.1074*** | 7.1074*** | 7.0887*** | 7.0906*** |
| | (0.0206) | (0.0269) | (0.0184) | (0.0183) | (0.0184) | (0.0183) | (0.0186) | (0.0186) | (0.0220) | (0.0439) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 47: Higher Polynomial Working Time Regression - Month

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (month) | 9.671*** | 6.166 | | | | | | | | |
| | (1.769) | (7.753) | | | | | | | | |
| avg. temp. $^2$ (month) | -0.120** | 0.049 | | | | | | | | |
| | (0.042) | (0.381) | | | | | | | | |
| avg. temp. $^3$ (month) | | -0.003 | | | | | | | | |
| | | (0.006) | | | | | | | | |
| avg. precip (month) | | | 8.560*** | 13.939*** | | | | | | |
| | | | (1.298) | (1.986) | | | | | | |
| avg. precip $^2$ (month) | | | -0.903*** | -2.154*** | | | | | | |
| | | | (0.119) | (0.353) | | | | | | |
| avg. precip $^3$ (month) | | | | 0.066*** | | | | | | |
| | | | | (0.017) | | | | | | |
| tot. precip (month) | | | | | 0.300*** | 0.487*** | | | | |
| | | | | | (0.046) | (0.070) | | | | |
| tot. precip. $^2$ (month) | | | | | -0.001*** | -0.003*** | | | | |
| | | | | | (0.000) | (0.000) | | | | |
| tot. precip. $^3$ (month) | | | | | | 0.000*** | | | | |
| | | | | | | (0.000) | | | | |
| hdd (month) | | | | | | | 0.079 | 0.309 | | |
| | | | | | | | (0.152) | (0.203) | | |
| hdd $^2$ (month) | | | | | | | -0.000 | -0.002* | | |
| | | | | | | | (0.000) | (0.001) | | |
| hdd $^3$ (month) | | | | | | | | 0.000* | | |
| | | | | | | | | (0.000) | | |
| heat index (month) | | | | | | | | | -3.130 | 6.892 |
| | | | | | | | | | (1.711) | (7.898) |
| heat index $^2$ (month) | | | | | | | | | 0.051 | -0.303 |
| | | | | | | | | | (0.032) | (0.290) |
| heat index $^3$ (month) | | | | | | | | | | 0.004 |
| | | | | | | | | | | (0.003) |
| Constant | 1769.829*** | 1792.466*** | 1900.327*** | 1897.287*** | 1900.522*** | 1897.568*** | 1907.835*** | 1907.824*** | 1952.150*** | 1861.455*** |
| | (28.338) | (50.720) | (19.703) | (19.713) | (19.705) | (19.714) | (19.802) | (19.791) | (35.320) | (67.616) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Standard errors are clustered at the municipality level. ***p<0.01, ** p<0.05, * p<0.10

Table 48: Higher Polynomial Wage Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (3 mths) | 0.0027** | -0.0010 | | | | | | | | |
| | (0.0009) | (0.0036) | | | | | | | | |
| avg. temp. $^2$ (3 mths) | -0.0001*** | 0.0001 | | | | | | | | |
| | (0.0000) | (0.0002) | | | | | | | | |
| avg. temp. $^3$ (3 mths) | | -0.0000 | | | | | | | | |
| | | (0.0000) | | | | | | | | |
| avg. precip (3 mths) | | | -0.0011 | 0.0002 | | | | | | |
| | | | (0.0011) | (0.0021) | | | | | | |
| avg. precip $^2$ (3 mths) | | | -0.0001 | -0.0004 | | | | | | |
| | | | (0.0001) | (0.0004) | | | | | | |
| avg. precip $^3$ (3 mths) | | | | 0.0000 | | | | | | |
| | | | | (0.0000) | | | | | | |
| tot. precip (3 mths) | | | | | -0.0000 | 0.0000 | | | | |
| | | | | | (0.0000) | (0.0000) | | | | |
| tot. precip. $^2$ (3 mths) | | | | | -0.0000 | -0.0000 | | | | |
| | | | | | (0.0000) | (0.0000) | | | | |
| tot. precip. $^3$ (3 mths) | | | | | | 0.0000 | | | | |
| | | | | | | (0.0000) | | | | |
| hdd (3 mths) | | | | | | | -0.0000 | -0.0001 | | |
| | | | | | | | (0.0001) | (0.0001) | | |
| hdd $^2$ (3 mths) | | | | | | | 0.0000 | 0.0000* | | |
| | | | | | | | (0.0000) | (0.0000) | | |
| hdd $^3$ (3 mths) | | | | | | | | -0.0000* | | |
| | | | | | | | | (0.0000) | | |
| heat index (3 mths) | | | | | | | | | 0.0021 | -0.0003 |
| | | | | | | | | | (0.0014) | (0.0054) |
| heat index $^2$ (3 mths) | | | | | | | | | -0.0000 | 0.0000 |
| | | | | | | | | | (0.0000) | (0.0002) |
| heat index $^3$ (3 mths) | | | | | | | | | | -0.0000 |
| | | | | | | | | | | (0.0000) |
| Constant | 7.0839*** | 7.1083*** | 7.1124*** | 7.1113*** | 7.1123*** | 7.1112*** | 7.1074*** | 7.1074*** | 7.0860*** | 7.1079*** |
| | (0.0225) | (0.0343) | (0.0179) | (0.0176) | (0.0179) | (0.0176) | (0.0186) | (0.0186) | (0.0259) | (0.0554) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 | 0.425 |
| N | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 | 5,950,093 |

