Do Typical Weather Shocks Disrupt U.S. Labor Markets?*

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Abstract

Not for most hourly workers. This short paper addresses a debate in the prior literature concerning the effect of typical (non-extreme) weather shocks on the U.S. labor market. In contrast to these prior studies, which rely on survey data of time-use, I leverage administrative records from a large payroll processor. I find that after accounting for long-run adaptation, the overall impact of typical weather shocks on hours worked is minimal for hourly workers. Specifically, each additional inch (2.54 cm) of weekly rainfall reduces weekly hours worked by only 12 minutes, with even smaller effects for snowfall and temperature extremes. In the long run, hourly workers in regions with higher annual precipitation exhibit less sensitivity to rainfall, suggesting that adaptation will mitigate future labor market disruption caused by projected increases in the frequency and severity of typical weather shocks.

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1 Introduction

As anthropogenic climate change is expected to increase the incidence and severity of typical weather shocks, it becomes increasingly critical to precisely identify the effect of weather on the labor market (IPCC, 2023). Estimates of the impact of these shocks are a fundamental input to models that assess the long-run risk climate change poses to workers and firms.

Despite the importance of these estimates, there is disagreement about weather's impact between two conflicting branches of literature. The first, a literature on intertemporal labor supply with roots in Lucas and Rapping (1969), finds that adverse weather events are associated with an *increase* in hours worked. The second, a newer literature on climate risk, finds that workers modestly *decrease* their labor supply in response to poor weather conditions (Dell, Jones and Olken, 2014).

This paper makes progress on this debate by studying the effect of non-extreme weather shocks on paid-weekly, hourly workers using administrative records from a large payroll processor. In contrast to the prior literature, my main finding is that rainfall, snowfall, and temperature shocks all have a minimal effect on the labor supply and demand decisions of most hourly workers and firms. After accounting for long-run adaptation, the effect of weather on hours worked is neither positive (as previously estimated in the intertemporal labor supply literature), nor negative (as previously estimated in much of the climate risk literature), but close to zero.

The use of administrative payroll data in this analysis provides a significant advantage in accuracy (i.e. reduced bias) and precision relative to prior studies that rely on survey data of time-use. Time-use surveys are prone to sampling bias, memory bias (Diener and Tay, 2014), and non-random, non-response bias (Hamermesh, Frazis and Stewart, 2005). In contrast, the reliability of payroll accounts – which underlie employer tax withholding data – is well established in the literature on tax evasion (Kleven et al., 2011; Adhikari, Alm and Harris, 2020).

Adapting the econometric specification in Graff Zivin and Neidell (2014), I estimate hourly workers' and firms' hours response to a variety of weather phenomena. I limit my analysis to hourly workers, because their no-show decisions impose the largest costs on workers, who forgo wages, and firms, which experience labor supply and salary disbursement disruptions. I find that an additional inch (2.54 cm) of weekly rainfall results in a 12 minute decrease in weekly hours worked for the typical paid-weekly, hourly employee. Taking the panel median 40-hour work week, this translates to a 0.5% reduction in weekly hours worked. The average worker in this panel experiences 0.86 inches (2.18 cm) of weekly rainfall with a 1 inch standard deviation. Snowfall and temperature effects are negligible, with an additional inch of snowfall reducing hours by just four minutes (0.16%). Temperature's effect on hourly workers is statistically indistinguishable from zero. As a result, subsequent analysis focuses primarily on rainfall-induced changes in hours.

After accounting for adaptation, the impact of rainfall on hours worked is even smaller than my headline estimate suggests. I find suggestive evidence that, in the long run, hourly workers and firms adapt as the climate becomes wetter. Employing methodology pioneered in Mendelsohn, Nordhaus and Shaw (1996) and Butler and Huybers (2013), I exploit county-level variation in average rainfall and document evidence that hourly workers and firms in drier counties are more affected by week-to-week variation in precipitation. In contrast, workers in wetter counties are less sensitive to rain, suggesting that the large rainfall-induced hours reductions observed in dry counties will moderate as climate change increases the frequency of typical rainfall events throughout the United States. However, I also find evidence of a likely upper bound to this adaptation as the largest projected increases in rainfall are expected in areas where further adaptation may no longer be possible. The impact of extreme weather events like hurricanes and drought on the labor market falls outside the scope of this short paper and is a promising area for future analysis using these data and research design.

This paper connects two branches of economic literature that provide conflicting estimates of the impact of weather shocks on labor supply and demand.

The first uses exogenous and transitory weather variation to understand worker substitution between work and leisure. Studies in this literature, which typically rely on time-use surveys, find modest substitution away from leisure (and toward labor) when it rains. Directly relevant is Connolly (2008) which employs data from the American Time Use Survey (ATUS) to estimate a structural model of intertemporal labor supply. The study finds that men work an average of 30 additional minutes on rainy days, but is unable to identify a significant effect for women. Using German time-use data, Krüger and Neugart (2018) finds an insignificant effect of rainfall on hours worked for both men and women.

The second body of literature quantifies the labor response to weather shocks to inform estimates of long-term climate risk. This literature finds that adverse weather, particularly higher temperatures, reduce both hours worked and worker productivity. As was the case for the intertemporal substitution literature, this literature is highly reliant on time-use surveys. Dasgupta et al. (2021) employs time-use surveys to find global evidence that workers supply fewer hours and are less productive when temperatures rise. Somanathan et al. (2021) observes comparable patterns in microdata from India while Garg, Gibson and Sun (2020) leverages a longitudinal time-use panel from China to arrive at the same conclusions. In the United States, Behrer and Park (2017) finds similar results using annual census data. Most relevant to this paper is Graff Zivin and Neidell (2014) which uses time-use data to show that high temperatures reduce daily hours worked in industries such as construction, where workers are more exposed to weather. However, given the small sample size of the ATUS, this analysis lacks sufficient statistical power to generalize to the broader workforce.

High-frequency administrative data provides a possible resolution to this disagreement. By overcoming the precision and accuracy limitations in the prior literature, I find that after accounting for long-run adaptation, typical weather shocks have a minimal effect on labor supply or demand for hourly workers. These findings suggest that hourly employees are unlikely to be substantially impacted by the projected rise in typical weather shocks caused by climate change.

2 Data and Benchmarking

The data used for this study is a panel of weekly weather conditions and worker earnings from 2628 firms in 438 U.S. counties between the years 2010 and 2023. The panel was constructed by combining de-identified administrative payroll records from an anonymous payroll provider (henceforth "PayrollCompany") with public daily precipitation and temperature records from the National Oceanic and Atmospheric Administration (NOAA).

2.1 PayrollCompany

The primary dataset used in this analysis comes from a large U.S. payroll provider servicing millions of workers across hundreds of thousands of firms. The data in this paper is taken from a 0.5% random sample of PayrollCompany firms that have maintained client relationships for more than three years and average more than five employees in each month.

The unit of analysis in PayrollCompany data is a "pay item," which captures a unique component of check-specific worker earnings and hours. In most months, the two most common pay items in PayrollCompany data are base pay and overtime. A single paycheck could – and often does – include multiple pay items where the sum of all items is what appears in the employees' bank account. Only pay items associated with hours worked have hours reported alongside pay. Items such as overtime and base pay have hours reported while reimbursements and bonus payments do not.