Table 49: Higher Polynomial Working Time Regression - 3 Months

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| avg. temp. (3 mths) | 4.729* | -60.585*** | | | | | | | | |
| | (2.124) | (9.292) | | | | | | | | |
| avg. temp. $^2$ (3 mths) | -0.025 | 3.069*** | | | | | | | | |
| | (0.048) | (0.451) | | | | | | | | |
| avg. temp. $^3$ (3 mths) | | -0.046*** | | | | | | | | |
| | | (0.007) | | | | | | | | |
| avg. precip (3 mths) | | | 6.698*** | 8.694** | | | | | | |
| | | | (1.759) | (2.774) | | | | | | |
| avg. precip $^2$ (3 mths) | | | -0.950*** | -1.481** | | | | | | |
| | | | (0.189) | (0.552) | | | | | | |
| avg. precip $^3$ (3 mths) | | | | 0.034 | | | | | | |
| | | | | (0.030) | | | | | | |
| tot. precip (3 mths) | | | | | 0.080*** | 0.105** | | | | |
| | | | | | (0.021) | (0.033) | | | | |
| tot. precip. $^2$ (3 mths) | | | | | -0.000*** | -0.000** | | | | |
| | | | | | (0.000) | (0.000) | | | | |
| tot. precip. $^3$ (3 mths) | | | | | | 0.000 | | | | |
| | | | | | | (0.000) | | | | |
| hdd (3 mths) | | | | | | | 0.079 | 0.309 | | |
| | | | | | | | (0.152) | (0.203) | | |
| hdd $^2$ (3 mths) | | | | | | | -0.000 | -0.002* | | |
| | | | | | | | (0.000) | (0.001) | | |
| hdd $^3$ (3 mths) | | | | | | | | 0.000* | | |
| | | | | | | | | (0.000) | | |
| heat index (3 mths) | | | | | | | | | 0.970 | -17.110 |
| | | | | | | | | | (2.554) | (10.968) |
| heat index $^2$ (3 mths) | | | | | | | | | -0.009 | 0.637 |
| | | | | | | | | | (0.045) | (0.379) |
| heat index $^3$ (3 mths) | | | | | | | | | | -0.007 |
| | | | | | | | | | | (0.004) |
| Constant | 1820.357*** | 2255.304*** | 1900.817*** | 1899.099*** | 1900.705*** | 1898.915*** | 1907.835*** | 1907.824*** | 1889.565*** | 2052.508*** |
| | (32.013) | (65.414) | (19.563) | (19.369) | (19.560) | (19.370) | (19.802) | (19.791) | (42.111) | (105.596) |
| Controls | × | × | × | × | × | × | × | × | × | × |
| Sector fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Qtr fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fe | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ind./mun. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe | muind. fe |
| Adjusted $R^2$ | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 | 0.157 |
| N | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 | 7,642,920 |

Standard errors are clustered at the municipality level. ***p<0.01, ** p<0.05, * p<0.10

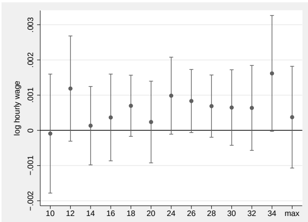
# H Bin Regressions - Alternative Time Definitions

## H.1 Individual Fixed Effects

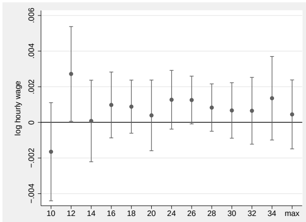
Figure H.1: Weather Bins Alternative Time Specification - Wage Regression