To facilitate linkage with the NOAA weather data, I take four steps to clean this administrative panel. First, I aggregate pay items such that the new level of observation becomes an individual worker's paycheck. Throughout my analysis, I use a worker's gross pay, or earnings inclusive of deductions such as retirement and health insurance contributions. Second, I remove salaried workers, who, by nature of their contract type, have significant flexibility over the time and location of their work day. In contrast, hourly employees' no-show decisions impose large costs on workers, who forgo wages, and firms, which experience labor supply and salary disbursement disruptions. Given hourly workers disproportionate contribution to labor market disruption, they serve as the relevant group for this analysis. As noted in Table 1, 60% of workers in PayrollCompany are hourly which matches a CPS benchmark of firms of comparable size to PayrollCompany. Third, I include only the 26.4% of workers who are paid weekly, the shortest duration between checks allowed among commonly used payroll frequencies. A short duration ensures that I observe hours reductions that are "made up" in the week following a rainfall event. This constitutes a limitation of payroll data which could be addressed by the use of time and attendance (punch-card) data in future research. Finally, I limit analysis to workers whose pay period ends at the end of the standard work week (Friday) as is the case for 73% of observations in my panel. By doing so, all workers in the same geographic area have their checks influenced by the same set of environmental factors.

2.2 NOAA Data

The secondary dataset used in this paper provides detailed daily accounts of global weather conditions at 72,287 NOAA weather stations. While stations track a variety of local environmental conditions including temperature, humidity, and pressure, I primarily focus on total daily rainfall, snowfall, and maximum temperature from 3,897 stations in the contiguous United States. Along with data on weather conditions, each weather station is associated with a coordinate pair. To align the time aggregation with that of PayrollCompany, I aggregate the daily, station-specific weather observations such that the level of observation in the primary analysis becomes the county-calendar week. For robustness, I construct a secondary sample where the level of observation is the zip code-calendar week. The primary variables of interest are total weekly rainfall and maximum temperature. I compute the first as the daily average of rainfall recorded at all weather stations within a county(or zip)-week cell multiplied by seven. I implement this smoothing procedure to avoid treating days without NOAA weather data as days without any precipitation. I compute the second as the number of days where the maximum temperature exceeds specified cut-off points. Section 3 provides additional explanation for the use of maximum, rather than average, temperature in my analysis.

2.3 Combining and Benchmarking

I combine weekly weather and payroll observations using a point-in-polygon spatial join to match zip and county-level weather observations to PayrollCompany client addresses. After cleaning and combining I am left with a panel consisting of 269,390 unique workers, 10.9 million individual paychecks, and 438 U.S. counties. The zip-code level robustness panel consists of only 4.8 million observations because many firms in the county-level panel are established in counties, but not zip codes with NOAA weather stations. Workers' locations are moderately geographically distributed throughout the contiguous United States, though concentrated in the Northeast and align with several public benchmarks (see Table 1).

2.4 Advantages Over Time Use Survey Data

The use of administrative payroll data in this analysis offers significant advantages in accuracy (i.e., reduced bias) and precision relative to prior studies that rely on time-use survey data (Krüger and Neugart, 2018; Dasgupta et al., 2021; Connolly, 2008).

First, time-use surveys are prone to bias absent in payroll data. Documentation from the Bureau of Labor Statistics notes that sampling bias and the inability to account for secondary

Table 1: Comparison to Representative Benchmarks

	PayrollCompany Panel	United States
Median hours worked per week	40 hrs.	40 hrs.
Median weekly earnings	$644	$640
Median hourly wage	$15.5/hr	$17/hr
Share of workers hourly	60%	60%
Share of workers paid weekly	26.4%	31.8%
Weekly average rainfall	0.86 in/week	0.88 in/week

Notes: The labor-related, representative benchmarks in the top four rows of this table come from the Current Population Survey using a sample of workers at firms with fewer than 100 employees who responded to both the Merged Outgoing Rotation Group survey and Annual Social and Economic Supplementfrom 2010 to 2023. Row five comes from the Bureau of Labor Statistics' Current Employment Statistics. The weather-related benchmark in row 6 comes from the NOAA 2020 Annual National Climate Report for the Northeastern region where the majority of firms in the panel are established.

activities limit the reliability of the ATUS. More concerning is evidence that these surveys often suffer from non-random, non-response bias linked to unobserved variables (Hamermesh, Frazis and Stewart, 2005) as well as memory bias documented in Diener and Tay (2014). Chou and Shi (2021) emphasize that measurement error in time-use data requires careful examination.