*Temperature*

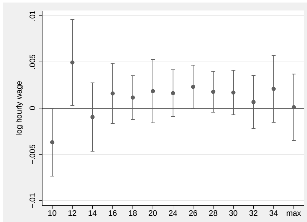
(a) Week




(b) Month

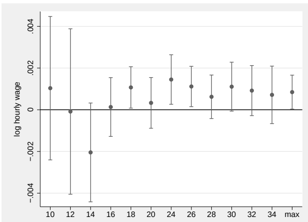



(c) 3 Months

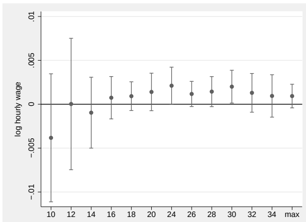



*Heat Index*

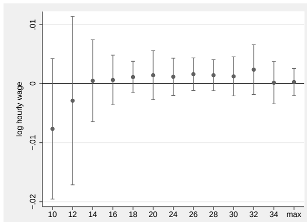
(d) Week




(e) Month

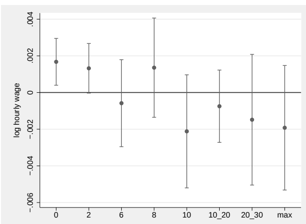



(f) 3 Months

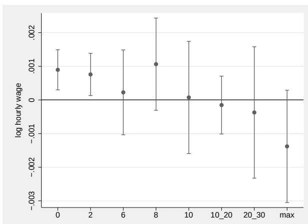



*Precipitation*

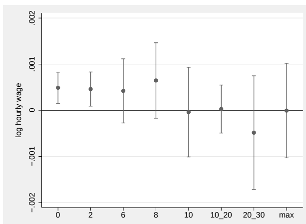
(g) Week




(h) Month




(i) 3 Months

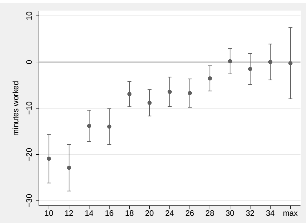



Note: Relationship between hourly wages and weather for all individuals. N=6,131,012 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on hourly wages based on equation 1 in the methodology section. Covariates include individual, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (4-6] *mm*.

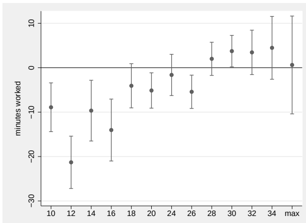
Figure H.2: Weather Bins Alternative Time Specification - Working Time Regression

*Temperature*

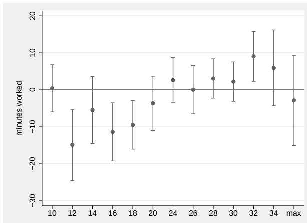
(a) Week




(b) Month

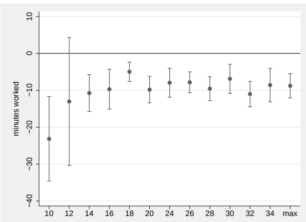



(c) 3 Months

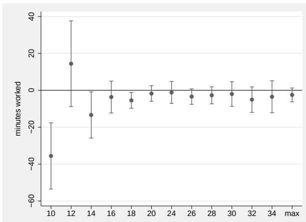



*Heat Index*

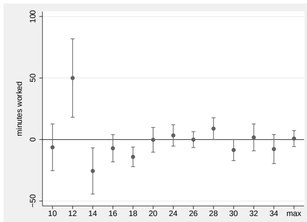
(d) Week




(e) Month

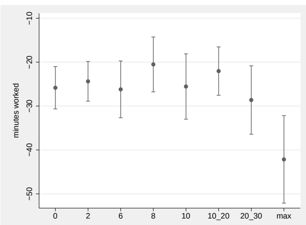



(f) 3 Months

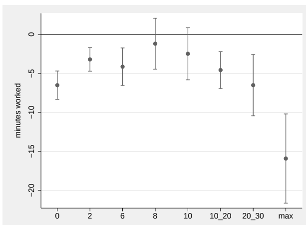



*Precipitation*

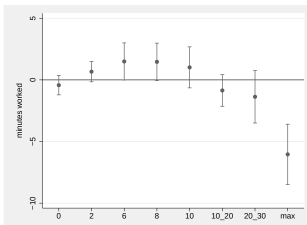
(g) Week




(h) Month




(i) 3 Months



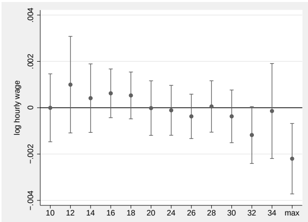

Note: Relationship between hourly wages and weather for all individuals. N=7,964,917 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on hourly wages based on equation 1 in the methodology section. Covariates include individual, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] $^{\circ}$C, for precipitation it is (4-6] *mm*.

## H.2 Municipality Fixed Effects

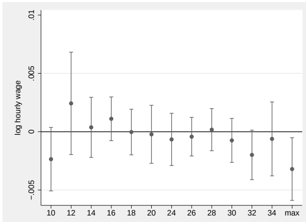
Figure H.3: Weather Bins Alternative Time Specification- Wage Regression

*Temperature*

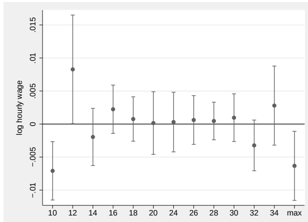
(a) Week




(b) Month

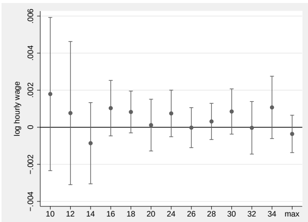



(c) 3 Months

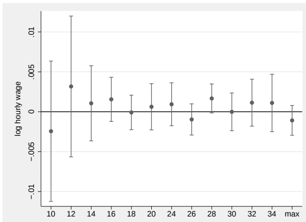



*Heat Index*

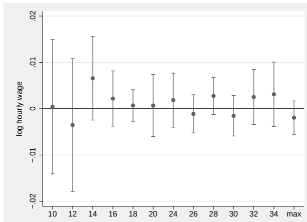
(d) Week




(e) Month

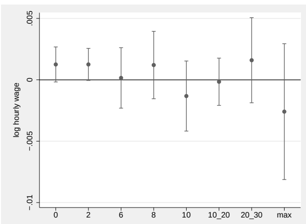



(f) 3 Months

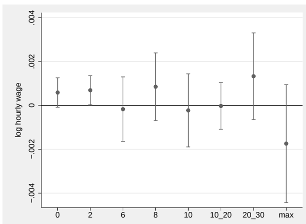



*Precipitation*

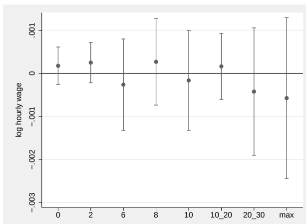
(g) Week




(h) Month




(i) 3 Months

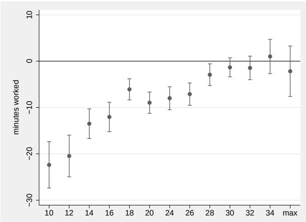



Note: Relationship between minutes worked and weather for all individuals. N=5,950,093 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly minutes worked based on equation 2 in the methodology section. Covariates include individual controls, and municipality, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (4-6] *mm*.

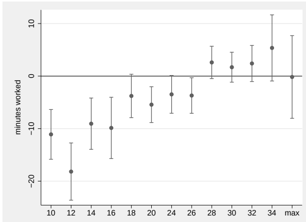
Figure H.4: Weather Bins Alternative Time Specification- Working Time Regression

*Temperature*

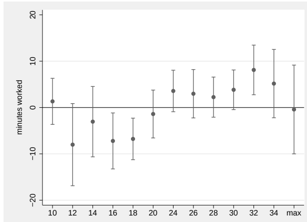
(a) Week




(b) Month

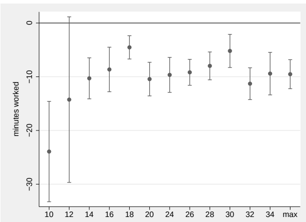



(c) 3 Months

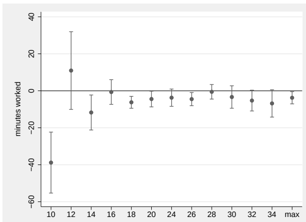



*Heat Index*

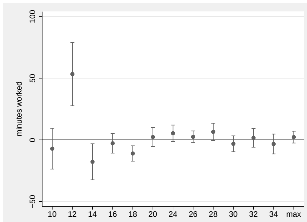
(d) Week




(e) Month

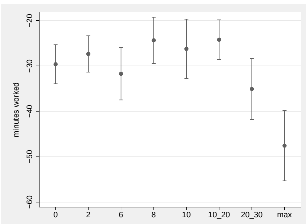



(f) 3 Months

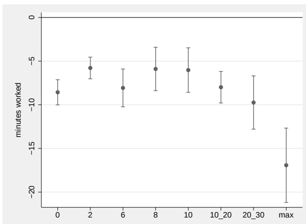



*Precipitation*

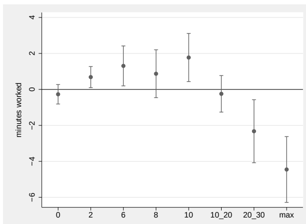
(g) Week




(h) Month




(i) 3 Months

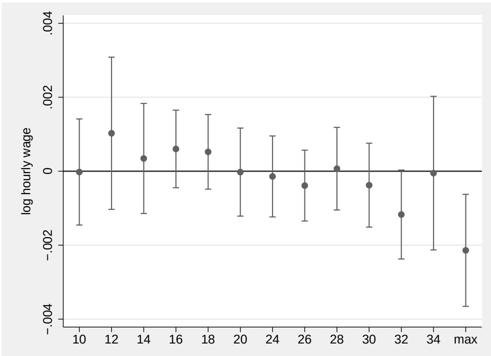



Note: Relationship between minutes worked and weather for all individuals. N=7,964,917 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly minutes worked based on equation 2 in the methodology section. Covariates include individual controls, and municipality, year and quarter fixed effects. The reference bin for temperature and the heat index is (20-22] °C, for precipitation it is (4-6] *mm*.