In contrast, the reliability of payroll data is well established in the literature on taxation as these data serve as the primary input for employer tax withholding. Both Kleven et al. (2011) and Adhikari, Alm and Harris (2020) demonstrate that tax evasion rates for employer-reported earnings are effectively zero, reflecting the accuracy of these accounts. Supporting this, Lachowska, Mas and Woodbury (2022) provides further empirical evidence of the reliability of administrative payroll data using records from Washington State.

Second, administrative payroll data allows for substantially larger sample sizes, enabling greater precision than time-use surveys. In comparison to Krüger and Neugart (2018), Connolly (2008), and Graff Zivin and Neidell (2014) which each analyzed fewer than 14,000 observations, this study utilizes 10.9 million observations from 269,000 employees. Differences in specification choices make direct comparisons of standard errors challenging. However, Graff Zivin and Neidell (2014), which employs a methodology most comparable to this study, reports standard errors that are approximately ten times larger than this analysis'.

3 Typical Weather Shocks Minimally Affect the Labor Market for Hourly Workers

This section describes the empirical relationship between typical weather shocks and changes in labor supply and demand for the typical hourly worker. I conclude that while rainfall has the largest effect on hours changes as compared to snowfall and temperature shocks, it is still not a large driver of the week-to-week variation in hours worked for paid-weekly, hourly employees.

3.1 Rainfall

In Table 2, I document evidence of a small but negative relationship between hours worked and weekly rainfall across all OLS specifications. To obtain these estimates I modify the econometric model in Graff Zivin and Neidell (2014) such that rainfall rather than temperature becomes the independent variable. In my preferred specification, I estimate:

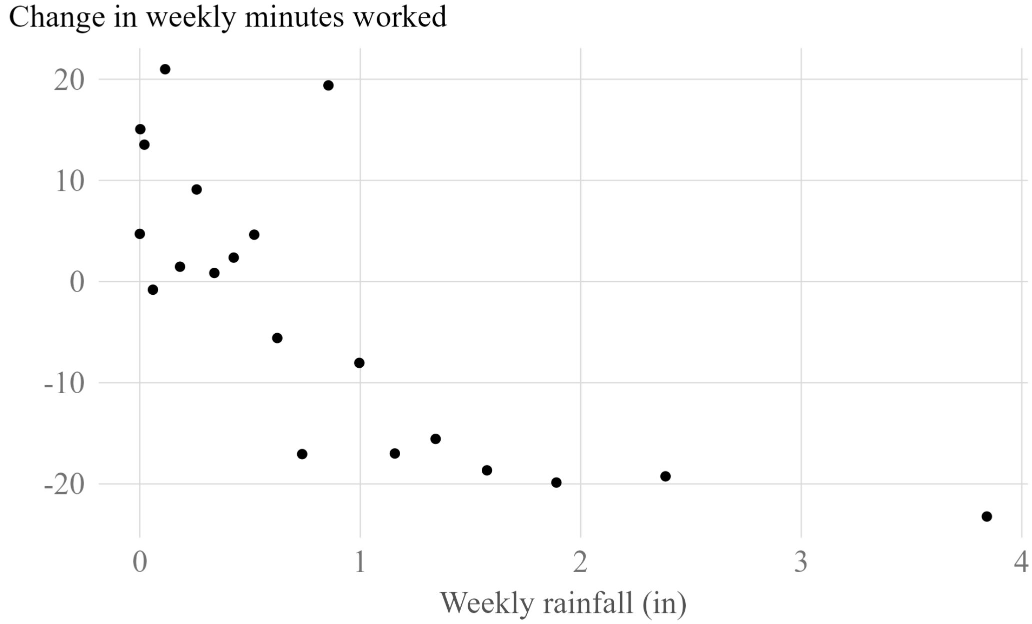
$$\Delta hours_{c,i,t} = \beta Rainfall_{c,i,t} + \delta Z_{c,t} + \gamma_i + \alpha_c + \rho_t + \epsilon_{c,i,t} \tag{1}$$