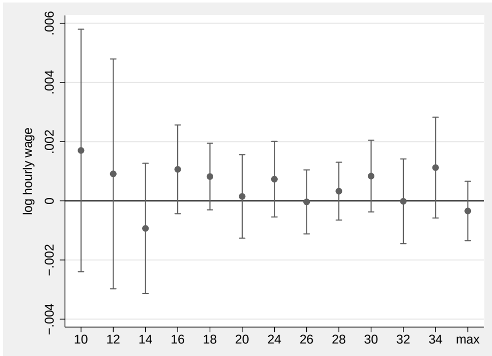
## H.3 Alternative Survey Completion Time

Figure H.5: Weather Bins Wage Regression - 7 Days Completion

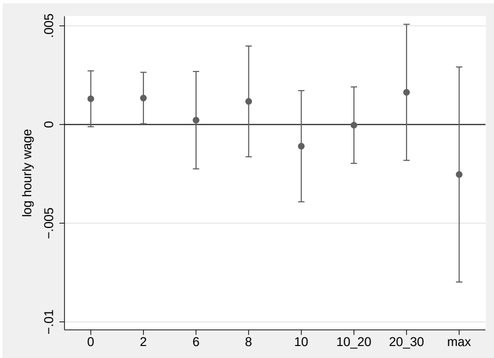
(a) Temperature




(b) Heat Index

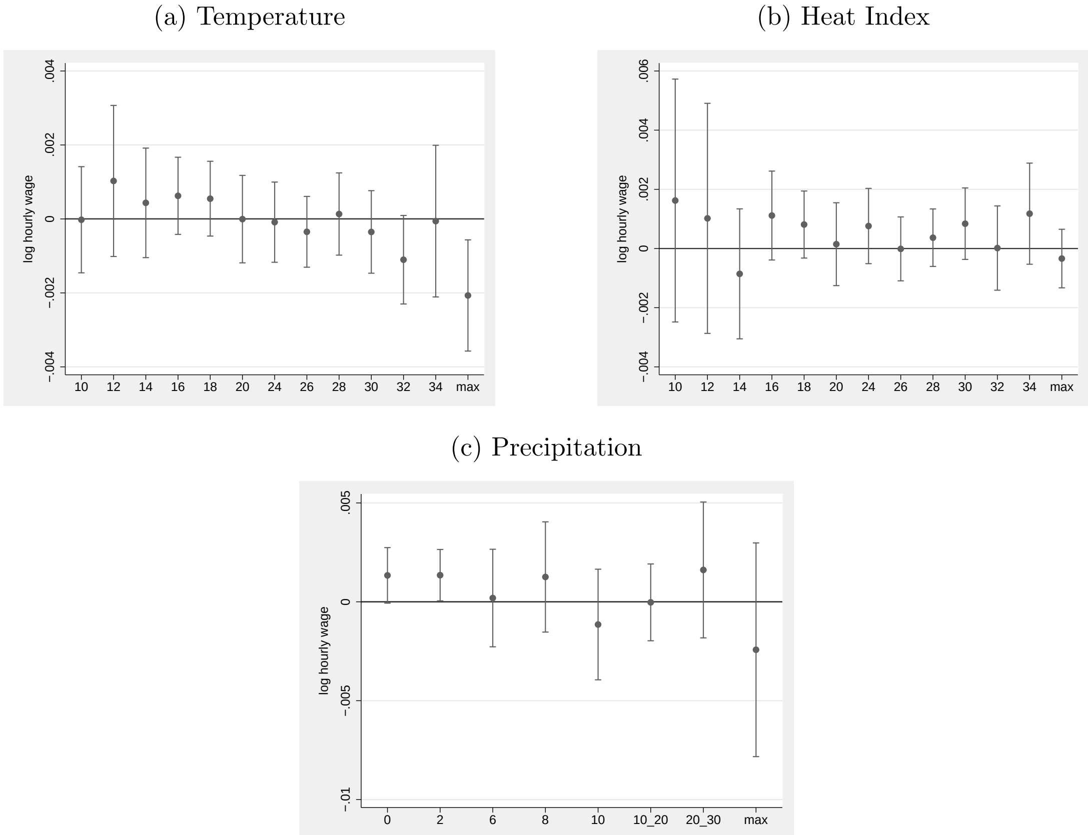



(c) Precipitation




Note: Relationship between log. hourly wages and weather for all individuals. N=5,994,768 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^\circ$C, for precipitation it is (2-4] $mm$.

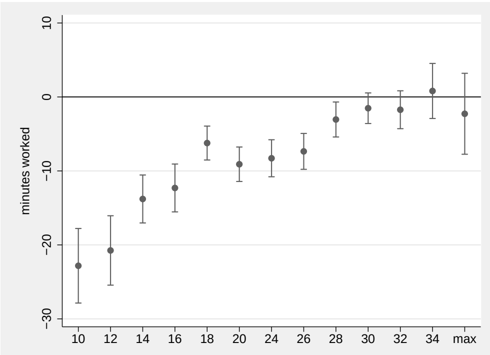
Figure H.6: Weather Bins Wage Regression - Anytime Completion



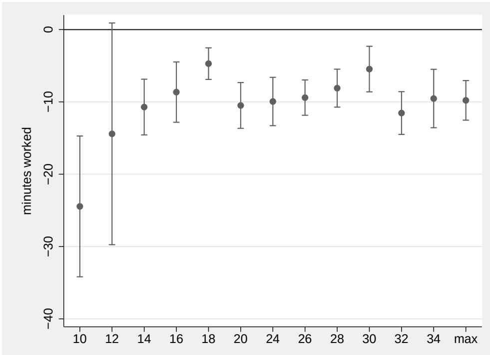

Note: Relationship between log. hourly wages and weather for all individuals. N=6,018,586 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^\circ$C, for precipitation it is (2-4] $mm$.

Figure H.7: Weather Bins Working Time Regression - 7 Days Completion

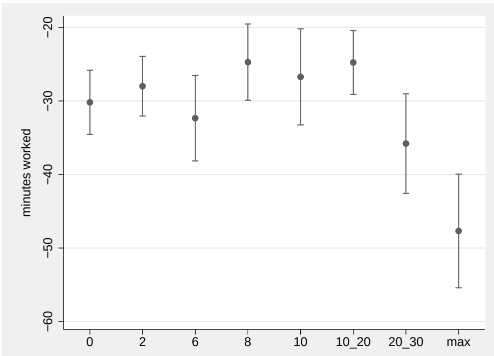
(a) Temperature




(b) Heat Index



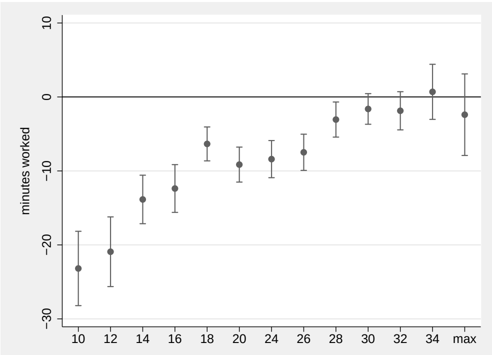

(c) Precipitation



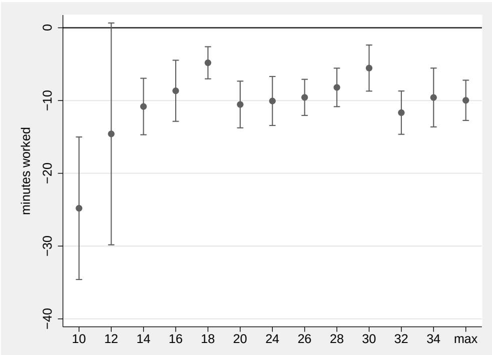

Note: Relationship between weekly working minutes and weather for all individuals. N=7,702,938 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] $mm$.