Let t represent the week a worker i is observed while c represents the county a worker i is observed in. The left-hand side then specifies $hours_{c,i,t} - hours_{c,i,t-1}$ or the change in labor hours, measured in minutes, reported for an individual i, in county c between periods t and $t-1$. I use first differences (rather than levels) to account for differences in workers' baseline hours. I make two small modifications to the right-hand side relative to Graff Zivin and Neidell (2014). First, unlike their model which permits non-linearity between maximum temperatures and labor, I find an empirical linear relationship between hours changes and precipitation for hourly workers (see Figure 1). To that effect, I estimate the right-hand side without this non-linearity. Second, I cluster standard errors at firm j to account for within-firm error correlation. Like Graff Zivin and Neidell (2014), I use week fixed effects ρ_t to control for seasonality and γ_i to capture the individual fixed effect. $\delta Z_{c,t}$ captures environmental and non-environmental, *time-varying* county-level factors such as humidity, sunlight, and changes in localized economic conditions while α_c captures environmental and non-environmental *time-invariant* county-level factors like climate and infrastructure.

Figure 1 presents the data without modification and shows that increases in weekly rainfall correlate negatively with changes in weekly hours worked for hourly employees. Under this unmodified, bivariate specification, summarized in column 1 of Table 2, I find that each additional inch (2.54 cm) of weekly rainfall correlates with an 11 minute (0.5%) decrease in hours worked. The 18.4% of worker-weeks with fewer than .01 inches (0.025 cm) of rainfall have a mean increase in hours worked of 11 minutes. This suggests that hourly workers substitute hours between rainy and dry weeks moderating the already small effect of rainfall on hours changes.

My reduced-form estimates, summarized in Table 2, show my results to be robust to a variety of specification choices. These estimates range from a 7 to 12 minute decrease in hours worked. As noted earlier, the first column of Table 2 summarizes the bivariate correlation between rainfall and hours worked for hourly workers that is visualized in Figure 1. Column 2 uses a two-way fixed effects specification to control for time-invariant worker characteristics and seasonality. Column 3 reports results from my preferred specification, the modification

Figure 1: County-level Rainfall and Hours Changes



Notes: This binscatter plots vigintiles of weekly rainfall for 10.9 million worker-week observations. On the x-axis, I plot $Rainfall_{c,i,t}$, as measured in inches per week. On the y-axis, I plot the change in weekly minutes worked ($\Delta hours_{c,i,t}$).

of Graff Zivin and Neidell (2014) specified in Equation (1). Coefficients across all three of these specifications are statistically indistinguishable. Columns 4, 5, and 6 add additional controls to column 3. Column 4 controls for the effect of snow as Section 3.2 indicates a role for snowfall in worker hours reductions. In column 5, I control for temperature. In line with Deschênes and Greenstone (2011) and Graff Zivin and Neidell (2014), I specify temperature non-parametrically as the number of days where maximum county temperature exceeds 90°F. Column 6 combines columns 4 and 5 by controlling for both snowfall and temperature. Controlling for each of these covariates minimally reduces my estimate for β. The seventh column changes the unit of spatial aggregation from the county level to the zip code level. In other words, I change c to represent the zip code an individual i is observed in rather than the county. This modification allows me to more granularly connect workers and their exogenous weather shocks at the expense of my ability to observe multiple firms within the same geographic entity. In nearly all cases, zip codes pair one-to-one with firms. Across all specifications, I find a small but statistically significant and negative relationship between rainfall and changes in hours worked for hourly workers.

3.2 Snowfall and Temperature

This section documents the effect of other environmental factors, such as snowfall and additional hot and cold days, on hours worked for the typical paid-weekly, hourly worker. In all cases, I find that these weather phenomena have an even smaller impact than rainfall.