Figure H.8: Weather Bins Working Time Regression - Anytime Completion

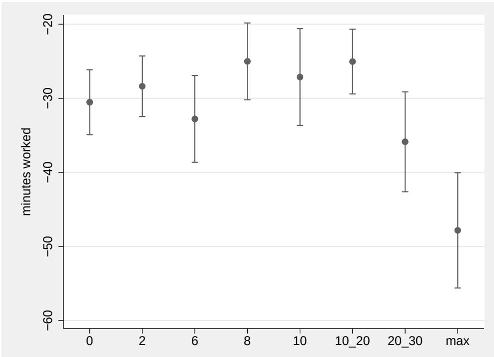
(a) Temperature




(b) Heat Index




(c) Precipitation



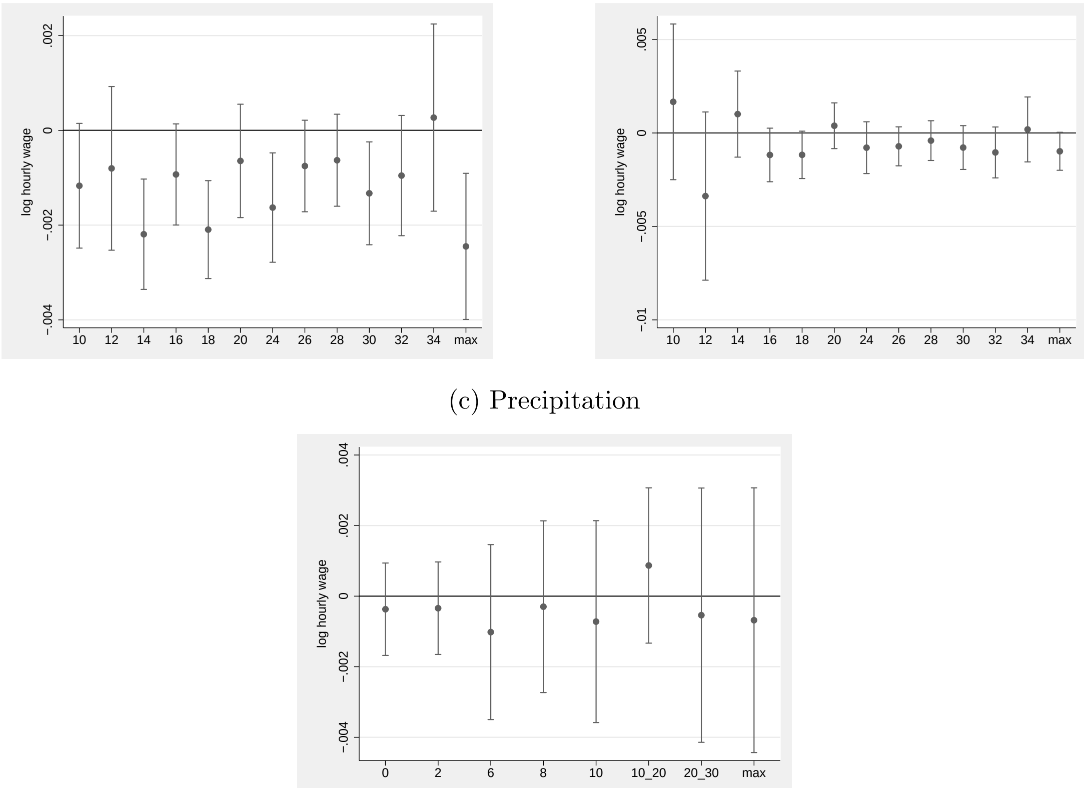

Note: Relationship between weekly working minutes and weather for all individuals. N=7,734,737 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*.

Figure H.9: Weather Bins Wage Regression - Placebo Weather

(a) Temperature

(b) Heat Index

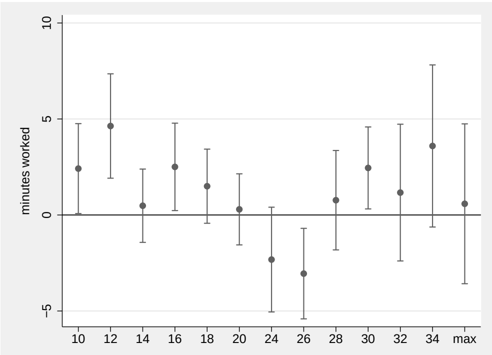
(c) Precipitation



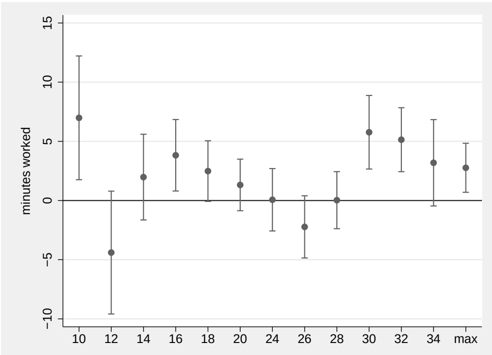

Note: Relationship between log. hourly wages and weather for all individuals. N=5,994,768 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*.

Figure H.10: Weather Bins Working Time Regression - Placebo Weather

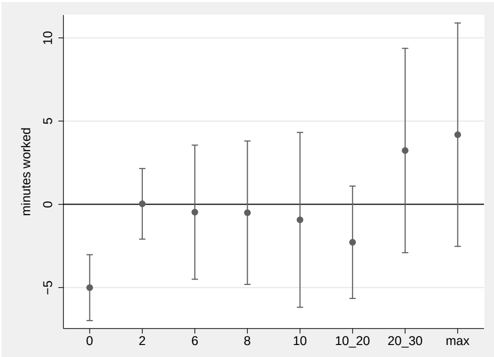
(a) Temperature




(b) Heat Index




(c) Precipitation

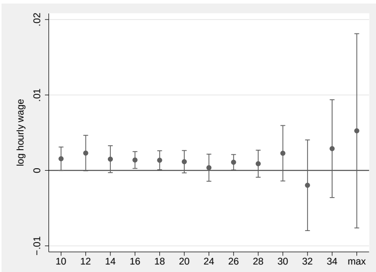



Note: Relationship between weekly working minutes and weather for all individuals. N=7,473,198 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] $^\circ$C, for precipitation it is (2-4] $mm$.