Table 2: County and Zip-level Rainfall and Hours Changes

	Bivariate	TWFE	Baseline	Control Snow	Control Temp	Control Both	Zip Level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rainfall (in)	-11.426^{***}	-10.903^{***}	-11.866^{***}	-11.112^{***}	-9.725^{***}	-8.773^{***}	-7.129^{***}
	(1.216)	(1.261)	(2.087)	(2.267)	(1.971)	(2.078)	(1.283)
Snowfall (in)				-3.338^{**}		-3.360^{**}	
				(1.368)		(1.460)	
90+ degree days					0.299	0.235	
					(0.800)	(0.735)	
Observations	10,914,789	10,914,789	10,914,789	10,813,307	10,270,224	10,188,427	4,854,987
Adjusted R^2	0.0001	0.014	0.125	0.125	0.126	0.126	-0.007
Spatial aggregation	County	County	County	County	County	County	Zip code
Two way fixed effects		✓	✓	✓	✓	✓	✓
County fixed effects			✓	✓	✓	✓	

*p<0.1; **p<0.05; ***p<0.01

Notes: This table shows the relationship between rainfall and changes in hours worked for paid weekly, hourly employees measured in minutes. In columns 1 - 6, I define the geographical unit of observation, c, as the county. In column 7, I define the geographical unit of observation as the zip code. The lower number of observations in column 7 reflects the fact that some firms are located in counties but not in zip codes where NOAA weather stations are present. To control for high temperatures, I use the number of days in a week in which the maximum temperature exceeds 90°F. Standard errors are clustered by firm.

To arrive at these estimates I modify Equation (1), replacing $Rainfall_{c,i,t}$ with measures of temperature and snowfall. I assess hours changes associated with temperature extremes for hourly workers using the same non-parametric approach I employ in Section 3.1. I then evaluate the impact of snowfall for these workers using two specifications. First, I model hours changes as a linear function of snowfall. This resembles how I model rainfall in Table 2. Second, I treat snow as binary and evaluate the mean hours change differential between periods with and without heavy snowfall which I define as weeks with more than 3 inches (7.62 cm) of snow.

Table 3 summarizes evidence that rainfall's effect on hours changes for hourly workers is greater than that of temperature or snowfall. In column 1, I document the nature of snowfall's impact on hours worked, with each additional inch (2.54 cm) of snow reducing hourly employees' hours by four minutes (0.16%). Column 2 shows that significant snowfall events have a larger impact. In weeks with more than 3 inches (7.62 cm) of snowfall, hourly employees, on average, worked 40 fewer minutes. However, these events are rare, constituting only 4.8% of worker-week observations. In these data and given the weekly level of time aggregation, I see no evidence that high temperatures reduce the number of hours worked (columns 3 - 4) and only modest evidence that cold extremes induce hours changes for hourly workers.

While these null and minimal results clearly diverge from the literature's findings on *weekly* weather risk (Garg, Gibson and Sun, 2020), it is still possible that interday substitution is responsible for my estimates' divergence from daily data. Indeed Graff Zivin and Neidell

Table 3: County-level Weather and Hours Changes

	Snow	Snow > 3 in	Temp > 85°F	Temp > 95°F	Temp < 30°F	Temp < 15°F
	(1)	(2)	(3)	(4)	(5)	(6)
Snowfall	-4.021^{***}	-40.762^{***}				
	(1.329)	(11.655)				
Additional hot days			0.893	1.701^{*}		
			(1.098)	(0.966)		
Additional cold days					-9.321^{**}	-19.610
					(4.229)	(13.760)
Observations	10,813,307	10,813,307	10,270,224	10,270,224	10,270,224	10,270,224
Adjusted R^2	0.125	0.125	0.126	0.126	0.126	0.126

*p<0.1; **p<0.05; ***p<0.01

Notes: This table summarizes regression coefficients across six modifications of Equation (1) measured in minutes. All columns use two-way as well as county-fixed effects with spatial aggregation at the county level. The independent variable in columns 3-6 is the number of days where the maximum temperature exceeds, or is below, the specified degree cut-off. Standard errors are clustered by firm.

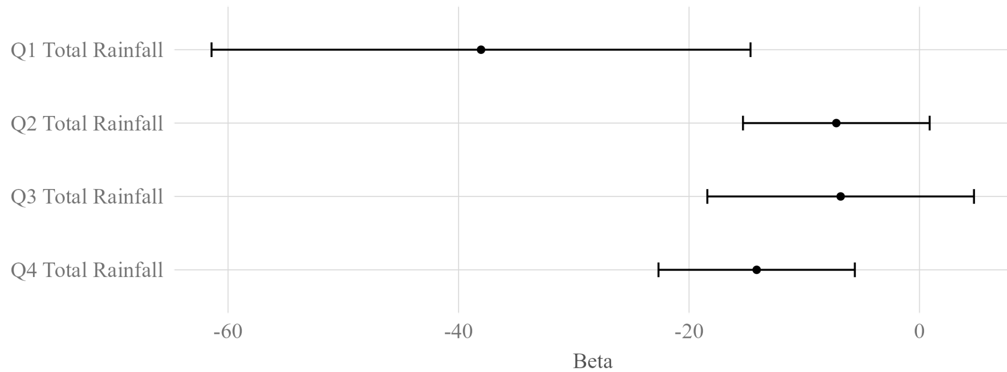
(2014) find that hours changes from high temperatures are often substituted intraweek and even intraday. Given the weekly frequency of workers' pay schedules, I am unable to observe the high-frequency substitution documented in Graff Zivin and Neidell (2014) and thus cannot fully rule out the possibility that my results align with prior estimates of daily weather risk.

4 Rainfall's Impact on Hourly Workers is Moderated by Long Run Adaptation

In this section, I exploit county-level differences in annualized rainfall to document suggestive evidence that hourly workers and firms will adapt to projected climate change, attenuating the effect of rainfall on hours changes. However, spatial heterogeneity in where rainfall is expected to increase along with the small, persistent effect of rainfall in all counties suggests an upper bound for possible adaptation. I use two methodological approaches summarized in Kolstad and Moore (2020) to estimate the extent of adaptation. Each utilizes natural climate variation to compare the marginal effect of rainfall on hours changes in areas where rain is more common to areas where rain is less common. I use rainfall, rather than snowfall or temperature, as the independent variable throughout the subsequent analysis given its comparatively large effect on hours changes relative to other weather phenomena.

First, I employ an approach pioneered in Mendelsohn, Nordhaus and Shaw (1996) that compares the effect of short-run weather changes on economic outcomes in differing climates. Figure 2 visualizes this comparison by plotting β from Equation (1) for four quartiles of average annual rainfall. Each row represents one quarter of all county observations. Observations in the lowest quartile (Q1) represent counties where annual precipitation is the lowest while workers in quartile four (Q4) experience the highest levels of annual precipitation in the panel. The geographic concentration of firms in the northeastern United States leads to similar amounts of annualized rainfall in quartiles two through four.

Figure 2: Climate Heterogeneity in Rainfall-induced Hours Changes



Notes: This figure plots β from $\Delta hours_{c,i,t} = \beta Rainfall_{c,i,t} + \delta Z_{c,t} + \gamma_i + \alpha_c + \rho_t + \epsilon_{c,i,t}$ for 4 quartiles of average annual rainfall. Horizontal whiskers represent 95% confidence intervals which test the hypothesis that β is significantly different from zero. The average annual rainfall in quartiles 1, 2, 3, and 4 are 26.6, 44.9, 50.0, and 56.7 inches (67.6, 114.1. 127.0, and 144.0 cm) respectively.