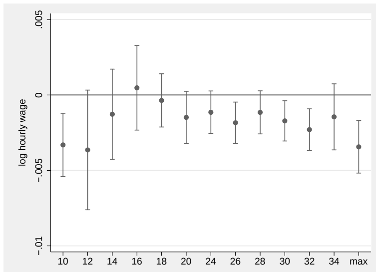
Figure H.11: Weather Bins Wage Regression - Warm vs Cold Municipality

*Temperature*

(a) Cold Region

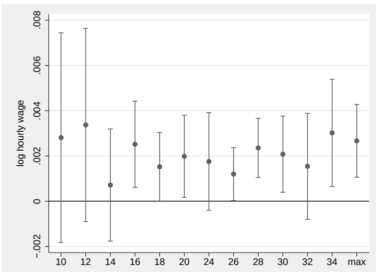



(b) Warm Region

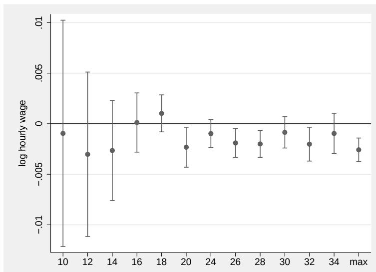



*Heat Index*

(c) Cold Region

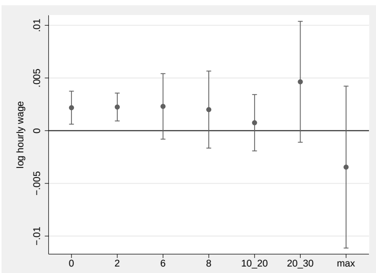



(d) Warm Region

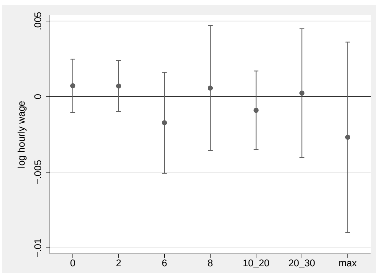



*Precipitation*

(e) Cold Region




(f) Hot Region

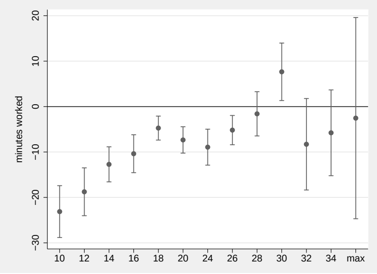



Note: Relationship between log. hourly wages and weather for all individuals. N=5,994,768 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*.

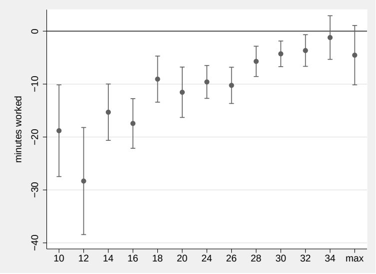
Figure H.12: Weather Bins Working Time Regression - Warm vs Cold Municipality

*Temperature*

(a) Cold Region

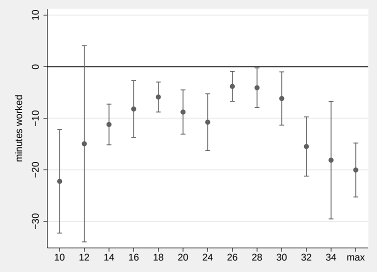


(b) Warm Region

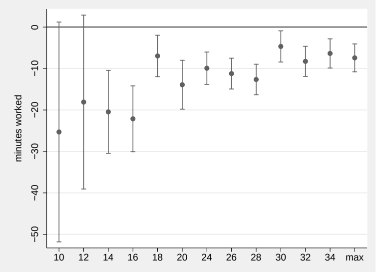


*Heat Index*

(c) Cold Region

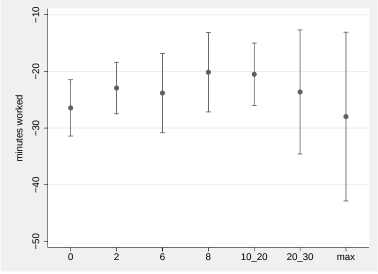


(d) Warm Region

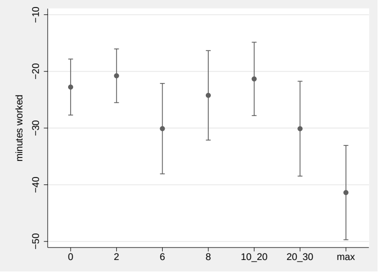


*Precipitation*

(e) Cold Region



(f) Warm region



Note: Relationship between weekly working minutes and weather for all individuals. N=5,994,768 in all regressions. The 95% confidence interval indicated by markers. Each figure displays the estimated impact of the weather variable on weekly working minutes based on equation 2 in the methodology section. Covariates include marital status, age, gender, education, rural, sector, informal employment, contract type, firm size, and municipality, year and quarter fixed effects. The reference bin for both temperature and the Heat Index is (20-22] °C, for precipitation it is (2-4] *mm*.