My primary finding from this cross-sectional approach is that hourly workers and firms in counties with low levels of rainfall have a larger hours response to precipitation than workers in wetter climates. I view this as suggestive evidence that workers will adapt to the projected increase in typical weather shocks. Anthropogenic climate change will increase rainfall such that counties in the first quartile will have long-run rainfall levels closer to the second quartile. This will likely decrease the marginal effect of rainfall on hourly workers in drier (first quartile) regions.

Next, I employ the two-stage approach developed in Butler and Huybers (2013). For the first stage, I run regressions similar to those specified in Equation (1) for each county (c) in the panel such that I have an estimate β_c for each county cell. Doing so necessitates that I remove county-level fixed effects from the regression. Second, I regress:

$$\beta_c = \eta AvgRainfall_c + \epsilon_c \tag{2}$$

where β_c is the resulting set of coefficients from the first stage and $AvgRainfall_c$ denotes the average annual rainfall in county c. My estimate for η, which qualitatively mirrors the findings visualized in Figure 2, show that when average annual precipitation increases by one inch (2.54 cm), the marginal effect of one inch of rainfall on hourly workers' hours decreases by 1.5 minutes. In other words, as regional climates become wetter, rainfall becomes less disruptive for hourly workers. Concerns of omitted variable bias in these approaches by, among others, Schlenker, Roberts and Lobell (2013) along with the focus on typical, rather than extreme, weather shocks, make this evidence merely suggestive.

My second finding is that there is likely an upper bound on adaptation for hourly workers. I see two reasons for this. First, the value for β in Q2 - Q4 suggests a persistent, small, non-zero effect of rainfall on hours worked even as regional climates become wetter. While the wettest counties see less labor market disruption for hourly workers, they still see some. Second, within the United States, the extent of adaption will be limited by spatial heterogeneity in climate change's predicted impact on local rainfall. While country-wide rainfall is expected to rise, estimates from an average of ten climate models complied by the Royal Netherlands Meteorological Institute (KNMI) predict that southwestern states will see a 15% decrease in average annual rainfall while regions in the Northeast will see a 10% increase. Many (though not all) of the regions in Q1 will thus maintain their high β as they will not be forced to adapt to increased rainfall. On the other hand, most regions in Q2 - Q4 will indeed see an increase in rainfall but are approaching their previously discussed adaptation upper bound. These regions' β values may get smaller, but will likely never reach zero.

While spatial heterogeneity in climate change's impact may limit the extent to which labor market disruptions are moderated by adaptation, the existence of an upper bound is only further evidence of rainfall's limited effect on hourly workers and firms. Average rainfall is expected to increase in precisely the areas where its impact on hourly workers is the least significant and decrease in the areas where its impact is greatest.

5 Conclusion

In this paper, I leverage administrative records from a large payroll processor to document weather's limited impact on paid-weekly, hourly workers in the U.S. labor market. These findings make progress on a debate between the intertemporal substitution and climate change literatures which have been limited by their use of time-use surveys. I find that rain generates a small reduction in labor hours supplied and demanded while snowfall and temperature have a minimal effect on hourly workers. Weather's small effect is further moderated by long-run adaptation to climate change. Precise estimates of these shocks are fundamental to models that assess the long-run risk climate change poses to workers and firms.

These findings suggest three possible directions for future research. First, the majority of my analysis explores the impact of short-run weather changes. While I begin to quantify the potential long-run effects of increased rainfall, models like those used by Auffhammer (2018) and Heutel, Miller and Molitor (2021) could provide better answers regarding the long-run impact of increased precipitation and temperatures. Second, while I focus on hours changes and risk for *workers*, additional research on *firm-side* risk could provide a more holistic view of weather's impact on the U.S. labor market. Third, my results suggest a large degree of intraweek and intraday hours substitution, particularly in response to temperature extremes. Administrative data on workers' daily time and attendance would answer the high-frequency substitution questions raised here and in Graff Zivin and Neidell (2014) without the shortcomings associated with time-use surveys.

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